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Published Version:
Amidei, A., Poli, A., Iadarola, G., Tramarin, F., Pavan, P., Spinsante, S., et al. (2022). Driver Drowsiness Detection based on Variation of Skin Conductance from Wearable Device. 345 E 47TH ST, NEW YORK, NY 10017 USA : IEEE [10.1109/MetroAutomotive54295.2022.9854871].

Availability:
This version is available at: https://hdl.handle.net/11585/943518 since: 2023-10-02

Published:
DOI: http://doi.org/10.1109/MetroAutomotive54295.2022.9854871

(Article begins on next page)

A. Amidei *et al.*, "Driver Drowsiness Detection based on Variation of Skin Conductance from Wearable Device," ***2022 IEEE International Workshop on Metrology for Automotive (MetroAutomotive)*****, Modena, Italy, 2022, pp. 94-98.**

The final published version is available online at:

https://doi.org/10.1109/MetroAutomotive54295.2022.9854871

Driver Drowsiness Detection based on Variation of Skin Conductance from Wearable Device

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***Abstract*—The majority of road traffic crashes worldwide are caused by driver drowsiness. For this reason, it is necessary to recognize an incoming drowsiness status for alerting the driver as early as possible, preventing serious accidents. Variation of physiological signals can result from incipient drowsiness that the driver is unaware of, so it is worth investigating if such variation may be exploited for early drowsiness detection, in order to raise a warning. To such an aim, several studies involved mainly bulky and intrusive multimodal acquisition systems to collect driver-related information from several sensors, either worn by the individual and embedded in the car-cabin. The aim of this study is to detect the driver drowsiness through a comfortable wrist-worn device, by analysing only the Skin Conductance (SC) physiological signal. To automatically classify the drowsiness status, three ensemble algorithms have been tested, among which Random Forest results to be the best, featuring an overall accuracy of 84.1%. The obtained results prove that it is possible to classify the drowsy status of a driver from SC signals only, collected on the wrist, and motivates further research aimed at the early identification of the incipient drowsiness, for the implementation of a real-time warning system.**

***Index Terms*—Internet of Things, Machine Learning, wearable devices, driver monitoring, drowsiness detection, Skin Conductance.**

I. Introduction

The last available report from the World Health Organization (WHO), in 2018, estimated that approximately 1.35 million people die each year because of car accidents worldwide [1]. Several studies demonstrate that deaths and injuries from road traffic crashes are mainly caused by human factors, such as distraction and fatigue [2], strictly related to driver drowsiness. As a result, research in the field of driving safety is moving towards the detection of the drowsiness status through the use of Machine Learning (ML) and artificial intelligence algorithms, to alert the driver as soon as possible through Internet of Things (IoT)-oriented systems.

Existing safety technologies, based on the monitoring of lane departure combined with the analysis of the steering wheel rotation, can detect a sleepy driving behaviour and warn the driver. Ford Motor Company and Volkswagen are two examples of multinational automobile manufacturers that embedded these alert systems in their vehicles [3], [4]. These systems detect the sleep status, not the drowsy one. Other solutions exploit the cameras embedded in the car-cabin, to track the driver behaviour (e.g., eye-movements, facial expressions and head positions) [5], as the driver attention monitoring system developed by Lexus and Toyota [6]. Camera-based solutions are more trustworthy, but they may suffer several limitations or impairments due to the operating conditions (e.g. different and variable light scenarios, possible face occlusions such as glasses or sunglasses). For these reasons, researchers and car-makers have explored different and innovative solutions. As a condition affecting the driver behaviour, drowsiness is associated to the Autonomous Nervous System (ANS) activity that reflects on physiological changes [2]. Such variations can be monitored by means of comfortable wearable systems available either on the market or as research prototypes (e.g., bracelet [7], double ring [8] and wristband [9]). To collect biomarkers strictly related to the ANS, the electroencephalography (EEG) is generally used as the reference method, often in conjunction with the electrocardiography (ECG, from which heart rate and heart rate variability can be derived), in drowsiness studies [10]–[12].

For example, Awais et al. [11] proposed the combined EEG and ECG for discriminating between alert and drowsy states, revealing a level of accuracy equal to 80.90% with the support vector machine ML classifier. Similarly, in [12], the authors present a drowsiness detection model including physiological (from ECG, respiration sensor and camera), postural and vehicular information. Recently, Arjunan et al. [13] proposed a monitoring system with a combination of multiple wearable sensors (i.e. blood pressure, heart rate, blood oxygen, body temperature, electroencephalography and electromyography sensors) to detect the status of drivers. By focusing on the skin, ANS activity can be explored with the analysis of Skin Conductance (SC), a biomarker which varies as a consequence of the sweat glands secretion. The SC signal can be decomposed in two main components: a tonic one, slowly varying, also known as Skin Conductance Level (SCL) [14], and a phasic component, characterized by rapid changes in signal amplitude, also known as Skin Conductance Response (SCR) [15], which is typically associated to stimuli-related events.

Several studies propose the analysis of SC to investigate a subject's drowsiness, either alone or in conjunction with other physiological signals, with or without automatic classification performed by ML algorithms. For example, in [16], an SC-based wearable device designed by the authors is described, along with the physiological variation evident in drowsy driving. Similarly in [17], significant changes in SC are visible when the subject was falling asleep, acting as a meaningful property to graphically identify the drowsiness. In both the studies, no classification is performed. Contrarily, Horng et al. [18] and Choi et al. [19] focused on physiological prediction of drowsiness by using a multimodal system with several sensors. Both works used ML classifiers to recognise the driver status. Results shown a good accuracy, by exploiting several physiological signals, such as SC, EEG and ECG. However due to the bulky setup (e.g., EEG electrodes placed on the head, ECG on the chest and SC sensors on the fingers/wrist), multimodal systems are uncomfortable and intrusive arrangements for real-life application in driving. Moreover, when multiple signals are used (from both wearable and ambient sensors), the acquisition system complexity increases by affecting the data analysis procedure; consequently the driver status assessment becomes more time-consuming and this could lead to a delay in warning generation, thus becoming less safe for the driver.

The aim of this work is to explore the real-life application of a wearable device to detect the driver drowsiness, by using the SC physiological signal only, exosomatically collected from the wirst. The proposed approach exploits a non-invasive and relatively simple system with respect to SC acquisition boards (e.g., ProComp Infinity [20]) and the above mentioned systems. In conjunction, three ML approaches (namely Random Forest (RF), Bagging and Boosting - the most common ensemble algorithms used for multiclass classification purposes in previous similar works [21], [22]) were tested and compared in terms of classification performance.

The paper is structured as follows. In Section II, the acquisition methodology is described, including the description of the driving simulator, the acquisition device and the test procedure. Section III presents the data analysis. Section IV discusses the experimental results. Conclusions and perspectives for future studies are explained in Section V.

II. Acquisition Methodology

A. Driving Simulator and Acquisition Device

The experiments were conducted in a room hosting a driving simulator (see Figure 1). The driving simulator showed an overnight driving path, realised as a three-lane highway with no traffic and a length of around 80 km. The average temperature in the room hosting the driving simulator was maintained quite stable (around 23 °C) to reduce the influence of ambient temperature on SC signals.

The idea presented in this paper was to emulate an approach similar to the real-life context, where a driver can wear the own smartwatch, equipped with the capability to monitor physiological parameters. In particular, a multi-sensor Empatica E4 [9] wrist-worn device was used for collecting the user's skin conductance changes during the driving simulation, through the SC sensor. A very small amount of alternating current (maximum peak-to-peak value of 100 μA) passes at a frequency of 8 Hz between two Ag/AgCl electrodes located on the bottom side of the bracelet, and the electric conductance across the skin is recorded in μS. The sampling frequency of the SC sensor is set at 4 Hz with a resolution of 900 pS and a dynamic range of [0.01-100] μS.

B. Test Procedure

Nine volunteer healthy subjects, 4 males and 5 females, were enrolled in this study. Age and gender can highly influence the physiological data changes. Therefore, a male and a female were selected in each cohort of 10 years width, from 20 to 60 years of age, to cover a wide range of active drivers. The test procedure was explained in detail to the subjects before

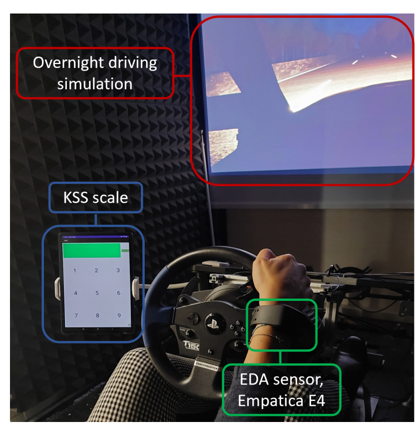

Fig. 1. Experimental setup: driving simulator, monitor with overnight simulation, Empatica E4 device position and tablet with KSS scale.

signing an informed consent. The driving simulation, lasting around 40 min, involved the usage of Empatica E4 device worn on the dominant wrist. During the whole driving recording session, participants were provided with a tablet where, every 10 min, they were requested to assess their own perceived alertness/drowsiness status through the 9-point Karolinska Sleepiness Scale (KSS) questionnaire [23], that matches verbal sentences to the psycho-physical status experienced.

III. Data Analysis

To examine the feasibility of the proposed approach for detecting driver drowsiness, data analysis was performed first in MATLAB environment and then by using the WEKA tool [24] for the ML performance evaluation.

A. Artifacts removal

Movements of the wrist while driving, and undesirable electrodes contact losses, can strongly affect the quality of SC signal acquired from the wrist-band, and consequently the performance of ML algorithms in classifying the driver drowsiness. Therefore, according to the literature [25], the Stationary Wavelet Transform (SWT) denoising with *haar* mother wavelet (7 levels of decomposition) was implemented to detect, and then remove, changes in the SC signal typically due to motion artifacts. In particular, according to a previous similar study [26], the N wavelet coefficients d_j were modelled using a zero-mean Laplace distribution, where j is the wavelet decomposition level. Motion artifacts were removed from the samples if the corresponding coefficents are out of the two thresholds, namely T_{high} and T_{low}, calculated for every level and defined as in [26]:

$$\begin{cases} T_{low} = (\frac{1}{N}\sum_{n=1}^{N}|d_j|) \cdot \log_e(\delta) \\ T_{high} = -T_{low} \end{cases} \tag{1}$$

where δ is the proportion of motion artifacts in the original signal and it quantifies how much motion artefacts affect the signal. As in [25], [26], δ is set by exploiting the 3-axial accelerometer embedded in Empatica E4, which collects wrist acceleration values simultaneously with the SC samples: thus, δ can assume two different values depending on the subject's wrist movement amplitude. In our study, the value of δ depends on the standard deviation (σ) of the acceleration samples from each single directional component (acc_x, acc_y, acc_z), as follows:

$$\begin{cases} \delta = 0.01, & \sigma_{(acc_x, acc_y, acc_z)} < 0.04\ m/s^2 \\ \delta = 0.10, & otherwise \end{cases} \tag{2}$$

The limit on the value of σ has to be satisfied by all the three acceleration components. The acceleration threshold of 0.04 m/s^2 was heuristically selected by joint visual inspection of acceleration and SC signals. As a matter of facts, similarly to [25], the presence of motion artifacts was defined by the σ of one of the three acceleration components. As a matter of facts, similarly to what was done in [25], the presence of motion artifacts has been located by evaluating the σ of the acceleration components: if just one out of the three is greater than 0.04 m/s^2 then the motion artifact is identified. Inverse SWT is applied to reconstruct the denoised signal.

TABLE I
Features extracted from the SC signal and its components

Type of signal	Domain	Features
SC signal	Time	Mean (μS), standard deviation (μS), minimum (μS), maximum (μS), kurtosis (μS), skewness (μS), variance ((μS)^2), range (μS), median (μS)
	Frequency	Mean (μS/Hz), standard deviation (μS/Hz), minimum (μS/Hz), maximum (μS/Hz), kurtosis (μS/Hz), skewness (μS/Hz), variance ((μS/Hz)^2), range (μS/Hz), median (μS/Hz)
SC components	Time	SCR number of peaks, SCL mean (μS), SCL standard deviation (μS), SCL minimum (μS), SCL maximum (μS)

B. Segmentation and feature extraction

After the filtering phase, both SC signal and its components (SCR and SCL) were divided in short-term time windows with fixed size of 15 s [22], corresponding to 60 samples; then, each segment was labeled with the KSS scale's response given by the users. To investigate the drowsiness prediction, the KSS scores were grouped from the original 9 possible values into three classes, depending on the drowsiness level: KSS scores between 1 and 5 in class 1 (labelled as *alert*), 6 and 7 in class 2 (labelled as *slightly drowsy*), 8 and 9 in class 3 (labelled as *drowsy*). Then, from samples contained in each window, a total of 23 features listed in Table I (some used in previous study [15], [27], [28], [29]) were estimated in time and frequency domains to explore the temporal and spectral information content. For what concerns the frequency domain, before computing the features, the Fast Fourier Transform (FFT) was applied on the original data. Finally, each feature was associated to the related label.

C. Features selection

Among the features extracted, some might have similar information content, resulting in high correlation, and hence in redundancy for discriminating classes with an ML algorithm [30]. As a result, to select only the relevant features, the correlation coefficient (ρ), quantifying the strength of the features relationship, was computed; ρ > 0.90 was assumed as the condition for a strong correlation among the features tested. According to this, five features, namely SC mean, SC maximum, SC median, SCL mean and SCL maximum, were discarded, resulting in 18 features to use.

D. Machine learning algorithms

Once selected the relevant features, three ML algorithms were tested and their classification performances were compared. In particular, RF, Bagging and Boosting were considered, as in previous similar works [21], [22]. The proposed ML-based drowsiness detection models were evaluated through the 10-fold cross-validation method. Then, according to [31], the classification performance was assessed by using accuracy (number of correctly classified instances related to driver status over the total number of instances). Values of precision (number of correctly classified instances over the total number of instances labelled as belonging to the correct class) and recall (number of correctly classified instances over the total number of instances that actually belong to the correct class) result from the average of three classes. Moreover, the confusion matrix was computed to summarise the classification performance of the best ML algorithm.

IV. Experimental Results

The figures used to evaluate the classification performance are summarised in Table II. The overall accuracy in the identification of *alert* (class 1), *slightly drowsy* (class 2) and *drowsy* (class 3) is equal to 84.1% for RF, 83.2% and 82.8% are obtained for Bagging and Boosting, respectively. Precision and recall are equal to 84.2% and 84.1%, respectively, for RF; they amount to 83.3% and 83.2% for Bagging, and they are both equal to 82.8% for Boosting. The RF classifier proves to be the best one, among those tested, according to all the performance figures evaluated. Table III represents the confusion matrix related to the RF algorithm, performing as the best classifier. The main diagonal indicates the number of instances correctly classified, hence those for which the predicted instances equal the actual ones. The values outside the diagonal identify the prediction errors. It can be observed from the matrix that, if considered together, class 2 and class 1, representing the *slightly drowsy* and *alert* conditions respectively, are well-distinguished (867 instances classified, out of the 1045 actual instances), except for a few instances. This means that there are clear and meaningful physiological variations captured by the collected signals, which characterise the *alert* and the *slightly drowsy* statuses. Such changes allow the ML classifier to discriminate the features extracted from the two conditions, against the *drowsy* class, and this capability could be exploited in the future to design automatic systems to warn the driver. Contrarily, the instances related to class 2 (*slightly drowsy*) alone, are often misclassified with those labelled as class 3, i.e. *drowsy* status. Features related to the *drowsy* stages of the acquisition sessions are quite similar to those computed over the data collected during the *slightly drowsy* ones. Anyway, from a possible real-life application point of view, the most important challenge in this kind of safety systems is the capability to detect the physiological variation in short-terms between the *alert* and the *slightly drowsy* conditions.

TABLE II
Classification performance of proposed approach

Classifier	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Random Forest	84.1	84.2	84.1
Bagging	83.2	83.3	83.2
Boosting	82.8	82.8	82.8

TABLE III
Confusion matrix for RF algorithm

Predicted Instances		**Actual Instances** 1	2	3
	1	85.7%	11.7%	2.6%
	2	6.1%	83.0%	10.9%
	3	3.9%	12.2%	83.9%

V. Conclusion

This study was focused on detection of driver drowsiness based on SC physiological variation, recorded through a wrist-worn device. In particular, the *alert* status, the *slightly drowsy* status and the *drowsy* status were classified, by testing three ML algorithms. A total of 18 features have been extracted from SC signals obtained from a realistic data collection conducted during an overnight driving simulation by the 9 subjects involved in the study.

The considered classifiers, namely RF, Bagging and Boosting, achieved accuracy values over 82.0%, in distinguishing the *alert*, *slightly drowsy* and *drowsy* classes. Among them, RF provided the highest accuracy, equal to 84.1%, along with the figures quantified to evaluate the classification performance (i.e., precision and recall equal to 84.2% and 84.1%, respectively). It should be underlined that, based on a heterogeneous population, in terms of gender and age, the findings demonstrate the feasibility of detecting driver drowsiness exploiting only SC signals, acquired from a single wrist-worn device. Moreover, the classification performance is obtained with short-term time windows, essential for detecting short-term events as the natural drowsiness onset. This way, when abnormal changes in skin conductance are detected, proper timely alert can notify the driver, for example suggesting to take a short break to rest.

Future experimental activity will consider a wider test population to expand the dataset and improve the detection accuracy, especially for distinguishing the two classes *alert* and *drowsy*. Besides, different cross validation techniques (e.g., Leave-One-Subject-Out Cross Validation, LOSO) will be employed.

Acknowledgment

The research activity leading to the results shown in this paper was partially funded from the National Funded Programme 2014-2020 under grant agreement n. 1733, (ADAS+ Project). The research activity was also partially supported by the POR MARCHE FESR project "*Marche Innovation and Research fAcilities for Connected and sustainable Living Environments (MIRACLE)*"- CUP B28I19000330007 and by the financial program DM MiSE 5 Marzo 2018 project "*ChAALenge*" - F/180016/01-05/X43.

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