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DriveSafe: an App for Alerting Inattentive Drivers and Scoring Driving Behaviors

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Abstract— **This paper presents DriveSafe, a new driver safety app for iPhones that detects inattentive driving behaviors and gives corresponding feedback to drivers, scoring their driving and alerting them in case their behaviors are unsafe. It uses computer vision and pattern recognition techniques on the iPhone to assess whether the driver is drowsy or distracted using the rear-camera, the microphone, the inertial sensors and the GPS. We present the general architecture of DriveSafe and evaluate its performance using data from 12 drivers in two different studies. The first one evaluates the detection of some inattentive driving behaviors obtaining an overall precision of 82% at 92% of recall. The second one compares the scores between DriveSafe vs the commercial AXA Drive app obtaining a better valuation to its operation. DriveSafe is the first app for smartphones based on inbuilt sensors able to detect inattentive behaviors evaluating the quality of the driving at the same time. It represents a new disruptive technology because, on the one hand, it provides similar ADAS features that found in luxury cars, and on the other hand, it presents a viable alternative for the "black-boxes" installed in vehicles by the insurance companies.**

I. Introduction

Driving while being inattentive (drowsy or distracted) is dangerous. According to the National Highway Traffic Safety Administration (NHTSA) about 25% of police-reported crashes involve some form of driver inattention [1]. In 2010 only in USA, 3,092 people were killed and 416,000 injured during accidents directly attributed to inattention [2]. These figures are similar in Europe [3]. According to experts, many drivers fail to recognize they are in a fatigued state. In consequence, developing technologies to detect and alert inattentive drivers is essential to avoid vehicle accidents and to stimulate safe driving practices in drivers.

In the last years, there have been active research toward developing systems that make driving safer [4, 5]. These include collision-avoidance, lane departure warning, blind spot warning and driver inattention monitoring systems. Some systems even trigger automatic steering when the vehicle drifts into another lane or brake before getting dangerously close to the vehicle in front. 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. Toward developing an affordable alternative for bringing safety features to economy vehicles our approach is to leverage smartphones that are always present with people.

Fig. 1. DriveSafe app running on iPhone 5

On the other hand, the advent of mobile sensing platforms 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]. In the motor insurance sector, such data can be used to improve the assessment, communication and mitigation of insured risk, thereby creating value for insurers and policyholders alike. The premise of this approach is that providing feedback of recorded driving actions to drivers, they are encouraged to change their behavior and reduce their individual accident risk. However, in the current insurance markets, consumers have rejected the so-called Pay-As-You-Drive due to two main reasons [7]: the required installation of "black-boxes" in vehicles makes drivers perceive the monitoring as intrusive, and the installation and operation of these units incurs 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.

With this background, we propose DriveSafe. The driver's iPhone must be placed on the windshield, just below the rearview mirror and aligned with the relevant axes of the vehicle, as it is depicted in Fig. 1. Using the information obtained from some inbuilt iPhone sensors, DriveSafe applies computer vision and pattern recognition techniques on the phone to detect the most commonly occurring inattentive driving behaviors divided into two main groups: drowsiness and distractions. Lane weaving and drifting behaviors are measured to infer drowsiness. Lane weaving happens when a driver performs lane changes without turning the blinkers. Lane drifting is the inability of the driver to keep its vehicle

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within the center of the lane. Distractions are based on sudden longitudinal and transversal movements. In addition, the app scores the driving as a function of the frequency and level of these dangerous behaviors. In case they get over a certain threshold an alarm is generated. On the one hand, DriveSafe aims to mimic some safety features found in many top-end vehicles on the market today but using a commodity iPhone. On the other hand, it persuades insurers this app is an interesting alternative to conventional "black-boxes" improving other proposals of the state of the art.

II. Related Works

Monitoring driving behavior using fixed vehicle-mounted devices is an active area of research. In the case of inattentive driving, a good review of the current state of the art can be found in [8]. The systems used by many auto manufacturers are mainly based on core technology from Mobileye [4] and Iteris [5]. Both companies use radars as well as 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, 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 and disruptive technology. This is the reason why in the last years there has been an active work on using smartphones to assist drivers. Hereafter, we review some of the most important references. SignalGuru [9] advises the driver to maintain a certain speed while approaching a signal for fuel efficiency. iOnRoad [10] and Augmented Driving [11] are apps that warn drivers when they get too close to a vehicle. SmartLDWS [12] offers warning sounds when the vehicle departs a lane marker. CarSafe [13] alerts drowsy and distracted drivers using dual cameras on smartphones, one for detecting driver state and the other for tracking road conditions. However, it works in quasi real-time and the driver's indicators get worse at night and with bad lighting conditions. In [14], a recognition system of the driver aggressiveness based on sensor-fusion is presented. In the same line, [15] estimates if a driving behavior is safe or unsafe. The last two cases need a previous learning and are dependent of the road curvature. Other works have proposed to extend smartphone's sensors capabilities by connecting them to a vehicle's OBD-II diagnostic interface for driver classification [16] or reduction of fuel consumption purposes [17].

In developing DriveSafe, we've revised some techniques available in our group [18][19] and we have adapted them to be run on an iPhone. To the best of our knowledge, none of the related works detects driver inattentions (drowsiness and distractions) by using lane weaving/drifting and sudden longitudinal/transversal movements from the inbuilt sensors of an iPhone, evaluating the quality of the driving at the same time, independently of the road geometry and running in real-time. DriveSafe comes to fill this gap.

III. DriveSafe Implementation

In this section, we present an overview of DriveSafe architecture and its algorithms, as it is illustrated in Fig. 2. This app is activated when the vehicle overtakes 50 Km/h (about 31 Mph) because it has been conceived as an assistant for roads and not for cities driving. Our app is divided in four main modules: sensors pre-processing, detection of inattention behaviors, driving evaluation and user interface. We apply a different methodology depending on the inattention to be detected. Drowsiness is based on image analysis because this is a low frequent behavior that can be faced at the image processing rate (25 to 30 fps) adapting our previous knowledge. Distractions are very fast behaviors that need the fastest possible detection. We use inertial sensors at 100 Hz for this purpose instead camera images. Hereafter, we explain the two methodologies carried out.

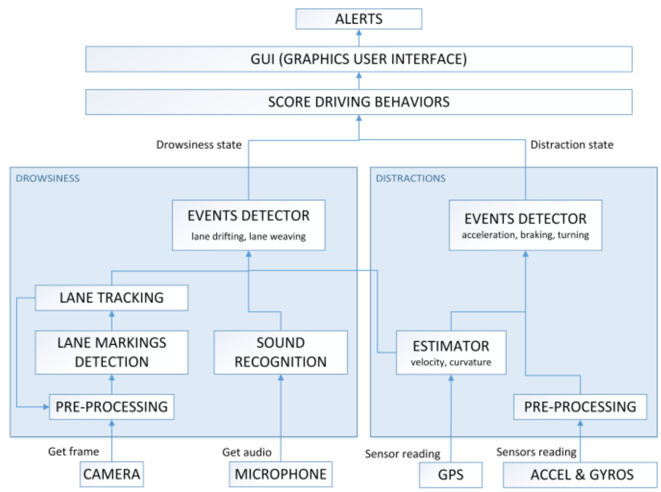

Fig. 2. DriveSafe architecture

A. Drowsiness

Drowsiness is evaluated through the detection of lane drifting and weaving events obtained from a modification of the Dickmans road model-based method [20]. The combined effect of low resolution and lack of real camera parameters has made unreliable the deployment of some algorithms based on Inverse Perspective Mapping. It employs road images captured by the rear-camera to detect lane markings on the road ahead and to estimate the position of the vehicle relative to the lane and lane crossings. The microphone is used for blinking detection and the GPS for estimating vehicle speed and road curvature. Our lane detection algorithm is robust to failures and guaranties a correct detection. It is based on three functionalities which are contained in the pre-processing module: calibration, initialization and detection.

Pre-processing. This module transforms the color image to gray scale, resizes it to 320 x 240 pixels and adapts the ROI for the lane markings detection in the next frame. There is only a trapezoidal ROI in the calibration and initialization, but in the detection it is divided in two, one for the left markings and another for the right one (see Fig. 3(a)). The width of these areas is adaptive and depends on the tracking module. As long as the tracking gets worse, the width increases, and vice versa. Then, this module is in charge of the switching among the different functionalities based on tracking performance.

Lane markings detection. Lane markings are assumed to be edges. Then, an edge detection stage is carried out by using an adaptive Canny algorithm which maximizes the edges in each ROI (see Fig. 3(b)). After that, the Hough transform algorithm is applied to obtain candidate lines for each of the two ROIs, limiting the solution space by imposing some geometrical constraints (see Fig. 3(c)). Among all the segmented lines, we choose a representative line per ROI maximizing the length of the line, minimizing the angle difference between the candidate and the road model and the difference between the model vanishing point and the vanishing point obtained among the candidates for the left and the right side. After this process, we will have a winner line for each ROI aligned with the lane boundaries (see Fig. 3 (c) winner lines in white color).

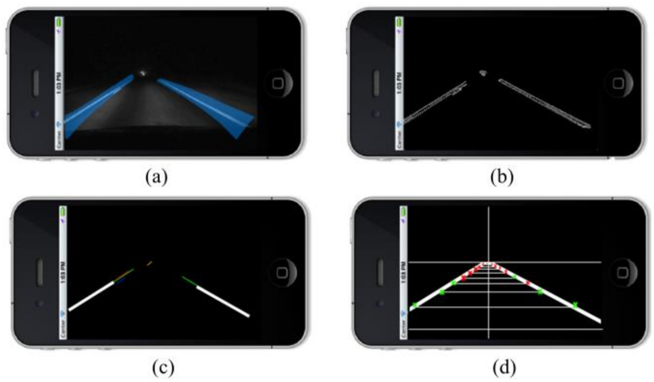

Fig. 3. Illustrative example of lane detection process at night. a) ROIs in the gray scale image, b) Canny edges, c) Segmented and winner lines, d) Marker measures and lane model

To increase detection robustness we use a 3D road model in the real world and the position of the road edges in the image, following a clothoidal model defined in [20]. The mathematical problem is that of computing the clothoidal parameters as well as road parameters and the position of the ego-vehicle with respect to the road edges. This amounts to a total of 5 different parameters: C_0 (initial curvature), C_1 (velocity of the clothoidal curve), w (road lane width), x_0 (lateral displacement of the car with regard to the center of the lane), and ψ (angular displacement of the car with regard to the lane orientation). The meaning of these parameters is described in Fig 4.

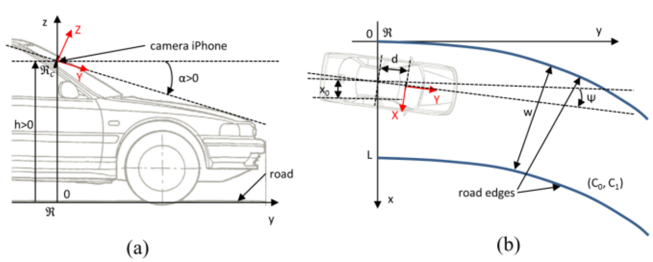

Fig. 4. Definition of parameters. a) Side view. b) Bird's eye view.

Measurements in the image plane must be related to measurements in the 3-D scene. Following the perspective projection equations of a camera and the equations of clothoidal curves, a measurement model is set as follows.

$$\theta = a\tan\left(\frac{h}{L}\right) \qquad v = f_v \cdot \tan(\theta - \alpha) \tag{1}$$

where v stands for the vertical coordinate of the road edge feature in the image plane, h is the camera height, α is the camera pitch angle, L is the distance from the car to the edge feature in the 3-D scene, and f_v is the vertical size of the camera focal length. Horizontal coordinates are computed from Eq. (2).

$$L_{cv} = L + d \qquad u = \frac{f_u}{L}\cdot\left(C_0\cdot\frac{L_{cv}^{\;2}}{2} + C_1\cdot\frac{L_{cv}^{\;3}}{6} - x_0 \pm 0.5\cdot w - L_{cv}\cdot\psi\right) \tag{2}$$

where d stands for the distance between the vehicle gravity center and the camera position, f_u is the horizontal dimension of the camera focal length, and u is the horizontal coordinate of the edge feature pixel in the image plane. Camera parameters, h and d are set in the calibration. Eq. (2) is computed for all lane markings detected in the neighborhood of the winner lines for every meter (Fig. 3 (d) points in red and green). Then, the road model is estimated (in white).

Lane tracking. It is implemented using Kalman filtering based on the previous measurement model and the dynamic state model for the following state vector:

$$x = \begin{bmatrix} C_0 & C_1 & x_0 & \psi & w \end{bmatrix}^T \tag{3}$$

When the lateral position (x_0) is about to leave the lane, a new lane model is generated by shifting the current model to the left or the right a current lane width. If enough lane marking measures are detected with the new model, a lane switch is carried out. Otherwise, the current lane model is kept. A lane change is detected when the lateral position overtakes half of the lane width ($w/2$).

Event detector Lane drifting. It is based on the indicator called Lanex (fraction of Lane exits), which is a measure of driver's tendency to exit the lane [19]. It is defined as the fraction of a given time interval spent outside a virtual driving lane around the center of 1.2 m width. It is calculated by applying windowing techniques over the lateral position of the vehicle (x_0) during 60 s.

Event detector Lane weaving. It evaluates involuntary lane changes. Analyzing the presence or absence of the directional indicator, the event detector module can conclude whether a lane change is intentional or not. We have used the built-in microphone to capture the clicking sound generated by the indicator, in order to avoid external dependencies. We enable the sound recognition module when the vehicle is about to leave the lane. The details on how the sound is captured and identified are beyond the scope of this paper.

B. Distractions

According to the state of the art, the most established method for assessing driving distractions is to analyze the frequency of critical driving events [21], which are generated by different means of sensor fusion. They can be aggregated by summation and normalized over the driven distance, and are thus suitable metrics of driving behavior. For the scope of this paper, we consider critical driving events as violations of certain thresholds imposed on vehicle acceleration measured by iPhone IMU. A major part of smartphone-based applications for the assessment of driving behavior follow this approach.

There are three accelerometers and three gyroscopes available on the iPhone IMU for the measurement of lateral and angular accelerations along three fixed axes. These axes form the coordinate frame of the device. The x-y plane of the accelerometer sensor is parallel to the touch screen and the z component is perpendicular, as it is depicted in Fig. 5. In our case and after the setup process, the device is mounted in a vehicle with its three axes aligned with the relevant axes of the vehicle. Thus, the vehicle-fixed z-axis is tangential to the vehicle trajectory and the y-axis is perpendicular. Then, four different maneuvers can be detected by thresholds on these measurements. Along the z-axis, forward acceleration corresponds to the throttle use of the driver, where abrupt peaks indicate aggressive increases of velocity. Sudden deceleration is an indicative of harsh braking, and therefore indirectly of not retaining a minimum distance to the vehicle ahead. Along the y-axis, high lateral acceleration points toward excessive velocity in left or right turns, and may result in the vehicle loosing traction. The thresholds needed to detect these four event types have been taken from [6]. Additionally, we have established three different levels for each one in order to get a better evaluation of the driver's behavior, as shown in Table I.

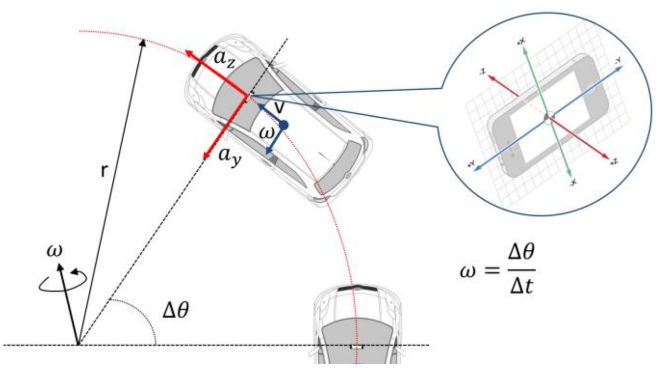

Fig. 5. Coordinate frame of the iPhone vs vehicle.

TABLE I. DISTRACTION EVENT THRESHOLDS

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	$0.1g < \lvert a'_y \rvert < 0.2g$	$0.2g < \lvert a'_y \rvert < 0.4g$	$\lvert a'_y \rvert > 0.4g$

Pre-proccesing. Accelerometer data is sampled at a rate of 100 Hz. The raw data from the iPhone contains significant amounts of noise from the vibrations onboard the vehicle. Thus, this signal is cleaned using a Kalman filter with a state vector formed by the three components of the accelerometer (a_x, a_y, a_z). The filtered features prove to be highly correlated with the vehicle movements.

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 thresholds in Table I. When an event is activated, a hysteresis period is enabled to account for potential activations in the near future.

As it is remarked in [6], none of the currently available applications for the assessment of driving behavior consider the dependence of the event counts with the road geometry. To solve this problem we propose 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 center of the turn. This centripetal force generates a centripetal acceleration, a^c_y, also pointing toward the center of the curve. Assuming a turn following a perfect circle, the centripetal acceleration (a^c_y) can be obtained by using the angular speed (ω), the tangential velocity (v) and the radius of the turn [22].

$$a_y^c = \frac{v^2}{r} = r \cdot \omega^2 = \omega \cdot v \tag{4}$$

Based on Fig. 5, it can be seen that vehicle and iPhone have the same radii, then, they will have the same centripetal acceleration. Taking into account that (v,ω) can be estimated each second from the GPS, we have a coarse estimation of the centripetal acceleration of the vehicle due to the road. Subtracting the lateral acceleration measured by the iPhone from the centripetal acceleration of the vehicle, we estimate the lateral vehicle acceleration due to defective driving maneuvers ($a'_y = a_y - a^c_y$). Inspired by this simple yet useful physics observation, we have reached to solve an important gap of the state of the art.

C. Score Driving Behaviors

We propose a preliminary evaluation technique that has shown good practical results. Drowsiness is evaluated with only one indicator that takes into account the mean and the standard deviation of Lane Drifting (m_{LD},σ_{LD}) and Lane Weaving (m_{LW},σ_{LW}) signals each second.

$$Score_{Drow} = 1 - \left(\left(\frac{m_{LD} + \sigma_{LD}}{2} \right) + \left(\frac{m_{LW} + \sigma_{LW}}{2} \right) \right) \tag{5}$$

Distractions are evaluated with three different indicators (e={acceleration, braking, turning}) in order to compare our results with another system of the state of the art. We score the indicators taking into account the number and intensity of the events detected per Km through the Eq. (6). (k_1, k_2, k_3) are constants experimentally calculated. CDF_e represents cumulative distribution functions of the Gaussians for a normal driving, previously obtained for one of the users in the highway route.

$$\begin{aligned} Event\_km_e &= \left[\left(k_1 \cdot Low_e + k_2 \cdot Medium_e + k_3 \cdot High_e \right) / Km \right] \\ Score_{Dist_e} &= 1 - CDF_e\left(Event\_km_e \right) \end{aligned} \tag{6}$$

D. Graphics User Interface (GUI)

DriveSafe is a stand-alone application which GUI consists in augmented reality of the road with the position of the vehicle in the lane. It has a color bar in the right side indicating on-line driver inattention level. Then, it offers some visual and acoustic alarms that can be switched on/off in the configuration menu. To avoid visual distractions, augmented reality can be switched off. Our app has a complete repository where users can find useful information about their trips as: date, starting and ending time, driving time, distance, max and average speed, driving scores, number of detected events, a map of the driving route and automatically recorded videos of the dangerous behaviors.

IV. EXPERIMENTAL RESULTS

DriveSafe is embedded on iPhone 5 and has been written in C/C++ based on the OpenCV libraries. It is able to run at 25-30 fps in average. The first version of this app was uploaded to the Apple store in June 2013 with some limited functions (Version 1.0). In the first 6 months, more than 2,500 downloads were carried out. In this paper, we present the version 2.0, which will be uploaded to the market in the near future. This version has been tested by the developers in thousands of kilometers in different roads (city, country and highways) with different drivers and vehicles, at different daytime (day and night) and with bad weather conditions (rain, snow, fog, wind) reaching a subjective good behavior. In this section we present a quantitative evaluation of our system based on a controlled test-bed. Two studies are done. On the one hand, we analyze the performance of the events detection using a supervised ground-truth. On the other hand, we study the driving behavior evaluation comparing the scores provided by DriveSafe with the scores provided by AXA Drive [23].

A. Test-bed

Collecting datasets to adequately evaluate DriveSafe is challenging. This is because dangerous driving events are not guaranteed to happen during normal/routine driving experiences. Thus, we can't accumulate enough examples of poor or dangerous driving to fully evaluate DriveSafe. Furthermore, it would be irresponsible to run an experiment that promoted risky behaviors. For these reasons, we evaluate DriveSafe using two different tests: (1) aggressive driving under controlled vehicle maneuvers, where we safely "stage" dangerous driving events under controlled conditions, in which each driver is accompanied by a "co-pilot" who launches the controlled maneuvers only when external conditions on the road are safe; (2) normal driving, which only contains data collected during everyday driving routines, but in this case with the presence of a "co-pilot" that only takes some notes.

We recruited a total of 12 participants (9 males and 3 females) of our Lab. Each participant carried out the two tests (aggressive and normal), 20 min long each one, in different days and varied daytime (4 at morning, 4 at afternoon and 4 at night). In 20 tests, the weather conditions were mainly bright and sunny, 2 were raining and 2 foggy. The test vehicle was a Renault Laguna with manual shift, as a reasonable representation of mid-sized cars. All sequences together added up 480 minutes of driving data and they were staged in a predefined highway under normal traffic. For the aggressive driving test, each participant was invited to perform the following maneuvers: 2 x lane drifting, 6 x lane weaving, 4 x sudden acceleration, 6 x sudden brake and 2 x sudden turn. All the events were instantaneous except lane drifting. In the case of lane drifting the user was forced to drive out of the lane center during 30 s. The number of events was chosen depending on the priori event dangerousness. Under normal daily driving conditions, participants tend to drive their cars carefully, and therefore perform few dangerous driving events. A total of 282 inattentive driving events were recorded, 245 coming from the controlled experiments and 37 coming from the normal daily driving dataset. The most common dangerous driving event found in the normal daily driving was braking.

The test car was instrumented with two smartphones in order to get the ground-truth for the performance analysis events detection, and to have data for comparing driving scores. One runs DriveSafe, with an additional skill for recording data, and the other runs AXA Drive app. Upon completion of the experiments, we manually labeled inattentive driving events analyzing recorded driving data and the co-pilot information. A lane drifting event was marked when the Lanex is over 80%. A lane weaving event was marked when an involuntary lane change happened. For the acceleration, breaking and turning signals we labeled an event when the low threshold was reached. In the classification phase, an event was true if it was detected in a temporal window of 2 s around the ground-truth position.

B. Events Detection Performance

The key feature in DriveSafe performance is its ability to detect instances of inattentive driving under real-world conditions. Table II provides the precision and recall results across all tested driving scenarios (aggressive and normal). We get an overall precision of 82% at 92% of recall. LW and LD yielded best results with a precision about 90% at high recall. This shows that indicators based on vision are very robust. We have studied the 3 FPs of LD and are due to the car being close to the lane markers for some periods before overtaking the vehicle ahead. FPs of LW are mainly due to shadows and near crossings. Some AC and BR wrong detections are due to road bumps or confusions between them. Finally, some false TNs are occasioned by the delay in the estimation of the centripetal acceleration due to the road curvature regarding the current acceleration measures by the inertial sensor. Besides, we observed that differences found between daytime in IMU and vision indicators were very low. In the case of vision, indicators are less noisy at night. A high influence of weather conditions on measured data could be excluded as well.

TABLE II. EVENTS DETECTION PERFORMANCE. TRUE POSITIVES (TP), FALSE POSITIVES (FP), GROUND-TRUTH (GT), PRECISION (PR), RECALL (RC)

Event	TP	FP	GT	PR	RC
Lane Drifting (LD)	25	3	25	0.89	1.00
Lane Weaving (LW)	75	6	78	0.93	0.96
Acceleration (AC)	51	19	58	0.74	0.88
Braking (BR)	80	20	91	0.80	0.88
Turning (TN)	28	10	30	0.74	0.93
Overall	260	57	282	0.82	0.92

C. Driving Behavior Evaluation

We employ the same database as in the previous section. In this case, we compare the number of events and the mean score for each event given by both apps. For AXA Drive we consider all the detections (low, medium, high) over the three events that this app evaluates: ACs, BRs and TNs. Only DriveSafe (DS) detects LDs and LWs, then, these events are excluded from this comparison. However, it must be remarked that AXA app begins when the car starts moving while DS detects events when the car is over 50 km/h. Besides, AXA only use inertial sensors and DS uses inertial and camera sensors. Further, a subjective comparison is done. At the end of the two tests, each user is invited to fill a survey where he evaluates which of the scores obtained for each event is closer according to his/her own driving feeling in a hidden way. Results are depicted in Table III.

TABLE III. COMPARATIVE DRIVING BEHAVIOR EVALUATION.

	Normal driving				Whole subjective score (%)	
	Detections		Score (Mean)			
Event Type	**DS**	**AXA**	**DS**	**AXA**	**DS**	**AXA**
Acceleration	12	15	8.85	6.37	62.50	37.50
Braking	13	11	9.92	7.27	87.50	12.50
Turning	8	28	8.10	6.18	80.00	20.00
	Aggressive driving					
	Detections		**Score (Mean)**			
Event Type	**DS**	**AXA**	**DS**	**AXA**		
Acceleration	58	56	4.54	5.00		
Braking	87	80	4.73	3.70		
Turning	30	58	3.60	2.20		

DS detections are similar for AC, a bit higher for BR and lower for TN. Scores differ between normal and aggressive driving, being lower in the last case in both apps, indicating worst driving behaviors. Scores from DS are higher than AXA. The highest difference is in the turns because in AXA the turns of the driver and the road curvature are coupled, then, this app is unable to differentiate between them. As a consequence, the higher road curvature, the higher number of events is detected. Our proposal is able to decouple these two effects and the detected turns mainly come from dangerous maneuvers. This improvement is noticed in the subjective evaluation, where DS gets better score than its competitor. Similar findings can be regarded for AC and BR (see Table III).

V. CONCLUSIONS AND FUTURE WORKS

This paper has presented the motivation, implementation and evaluation of DriveSafe, a new driver safety app for iPhones that detects inattentive driving behaviors, generating some alarms in case they are unsafe, and scoring driving style at the same time. A quantitative evaluation based on a controlled test-bed in real scenarios has been carried out analyzing the detection performance of some inattentive driving events and a comparative study between the driving scores provided by our app and the commercial AXA Drive app. In the near future we plan to include new functionalities, e.g. forward collision warnings with other vehicles, and to upload Drivesafe version 2.0 to the Apple store after deeper tests with more vehicles, roads and users. Moreover, we plan to use Machine Learning techniques for improving event detection and scoring.

REFERENCES

[1] Ranney, T.A.; Mazzai, E.; Garrott, R.; Goodman, M.J. “NHTSA Driver Distraction Research: Past, Present, and Future”. Technical report, HTSA, 2000

[2] “NHTSA’s National Center for Statistics and Analysis Distracted Driving 2010”. Technical Report DOT-HS-811-650, National Highway Traffic Safety Administration, Sep. 2012.

[3] European Commission. Communication on the Future of Transport on 17 June 2009. http://ec.592 europa.eu/transport/strategies/2009 future of transport en.htm, 2009.

[4] “Mobileye applications,” http://www.mobileye.com/en/manufacturer-products/applications.

[5] “Autovue lane departure warning,” http://www.iteris.com/upload/datasheets/LDW_Final_web.pdf.

[6] Paefgen, J.; Kehr, F.; Zhai, Y.; Michahelles, F. “Driving Behavior Analysis with Smartphones: Insights from a Controlled Field Study”, in Int. Conf. on Mobile and Ubiquitous Multimedia (MUM), 2012

[7] C. Troncoso, G. Danezis, and E. Kosta, “Pripayd: privacy friendly pay-as-you-drive insurance,” ACM workshop on Privacy, 2007.

[8] Dong, Y.; Hu, Z.; Uchimura, K.; Murayama, N. “Driver Inattention Monitoring System for Intelligent Vehicles: A Review”. IEEE Trans. Intell. Transp. Syst. 2011, 12, 596–614.

[9] E. Koukoumidis, L.S. Peh, and M.R. Martonosi, “Signalguru: Leveraging mobile phones for collaborative traffic signal schedule advisory,” in ACM MobiSys, 2011.

[10] iOnRoad. http://www.ionroad.com/

[11] Augmented Driving.https://itunes.apple.com/tw/app/augmented-driving/id366841514?mt=8.

[12] Lan, M.; Rofouei, M.; Soatto, S. and Sarrafzadeh, M., “SmartLDWS: A robust and scalable lane departure warning system for the smartphones”, in Int. Conf. on Intelligent Transportation Systems (ITSC), 2009.

[13] You, C-W; Lane, N D; Chen F; Wang, R; Chen, Z; Bao, T J; Montes-de-Oca, M; Cheng, Y; Lin, M; Torresani, L; Campbell, A T. “CarSafe App: Alerting Drowsy and Distracted Drivers using Dual Cameras on Smartphones”, in Proceedings of MobiSys’13, 2013

[14] D. A. Johnson and M. M. Trivedi. “Driving style recognition using a smartphone as a sensor platform”, in Int. Conf. on Intelligent Transportation Systems (ITSC), pp: 1609–1615, 2011

[15] Eren, H.; Makinist, S.; Akin, E.; Yilmaz, “A. Estimating driving behavior by a smartphone”. Proceedings on IEEE Intelligent Vehicles Symposium (IV), 2012

[16] Minh Van Ly; Martin, S.; Trivedi, M.M. “Driver classification and driving style recognition using inertial sensors”. Proceedings on IEEE Intelligent Vehicles Symposium (IV), 2013

[17] Araujo, R.; Igreja, A.; de Castro, R.; Araujo, R.E. “Driving coach: A smartphone application to evaluate driving efficient patterns”. Proceedings on IEEE Intelligent Vehicles Symposium (IV), 2012

[18] Bergasa, L.M.; Nuevo, J.; Sotelo, M.A.; Barea, R.; Lopez, M. “Real-time system for monitoring driver vigilance”. IEEE Transactions on Intelligent Transportation Systems 2006, 7, 63–77.

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

[20] Dickmanns, E.D.; Mysliwetz, B.D. “Recursive 3-D road and relative ego-state recognition”. Pattern Analysis and Machine Intelligence, IEEE Transactions on (Volume:14 , Issue: 2), 1992

[21] M. Li, J. Dai, S. Sahu, and M. Naphade, “Trip analyzer through smartphone apps,” Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in GIS ’11, p. 537, 2011.

[22] Yan Wang, Jie Yang, Hongbo Liu, Yingying Chen, Marco Gruteser, and Richard P. Martin. “Sensing vehicle dynamics for determining driver phone use”. In Proceeding of the Int. Conf. on Mobile Systems, applications and services (MobiSys '13). 2013

[23] AXA Drive. https://itunes.apple.com/es/app/axa-drive/id716514409?mt=8