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EXTENDED-ABSTRACT

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Continuous Stress Detection Using a Wrist Device – In Laboratory and Real Life

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Abstract
Continuous exposure to stress is harmful for mental and physical health, but to combat stress, one should first detect it. In this paper we propose a method for continuous detection of stressful events using data provided from a commercial wrist device. 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 exploits the output of the laboratory stress detector and the user's context in order to provide the final decision on 20 minutes interval. The method was evaluated in a laboratory and a real-life setting. The accuracy on 55 days of real-life data, for a 2-class problem, was 92%. The method is currently being integrated in a smartphone application for managing mental health and well-being.

Author Keywords
Stress detection; real life; wrist device; Empatica; machine learning; context; mental health.

Figure 1. Empatica wrist device used in the study.

Figure 2. Laboratory setting for collecting the laboratory data.

ACM Classification Keywords
J.3 Computer Applications: Health

Introduction

Stress is a process triggered by a demanding physical and/or psychological event [15]. It is not necessarily a negative process, but when present continuously it can result in chronical stress, which has negative health consequences such as raised blood pressure, bad sleep, increased vulnerability to infections, slower body recovery and decreased mental performance [25]. Regarding the economic costs of stress, in 2002, the European Commission calculated the costs of work-related stress at €20 billion a year. This is because work-related stress leads to increased absenteeism and decreased productivity [4]. Therefore, a stress-detection system would be useful for self-management of mental (and consequently physical) health of workers [6] students and others in the stressful environment of today's world.

To develop a stress-detection application, we must better understand the stress process. When humans undergo a vigorous event (e.g., intense training, meeting, exam, etc.), the body is faced with a large physical and psychological stressor, invoking a response of the sympathetic nervous system to meet the increased metabolic demands [1]. The sympathetic nervous system essentially speeds up certain processes within the body ("fight-or-flight" response) [3]: it raises the heart rate, sweating rate, blood pressure, etc., some of which can be detected with wearable sensors. After the vigorous event, the sympathetic nervous system slows down, and the parasympathetic nervous system initiates the rest and repair processes [18]. Ideally, these two nervous systems remain balanced in their efforts. If the sympathetic-parasympathetic ("yin-yang") balance is not maintained (e.g., the body experiences stressors too often), and the activation of the sympathetic response is continuously higher, chronic stress is triggered. To prevent chronic stress from showing up in the first place ("prevention is better than cure"), a continuous acute stress detection system – such as the one described in this paper – can be used, which can recommend relaxation exercises or lifestyle changes.

In recent years there have been attempts to diagnose stress and prevent or decrease its negative effects, and some of such systems were based on non-expensive mobile devices [21]. Thanks to the recent technological advancement, some of the "fight-or-flight" components (also known as components of the stress response) can be captured using an unobtrusive wrist device equipped with sensors, e.g., Empatica [7] or Microsoft Band. Our approach is also based on the data captured by such device, on which we use advanced machine learning in combination with context information.

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 [12]. With the advancement of the technological devices equipped with physiological sensors, the method, which in 2005 required intrusive wires and electrodes, can finally be implemented comfortably. Fast forward to 2015, Hovsepian et al. [14] proposed cStress, a method for continuous stress assessment. They have developed their method using two separate datasets of 25 participants and tested it on a third dataset of 30 participants. They proved that stress can be detected using a chest belt which provides respiration and electrocardiogram (ECG) data. As future work they suggested smartwatches as a source of ECG data, better handling of physical activity and including context information in the process of stress detection – which is what we have done in our study. We used the Empatica wrist device as the source of data, and our proven activity-recognition algorithms [9] for handling user activity and providing context information for the stress detection.

Since 2005, various studies were conducted to implement stress detection using a combination of signal processing and machine-learning. Most of them used data from a respiration sensor [12, 14, 17], ECG sensor [12, 14, 17, heartrate (HR) sensor [24], acceleration sensor [20, 21], galvanic skin response (GSR) sensor [12, 24, 17, 21, 13], blood volume pulse (BVP) sensor [11] and electromyogram sensor [12, 28]. 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 [16, 2, 22]). In our study we use a device that provides acceleration, BVP, GSR, and HR data, RR intervals (time between heartbeats), and skin temperature (ST). Besides the unique combination of sensors, this is to the best of our knowledge the first study in which RR intervals from a wrist device are used for stress detection in real-life.

Another key difference between related work is the environment for which it is intended. As with many scientific problems, first the problem is analyzed in constrained environments, e.g., a laboratory [24], office [28], car (analysis while driving) [12], bed (analysis while sleeping) [17], and call center [13]. Ramos et al. [20] presented an approach that is one step closer to real world: one by and another by Mohino-Herranz et al. in which the subjects are allowed to be active based on a predefined scenario. And finally, very few approaches are tested in a completely unconstrained environment, out which Sano et al. did not report results for person-independent evaluation (only 10-fold cross validation) [21], Adams et al. [2] did not report performance measures (they focus on comparing techniques for measuring stress in the wild), and Hovsepian et al. [14] used a chest-belt, which can be uncomfortable sensor placement [30]. Our method uses a wrist device and is tested completely in the wild.

Data

The data used in this study consist of laboratory and real-life data. For collecting the laboratory data we used standardized stress-inducing experiment [5]. Additionally, baseline (no-stress) data was recorded on a separate day when subjects were relaxed. During the experiment, there were no movement constraints, making it as close as possible to real life. On the other hand, the real-life data was gathered on ordinary days where five subjects were wearing the wrist device, and were keeping track of their stressful events. Table 1 presents an overview of the overall data in this study. All of the subjects were healthy adults. The following two subsections provide detailed description of the data in this study.

	Lab	Real
# Participants	21	5
Age Mean	28	28
Age StdDev	4.1	4.3
No Stress	840	73k
Low Stress	356	4.2k
High Stress	368	2.5k

Table 1. Data overview. Number of participants in the two datasets, age (mean and standard deviation) and duration in minutes for the three levels (No Stress, Low Stress and High stress).

Period	STAI score
Begin	10.95
After Easy	13.33
After Medium	14.05
After Hard (End)	13.81

Table 2. Laboratory data – questionnaires summary.

Laboratory Data

For collecting the laboratory data, a web application was developed in collaboration with psychologists. The application implements a variation of the stress-inducing method presented by Dedovic et al. [5]. The main stressor is solving a mental arithmetic task under time and evaluation pressure. In short, a series of randomly generated equations were presented to subjects, who provide answers verbally. The time given per equation was dynamically changing. For each two consecutive correct answers the time was shortened by 10%, and for each two consecutive wrong answers the time was increased by 10%. Each session consisted of three series of equations with increasing difficulty: easy, medium and hard. Each series of equations lasted for five minutes. For motivation, a reward was promised to the top three participants. After each stage, the participant was shown false ranking score, positioning him/her in the top five, and this way motivating him/her to try harder in the next stage and try to win the award. The application is available on-line: http://dis.ijs.si/thestest/.

Four Short STAI-Y anxiety questionnaires [26] were filled by each participant: before the experiment (1), and after the easy (2), medium (3) and hard session (4). The mean STAi score is presented in Table 2. We performed statistical analysis using repeated measures ANOVA as proposed by Eftimov et al. [9]. The resulting p-value was 0.0014, confirming that there is a statistically significant difference in the answers. The answers of the STAI questionnaire were used for subject-specific labelling of the data. For each subject, the period before answering the STAI questionnaire in which they achieved the lowest score is labelled as low stress, and for each +3 STAI points (the statistical tests showed that difference of 2.38 is enough), the stress label is increased by one, thus we get no stress (baseline data), low stress (lowest STAI score), medium stress (lowest STAI score +3) and high stress (lowest STAI score +6). In the final experiments the medium and high stress were merged because only two subjects achieved a high level of stress, so we had three degrees of stress: no stress, low and high.

Real-life data

For the real-life data we used a combination of stress log and Ecological Momentary Assessment (EMA) prompts [27] implemented on a smartphone. The subjects had to answer 4-6 EMA prompts at random periods of the day, and in the case of a stressful situation, they were logging the start, the duration and the level of stress on a scale from 1 to 5 (1-no stress, 2-low stress, 3 to 5-high stress). The answers of the EMA prompts and the stress log were used to label the real-life data.

Stress-Detection Method

The method presented in Figure 3 consists of three main ML components (a base stress detector, an activity-recognition classifier and a context-base stress detector). The base stress detector is built on the laboratory data. This classifier uses a data window of 4 minutes with 2 minutes overlap (thus it provides a prediction every 2 minutes). The window of 4 minutes was chosen empirically to provide enough data for HRV analysis. The activity-recognition classifier uses the accelerometer data to recognize the user's activity (i.e., sitting, walking, running, and cycling) and to provide context information for context-based stress detector. The context-based stress detector aggregates the predictions of the base classifier for stress detection,

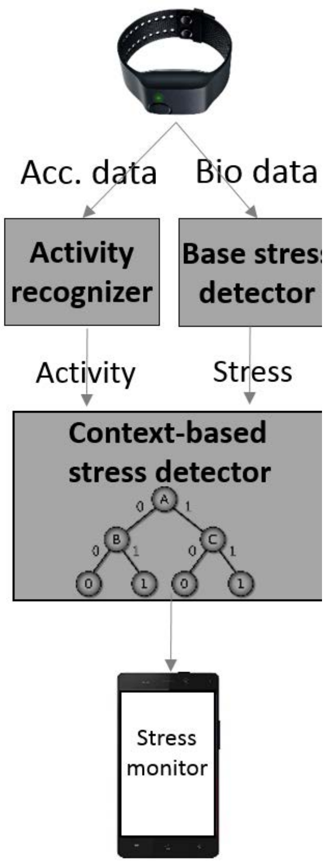

Figure 3. Proposed method for stress detection.

uses context information and provides a prediction every 20 minutes. The interval of 20 minutes was chosen empirically. We decided to use the context-based classifier to distinguish between true stress and the many situations which induce a similar physiological arousal (e.g., exercise, eating, hot weather, etc.). By introducing the context-based classifier we can provide more information about the real-life circumstances, and the user, improving the detection performance.

Base stress-detection classifier

For the creation of the base stress-detection classifier, we used a typical machine-learning pipeline. First, the data was stored locally on the Empatica device, then transferred to a computer where the rest of the processing was performed. After thoroughly analyzing the related literature about feature extraction from biological signals, we extracted the following features:

- For the BVP, HR ST and GSR signals, statistical features were computed: mean, standard deviation, quartiles, and quartile deviation [24, 12]. Additionally, for the HR, ST and GSR, regression features (slope and intercept of signal) were calculated.
- Additionally, on the GSR signal, the algorithm for peak detection [19] was used to detect the GSR responses. The additional features were the number of responses, the power of responses, the number of significant responses (responses which have a value over some threshold) and the power of significant responses.
- For the RR signal, we used heart rate variability analysis in the frequency and time domains. The RR signal is segmented on neighboring RR intervals and a power spectrum is calculated using the Fast Fourier Transformation on all neighboring streams of 32 samples in one data window. The time-domain features were the average RR intervals, the standard deviation of RR intervals, the square root of the mean of the squares of differences between adjacent RR intervals, and the percentage of differences between adjacent RR intervals that are greater than *x* ms (*x* = 20, 50, 70). The frequency domain features were the total spectral power of all RR intervals in power bands up to 0.04 Hz, between 0.003 and 0.04 Hz, between 0.04 and 0.15 Hz, and between 0.15 and 0.4 Hz, and ratio of low to high frequency power.

In total, 63 features were extracted and passed to a machine-learning algorithm to learn the base stress detector. For learning we used WEKA's Random Forest algorithm, which was chosen experimentally. The evaluation of the model is described in the section on experiments.

Activity-recognition classifier

The activity-recognition classifier uses the accelerometer data to recognize the user's activity: sitting, walking, running, and cycling. It is based on our previous method which was recently evaluated on large amount of data for activity recognition [8]. It outputs an activity every 2 seconds. The outputs are aggregated over the data window of 4 minutes, by changing each to "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.

Context-based stress detector

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

	0	1	2
No Stress (0)	367	39	14
Low Stress (1)	43	80	55
High Stress (2)	36	30	105
Recall (%)	87	54	60
Precision (%)	82	45	61
F1 score (%)	85	49	60
Accuracy (%)	72		

Table 3. Laboratory stress detection: confusion matrix and LOSO evaluation for a 3-class problem.

	0	(12)
No Stress (0)	367	53
Stress (12)	79	267
Recall (%)	87	77
Precision (%)	82	83
F1 score (%)	85	80
Accuracy (%)	83	

Table 4. Laboratory stress detection: confusion matrix and LOSO evaluation for a 2-class problem

of the base stress detector, the previous output of the context-based detector, and context features: whether there was any high-intensity activity in the last 30 minutes, whether there was any medium-intensity activity in the last 20 minutes, the hour of the day, and the type of the day – workday/weekend. 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.

Experiments

Two types of experiments were performed: on the laboratory data, and on the real-life data. The differences in the experimental setup in both experiments proved quite important. In the laboratory, the labelling of stress was simplified because it was clear when a stressor was present and the context of the situation was implicitly known (e.g., the physiological arousal was stress-related). However, in real life, the context was not known and the accuracy of the labels was questionable, as we explain later.

The first experiments on the lab data were performed to evaluate the base classifier for stress detection. We used the leave-one-user-out (LOSO) evaluation technique in order test the generalization of the model and see how it performs on a user that is not in the training data. The confusion matrix, recall, precision, F1 (F-measure) and accuracy are presented in Table 3, where each instance represents four minutes of sensor data. The results show that the "Low stress" is almost equally confused with "No stress" and "High stress". This is expected since the data is analyzed as a continuous stream using a sliding window of 4 minutes with 2 minutes overlap, so two neighboring data windows with different labels always have 50% equal data. Additionally, it is almost impossible to define a strict border between different stress events. If we look only at the "No stress" vs. "Stress" instances in Table 4 (by merging "Low stress" and "High stress"), the accuracy of the classifier is 83%. However, to provide a finer granularity of the base classifier for the benefit of the context-based classifier, we decided to continue with the three-class problem. Moreover, for training the final version of the classifier we used only the instances that were correctly classified in the LOSO evaluation phase. Thus, the classifier was trained using only the instances on the diagonal of the confusion matrix (367 "No stress", 80 "Low stress" and 102 "High stress" instances. The rationale is that we want to use clearly representative instances of each class.

The second type of experiments was performed on the real-life data. To do so, we had to address the well-known problem of subjective stress labeling [14]. In addition to the perception of stress being subjective, a time lag is often a problem. For example, the user marked that a stressful situation occurred from 14:00 till 15:00, but this happened to be a scheduled exam, and the physiological arousal (which the sensors capture) started at 13:00. So, if we run the base stress-detection classifier, it would start to predict stress at 13:00 (which is correct), but the labels of the data would say that the stress situation started at 14:00. This also goes the other way around – users may mark that a stressful situation started before it actually did when labelling retroactively, because the experience of stress can affect the memory. To reduce the lag between a stressful event and its label, we implemented event-based evaluation. The overall stream of real-life data is split into events. Each event can have a minimum length of one hour. If there is a

	No Context		With context	
	0	**12**	**0**	**12**
No Str. (0)	638	175	790	23
Stress (12)	44	70	51	63
Rec. (%)	78	61	97	55
Prec. (%)	94	29	94	73
F1. (%)	85	39	96	63
Acc. (%)	76		92	

Table 5. Real-life stress detection: Context vs. No context confusion matrix and event valuation.

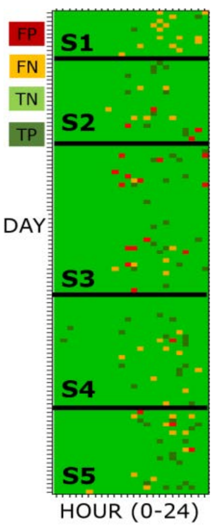

Figure 4. Real-life stress detection: Classification errors (false/true positive and false/true negative) for the 5 subjects.

stressful situation in the event (labeled by the user), the event duration is 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.

After splitting the data onto events we used the LOSO technique for evaluation. Table 4 presents the confusion matrices for the event-based evaluation. The overall real-life data is split into nearly 950 events, each lasting for a minimum of 1 hour. The accuracy for distinguishing No stress vs. Stress events is 92%. Additionally, Figure 4 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 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). From the figure it can be seen that subject 1 (S1) has many FN events, and subject 2 (S3) has many FP events compared to the rest of the subjects.

Conclusion and discussion

We conducted a study of continuous stress detection with wrist device in a laboratory and real-life, and compared the methods and results for each setting. It is difficult to compare the performance to existing related approaches because each approach uses a different dataset recorded with different sensors and different protocols (e.g., the way of labeling the stress events); however, the main contributions of our study are the following:

- The use of a commercial wrist device and exploiting the multiple sensors inside providing HR, BVP, GSR, ST, RR and accelerometer data.
- An investigation of the differences between the laboratory and real-life. It turned out that the experiments in the two settings are different although they have the same goal. In the laboratory, stress is deliberately induced, relatively objectively labelled, and there are few disturbances of the physiological measurements. In real life, stress is less common and distinct, it is subjectively labelled, and physical activity and other factors interfere with physiological measurements. As a consequence, stress detection has to performed and evaluated differently.
- The use of context information (e.g., the activity of the user) to improve stress detection in real life. The results show that the context-based classifier improved the detection performance by 16 percentage points, which is in line with other studies where context proves to be useful for machine learning methods [10, 22].
- Continuous detection of stress in real life, which was evaluated on 55 days of real-life data.

Even though the results show that there is still room for improvement, they are encouraging for such a challenging problem. For a start, stress is a concept for which there is no strict definition in the literature. Additionally, it is highly subjective, it is a not a discrete, and it is difficult to define strict borders between different events. Because of that it is almost impossible to obtain ground truth about stress events. While the literature suggests that the best way to obtain objective measure of stress level is by measuring the cortisol level in the body, our experience with measuring cortisol was discouraging since we got inconsistent results even in the laboratory experiments, and moreover cortisol testing during prolonged real-life stress study is an additional challenge.

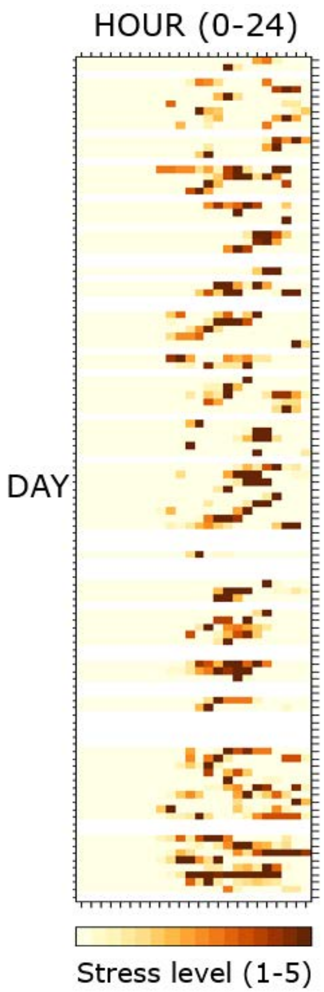

Figure 5. Detected stress levels for the whole data using LOSO evaluation technique.

Currently, we are integrating our stress-detection method in an application that will provide relaxation and lifestyle advice upon detected stress. The application is intended for older workers and will be developed in the European project Fit4Work [8].

Besides the "stress/no stress" output used for evaluation purposes (Figure 4), the method has a potential for detecting the level of stress. Figure 5 depicts the output of the method for the whole data. However, this module still need to be evaluated. In addition, we plan to further investigate the relation between labelled stress level, recognized stress level and cortisol levels. Finally, the method is highly dependent on physiological signals that depend on subject's age, gender, and physical fitness. The need for personalization was confirmed by the visualization in Figure 4, in which it can be seen that distribution and the type of the classification errors (e.g., FP vs. FN) is subject-specific. Because of the subjectivity, we plan to implement personalization methods and therefore to allow user adaptation.

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