Increasing Road Safety with Machine Learning - A Fatigue and Drowsiness Detection System

António Cerca[a]
a40232@alunos.isel.pt

André Lourenço[a][b][c]
andre.lourenco@isel.pt

Artur Ferreira[a][c]
artur.ferreira@isel.pt

[a] ISEL, Instituto Superior de Engenharia de Lisboa
Instituto Politécnico de Lisboa

[b] CardioID Technologies

[c] Instituto de Telecomunicações

Abstract

In order to make the roads safer both for drivers and pedestrians, there is an increasing interest in monitoring drivers conditions. In this paper, we propose a system that monitors the drivers fatigue and drowsiness, based on both the persons ElectroCardioGram (ECG) signal and the motion of the steering wheel. The acquired data is compressed and transmitted, with a Bluetooth Low Energy profile. A machine learning approach is taken to detect fatigue and drowsiness patterns. The Support Vector Machines classifier proved to achieve the highest accuracy on this task. The low-cost proposed prototype has the ability to warn the driver about his physiological and physical states, thus increasing road safety.

1 Introduction

The driving abilities of a person are affected by two key factors: fatigue and drowsiness. Fatigue is a physical or psychological exhaustion. A person feels fatigued when, for instance, goes to a gymnasium for a reasonable amount of time or when one has solved a large amount of complex problems. Fatigue, usually results from doing the same task repeatedly or in an exhaustive way. 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.

In the past years, we have seen an increasing interest in the development of Advanced Driver Assistance Systems (ADAS), which monitors the vehicle performance and behaviour, as well as the physiological and physical conditions of the driver. These systems resort to accelerometers and other devices to measure the acceleration and other physical quantities. These devices can be placed on the automobile steering wheel to monitor the movements. Moreover, some physiological signals such as electrocardiogram (ECG) [11], can acquired and monitored. The ECG signal can be obtained with the aid of dry-electrodes placed on the vehicle steering wheel. Thus, fatigue and drowsiness detection can be achieved with machine learning algorithms working on these signals. We can 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.

The remainder of this paper is organized as follows. Section 2 briefly reviews some concepts on fatigue, drowsiness, and monitoring systems. Section 3 describes our solution. Some experimental results and concluding remarks are reported in Section 4.

2 Monitoring Systems

2.1 Drowsiness scale

The Karolinska Sleepiness Scale (KSS) [9] classifies the drowsiness state with a 10-point Likert scale [4], in which the person classifies his/her sleepiness in periods of 5 minutes. Table 1 describes the KSS scale.

Monitoring systems use sensors and devices to measure parameters for a given purpose. There are two main types of monitoring: direct monitoring and indirect monitoring. Direct monitoring systems deal with physiological signals or with a person behaviour [2]. 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) and sitting position. This kind of monitoring has the advantages of being more robust (usually not influenced by external sources) and more private, since the methods are non-intrusive to the person. Moreover, indirect monitoring systems are easier to use, as compared to direct monitoring systems, on a person that is driving.

2.2 Biometric signals

The electrocardiogram (ECG) signal is the electrical signal that the heart emits [3, 6, 7, 11]. The acquisition of ECG signals can be done in two different ways: using intrusive or non-intrusive methods [1]. Intrusive methods are used in clinical settings where biological signals are extracted using devices placed in the human skin. 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 acquisition of these signals with dry-electrodes is almost involuntarily, without having an impact on the person's daily actions. Figure 1 shows a typical ECG waveform.

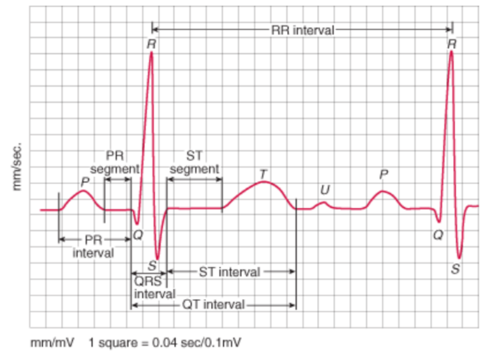

Figure 1: An example of a typical ECG signal [3, 6, 7, 11].

3 Proposed Solution

3.1 Block diagram and prototype placement

The proposed approach is based on the idea that fatigue and drowsiness lead to modifications in the persons biological signals and behaviour. Thus, the monitoring of the fatigue and drowsiness states lead to an adequate approach to warn the driver about his/her state. The acquisition device transmits the data to the gateway and the classification algorithm labels 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 2 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; the gateway solution, for data reception, classification, and alarm activation.

3.2 Acquisition, compression and transmission

Our solution can collect, in a non-intrusive way, the driver ECG signal using dry-electrodes placed in a conductive leather cover (that can fit into

Table 1: The 10-point Karolinska Sleepiness Scale (KSS) [9]

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

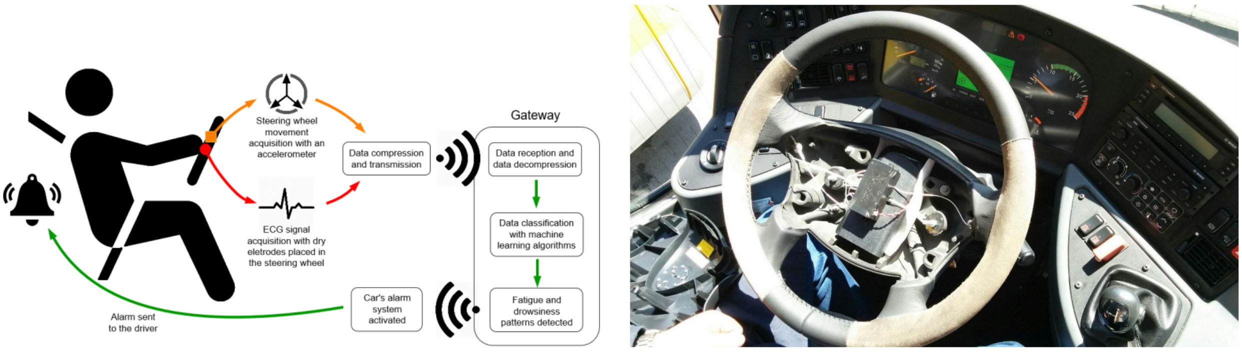

Figure 2: Block diagram of the proposed system (left) and its placement on the automobile (right).

any automobile), and the Steering Wheel Angle (SWA) signal, using an three-axis accelerometer, placed in the centre of the steering-wheel behind the airbag. 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 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. For data compression, we have considered transform-based methods followed by a lossless source coding block [5, 8]. Transform-based methods are the most used techniques to perform lossy encoding of audio and image data. The transform methods are lossless being applied to enable better coefficient quantisation, introducing loss, which results in a lower quality output with high compression ratio. These techniques consist in discarding less significant information, on the quantisation stage, which tends to be irrelevant to the human and (machine) perception of the signal. For transmission, we have considered the Bluetooth Low Energy (BLE) [12] technique, since the devices are battery-powered. BLE allows communications up to 100 meters, in the 2.4 GHz frequency band with rates up to 2 Mbit/s. The current consumption with this technology is around 15 mA.

3.3 Classification

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. We have considered sets of 3, 5, and 8 features for the ECG signal, the SWA signal, and both the ECG and SWA signals. For classification purposes we have considered different typical classifiers. Our experimental results have shown that Support Vector Machines (SVM) provide the best results.

4 Experimental Results and Discussion

We have used the dataset provided by the Swedish National Road and Transport Research Institute [1], which contains signals from 18 different people, 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. The dataset holds 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 KSS test while driving, adding a KSS value to each data sample. The 9-class output was transformed into a binary classification problem, such that the KSS values above 6 are labelled as a drowsy state [10].

Table 2 reports the experimental results for the classification task, with Linear Regression (LinReg), Logistic Regression (LogReg), Artificial Neural Networks (ANN), using common standard accuracy measures, on the ECG + SWA signals. 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. The SVM classifier, with default parameters, achieves the best results, although it seems to exist some room for improvement. The developed low-cost solution is easy to install on any automobile. It requires no driver cooperation and it achieves interesting results regarding drowsiness detection. As future work, we intend to fine-tune the SVM classifier and to extend this approach to a multi-class classification task.

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

Table 2: Experimental results for classification of the ECG + SWA signals

Method	Accuracy	Specificity	Recall	Precision	F1-Score
LinReg	0.55	0.58	0.52	0.55	0.50
LogReg	0.55	0.60	0.49	0.55	0.51
ANN	0.54	0.55	0.53 4	0.54	0.51
SVM	**0.62**	**0.56**	**0.68**	**0.61**	**0.64**

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