Towards Unobtrusive Stress Detection

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Abstract. This paper presents a machine-learning method for unobtrusive stress detection system. The idea is to automatically monitor three components of the stress response, i.e. emotional, behavioural and physiological. The emotional response is monitored using smartphone's microphone and emotional voice analysis. The physiological response is monitored using a sensor-equipped wristband and bio-signal analysis. And, the behavioural response is monitored using smartphone's sensors and smartphone-usage analysis. All three modules are combined using machine-learning methods to predict stress levels. We present approaches to monitor three components of the stress response with preliminary results and an indication of the feasibility of the proposed system.

Keywords: Stress Detection, Emotion Recognition, Stress Behaviour, Physiological Signs, Machine Learning.

1 Introduction

In the 21 century, stress has become one of the important health concerns impacting human life and human society. Among the negative consequences of chronic stress are raised blood pressure, bad sleep, increased vulnerability to infections, slower body recovery processes [1], and overall decreased mental performance. The National Alliance on Mental Illness's survey [2] revealed that 64% of the students who drop out of college do so for mental health reasons. In a recent EU-funded project [3], the cost to Europe of work-related mental health problems was estimated to €617 billion annually. In Slovenia, the economic cost of work-related stress in 2009 was estimated to €1.2 billion, or approximately €1.300 per worker annually [4]. Therefore, a system for early detection of stress leading to appropriate counter-measures could improve many aspects of human life, including general health, education and economy.

Our research is based on the definition of stress by Ice and James [5]: "Stress is considered a process by which a stimulus elicits an emotional, behavioural and/or physiological response, which is conditioned by an individual's personal, biological and cultural context". Figure 1 illustrates the stress process. Stressors are defined as stimuli which elicit a response; mediators and moderators affect one's appraisal of stressors and influence the emotional, behavioural and physiological responses; appraisal determines which potential stressors result in stress response. All components of the stress response influence one's physical and mental health.

We focus only on the stress response, including its three components (emotional, behavioural and physiological), in order to develop an unobtrusive stress detection system.

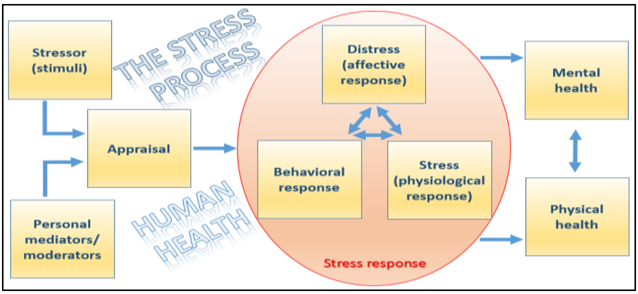

Figure 1. The stress process

2 Related work

The following section provides literature overview through the prism of computer science and engineering. In general, three different approaches exist for stress detection. The first uses physiological sensors (e.g. sensors for sweating rate, heart rate, etc.), the second uses voice analysis and the third is uses smartphone sensors.

The most exploited approach, presented in studies such as [6][7][8][9], is tested in controlled laboratory environment where the subjects' physiological signs are monitored and stress is invoked intentionally by using some kind of stress test [10]. Healey and Picard [11] presented quite an accurate stress detection system in a real-life scenario (while the subject is driving a car), but the drawback is the number physiological sensors.

Another approach to stress detection includes the subject's voice analysis [12][13][14]. For example, recently Aguilar et al. [15] presented a stress detection system using voice analysis where the subjects' were taking an exam.

The enhanced technology of mobile devices has significantly contributed to the direction of using smartphones for stress detection. "MoodSense" [16] and similar approach [17] try to infer stress-related changes in people's behavioural through their smartphone usage patterns and location information. "StressSense" [18] detects stress using speech cues from dialogues. Few studies exist where combination of wearable sensors and smartphones are used [19][20].

3 Proposed approach for unobtrusive stress detection

Figure 2 shows the proposed approach for unobtrusive stress detection. The idea is to automatically monitor all three components of the stress response, namely emotional, physiological and behavioural response. For the emotional response, smartphone microphone is used along with emotional voice analysis. The subjects occasionally record an audio message, or some of their phone calls can be analysed while respecting their privacy (e.g. on-the-fly voice analysis which extracts features from the audio recording without saving the actual recording). For the physiological response, a wrist worn device is be used to provide readings of the subjects physiological signals (e.g. blood volume pulse, sweating rate, heart rate, skin temperature, etc.). To extract features from the subject's physiological signs, bio-signals analysis can be used. For the behavioural response, data from the smartphone sensors (accelerometers, light sensor, GPS, Wi-Fi, etc.) and smartphone usage data (e.g., when was the smartphone last used and for how long), can be analysed. All the features (cues) extracted using voice analysis, bio-signal analysis and smartphone sensor and usage analysis, can be combined to extract useful high level information which can be either real-time information (e.g. emotional state, physiological state, location, activity, …) or general information (e.g. sleep hygiene, energy expenditure,…). Finally, the high level information can be used to detect real-time stress and overall daily stress levels.

The following three subsections provide short overview of two conducted studies and one ongoing study, which are in line with the proposed unobtrusive stress detection system.

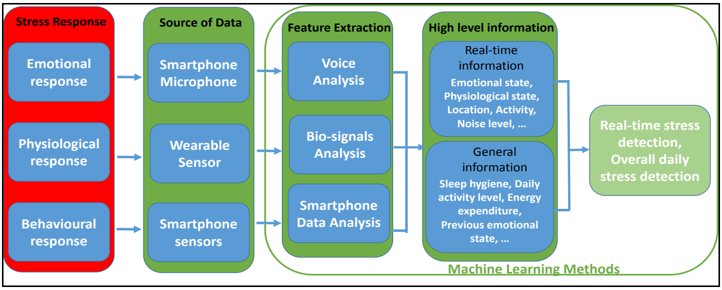

Figure 2. Proposed approach for unobtrusive stress detection

3.1 Emotion recognition from speech (Emotional response)

Disruptive, unpleasant thoughts and emotions play a major role both in contributing to stress and as key components in the manifestation of reactions to stress [21], so an emotion recognition module should be considered as a part of a stress detection system. The goal of a voice-based emotion recognition module is to recognize the emotional state experienced by the speaker. Compared to stress detection, emotion recognition is a much better explored subject in the research community and much better results are achieved so far. Figure 3 shows the machine-learning approach presented in our previous research [22]. Berlin emotional speech database [23] was used, which is one of the most exploited databases for speech emotion analysis. It consists of 535 audio files, where ten actors (five male and five female) are pronouncing ten sentences (five short and five long). The feature extraction tool used in this research is OpenSmile [24]. For feature selection, features were ranked with an algorithm for feature ranking and experiments were performed with varying numbers of top ranked features. Three commonly used algorithms for classification were tested, K-Nearest Neighbours, Naïve Bayes and Support Vector Machine. The models were evaluated with 10-fold and leave-one-speaker-out cross-validation.

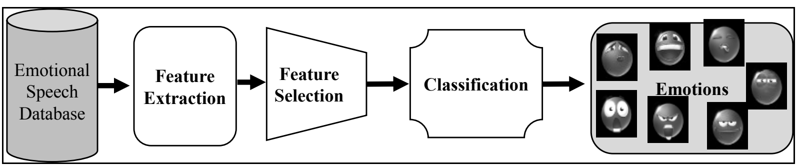

Figure 3. Emotions recognition from speech

Figure 4 shows per-emotion accuracy results obtained by the machine-learning methods compared with human recognition accuracy. The human recognition accuracy is obtained during the construction of the database where twenty volunteers had been asked to recognize the emotions by listening the audio files in random order. The recognition accuracy achieved by the SVM using 10 fold cross-validation is similar to the one achieved by human; in both cases the accuracy is 86%.

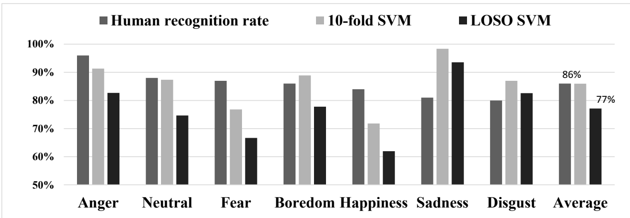

Figure 4. Per-emotion accuracy

3.2 Stress detection by monitoring behavioural changes (Behavioural response)

When an individual is confronted with a stressor they may adopt a number of behaviours which may have a positive, negative or neutral effect on the emotional and physiological response to stressors [5]. Part of one's behavioural response to a stressor can include sleep-hygiene changes (e.g. sleep duration, sleep quality), changes in social behaviour (e.g. avoiding social meetings, conversations), changes in activity levels (e.g. avoiding exercise), etc. Bauer at al. [16] concluded that smartphones can detect stress-related behavioural changes. The team of the StudentLife study [25] concluded that a significant correlation exists between students' mental health and smartphone automatic sensing data. In our study [26] we tried to take the findings of the StudentLife study one step further by implementing a machine-learning method to detect the students' stress levels. We used their data (data of the StudentLife study), which is freely available on web [27]. The goal was to develop a machine-learning model that can unobtrusively detect the stress level in students using data from several smartphone sources: accelerometers, audio recorder, GPS, Wi-Fi, call log and light sensor. From these, features were constructed describing the students' deviation from usual behaviour.

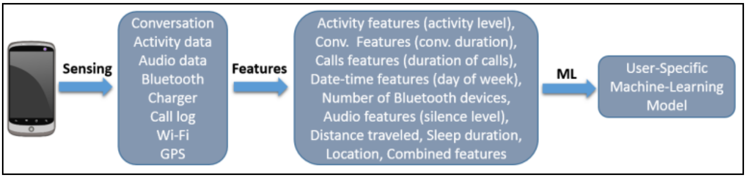

Figure 5. Stress detection using smartphones

As ground truth, we used the data obtained from stress level questionnaires with three possible stress levels: "Not stressed", "Slightly stressed" and "Stressed". Figure 5 shows our proposed approach.

Several machine-learning approaches were tested: building a general models for all the students, building a model for clusters of similar students, and building student-specific models. Our findings showed that significantly better results than majority class cannot be achieved even by clustering students' with similar behaviour using automatic sensing data, and building cluster-specific classification models. Figure 6 shows stress recognition accuracy for leave-one-user-out experimental setup where additionally the data of each test user is split in two parts, one part included in the training set, and one used as test set. The number of instances included in the training set is represented on the x-axis. The "General RF" classifier was trained on the whole training data, while the "Specific" classifiers were trained only on the user-specific training data. The approach that yielded the best accuracy was building a person-specific classification model using the Random Forest algorithm. Once the person-specific algorithm (red) had enough data to build a model, it performed better than the user-specific majority class classifier (Specific ZeroR, blue) and the general classifier (General RF, orange).

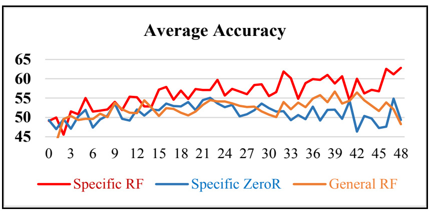

Figure 6. Accuracy with respect to the number of user-specific train instances

Perceived stress is very subjective and each individual is specific, so smartphone stress detection based on behavioural analysis can be performed by building person-specific models, where certain period of time (e.g. 20-25 days) user input is needed.

3.3 Physiological response

In our ongoing study subjects' stress levels are monitored in real-life scenarios. This study aims to integrate the previous two approaches (emotion recognition and stress detection by monitoring behavioural changes) and an approach for stress detection using physiological signs monitored by a wristband with sensors for electrodermal activity (EDA), blood volume pulse, skin temperature, heart rate (HR), and accelerometers [28]. Since the study is at its beginning, we cannot go into details yet. However, we are going to present some interesting preliminary findings. Figure 7 shows an example for physiological signals (EDA and HR) extracted from two real-life scenarios. The signals under stressful conditions (first two graphs) are extracted when the subject was taking a group exam (several students at once). The exam lasted three hours including two presentations and one question-answering session per student. The second two graphs present the subject's physiological signals during an ordinary work-day. During the stressful event, the subject's maximum EDA is near 8 μS, whereas during the ordinary work-day his maximum EDA is near 5 μS. Similarly, during the stressful event, the subject's average HR is near 80-90 bpm, whereas during the ordinary work-day his average HR is around 60 bpm. This means the subject's EDA and HR are significantly increased during the stressful event.

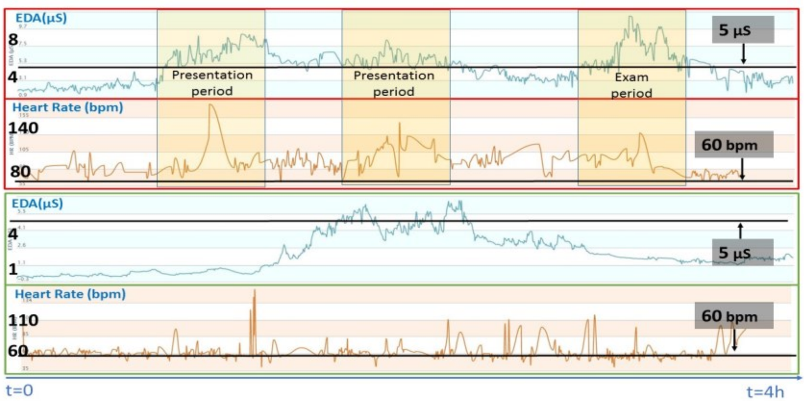

Figure 7. EDA and HR for stressful (upper two graphs) and non-stressful

4 Conclusion and Discussion

The proposed machine-learning method for unobtrusive stress detection by monitoring three components of the stress response (emotional, behavioural and physiological) is in line with the medical theory behind stress. The proposed approach for emotion recognition showed promising results, but it was tested for recognizing acted emotions. Recognizing real-life emotions brings additional problems (e.g. less clearly expressed emotions, recordings quality, privacy, obtaining ground truth, etc.). The proposed approach for stress detection using smartphones by monitoring subjects' behavioural changes is a real-life study, but it appears not to be adequate on its own. The approach for stress detection using physiological signs is a reasonably well researched but nevertheless quite challenging topic. Finally, integrating all three approaches into a single multimodal stress detection system has – to our knowledge – not been done before, but we hope it will be able to overcome the problems of individual approaches and offer better performance than any of them.

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For wider interest

A system for early detection of stress leading to appropriate counter-measures could improve many aspects of human life, including general health, education and economy. Among the negative consequences of chronic stress are raised blood pressure, bad sleep, increased vulnerability to infections, and overall decreased mental performance. One survey revealed that 64% of the students who drop out of college do so for mental health reasons. The cost to **Europe** of work-related mental-health problems in 2013 was estimated **to €617 billion** annually. In **Slovenia**, the economic costs for work-related stress in 2009 was estimated to **€1.2 billion**, or approximately **€1.300** per worker annually.

This paper presents a method for developing a system that can unobtrusively monitor (detect) human stress levels. The idea is to automatically monitor three components of the stress, i.e. **emotional, behavioural and physiological.** The emotional response is monitored using smartphone's microphone and emotional voice analysis. The physiological response is monitored using a sensor-equipped wristband and bio-signal analysis. And, the behavioural response is monitored using smartphone's sensors and smartphone-usage analysis.

Regarding the **emotional response,** we conducted a study for voce-based emotion recognition which showed promising results. The recognition accuracy for 7 basic emotions (happiness, anger, boredom, fear, disgust, sadness and neutral) is 86%.

Regarding the **behavioural response**, we conducted another study for detecting stress level in students using data from several smartphone sources: accelerometers, audio recorder, GPS, Wi-Fi, call log and light sensor. From these sources, information is extracted for describing the students' deviation from usual behaviour. We concluded that smartphone stress detection based on behavioural analysis can be performed by building person-specific models.

In our ongoing study subjects' stress levels are monitored in real-life scenarios. This study aims to integrate the previous two approaches (**emotion** recognition and stress detection by monitoring **behavioural** changes) and an approach for stress detection using **physiological** signs monitored by a wristband equipped with sensors for electrodermal activity, blood volume pulse, skin temperature, heart rate, and accelerometers. The final idea is integrating all three approaches into a single multimodal stress detection system, which – to our knowledge – has not been done before.