Analysis of Aggressive Driver Behaviour using Data Fusion

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Abstract: This work describes recent advances in the analysis of driver aggressiveness in real road environments, based on on-board sensors, and Inertial Measurement Unit (IMU) with GPS information. In order to provide driver behaviour identification, a low-cost hardware architecture had been developed to retrieve Controller Area Network (CAN) Bus information. These data, combined with the IMU and the GPS, allow to provide driver behaviour identification. Therefore, features such as steering angle, throttle pressed percentage, linear accelerations, etc. are fused to classify driver behaviour through an expert system. This development has been exposed in real-traffic situations, with 10 different drivers. Tool showed, will allow researchers, drivers, and insurance companies to better understand risky driving behaviours.

1 INTRODUCTION

Traffic accidents are a major cause of injury and death in the world. With the increase in the number of vehicles, the protection of pedestrians and vehicle users is one of the priority topics for vehicle manufacturers.

Road accidents cause around 1,275,000 deaths per year, according to (OECD 2014). Inappropriate speed was a factor in nearly 35% of fatal accidents and about 16% of injury accidents in 2012. Velocity, in combination with other high-risk behaviours, is often cited as a factor in these accidents.

A traffic accident is the result of the coincidence of a series circumstances related to users, vehicles, infrastructure, traffic and environment giving rise to an unforeseen event of circumstances. It is well established that in a very high percentage, the main factor is related to the human factor. But not only deaths occur in accidents, there is also a much larger number of injured. It is estimated that around 50 million people are injured in road accidents every year.

According to the World Health Organization (Toroyan et al. 2015)road accidents are the leading cause of death among young people aged between 15 and 29 years, and cost governments approximately 3% of GDP. It is clear that an urgent solution is required.

Recent studies focused on driver behaviour modelling, such as analysis and modelling of behaviour (Belén et al. 2014) with a Gaussian Mixture Model (GMM) based on a framework with driving signals (e.g., following distance, vehicle speed). Human behaviour modelling and prediction system is presented in (Pentland and Liu 1999)based on a set of dynamic models, sequenced together by a Markov chain with driving signals (e.g. steering wheel angle, brake position, and accelerator position). Other examples in literature also try to provide added value based on on-board sensors, (Wakita et al. 2005) provides driving pattern based identification of driver. (Krajewski et al. 2010) provides driver's fatigue identification based on information of the steering wheel movement, and similar approach is presented by (Takei and Furukawa 2005). Finally, (Choi et al. 2007) provides behaviour analysis based on the CAN-Bus information by the use of Hidden Markov Models (HMM).

Motivation and Objectives

In order to reduce the death toll, driver behaviour identification can help to identify misbehaviours or changes in the attitude due to secondary tasks, fatigue, or urgency to reach to the destination, provoking erratic, or even aggressive behaviours (Shinar 1998). Furthermore, an integrated system that allows drivers to check their own driving experience through recorded notes, related to risky driving behaviour, and instructions of how to improve their behaviour, may help them to improve and encourage safe driving habits.

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The main objective of this work is to characterize the effect of aggressiveness behaviour in driving signals such as speed, lateral and longitudinal accelerations, and etcetera. Here, we propose a theoretical model describing this effect and test against real driving scenarios with different drivers, vehicles and road types (round, straight, curved, etc.). The second objective is to identify aggressive behaviour in a real roads experiments.

Figure 1: IVVI 2.0: research platform.

2 GENERAL DESCRIPTION

This work is included in the platform Intelligent Vehicle based on Visual Information (IVVI) 2.0 (Martín et al. 2014), Figure 1. This project is developed entirely at the Intelligent Systems Laboratory, Universidad Carlos III de Madrid.

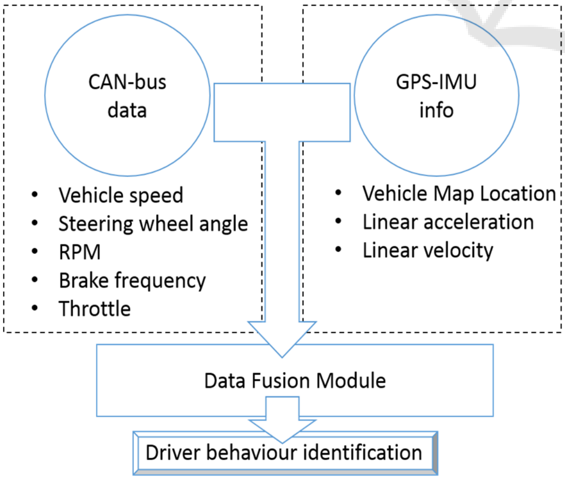

Figure 2: Information flow provided by CAN-Bus and GPS-IMU ground-truth device.

IVVI 2.0 is a research platform created to test and develop different Advanced Driver Assistance System (ADAS) technologies.

At this moment, different sensing capabilities are being researched, including road lane detection; pedestrians, vehicles and traffic signs detection and identification, driver monitoring and advance positioning and odometry systems (Martín et al. 2014). All of them focused on the development of computer vision algorithms and data fusion techniques.

In order to provide driver behaviour identification, a novel hardware-software architecture was designed. It acquires real-time information from the CAN-Bus related to the driver manoeuvres (steering wheel, braking pedal, throttle pedal...) and vehicle state (speed, rpm.) and sends it to the main data processing unit, available in the platform, through TCP/IP connection. This information is later fused with on board inertial Measuring Unit (IMU) and Global Positioning System (GPS). The processing unit, included in IVVI 2.0 is based on Robotic Operative System (ROS) for data acquisition and synchronization (Quigley et al. 2009) ROS allows a collection of tools that aims to simplify the complex task of global data acquisition and synchronization of sensors.

Driver behaviour is divided into aggressive and normal (not aggressive). Furthermore different scenarios according to the location (i.e. urban, interurban, or highway) are defined.

3 HARDWARE ARCHITECTURE

The aim of this study is to understand and identify the behaviour of drivers by the use of the available information in the vehicle. The CAN-Bus provides a reliable and adequate source of information, instead of adding additional sensors. Furthermore, data obtained from GPS and IMU devices, is merged to achieve the objective of this work, to classify the driver behaviour.

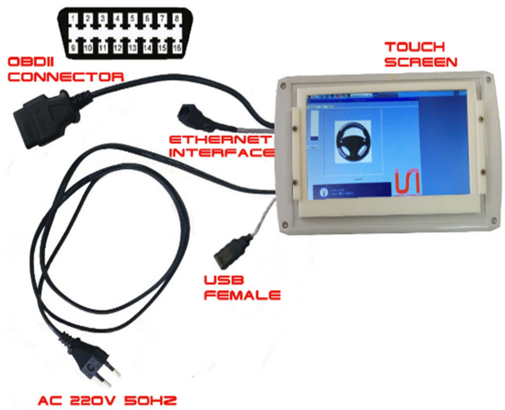

Figure 3: Full driver monitoring system module.

3.1 Simba

CAN-Bus carries vital information, such as engine temperature, air pressure, and monitoring fuel, which reflects the current condition of the vehicle. Furthermore, it carries information regarding to the driver direct manoeuvre such as steering wheel angle, speed, braking, throttle pedal, etc. All this information can be accessed through the on-board diagnostic port (OBD II).

In order to acquire this CAN-Bus information an embedded device was developed, able to acquire and process CAN-Bus data, without interfering with the CAN-Bus car line. The system named SIMBA which is the Spanish acronym for **B**idirectional **I**ntegrated **M**onitoring **S**ystem for **A**utomobile is an original IVDR.

Most of relevant information is transported through high speed CAN-Bus, the transmission protocol is described in ISO 11898 (ISO 11898 2003), however decoding work to identify the data information had to be carried out.

All the information is retrieved via the high speed bus at 500 kbps. However, the device is designed to read/write up to 1024 kbps. SIMBA includes a touch screen, Ethernet interface, USB female and a power supply, Figure 3.

The developed software provides on-line and off-line data processing. For the first, real time information is sent to the IVVI 2.0 server by Ethernet and TCP/IP. Thus, each CAN-Bus message is entered as a “message” under the given topic in ROS architecture.

3.2 GPS+IMU

This subsystem is formed of two devices, a Differential Global Position in System (DGPS) and an IMU. The DGPS is composed of a base station that transmit differential corrections in real-time. The accurate localization is used to identify environments based on digital maps. The IMU has embedded accelerometers and gyroscopes, all of them are embedded in a compact enclosure for outdoor applications (model: Flex Pak-G2-VG), as showed Figure 4.

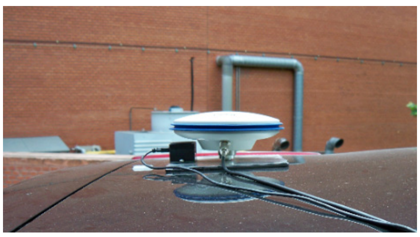

Figure 4: GPS + IMU module set up on IVVI 2.0 roof.

Precision technical data are summarized in a DGPS using L1 C/A-code mode data for differential solution, where the accuracy is less than 1 m. IMU module integrates a triaxle accelerometer, triaxle gyroscope and triaxle magnetometer, with an acquisition frequency up to 100Hz.

4 SOFTWARE MODULE

The software module is characterized by the use of an expert system for driver behaviour identification. The intelligent approach is based on the use of signal descriptors, which identifies specific patterns in the driver's behaviour. The descriptors are obtained in both time and frequency domains, which are later used to identify different features for the intelligent detection system. Thus, deliberation behaviour is not based in the sole information of a single signal, but the fusion of the different descriptors.

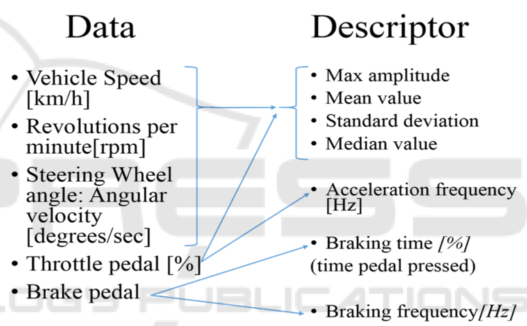

Figure 5: Descriptors used, extracted from CAN-Bus module.

4.1 CAN-Bus Descriptors

Information in time domain from CAN-Bus is related to the statistical information of the signal. It is integrated into a predefined time window that gives an estimation of the driver behaviour on the defined time. The descriptors used are different according to the signal used, as presented in Figure 5.

Descriptive statistics summarize large sets of quantitative information. Central tendency refers to the idea that there is one number that best summarizes the entire set of measurements. For our algorithm mean and median have been used, equation 1, 2.1 and 2.2.

$$\bar{x} = \frac{1}{N}\sum_{1}^{N} x\_k[t] \quad (1)$$

$$\tilde{x}_{\mathrm{odd}} = \left(\frac{n}{2}+1\right)^{th} term \quad (2.1)$$

$$\tilde{\chi}_{\text{even}} = ((\frac{n}{2})^{th}\ term + (\frac{n}{2}+1)^{th}\ term\,)/2 \quad (2.2)$$

Dispersion tells us how spread all the measurements are, from the defined value i.e. standard deviation.

$$\sigma_x = \sqrt{\frac{1}{N}\sum_{1}^{N}(\bar{x} - x[t])^2} \qquad (3)$$

Specific descritor according to the type of information where also added, e.g. throttle pedal signal, which not only has been processed with statistical descriptors, it was obtained the press frequency.

$$f = \frac{\#\ times\ pedal\ pressed}{total\ time} \qquad (4)$$

Braking signal had specific descriptors due to its binary nature (pressed/not pressed) i.e. braking time (time pedal pressed) [%], as given in equation (5), and braking frequency (times pedal pressed) [Hz], as shown in equation (4) for throttle pedal.

$$bt = \frac{time\ pedal\ pressed}{total\ time} \qquad (5)$$

4.2 GPS+IMU Descriptors

Accelerations are important to measure the comfort level of the vehicle occupants. Linear accelerations in three axes can be acquired from the IMU sensor. Due to the ground nature of the vehicle displacement, vertical axis was discarded from the system.

Figure 6 displays, the use of some central measurements (mean, median) and a statistical dispersion (standard deviation) for accelerations. GPS coordinates had been entered into the system, thanks to digital maps, it can be used to label the environment, and to acquire the maximum speed allowed.

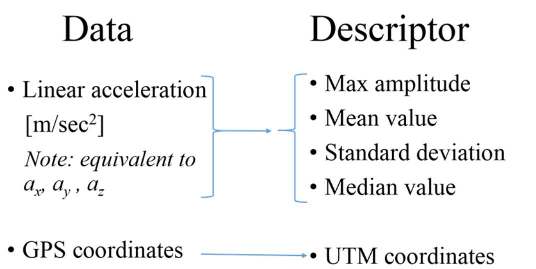

Figure 6: Descriptors used, extracted from GPS + IMU module.

5 TEST

Different routes were tested, as shown in Figure 7 where it is displayed an example of urban environment. The route includes different traffic situations, such as curves, lines, roundabouts, traffic lights, stops and overtaking manoeuvres. The length of the route was variable, depending on the type of environment, but fixed for all drivers. The weather conditions where sunny and dry. Sequences were conducted during July 2015. Ten different drivers were involved in performing the experiments, driving the same car, IVVI 2.0.

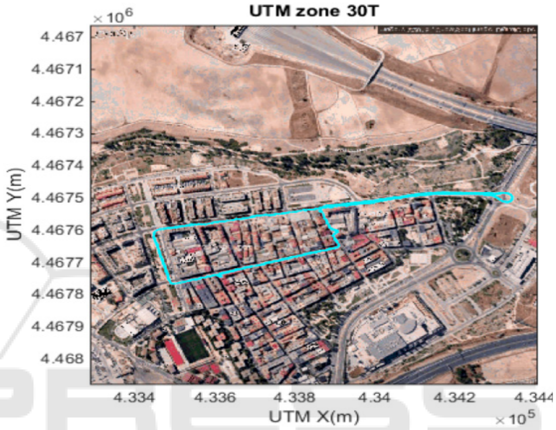

Figure 7: Driving Scenarios.

Each of the drivers made a round of aggressive driving and a series of rounds of smooth driving; depending on the driver.

They were not given any prior definition, or suggestions about aggressive driving.

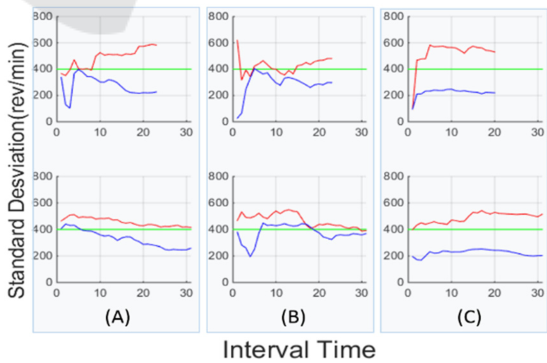

Figure 8: R.P.M, (standard deviation), for three subjects (A, B, C). First row: urban environment, second row interurban environment.

6 RESULTS

First, we analysed the features of driver behaviour with different labelled sequences (aggressive and non-aggressive). Data was collected and descriptor computer in temporary windows of 20 seconds, with a 50% overlap.

The data collected is shown in Figures 8 to 12, where red colour represents the information obtained for an aggressive driver, and blue colour represents a normal driver (non-aggressive) behaviour.

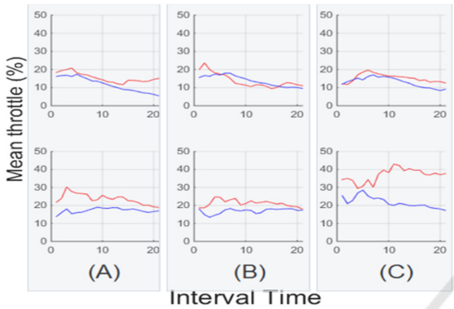

Figure 9: Mean for throttle signal for three different. Drivers (A, B, C). First row: urban environment, second row interurban environment.

In urban environment with more “stop & go” manoeuvres, the standard deviation could be a good tool to classify the grade of aggressiveness. In other scenarios such as motorways, central values provide more information. Figure 8 compares the standard deviation for R.P.M, with aggressive and non-aggressive drivers using the same vehicle route for three different drivers. It was noted, while performing aggressive driving, drivers reach to a level over 400 R.P.M. In this case, we implemented a threshold, shown in green line.

The goal is to create a robust system, merging different signals, from different sources, explained in previous sections. Thus further information is needed in order to provide accurate information.

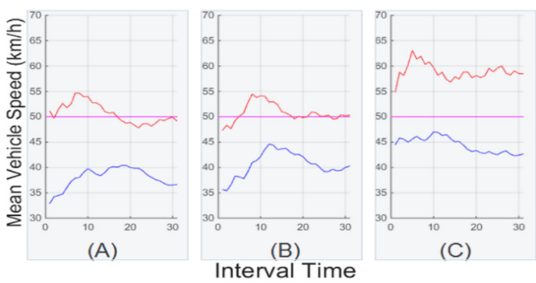

Figure 10: Mean for Vehicle speed in a 20s time window. Maximum speed of the road: 50km/h.

Throttle pressed information, may show a lack of driving stability. As Figure 9 shows, mean value for throttle signal present values much higher for aggressive conditions. This is especially useful to highway environments, where R.P.M, is much more stable.

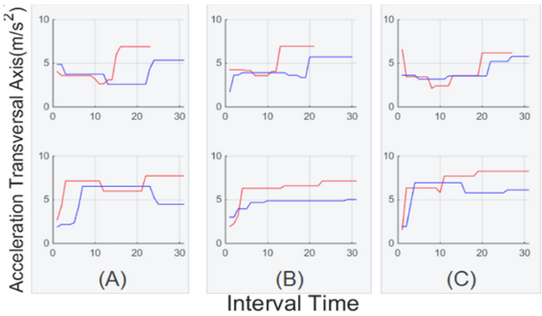

Figure 11: Plotting STD for longitudinal axis, principal movement. First row: urban environment, second row interurban environment.

Displayed in Figure 10**,** the vehicle speed mean value is interesting if we know the maximum allowed in the road. This is possible thanks to the GPS signal and digital maps. The algorithm determines aggressive driver as a driver who exceeds the speed of the road, according to the average of the defined window. As it stated in the introduction section, speed is often cited as a factor in aggressive behaviour, i.e. speed is a critical feature. Here, the maximum speed was highlighted in pink. Automatically labelling as aggressive a driver who exceeds the legal speed several times during a time window.

Further CAN-Bus signals, such as steering wheel movement (angular speed) show higher values for aggressive driver behaviour. This information, together with IMU information, can help to identify misbehaviours due to strong lateral movements. Tests evidenced standard deviation represented better descriptor in all environments for IMU data, as Figure 11 and Figure 12 show for longitudinal and lateral axis.

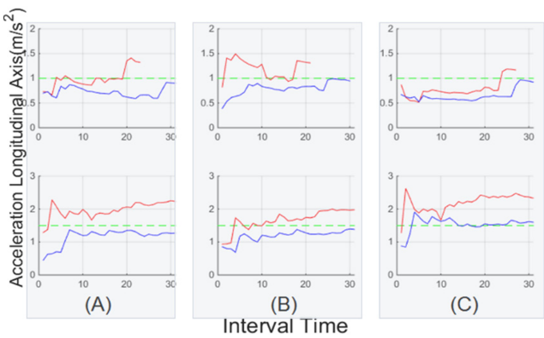

Figure 12: Local peaks in lateral axis, obtained by IMU hardware for three different drivers (A, B, C). First row: urban environment, second row interurban environment.

7 CONCLUSIONS

The work presented represents a step forward in several fields, with an extent field of application, including insurance companies, public entities, human factors research and etcetera.

Intended to be used in any vehicle, the system is a low-cost device for driver monitoring through CAN-Bus information and on-board sensors. The application is based on data fusion techniques with temporal and frequency descriptors, merged in a crisp ruled-based expert system.

Results section showed an important point to be taken into account, the necessity of multiple signals in order to provide an accurate identification. Analysis based on a single signal, can lead to misinterpretation, e.g., a non-aggressive driver having constant speed changes due to the situation of the urban environment.

Future works will focus on the addition of further information already available in the vehicle, such as visual information based on advanced perception systems, already available in the IVVI 2.0 platform.

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REFERENCES

Belén, A. et al., 2014. Modeling and Detecting Aggressiveness From Driving Signals. , 15(4), pp.1419–1428.

Choi, S. et al., 2007. Analysis and classification of driver behavior using in-vehicle can-bus information. *Biennial Workshop on DSP for In-Vehicle and Mobile Systems*, (November 2015), pp.17–19.

ISO 11898, 1993, 2003. *Road vehicles - interchange of digital information - controller area network (can) for high-speed communication*,

Krajewski, J. et al., 2010. Detecting Fatigue from Steering Behaviour Applying Continuous Wavelet Transform. *Proc. Measuring Behaviour*, pp.326–329.

Martín, D. et al., 2014. IVVI 2.0: An intelligent vehicle based on computational perception. *Expert Systems with Applications*, 41(17), pp.7927–7944. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0957417414003947 [Accessed October 28, 2014].

OECD, 2014. Road Safety Annual Report 2014 Road Safety Annual Report 2014.

Pentland, A. and Liu, A., 1999. Modeling and Prediction of Human Behavior. *Neural Computation*, 11(1), pp.229–242.

Quigley, M. et al., 2009. ROS : an open-source Robot Operating System.

Shinar, D., 1998. Aggressive driving: the contribution of the drivers and the situation. *Transportation Research Part F: Traffic Psychology and Behaviour*, 1(2), pp.137–160. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1369847899000029.

Takei, Y. and Furukawa, Y., 2005. Estimate of driver's fatigue through steering motion. *2005 IEEE International Conference on Systems, Man and Cybernetics*, 2(1), pp.1–6.

Toroyan, T., Peden, M.M. and Iaych, K., 2015. Global status report on road Safety. *Injury prevention : journal of the International Society for Child and Adolescent Injury Prevention*, 19(2), p.150. Available at: http://www.ncbi.nlm.nih.gov/pubmed/23513037\nhttp://www.who.int/violence_injury_prevention/road_safety_status/2015/en/.

Wakita, T. et al., 2005. Driver identification using driving behavior signals. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, 2005(3), pp.907–912.