Continuous Live Stress Monitoring with a Wristband

Martin Gjoreski[12] and **Hristijan Gjoreski**[12] and **Mitja Luštrek**[12] and **Matjaž Gams**[12]

Abstract. In this paper we propose a method for continuous stress monitoring using data provided by a commercial wrist device equipped with common physiological sensors and an accelerometer. The method consists of three machine-learning components: a laboratory stress-detector that detects short-term stress every 2 minutes; 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 in order to provide the final decision in a 20 minute 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 currently being implemented as a smartphone application, which will be demonstrated at the conference.

1 Introduction and motivation

Stress is a process triggered by a demanding physical and/or psychological event [12]. 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 [11]. 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 (e.g., increased heart rate) can be captured using an unobtrusive wrist device equipped with sensors, e.g., Empatica[3] or Microsoft Band. Our method is also based on the data captured by such a device, on which we use advanced machine learning (ML) along with context information.

The pioneers in the field of stress detection are Healey and Picard who showed in 2005 that stress can be detected using physiological sensors [5]. Since 2005, various studies were conducted to implement stress detection using a combination of signal processing and ML using data from physiological sensors and accelerometers [5][6][7][9][10]. The problem of stress detection was first analyzed in constrained environments such as a laboratory/office [10], car [5], and call center [6]. Some approaches in which the subjects were allowed to be active based on a predefined scenario came one step closer to the real world [9]. Most recently, Hovsepian et al. [7] proposed cStress, a method for continuous stress assessment in real-life using a chest belt. Similarly, our method is tested in real life, however, we use a commercial wrist device instead of a chest belt. For future work Hovsepian et al. [7] suggested better handling of physical activity (which can reduce stress detection performance) and using context information in the process of stress detection – which is what we have done in our study.

2 Method for stress detection in real life

For the purpose of this study, two datasets were recorded: a laboratory dataset, which includes 21 subjects, and a real-life dataset, which includes 5 subjects. The Empatica[2] wrist device was used to collect data for both datasets. It 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[3]. 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 [8]. 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 label 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.

[1] Jožef Stefan Institute, Department of Intelligent Systems
[2] Jožef Stefan International Postgraduate School

[3] https://www.empatica.com/
[4] http://dis.ijs.si/thestest/

Figure 1. Method for stress detection in real life.

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 SVM, which was chosen experimentally.

3 Experiments

The evaluation of our method was performed on the real-life data. Because labeling stress is quite subjective [6] 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. This allows 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.

Table 1 presents the confusion matrices for the event-based evaluation using leave-one-subject-out (LOSO) cross-validation. On the left are the classification results without context (based only on the predictions of the laboratory stress detector) and on the right are the results for the context-based stress detector. The accuracy achieved by the context-based stress detector (for distinguishing stressful vs. non-stressful events) is 92%, which is for 16 percentage points better than the no-context classifier. Additionally, Figure 1. depicts the output of the context-based stress detector for the real-life dataset. On the x-axis is the day, on the y-axis is the hour of the day, the black stripes label which subject the data belongs to, and the colored squares correspond to the false positive (FP), false negative (FN), true positive (TP) and true negative events (TN). From the figure it can be seen that subject 1 (S1) has many FN events, and subject 2 (S3) has more FP events compared to the rest of the subjects.

	No Context		With context	
	0	1	0	1
0	638	175	790	23
1	44	70	51	63
Recall	78%	61%	97%	55%
Prec.	94%	29%	94%	73%
F1	85%	39%	96%	63%
Acc.	76%		92%	

Table 1. Confusion matrices for event-based evaluation. Context vs. no-context.

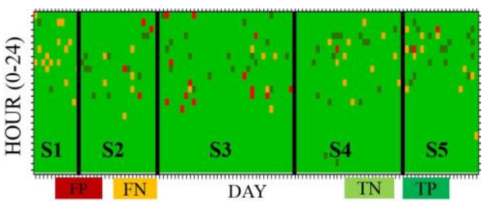

Figure 2. Context-based output with LOSO evaluation.

4 Discussion and conclusion

We developed a method that can continuously detect stress in real life. By introducing a context-based classifier we provided more information about real-life circumstances and the user, which improved the detection performance.

While still leaving room for improvement, the results are encouraging for such a challenging problem. For now, the context-based stress detector receives information from the laboratory detector and the activity recognizer. Additional context information can be provided from other components that recognize events which induce similar physiological arousal to a stress event (e.g., exercise, eating, hot weather etc.). Because stress is perceived differently, we plan to implement personalization to allow to the general model to adapt to new users. Figure 1 confirms the need for personalization where it shows that the distribution and the type of the classification errors (e.g., FP vs. FN) is subject-specific.

We are currently implementing the method as a real-time smartphone application. It will be demonstrated at the conference, where the participants will wear the wristband during stressful events, e.g., while giving a presentation. We will also integrate our method into an existing application that provides relaxation and lifestyle advice upon detected stress. It is intended for older workers and will be used in the European project Fit4Work [3].

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