Journal of Biomedical Informatics 73 (2017) 159–170

Contents lists available at ScienceDirect

Journal of Biomedical Informatics

journal homepage: www.elsevier.com/locate/yjbin

Monitoring stress with a wrist device using context

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ARTICLE INFO

Article history:
Received 7 December 2016
Revised 24 July 2017
Accepted 9 August 2017
Available online 10 August 2017

Keywords:
Stress detection
Real life
Wrist device
Machine learning
Context
Healthcare

ABSTRACT

Being able to detect stress as it occurs can greatly contribute to dealing with its negative health and economic consequences. However, detecting stress in real life with an unobtrusive wrist device is a challenging task. The objective of this study is to develop a method for stress detection that can accurately, continuously and unobtrusively monitor psychological stress in real life. First, we explore the problem of stress detection using machine learning and signal processing techniques in laboratory conditions, and then we apply the extracted laboratory knowledge to real-life data. We propose a novel context-based stress-detection method. The method consists of three machine-learning components: a laboratory stress detector that is trained on laboratory data and detects short-term stress every 2 min; an activity recognizer that continuously recognizes the user's activity and thus provides context information; and a context-based stress detector that uses the outputs of the laboratory stress detector, activity recognizer and other contexts, in order to provide the final decision on 20-min intervals. Experiments on 55 days of real-life data showed that the method detects (recalls) 70% of the stress events with a precision of 95%.

1. Introduction

In 1908, Yerkes and Dodson presented the Yerkes–Dodson law of empirical relationship between arousal and performance. According to the Yerkes-Dodson law, the human performs at a near-optimal level under a certain amount of stress. Consequently, stress is not necessarily a negative process, but when present continuously it can result in chronical stress. Chronical stress has negative health consequences, such as raised blood pressure, bad sleep, increased vulnerability to infections, decreased performance, and slower body recovery [1].

Work-related stress is defined as a harmful psycho-physiological response that occurs when the requirements of a job do not match the capabilities, resources or needs of a worker, which can lead to poor health and injury [2]. Regarding the economic costs of stress, the European Commission estimated the costs of work-related stress at €25 billion a year for 2013 [2]. This is because work-related stress leads to an increased number of accidents, absenteeism and decreased productivity. Therefore, having an automatic stress-monitoring system would be beneficial for the self-management of mental (and consequently physical) health of workers [3], students, and others in the stressful environment of today's world.

The three characteristics that make the problem of monitoring stress challenging and worth researching are:

- **Stress is highly subjective.** A stimulus that triggers the stress process in one person may not trigger it in another.
- **It is difficult to define the ground truth for the detection of stress.** Because of the high subjectivity and the continuous nature of the stress process, it is difficult to define the start, the duration and the intensity of a stress event.
- **Stress cannot be monitored directly.** The stress response consists of three components: physiological, behavioral and affective response [4]. A part of the physiological response (e.g., increased heart rate, increased sweating rate, etc.) can be monitored directly using wearable devices (e.g., Microsoft Band fitness tracker). However, there are no direct methods for monitoring the other two components (behavioral and affective response) of the stress response.

Recent technological advances have brought wearable biosensors (e.g., ECG sensors [5], sweating-rate sensors [6], respiration-rate body sensors [7], etc.) into everyday life. In our experiments, we chose a wrist device because users are mostly accustomed to wrist wearables (due to hand watches), and it is one of the least obtrusive placements. However, the wrist is also subject to frequent movement due to the hands activity, which introduces noise in the data and therefore additionally complicates the already challenging problem of stress detection.

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http://dx.doi.org/10.1016/j.jbi.2017.08.006
1532-0464/

The current state of the art studies for automatic stress detection in real life [8,9] propose a methodology using a chest sensor. In their approach, they first tune their machine-learning model in a laboratory and then apply it in real-life environments using some simplifications, e.g., they discard periods of moderate to high activity. As future work they suggest smartwatches as a source of physiological data, better handling of physical activity and including context information in the process of stress detection. In our study we tackle all of these issues by:

- Using only a wrist device as the source of physiological data.
- Recognizing the user's activity by analyzing the acceleration data from the wrist device using an award-winning machine-learning method [28].
- Using real-life contextual information in the machine-learning process to improve the performance of the method.

In addition, building upon state-of-the-art studies, we analyze the problem of stress detection first in laboratory conditions using an off-the-shelf wrist device equipped with bio-sensors, and apply the extracted laboratory knowledge to real life, on data gathered completely in the wild. In addition to laboratory knowledge, real-life context information is extracted so the method may be successfully applied to real-life data. The context information is required to distinguish between psychological stress in real life and the many situations which induce a similar physiological arousal (e.g., exercise, eating, hot weather, etc.).

The proposed method is evaluated on 55 days of real-life data from 5 subjects. Real-life evaluation is poorly explored in the related work. It poses numerous problems, which are discussed in this paper. Among them are: how to gather the real-life data, how to segment the data, and how to label the data. In this study we additionally provide guidelines for how to tackle these issues, which is an additional improvement compared to the related work, since the majority of the related-work methods for stress detection are tested only on laboratory data.

The rest of the paper is organized as follows: in Section 2, an overview of the related work on stress detection is presented. In Section 3, the method for stress detection in constrained environments and its evaluation are presented. In Section 4, the context-based method for stress detection in unconstrained environments and its evaluation are presented. In Section 5, practical usage of the context-based method for stress detection is presented. Finally, Section 6 summarizes the study, and presents discussion and ideas for future work.

2. Related work

The analysis of the related work on stress detection through the prism of computer science shows that the focus shifts from stress detection in a constrained environment using less comfortable sensors to stress detection in an unconstraint environment using more comfortable sensors. The pioneers in this field are Healey and Picard who showed in 2005 that stress can be detected using physiological sensors [10]. With the advance of the technological devices equipped with physiological sensors, the method, which in 2005 required intrusive wires and electrodes, can finally be implemented comfortably.

In the period 2005–2016, various studies were conducted to implement stress detection using a combination of signal processing and machine learning (ML). Most of them used data from a respiration (Resp.) sensor [8,10,11], ECG sensor [8,10,11], heartrate (HR) sensor [12], acceleration (ACC) sensor [13,14], electrodermal activity (EDA) sensor [8,10,11,14,15], blood volume pulse (BVP) sensor [18] and electromyogram (EMG) sensor [10,19]. Some are more constrained, either physically (e.g., brain activity analysis [20]) or with respect to privacy (e.g., analyzing the user's audio or video [21]). In our study we use a device that provides acceleration, BVP, EDA, HR, inter-beat interval (IBI), and skin temperature (ST) data.

A key difference between previous approaches in the related work is the environment for which they are intended. As with many scientific problems, the problem is first analyzed in constrained environments, e.g., a laboratory [8,17], office [16], car (analysis while driving) [10], bed (analysis while sleeping) [11], and call center [15]. One step closer to real life are Ramos et al. [13], Mohino-Herranz et al. [22] and Lu et al. [23], who presented studies in which the subjects are allowed to be active based on a predefined scenario.

Very few approaches are tested in a completely unconstrained environment. Sano et al. [14] collected 5 days of data for 18 participants using wrist-worn sensors (accelerometer and EDA) and smartphone (calls, SMS, location and screen on/off) for stress detection in real-life environments. The reported accuracy for a 2 class problem is 74% by using 10-fold cross-validation. They did not present results for person-independent models, and the wrist-worn accelerometer data is not used for distinguishing EDA caused by physical activity or stressful event, which is something that we are proposing in our study.

Adams et al. [24] collected data from seven participants as they carried out their everyday activities over a ten-day period. They used smartphone audio-sensing and a wrist-worn EDA sensor. They analyzed correlations between stress self-reports and smartphone audio-sensing. They did not use machine learning to detect stress. They concluded that context information is needed to distinguish between pleasant and negative experiences. Our proposed machine-learning method exploits context information to detect stress.

Wang et al. [25] and Bauer at al. [26] presented studies in which smartphone data was analyzed to detect behavioral changes related to stress, but they did not build models for stress detection. In our previous work, we used the data from the Wang's et al. [25] study to build machine-learning models for stress detection based only on the smartphone data. The conclusion was that only person-dependent models perform accurately enough [27].

Finally, in 2015 Hovsepian et al. [8] proposed cStress, a method for continuous stress assessment in real life, and in 2016, cStress is used in another real-life study [9]. They proved that stress can be detected using a chest belt which provides respiration and electrocardiogram (ECG) data. Building upon their guidelines for future work, we used the Empatica E3 and E4 wrist devices as the source of data, and our proven activity-recognition algorithms [28] for handling user activity and providing context information for the stress detection in real life.

This paper extends our previous short papers [29,30] which present the main idea of the method for stress detection. As a significant improvement in this paper, the method and the experimental results are described thoroughly for the first time. We also present additional and improved experimental results.

Table 1 presents a summary of the related work described in the previous subsections. The studies are grouped with respect to the environment in which they are performed (constrained – a laboratory, a car, a bus; semi-constrained – a laboratory with physical activities; unconstrained – completely in real life). Additionally we present the sensors used in the studies, the type of stressor and the number of participants. This study falls into two categories. On one hand we have experiments performed in constrained environments (in laboratory) and on the other hand we have experiments performed in unconstrained environments (real-life). The sensors used are BVP, EDA, ST, ACC, which besides the raw data also provide HR and IBI data. The stressors we analyze