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Fuzzy Detection of Events in driving for DriveSafe Application

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"Fuzzy Detection of Events in driving for DriveSafe Application"

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Quiero aprovechar estas líneas para agradecer a todas aquellas personas que de alguna manera me han ayudado y han hecho posible que haya llegado hasta aquí.

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Resumen

En los últimos años, ha habido un creciente interés en monitorizar el comportamiento de los conductores usando para ello “smarphones” dada su alta tasa de penetración en el mercado. Los sensores inerciales embebidos en estos dispositivos son clave para realizar esta tarea de monitorización. La mayor parte de aplicaciones hoy en día hacen uso de umbrales fijos para detectar los eventos que se producen en la conducción a partir de los datos aportados por los sensores inerciales. Sin embargo, los valores dados por los sensores puedes ser distintos ya que dependen de muchos parámetros. En este documento presentamos un clasificador adaptativo basado en Lógica Borrosa para identificar repentinas acciones que se producen en la conducción (acelerones, frenazos, volantazos) así como baches e irregularidades presentes en la carretera, a partir únicamente de la información de los sensores inerciales y el GPS. En primer lugar, se propone un método de calibración continuo para ajustar los umbrales de decisión de las funciones miembro, para determinar la posición del teléfono y las características dinámicas del vehículo. En segundo lugar, se desarrolla una capa de alto nivel para hallar otras maniobras que realice el conductor y puedan ser útiles para evaluar su comportamiento. Para validar el clasificador usamos la base de datos UAH-Driveset que incluye más de 500 minutos de conducción naturalista, y comparamos los resultados con los obtenidos en la anterior versión de DriveSafe, basada en umbrales fijos. Los resultados muestran una notable mejora en la detección de eventos respecto a la anterior versión.

Abstract

In the last years there has been a rising interest in monitoring driver behaviours 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 document, we present an Adaptive Fuzzy Classifier to identify sudden driving events (acceleration, steering, braking) and road bumps from the inertial and GPS sensors. Firstly, 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. Secondly, a high-level layer is developed to find other manoeuvers performed by the drivers and can be useful to assess driver behaviour. To validate our method, we use the UAH-Driveset database, which includes more than 500 minutes of naturalistic driving, and we compare results with our previous DriveSafe app version, based on fix thresholds. Results show a notable improvement in the events detection regarding our previous version.

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Chapter 1

Introduction

1.1. Motivation

In 2015, more than 26,000 people lost their lives on EU roads. The European Commission estimates that 135,000 people were seriously injured this year on EU roads. The social cost (rehabilitation, healthcare, material damages, etc.) of road fatalities and injuries is estimated to be at least €100 billion [1]. Studies about accident causation, like NHTSA's [2], attribute 94% of accidents to driver-related reasons, such as distraction or inattention. In addition, driver distraction has been a growing phenomenon in recent years and it is becoming a major contributing factor in road crashes [3].

In the last few years, a lot of researches have been performed towards developing systems that make safe driving. [4] [5]. Some advances are lane departure warning, collision-avoidance, blind spot warning and driver inattention monitoring systems. Even there are systems with trigger automatic steering when the vehicle drifts into another lane or brake before getting dangerously close to the vehicle in front/obstacle. While these systems are quite valuable in enhancing the safety, they are pricey too. Therefore, these safety features are commonly fitted only in top-end vehicles. An affordable alternative for bringing safety features to vehicles that they do not have it, it is to leverage Smartphone since people always carry it with them.

Furthermore, other smartphone advantage is to have access to mobile sensing platforms which facilitates the cost-effective capturing and processing of data from the real world, thus increasing the information base of business processes and decision making [6]. Such data are of great value for motor insurance companies, as they can be applied to improve the assessment, communication and mitigation of insured risk, thereby creating benefits for insurers and policyholders. In the current insurance markets, consumers have rejected the so-called Pay-As-You-Drive due to two main reasons [7]: it is required installation of "black-boxes" in vehicles, which makes drivers perceive the monitoring as intrusive, and the installation and operation of these units incurs in additional costs to insurers and consumers. Our alternative approach is to use a smartphone application that is operated at the users discretion, emphasizing that it is more a driving support tool than a "black-box" monitoring device.

Using the information obtained from some inbuilt smartphone sensors, there are applications that apply techniques on the device to detect the most commonly occurring inattentive driving behaviours. But in order to apply the appropriate techniques for correct identification of manoeuvers and events driving, it is necessary to have a complete database and organized with the data captured by the smartphones sensors. Last but not least, it is essential to have tools that allow us to correlate the data provided by these sensors with the manoeuvers and events happening while driving.

The present Master Thesis takes as a starting point the application DriveSafe presented in [8] to try to enhance its event detections. Three main items have been followed in the development of This thesis as the targets to improve in the current version of DriveSafe: Firstly, we have developed a new detector of events in driving based on Fuzzy Logic along with the use of new data inputs, with the aim to improve the events detection (acceleration, braking, steering) and also to detect new events as are the bumps. Secondly, we focus on the fact that the application lacked of an adaption process to the vehicle performance, then, we have implemented a calibration mechanism to set the thresholds for events detection for each user. Finally, it has been created a layer at a high level of decision for a more thorough analysis of the events found out in the detection phase along with the other information that gives us the application in order to identify risky driving manoeuvers such as overtaking, gear shifts and overtaking attempts, This high level layer has been implemented by a Finite State Machine (FSM).

1.2. Related Work

The systems used by many auto manufacturers [4] [5] are based on onboard vehicle-mounted devices to detect inattentive driving events. Those companies use radars as well as laser or cameras for this purpose. However, none of the cited examples consider the limitations and challenges of a smartphone-based implementation.

Although the cost of vehicle safety technology is dropping in the last few years, most safety technologies are not available in economy vehicles and it will be a decade before the vast majority of cars on the road today have these safety features built-in. In contrast, smartphone solutions can be used in all vehicles (new or old) and represent a cheap alternative. This is the main reason why in the last years there has been an active work on using smartphones to assist drivers. Hereafter, we classify some applications assessing driver behaviour depending on the requirements of the proposed solution:

- *Driver Assistance Systems* (DAS) have become increasingly popular with the advances in vehicle technology [9]. There are many reasons for this increase in popularity, most importantly road safety, as drivers are normally unaware of the fact that they committee potentially dangerous daily actions [10]. Real-time analysis and auditory alerts of risk will increase a driver's overall attentiveness and maximise safety [11]. DAS can mitigate or prevent road accidents by providing supportive information on approaching traffic in various circumstances. Therefore, these DAS are specifically developed to enhance, automate and adapt vehicle systems for improved safety, enriched driving experience and improved travel comfort. Advanced driving assistance systems (ADAS), such as lane-changing warning systems, forward collision warning systems, have been introduced lately by vehicle manufacturers in an attempt to address driver safety [11]. Some available applications for smartphones are Drivesafe [8], Augmented Driving [12] and iOnRoad [13].

- *Drowsiness Detection*: Many possibilities exist for monitoring drowsiness, depending on the type of sensors used, which could include steering wheel gripping force measures, lane keeping drift and instantaneous swerving patterns. Driver biomedical evaluation can prove very effective in real-time determination of driver drowsiness, but requires for instance electrodes attached to the body of the driver. This approach is extremely invasive, and may cause irritation of the driver. Instead, driver performance approaches involve variations in the lateral position of the vehicle, steering wheel angle, velocity, acceleration and lane keeping drift [14] . This approach is ideal due to meaningful and easily accessible data, and has already entered commercial markets like as DriveSafe [8] or CarSafe [15].

- *Eco Driving*: According to [16], the difference in fuel consumption (and thus gas emissions) between a normal driving style and an aggressive driving style is estimated to be above 40%, in favour of the normal driving style. Some tools for fuel consumption reduction are Ecosmart and TutorDrive [17]. Therefore, an eco-friendly driving style can be maintained avoiding sudden accelerations, rapid braking, and cornering actions. Others solutions based on the use of a driver scoring, get to reduce fuel consumption using a smartphone (DriveSafe, MobiDriveScore, Aviva RateMyDrive…)

- *Fleet Management:* Through effective fleet management, companies can minimise the risks for vehicles and drivers, improving the efficiency of their service and reducing the overhead costs. Feet management systems that utilise two-axis accelerometer and GPS readings, are [18], MIROAD and applications like SenseFleet [19] and Greenroad [20].

- *Road Condition Monitoring*: A pattern recognition system on a smartphone was developed in [21] that detects road condition from accelerometer and Global Positioning System (GPS) readings. This was accomplished through spectral analysis of tri-axis acceleration signals to find out the road surface anomalies. The accelerometer data and techniques used in this application are similar to those applied in classifying driving styles, and therefore it is concluded that road surface condition monitoring functionality can also be adopted in the applications of driving style and driver behaviour analysis, through driver-vehicle coupling techniques.

- *Accident Detection*: Certain early-accident detection applications include immediate dispatch of emergency services and road-side assistance services directly upon accident detection [22]. This means that emergency assistance services can be aware of accidents, and the severity thereof, before or without the incident being reported. Accidents can be detected based on impact readings based on longitudinal and transversal acceleration measurements.

- *Early-Warning Applications*: One way to reduce the risk is to warn the driver prior to an incident of the risk, which can either be distraction, aggression, drunk driving or external risk originating from another vehicle or object. Computer-vision alert systems exist such as DriveSafe [8], a driver safety application identifies inattentive driving styles and provides relevant feedback to drivers, and SmartV [23], an intelligent vigilance monitoring smartphone application to prevent road traffic accidents with audible smartphone alerts.

- *Hijacking/ theft Detection*: A valuable application using driver behaviour and driving style analysis techniques would be able to detect hijack occurrence shortly after the hijacking took place, by recognising different driving patterns and notifying authorities of suspicious activity and the possibility of a hijacking having just occurred. This application can assess the driver's behaviour and is based on differences identified between the different driving styles. Therefore, the application might be able to infer that another driver is driving the vehicle [14].

- *Insurance Applications*: The insurance industry, especially the motor insurance sector, generally calculates their premiums basing on statistical data through the evaluation of factors that are believed to impact over expected costs of future claims. These factors include among others, the type of vehicle, the value and characteristics of the vehicle, as well as the profile of the driver (age, gender, marital status, driver experience, etc.), which do not always fairly represent each individual driver's propensity to risk [14]. However, driving behaviour analysis can assist to provide a more accurate representation of an individual. Some applications are Aviva RateMyDrive [24], StateFarm DriverFeedback [25] and AXA Drive [26] (one of the most popular mobile applications to score driving of insurances companies).

On the other hand, it is noticed that there is a relationship between the used algorithms and the detected driver behaviour or driving style. In the following table it is shown that relation:

Driver Behaviour / Driving Style	***Algorithms***
Drowsiness detection	Artificial Neural Networks (ANNs), Fast Fourier Transform (FFT), Decision Trees, Support Vector Machines (SVM)
Driver distraction detection	Computer vision techniques, Hidden Markov Models, Gaussian Mixture Models (GMMs)
Steering prediction	Computer vision techniques
Driving style distinction	Clustering techniques, Fuzzy Logic, Hidden Markov Models
Individual driver identification	k-means clustering techniques
Road condition monitoring	k-means clustering techniques, Gaussian Mixture Models (GMMs)
Driver manoeuvre recognition	State Machine, Hidden Markov Models, Gaussian Mixture Models (GMMs)
Driver decision making modelling	Finite State Machine (FSM)
Driver fatigue detection	Fuzzy Logic
Distraction identification	Fuzzy Logic
Scoring applications	Fuzzy Logic
Driver risk profile classification	Dynamic Time Warping (DTW)
Driver assistance	Dynamic Time Warping (DTW)
Predict and model human behaviour	Kalman filter
Driving event detection	Support Vector Machines (SVM),
Vehicle state estimation	Support Vector Machines (SVM)
Calibration process of car following	Genetic Algorithms

Table 1.1: Algorithms used to evaluate the driving styles [14]

Most of the state-of-the-art proposals for detecting acceleration, braking or steering events from inertial sensors are based on fix thresholds [27] . In the previous version of DriveSafe [8], 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 [28], 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 [29], 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 manoeuvers) 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.

1.3. Objectives

By the start of this Thesis, DriveSafe is an application for mobile devices that is available for several months. The purpose of this work is to make a first phase of analysis of the techniques used by the application in its current state, to subsequently propose improvements in the modules that enhance its functionality and try to transform it in one of the most complete sensing platforms that there is available for smartphones in these days. Thus, the objectives of this work might be divided in three main contributions:

- **Detector of events based on Fuzzy Logic:** It has been designed and developed a new detection of events in the driving based on Fuzzy Logic instead of fix thresholds. Furthermore, it has taken new input variables, with the aim of improving the results obtained so far and find new types of events useful to assess the behaviour of drivers (e.g. bumps).
- **Calibration process:** Different vehicles have different acceleration, braking and steering patterns, in order to detect events independently of vehicle conditions, we propose a calibration process to establish the boundaries of the Fuzzy Membership functions for input variables in order to standardize their behaviours.
- **High-level analysis:** A Finite State Machine (FSM) has been implemented to process the events detected by the fuzzy classifier adding information given by other DriveSafe modules in order to identify risky driving manoeuvers such as overtaking, gear shifts and overtaking attempts.

1.4. Document structure

Chapter 2: DriveSafe App Description

This chapter introduces DriveSafe. It describes the current state of the application modules, which is the starting point of the contributions of the present work and a brief analysis of the modules to improve.

Chapter 3: DriveSet and DriveReader

It describes DriveSet database and tools that help in the analysis of driving behavior. It delves into the structure in the database and the available tool to correlate the expert knowledge with the information given by the sensors.

Chapter 4: Fuzzy Logic classification

It explains how a new classification of events in the driving has been designed and developed, based on fuzzy logic. And the new used data inputs and the detected events are detailed as well.

Chapter 5: Calibration method

It defines the techniques and the used method to calibrate the thresholds of the algorithm (used for the detection) to get a correct adaptation to the characteristics target vehicle.

Chapter 6: High-level analysis

It describes, the algorithm implemented in order to find out new events that are performed by drivers and these manoeuvres are interesting to evaluate the driving behaviour.

Chapter 7: Conclusions and Perspectives

It contains conclusions and future work discussion.

Chapter 2

DriveSafe App Description

This chapter introduces DriveSafe App. This section describes and analyzes all the features that were already developed and constitutes the starting point of this Thesis.

DriveSafe is a sensing platform that collects data to evaluate and profile driver behaviours. During driving, it shows information of the road by augmented reality and alerts driver of several events. At the end of each trip, the driver receives a score and is allowed to review all the trip information to learn how they performed and what they can do to improve their driving skills. DriveSafe is strictly not designed to replace, substitute or complement any vehicle control system but to alert and valuate driving behaviours to encourage safe driving.

2.1. Architecture

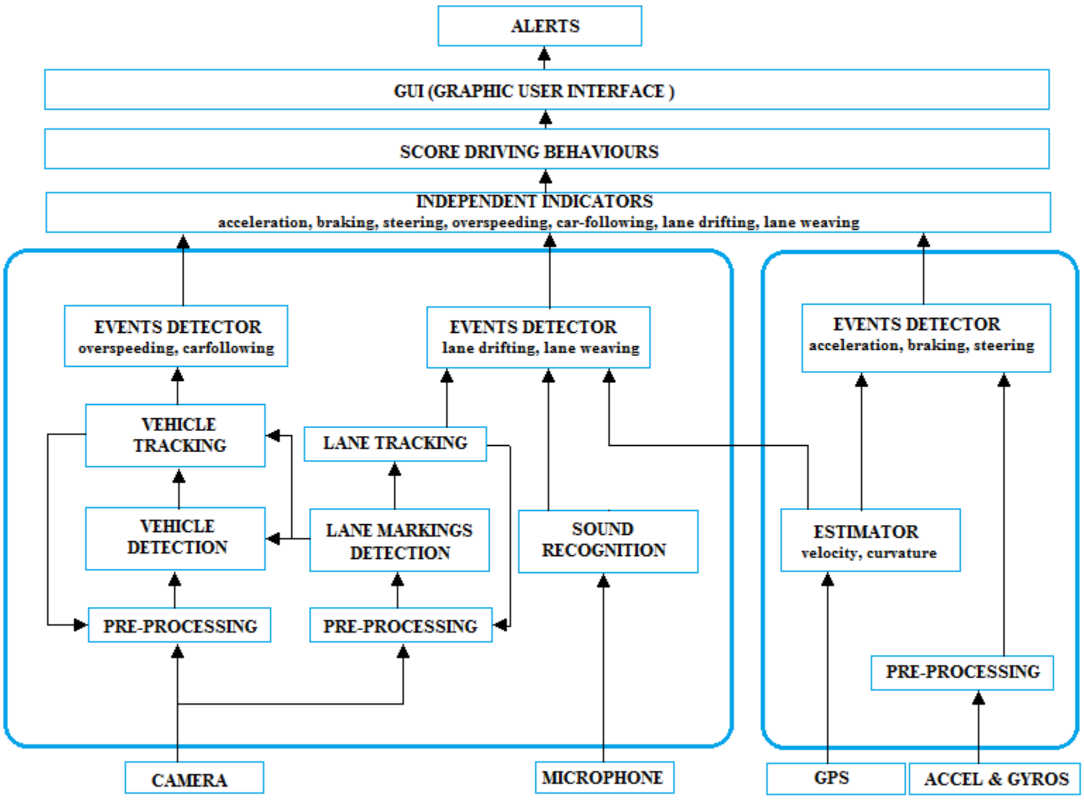


Figure 2. 1: Architecture of DriveSafe App

DriveSafe makes use of all the available sensors on the smartphone to evaluate driving. Fig. 2.1 shows the full architecture of the application. The images captured by the camera are processed in order to detect the road markings and obtain an estimation of the vehicle position with respect to the driving lane. The microphone is used to analyse the turn signals to infer whether a lane change is voluntary or involuntary. Also the images captured are used for the vehicle detection and tracking. The GPS provides speed and course information. Finally, the inertial sensors (accelerometers and gyroscopes) are used to detect sudden acceleration, braking and turning events. All together is used to produce scores and infer driving states according to seven independent indicators (sudden accelerations, sudden brakings, sudden turnings, lane drifting, lane weaving, overspeeding and car-following).

The present Thesis improves the inertial processing module that is presented in the scheme in Fig. 2.1. and it will be explained in Chapters 4 and 5. Finally a high level module is added to detect some new events to produce richer behaviour modelling based on more specialized indicators.

2.2. Interface

DriveSafe App was developed with the aim to evaluate the drivers and give feedback in order to help them to improve their driving. A clear interface achieves this target, avoiding to introduce additional distractions in the driving environment.

2.2.1. Start and calibration

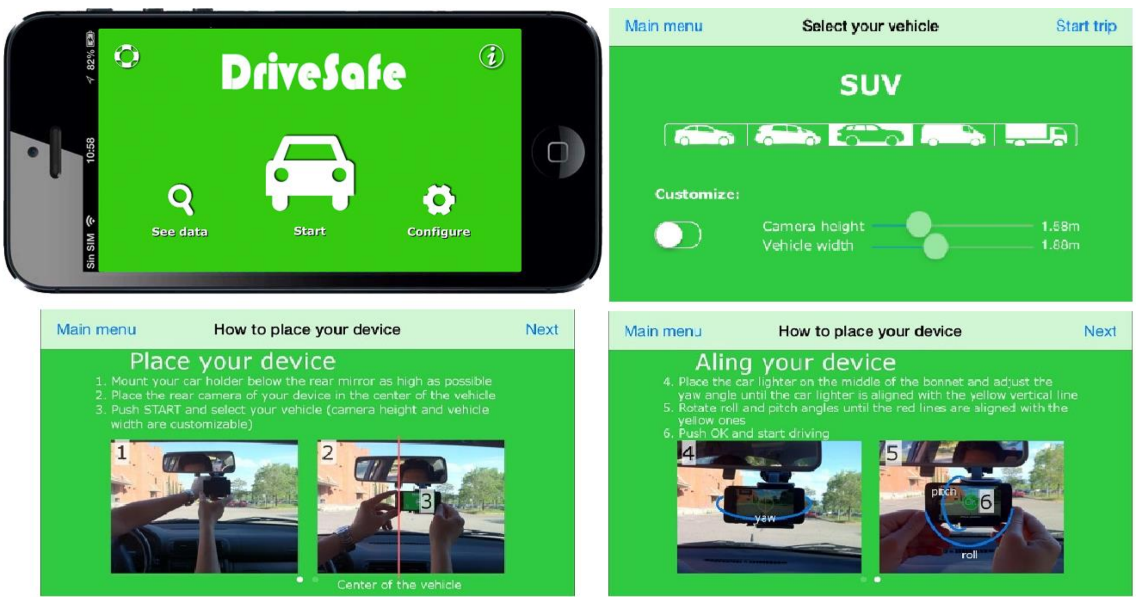


Figure 2. 2: Some captures about the start and calibration process.

As it is shown in Fig. 2.2, the initial interface allows the user to start a new route by introducing a reduced set of parameters of the vehicle and performing a simple calibration process which sets the smartphone in the correct axis with respect to the ground. This process is assisted by the smartphone gyroscopes, so the driver must only make sure that the phone holder is approximately centred in the wind-shield and then slightly rotated regarding to until two simple axis lines painted on DriveSafe interface become.

2.2.2. Driving Interface

During the driving, DriveSafe shows road information in the form of augmented reality. This information comprises:

- Detected road lane, with a coloured indicator that depicts position inside lane.
- Detected vehicles, with their distance and time to impact (respect to own speed).
- Speed obtained by GPS.
- Inattention indicator with 6 coloured levels.
- Several labels that pop up on different events such as lane departures, rest recommendations, etc.

With the aim of avoiding the driver to regularly look at the smartphone and hence distracting the driver, DriveSafe also produces sounds to indicate some events, such as “too close to ahead vehicle”, “close to lane change” and “lane change produced”. The user might also disable the augmented reality interface to avoid any distraction.

2.2.3. End of the Route

A view in the form of a list of trips (Fig. 2.3) allows the user to review each of the trips performed with the application. By clicking individually on each item, another view (Fig. 2.4) shows all the information available for that specific route: list of scores, list of inertial events, route statistics, access to map view and recorded videos.

The map view (Fig. 2.5) allows the user to review the trip route and find all the driving events located on the map. Different tags display the importance of each event and the route sections are coloured according to the inattention score that the driver had on that specific kilometre.

DriveSafe also records short videos on the detection of very remarkable inertial events. On a normal driving environment, events such as accelerations, brakes and turns are common during the driving operation and do not necessarily suppose a dangerous situation. However, a significant event such as a sudden brake that highly exceeds the average braking level might indeed precede an accident. Upon the detection of a sudden event, a video buffer of 10 seconds (kept during driving) is put together with the ten seconds posterior to the event, producing a video 20 seconds long. The speed during the recording is tagged in each frame. These videos might be reviewed together with the route information, and they might be useful for the driver in order to learn what was the cause that produces that event (e.g. following ahead vehicle too close) or even as a tool to clarify an accident.

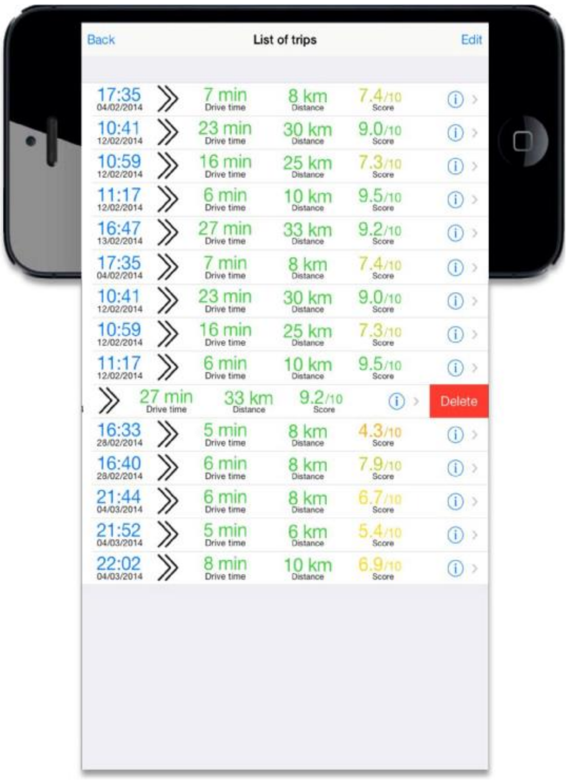


Figure 2. 3: Route selection.

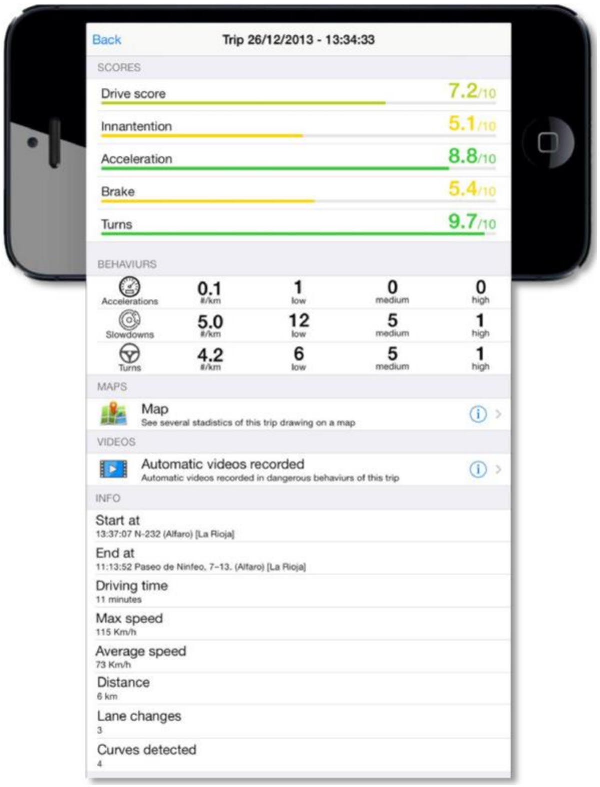


Figure 2. 4: Scores and route information.

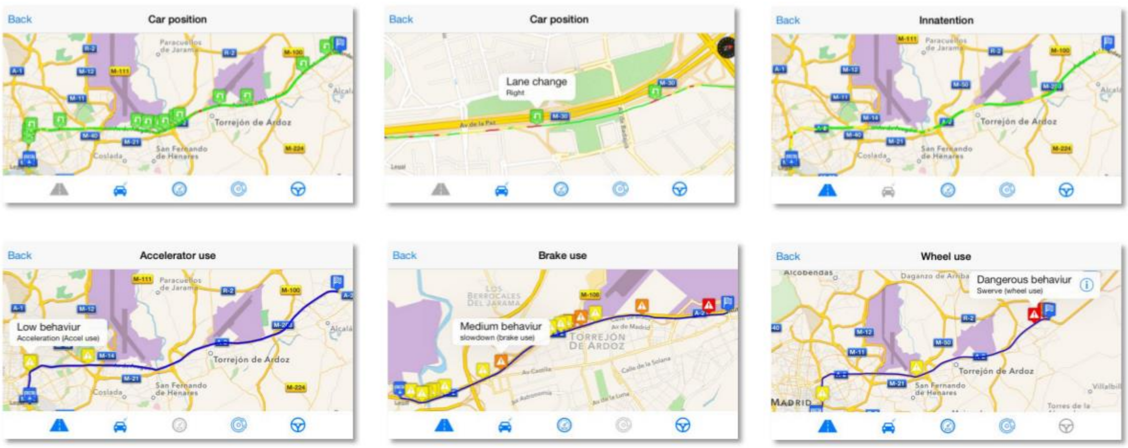


Figure 2. 5: Remarkable information of the route depicted on the map.

2.3. Inertial sensors

As shown in Figs. 2.6 and 2.7 the smartphone is positioned in a specific way on the calibration process. This allows to differentiate the driving axes between longitudinal and lateral. Thus, the accelerometer values in axis Z are used to detect sudden accelerations and brakings, and the values in axis Y are used to detect sudden turnings on the road.

Figure 2. 6: Initial phone positioning.

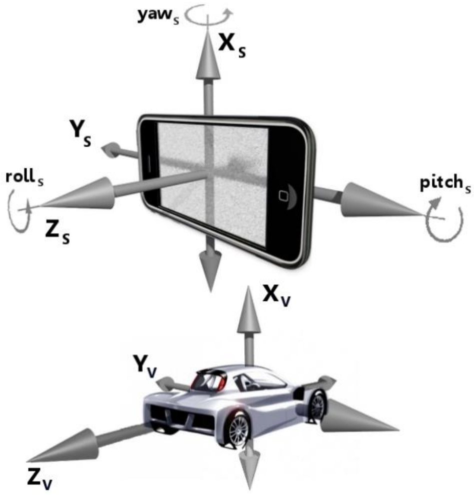


Figure 2. 7: Coordinate frame of iPhone vs vehicle

2.3.1. Capture data of Inertial sensors

One of the most suitable measurements to evaluate driving are inertial sensors. Nowadays, almost every smartphone carries a set of accelerometers in every axis (X,Y,Z) and gyroscopes (pitch, roll, yaw). In the case of gyroscopes, they are only used in the calibration process to position the device perpendicular to ground, aligned with longitudinal and lateral vehicle axis. Accelerometers, however, are an excellent way of evaluating the brusqueness of movement during driving. Sudden accelerations, braking or turnings often imply a distraction, or an aggressive behaviour if they are frequent.

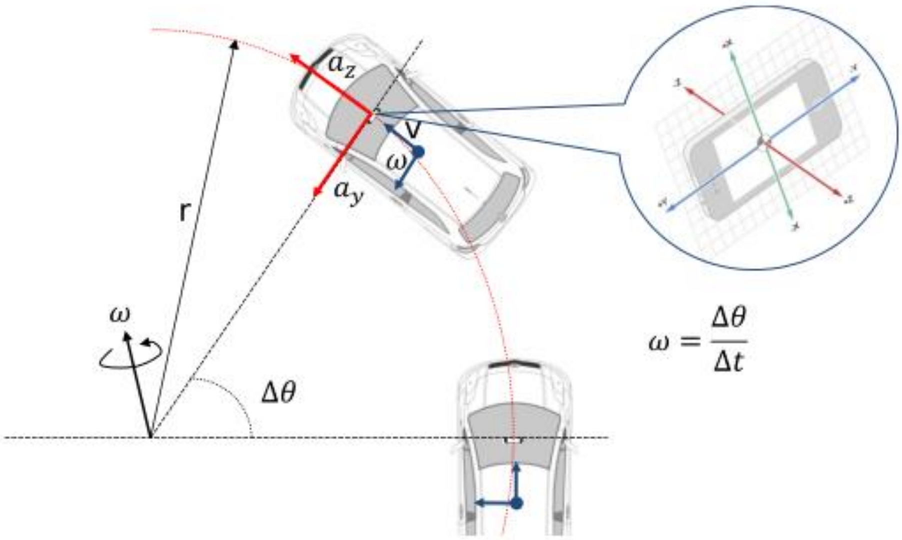


Figure 2. 8: Coordinate frame of iPhone vs vehicle

As it is depicted in Fig. 2.8, the phone is positioned in a way such that Z axis is aligned with the vehicle's longitudinal axis, and Y is aligned with the vehicle's lateral axis. Thus, a sudden positive increase in Z accelerometer represents 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, and therefore the driver is not maintaining a minimum distance to the ahead vehicle. Finally, high increases or decreases in Y axis are indicatives of excessive velocity in left or right turns, which may result in the vehicle loosing traction.

2.3.2. Pre-processing

Accelerometer data are sampled at a rate of 100 Hz. The raw data from the iPhone contains significant amounts of noise from the vibrations on board the vehicle. Thus, this signal is cleaned using a Kalman filter with a state vector formed by the three components of the accelerometer (ax, ay, az). The filtered features prove to be highly correlated with the vehicle movements.

2.3.3. Event Detector

We use a triple threshold that comprises a minimum absolute acceleration value, a minimum time period during which this value is exceeded and a minimum longitudinal velocity of 50 Km/h. Moreover, each event is identified with its intensity (low, medium, high) depending on the fixed thresholds in Table 2.1. When an event is activated, a hysteresis period is enabled to account for potential activations in the near future.

Event Type	Threshold sensitivity		
	Low	Medium	High
Acceleration	$0.1g < a_z < 0.2g$	$0.2g < a_z < 0.4g$	$a_z > 0.4g$
Braking	$-0.1g > a_z > -0.2g$	$-0.2g > a_z > -0.4g$	$a_z < -0.4g$
Turning	$0.1g < \lvert a'_y \rvert < 0.2g$	$0.2g < \lvert a'_y \rvert < 0.4g$	$\lvert a'_y \rvert > 0.4g$

Table 2. 1: Distraction event thresholds.

To decouple the lateral acceleration due to the road curvature from the one caused by wrong driver movements. When a vehicle makes a turn, it experiments a centripetal force, which has its direction orthogonal to the direction of movement of the vehicle and toward the centre of the turn. This centripetal force generates a centripetal acceleration, a, also pointing towards the centre of the curve. Assuming a turn following a perfect circle, the centripetal acceleration (a_y^{Theo}) can be obtained by using the angular speed (ω), the tangential velocity (υ) and the radius of the turn [30].

$$a_y^{Theo} = \frac{v^2}{r} = r \cdot \omega^2 = v \cdot \omega \tag{2.1}$$

Taking into account that (ω, v) can be estimated each second from the GPS, it have a coarse estimation of the centripetal acceleration of the vehicle due to the road. Subtracting the lateral acceleration measured by the sensors from the centripetal acceleration of the vehicle, it is estimated the lateral vehicle acceleration due to defective driving manoeuvers ($a'_y = a_y - a_y^{Theo}$).

2.4. GPS

DriveSafe makes also use of the GPS available in the smartphone to obtain the vehicle speed each second. The heading/course value offered by GPS (i.e. the direction in which the device is traveling) is used to correct turning events that might be detected during a road curve and are not supposed to be driver's fault.

The values obtained from the GPS sensor are:

- Speed: The vehicle speed in kilometres/hour is an essential measurement to evaluate overspeed or to relate distance to ahead vehicle with the estimated time of impact.
- Course: The GPS course allows detecting curves to decouple sudden turnings (as explained in previous section).

Although GPS values are instantaneously measured every second (1Hz), in some cases it is necessary to predict future GPS positions, for instance, to request information from

APIs such as OpenStreetMap. These APIs delay the response on the range of various seconds (between 2-5 seconds in our tests), so it is necessary to request information on a predicted position to solve this delay.

2.5. Lane detection

The lane detection module allows the extraction of two main indicators:

- Lane drifting: Driver's tendency of moving inside current road lane. This may indicate inattention due to the incapacity to keep in the centre of the lane. It is based on the indicator called Lanex (fraction of Lane exits), which is a measure of driver's tendency to exit the lane [27]. It is defined as the fraction of a given time interval spent outside a virtual driving lane around the centre of 1.2 m width, calculated by applying windowing techniques over the lateral position of the vehicle (x) during 60 s.
- Lane weaving: It measures driver's tendency to switch between lanes. It is evaluated as the amount of lane departures and their wilfulness. A high number of involuntary lane departures might be an indicative of drowsiness. Wilfulness of lane departures was firstly evaluated in DriveSafe via the inbuilt microphone by analysing patterns in the sound to infer whether the driver had pressed the turn signal or not. But empirically normal and voluntary lane departures are performed within a short time window. On the other hand, involuntary lane departures that are due to inattention are normally performed in a long time period, as vehicle exits lane slowly without driver's notice. Following this reasoning, we have made use of the road lane separation in submarkers to detect an imminent lane departure and start a timer that counts the time spent between its start and finish.

2.6. Ahead vehicle detection

As the surrounding dynamical environment, other vehicles affect driving, as they constrain the range of movements that one can perform on the road. For instance, a sudden braking may be produced when driver sees that the vehicle that is ahead is suddenly braking, or one cannot turn to left lane if there is already a vehicle on that lane. Furthermore, the way of behaving around other vehicles is different for each driver and it may give clues about behaviours such as aggressiveness.

Therefore, vehicle detection is an essential sense in a platform dedicated to driver analysis, whether it is to infer a behaviour model or to encourage good driving practices by alerting and scoring the driver.

(a) (b)

Figure 2. 9: Examples of vehicle detection. (a) Driver keeps a relatively close distance (19.5 meters, 0.6 seconds) that is depicted in yellow colour. The module also detects 6 vehicles in the same frame, indicative of high traffic density. (b) Driver is at a very close distance to ahead vehicle, depicted in red colour. DriveSafe also emits an alerting sound on these dangerous cases.

Coupling this sense with the lane detection allows to obtain several indicators that are useful in driver analysis:

- Distance to ahead vehicle: Lane estimation allows to estimate whether an ahead vehicle is in the same lane as the DriveSafe user. In those cases, the distance that the user keeps to ahead vehicle gives rich information about his behaviour. It is possible to estimate the distance to ahead vehicle even though the image is captured by a monocular camera, by applying the pinhole camera model and considering an approximate lane width.
- Time of impact to ahead vehicle: Distance coupled with GPS speed allows to better weigh its relevance. For instance, keeping 50m to ahead vehicle is much more relevant in terms of aggressiveness if the speed is 120Km/h than if it is 50Km/h. Thus, in some cases it is more interesting to treat directly the time of impact, in seconds, than the raw distance.
- Amount of vehicles detected: Although the camera can only reach ahead vehicles and until a certain distance, keeping a record of the vehicles detected in a time window provides an estimation of traffic density. A driver gets clearly influenced by the amount of surrounding vehicles and he does not behave equally when there is high traffic than when he is alone in the road.
- Overtakings: A high frequency of overtakings (i.e. passing other vehicles on the road) may imply impatience and a certain degree of aggressiveness.

Chapter 3

DriveSet and DriveReader

In order to investigate the most suitable techniques for detecting events occurring on driving, it is required one the large and heterogeneous database. Thus, it can be concluded that the modules and algorithms designed will be highly accurate when they are implemented on a mobile device by using previous dataset information for later performance in real environments. The database that combines these requirements and therefore is chosen in this work is UAH-DriveSet [31]. No less important than having access to a proper database is to have a tool to exploit the information contained in it, DriveSet reader is an ideal tool for working with the selected database.

3.1. DriveSet

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 camera, to log and analyze driving parameters and behaviours as it was said in chapter 2.

3.1.1. Data collected

The tests were performed on the vehicles of each of the users by placing two phones on their windshield. The first of them, an iPhone with DriveSafe App running, is set on the centre of the windshield, with the rear camera aiming at the road. A second phone is set closely on its right in order to record a video of the whole route. At the beginning of the designed routes, both the recorder and the DriveSafe App, are started and the testers perform each full route without interfering with the phones.

The test bed is shown in Table 3.1. It is composed by 6 different people of different ages and with different types of vehicles, including a fully electric car.

Driver	Genre	Age range	Vehicle Model	Fuel type
D1	Male	40-50	Audi Q5 (2014)	Diesel
D2	Male	20-30	Mercedes B180 (2013)	Diesel
D3	Male	20-30	Citröen C4 (2015)	Diesel
D4	Female	40-50	Kia Picanto (2004)	Gasoline
D5	Male	30-40	Opel Astra (2007)	Gasoline
D6	Male	40-50	Citröen C-Zero (2011)	Electric

Table 3. 1: List of drives and vehicles included in the database.

Each driver repeats predesignated routes by simulating a series of different behaviours. These are: normal, drowsy and aggressive driving. In the case of normal driving, the tester is only told to drive as he usually does. In the drowsy case, the driver is told to simulate slight sleepiness, which normally results in sporadic unawareness of the road scene. Finally, in the case of aggressive driving, the driver is told to push to the limit their aggressiveness (without putting the vehicle at extreme risk), which normally results in impatience and brusqueness while driving.

The two different routes were covered in the tests. In the first route most of the travel is on a motorway, with between 2 and 4 lanes on each direction and around 120 Km/h of maximum allowed speed. The second route mostly covers a "secondary" road, with normally 1 lane on each direction and around 90 Km/h of maximum speed. Each driver performed three trips on the motorway road (round-trip, of around 25 km), simulating each of the three behaviours, and four trips on the secondary road (one-way each, of around 17km), which consist of: departure as normal, return as normal, departure as aggressive and return as drowsy.

3.1.2. Structure

DriveSafe captures plenty of information of each route in the form of both raw measurements and processed signals, such as the image captured by the rear camera. All this data were gathered into files to create the UAHDriveSet. Therefore, the detailed files are available in DriveSet to facilitate driver behaviour analysis.

The dataset is split into folders for each of the drivers. Into these folders each full route performed with a different behaviour is stored in a folder with the name format "Date(YYYYMMDDhhmmss)Distance(Km)-Driver-Behaviour-Road". These folders contain the video recorded during the route and all the files in which the application logged the data, which are:

- RAW_GPS.txt
- RAW_ACCELEROMETERS.txt

- PROC_LANE_DETECTION.txt
- PROC_VEHICLE_DETECTION.txt
- PROC_OPENSTREETMAP DATA.txt
- EVENTS_INERTIAL.txt
- EVENTS_LIST_LANE_CHANGES.txt
- SCORES.txt
- PARTIAL_SCORES.txt
- USER_DATA.txt

The files used in this Thesis are detailed in the following sections. All the variables are disposed on different columns in the files, where the first column is always a "timestamp" that means the seconds since the start of the route, which allows to synchronize between the different files and the corresponding video.

- GPS Raw real-time data (RAW_GPS.txt) contains the data collected from GPS, at 1Hz. The contents of each column are listed below:

  1. Timestamp (seconds)
  2. Speed (km/h)
  3. Latitude coordinate (degrees)
  4. Longitude coordinate (degrees)
  5. Altitude (meters)
  6. Vertical accuracy (degrees)
  7. Horizontal accuracy (degrees)
  8. Horizontal accuracy (degrees)
  9. Difcourse: course variation (degrees)

- Accelerometers Raw real-time data (RAW_ACCELEROMETERS.txt) contains all the data collected from the inertial sensors of the phone, at 10Hz. The iPhone is fixed on the windshield at the start of the route, so the axes are the same during the whole trip. These are aligned in the calibration process of DriveSafe, being Y aligned with the lateral axis of the vehicle (reflects turnings) and Z aligned with the longitudinal axis (positive value reflects an acceleration, negative reflects a braking). The contents of each column are:

  1. Timestamp (seconds)
  2. Boolean of system activated (1 if >50km/h)
  3. Acceleration in X (Gs)
  4. Acceleration in Y (Gs)
  5. Acceleration in Z (Gs)
  6. Acceleration in X filtered by Kalman (Gs)
  7. Acceleration in Y filtered by Kalman (Gs)
  8. Acceleration in Z filtered by Kalman (Gs)
  9. Roll (degrees)

10. Pitch (degrees)
11. Yaw (degrees)

- Vehicle detection by processed in real-time file (PROC_VEHICLE_DETECTION) contains all the data processed from vision by DriveSafe's vehicle detector, at around variable 10 Hz (FPS). The contents of each column are listed below:

1. Timestamp (seconds)
2. Distance to ahead vehicle in current lane (meters)[value -1 means no car is detected in front]
3. Time of impact to ahead vehicle (seconds) [distance related to own speed]
4. # of detected vehicles by the algorithm (traffic)
5. GPS speed (km/h) [sames as in RAW GPS]

- Events detected by inertial sensors (EVENTS_INERTIAL.txt) contains a list of the inertial events detected during the route: brakings, turnings and accelerations. The level depends on three thresholds fixed that were described in [32]. However, if the speed is less than 50Km/h (see boolean of system activated in RAW_ACCELEROMETERS.txt), the events are not saved in this list. The contents of each column are listed below:

1. Timestamp (seconds)
2. Type (1=braking, 2=turning, 3=acceleration)
3. Level (1=Low, 2=Medium, 3=High)
4. GPS Latitude of the event
5. GPS Longitude of the event
6. Date of the event in YYYYMMDDhhmmss format

- EVENTS_LIST_LANE_CHANGES.txt contains the list of lane changes (departures) produced during each the route. The contents of each column are listed below:

1. Timestamp (seconds)
2. Type [+ indicates right and - left, 1 indicates voluntary and 2 involuntary]
3. GPS Latitude of the event
4. GPS Longitude of the event
5. Duration in seconds of the lane change
6. Threshold to consider a change voluntary or involuntary

3.2. Tool: DriveSet Reader

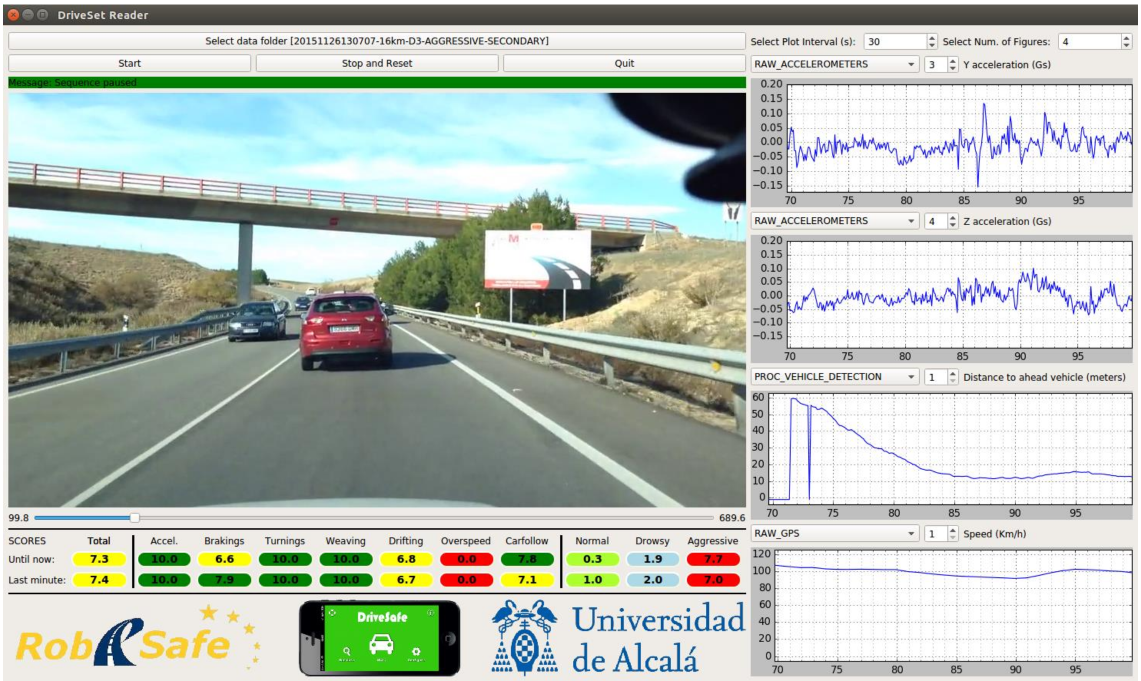


Figure 3. 1: Screenshot of the DriveSet reader to perform analysis with UAH-DriveSet.

DriveSet Reader is a tool that is available with the dataset DriveSet, as there are several variables and files for every route and syncing them with the recorded video may suppose difficulties. 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 (Fig. 3.1). This tool can be used to find patterns in the driving behaviours by reviewing all the variables available in the dataset together with the videos that show what did actually happen during the tests. For example, the user may analyse any sudden braking manoeuver detected and reviews all values available in dataset for this moment finding correlation among them.

Chapter 4

Fuzzy Classifier

4.1. Fuzzy Logic

Before explaining the Fuzzy Classifier designed to detect the different driving events, an introduction about the fuzzy logic is shown. Basically, Fuzzy Logic (FL) is a multivalued logic [33], which allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be mathematically formulated and processed by computers, in order to apply a more human-like way of thinking in the programming of computers [34]. Fuzzy systems is an alternative to traditional notions of set membership and logic that has its origins in ancient Greek philosophy.

4.1.1. Fuzzy Sets and Crisp Sets

The very basic notion of fuzzy systems is a fuzzy (sub)set. In classical mathematics we are familiar with crisp sets. For example, the possible interferometric coherence "g" values are the set X of all real numbers between 0 and 1. From this set X a subset A can be defined, (e.g. all values 0≤ g ≤0.2). The characteristic function of A, (i.e. this function assigns a number 1 or 0 to each element in X, depending on whether the element is in the subset A or not) is shown in Fig. 4.1.

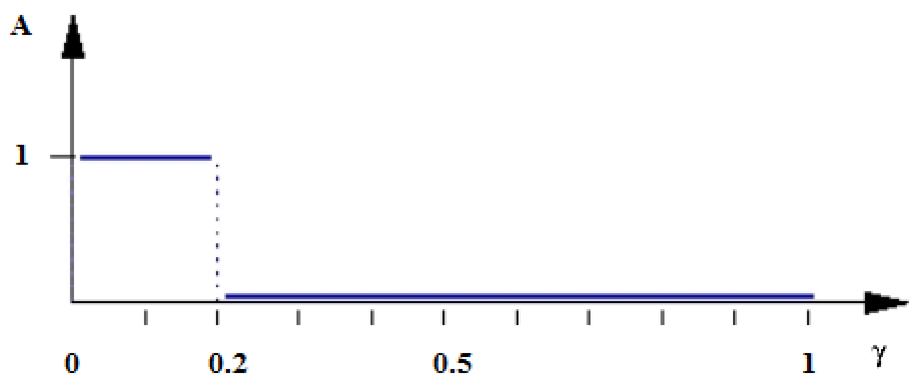


Figure 4. 1: Characteristic Function of a Crisp Set.

The elements which have been assigned the number 1 can be interpreted as the elements that are in the set A and the elements which have assigned the number 0 as the elements that are not in the set A. This concept is sufficient for many areas of applications, but it can easily be seen, that it lacks in flexibility for some applications as classification of remotely sensed data analysis. For example, it is well known that water shows low interferometric coherence “g” in SAR images. Since “g” starts at 0, the lower range of this set ought to be clear. The upper range, on the other hand, is rather hard to define. As a first attempt, we set the upper range to 0.2. Therefore we get B as a crisp interval B=[0,0.2]. But this means that a “g” value of 0.20 is low but a g value of 0.21 not. Obviously, this is a structural problem, if we moved the upper boundary of the range from g =0.20 to an arbitrary point we can pose the same question. A more natural way to construct the set B would be to relax the strict separation between low and not low. This can be done by allowing not only the (crisp) decision Yes/No, but more flexible rules like ” fairly low”. A fuzzy set allows us to define such a notion. The aim is to use fuzzy sets in order to make computers more ’intelligent’, therefore, the previous idea has to be coded more formally. According to the example, all the elements were coded with 0 or 1. A straight way to generalize this concept, is to allow more values between 0 and 1. In fact, infinitely many alternatives can be allowed between the boundaries 0 and 1, namely the unit interval I = [0, 1].

The interpretation of the numbers, now assigned to all elements is much more difficult. Of course, again the number 1 assigned to an element means that the element is in the set B and 0 means that the element is definitely not in the set B. All other values mean a gradual membership to the set B.

This is shown in Fig. 4.2. The membership function is a graphical representation of the magnitude of participation of each input. It associates a weighting with each of the inputs that are processed, define functional overlap between inputs, and ultimately determines an output response. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion.

The membership function (MF), operating in this case on the fuzzy set of interferometric coherence “g”, returns a value between 0.0 and 1.0. For example, an interferometric coherence “g” of 0.3 has a membership of 0.5 to the set low coherence (Fig. 4.2). It is important to point out the distinction between fuzzy logic and probability. Both operate over the same numeric range, and have similar values: 0.0 representing False (or non-membership), and 1.0 representing True (or full-membership). However, there is a distinction to be made between the two statements: The probabilistic approach yields the natural-language statement, “there is a 50% chance that “g” is low,” while the fuzzy terminology corresponds to “g’s degree of membership within the set of low interferometric coherence is 0.50.” The semantic difference is significant: the first view supposes that “g” is or is not low; it is just that we only have a 50% chance of knowing which set it is in. By contrast, fuzzy terminology supposes that "g" is "more or less" low, or in some other term corresponding to the value of 0.50.

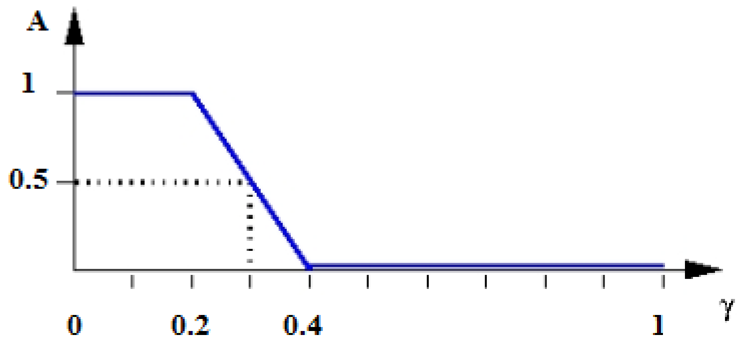


Figure 4. 2: Characteristic Function of Fuzzy Set.

4.1.2. Operations on Fuzzy Sets

We can introduce basic operations on fuzzy sets. Similar to the operations on crisp sets we also want to intersect, unify and negate fuzzy sets. In his very first paper about fuzzy sets [35], L. A. Zadeh suggested the minimum operator for the intersection and the maximum operator for the union of two fuzzy sets. It can be shown that these operators coincide with the crisp unification, and intersection if we only consider the membership degrees 0 and 1. For example, if A is a fuzzy interval between 5 and 8 and B be a fuzzy number about 4 as shown in the Figure 4.3 the resultant fuzzy set with AND operator is displayed in the Figure 4.4.

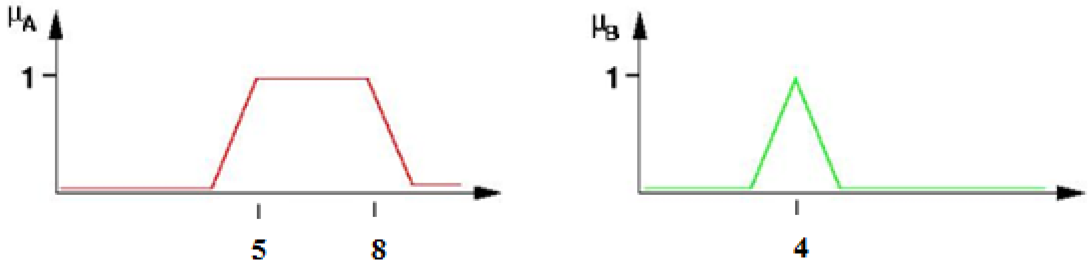


Figure 4. 3: Example Fuzzy sets

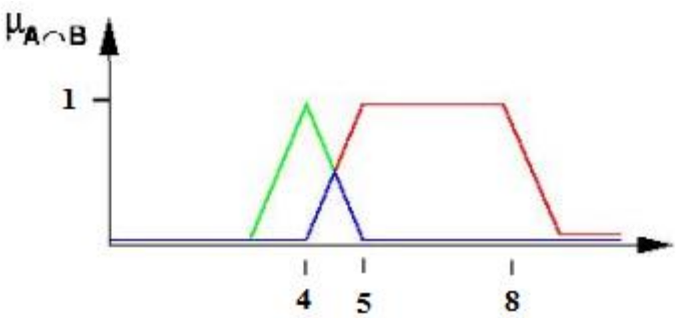


Figure 4. 4: Example of Fuzzy AND operation

The resultant fuzzy set to apply OR operator is shown in the figure 4.5

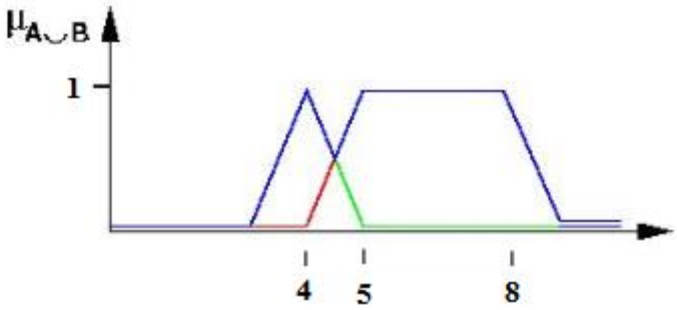


Figure 4. 5: Resultant Fuzzy set of OR operation

4.2. Fuzzy Classifiers

Fuzzy pattern recognition is sometimes identified with fuzzy clustering or with fuzzy if-then systems used as classifiers. To a certain extent fuzzy pattern recognition is dual to classical pattern recognition, and thereby consists three basic components: clustering, classifier design and feature selection.

The diversity of applications in the studies retrieved upon the keyword "fuzzy classifier" is amazing. Remote sensing; environmental studies; geo-science; satellite and medical image analysis; speech, signature and face recognition are few examples of highly active areas. Even more curious are the concrete applications such as grading fish products and student writing samples; analysis of seasonal variation of cloud parameters; speeding up fractal image compression; development of metric-based software; classification of odours, road accidents, military targets and milling tool ware; estimating a crowding level in a scene; tactile sensing; glaucoma monitoring; and even quality evaluation of biscuits during baking.

The fuzzy classifier are used to solve the following problems:

- In some cases, there is insufficient information to properly implement classical (e.g., statistical) pattern recognition methods. Such are the cases where we have no data set.
- Sometimes the user needs not only the class label of an object but also some additional information (e.g., how typical this object is, how severe the disease is, how desirable the option is).
- Sometimes characteristics of objects or class labels are conveniently represented in terms of fuzzy sets. For example, in a medical inquiry we may wish to quantify the "degree of pain" or "the extent of alcohol abuse" with numbers in (0,1).

- Fuzzy set theory gives a mathematical tool for including and processing expert opinions about classification decisions, features and objects.
- Fuzzy classifiers based on if-then rules might be "transparent" or "interpretable", i.e., the end user (expert) is able to verify the classification paradigm. For example, such verification may be done by an expert judging the plausibility, consistency or completeness of the rule-base in fuzzy if-then classifiers. This verification is appropriate for small-scale systems, i.e., systems which do not use a large number of input features and big rule bases.

A formal definition of fuzzy classifier is a fuzzy if-then inference system (a fuzzy rule base system) which yields a class label (crisp or soft) for a vector in an n-dimensional real space.

4.2.1. Rules and Expert knowledge

Fuzzy classifiers are one application of fuzzy theory. Expert knowledge is used and can be expressed in a very natural way using linguistic variables, which are described by fuzzy sets. Now the expert knowledge for these variables can be formulated as a rules like:

IF feature A low AND feature B medium AND feature C medium AND feature D medium THEN Class = Class 4

The rules can be combined in a table calls rule base:

Rule #	**Feature A**	**Feature B**	**Feature C**	**Feature D**	**class**
1	Low	Medium	Medium	Medium	Class 1
2	Medium	High	Medium	High	Class 2
3	Low	High	Medium	High	Class 1
4	Medium	Medium	Medium	Medium	Class 3
...	...	...	...	...	...
N	Low	High	Medium	Low	unkown

Table 4. 1: Example for a fuzzy rule base: Rules read as (e.g. RULE No.1: IF A is low AND B is medium AND C is medium AND D is medium THEN is Class 1)

Linguistic rules describing the control system consist on two parts; an antecedent block (between the IF and THEN) and a consequent block (following THEN). Dependig on the system, it may not necessary to evaluate every possible input combination, since some may rarely or never occur. By making this type of evaluation, usually done by experienced operator, fewer rules can be evaluated, thus simplifying the processing logic and perhaps even improving the fuzzy logic system performance. The inputs are logically combined using the AND operator to produce output response values for all expected inputs. The active conclusions are then combined into a logical sum for each Membership Function (MF). A firing strength for each output MF is computed. All that remains is to combine these logical sums in a defuzzication process to produce the crisp output. E.g., for the rule consequents for each class a so-called singleton or min-max interference can be derived which is the characteristic function of the respective set.

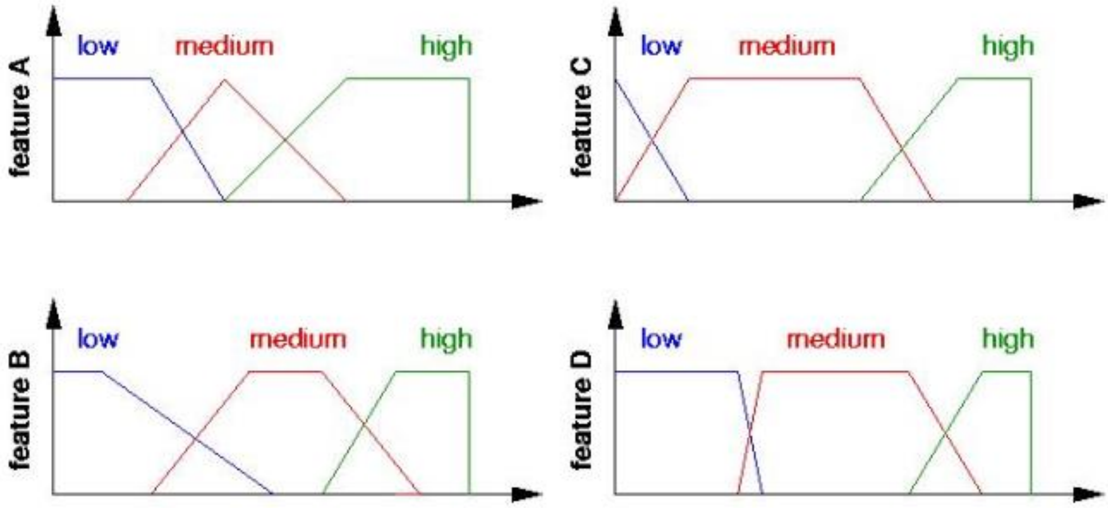


Figure 4. 6: Linguistics variables

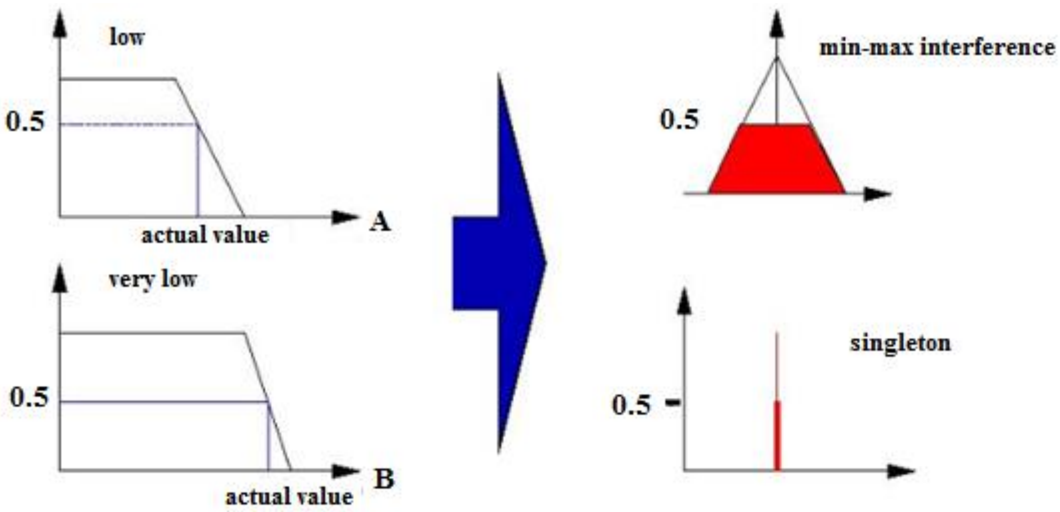


Figure 4. 7: Interference for rule 1 →A is very low AND B is low THEN Class=class1

The fuzzy outputs for all rules are finally aggregated to one fuzzy set to obtain a crisp decision from this fuzzy output. We have to defuzzify the fuzzy set, or the set of singletons. Therefore, we have to choose one representative value as the final output. There are several heuristic methods (defuzzifications methods), one of them is to take the centre of gravity of the fuzzy set as shown in Fig. 4.8, which is widely used for fuzzy sets. For the discrete case with singletons the maximum-method is usually used where the point with the maximum singleton is chosen.

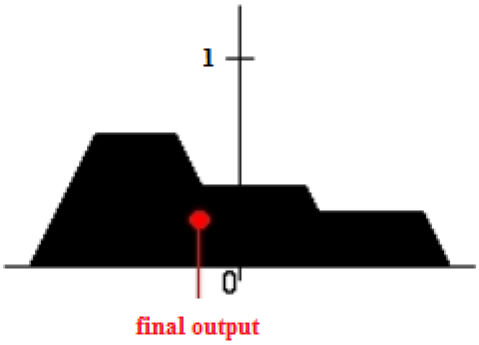


Figure 4. 8: Defuzzification using the centre of gravity approach.

4.2.2. Sugeno Fuzzy Model

The Sugeno Fuzzy model (also known as the TSK *fuzzy model*) was proposed by Takagi, Sugeno, and Kang in an effort to develop a systematic approach to generating fuzzy rules from a given input-output dataset. A typical fuzzy rule in a Sugeno fuzzy model has the form:

$$if\ x = A\ and\ y = B\ then\ z = f(x, f)$$

Where A and B are fuzzy sets in the antecedent, while z=f(x,y) is a crisp function in the consequent. Commonly f(x, y) is a polynomial in the input variables x and y, but it can be any function as long as it can appropriately describe the output of the model within the fuzzy region specified by the antecedent of the rule. When f(x, y) is a first-order polynomial, the resulting fuzzy inference system is called a first-order Sugeno fuzzy model, which was originally proposed. When f is a constant, we then have a zero-order Sugeno fuzzy model, which can be viewed as a special case of the Mamdani Fuzzy inference system, in which each rule's consequent is specified by a fuzzy singleton (or a pre-defuzzified consequent), or a special case of the Tsukamoto fuzzy model, in which each rule's consequent is specified by an MF of a step function centre at the constant. Moreover, a zero-order Sugeno fuzzy model is functionally equivalent to a radial basis function network under certain minor constraints.

The output of a zero-order Sugeno model is a smooth function of its input variables as long as the neighbouring MFs in the antecedent have enough overlap. In other words, the overlap of MFs in the consequent of a Mamdani model does not have a decisive effect on the smoothness; it is the overlap of the antecedent MFs that determines the smoothness of the resulting input-output behaviour.

The output of a TSK fuzzy model is composed by m rules and it is obtained like a the weighted sum the individual outputs of each rules, y_i, $i = 1, \dots, m$. [Equation 4.1]

$$\frac{\sum_{i=1}^{m} h_i \cdot y_i}{\sum_{i=1}^{m} h_i} \qquad (4.1)$$

Where $h_i = T(A_{i1}(x_1), \dots, A_{in}(x_n))$ is the degree of fit between the antecedent part of the i-rule and current system inputs, x.

4.3. Design of Fuzzy classifier

Our Fuzzy Classifier system bases their decisions on inputs in the form of linguistic variables derived from membership functions which are formulas used to determine the fuzzy set to which a value belongs and the degree of membership in that set. The variables are then matched with the preconditions of linguistic IF-THEN rules, and the response of each rule is obtained through fuzzy implication. To perform compositional rule of inference, the response of each rule is weighted according to the confidence as membership degree of its inputs, and the centroid of the responses is calculated to generate the appropriate output. At present, there is no systematic procedure for the design of fuzzy logic systems. The most straightforward approach is to define membership functions and rules subjectively by studying a human decision or existing classifier.

In this case, as a starting point, we have a classifier based on fix thresholds and take the decisions based on only one input. This solution have some disadvantages:

- The decision threshold for the event detection in driving is not clear for the experts. Sometimes over the same manoeuvre, the degree of intensity that has been determined by the experts is different, then fuzzy set theory is an ideal mathematical tool for including and processing expert opinions about classification decisions.
- The current classifier implemented on DriveSafe application uses only one input variable to determinate the events and the degree of severity, this method causes some problems as false events detection, errors in the degree of intensity, errors in the type of event, etc.
- Using the DriveReader tool, it is observed that some import events were not classified, but these manoeuvers (that are important to evaluate the driving style) can be discovered using the information of other sensors that are available in the smartphone.
- An important limitation of motion sensors (e.g., accelerometer, magnetic sensor) is the high exposure to noise, which is mainly due to electromagnetic interference and device vibration. For this reason, in the proposed mechanism we fuse some

motion sensor data with GPS data in order to accurately detect driving events. On this way we avoid false detections because the detections depend on several sensors.

4.3.1 Input and Outputs variables for our 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. 4.9:

- Linear velocity (v_L) is obtained from the GPS and is given in kilometres 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 kilometres 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 speed. 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 behaviour 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 [31] is 10 Hz and the GPS frequency is 1 Hz. We implemented a Sensor Fusion layer to synchronize inertial and GPS samples (Fig. 4.9). 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.

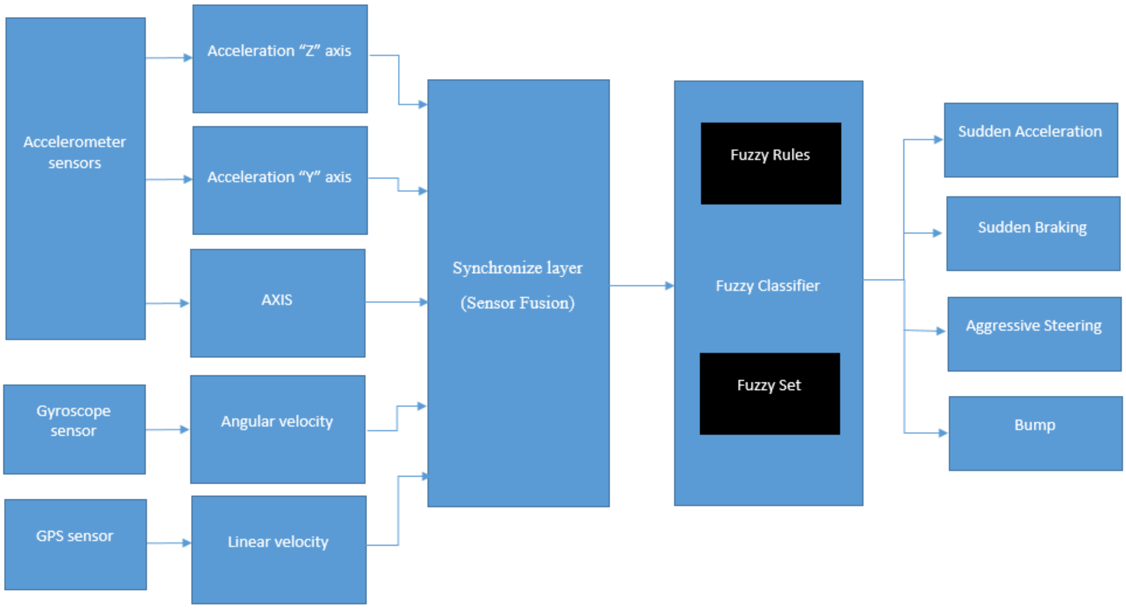


Figure 4. 9: Event Detection Scheme.

The outputs of our fuzzy classifier are:

- Braking & Acceleration
- Bumps
- Steering

4.3.2. Expert Knowledge

In the systems based on fuzzy inference (FIS), the expert knowledge is concentrated on definition of fuzzy sets of input and output variables, fuzzy inference mechanism and the fuzzy rules. One way to represent inexact data and knowledge, closer to humanlike thinking, is to use fuzzy rules instead exact rules when representing knowledge.

4.3.2.1. Initial values of Member Functions (after calibration process)

The fuzzy sets for the variables are stated in table 4.2:

Variable	Sets
Linear Velocity	VLV, LV, MV, HV
Angular Velocity	VL, L, MHV, MMV, H
AXIS	NoX, X
Acceleration Y	VLY, LY, MY, HY
Acceleration Z	NH, NM, NL, Zero, PL, PM, PH

Table 4. 2: Fuzzy sets for inputs

The MFs of the fuzzy sets defined for the inputs are shown in Fig. 4.10.

For the $|a_y|$ input we define 4 trapezoidal MFs (Fig. 4.10.a) named as VLY (Very Low Acceleration in Y axis), LY (Low Acceleration in Y axis), MY (Medium Acceleration in Y axis) and HY (High Acceleration in Y axis). 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.

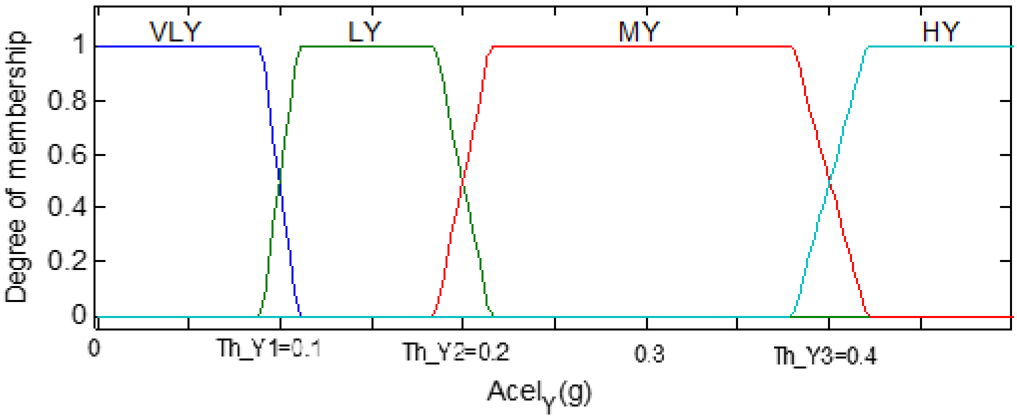
For the a_z input we define 7 trapezoidal MFs (Fig. 4.10.b) named as NH (Negative High), NM (Negative Medium), NL (Negative Low), Zero, PL (Positive Low), PM (Positive Medium) and PH (Positive High). The decision thresholds for this input are: Th_{Z1}, Th_{Z2}, Th_{Z3}, Th_{Z4}, Th_{Z5} and Th_{Z6}. 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 named as VLV (Very Low Linear Velocity), LV (Low Velocity), MV (Medium Velocity), HV (High Velocity) and 3 fix thresholds due to its samples are obtained from GPS (Fig. 4.10.c).

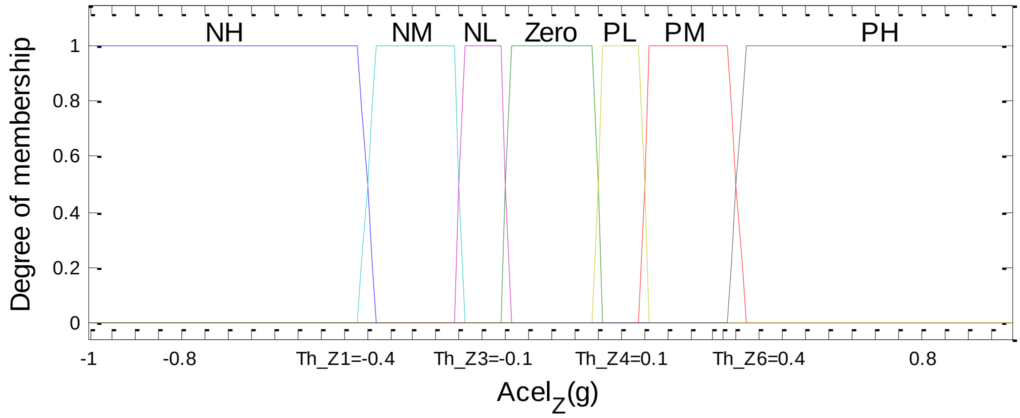
For the AXIS input we define 2 trapezoidal MF´s named NoX (no bumps) and X (to detect bumps and avoid false detections) (Fig. 4.10.d). We define only a fix threshold to optimize the general working.

For the $|\omega|$ input we define 5 trapezoidal MFs (Fig. 4.10.e) named VL (Very Low angular velocity), L (Low angular velocity), MHV (Medium angular velocity at High linear Velocity), MMV (Medium angular velocity at Medium linear Velocity) and H (High angular velocity). 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

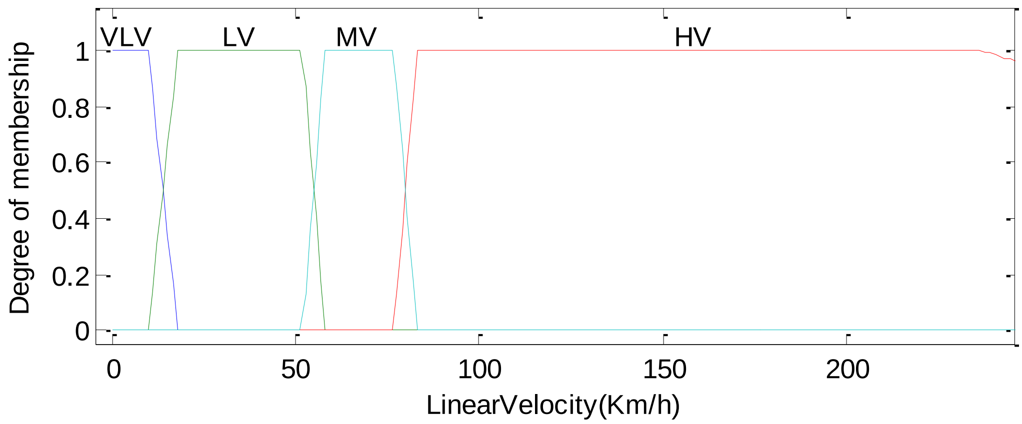
Although fuzzy membership functions can have various shapes depending on the designer's preference, in this work trapezoidal shapes are chosen to simplify the computation, in this way, we get a better performance and the smartphone will not be overload.


VLY
LY
MY
HY
Degree of membership
1
0.8
0.6
0.4
0.2
0
Th_Y1=0.1
Th_Y2=0.2
0.3
Th_Y3=0.4
Acel$_Y$(g)

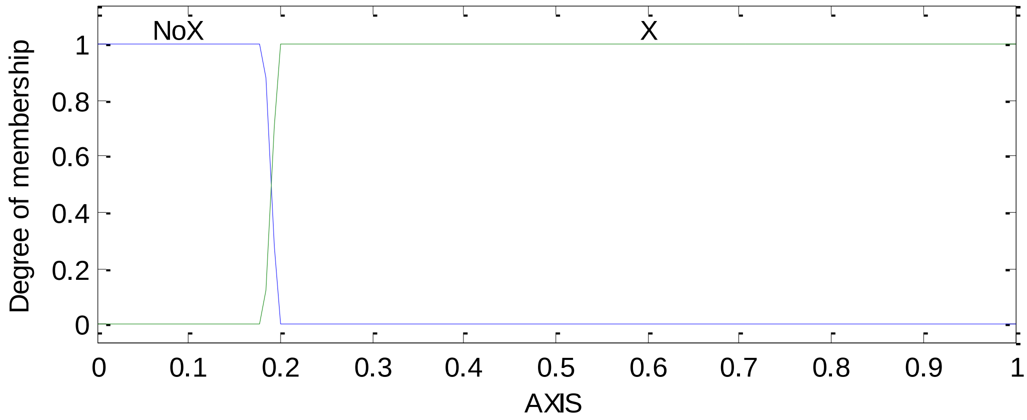
(a)


NH
NM
NL
Zero
PL
PM
PH
Degree of membership
1
0.8
0.6
0.4
0.2
0
-1
-0.8
Th_Z1=-0.4
Th_Z3=-0.1
Th_Z4=0.1
Th_Z6=0.4
0.8
Acel$_Z$(g)

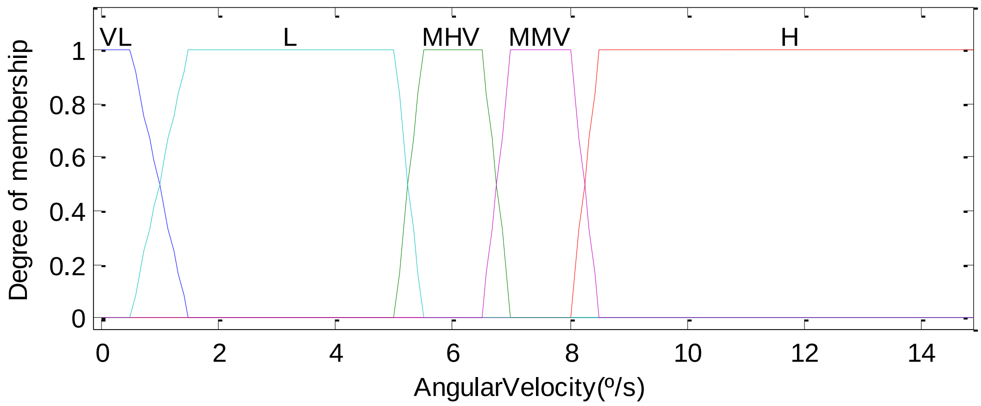
(b)


VLV
LV
MV
HV
Degree of membership
1
0.8
0.6
0.4
0.2
0
50
100
150
200
LinearVelocity(Km/h)

(c)



(d)



(e)

Figure 4. 10: Membership functions defined on the inputs.

For the output variables, we consider a single crisp value for each different type of event to allow the center-of-gravity defuzzification process to detect events individually. The output values of fuzzy classifier are shown in table 4.3, where the linguistic terms have the following meanings: 'NoSt' is not steering event, 'High' is hard steering, 'Medium' is a medium steering, 'Low' is low steering, 'A_Low' is low acceleration, 'A_Medium' is medium acceleration, 'A_High' is high acceleration, 'No_Event' is not acceleration or braking, 'B_Low' is a low braking, 'B_Medium' is a medium braking, 'B_High' is a low braking, 'Yes' is a bump, 'No' is no bump.

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

Table 4. 3: Output values.

In the Fig. 4.10 is shown the initial values and form of the MFs as long as the calibration process adapt the thresholds of Acceleration “Z” and “Acceleration Y” input sets the values and form of the member functions are changed.

4.3.2.2. Fuzzy Rules

Fuzzy rules represent in a straightforward way “commonsense” knowledge and skills, or knowledge that is subjective, ambiguous, vague or contradictory. This knowledge might have come from many different sources. Commonsense knowledge may have been acquired from long-term experience from the experience of many people, over many years.

Given the large number of member functions that we have, a complete fuzzy rules set is not optimum. A reduced number of 28 rules (Table 4.4) 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)

Rule	**Inputs values**					**Outputs**		
#	*Linear Velocity*	*Angular velocity*	*AXIS*	$Acel_Y$	$Acel_Z$	*Steering*	*Braking & Acceleration*	*Bumps*
1	*VLV*	*Any*	*Any*	*Any*	*Any*	*No_St*	*No_Event*	*No*
2	$\overline{VLV}$	*Any*	*NoX*	*Any*	*PL*	*No_St*	*A_Low*	*No*
3	$\overline{VLV}$	*Any*	*NoX*	*Any*	*PM*	*No_St*	*A_Medium*	*No*
4	$\overline{VLV}$	*Any*	*NoX*	*Any*	*PH*	*No_St*	*A_High*	*No*
5	$\overline{VLV}$	*Any*	*NoX*	*Any*	*NL*	*No_St*	*B_Low*	*No*
6	$\overline{VLV}$	*Any*	*NoX*	*Any*	*NM*	*No_St*	*B_Medium*	*No*
7	$\overline{VLV}$	*Any*	*NoX*	*Any*	*NH*	*No_St*	*B_High*	*No*
8	$\overline{VLV}$	*Any*	*X*	*Any*	*Any*	*No_St*	*No_Event*	*Yes*
9	*LV*	*L*	*NoX*	*LY*	*Any*	*Low*	*No_Event*	*No*
10	*LV*	*L*	*NoX*	*MY*	*Any*	*Medium*	*No_Event*	*No*
11	*LV*	*L*	*NoX*	*HY*	*Any*	*High*	*No_Event*	*No*
12	*MV*	*L*	*NoX*	*LY*	*Any*	*Low*	*No_Event*	*No*
13	*MV*	*L*	*NoX*	*MY*	*Any*	*Medium*	*No_Event*	*No*
14	*MV*	*L*	*NoX*	*HY*	*Any*	*High*	*No_Event*	*No*
15	*HV*	*L*	*NoX*	*LY*	*Any*	*Low*	*No_Event*	*No*
16	*HV*	*L*	*NoX*	*MY*	*Any*	*Medium*	*No_Event*	*No*
17	*HV*	*L*	*NoX*	*HY*	*Any*	*High*	*No_Event*	*No*
18	*LV*	*MHV*	*NoX*	*LY*	*Any*	*Low*	*No_Event*	*No*
19	*LV*	*MHV*	*NoX*	*MY*	*Any*	*Medium*	*No_Event*	*No*
20	*LV*	*MHV*	*NoX*	*HY*	*Any*	*High*	*No_Event*	*No*

21	*MV*	*MHV*	*NoX*	*LY*	*Any*	*Low*	*No_Event*	*No*
22	*MV*	*MHV*	*NoX*	*MY*	*Any*	*Medium*	*No_Event*	*No*
23	*MV*	*MHV*	*NoX*	*HY*	*Any*	*High*	*No_Event*	*No*
24	*HV*	*MMV*	*NoX*	*LY*	*Any*	*Low*	*No_Event*	*No*
25	*HV*	*MMV*	*NoX*	*MY*	*Any*	*Medium*	*No_Event*	*No*
26	*HV*	*MMV*	*NoX*	*HY*	*Any*	*High*	*No_Event*	*No*
27	*Any*	*Any*	*Any*	*VLY*	*Any*	*No_St*	*No_Event*	*None*
28	*Any*	*Any*	*Any*	*Any*	*Zero*	*No_St*	*No_Event*	*None*

Table 4. 4: Rules of fuzzy classifier

Hereafter we shows small summary of the meaning that these rules have:

- 1st: Below 14 km / h no events are detected.
- 2nd-7th: Detection of sprinting & braking and corresponding levels.
- 8th: If a Bache is detected the detection of other events are cancelled.
- 9th-26th: Detection of steering controlled by the rules indicated in the Table 4.5.
- 27th-28th: No events instants

		Angular velocity				
	MFs	***VL***	***L***	***MHV***	***MMV***	***H***
Lineal Velocity	***VLV***	NoSt	NoSt	NoSt	NoSt	NoSt
	L	NoSt	High/ Medium /Low *	High/ Medium /Low *	High/ Medium /Low *	NoSt
	MV	NoSt	High/ Medium /Low *	High/ Medium /Low *	NoSt	NoSt
	HV	NoSt	High/ Medium /Low *	NoSt	NoSt	NoSt

*The specific activated MF is defined by the a_z input

Table 4. 5: Resume of knowledge for steering output

4.3.4.3. Inference mechanism

The fuzzy classifier that has been developed, is based on fuzzy inference system (FIS) type zero order Sugeno because the way for classifying the detected events is by a constant output, therefore the Sugeno Inference method is computationally more efficient than the Mamdani method. The main characteristics of the inference mechanism are summary in the Table 4.6.

FIS	**Sugeno**
AND method	Productor operator
Implication	Minimum operator
Aggregation	Maximum
Defuzzication	Centroid´s method

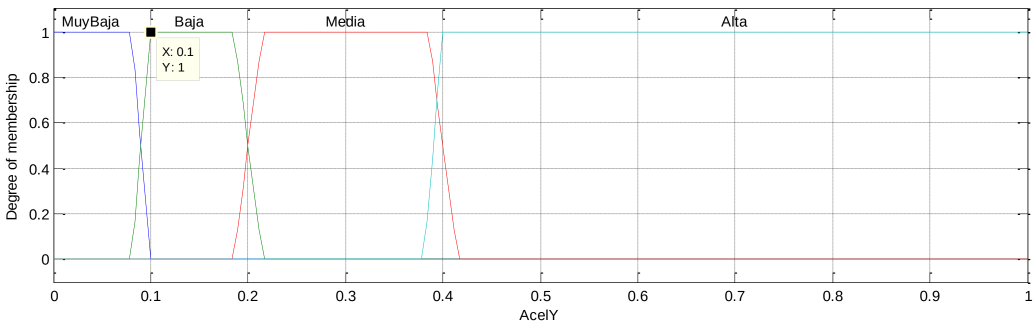
Table 4. 6: Characteristics of fuzzy classifier.

4.3.4.4. Update Fuzzy Sets

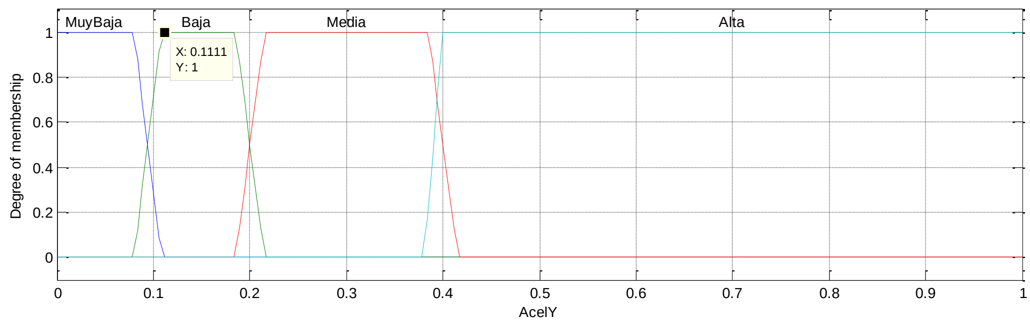
When a new threshold is proposed by the calibration process (detailed in the chapter 5) for an input of our fuzzy classifier, this is sent to update fuzzy sets process in order to adjust the values of the member functions that are involved, that is, some parameters are changed, as the shape of member functions.

Figure 4. 11: Adjust of parameters of member functions.

When the new proposed threshold is different than the previous value, the shape of trapezoidal functions is minor (the grade of inclination is smoothing), thus the zone where the two member functions coexist increases [Figure 4.12]. The aim is that each time a new threshold is sent to the Update Fuzzy sets process represents the opinion of a new expert.



(a)



(b)

Figure 4. 12: Real adjust of first threshold for accelerometer in “Z” axis for Audi Q5, the original value was 0.09G and the new threshold proposed is 0.0956G. In the figure (a) shows the original characteristics of fuzzy set and the figure (b) shows the fuzzy after adjusts the member functions

4.4. Results for Bumps detection

The new classification method of driving events uses several inputs to evaluate driving events (acceleration, braking, steering or bump), it means a great advantage because we have more information about the environment. In this section, we focus on detected bumps. To measure the performance of the bumps detection we use of three parameters over the sequences recorded in the UAH-Driveset database. First, we computed the number of True Positive (TP) bumps, i.e., the number of bumps that were actually in the road and detected by the system. Then, we considered the False Positive (FP) bumps as the number of bumps that were detected by the system but that were not actually in the road. Finally, the True Negative (TN) events are those events that were due to the road but were not detected by the system. The results of this experiment are shown in table 4.7.

Vehicle	***Bumps***		
	TP	***TN***	***FP***
Audi Q5	57	14	1
Mercedes B180	69	3	5
Citroën C4	67	5	4
Kia Picanto	72	0	12
Opel Astra	61	11	1
Citroën C0	72	0	22

Table 4. 7: Table of detected bumps

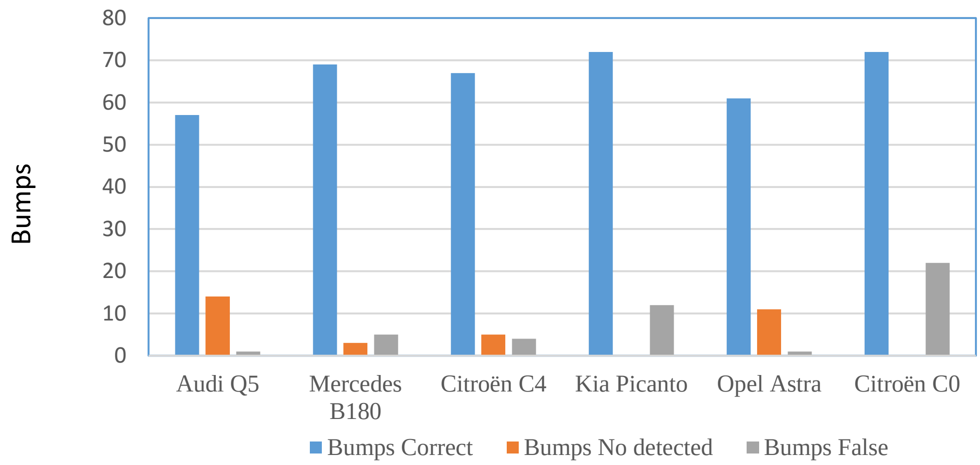


Figure 4. 13: Bumps detected for each vehicle.

In order to measure the accuracy of the events, we use precision (PR) and recall (RC) performance indicators.

$$Precision\ (PR) = \frac{TP}{TP+FP}$$

$$Recall\ (RC) = \frac{TP}{TP+TN}$$

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**

Table 4. 8: Bumps detected in each vehicle.

The results obtained in the Table 4.8 for Total Precision is near 90% and Total Recall is higher than that value. The bumps presented in the road are not a subjective measurement because they are intrinsic characteristics of the road. Accuracy obtained bumps indicator is useful to assess the road conditions. In our case, obtained numbers are quite good and detections mainly happen in the same locations for the different vehicles.

Chapter 5

Calibration Process

Analysing the structure of today's vehicles can be seen that the violent movements that occur during driving are softened by the springs, shock absorbers and tires.

The stabilization systems consisting on tires, springs and shock absorbers, differ among vehicles of different brands and models. Even between two cars of the same model this system can give different benefits only changing the tire pressure or its weight. For this reason it is necessary to perform a mechanism to detect the conditions in which the vehicle is. Therefore, it has been developed a calibration process in which event thresholds (acceleration, braking and steering) are adjusted, in order to get a correct detection of events independently of vehicle conditions.

5.1. Analysis of vehicle dynamics

The car is a mobile that moves under control of the driver. It is accelerated with the force (torque) and engine power and decelerated with friction resistance, but especially with the application of the brakes, the primary system Safety. A car is a mole that weighs between 800 and 2500 kg (depending on size and equipment) whose inertia varies with speed.

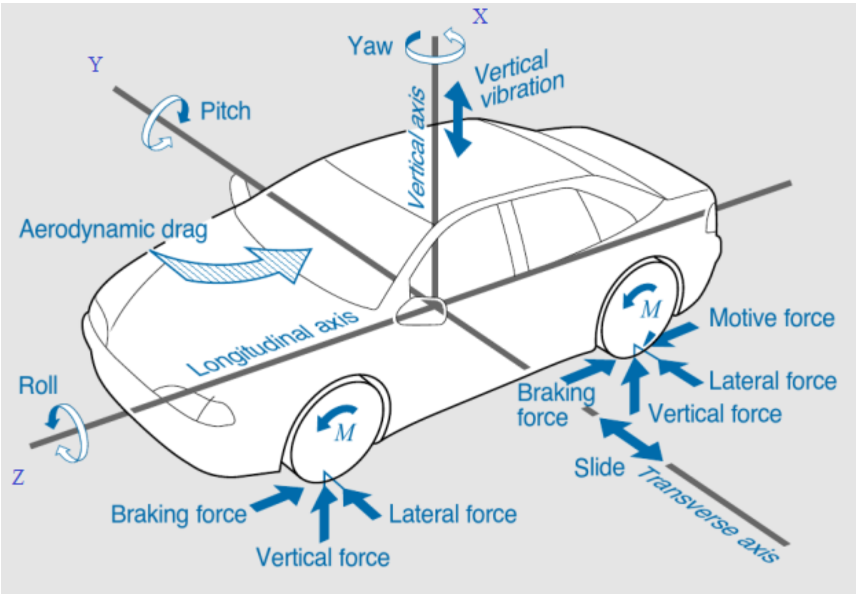


Figure 5. 1: Forces acting on a vehicle in the braking

The brakes should respond as closely as possible to the request of the driver. They must be both sensitive and gradual to modulate the speed, and ensure completed detection and total vehicle immobilization.

We briefly describe the dynamic forces that suffer the vehicles when perform events detected by the indicators under study.

1. Braking: When the brakes are activated, the fixed portion is pressed to the moving part and friction is achieved to decelerate the car. This friction gives off heat and absorbs the inertial energy (120 km / h car 1,200 Kg applies a braking force of more than 200 HP, which dissipate heat up to a temperature of 800 ° C) [36].

2. Steering: When a vehicle is performing a curve, the faster we go the higher will be the centrifugal force over it. Springs and dampers soften violent movements, thus the vehicle directs its mass to the wheels increasing their pressure on the ground. Adherence is essentially the product of tire friction with the ground and the pressure exerted on it. This pressure increases in the curves due to the centrifugal force effect that moves the vehicle to the outside wheels [13]. To get a good dynamic response, the friction coefficient between the tire and the asphalt must be high. Especially if you consider all the centrifugal force must be compensated by the adhesion area (that is the area of a tire which is in contact with the ground).

3. Acceleration: When you accelerate, the weight of the vehicle is thrown backwards. This causes the rear suspension to compress slightly and increases the available grip at the rear

4. Bumps: 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 located in the vertical axis.

Vehicle Model	Tire width (mm)	Weight basic (Kg)	Motor (Horsepower)
Audi Q5	235	1850	240
Mercedes B180	205	1425	110
Citröen C4	205	1260	120
Kia Picanto	165	852	65
Opel Astra	205	1245	110
Citröen C-Zero	145(front) 175 (rear)	1195	67

Table 5. 1: Tire width and weight of vehicles included in the database

5.2. Calibration Fuzzy Set definition

In order to detect events independently of vehicle conditions, we perform a calibration process which continuously establisher the boundaries of the fuzzy membership functions for the input variables, because different vehicles have different acceleration, braking and steering patterns.

This process is on-line performed some variables of the cars can suddenly change as e.g. the pressure of the tires or the vehicle weight (Table 5.1). This makes the energy that our vehicle is able to absorb is different.

This calibration phase consists of a continuous collection of input samples that are given under certain conditions to calibrate each of the thresholds. The conditions are set by the values given by the different sensors that are being calibrated, in order to converge to a correct value regardless of the starting values. The architecture is shown in Figure 5.2.

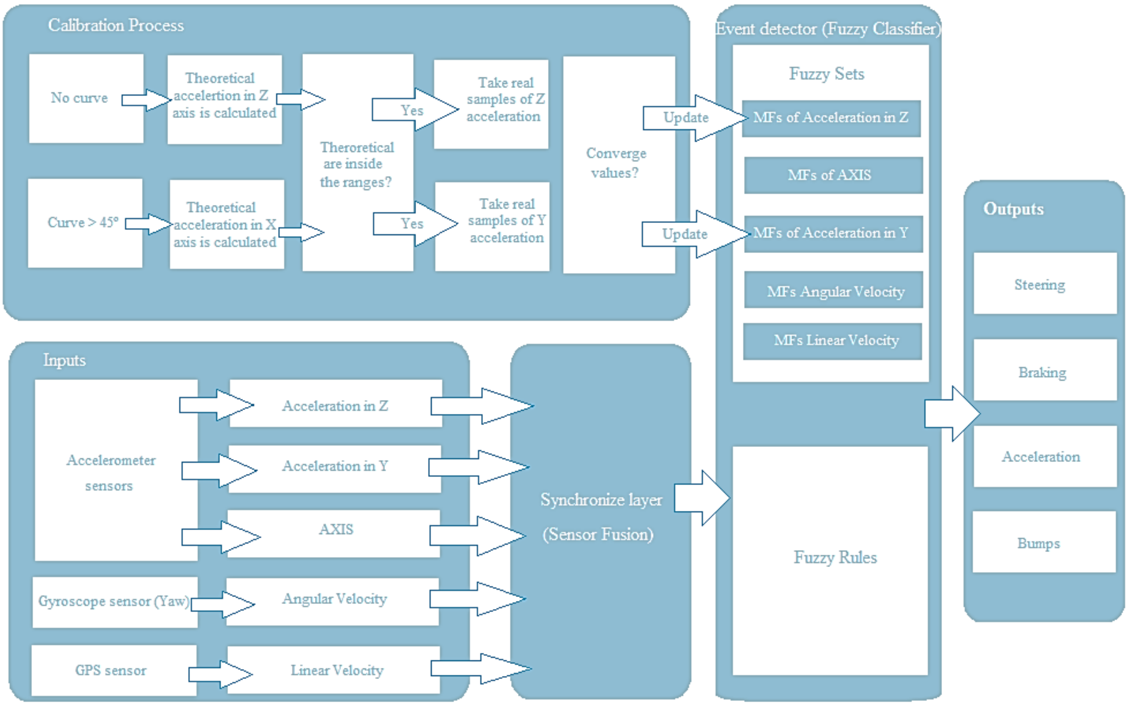


Figure 5. 2: Calibration method of fuzzy classifier architecture.

5.2.1 Calibration of accelerometer Y

The a_y input is used together with $|\omega|$, 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. These decision thresholds were shown in Fig. 4.10.a:

- Th_{Y1}: Acceleration in y axis for which the member functions VLY and LY take the same degree of membership. After the calibration have default value of 0.1g.
- Th_{Y2}: Acceleration in y axis for which the member functions LY and MY take the same degree of membership. After the calibration have default value of 0.2g.
- Th_{Y3}: Acceleration in y axis for which the member functions MY and HY take the same degree of membership. After the calibration have default value of 0.4g.

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 manoeuvers carries great risk and are carried out in a previous setup [29]. We choose a different approach based on an online calibration method over sections of curve where the centrifugal forces (Fig 5.3) 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, taking only data in curves to find out correlations among 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}).

$$a_y^{Theo} = a_y + a_y^{Abs} \rightarrow a_y = a_y^{Theo} - a_y^{Abs}$$

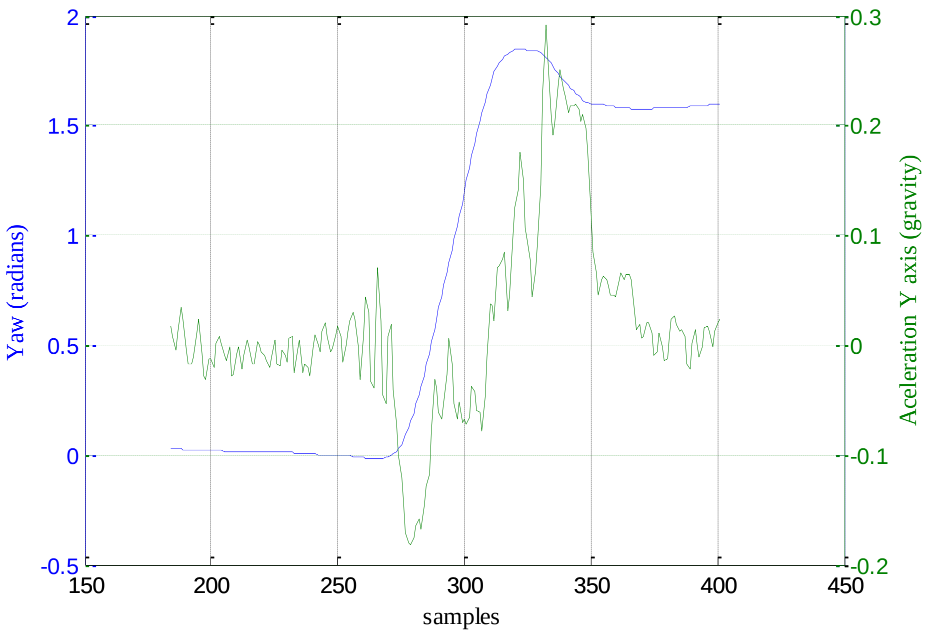


Figure 5. 3: Centrifugal force in curve sections.

For calibration we choose those curve sections where we detect continuous course change in the same direction of at least 45^0 without any event detected (Fig. 5.5). We calculate the angular velocity (ω) from the gyroscope (yaw) and the linear velocity from GPS in these sections. Then, a_y^{Theo} is calculated as the product of ω and v_L (5.3).

$$\omega = \frac{\Delta yaw}{\Delta time} \tag{5.2}$$

$$a_y^{Theo} = v_L \cdot \omega \tag{5.3}$$

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. 5.5). To do that, a study with a master vehicle was made to decide which a_y values determine the level of the sharp turns. 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, in order to have a reference vehicle in which establish ranges of theoretical acceleration. 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 5.2.

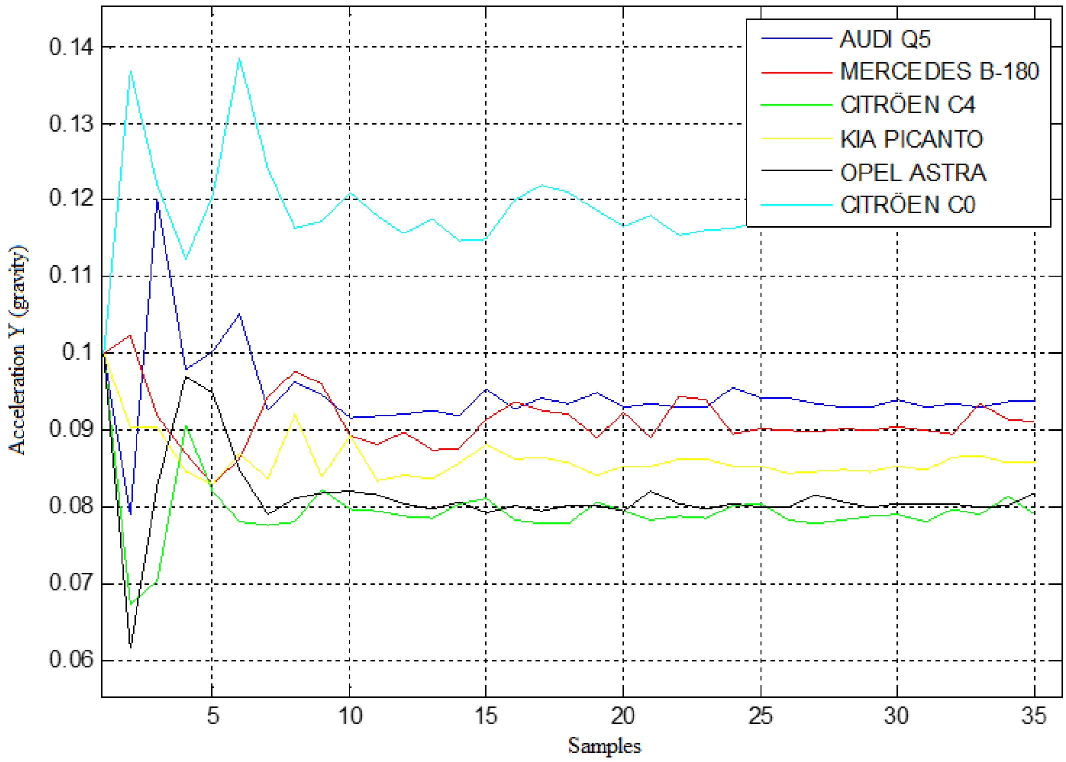


Figure 5. 4: Evolution of Th_{Y1} for each vehicle in a single trip

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 (centripetal acceleration).

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

Table 5. 2: Calibrated values for the Y accelerometer thresholds in each vehicle

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 greater centrifugal acceleration, ergo as speed increases the centrifugal force also increases.

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 5.4 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).

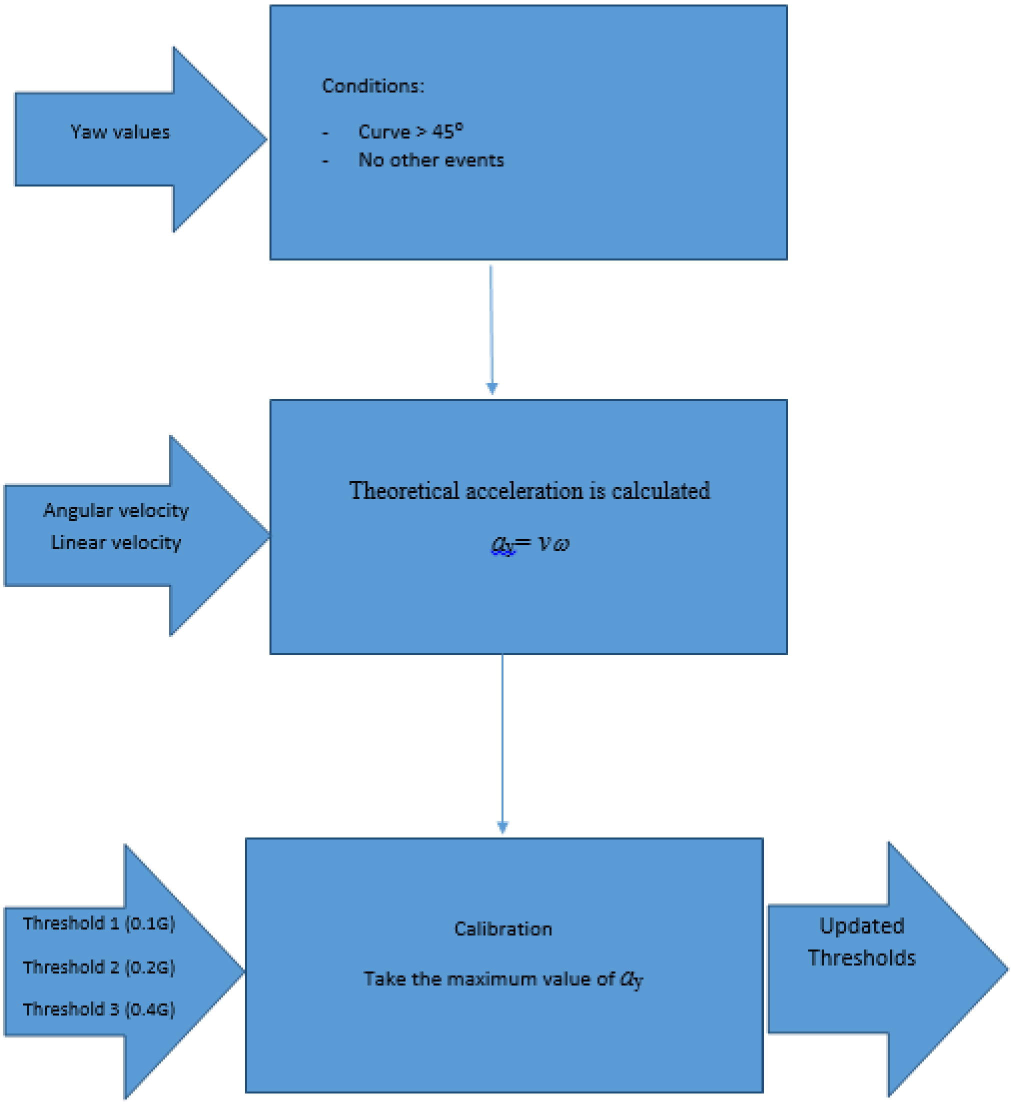


Figure 5. 5: Flowchart for calibration of Y accelerometer

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.

In the previous version of DriveSafe in one of the trips carried out with the Citröen C0 by secondary road with a normal driving style (speed limits and other traffic regulations are respected avoiding abrupt manoeuvers) were detected a total of 12 sharp turn of low level in 16 kilometres. Reviewing the recording path that amount of detections did not occurs, that makes us think that the threshold of detection had a lower value and consequently false detections occurred. Using the adaptive thresholds the number of sharp turn detections for the low level become to be two.

With this calibration process for the thresholds we get to decouple vehicle features to the driving style.

Other conclusion that we can extract from Fig. 5.4 is that in a few samples the threshold has converged, then in a few kilometres the threshold is adjusted to the new vehicle features.

The method to calibrate the other two decision thresholds (Th_{Y2} and Th_{Y3}) is similar although it should be noted that the range of values for these theoretical acceleration thresholds is higher and fewer samples are gotten unless driving is aggressive. To solve this problem, we make a preliminary estimation of these thresholds once you have calibrated the first threshold because linearity in the calibrated values for these thresholds is observed [Table 5.2]. That is, the second threshold is doubled regarding the first and third threshold is four times the first.

5.2.2. Calibration of accelerometer Z thresholds

The accelerometer input variable in the "Z" axis (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. These decision thresholds are shown in Fig. 4.10.b:

- Th_{Z1}: Acceleration in y axis for which the member functions NH and NM take the same degree of membership. After the calibration have default value of -0.4g.
- Th_{Z2}: Acceleration in y axis for which the member functions NM and NL take the same degree of membership. After the calibration have default value of -0.2g.
- Th_{Z3}: Acceleration in y axis for which the member functions NL and Zero take the same degree of membership. After the calibration have default value of -0.1g.
- Th_{Z4}: Acceleration in y axis for which the member functions Zero and PL take the same degree of membership. After the calibration have default value of 0.1g.
- Th_{Z5}: Acceleration in y axis for which the member functions PL and PM take the same degree of membership. After the calibration have default value of 0.2g.
- Th_{Z6}: Acceleration in y axis for which the member functions PM and PH take the same degree of membership. After the calibration have default value of 0.4g.

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.A study was performed for all trips taken by a singular vehicle, taking only the data in straight sections of the road to find out correlations between a_z and v_L.

The foundation of our calibration method for this sensor is based on uniform acceleration (Fig. 5.6). 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:

$$a_z^{Theo} = \frac{V_t - V_{t-1}}{t-1} \tag{5.4}$$

$$a_z = a_z^{Theo} - a_z^{Abs} \tag{5.5}$$

Where: a_z^{Theo} is the acceleration suffers for a solid-rigid and a_z^{Abs} the absorbed acceleration.

The Th_{Z1}, Th_{Z2} and Th_{Z3} are calibrated in the straight sections of the road in which a continuous deceleration is detected, we use the linear velocity (v_L) from GPS. Th_{Z4}, Th_{Z5} and Th_{Z6} are calibrated in the straight sections of the road where a continuous acceleration is detected.

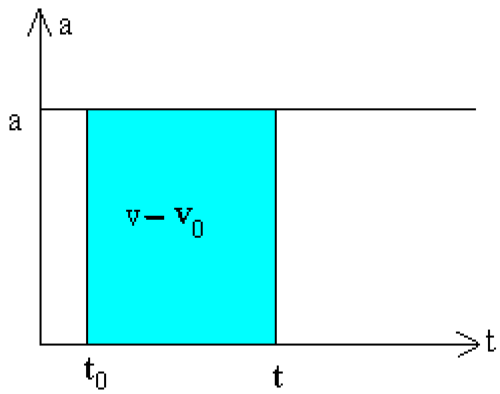


Figure 5. 6: Representation uniform acceleration.

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 (Figure 5.7). A study with a master vehicle was carried out to decide the a_z values 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 5.3.

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 detected linearity among the calibrated values, as it can be observed in Table 5.3. Calibration of these thresholds are not as relevant as already mentioned because these events occasionally occur.

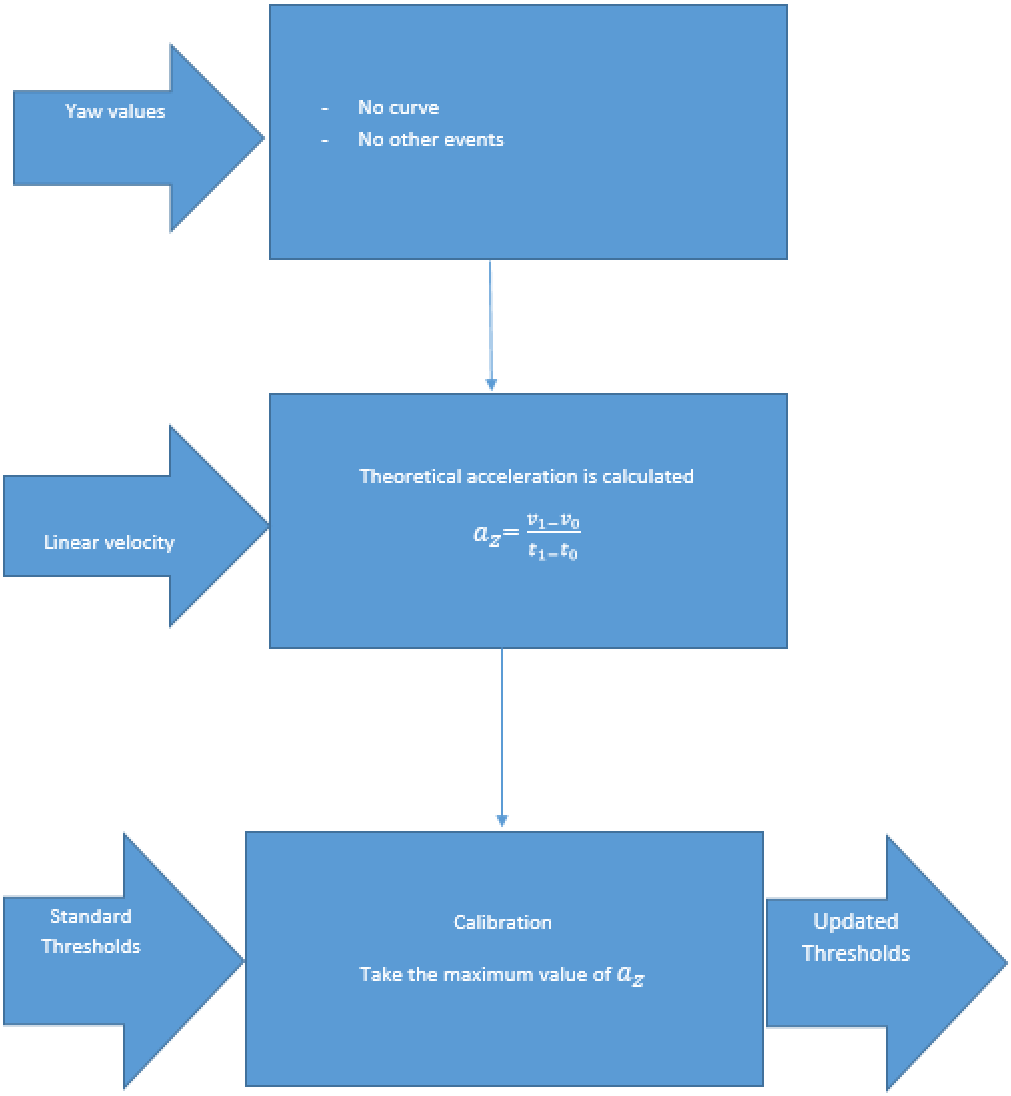


Figure 5. 7: Flowchart for calibration Z accelerometer

As it was mentioned in Section 5.1 the vehicle weight, width and tire pressure determine the behaviour of the vehicle in the accelerations and braking manoeuvers. In equality of the rest conditions, the wider the tire is the greater the friction surface is and as consequence it can absorb more energy (linear acceleration).

The absorbed energy by the damping system increases when the mass of the vehicle increases. The vehicles with a great mass need to absorb more energy than the vehicles with few mass. If this energy is not absorbed by the damping system therefore the smartphone will suffer it.

Threshold			**Adapted Threshold**		
Initial value		**Range values for calibration**	**Opel Astra**	**Citroën C0**	**Audi Q5 (master)**
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

Table 5. 3: Calibrated values for Z accelerometer Thresholds in a single trip.

Opel Astra and Audi Q5 have similar performance and it is observed that converge to 0.088g for Th_{Z1}, this means that both vehicles have the same response to low-level sudden accelerations.

5.3. Results and Conclusions

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 [31], which includes 18 trips performing by 6 different drivers and vehicles. To measure the performance of the event detection we use a metric based on three parameters. First, we computed the number of True Positive (TP) events, i.e., the number of events that were actually been due by the driver and detected by the system. Then, we considered the False Positive (FP) events as the number of events that were detected by the system but that were not actually due to the driver. Finally, the True Negative (TN) events are those events that were due to the driver but were not detected by the system. The results of this experiment are shown in Table 5.4.

Vehicle	**Events by DriveSafe**								
	Acceleration			***Braking***			***Steering***		
	TP	***TN***	***FP***	***TP***	***TN***	***FP***	***TP***	***TN***	***FP***
Audi Q5	0	21	0	32	12	5	19	6	2
Mercedes B180	24	12	23	27	13	21	18	7	3
Citroën C4	17	21	6	26	9	10	16	20	0
Kia Picanto	30	17	8	12	21	0	33	17	1
Opel Astra	34	13	7	25	7	8	47	21	6
Citroën C0	21	5	18	30	1	18	23	0	98
Vehicle	**Events by DriveSafe Improved**								
	Acceleration			***Braking***			***Steering***		
	TP	***TN***	***FP***	***TN***	***TN***	***FP***	***TP***	***TN***	***FP***
Audi Q5	16	5	1	41	3	6	23	2	3
Mercedes B180	29	7	12	39	1	6	23	2	3
Citroën C4	33	5	6	33	2	7	33	3	4
Kia Picanto	41	6	5	26	5	4	46	4	5
Opel Astra	40	7	9	31	1	4	61	7	7
Citroën C0	23	3	9	31	0	6	21	2	3

Table 5. 4: General Results

In order to measure the accuracy of the events, we use precision (PR) and recall (RC) performance indicators (Table 5.5).

$$Precision\ (PR) = \frac{TP}{TP+FP} \tag{5.1}$$

$$Recall\ (RC) = \frac{TP}{TP+TN} \tag{5.2}$$

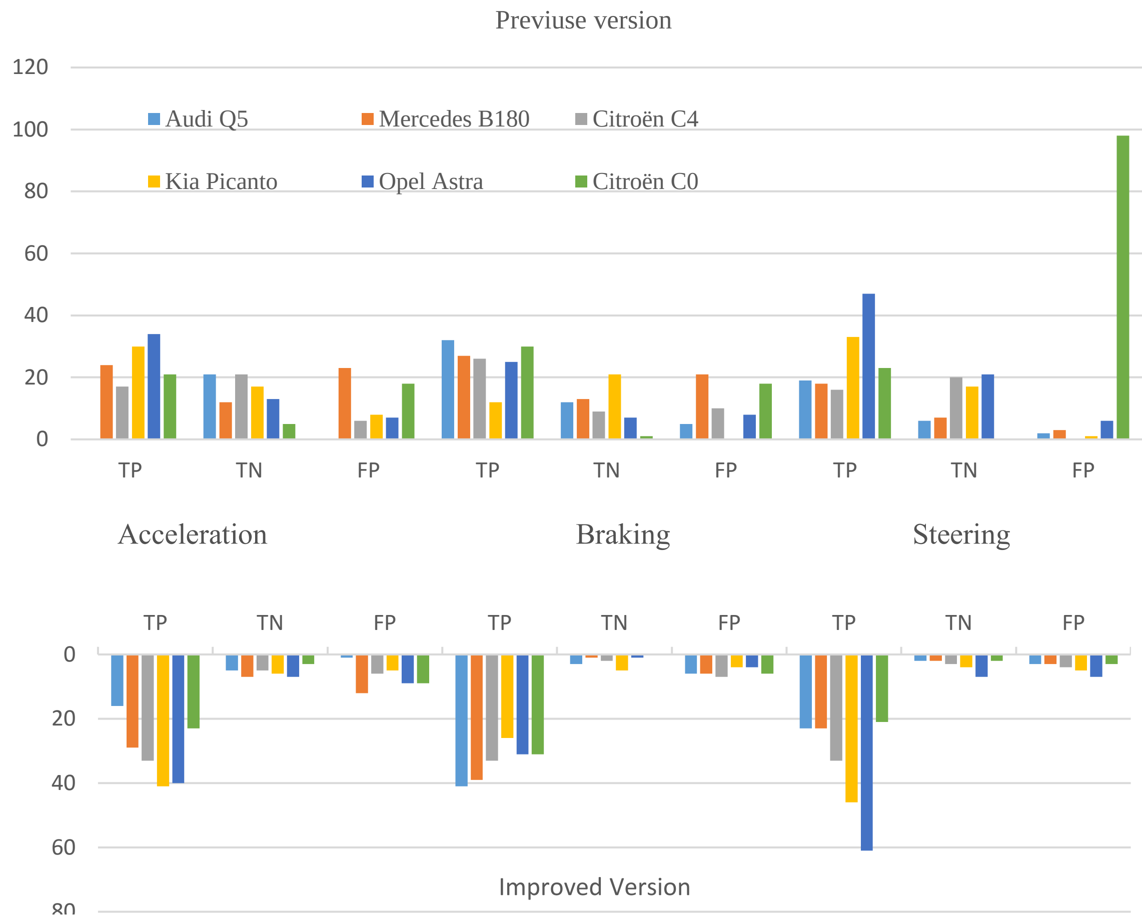


Figure 5. 8: Events detected for each vehicle

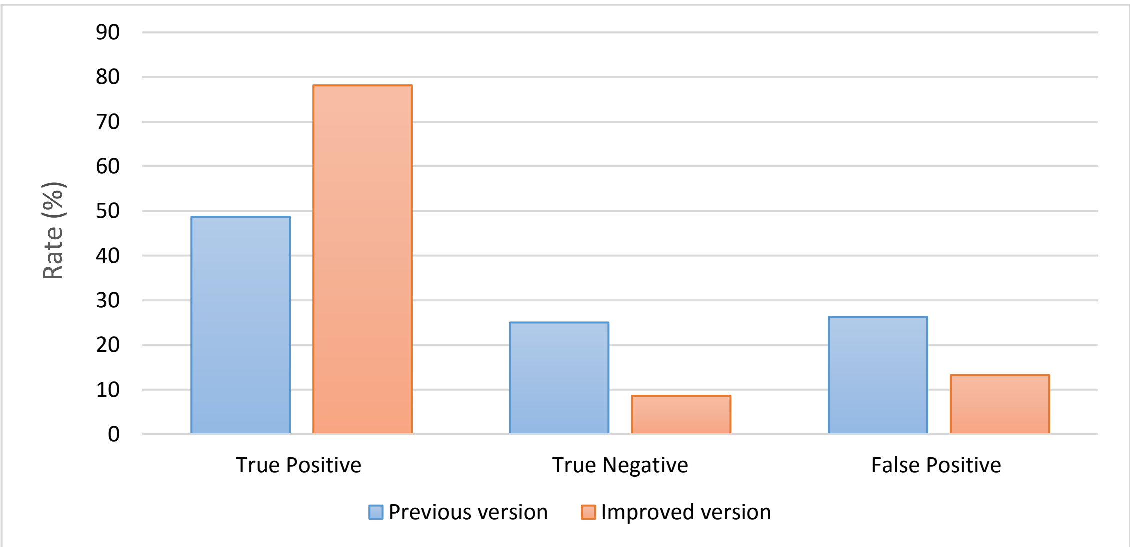


Figure 5. 9: Rate of detected events for each method

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**

Table 5. 5: Comparative of detected events

The results obtained in the Table 5.5 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.

Elimination of false detections. 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 a sudden braking or acceleration when the a_z in absolute value is higher. The same method is applied for steering events taking in account a_y. This strategy removes many false detections.

Detection of bumps or irregularities of the asphalt. Using this data we can identify the type of the road and adjust the detection thresholds if the quality of the road changes, because if the conditions of the road are bad the motion sensors will be exposure to higher levels of noise.

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.

The new classifier detects events at velocities lower than 50 km/h, it is a very relevant detail because a great number of journeys are performed in urban roads and the speed limit is 50 km/h. The events detected by the new classifier at low velocities are better thanks to the fuzzy inference between acceleration in Y axis and angular velocity. It is possible to distinguish between steering and sharp turn.

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 the previous version.

Chapter 6

High level analysis

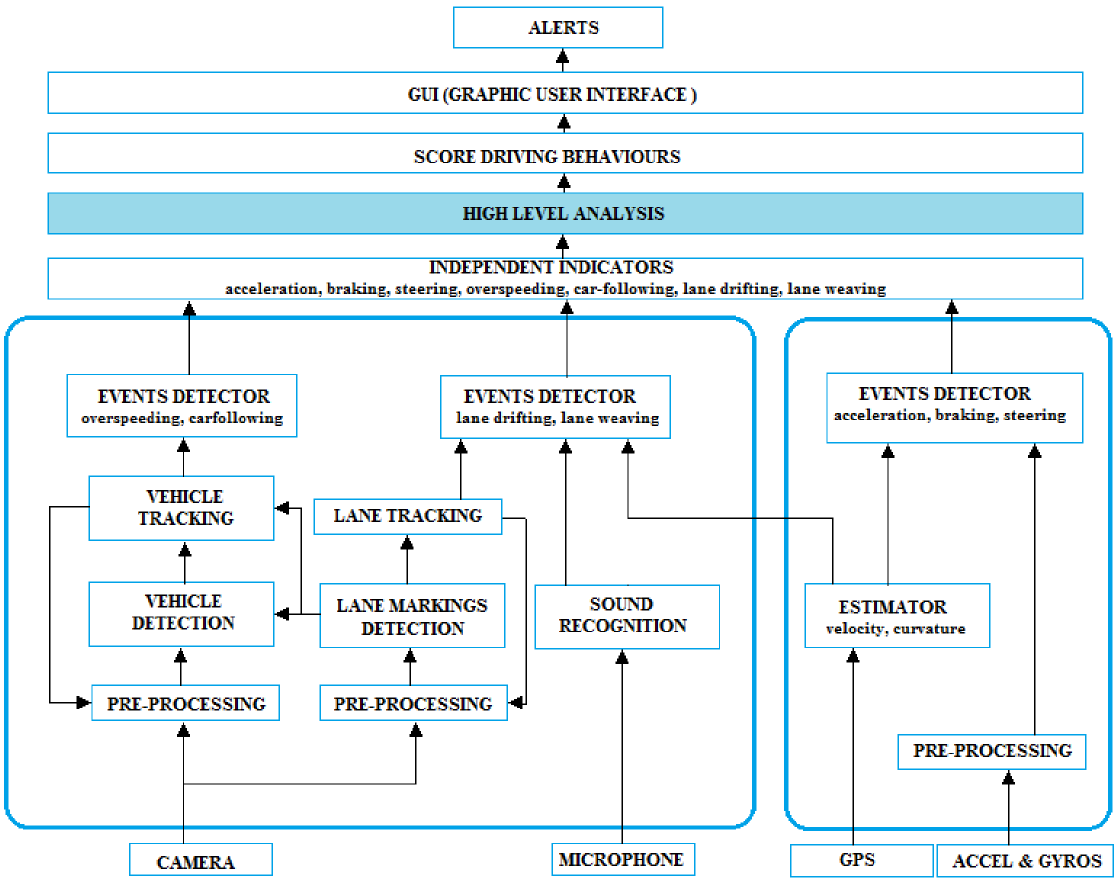


Figure 6. 1: Architecture with High level Analysis

A high level layer has been implemented (Fig. 6.1) in order to find out new events (manoeuvres) that are accomplished by drivers and which are interesting to evaluate the driving behaviour. Our techniques are based on a Finite State Machine (FSM) and high level classifier, that it has been implemented to process the events detected in the below level (fuzzy classifier), over which we add information given by other DriveSafe modules in order to identify the following risky manoeuvers:

- Overtaking manoeuvres: It is one of the most dangerous manoeuvres in driving and get information about the number of overtaking performed in a journey can be a measure to evaluate the aggressiveness of the driver and the traffic congestion.

- Abrupt gear shifts: The best-selling vehicle in Europe are with manual gearbox. Make a gear shift means that the driver have to hold the steering wheel with a single hand while the other hand activates the shifter, some drivers tend to make this action in aggressive way (e.g. sudden accelerations, engine brake, overtaking, inputs highway…).

- Overtaking attempts: This manoeuvre is more dangerous than a full overtaking because it involves invading the opposite lane to start overtaking when a vehicle approaches. A great amount of these attempts made by driver is a good indicator of aggressive style in the driving.

Other advantage that provides this layer is to correct detections of events that have been erroneously classified.

6.1. New Manoeuvres

Using the independent indicators given by DriveSafe modules can be identified other events (manoeuvers) as we describe following.

6.1.1. Overtaking and Overtaking attempts

After making a detailed study of overtaking manoeuvres over doble lane roads, it is observed that sometimes a steering event is associated to it (Fig. 6.2). These actions can be considered as a good indicator of aggressive in driving.

To detect the overtaking manoeuvres the following variables are used in addiction to steering events:

- “Type” of EVENTS_LIST_LANE_CHANGES.txt file.
- “Distance to ahead vehicle in current lane” of PROC_VEHICLE_DETECTION.txt, (meters).

When an overtaking occurs in secondary road first the vehicle performs a lane change to the left and a steering event might be detected. Then, the variable “Distance to ahead vehicle in current lane “ takes “-1” and few seconds (between 8-20) after the vehicle performs a lane change to the right and a possible steering event (Fig. 6.3).

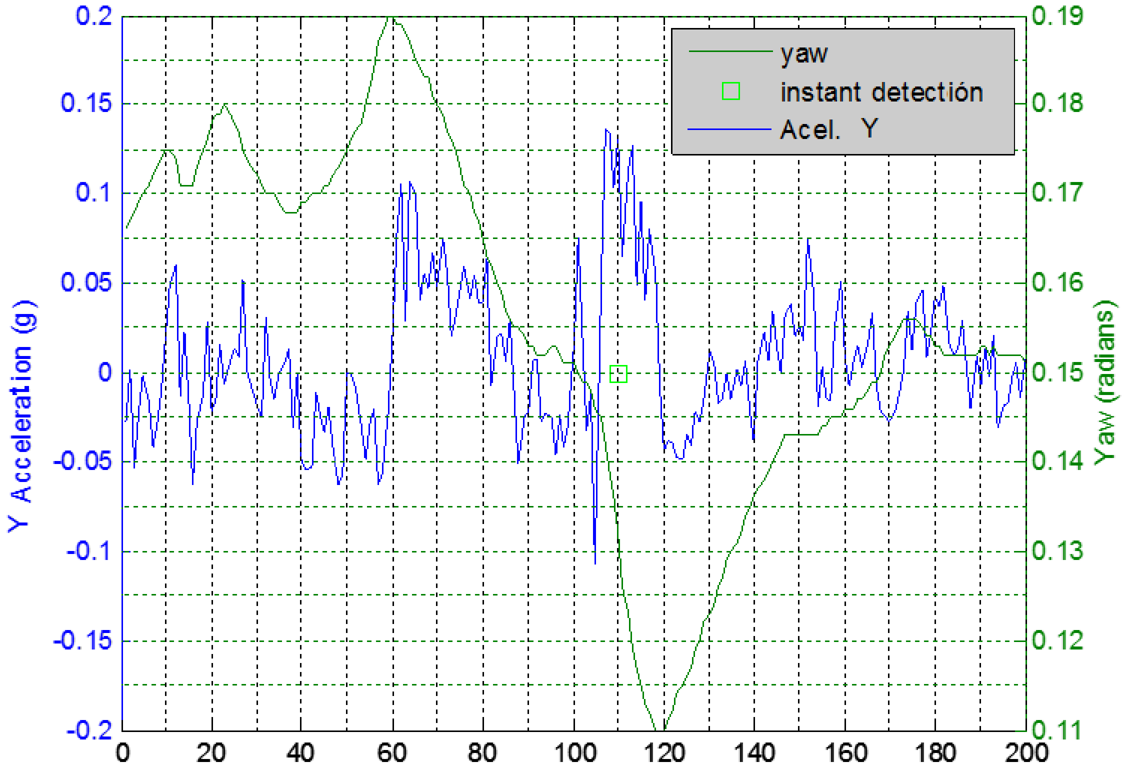


Figure 6. 2: Representation of acceleration in Y axis and Yaw

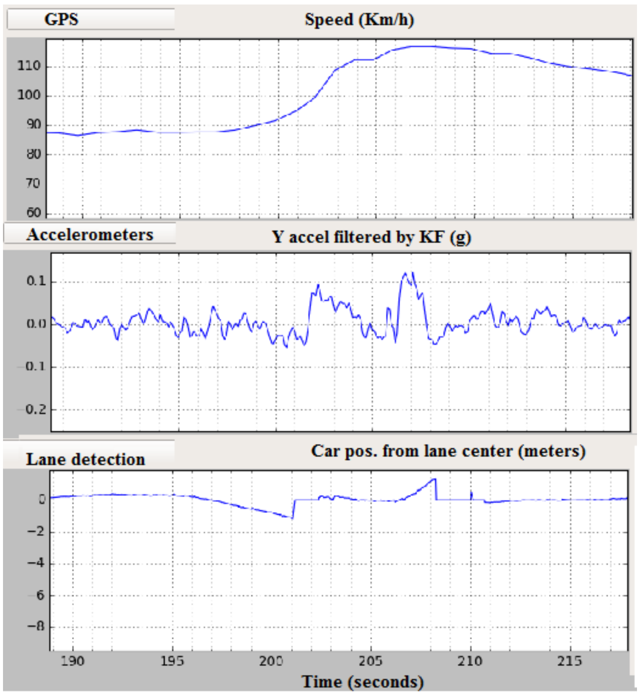


Figure 6. 3: Representation of Speed, Y acceleration and lane detection

Overtaking attempt is more dangerous than a full overtaking because it involves invading the opposite lane to start overtaking when a vehicle approaches. A great amount of these attempts made by a driver is a good indicator of aggressive style in the driving.

When an overtaking attempt occurs in secondary road, firstly it will have a lane change to the left jointly with a possible steering event. Then the variable ‘Distance to ahead vehicle in current lane’ takes ‘-1’ and few seconds (after less than 8) a vehicle is detected in the current lane. After that, a lane change to the right will happen and a steering event or/and a braking of medium or high level might be detected.

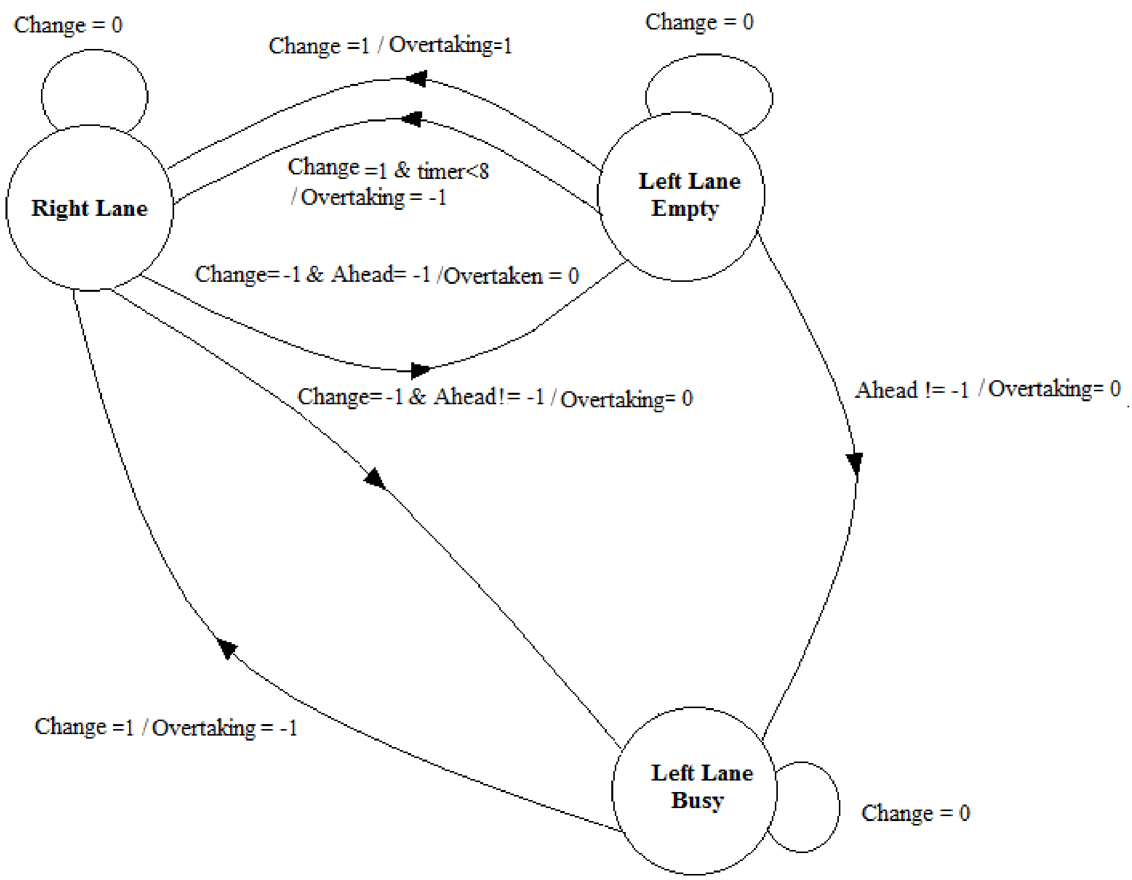


Figure 6. 4: Flowcharts of Overtaking manoeuvre

The flowcharts shows in Fig. 6.4 is proposed to detect overtaking manoeuvres and overtaking attempts. The inputs variables used are:

- ‘Change’: To obtain information of lane change. It is activated with a positive value if there is a right lane change or a negative value if the lane change is to the left.
- ‘Ahead’: To obtain the distance to a head vehicle (in metres). If this variable takes a negative value (-1) means that no ahead vehicle is detected, a positive value indicates the ahead vehicle distance in meters.
- ‘Timer’: Time in the left lane (in seconds).

The output variable is ‘Overtaking’, if this variable takes value -1 means overtaking attempt has been detected and if takes a positive value means an overtaking has been detected.

Our FSM is composed of 3 nodes (states) which detail the vehicle situation on the road:

- Right lane: The vehicle occupies the right lane.
- Left lane Empty: The vehicle occupies the left lane and there is no vehicle in front.
- Left lane Busy: The vehicle occupies the left lane and there is a vehicle in front.

Our FSM can be represented by a state transition table, showing for each state (node), the new state and the output resulting from each input (Table 6.1)

Current State	**Inputs**			**Next State**	**Output (Overtaking)**
	Change	Ahead	Timer		
Right Lane	0	Any	Any	Right Lane	0
Right Lane	-1	-1	Any	Left Lane Empty	0
Right Lane	-1	>0	Any	Left Lane Busy	0
Left lane Empty	1	0	>8	Right Lane	1 (overtaking)
Left lane Empty	1	0	<8	Right Lane	-1 (attempt)
Left Lane Empty	0	-1	Any	Left Lane Empty	0
Left Lane Empty	0	>0	Any	Left Lane Busy	0
Left Lane Busy	0	>0	Any	Left Lane Busy	0
Left Lane Busy	1	Any	Any	Right Lane	-1 (attempt)

Table 6. 1: State transition for overtaking

6.1.2. Abrupt gear shifts

Using the DriveSet Reader tool to review the abrupt gear shifts manoeuvres, it is observed the following guidelines are repeated:

In abrupt “downshifting of gear actions” a false detection of acceleration event is identified when you are braking with the engine and this is disengaged to shift into a lower gear. In that moment the driver feels inertial movement that pushes him forward until the gear is engaged. Due to this, DriveSafe detects an acceleration event (Fig. 6.5).

In abrupt “upshifting of gear actions” a false detection of braking event is identified when you are accelerating with the engine spinning to a lot of revolutions, and then it is disengaged to move to an upper gear. In that moment the driver feels inertial movement that pushes him backward until the gear is engaged. Due to this, DriveSafe detects a braking event (Fig. 6.6).

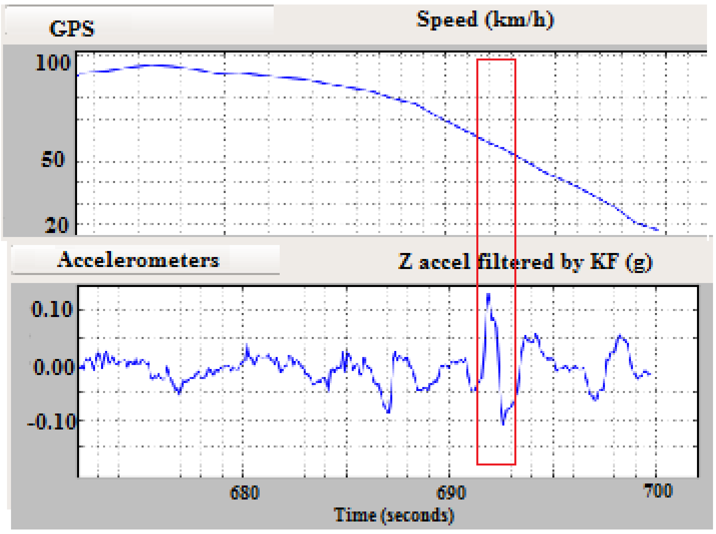


Figure 6. 5: Example of abrupt “Downshifting of gear” manoeuvre

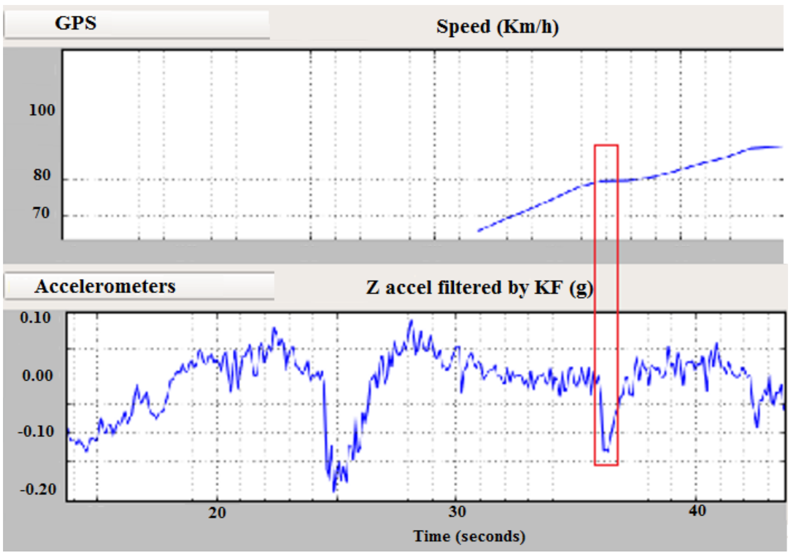


Figure 6. 6: Example of abrupt “upshifting of gear” manoeuver.

To detect these types of manoeuvres and avoid false detections, we propose a new classification of high level based on the criteria shown in the table 6.2. The inputs variables used are:

- Acceleration and Braking events detected by Fuzzy Classifier.
- Speed variation in the last 2 seconds previous to the event detection. This value is calculated from GPS sensor.

The output variables of our high level classifier are:

- “Abrupt gear shifts”: If this variable takes value “-1” means the driver performs an abrupt downshifting; if takes value “1” means the driver performs an abrupt upshifting manoeuvre and if takes value “0” means no abrupt gear shift.

- "Filtered Events": If this variable takes value "-1" means braking event; takes value "1" means acceleration event and takes value "0" means a false events was corrected.

Inputs		Outputs	
Detected Events (by Fuzzy Classifier)	***Speed variation***	***Abrupt gear shifts***	***Filtered Event***
Acceleration	Increase	0	1 (acceleration)
Acceleration	Decreasing	-1 (downshifting)	0 (false acceleration)
Braking	Increase	1 (upshifting)	0 (false braking)
Braking	Decreasing	0	-1 (braking)

Table 6. 2: Criteria of high level Classifier

6.2. Results

We perform experimental evaluation of our proposal of high level analysis comparing the manoeuvres detected and the manoeuvres observed in the video recorded in the UAH-Driveset database [31]. To measure the performance of the event detection we use a metric based on three parameters. First, we computed the number of True Positive (TP) events, i.e., the number of events that were actually been due by the driver and detected by the new layer. Then, we considered the False Positive (FP) events as the number of events that were detected by the new layer but that were not actually due to the driver. Finally, the True Negative (TN) events are those events that were due to the driver but were not detected by the new layer. The results of this experiment are shown in Table 6.3.

Manoeuvres	Metrics		
	TP	***TN***	***FP***
Overtaking	11	1	0
Overtaking attempt	3	0	0
Abrupt gear shifts	19	2	1

Table 6. 3: Metrics of High level analysis

In order to measure the accuracy of the manoeuvres, we use precision (PR) and recall (RC) performance indicators (Table 6.4).

Manoeuvres	**Accuracy**	
	PR	***RC***
Overtaking	1	0.92
Overtaking attempt	1	1
Abrupt gear shifts	0.95	0.9

Table 6. 4: Accuracy of the new manoeuvres

The results obtained in the Table 6.4 for Precision and Recall metrics get a success near to 100%. These kinds of manoeuvers are not performed very often.

This high level layer contributes to the elimination of false detections in the events detected by Fuzzy Classifier. Each detected abrupt gear shift manoeuvre means eliminate a false detections of braking or acceleration.

Chapter 7

Conclusions and Perspectives

This Thesis is focused on proposing some improvements for DriveSafe application. Firstly, it has been performed driving event detection for multiple devices and vehicles; we used a calibration phase that allows adapting the fuzzy set thresholds of the event detection algorithm. Secondly, other driving indicators have been identified in a high level analysis. Thirdly, in contrast to existing solutions, we have described an online calibration method. This is not a previous calibration phase, the driver does not to spend an extra time in adjust the system, the calibration is performed during the trip. Also it is adaptive if the vehicle dynamic parameters or the phone pose change during the trip, then the thresholds are updated obtaining a great performance in the detected events. Finally, a bump indicator has been incorporated to the system to provide us information about road conditions.

The experimental results were compared to a subjective opinion provided by each individual driver in order to evaluate the accuracy of the detected events, they were also compared to results obtain in the previous version. The results show that our method based on adjusting our fuzzy classifier decision thresholds using data obtained in certain route sections (uniform turns and uniform accelerations) performs better than our previous version based on fix thresholds. The overall results obtained for precision indicator in the revised version improves around 25% regarding the previous one. Total Recall improves around 27% 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.

7.1 Main Contributions

The main contributions of this Thesis that have been presented in previous chapters are summarized below:

- **Detector of events based on fuzzy logic:** It has been designed and developed a new classification of events in the driving based on fuzzy logic instead of fix thresholds. Furthermore, it has taken new input variables, with the aim of improving the results obtained so far and find new types of events useful to assess the road conditions (e.g. bumps).

- **Calibration process:** Different vehicles have different acceleration, braking and steering patterns, in order to detect events independently of vehicle conditions, we propose a calibration process to establish the boundaries of the fuzzy membership functions for input variables in order to standardize their behaviours.
- **High-level analysis:** A Finite State Machine (FSM) has been implemented to process the events detected by the fuzzy classifier adding information given by other DriveSafe modules in order to identify risky driving manoeuvers such as overtaking, gear shifts, sudden swerves and overtaking attempts. Also applying this level we get to correct detections of events that have been mistakenly classified.

7.2 Future work

Future work will involve both incorporate this method proposed technical improvements in the application and further development of the theoretical concepts applied to driver analysis. On the technical case, this comprises perform the integration of the calibration method, the fuzzy classifier and the high level layer in order to offer more indicators to score the driving behaviours. On the theoretical case, this could involve developing techniques to perform an on-line calibration of other inertial sensors in order to improve the accuracy in the event detection. The specific ideas about what will comprise future work related to this Thesis are summarized below:

- **Calibration of other inertial sensors**: We will propose an adaptive method to calibrate the decision thresholds of X accelerometer and 'yaw' gyroscope in other to improve the accuracy in the detection of bumps and steering events. Moreover, we intend to evaluate different approaches for the fuzzy set definition, considering other types of membership functions and statistical analysis over calibration data.
- **Driver analysis**: The driver analysis could be improved by adding more variables to the ones presented in this work or by making more complex the use of the ones that are currently used. Higher integration with the vehicle by means of Bluetooth or an OBD-II connector could be used to extract objective vehicle parameters and infer a consumption model of the driver.
- **Post-Evaluation**: We aim to validate the accuracy of the obtained scores in a second sensing campaign involving the same drivers that have been informed about their score from the first campaign. In this second experiment, we will focus on the analysis of driving behaviour changes, since all drivers will tend to drive more efficiently in order to reduce their scores.

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