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Detecting Work-related Stress using Physiological Signals and Psychological Stress-Coping Profiles

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Much work has gone into employing emerging technologies to monitor and diagnose stress in an attempt to reduce rates of depression. However, building generic models is often difficult due to the subjectivity of stress responses. In psychology, proper diagnosis must take into account the psychological differences between individuals. Another issue is the prolific use of artificial tests to acquire expressive training data where using authentic data mirroring the actual application environment would be more appropriate. This work is geared towards designing a system to gather and track psychological profiles and authentic work activities. A modified version of Sidekick was used to guide subjects through the monitoring process and wearable ECG sensors were used to track heart rates. Psychological profiles were acquired using the COPE inventory and the TAS-20, and self-reported stress labels were acquired through an in-built annotation module. These were used to build and test machine-learned models.

1. Introduction

Stress has long been recognized as a key risk factor in the development of major depressive disorder (MDD) [7], one of the most common debilitating mental illnesses in the world. According to statistics from the World Health Organization, it is a leading cause of work disabilities worldwide and is estimated to affect 350 million people [8], resulting in lost revenue due to medical costs and lost productivity. In this paper, we focus on stress from a psychological or mental point of view, as opposed to physical stress.

A key consideration when tackling the issue of any kind of stress, is that it is imperative that it be addressed at the source. According to [13], together with family, the workplace is the most dominant area where adults experience the most satisfaction and consequently also the most mental stress. It should then come as no surprise that working conditions such as workload, work hours, job security, and corporate structure have significant effects on the depressive tendencies of employees.

Some companies make efforts to address these issues by employing the service of healthcare providers to assess the mental health of employees and to discover ways improve the working environment. Unfortunately, not all companies can afford to enact this type of solution on a regular basis. This is not only due to the cost of employing the experts, but also because of the potential loss of productivity resulting from employees taking time to performing these regular check-ups.

A potential solution to the above concerns is the automation of simple or preliminary stress diagnosis tasks. In fact, a great deal of effort has gone into studying the application of emerging technologies such as wearable sensors [11, 12, 14] and advanced signal processing algorithms [3, 5] to study psychological states. These, coupled with machine learning techniques, can be used to model and automatically detect signals related to emotions and stress. The resulting automatic systems can potentially be used for real-time observation of subjects as they perform their normal activities at a minimal cost. However, challenges exist towards a practical implementation of this type of system. In order to be effectively enforced on a large-scale (i.e., corporations), it is imperative that a flexible general model be built. In addition, the model must also be trained and tested on naturalistic samples obtained from scenarios that mirror the actual deployment environment. These two issues are the focus of this work.

The goal of this study is to realize a more flexible general model of stress by combining data from physiological signals and psychological coping profiles. Through a custom-built monitoring and annotation system and research-grade wearable physiological sensors, subjects were observed and tracked as they performed work-related activities at a personal computer. Subjective stress coping profiles were obtained using standard profiling tools used in psychology. Finally, machine learning algorithms were used to model the relationships between these features and self-reported stress annotations.

2. Related Works

The following section discusses some of the recent works on automatic stress detection and naturalistic stress analysis.

2.1 Automatic Stress Detection

Stress analysis has garnered increased attention in recent years with the bulk of the work focusing on physiological signals such as galvanic skin response (GSR)[11, 12, 14], heart rate (HR)[9, 10, 11, 12, 14], facial expressions[3] and vocal tone[5]. In this work, we focus primarily on HR since it is autonomic and has a more immediate response to stress than GSR.

In [11], they attempted to make a comparison between generic and personalized models of stress. They used data

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acquired from GSR, HRV and skin temperature sensors to build their models. Data was acquired from sessions featuring stressors such as public speaking, mental arithmetic, and cold pressor. Support Vector Machines (SVM) were used for classification and performance was evaluated using leave-one-subject-out cross validation. Results showed that using personalized models performed significantly better than generic ones. The results supported their initial hypothesis that generic models of stress would not achieve acceptable performance.

In [12] in an attempt increase the flexibility of their HRV-GSR stress model, they added contextual information in the form of user activity. Using accelerometer data, they were able to detect activities such as sitting, standing, and walking. SVMs were used for the final classification task and based on their results, it was found that the addition of activity context lead to significant increases in the accuracy of the models. Still, they also noted that physiological signals seemed to be heavily user-dependent and that personalized models were unable to achieve acceptable performance. The goal of the current work is to improve generic model flexibility by introducing psychological features in addition to the physiological data.

2.2 Naturalistic Data

Many of the previous works on stress analysis used artificial scenarios to elicit the desired stress responses. These usually come in the form of batteries such as the Stroop test, mental arithmetic tests, and other stress-inducing methods. While these may be able to evoke clear stress responses, they do not necessarily reflect the subtle responses that we see in authentic scenarios. In recent years, researchers have been exploring the use of more authentic datasets. These scenarios usually involve gathering data from subjects involved in actual, or at least close to real-world, stress scenarios.

In an effort to study the use of ECG as an indicator of real-life stress conditions, [9] studied the correlations between non-linear HRV features and stress. They gathered ECG data from students on two occasions: while undergoing a university examination and after holidays. Using a variety of non-linear analysis measurements on the data, they created a Linear Discriminant Analysis (LDA) classifier. Analysis showed a significant reduction in HRV features during the stress sessions, and the generated LDA was able to perform with a 90% accuracy. Their work showcases the promise of HRV even when analysing naturalistic data, a similar goal to the current work. However, in Melillo's work the discrimination task was between two different experiences and environments (exam vs. holiday) and is therefore expected to be more unambiguous. In the current work, we are interested in stress analysis in a fixed working environment.

It has also been shown in [10] that stress may also show long-term effects on some HRV features. In the aforementioned study, subjects answered a Stress Response Inventory to measure the emotional, somatic, cognitive and behavioural responses of subjects to stress. Using K-means clustering analysis, they were able to divide the subjects into low and high stress groups. In this work, we are also interested in using clustering analysis for data separation, however for immediate to short-term stress states.

3. Methods

This study aims to design and build an automatic work stress monitoring and assessment system that tracks physiological signals from heart rate and psychological coping profiles in order to build a flexible model of stress.

3.1 Monitoring Software

A custom-built monitoring and annotation tool was used to track subjects' personal profiles and work activities. The monitoring software used was a modified version of *Sidekick* [6], a tool originally designed for tracking and analysing student learning behaviours. Modifications were made to switch the focus towards parameters related to mental stress. These changes include additional psychological profiles relating to stress and a different set of annotation labels. For this initial work, volunteers from among the students of Osaka University were used as research subjects.

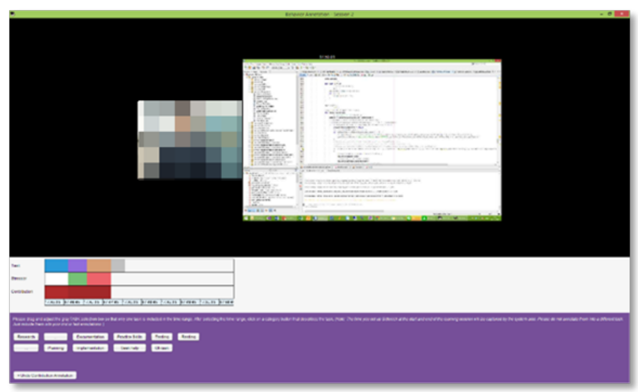

Figure 1: A screenshot of Sidekick's annotation module.

3.2 Procedures

Subjects are guided through experimental procedure through the various modules included in Sidekick. This allows experimentation and data gathering with minimal influence from the experimenter. The advantage of such an approach is two-fold. First, it minimizes the interaction and therefore the biases that can be relayed from experimenter to subject. And second, it makes the process easier to performed outside of the experimental environment and into a large-scale implementation. The following modules are supported by Sidekick: profile creation, (work) activity planning and observation, and self-reported annotation.

Profile Creation

Upon first arriving at the experiment room, subjects were instructed to create a personal account on Sidekick. Next, they are guided through a confidentially agreement and a some psychology questionnaires.

The first questionnaire is the COPE Inventory [2], a tool developed to assess coping responses in response to stressful situations. It determines a person's inclination towards exhibiting responses that are expected to be either functional or dysfunctional. Those with dysfunctional coping mechanisms are expected to be more prone to the negative effects of stress.

The next questionnaire is the Toronto Alexythimia Scale (TAS-20) [1], a tool designed to measure and diagnose Alexythimia. People with this condition generally have difficulty identifying their own emotions and instead minimize emotional experiences. Subjects with high enough scores may be excluded from the experiments. In general, the scores may also be used to measure subjective sensitivity to stressors and emotions. For the current work, these questionnaires only need to be filled out once. After completing the profile, subjects may then proceed to planning the work activity for the session.

Work Activity

The target of the next module is for the subject to plan a brief work activity. For this study, sessions were around 30 minutes to 1 hour long. To create a work plan, subjects must enter a general description of the current task as well as list down goals which must be achieved by the end of the session. Once this is completed, subjects are then asked to answer a a few questions about their current emotional state as well as provide details such as the importance and and required effort of the current task.

Annotation

Self-reported annotations are made immediately after the hour-long work session is completed. Figure 1 shows a screenshot of the Sidekick annotation module. Using webcam and desktop recordings, subjects are able to review and select time segments in the recorded video where they performed various work tasks. For each task, they also label the amount of stress they felt at the time, the primary stressor, and the importance of the tasks towards achieving the goal.

3.3 Physiological Signals

Participant heart rates were measured using the Imec wearable ECG sensor. Data from the sensor were aligned to the timestamp labels in the monitoring software to build the feature vectors. As noted in [9], features of heart rate are influenced by various environmental factors such as body position, activity level, verbalization and breathing. In order to minimize the effect of these factors, environmental setup and time-of-day conditions were kept similar throughout all sessions. Furthermore, a 15 minute adaptation period was allotted at the beginning of each session to allow subjects to adjust to the experimental conditions.

One of the most popular indicators of mental stress is heart rate variability (HRV). HRV has been found to be a reliable marker of the activity of the autonomic nervous system in response to stressors [9]. For each session the following HRV metrics were calculated: Average of NN intervals (AVNN), Standard deviation of NN intervals (SDNN), root-mean-squared differences between adjacent NN intervals (rMSSD), percentage of differences between adjacent NN intervals greater than 50ms (pNN50), spectral power measures of NN intervals of varying frequencies (ULF, VLF, LF, HF) and the ratio of low to high frequency power (LF/HF).

HRV analysis was performed over the HR recordings at the session level. RR interval time series was extracted using the PhysioNet library's [4] QRS detector (WQRS). The WQRS detector uses a length transform algorithm to detect nonlinearly scaled ECG curve length features. Based on previous literature[9], this algorithm is capable of attaining a NN/RR ratio of over 90%, indicating a high level of data reliability for "normal" heart beats. No additional cleaning was performed on the raw ECG data.

3.4 Machine Recognition of Stress

Standard supervised and unsupervised machine learning techniques were used to build the final stress models in this work.

Support Vector Machine

Support vector machines (SVM) are a popularly used machine learning technique that involves learning a linear separation between classes by building a hyperplane based "supports" by vectors from opposing classes found in the training data. In addition to this, it uses an kernel function to lift data into higher dimensions, enabling non-linear separation. It is also one of the most common machine learning algorithm used by similar works [11, 12, 14].

K-means Clustering

K-means clustering is another simple, but popular algorithm also used in a related work [10]. Unlike SVMs, it is an unsupervised machine learning technique that allows grouping of samples based on their relative distances from a set of centroids. The training of these centroids determines the class membership. Using cluster analysis we can observe the inherent relationships between the data even without the class labels.

4. Experiments

Data was gathered from 4 subjects, all males with ages ranging from 20-32. Each subject used Sidekick to perform a work activity that lasted around 30 minutes each and made annotations for the entire session. Based on their scores on the Alexythimia scale, none of the subjects needed to be excluded from the experiment.

The sessions were divided based on the annotated task segments. For each segment, a feature vector was built based on annotation data and HRV metrics. Specifically, the features used were segment length, contribution, and the HRV values discussed in Section 3.3. To test the impact of the subjective profiles on the models, two set of models were built one with only the base feature vectors, and another inclusive of stress coping profile results. For each set, SVM and K-means machine learners were trained and the models were evaluated using 10-fold cross validation. Additional data gathering and results analysis is currently ongoing.

5. Discussion

This paper presents a system for observing and analysing subjects engaged in authentic work-related activities. Psychological profiles were constructed using the COPE inventory and TAS-20, and physiological data was gathered through the Imec wearable ECG sensor. Preliminary data and self-reported annotations were gathered from the work activities of students from Osaka University. The work proposes that the use of stress models that include psychological profiles would lead to better generalization. A combination of extracted HRV features and psychological profiles from COPE were used to train a number of machine learned models. Additional data collection, analysis and testing is currently ongoing.

Based on initial comments from the subjects, while the initial answering of the questionnaires was long and tedious sometimes taking up to 15 minutes to complete, subsequent sessions became less troublesome and could be completed in a few minutes. More work is currently under way to reduce the number of questionnaire items while retaining the profiling ability of the tools. In addition, efforts are also being made to construct a Japanese translation of all the standard tools. Another interesting phenomenon that we have observed was that some subjects noted that using the system allowed them to be more aware of how they spent their time. This enabled them to make adjustments that lead to an increase in perceived task efficiency. This will be investigated in more detail in proceeding works.

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