SmartCoping
A Mobile Solution for Stress Recognition and Prevention

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Abstract: The paper describes the development of a mobile solution based on smartphones and sensors for the early recognition of stress. The solution is based on real-time capture and analysis of vital data such as heart rate variability as well as activity and contextual data such as location and time of day. Individual recognition patterns for stress are derived from combining vital and contextual data by using subjective stress assessments via mood maps as additional input during an initial learning phase. The reliability of stress alerts and therapeutic impact will be tested in a clinic specialised on the treatment of alcoholics since stress tends to cause craving and therefore trigger relapses.

1 INTRODUCTION

Stress is the body's normal response to a real or implied threat. In small doses, stress can help us perform under pressure, make us stay focused, energetic and alert. However, if stress symptoms persist, it starts causing major damage to our health, productivity, relationships and quality of life. Chronic stress can cause hypertension, suppress the immune system, increase the risk of heart attack and stroke, and make people more vulnerable to anxiety, addictive behaviour and depression (e.g. Legendre and Harris, 2006; Ornish, 1990). Excessive and prolonged stress may also cause burnout, which is a state of emotional, mental and physical exhaustion.

We cannot completely eliminate stress from our lives, but we can learn how to cope with it by controlling stress-inducing situations and physiological reactions. This, however, requires that we are aware of the fact that we are stressed at a particular moment, by certain events or by encounters with specific persons. The timely recognition of stress is therefore a major goal of the SmartCoping project.

The app being developed facilitates the continuous monitoring of a user's stress level and gives a warning when it exceeds a previously defined threshold. The user can then either choose the exit strategy by withdrawing from a stressful situation or apply relaxation techniques derived from muscle relaxation, meditation practice or mindfulness training. The effect of these exercises is visualised – and thus reinforced – by means of biofeedback.

The SmartCoping app addresses two scenarios:

1. *The Prevention of Chronic Stress:* The target group consists of individuals who are or feel threatened by stress or aficionados of the Quantified Self movement who are interested in measuring and documenting their vital as well as contextual data so as to increase their self-awareness and long-term health (Swan, 2012).
2. *Therapeutic and Rehabilitation Support for conditions caused by Stress:* Here the target group are in- or outpatients or patients who continue to need support after treatment in avoiding stress, e.g. patients after alcohol detoxification, burn-out patients, or patients suffering from depression. In this scenario the therapist or nurse may have access to the data if the patient agrees.

In the following section we briefly discuss the challenges we face in this endeavour as well as the innovative aspects of our project. Section 3 describes the mobile solution under development including its technological implementation. Finally, we outline the current state of the project and discuss how we will measure its impact.

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2 CHALLENGES AND INNOVATIVE ASPECTS

There is a plethora of health-related apps on the market including apps for coping with stress, such as the Stress Tracker from AboveStress Inc., one of the most downloaded apps which also offers progressive muscle relaxation and guided imagery exercises. Another well-known example is the iStress app from PsiApps Inc. which apart from stress warnings encourages the users to record their negative emotions and thoughts. Whereas some apps try to determine the individual stress level by asking a series of questions, the more innovative apps use the sensors integrated in many of today's smartphones as well as external sensors to recognise and display stress symptoms and monitor them over time. A very interesting approach was pursued by the Mobile Heart Health Project driven by Intel researchers. They used a wireless ECG to detect changes in stress levels as measured by heart rate variability (HRV) and to trigger mobile therapies such as breathing techniques (Morris and Guilak, 2009). So-called "mood maps" adapted from clinical scales were used for subjective assessment to correlate HRV measurements with self-perception. In the end, the HRV measurement was discontinued because of the challenges posed by the continuous capturing of sensor data in everyday life and the focus shifted to the use of mood maps.

Stress is also a topic in several large-scale projects funded by the EU, namely Interstress, Monarca, Optimi and Psyche (for an overview see Riva et al., 2011). These projects tend to have a mainly therapeutic focus and aim at developing personal health systems for people with mental problems or disorders where stress plays a role. Some of the projects capture contextual data such as physical activity and location in a continuous way – as is the case in SmartCoping. However, vital data such as ECG are captured at certain pre-defined intervals using stationary equipment, which makes stress alerts triggered by stressful situations – a major goal in the SmartCoping project – impossible.

For reliable stress alerts the display of stress symptoms (such as HRV and accelerated heart rate) alone does not suffice. For an app that warns its users against imminent stress, much more complex logic is required that goes well beyond the apps currently available on the market.

In short, SmartCoping will go beyond existing stress apps by the following innovative features:

Interpreting vital data in context: It has been shown (e.g. Clifford, 2007 or Ritter, 2009) that due to artefacts it is very difficult to interpret vital data gathered in real-life settings as opposed to laboratory settings. This also applies to HRV, even when one uses a chest strap, which yields more accurate measurements than a bracelet or smart watch. For this reason, we also take into account contextual information such as location, activity and the user's subjective stress experience.

Automatic user adaptation: A major challenge is posed by the fact that HRV stress measures vary greatly between individuals depending on age, health status and other factors. Therefore, each subject's baseline and stress threshold has to be established so the stress warnings can be adapted to each individual.

Subjective stress assessment: Studies have shown (e.g. Mandryk and Atkins, 2007) that stress as experienced by a subject largely coincides with normalised physiological measurements. This is why in the adaptation/learning phase the user is prompted to rate his or her own emotional state, so the system can continually calibrate its threshold values in accordance with the user's response.

Therapeutic effectiveness: Since the app is to be used for therapeutic purposes evidence for its efficacy is required. The user testing in the final phase of the project, which will be conducted in cooperation with a clinic, is expected to provide the proof of concept for our approach.

3 METHODOLOGICAL APPROACH AND ITS IMPLEMENTATION

In the following sub-sections we discuss the various concepts, parameters, and models that form the underpinning of SmartCoping.

3.1 Physiological Indicators for Stress

Heart rate variability (HRV) is considered a reliable indicator for stress (e.g. Delaney and Brodie, 2000). Increased stress reduces the fluctuation in beat-to-beat intervals, whereas decreased stress increases fluctuation.

For measuring HRV we require a wireless ECG sensor, which operates continuously and provides a high-quality ECG signal to capture the minute changes in beat-to-beat intervals measured in milliseconds. At present, these requirements are only fulfilled by chest straps. Whilst the wearing of a chest strap may be perfectly acceptable for fitness or training purposes, bracelets or smart watches would be much more convenient and unobtrusive for continuous measuring as needed for the SmartCoping app. Currently, certain new devices are in the pipeline that are more comfortable to wear than a chest strap, but still have an adequate degree of accuracy.

HRV is calculated based on the ECG signal from an ECG sensor and transmitted via Bluetooth 4.0. The sensor either transmits a signal for each heart beat or provides the time between two heart beats. Every minute, the app calculates the variations between two heart beats over a time-window of four minutes. We use different algorithms for calculating HRV, three time-based, one frequency-based:

- SDNN: standard deviation of RR intervals in the current time frame;
- RMSSD: root mean square difference of successive RR intervals in the time frame;
- PNN50: percentage of pairs of adjacent RR intervals differing by more than 50 ms in a time frame (Bilchick and Berger, 2006);
- LF and HF: low and high frequency spectral powers (Fagard et al. 1998);
- LF/HF: ratio between LF and HF, indicating the balance between the sympathic and parasympathic nervous system.

Figure 1: Current Visualisation of HRV values.

The HRV values obtained are aggregated to provide an overall measurement of the stress level on a scale from 0 to 10 (see Figure 1).

The current version of the app allows the inspection of the HRV values underlying the computed stress level. Figure 2 gives an example of how the HRV history is visualised, in this case for the metric PNN50. At the bottom of the figure, all the HRV metrics are listed. By selecting a metric the corresponding history curve is displayed. The user can also select individual “drops” that indicate the aggregate measurements computed at pre-defined intervals. They give information concerning the date when the data were captured as well as average (straight line), minimum and maximum values (dotted lines) along the timeline. In Figure 2 the green drop has been selected. By pinching in or out, the user can change the granularity of time: single values, hourly, daily, weekly, monthly and yearly. Finally, the arrows in the upper left-hand and right-hand corner allow scrolling to the left and right along the time line, respectively.

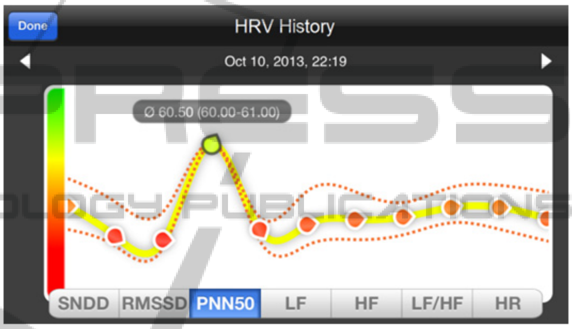

Figure 2: HRV History.

The curve depicted in Figure 2 illustrates the effect of a user’s sports activity on HRV. During the time covered by the red drops that precede the green one, the user had finished his work and had some physical exercise. Afterwards, relaxation set in so that the HRV went up (the green drop). When returning to work, the HRV dropped again.

3.2 Interpretation of Physiological Data

Even with more sophisticated and accurate sensors, measuring HRV will be affected by artefacts caused by body movements. Therefore on the one hand we have to integrate artefact detection and compensation into the app, on the other hand we cannot just rely on HRV, but also include contextual information. Together, vital and contextual data will serve as the basis for recognising stress patterns that are more reliable. At the moment, contextual data comprise information about:

- *Physical Activity* measured by an accelerometer integrated in the smartphone (or in the ECG sensor),
- *Location*, which is measured by the GPS receiver in people’s phones. The GPS coordinates, howev-

er, are only useful when associated with locations relevant to the individual users such as their house, flat or work place. By assigning particular labels to the relevant coordinates, these can be used in the history view of stress warnings and help users make sense of the data, e.g. to find out where stress is particularly high.
- *Change of Location*: Moving from one location to another may be an important indicator for stress and will therefore be included in the recognition of stress patterns.
- *Time of Day*: Exposure or experience of stress may vary substantially during the course of day, which is why it is also included as a variable in the recognition patterns for stress.

There are other contextual data that might be relevant such as people's communication patterns, i.e. incoming and outgoing calls, e-mails or text messages as logged on their smartphones or even a semantic analysis of their content. However, these cannot be taken into account for technical reasons, e.g. they cannot be accessed under iOS, and they would raise data protection and privacy issues.

3.3 Determining Individual Recognition Patterns for Stress

As mentioned before, stress measures vary greatly across individuals, which has been shown time and again both in lab and real-life settings. According to Morris and Guilak (2009), for instance, colleagues of similar age, physical fitness, profession, and personality style differed dramatically in their HRV baseline and threshold values. Therefore the SmartCoping app includes an adaptive component to identify the personal baseline and threshold values. Combined with contextual information a learning component determines user-specific stress patterns (see Figure 3). To this end, the mobile phone app queries the user during the learning phase at regular intervals about his or her personal experience of stress. Using this user feedback the system learns recognition patterns for stress by employing a supervised learning approach.

A major challenge is posed by the very heterogeneous nature of the input data which include numeric values for HRV and the number of steps, time values for the time of day as well as nominal values for both location and change of location. Besides, we are dealing with time series data where the time intervals to be examined are not defined a priori but have to be determined by the learning algorithm. For this purpose, we are using a special kind of neural network (BINN) developed by our project partner ai-one (Reimer at al., 2011), which has already been successfully applied to learning recognition patterns on time series data, e.g. for forecasting price developments on the stock exchange. The BINN is quite different to existing neural nets:
- It is biologically inspired, i.e. consists of neurons with dendrites to which the synapses from other neurons are connected, and an axon which ends in synapses on other neurons.
- Stimulation is via spikes, i.e. binary signals, which either fire or do not.
- Connections between neurons get strengthened when being traversed.
- Depending on the existence or absence of stimuli neurons are created or destroyed and connections reinforced or inhibited.
- In particular, there is no need for a predefined topology or a similarity function.

The learning process happens primarily during the initial phase of app usage and is gradually phased out once the patterns cease to show any major changes despite additional input. User response regarding the subjective assessment of stress level is prompted at previously defined intervals and whenever the app assumes the occurrence of stress based on the patterns learned up to that point. Besides, users are free to provide feedback any time, e.g. when they feel particularly stressed or relaxed.

3.4 Biofeedback for Reducing Stress

Apart from the continuous recording of stress levels and generating stress warnings, the SmartCoping solution will also comprise a biofeedback component to support users in emotional regulation aimed at reducing stress. This component will guide the user through relaxation exercises such as breathing exercises, and at the same time visualise the stress level based on HRV thus showing the immediate impact of an exercise. The reinforcing effect of HRV biofeedback has been well demonstrated in various studies (e.g. Lehrer, 2013, or Sakakibara et al., 2013).

3.5 Architecture

The SmartCoping system consists of sensors, the app on the mobile phone and the backend (cp. Figure 3). The app calculates the HRV based on the ECG signals from the sensor and transmits the HRV measures, the aggregated stress levels as well as all sensor and contextual data to the backend.
The data are stored at the backend and their history can be displayed either via a web browser (and

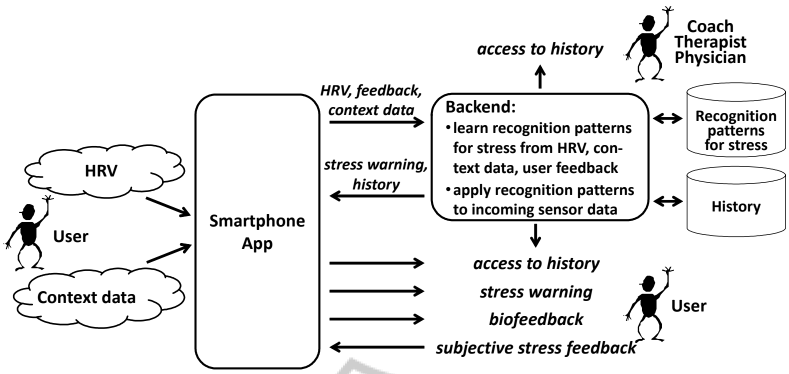

Figure 3: Data Flows and Architecture of SmartCoping.

viewed by a therapist or coach if the user agrees) or via the display on the mobile phone. The learning algorithm for recognising individual stress patterns runs in the backend. The stress patterns are defined as a (biologically inspired) neural network. The neural network prompts the mobile phone to generate a stress alert if a stress pattern is recognised in the input data. A simplified "light" version of the neural network will be installed in the smartphone app to allow a simpler, though less accurate stress recognition process when there is no connection to the backend.

4 PRELIMINARY RESULTS AND NEXT STEPS

This paper discusses work in progress. Currently, the learning algorithm is being implemented and different versions of the mood map are being tested with potential users.

Originally we considered using a similar mood map as in the Mobile Heart Health project (Morris and Guilak, 2009) that integrates the two dimensions of valence (emotion) and arousal (energy) in one matrix. However, a series of user tests showed that some users found the matrix too complex and therefore had difficulty in finding the appropriate point that corresponded to their mood.

As a result, we decided to split the two dimensions into two separate columns "Emotion" and "Energy", which enables the user to focus on one specific dimension at a time (see Figure 4).

Additionally, we might pre-define the characteristics of certain activities, such as being absorbed in non-physical work, strenuous physical work, sports or non-active leisure time (e.g. reading, watching movies) and present them as a menu to the user. Those activities combined with the feedback about the mood will allow the learning algorithm in the backend to obtain a more adequate as well as a more comprehensive assessment of the user's stress levels and thus enhance the recognition of stress patterns.

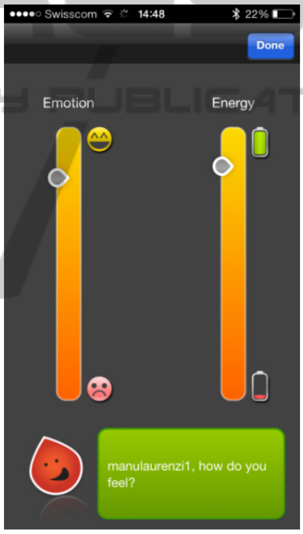

Figure 4: Mood Map.

Furthermore, we might prompt users for their sensations (e.g. visual, auditory, olfactory, affective) as there is growing evidence that sensory impressions can affect physiological stress reactions (Hasson et al., 2013; Angelucci et al., 2013). To this end, we might either offer a series of options from which users can choose the most appropriate one or let users define sensations relevant to them. Besides, as a result of the feedback from some users whose HRV measures have shown fluctuations for no obvious reason, we will look closely at the question of time frames. Possibly, we will have to define different time frames for different HRV metrics to achieve a more reliable overall indication of stress.

For the time being, the app is tested only by healthy individuals. Once we have integrated the feedback of the test users and solved the various problems, the app will be validated in a field test with high-risk subjects, namely detoxified alcoholics. In stressful situations, they are overwhelmed by the urge to drink (craving) as a neurobiologically triggered stress reaction that is beyond their conscious control (Sinha, 2013).

The impact will be measured in terms of the perceived stress of the test persons. This will be measured with the German version of the Perceived Stress Questionnaire (PSQ), which has been shown to be a valid and economical tool for stress research (Fliege et al., 2005). Usability of the app and user satisfaction will also be measured, especially patients' judgements of the every-day practicability and convenience of the system and its perceived effectiveness with regard to the prevention of craving and thus relapse (Clarke et al., 2010).

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