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A CardioWheel-based Fatigue and Drowsiness Detection System

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***Abstract*— The interest in monitoring drivers conditions and performance has increased in the past years, to make the roads safer both for drivers and pedestrians. This raised the idea of developing systems to monitor the drivers conditions to prevent road disasters. In this paper, we propose a system to monitor the driver's fatigue and drowsiness, based on the CardioWheel system. The proposed system records the driver's ElectroCardioGram (ECG) signal and the motion of the steering wheel during the driving session. The acquired data is compressed and transmitted with Bluetooth Low Energy (BLE), with an exclusive profile developed for this system. To detect fatigue and drowsiness patterns, a machine learning approach was taken. Among the evaluated classifiers, the Support Vector Machines technique proved to be the best classification method with the highest accuracy. Thus, the developed prototype has the ability to warn the driver about his physiological and physical states, increasing road safety.**

Keywords: Electrocardiogram; Fatigue Detection; Drowsiness Detection; Driver Assistant; CardioWheel; Road Safety

I. INTRODUCTION

Fatigue and drowsiness are two factors that affect the driving abilities of a person. There is an increasing interest in the development of Advanced Driver Assistance Systems (ADAS)[1], which monitors the vehicle performance and behaviour, as well as the physiological and physical conditions of the driver. To perform this monitoring, we can resort to accelerometers, which are inertial sensors that measure the proper acceleration applied to an object, called g force. They can be placed on the automobiles steering wheel to monitor their movements. In addition, physiological signals such as ElectroCardioGram (ECG) [21], can be monitored. The ECG signal can be obtained with the aid of dry-electrodes placed on the vehicles steering wheel, such that, in contact with the human skin, detect the electrical signals generated by the heartbeat. The fatigue and drowsiness detection can be achieved with machine learning algorithms working on these signals. With these methods, it is possible to identify sleepiness in both the ECG and the steering wheel accelerometer data and to predict if the driver is entering in a state of sleepiness. This detection triggers an alarm to the driver.

[1]`https://www.mobileye.com/ourtechnology/adas/`

In this paper, we report the development of a prototype for driver fatigue and drowsiness detection, based on the CardioWheel system. The prototype is composed by two main blocks:

- the acquisition system, for data collection, pre-processing, and transmission tasks;
- the gateway solution, to receive data and to perform classification, and alarm activation.

In the acquisition system, the accelerometer and the ECG recording module work for the entire driving period. The volume of generated data is such that it needs to be compressed in order to occupy less storage space and less transmission time. The acquired data is stored on a remote database, not physically attached to the acquisition system, thus wireless technologies are adequate to transmit the data.

The CardioWheel system [11], developed by CardioID and depicted in Figure 1, allows the acquisition of off-the-person ECG signals [2] and accelerometer signals in a non-intrusive way, with a Bluetooth Low Energy (BLE) module for wireless transmission purposes. To achieve an acceptable biometric signal, only two electrodes are required. However, the method is more sensitive to noise, as compared to the on-the-person ECG acquisition methods. Thus, in some cases it leads to the need of additional signal processing techniques on the acquired signal. After these signal processing opera-

Fig. 1. CardioWheel [11]: a steering wheel cover with a conductive leather connected with a box containing embedded electronics.

tions, it is possible to achieve an ECG signal quality similar to that of hospital systems.

The off-the-person ECG techniques acquire ECG signals in a less intrusive way using hands as contact points, allowing the acquisition of signals without sensors placed on the body, but rather in objects of everyday use [2]. The purpose of these methods is to make the acquisition of signals almost involuntarily, without impact on the person's daily actions. The components used in this method are named dry-electrodes as they do not require the use of any conductive gels or pastes, using human perspiration to a better contact with the person's skin.

In the gateway solution, a machine learning algorithm classifies the incoming data and to predict the driver's patterns of sleepiness for both ECG and steering wheel angle accelerometer signals. The gateway solution is responsible for the activation of the system that can warn the driver if fatigue and drowsiness patterns are found in the extracted signals. Figure 2 shows two pictures of the CardioWheel mainboard [11], over which we will develop our prototype.

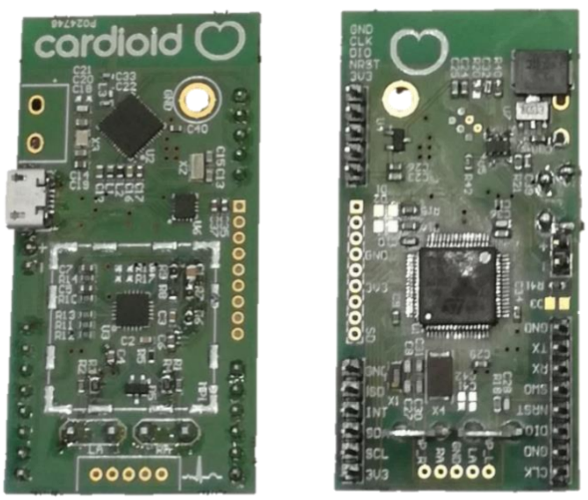

Fig. 2. CardioWheel [11]: top side (left) and bottom side (right) of the CardioWheel mainboard.

II. Monitoring Systems, Sensors and Biological Signals

This section provides some background concepts on fatigue, drowsiness and the monitoring aspects related to the acquisition of the steering wheel angle and ECG signals.

A. Fatigue and drowsiness

Sometimes, fatigue and drowsiness are used to describe the same situation. These two words are quite related, however they have a distinctive meaning[2].

Fatigue is a physical or psychological exhaustion. A person feels fatigued when, for instance, goes to a gymnasium and works out his muscles and heart-rate for a reasonable amount of time or when one has solved a large amount of complex mathematical problems. Fatigue, usually outcomes from doing the same task repeatedly or in an exhaustive way. When the fatigue state requires a rest, it could cause a person to fall in a drowsiness state.

Drowsiness is defined as the state before sleep. When someone is drowsy, one requires to sleep, and one's body is fighting to stay awake. Drowsiness can interfere more actively than fatigue in the daily basis affecting concentration, reaction time, productivity and safety. Some medications induce drowsiness, but it is mostly related with sleeping habits, as people that have a good quality and a good quantity of sleep have more resistance to enter in a drowsiness state, for a longer period.

To classify the drowsiness state, there is a metric named Karolinska Sleepiness Scale (KSS) [17]. This is a subjective method, using a 10-point Likert scale [9], in which the person classifies his/her sleepiness in periods of 5 minutes. Table I describes the KSS scale.

B. Direct and indirect monitoring systems

Monitoring systems are composed by sensors and devices that measure parameters for a given purpose. There are two main types of monitoring: direct monitoring and indirect monitoring, which are addressed in this section.

Direct monitoring systems deal with physiological signals or with a person's behaviour. Among these, we have facial expressions, yawning, eye tracking and blinking, electrooculogram (EOG), electroencephalogram (EEG), electrocardiogram (ECG) heart rate, and body temperature, for instance. The main advantages of these methods are [6]:

- accuracy - because measurements are under medical investigation and supervision;
- universality - since the results are valid or are directly connected with scientific or commercial domains;
- versatility - given that the experiments can be tested in a laboratory environment since it is simple to reproduce adequate real conditions for the task of interest.

However, by using this kind of monitoring, there are also some disadvantages, such as [6]:

- privacy invasion - since the measurements can describe a lot of physical and psychological conditions of the person;

TABLE I

The 10-point Karolinska Sleepiness Scale (KSS) [17]

Level	Description
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep awake
8	Sleepy, but some effort to keep awake
9	Very sleepy, great effort to keep awake, fighting sleep
10	Extremely sleepy, cant keep awake

[2]https://drowsydriving.org/about/

- high sensitivity - to light, weather, clothes or accessories;
- current health conditions - may decrease the precision of the measures.

Indirect monitoring systems interact with the objects controlled by the individual, for example, in an automobile, it is possible to monitor the steering wheel movements, pedal acceleration (gas or break), sitting position, as well as other indicators. Unlike direct monitoring systems, the main advantages of this kind of monitoring are [6]:

- robustness - since the influence caused by external sources like weather, cannot disturb the measurement;
- privacy - because the methods are non-intrusive to the person.

These systems also have their drawbacks, namely [6]:

- experimental rigorous - to achieve significant results, the tests should be done using real conditions to best suit the measurements to the real working environment;
- low applicability - because even the promising results usually cannot be reused in other research domains and are focused on a specific problem.

Thus, the best choice between these techniques depends on the specific goals of the application at hand. Both these types of monitoring are adequate to get relevant data for the intended detection. However, indirect monitoring systems are easier to apply for a driver.

C. Accelerometers

An accelerometer is an inertial sensor that measures the proper acceleration of an object, named as g force [25]. This acceleration differs from the common speed/time rate concept; instead, the speed variation is measured according to an axial complex located in the device. Some accelerometers have three axes (x, y, and z) while others have six axes, being named as gyroscopes. These more complex accelerometers have the ability to detect rotations on each of the three axes, making possible to monitor rotational movements besides the axial acceleration.

Mechanical accelerometers are composed by a moving mass between fixed masses. As the moving mass comes near or moves away from the fixed masses, the capacitance measured in each fixed mass changes with the distance to the moving mass, allowing the measurement of the proper acceleration. Figure 3 depicts a model for the measurement of the proper acceleration in one axis.

Nowadays, accelerometers are used in a wide range of applications, such as in seismographs, impact measurement systems, motion sensors used in some gaming controllers, tilt sensors found in almost all smartphones as well as in the automobile steering wheel for motion monitoring.

D. ECG signal and acquisition

The electrocardiogram (ECG) signal is the electrical signal that the heart emits through successive contractions and distensions of the heart muscle, named myocardium [8], [14], [15], [21]. The acquisition of ECG signals can be done using intrusive or non-intrusive methods [2].

Intrusive methods are used in clinical settings where biological signals are extracted using devices placed in the human skin. These components are placed on the surface of the human body using a gel or a conductive substance paste that provides a suitable contact with the skin and, consequently an adequate capture of the cardiac signals. These clinical methods may require the placement of, for example, up to twelve electrodes on the surface of the body to extract a good ECG signal and are limited to a small physical space of use, such as an ambulance, or a treatment room.

Non-intrusive methods allow the acquisition of signals with sensors not placed on the person's body, but rather in objects of everyday use. The purpose of these methods is to make the acquisition of signals almost involuntarily, without having an impact on the person's daily actions. The components used in this method are called dry-electrodes as they do not require the use of any conductive gels or pastes, taking advantage of human perspiration to improve contact with the persons skin. These electrodes can be placed on any equipment, such as, for example, computer mice, keyboards, mobile phones, watches and cars' steering wheels. To obtain an acceptable biometric signal using this method only two electrodes are required.

The ECG signal is easily distinguished from other waveforms, because it presents a distinctive format where it is possible to identify five types of wave, namely P, Q, R, S, and T. In some cases, it is possible to identify a sixth wave named U. The clinical analysis of an ECG signal focuses mainly on the QRS wave complex. However, the P and T waves also have a high clinical value. Cardiac abnormalities are detected by considering the mean amplitude of each wave as well as the time intervals between them. Typically, the signal voltage values may range from 1 to 10 mV, with signal frequency components ranging from 0.05 to 100 Hz and a heart rate oscillating from 60 to 100 beats per minute [15]. Figure 4 presents a comparison of the signals acquired on the chest with the CardioWheel device, that acquires off-the-person ECG signals. In both cases, we are able to identify the types of wave P, Q, R, S, and T.

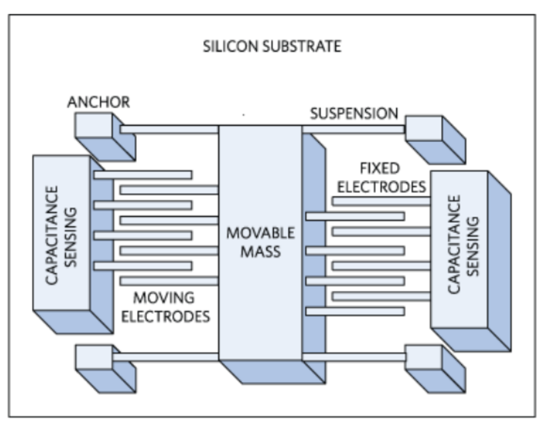

Fig. 3. Mechanical model of an accelerometer [25].

III. ECG SIGNAL COMPRESSION

On monitoring systems, we usually acquire a large amount of data. Thus, we need to address the use of data compression techniques to encode the information using fewer bits than the original representation. For this purpose, we can choose between direct time-domain techniques, lossless, and lossy techniques [10], [16].

The time-domain techniques are simple approaches made up by some operations directly on the time domain of the acquired signal. These methods are often used in heartbeat detection and counting, achieving good compression ratios but failing in the perfect reconstruction of the signals, introducing distortion to the ECG signal. Among these operations, we have: amplitude scaling, Differential Pulse Code Modulation (DPCM), Amplitude Zone Time Epoch Coding (AZTEC), Turning Point (TP), and Coordinate Reduction Time Encoding Scheme (CORTES) [8], [14].

In the lossless approach, also named compaction, the decoded signal is exactly the same as the original signal. On the lossy approach, the decoded signal is similar to the original version, thus it has some controlled distortion [10], [16], and it achieves much higher compression ratios than the lossless techniques.

The lossy transform-based methods are known as good compression methods for ECG signals [13], [16], [20] and thus we have chosen these techniques. These techniques consist in discarding less significant information, on the quantisation stage, which tends to be irrelevant to the human perception of the signal. Figure 5 depicts the lossy encoding process with its three key stages: transform, quantisation, and encoding.

IV. PROPOSED SOLUTION

The key idea behind the proposed solution in this paper, is that fatigue and drowsiness lead to a modification in the person's biological signals and behaviour. Thus, the monitoring of the fatigue and drowsiness states lead to an adequate approach to tackle the problem at hand.

The proposed solution for drowsiness detection is focused on the acquisition device that transmits the data to the gateway and in the classification algorithm that classifies the data and determines if the driver is drowsy or not. When the system determines that the driver is drowsy, the alarm is activated. Figure 6 depicts the block diagram of the proposed system. Our solution is composed by two main parts:

- the acquisition system, for data collection, preprocessing, and transmission tasks, depicted on the left-hand-side and centre of Figure 6;
- the gateway solution, for data reception, classification, and alarm activation, represented on the right-hand-side of Figure 6.

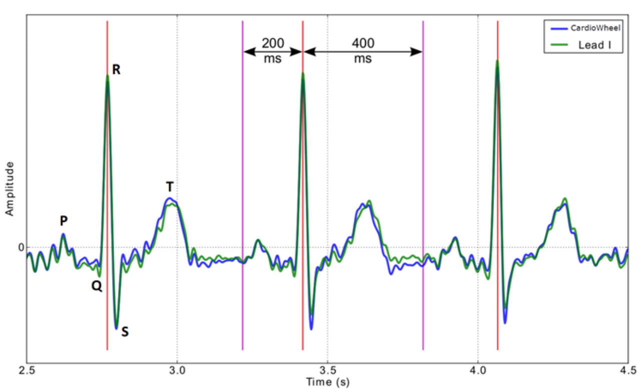

Fig. 4. Comparison between off-the-person (blue line) signal with on-the-person ECG (green line) signal. The PQRST complex.

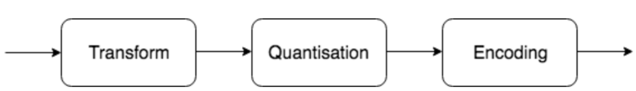

Fig. 5. The lossy encoding process block diagram with its three main operations: transform, quantisation, and encoding [10].

A. Electrocardiogram and steering wheel angle data

The CardioWheel system encompasses all the blocks of an acquisition system solution. This system can collect, in a non-intrusive way, the driver ECG signal, using dry-electrodes placed in a conductive leather cover (that can fit into any automobile), and the Steering Wheel Angle (SWA) signal, using an accelerometer placed in the centre of the steering wheel. The dry-electrodes can sense the heartbeat, by its electrical impulses, while the person places the hands on the steering wheel. This electrical continuous signal is converted from analogue to digital with an Analogue-to-Digital Converter (ADC) and the resulting samples are read by a microcontroller.

The SWA signal is recorded by a three-axis accelerometer, placed in the centre of the steering-wheel behind the airbag. The driver, while moving the steering wheel, causes a variation in each accelerometer axis, and with it, being possible to estimate the rotational angle of the steering wheel. Figure 7 shows where the CardioWheel mainboard is placed in the steering wheel.

The CardioWheel device has a ST ARM Cortex STM32F446RE microcontroller that acquires ECG and accelerometer data with, respectively, off-board dry-electrodes and an on-board STMLSM6DSL accelerometer. It also incorporates an on-board Nordic nRF52832 Bluetooth Low Energy (BLE) module for wireless communication.

B. Steering wheel angle motion monitoring

To estimate the steering wheel's rotation angle, it is necessary to know how the accelerometer is oriented. This means that, depending on the orientation of the accelerometer, the data could be understood in different ways. The main characteristic that can be recorded with the accelerometer is the rotation angle of the steering wheel θ, usually called SWA. Figure 8 illustrates a front view of a steering wheel with the axial orientation of the accelerometer.

Given this accelerometer's axial orientation, the rotation angle of the steering wheel, θ, is given by

$$\tan(\theta) = A_x/A_y \quad (=) \quad \theta = \text{atan}(A_x/A_y), \tag{1}$$

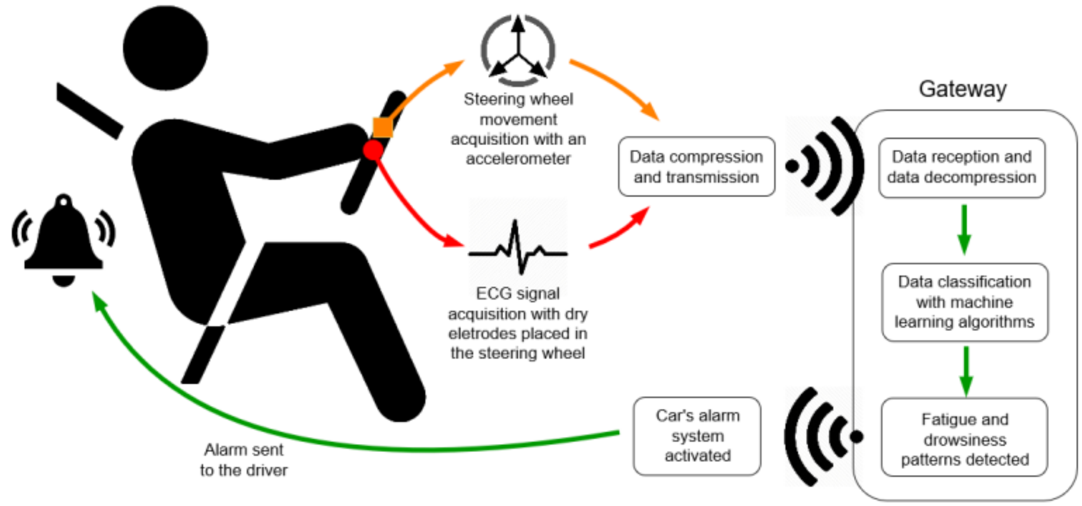

Fig. 6. Block diagram of the proposed system - the global use case scenario.

Fig. 7. The conductive leather on the outside steering wheel and the location of the mainboard in the steering wheel.

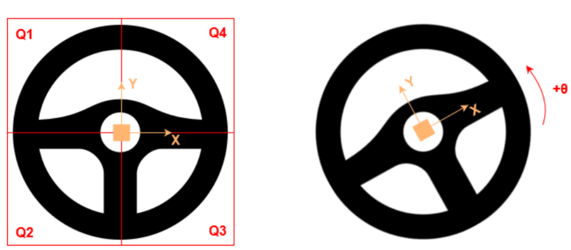

Fig. 8. Front view of a steering wheel with the rotational angle θ and the accelerometers axial orientation.

where A_x and A_y represent the measured accelerations with the same direction as x and y axes, respectively. Assuming that there are four quadrants, as represented in Figure 10, it is possible to estimate the instantaneous g force range for each quadrant [3].

Another important parameter to consider is the inclination angle of the steering wheel, η, as depicted in Figure 9. Depending on the vehicle and on the driver, the steering wheel could be adjusted to different inclinations to suit the driver body structure. In each case, the instantaneous g force will be distributed by the three axes in different way according to the inclination angle. Besides this, the

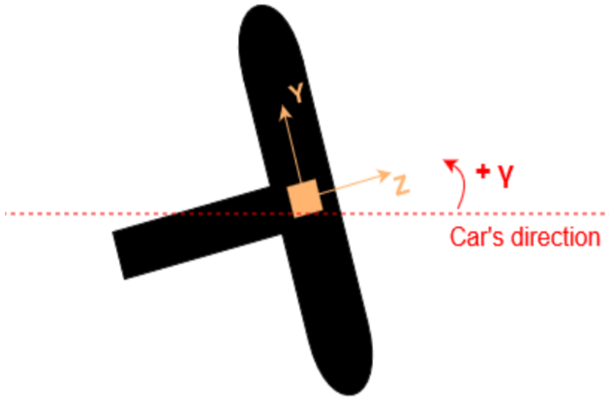

Fig. 9. Side view of a steering wheel with the inclination angle η and the accelerometers axial orientation.

automobile can also be in an inclined plane, therefore this inclination angle is relevant to calibrate the axial system of the accelerometer relative to the automobile direction, allowing a more accurate estimation of the SWA. Given this accelerometer's axial orientation, the inclination angle η can be written as

$$\tan(\eta) = A_z/A_y \quad (=) \quad \eta = \text{atan}(A_z/A_y), \tag{2}$$

where A_y and A_z represent the measured accelerations with the same direction as y and z axes, respectively.

With these two angles, rotation (θ) and inclination (η), it is possible to get accurate measurements for monitoring the behaviour of the steering wheel while driving.

Figure 10 depicts the initial calibration movement of the steering wheel. The final assessment for the accelerometer

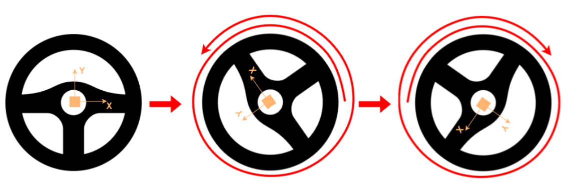

Fig. 10. Representation of the initial calibration movement.

can be done when the measures for steering wheel motion monitoring are working as expected. To test the accuracy of the device, the accelerometer was fixed, with the same orientation as in Figure 8, on a gaming steering wheel. The steering wheel, in turn, was linked to a PC that is running the driving simulator rFactor with the MoTec plugin, that enables data analysis. The acquisition system was composed by an Arduino ATMega 2560 that was sampling the accelerometer with a rate of 100 Hz and sending the data via Serial Port. The simulator was getting the SWA using the potentiometer inside the gaming steering wheel, with a sampling frequency of 10.24 Hz. The accelerometer and potentiometer sampling were done at the same time with the recording of one lap in a racing track. For these results, we notice that the accelerometer data and potentiometer data are similar, thus the accelerometer is getting a correct real-time SWA. Figure 11 shows the results obtained for the Estoril Circuit.

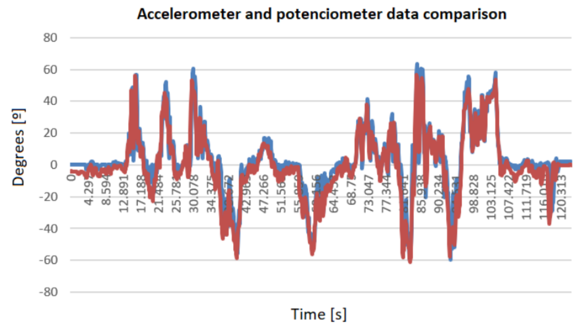

Fig. 11. Representation of the initial calibration movement.

C. Data compression and transmission

The accelerometer signals can produce waveforms similar to the ones found in ECG signals. Thus, the data compression techniques suited for ECG signals also works well for the SWA data. We have chosen to use the Discrete Cosine Transform (DCT)-based lossy data compression technique. The typical DCT transformed signals has high values on its first coefficients; however, from the 4800 coefficient and beyond there are no significant coefficient values, and from sample 11000 until the end, the amplitudes can be discarded.

Since we need a wireless data transmission technique, we have analyzed a wide range of wireless technologies, that allow communication to a large diversity of applications, having power consumption as the main concern. The Bluetooth technology [18] has emerged as a way to replace wired communications from computer peripherals such as mice, keyboards and headsets. At this time, Bluetooth is used in a wide range of health applications, such as blood pressure monitors and blood glucose meters, or in the fitness area, such as speed sensors or heart-rate meters. Considering that most of the Bluetooth devices are battery-powered, there is a growing need to reduce the energy consumption of this technology. The Bluetooth Low Energy (BLE) [22] technique addresses this issue. The BLE stack can be represented by three independent layers:

- Link layer - master-slave relationship;
- GAP (Generic Access Profile) layer - central-peripheral relationship;
- GATT (Generic ATTribute) layer - client-server relationship.

At the Link layer, the master acts as a Scanner and the slave as an Advertiser. The Advertiser continuously sends basic information about itself and once the Scanner receives the information it needs, it tries to connect to the Advertiser. When the Advertiser accepts, the connection is established.

In the GAP layer, the central is the one initiating a connection, establishing connection intervals and other connection parameters. Almost everything is initiated by the central, for example, a connection pairing or parameter update. Although a peripheral can request the central to perform these actions, it is always up to the central to decide what to do.

The roles of the GATT layer come into play once a connection has been established. The GATT Server can, in general, be described as the device sitting on information or data, while the GATT Client is the one seeking this data. The GATT Client sends requests for information to the GATT Servers, which respond with the information requested by the GATT Client.

BLE allows communications up to 100 meters, in the 2.4 GHz frequency band where transmission rates can go up to 2 Mbit/s but, for most applications, the required bit rate is usually around 0.3 Mbit/s. The average power consumption with this technology is around 15 mA of current, reducing the power consumption to about half as compared to the standard Bluetooth.

Since CardioWheel has a BLE module, it is necessary to create a custom profile to handle this data, transmitting it to a gateway. This device works as a BLE Server while the gateway works as a BLE Client that will request ECG and SWA data from the Server. The GATT protocol states that a BLE Profile is structured in three components: Services, Characteristics, and Descriptors. A Service is the part of the profile that encapsulates a specific behaviour. These Services are composed by Characteristics. A Characteristic is a value that defines each action for a specific behaviour and it is composed by Descriptors. Descriptors are attributes that define the Characteristic value, and could be, for example, read/write permissions, security roles, among others.

There are many Services that could be integrated in each BLE Profile, according to the needs. In this work, it was included the Battery Service, for battery analysis purposes, and the Device Information Service, for specific device related information. In this case, it is necessary to create two custom Services to handle the ECG data and the SWA data in distinctive ways.

Given that CardioWheel acts as a BLE Server, the two custom Services for the BLE Profile are composed by one single characteristic that is responsible to load the ECG or SWA data from memory. This characteristic is composed by two descriptors: Read Descriptor and Notify Descriptor. The Read Descriptor is responsible to provide the data to the BLE Client requests. Whenever the BLE Client wants data, it searches for the Read Descriptor identifier and asks for data. However, searching for the Read Descriptor without synchronisation could end up in getting repeated data, as the BLE Server may not have new data to deliver. For this situation, the BLE Client is continually searching for the Notify Descriptor identifier. Each time the BLE Server has new data, it updates the Notify Descriptor, and the BLE Client, only searches for the Read Descriptor if it has an update in the Notify Descriptor. Figure 12 represents the hierarchy of the custom BLE profile for this work, highlighting the ECG and the SWA services.

D. *Classification module*

In order to have classifier to work on the data, a feature-based vector must be composed. In the literature, some features were pointed out as being adequate to describe the relationship between ECG or SWA signals with the KSS scales. Table II describes the features for both signals that were used to train the classifiers.

For classification purposes we have considered different classifiers such as Support Vector Machines (SVM) [24], [23], Artificial Neural Networks (ANN) [1], [7], Linear Regression (LinReg) and Logistic Regression (LogReg) [5]. To summarize the proposed solution, highlighting the connection between the blocks described in this section, Figure 13 shows the block diagram of the proposed system.

V. EXPERIMENTAL EVALUATION

This Section reports the experimental evaluation of our solution on its different aspects. Due to the complexity and specificity of the involved test scenario, it is not possible to compare our solution with other similar approaches in detail. Our aim is to check if the developed prototype provides good enough results to be further improved.

A. *Dataset with ECG and SWA data*

To achieve the goal of fatigue and drowsiness detection, it is necessary an adequate data classifier to predict the drivers state according to the acquired data. Using the ECG and SWA data, it is possible to teach a machine to make that prediction. The dataset provided by the Swedish National Road and Transport Research Institute [3] contains signals from 18 subjects, including ECG and SWA, for the same car and track, in both awake and drowsy states, as well as the KSS values for each data sample. The features from those signals will be the input and the KSS values will be the output to train the classifier.

[3]https://www.vti.se/en/

TABLE II
SET OF FEATURES FOR THE ECG AND SWA SIGNALS

Signal	Feature
ECG + SWA	SDV - Standard deviation
	ENT - Shannon entropy
	RMS - Root-Mean-Square
ECG	NRP - Number of R peaks per window
	DBR - Mean difference between R peaks
	MAR - Mean amplitude of R peaks
	ADR - Amplitude deviation of R peaks
	VLF - Very-Low Frequency power [0, 0.04] Hz
	LFP - Low Frequency power [0.04, 0.15] Hz
	HFP - High Frequency power [0.15, 0.4] Hz
	LHR - Low-High frequency Ratio
SWA	ZCR - Zero-Crossing Rate
	HTR - Holding time below $\pm$ 3 degrees
	MAS - Mean acceleration applied to the steering wheel
	ASD - Angular Speed Deviation
	EXT - Number of extremes

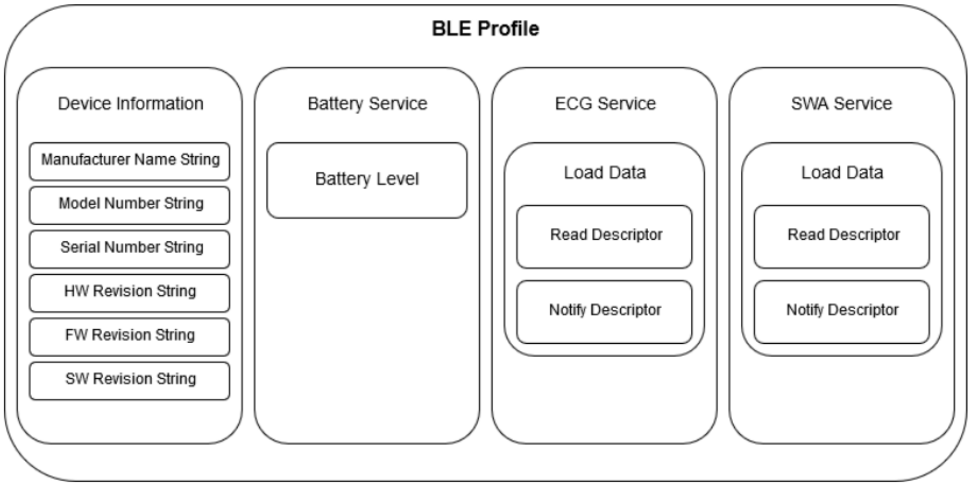

Fig. 12. Hierarchy of the custom Bluetooth Low Energy Profile.

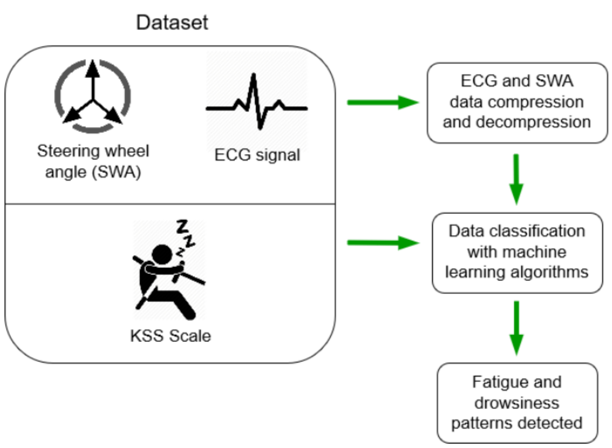

Fig. 13. Block diagram of the proposed system - the block functionalities.

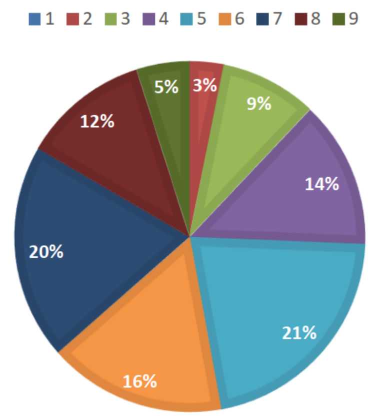

Fig. 14. Pie chart with the distribution of the different KSS classes in the dataset.

This dataset is composed by ECG, EEG, and EOG biometric signals, and car movement signals such as velocity, lateral and longitudinal acceleration, Steering Wheel Angle (SWA) and yaw rate. In the experiment, each person was classifying his sleepiness according to the Karolinska Sleepiness Scale (KSS) test while driving, adding a KSS value to each data sample. Figure 14 represents a pie chart with the distribution of the KSS values in the given dataset.

To simplify this 9-class output, we converted it into a binary classification problem, where 0 represents the awake state and 1 the drowsy state. According to the KSS scale, from the value 6, the driver is showing some signs of sleepiness, although they are not so significant. The most credible approach for a binary classification is considering the KSS values above 7 as a drowsy state [19], however, the approach in which the dataset becomes more balanced is using KSS values above 6 for classifying a drowsy person. To overcome the class imbalance for the first scenario, we use the oversampling method to synthesize more drowsy samples.

Figure 15 shows a pie chart with the distribution of the percentage of drowsy and non-drowsy states, considering the threshold at level 6 or at level 7.

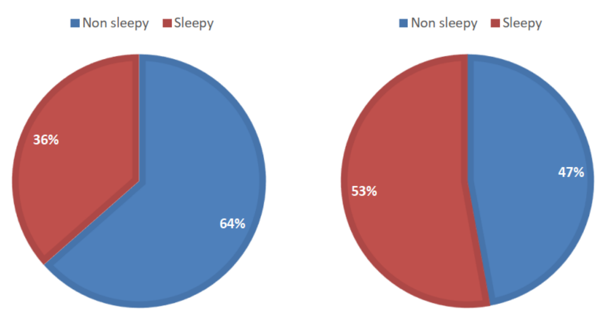

Fig. 15. Awake and drowsy state distribution for a KSS 7 and above (left) and KSS 6 and above (right).

B. Evaluation metrics for compression and classification

The Compression Ratio (CR) is one of the most used metrics in signal compression and measures the data reduction achieved by a given compression method. When testing a method, it is intended to obtain high CR while maintaining acceptable signal quality. For the original, $o[n]$ and the compressed, $c[n]$, signals, the CR is given by

$$\text{CR}(o[n], c[n]) = \frac{l_o}{l_c} : 1, \quad (3)$$

where l_c and l_o are the length of the compressed and the original signal, respectively. For instance, a compression with a reduction to half the original size is represented as 2:1.

The Root-Mean-Squared Error (RMSE) is one of the most used distortion metrics to measure differences between values, representing the differences between input samples and output samples. It represents how far the output samples are from the input and it is calculated by the squared root of the summation of the mean of the squared differences between the original signal $o[n]$ and the decoded signal $d[n]$,

$$\text{RMSE}(o[n], d[n]) = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}(o[n] - d[n])^2}. \quad (4)$$

The Signal-to-Noise Ratio (SNR) measures the quality of a signal affected by noise. In this case, the noise is given by the distortion introduced by the lossy encoding process on the quantisation stage. SNR, expressed in dB, is defined as

$$\text{SNR}(o[n], d[n]) = 10\log_{10}\left(\frac{P_o}{P_n}\right), \quad (5)$$

where P_o and P_n are the power of the original and noise/error signals, defined as

$$P_o = \frac{1}{N}\sum_{n=0}^{N-1} o^2[n], \quad (6)$$

and

$$P_n = \frac{1}{N}\sum_{n=0}^{N-1} e^2[n] = \frac{1}{N}\sum_{n=0}^{N-1}(o[n] - d[n])^2, \quad (7)$$

with $e[n] = o[n] - d[n]$. The use of SNR to denote the quality of the uniform quantisation procedure leads to the SNR-quantisation (SNRQ) expression,

$$\text{SNRQ} = 6.02R + 10\log_{10}\left(\frac{3P}{V^2}\right), \quad (8)$$

where R denotes the number of bits per sample, P is the power of the quantised signal and V is the maximum amplitude of the quantiser. SNRQ serves as the basis for comparing the attained transmission SNR (SNRt), after lossy encoding. Considering that the number of bits per symbol after quantisation is $R = 12$, the supply voltage of the microcontroller $V = 3.3$, and the power of the signal P is roughly its squared amplitude A^2, then SNRQ=111.93 dB, for the considered ECG signals.

To evaluate the performance of the classifier for a binary problem, it is required to consider the four possible situations, according to the actual and predicted values. Since "0" represents the awake state and "1" the drowsy state, the True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). The consequence of misclassifying a drowsy driver as awake has potentially more risk than the opposite case. It is important to minimise the number of false negatives. If a person is driving in a drowsy state, it is fundamental that the vehicle warns the driver, however, if the vehicle warns the driver when he/she is awake, the driver could simply ignore the alarm.

The dataset is composed by pairs, each pair representing the same person but in different sleepiness states. To apply cross-validation with a good reliability, each awake-drowsy pair will be used as a test set, reaching 33 results for each tested algorithm. Each pair will be tested, in order to reduce the standard deviation of the results.

C. Experimental results

Table III shows the experimental results of the considered data compression techniques, mentioned in section IV-C, regarding the CR, RMSE, and SNRt measures. We have considered the Differential Pulse Code Modulation (DPCM), Huffman, Linear Predictive Coding (LPC), DEFLATE, Discrete Wavelet Transform (DWT), and Lempel-Ziv-Welch (LZW) techniques [10], [16]. For more details on the data compression techniques used in the prototype, please see [4].

TABLE III
EXPERIMENTAL RESULTS ON COMPRESSION AND DISTORTION

Method	CR	RMSE	SNRt
DPCM + Huffman	1.5:1	0	∞
LPC (10 coefficients) + LZW	4.57:1	21.94	18.47
LPC + DEFLATE	3.45:1	21.94	18.47
DCT-based	5.36:1	0.33	54.94
Amplitude Scaling + DWT	5.99:1	3.56	34.26

According to the CR values obtained, the technique using Amplitude Scaling with DWT proved to be the one with higher compression and acceptable distortion. However, this is a lossy technique and it introduces some distortion in the signal, that cannot be acceptable for precise analysis, like medical analysis. For lossless compression, the technique using LPC and LZW is the one with the best CR, taking into account that this algorithm needs some time to correct the prediction error and to be effectively a lossless method.

Table IV reports the experimental results for the classification task, with the classifiers mentioned in section IV-D, using standard accuracy measures [12], on the ECG + SWA signals. In our experiments, we have found that it is preferable to use the ECG + SWA signals, as compared to the individual use of the ECG and SWA signals. On this dataset, the SVM classifier achieves the best results, although these results need to be improved. Thus, the use of this classifier can be improved by tuning its parameters, such as the type of kernel and the 'C' parameter. Moreover, we have to further investigate the effect of the choice on the grouping of several classes into two classes, and check for class imbalance issues, as depicted in Figure 14 and Figure 15. The chosen set of features, on the feature engineering stage reported in Table II, can also be readdressed.

TABLE IV
EXPERIMENTAL RESULTS FOR CLASSIFICATION OF THE ECG + SWA SIGNALS

Method	Accuracy	Specificity	Recall	Precision	F1-Score
LinReg	0.55 ± 0.08	0.58 ± 0.19	0.52 ± 0.26	0.55 ± 0.11	0.50 ± 0.18
LogReg	0.55 ± 0.07	**0.60 ± 0.15**	0.49 ± 0.21	0.55 ± 0.11	0.51 ± 0.14
ANN	0.54 ± 0.07	0.55 ± 0.21	0.53 ± 0.24	0.54 ± 0.09	0.51 ± 0.16
SVM	**0.62 ± 0.05**	0.56 ± 0.12	**0.68 ± 0.11**	**0.61 ± 0.06**	**0.64 ± 0.06**

VI. CONCLUSIONS

In order to prevent car accidents and to improve road safety, monitoring systems capable of detecting drowsiness patterns and to warn the driver about his/her physical and psychological condition are necessary.

In this work, a low-cost prototype for such a monitoring system was proposed, based on the CardioWheel board, developed by CardioID. This model consists in ECG and steering wheel movement data acquisition, compression, transmission and classification for detection of drowsiness and fatigue patterns.

From the CardioWheel model, the ECG data acquisition is performed using dry-electrodes in a conductive leather that is covering the steering wheel. While the driver has his hands on the steering wheel, the electrodes can sense the electrical impulses caused by the heartbeat, creating a continuous electrical signal.

The steering wheel motion monitoring is carried out by a three-axis accelerometer placed in the centre of the steering wheel. When the driver moves the steering wheel, it changes the acceleration measured in each axis of the accelerometer. Using an Arduino ATMega 2560, the SWA signal was extracted by applying trigonometry expressions with the magnitudes of the g force felt in each axis.

To compress the data before transmission, we have chosen a lossy transform-based DCT technique. Since the CardioWheel has a BLE module, the transmission is carried out by BLE with a profile created for the transmission of ECG and SWA. This profile enables a gateway for getting the ECG and SWA data from the acquisition system.

The fatigue and drowsiness detection was accomplished by testing different machine learning algorithms in a two-class problem. The algorithm that reached the best results was the SVM, with an accuracy of 0.62 ± 0.05. The percentage of false positives is 15.95 ± 5.4, meaning that from 10% to 20% of the times, the classifier cant predict that the driver is drowsy.

It is important to notice that the KSS scale, used as output in the supervised learning task, is a subjective scale and subjective measures are based in self-rating scores given by the drivers and, although they are helpful in understanding the drivers condition, they are highly depended on the personal evaluation and interpretation. With these reported results, we conclude that the developed prototype is an adequate approach to fatigue and drowsiness detection problem. However, the overall system still needs improvement on some specific parts.

A. Future work

There are some topics that should be investigated more deeply. In the acquisition device, more efficient compression algorithms can be implemented, that can enable higher compression ratios with a tolerant loss in the signal quality.

The results for data classification are very dependent from the dataset used to train the classifier. The tested conditions are the same for the entire dataset and this influences the data. For more reliable results, we should consider a more complete dataset that contains different circuits, different vehicles or different weather conditions.

Also, in the dataset, the ECG signal was extracted in an intrusive way, so when testing machine learning algorithms with signals acquired in a non-intrusive way, it is expected that the quality of the signal decreases and the extracted features could not be relevant enough to describe the signal differences. Besides this, a different set of features can be defined to improve the results for intrusive or non-intrusive ECG data.

Since the SVM method proved to be the best of the tested algorithms, it is necessary to further investigate it to see if is possible to improve the classification results. Besides this, different feature sets can also be explored.

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