Demo for Continuous Live Stress Monitoring with a Wristband

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*This work is also accepted as a short-paper at the PAIS 2016 conference.

Abstract. We will demonstrate a method for continuous stress monitoring using data provided by a commercial wrist device (Microsoft Band) equipped with physiological sensors and an accelerometer. The method consists of three machine-learning components: a laboratory stress-detector that detects short-term stress; an activity recognizer that continuously recognizes user's activity and thus provides context information; and a context-based stress detector that first aggregates the predictions of the laboratory detector, and then exploits the user's context to provide decision on 20 minutes interval. The method was trained on 21 subjects in a laboratory setting and tested on 5 subjects in a real-life setting. The accuracy on 55 days of real-life data was 92%. The method is integrated in a smartphone application, which will be demonstrated at the conference.

1 INTRODUCTION

Stress is a process triggered by a demanding physical and/or psychological event [10]. It is not necessarily a negative process, but continuous exposure can result in chronic stress, which has negative health consequences such as raised blood pressure, bad sleep, increased vulnerability to infections, decreased mental performance and slower body recovery processes [9]. It also has substantial economic consequences: the European Commission estimated the costs of work-related stress at €20 billion a year due to absence from work and decreased productivity [1]. Therefore, a stress-detection system would be useful for self-management of mental (and consequently physical) health of workers [3], students and others in the stressful environment of today's world.

Thanks to the recent technological advances, some of the stress-response components can be captured using an unobtrusive wrist device equipped with sensors, e.g., Microsoft Band. Our method is also based on the data captured by such a device, on which we use advanced machine learning (ML) in combination with context information. The method is tested in real life, but instead of a chest belt, we use a commercial wrist device. In 2015 Hovsepian et al. [6], as future work suggested better handling of physical activity (which can confuse stress detection) and including context information in the process of stress detection – which is what we have done in our study.

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2 METHODOLOGY

For developing the method for stress detection, two datasets were recorded: a laboratory dataset, which included 21 subjects, and a real-life dataset, which included 5 subjects. In both datasets the Empatica[2] wrist device was used to collect data, which provides heart rate (HR), blood volume pulse (BVP), galvanic skin response (GSR), skin temperature (ST), time between heartbeats (IBI) and accelerometer data. To collect the laboratory data we used a standardized stress-inducing experiment as proposed by Dedovic et al. [2]. The main stressor was solving a mental arithmetic task under time and evaluation pressure. The real-life data was gathered on ordinary days, when the subjects were wearing the wrist device and were keeping track of their stressful events.

Figure 1 presents the proposed method for stress detection in real-life. The method consists of three main ML components: a laboratory stress detector, an activity recognizer, and a context-based stress detector which provides the final output.

The laboratory stress detector is a ML classifier that distinguishes stressful vs. non-stressful events in 4-minute data windows with a 2-minute overlap. For each data window, features for stress detection are computed. From each physiological signal (BVP, HR ST and GSR), statistical and regression features are computed: mean, standard deviation, quartiles, quartile deviation, slope and intercept. Additional features to quantify the GSR response are computed with an algorithm for peak detection [7]. For the IBI signal, we use features obtained through heart-rate-variability analysis in the frequency and time domain. These features are fed into a classifier trained with the Random Forest ML algorithm, which was chosen experimentally

The activity recognition (AR) classifier is a ML classifier that uses the accelerometer data to recognize the user's activity: sitting, walking, running, and cycling. It is based on our previous approach for AR [4]. The classifier outputs an activity every 2 seconds. When aggregating these activities over the data window of 4 minutes, each activity is changed into an activity level (e.g., lying = 1, walking = 3, running = 5) and averaged over the window. The average activity level is passed as a feature to the context-based stress detector.

[3] https://www.empatica.com/

The context-based stress detector was developed to distinguish between genuine stress in real life and the many situations which induce a similar physiological arousal (e.g., exercise, eating, hot weather, etc.). As features, it uses the distribution of the last 10 outputs of the laboratory stress detector, the previous output of the context-based detector, and context features: whether there was any high-level activity in the last 20 minutes, the hour of the day, the type of the day – workday/weekend, etc. It classifies every 20 minutes as stressful or non-stressful. The context-based stress detector was trained with the SVM ML algorithm, which was again chosen experimentally.

Figure 1. Method for stress detection in real life.

3 EVALUATION AND DEMO APPLICATION

The evaluation of our method was performed on the real-life data. Because labeling stress is quite subjective [5] and it is almost impossible to strictly define starts and ends of stressful situations, we used a technique that splits the stream of real-life data into discrete events. Each event had a minimum length of one hour. If there was a stressful situation in the event (labeled by the user), the event's duration was extended to capture the stressful situation plus one hour before and after the situation. By this, we are allowing for a labeling lag of one hour. The 55 days of the real-life data was split into nearly 900 events, each lasting at least an hour. Figure 2. depicts the output of the context-based stress detector for the real-life dataset using leave-one-subject out evaluation (LOSO). On the x-axis is the hour of the day, on the y-axis is the day, the black stripes label to which subject belongs the data, and the colored squares correspond to the false positive (FP), false negative (FN), true positive (TP) and true negative events (TN). The achieved accuracy is 92% with an F1 score of 63% for detecting stress.

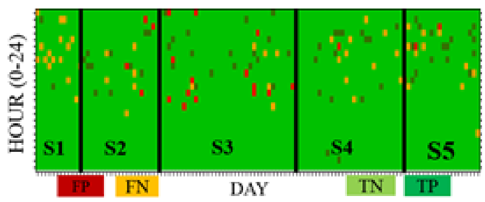

Figure 2. Context-based output with LOSO evaluation.

Figure 3 presents a screen-shot of the smartphone implementation of the context-based method for stress detection. The upper graph presents the output of the laboratory stress detector and the lower graph present the output of the context-based stress detector. The orange bar at the bottom presents the arousal level. The application is being developed for the Fit4Work project [3] which aims to help older workers for mental and physiological fitness.

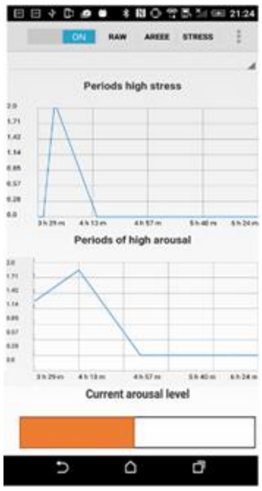

Figure 3. Context-based output with LOSO evaluation.

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