Stess@work: From Measuring Stress to its Understanding, Prediction and Handling with Personalized Coaching

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ABSTRACT

The problem of job stress is generally recognized as one of the major factors leading to a spectrum of health problems. People with certain professions, like intensive care specialists or call-center operators, and people in certain phases of their lives, like working parents with young children, are at increased risk of getting overstressed. For instance, one third of the intensive care specialists in the Netherlands are reported to have (had) a burn-out. Stress management should start far before the stress starts causing illnesses. The current state of sensor technology allows to develop systems measuring physical symptoms reflecting the stress level. We propose to use data mining and predictive modeling for gaining insight in the stress effects of the events at work and for enabling better stress management by providing timely and personalized coaching. In this paper we present a general framework allowing to achieve this goal and discuss the lessons learnt from the conducted case study.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; J.3 [**Life And Medical Sciences**]: Health

General Terms

Measurement, Experimentation, Design

1. INTRODUCTION

Stress at work has become a serious problem affecting many people of different professions, life situations, and age groups. The workplace has changed dramatically due to globalization of the economy, use of new information and communications technologies, growing diversity in the workplace, and increased mental workload. In the 2000 European Working Conditions Survey (EWCS) [8], work-related stress was found to be the second most common work-related

health problem across the EU. 62% of Americans say work has a significant impact on stress levels. 54% of employees are concerned about health problems caused by stress. One in four employees has taken a mental health day off from work to cope with stress (APA Survey 2004).

Stress can contribute to illness directly, through its physiological effects, or indirectly, through maladaptive health behaviors (for example, smoking, poor eating habits or lack of sleep) [4]. It is important to motivate people to adjust their behavior and life style and to use appropriate stress coping strategies to achieve a better stress balance far before increased level of stress results in serious health problems.

Yet, the avoidance of stress in the everyday working environment is impossible. Moreover, stress might not even be observed as problematic by the persons themselves, for high levels of stress are often perceived by people as a norm, a signal that they do their best to achieve their goals. The first necessary condition for early signalling and treatment of stress problems is introducing inexpensive, unobtrusive, and widely available technologies for creating awareness of the objective level of stress and understanding of its causes.

Due to modern sensor technologies, objective measuring of the stress level becomes possible. Such symptoms as heart rate, galvanic skin response (GSR) and facial expressions are known to be highly correlated with the level of stress a person experiences. Moreover, due to extensive use of social media and electronic agendas, it becomes possible to develop methods and tools for the analysis of correlations between the increases and decreases in the stress level with the characteristics of the events of daily lives (what, where, when, with whom, etc.).

In this paper, we propose a framework that allows for (1) measuring physiological reactions to stress, (2) suggesting possible interpretations of its causes based on the correlations between the changes in the stress level and the events that took place, and (3) giving effective advices for preventing the escalation of the stress level of a person to unhealthy proportions.

We have conducted a pilot case study aimed at the evaluation of the feasibility of the proposed approach and at the identification of likely challenges we need to address to make it work in practice.

The rest of this paper is organized as follows. We describe our general approach, focusing on the issue of stress level measuring, identification of causes of stress and stress coaching, in Section 2. In Section 3, we report on our pilot case study, emphasizing the lessons learnt from the explo-

ration of real data capturing stress at work. Finally, in Section 4, we give conclusions and discuss directions for further work.

2. STRESS@WORK APPROACH

There are a number of factors that are likely to cause stress, called stressors. We provide a concise overview and categorization of stressors at work before presenting our general approach for identifying them and coping with stress.

2.1 Stressors at work

Stress and health risks at workplace can be categorized as content- and social or organizational context-related. Those that are intrinsic to the job include long work hours, work overload, time pressure, difficult, demanding or complex tasks, lack of breaks, lack of variety, and poor physical work conditions (limited space, inconvenient temperature, limited or inappropriate lighting conditions)[7].

Yet other causes of stress at work are conflicts, limitations, and high responsibility. Also underpromotion, lack of training and job insecurity are considered stressful. Continuing, managers who are critical, demanding or unsupportive create stress as well. On the other hand, job development opportunities, positive social dimension of work and good team working are all important buffers against stress.

From the organizational point of view, a culture of unpaid overtime causes stress. Organizational changes, especially when consultation has been inadequate, are a huge source of stress. Such changes include mergers, relocations, restructuring or "downsizing", individual contracts, and redundancies within the organization [7].

We aim at the automation of the identification of the stress causes of an employee in question, as well as the identification of the common causes of stress for employees within an organisation. Some of the causes of stress can only be discovered by interviewing the person in question (e.g. underpromotion). We only aim at the causes of stress that can be discovered by unobtrusive monitoring of the employee's behaviour, and therefore we focus on the causes of stress that can be discovered from data sets including physiological measurements allowing to estimate the curve of stress level over a period of time and information about the events happened within this period of time.

We present a high-level illustration of the proposed framework in Figure 1. Particularly, it highlights three major steps of data fusion and mapping, stress detection and prediction with already available models and coaching in the operational i.e. online settings. In the offline settings the models for stress detection and prediction are discovered from the historical data using state-of-the-art data mining techniques [9] and then verified by the domain expects. In the rest of this section we consider the most essential parts in more detail and provide illustrative examples.

2.2 Measuring stress level

The physiological measurements providing the bio-signals reflecting the level of stress that we currently use are GSR and accelerometer data about movements. This data is gathered using a prototype device (similar to [12]).

Following the conclusions of [5], we assume that increases in the GSR correspond to emotional arousal. Our objective is to detect the cases and the types of such arousals reflected in the GSR changes. Then we discriminate the
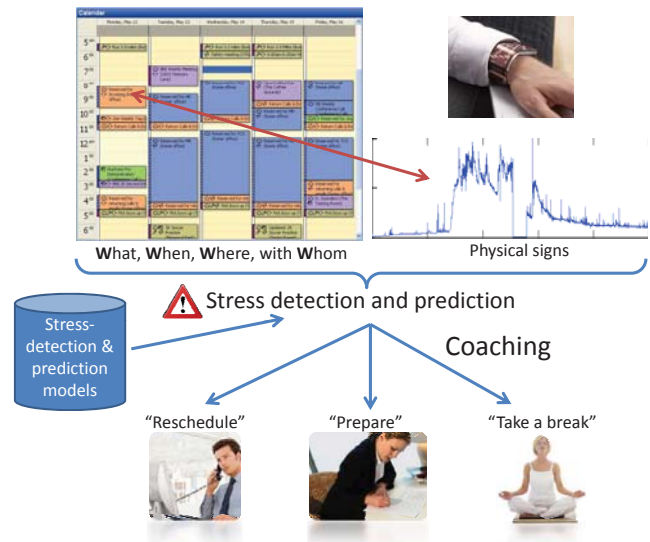
Figure 1: *Three major processes of the stress@work in the operational settings: i) mapping MS Outlook records to sensor data, ii) detecting or predicting stress based on already discovered patterns from the historic data and background knowledge of stress, iii) personalized coaching*

changes in the GSR based on the positive and negative labeling of stress.

Emotional arousal can be seen as a deviation from the "normal" relaxed state, so the occurrence of arousal is a form of concept shift or drift [11]. "Stress-as-concept-shift" occurs when a sudden startle effect of short duration is measured. However, in some cases the person feels stress long before the event in anticipation of it. In this case a slow drift could be present prior to the event. That also means that the time at which this change occurs varies. We also need to take into account that the response of a person can vary over time due to unobserved circumstances. From the algorithmic perspective we can use state-of-the-art approaches for detecting drift in time-series signal like ADWIN [2]. For the discussion of this problem formulation and preliminary experimental results see [1]. Potentially, we can also categorize the observed stress following shape-based time-series classification paradigm [13].

2.3 Identifying causes of stress

We currently use the data of employee's MS Outlook calendar in order to acquire information about the events that took place during the observation period. We take care of the privacy issues by anonymising all the calendar information and encoding it with a mapping from words used in the calendar into codes, with only codes being visible to the system support group (or to our project members, in our pilot case study). Since the same words are replaced with the same codes, we can use off-the-shelf data mining techniques in order to find correlations between the changes in GSR and the characteristics of the events that took place.

The most important characteristics of the events recorded in the calendar are *what* event took place (e.g. a project meeting, with the project title being included into MS Out-
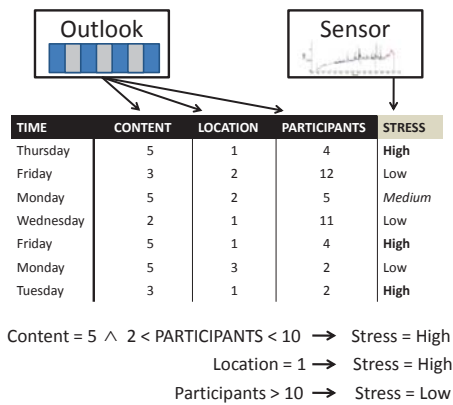
Figure 2: *Example of finding individual stress patterns with class association rules.*

Figure 3: *A possible stress intervention algorithm.*

Figure 4: *Example of possible coaching by providing visual overlay in MS Outlook.*

look record, and therefore it can be compared to other events related to this project), *when* it took place (e.g. at the end of the working day), *whom* the employee met at the event (which thus gives a way to signal problems in personal relations), *who* initiated the meeting (thus allowing to see the autonomy level of the employee) (see Figure 1).

Consider a hypothetical example presented in Figure 2. The observations suggest that there is a correlation between the stress level and the number of participants of the meeting (with passive behaviour and daydreaming when being in large groups of people as a possible reason), as well as a correlation of the stress level with the meeting location (that could be a room for meetings with clients). Automated discovery of such correlations is known as associative classification [6] in data mining.

Note that the information from the calendar allows us to identify possible indications to the causes of stress that are specific for an employee, like workload (overload and underload), pace, variety, autonomy, hours of work, interpersonal issues and communication patterns, and the causes of stress that are common to multiple employees within an organisation, like a stressful project (or a difficult class for teachers), bad scheduling practices, general work overload, etc.

We discover individual and organisational stress reaction patterns using standard data mining techniques [9]. Since physiological reactions to stress are highly individual, we ask the employees to tag events in their calendar reflecting their personal perception of the event (e.g. boring, or tense). This tagging is used for calibrating GSR and accelerometer data and for further interpretation of stress reaction patterns and understanding of the main causes of stress.

2.4 Stress coaching

Making an employee aware of his/her stress patterns and possible interpretations of stressors can already be of great help, but we go beyond that and aim at providing coaching services based on the discovered patterns and continuous information stream from both the sensor device and the calendar. Combining patterns with the information about forthcoming events and the current stress level of the employees, we can make a predictive model of stress level for the coming period of time and generate recommendations for adjustments that can prevent from escalating stress. Sim-
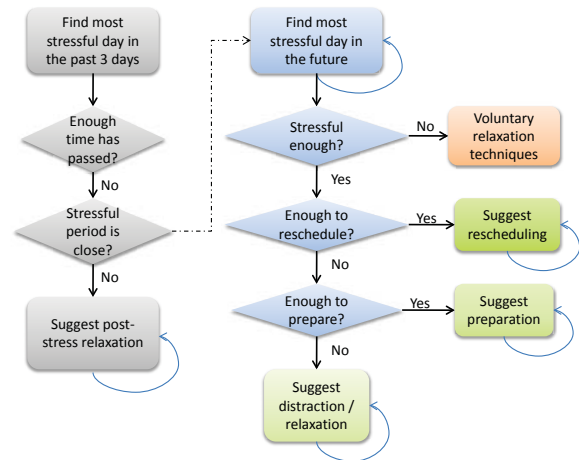
ple examples of such recommendations are rescheduling of certain activities to balance workload (see Figure 4) or to avoid combining too many stressful events one after another, scheduling (and executing) a timely preparation activity well before a stressful event, planning a relaxation event (which can be taking a coffee break with a nice colleague, a yoga session, going out in the evening, etc.). Figure 3 shows a possible intervention algorithm aimed at achieving a better stress/relaxation balance.
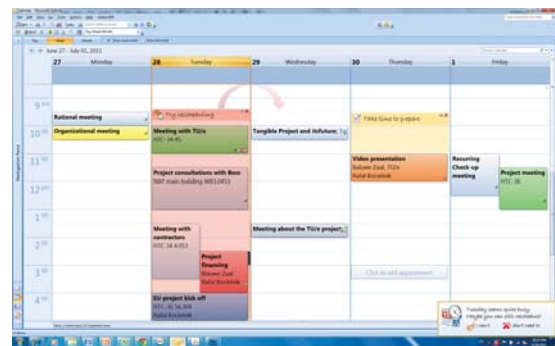
Note that we can detect not only negative reactions to stressors but also positive reactions to relaxation events. People are sometimes mistaken in their judgements about the types of activities that help them to relax. Activities that they like can still be stressful ones and they might be better be avoided in the extremely stressful periods. Our recommendations are therefore meant to be personalised based on the individual preferences and reactions to possible relaxation options. We ask the user about a feedback to the recommendations generated by our system in order to further tune the recommendations to individual preferences.

3. PILOT CASE STUDY

In this section we discuss the recently conducted pilot case study, in particular the highlights of our exploration of the collected data, and the main lessons learnt from it.
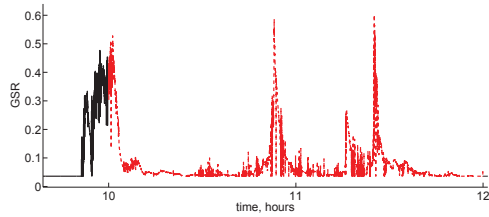
Figure 5: *A short-term stressful event.*

3.1 Data collection

The data was collected over the period of seven weeks from five employees wearing a prototype device for measurement of galvanic skin response (GSR) and movement (accelerometers) during working hours.

At the end of the working day, participants were downloading the data from the device to their computers and tagged their daily activities in their schedule in MS Outlook with one of the following five tags: *exciting* – for events that were very positive, *nice* – for events that were generally positive, *neutral* – for events that were generally not stressful, *annoying* – for events that were a somewhat stressful, and *tense* – for events that were very stressful. After tagging the events, the participants were asked to answer three questions that were presented on a scale from very good to very bad:"*How did you sleep last night?*", "*Did you have a stressful day?*", and "*How was your inner balance today?*" and to provide any additional information in the free-form text about any special circumstances or events that could have influenced them, or physical measurements, or individual stress coping techniques (e.g. jogging or careful planning of daily activities).

During the seven weeks period of the data collection the participants were provided neither with any real-time stress related feedback nor with an overview of the collected GSR measurements in order to prevent possible bias. The study as such was observational, i.e. no stressful events or interventions had been preplanned; the participating employees were acting as during regular working weeks.

3.2 Data exploration

We performed the visual exploration of the collected data, aligning raw GSR sensor signal with the employee calendar data. One of the most straightforward analysis that we performed and the only one that we report here (due to the space restriction) is relating GSR data with the provided labels of stress (or no stress).

The following three figures illustrate examples of annotated GSR signals. Stressful events are marked as red lines, neutral events as blue, and the black lines indicate regions where no event information was provided.

One of the easily recognizable patterns is the short-term response to a sudden cause of stress (see Figure 5). This pattern is a single peak that has a relatively short time span.

An important thing to know is how long a stressful event will have an effect on the person, since the body consumes more of its resources in such a state of arousal. In Figure 6, the GSR values do not go down to the original level after the stressful event has ended. This might be an indication that the relaxation after the stressful event does not happen.
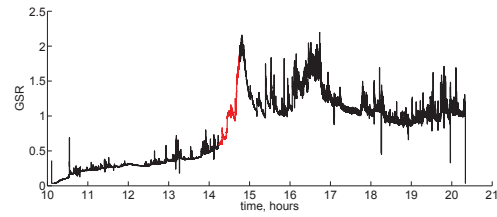

Figure 6: *A longer-tem stressful event not followed by an immediate relaxation phase.*
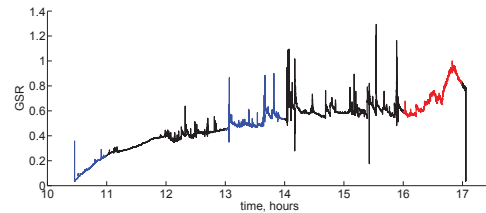

Figure 7: *The measured GSR increases before the stressful event takes place.*

Since the events are pre-scheduled meetings, it is possible that the stress level starts growing from the moment the person knows of some meeting. In Figure 7, the stressful event at the end of the day might have already been anticipated at the beginning of the day. From these instances we can see that there are indeed different types of change in response.

The example in Figure 8 illustrates that our stress level detection solutions should be context-aware, i.e. be sensitive to other relevant information describing current activity of the person and the environment (s)he is currently in. As the figure suggests, a physical activity causes sweating that may result in a false stress detection.

3.3 Main lessons learnt

The results of this pilot case study has confirmed some of our expectations about the challenges related to the analysis of GSR data. In particular, the baseline level and variance of the signal differ not only from one person to another but also e.g. from one day to another for the same person. There are many reasons for that, including e.g. the tightness and the exact placement of the device on the wrist, and physical activities (can be traced analyzing meta-data, e.g. labels like "meeting", and accelerometer's data) among others. This fact brings additional challenges into the task of finding common stress related patterns and the necessity of
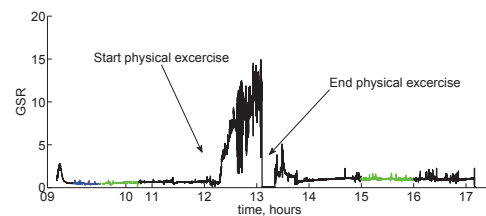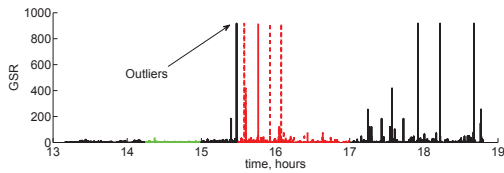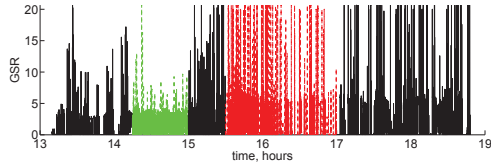

Figure 8: *The effect of the physical exercise on GSR.*

Figure 9: *Example of noisy signal due to the bad contact of sensor with the skin.*

Figure 10: *Example of noisy signal due to the exceeding volume of sweat near the sensor.*

continuous fine-tuning of the the models to an individual, current activities and, possibly, an environment.

There are different kinds of noise in GSR signal. Some of them are easy to filter out (single point outliers, see Figure 9) or to decide that the signal cannot be trusted during particular period (cases caused e.g. by poor contact between the sensor and the skin, or by too much sweating, see Figure 10). However, there are many less straightforward cases requiring algorithmic solutions to be developed.

We could see at least three distinct patterns of stress: bursts of stress, rapidly gained but long-lasting stress, and incremental stress. This calls for developing algorithmic approaches for detecting, categorizing and predicting different kinds of stress pattern occurrences.

4. CONCLUSION AND OUTLOOK

Stress at work is common for many professions. While some stress is a normal part of work, excessive stress or high levels of stress over prolonged periods of time can interfere with employee's productivity and have serious implications for the physical and emotional health of the person. As a worker, being aware of your own stress levels is already an important step towards the prevention of diseases and increase of the productivity. Our approach can make people more aware of the evolution and causes of their stress by relating stress patterns to their daily activities. In this paper we presented some of the lessons learnt from the case study aimed at the identification of the challenges we should anticipate in the development of the stress@work coaching services.

Our further research includes conducting larger scale experiments targeting specific professions with an increased exposure to stress, particularly school teachers and health carers working with elderly people. There we aim not only at the discovery of individual stress patterns, but also at the analysis of organization-wide patterns. An interesting problem is in helping an employee to relate the occurrence and volume of stress (s)he has with the productivity that can lead to the identification of personal "positive" and "negative" stress patterns. Our initial exploration of this problem shows that stress detection task is difficult on its own [1] and

further classification of stress patterns is an interesting and challenging task. We think that the use of additional information based on emotion recognition from the analysis of facial expressions, speech, these two modalities together [3] and personal correspondence [10] can facilitate more accurate classification of stress patterns first in research and later in real operational settings.

5. ACKNOWLEDGMENTS

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