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**Smart Coping with Stress:
Biofeedback via Smart Phone for Stress Reduction and
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Abstract

The paper presents the design plan for a mobile solution aimed at stress reduction. The solution will be developed by a team of medics, psychotherapists, HCI experts and knowledge engineers and will provide continuous data sensing and feedback about personal stress levels. At the same time contextual and activity information will be captured. Stress management is particularly important for high-risk populations such as former alcoholics to reduce the risk of relapse; they will therefore test and validate the solution. By combining and correlating psycho-physiological data with data on activities (e.g. walking or social interactions) and environment/location (e.g. ambient light) it is expected that sources of stress can be recognised which in turn will allow individuals to either avoid stress-inducing factors or develop appropriate coping strategies. To make sense of the data captured, it is proposed to use intelligent algorithms to recognise patterns in the data streams and semantic technologies to interpret the text messages of users. People with other stress-related health problems such as burn-out, smoking, depression or sleeping problems will also benefit from our research.

Keywords: stress management, relapse prevention, affective computing, ambulatory monitoring, mobile health, intelligent data analysis, semantic data analysis

1 Introduction

Stress is a widespread phenomenon in today's world which is full of deadlines, hassles, and demands in the workplace. It affects people from all walks of life. In small doses, it 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 raise blood pressure, suppress the immune system, increase the risk of heart attack and stroke, increase obesity and make people more vulnerable to anxiety 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 and how to control it. The simple realisation that one is in control of one's life is the foundation of stress management. It starts with identifying the sources of stress in one's life by looking closely at one's habits, attitude and excuses, looking at how one currently copes with stress (e.g. by drinking too much or smoking), and learning new coping strategies¹.

There are basically four ways of dealing with stressful situations:

1. Avoiding unnecessary stress, e.g. learning how to say "no";
2. Altering the situation, e.g. by expressing one's feelings instead of bottling them up;
3. Adapting to stressful situations, e.g. by changing one's attitude or reframing problems;
4. Accepting things one cannot change, e.g. not trying to control the uncontrollable.

None of these options works for everyone or in every situation since individuals respond very differently to stress and will adopt different strategies. For example, some may learn techniques (e.g. yoga, meditation, autogenic or mindfulness training) that help them relax and recharge. If practiced regularly, they will not only reduce stress but build up physical and emotional resilience.

Health professionals (see e.g. Plant 2007, Stull, Snyder and Denmark-Wahnefried 2007) agree that unless people accept responsibility for the role they play in creating or maintaining stress, their stress level will remain outside their control. Among other things, they recommend starting a stress journal to help them identify the regular

¹ The following recommendations are based on a web pages dedicated to stress management, e.g. from the Mayo Clinic (<http://www.mayoclinic.com/health/stress-management/MY00435>), the University of Maryland (<http://www.health.umd.edu/healthpromotion/stressandwellness>) or Smith, Jaffe-Gill, Segal on <http://www.helpguide.org>.

stressors in their lives. Keeping a daily log about what causes stress, how they feel, both physically and emotionally, how they act in response, should help them recognise patterns and common themes.

However, we know that people often (feel they) lack the time, will power and/or persistence to do so which is why we intend to use (semi-) automatic methods for recording physical signals, emotions, situations and events. We plan to develop a mobile solution which provides continuous data sensing and feedback about personal stress levels and which captures contextual and activity information. Biosensors will capture vital signals such as heart rate and skin conductance and transmit them wirelessly to smart phones (or other mobile devices) where they are visualised to reflect a person's psycho-physiological state.

To test the hypothesis that biofeedback on stress levels can assist alcoholics in coping with craving in real-life settings, health professionals, psychotherapists, HCI experts and knowledge engineers will closely work together. Test persons and control groups will be recruited after an alcohol abstinence program (randomized study design) and assessed with respect to the outcome parameters stress regulation, craving and abstinence at regular intervals.

2 Design Approach

The approach to the design and development of the mobile solution is based on the design analysis conducted by Simons and Hampe (2010), which they consider an example of design research rather than design science. Whereas the latter focuses on generating knowledge on design, design research, and consequently design analysis, is aimed at generating knowledge for solving particular problems. In their paper they explore what contribution electronic and/or mobile (e/m) health can make to postponing or reversing age-related diseases such as cardiovascular diseases, diabetes and even dementia. Rather than designing a specific solution, however, they concentrate on design cycle phases 1 and 2 – ‘first hunch’ and ‘assumptions and requirements’ – (Verschuren & Hartog, 2005) to examine

- which types of interventions are more or less effective in generating health improvements,
- which contents and formats are most promising, and
- what e/mHealth solutions could contribute.

To answer these questions, they rely on system and information quality concepts (DeLone & McLean, 2003; Lee et al., 2002), because these are widely discussed in information systems literature and can easily be transferred to the medical context, especially when studying e/mHealth applications.

As far as effectiveness of interventions is concerned they differentiate them in terms of ambition level (moderate vs. extensive changes), broadness (using many health factors simultaneously as opposed to only one) and primary vs. secondary interventions. When it comes to contents and formats, they consider smoking, food, physical exercise, stress management and social support as suitable targets for interventions.

Overall, they conclude

- that programs should aim for extensive interventions because they tend to produce fast results,
- that they should be broad rather than narrow because there might be positive interaction effects between different factors (e.g. diet, physical exercise and stress),
- that secondary interventions aiming at prevention of reversal hold particular promise, especially if they are supported by specialists and if they can capitalize on people's motivation to improve their health and avoid relapse.

With regard to system quality aspects such as flexibility, accessibility, integration or interoperability across organisations, efficiency and ease of use play a role. With regard to information quality we normally distinguish between intrinsic quality like accuracy and objectivity and contextual quality like relevance, timeliness and completeness as well as representational quality like conciseness and ease of operation (see e.g. Chaffey and Wood, 2005; Lee et al., 2002).

Simons and Hampe stress that many new mobile applications are particularly promising for raising health information quality because they can easily be incorporated into everyday activities, improve timeliness and relevance, allow accurate measurements of activities, and enhance accessibility.

In the following sections, we first outline the application scenario which will be used for developing and testing the proposed solution. In section 3 we describe in more detail the design of the mobile application, especially the sensor design and the physiological measures we intend to capture. Subsequently (section 4), we discuss the challenges such as making sense of the vast amounts of data or the need for continuous power supply, but also ensuring the privacy and security of personal, often highly sensitive, data. In section 5, briefly outline the methodology and implementation plan, before assessing the potential of health improvement of our mobile in terms of system and information quality in section 6. We also look at the extent to which our proposed solution can be integrated into existing health care practices and deliver (self-) management by and across stakeholders, which is a good indicator of its overall effectiveness. We conclude the paper by giving an outlook and work to be done.

3 Design of a Mobile Solution for Stress Reduction

3.1 Application Scenario

As said before, long-term exposure to stress can lead to serious health problems. Chronic stress disrupts nearly every system in your body. It can speed up the aging process and even rewire the brain, leaving people more vulnerable to anxiety and depression. Although stress reduction is therefore desirable in general, it is a must in certain high-risk populations such as alcohol-dependent subjects where stress can severely jeopardise the chances of ever “kicking the habit”. After having undergone treatment, subjects have to be monitored closely by health professionals. Besides, they tend to be highly motivated which is a prerequisite for participating in the extensive testing required for developing our prototype for stress management.

Stress not only leads people to consume alcohol, but acute or chronic alcohol intake will activate the stress system via the hypothalamic-pituitary-adrenal (HPA) axis (Lowery et al., 2010; Ciccocioppo et al., 2009; Barr et al., 2009; Clarke et al., 2009) and produce stress-related symptoms like palpitation, increased blood pressure, anxiety, depression, sleep disorders, or a craving for alcohol or other substances. Activation of the HPA axis increases the risk of relapse when people stop drinking after a treatment program (Clarke et al., 2010). In stressful situations, they are overwhelmed by the urge to drink (craving) as a neurobiologically triggered stress reaction which is beyond their conscious control. Reducing stress symptoms by an early warning system can therefore help disrupt stress-induced cravings and their associated consequences.

3.2 Sensor Design on Mobile Devices

Because of their near-omnipresence, mobile phones appear to be the best choice for such an early warning system that is within the reach of most people and highly accessible both in terms of affordability and availability. Modern smartphones have also become a platform for a wide range of portable health applications, e.g. monitoring blood glucose or heart rate, tracking calorie or alcohol intake or monitoring one’s exercise regime via accelerometers.

This is possible because mobiles are increasingly equipped with sensors, thus turning them into miniature smart systems measuring everything from users’ vital signs to how fast they run or how well they sleep to where they are (location) or the ambient light of their environment. In response to these new opportunities, a market for self-tracking devices and tools for better knowing and improving one’s mind and body has been emerging in recent years. These include wireless accelerometers that can track a user’s physical activity, e.g. Fitbit or DirectLife, or alarm clocks with headbands such as the Zeo Personal Sleep Coach to measure people’s brainwave activity at night and chart it on a private information space or on the Web.

Self-monitoring provides basic data for understanding and discovering how a person responds to internal and external stimuli such as fear, anxiety, joy on the one hand, ambient light, social interactions, temperature, physical environment etc. on the other.

Furthermore, the ongoing research in actor-/sensor technologies as well as the advances in body sensor networks (BSN) and their connectivity to the internet is enriching the field of medical monitoring and control. A body sensor network is a network of small sensor devices (biosensors) that capture physiological parameters of an individual and allow continuous monitoring. For example, using vibration sensors, best known as accelerometers, it is possible to read heartbeat rates and a person's movement. They provide biofeedback services by capturing the data, communicating with a base station or a special device known as sink node, which acts as an aggregation node that collects, stores and pre-processes the data captured by each sensor in a given BSN (Pereira, Caldeira & Rodrigues, 2010).

However, raw sensor data is not enough to achieve biofeedback. One of the challenges body sensor networks present is the processing of raw biosensor data, in order to achieve proper medical visualization of monitored parameters. Mobile devices, in particular smartphones, can become the centre of a BSN platform to provide the graphical user interface (GUI) to display the collected human parameters. These powerful devices have become small processing units that provide developers with tools capable to receive, analyse and present data from any BSN.

3.3 Physiological Parameters

For our scenario, we consider electrodermal activity (EDA) and heart rate (or ECG) as the most promising biofeedback markers since both are related to activation. Electrocardiograms (ECG) show the electrical activity of the heart during the various phases of heart beats. In the case of human-computer interaction ECGs usually serve as the basis for calculating other parameters such as heart rate variability, which is often analyzed in the frequency domain using spectral analysis techniques.

The resulting power spectrum is divided into different frequency bands: very low frequency (VLF, 0.0033Hz - 0.04Hz), low frequency (LF, 0.04Hz – 0.15Hz), and high frequency (HF, 0.15Hz - 0.4Hz). HF power spectrum is related to parasympathetic tone and variations due to spontaneous respiration, LF power spectrum indicates parasympathetic as well as sympathetic tone, whilst the very low frequency power spectrum, especially in shorter recordings, is considered an indicator for anxiety or negative emotions. The ratio of LF/HF is considered as a balance indicator between sympathetic and parasympathetic tone.

Whilst heart rate variability is a very promising indicator, variables in its processing, as well as the influence of artifacts or ectopic beats make it very hard to use reliably in uncontrolled environments (Clifford, 2007).

Electrodermal activity (EDA) is determined by measuring the electrical conductance of skin. Skin conductance is usually measured with electrodes placed on the index and middle finger or inside the palm (Dawson, Schell & Fillion, 1990). For parameterization skin conductance usually is divided into the tonal skin conductance level (SCL) and skin conductance responses (SCR). The latter can be used to detect physiological reactions to specific stimuli. However, it is difficult to distinguish between specific responses and non-specific responses when the occurrence of external stimuli is unknown.

Skin conductance level (SCL) is often related to the concept of activation (Duffy, 1972). SCL is especially used as an indicator for the activation level (Vossel & Zimmer, 1998), where longer term measurements allow for observations of the activation progress.

EDA is a very popular measure in HCI, because it can be easily measured on the fingers of the user, meaning there is no need for attaching electrodes underneath the clothes. Besides, Poh, Swenson, and Picard (2010) have demonstrated in a series of experiments that the accuracy of the electrodermal activity sensor developed at MIT, measured on the wrist shows similar phasic activity to the traditional placement on the fingertips. Therefore wrist watches are increasingly used as a highly available, instantly viewable and ideally located platform for various sensors. Bluetooth technology can be used to communicate between sensors and more powerful and GUI-enabled devices such as mobile phones.

If a particular threshold skin conductance and heart rate is reached, an alert is triggered. The user can either respond by applying the relaxation techniques he or she has learned previously or by following the advice provided by the system. The relaxation advice will be developed by medical experts assisted by usability and e-didactics specialists.

The final choice of sensors and devices will ultimately depend on a series of user-tests to find out which ones are more usable and least obtrusive in real-life settings. Besides, it is difficult to anticipate the technological developments in this highly dynamic field, which is why we are constantly looking out for promising devices for experiments.

3.4 Contextual Information

As mentioned above, measuring physiological signals in real-life settings as opposed to the controlled environment of research labs is much more challenging because of artefacts (usually caused by movements of the test persons) and signal distortions. As we know from field tests which we conducted with ambient assistive systems for the elderly (Maier, 2009; Maier & Kempster, 2007; Ritter, 2009), data streams are therefore often difficult to interpret. This is why we often ask test persons to record important incidents to shed light on phenomena such as sudden peaks in heart rate.

Logging daily events is also recommended by experts to gain an understanding of one's stress factors. Indeed, an increasing number of people keep meticulous digital records of things they do every day and put everything they have accumulated, written, photographed and presented in their local cyberspace or in the cloud. However, many people are reluctant or unable to do so which is why in this project we intend to complement the biosignals with context-specific data on location, movement, and ambient light which can all be captured automatically with today's smart phone applications.

Contextual information also includes communication events such as phone calls, writing SMSs or twitter, all of which is registered on mobile phones. Social interaction is considered a major influence on people's wellbeing and therefore may play an important role in stress management.

Together all this data will result in a sort of electronic diary which will provide a very comprehensive picture of a person's daily activities, habits, interactions and psycho-physiological state.

4 Main Challenges and Risks

4.1 Making Sense of Data

The biggest challenge is how to *make sense of the data* we collect. Besides, in uncontrolled environments physiological signals tend to be of inferior and unreliable quality and show great variance within measurements and between different measurements of the same individual. To interpret the biosignals as well as the contextual information captured by the smartphone, we propose a two-pronged approach:

1. Firstly, we will use advanced algorithms such as ai-one² (see Maier et al., 2010) to recognise patterns in the data streams from both the biosensors and the environmental sensors. For example, we might discover that strong ambient light leads to a buoyant mood and thus makes a person less vulnerable to stress, or that walking in the countryside helps a person relax, whereas shopping may exacerbate stress symptoms.
2. Secondly, we apply semantic technologies to analyse and interpret the text messages (e-mail or SMS) of users to gather additional information about their habits, emotions or attitudes. Thus we might discover that social interactions with friends can mitigate stress.

² The ai-one algorithm has been invented by the ai-one company, our partner in a current research project on patient self-management (see <http://www.semper-net.ch>).

We know that personal meaning is closely associated with emotions, which is why ‘making sense’ of data has to include both emotional and cognitive aspects. Measuring skin conductance and heart rate will no doubt provide insights into people’s affective states, but how do physiological signals correspond to people’s own assessment of their moods and emotional experiences? Besides, quite often the influence of emotions is subliminal and people may not be aware of them. Consequently, they cannot record them either.

Mandryk & Atkins (2007) have furnished evidence that normalised physiological measures of experience actually coincide with subjective reports to a large extent. Furthermore, given a time series of emotional output, researchers can use interesting features in the modelled emotion output to index other evaluative data sources such as screen captures or snapshots of the environment or other objective behavioural data such as physical activity or talking on the phone.

Data analysis and interpretation by means of intelligent algorithms will allow users to recognise stress-inducing factors and either deal with them, e.g. by way of relaxation exercises, or avoid them in future (see Fig.1). We will apply the biologically inspired neural network of our project partner ai-one (Reimer et al., 2011) to recognise patterns in the data streams from both the biosensors and the environmental sensors. We will also apply ontology-based semantic technologies to analyse and interpret the textual interactions of users (e-mail, SMS, web browsing). Particularly interesting are *patterns across the various data streams* (i.e. biosensors, environmental sensors, textual interactions) because the correlations underlying these patterns are indicators of what triggers and what relieves stress. Access to the information about stress triggers and reliefs from similar patients of the peer group can show further possibilities how to better cope with stress.

4.2 Power Supply

In terms of technology, power consumption is considered a problem with sensor networks. But not only are sensors becoming ever smaller and more versatile, they increasingly power themselves by drawing energy from their environment, for instance in the form of light and motion, or by hijacking power and bandwidth from the mobile phone’s audio interface as has been demonstrated by the Project HiJack³.

³ See <http://eecs.umich.edu/~prabal/projects/hijack/>.

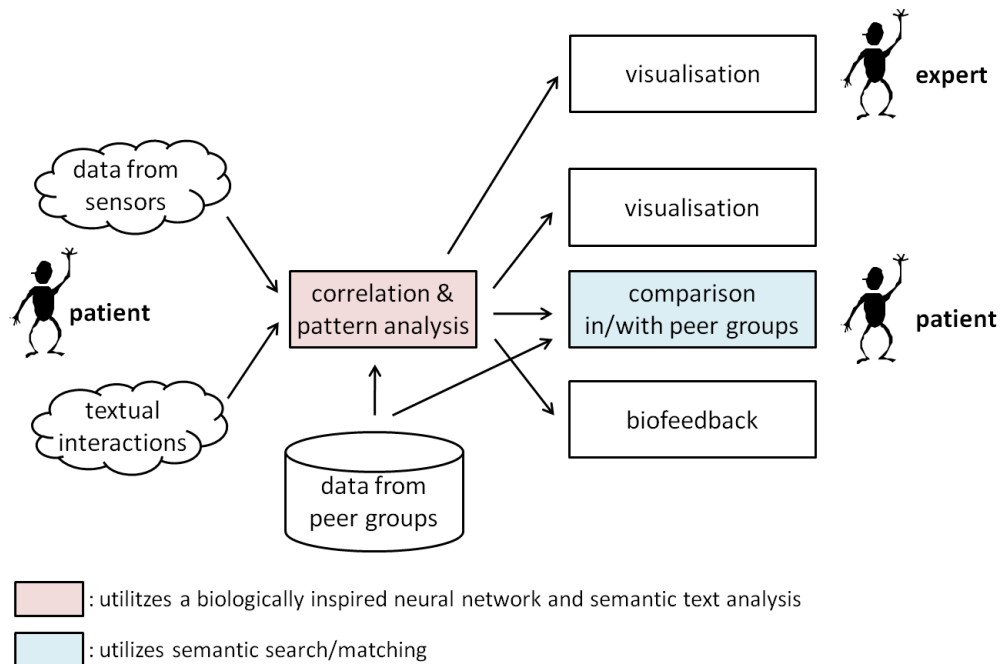


Figure 1: Integration of solution into care process across stakeholders

4.3 Data Protection and Privacy

While some people are anxious to keep at least some of their data strictly private, others are quite happy to make their personal information publicly available by putting it on the Web. Some m/e health applications incorporate links to virtual communities or self-help groups to enhance their impact since social support is considered to play a major role in behavioural change.

In any case, we have to acknowledge that at least three levels of information sharing need to be catered for: publicly available, sharing with a select group of people, and private. Unless we can ensure users that their personal data is protected, will not be adulterated or passed on to third parties without their explicit consent, our solution will not be accepted.

Some of the challenges mentioned such as the need for energy saving when creating wireless sensor networks will be solved thanks to rapid advances in technology. Other challenges are more complex and need further investigation. For example, so far emotional modelling tends to be restricted to basic emotions such as boredom, excitement, frustration or fun. But other emotional states relevant in health behaviour such as disappointment are more difficult to describe in the emotional dimensions of arousal and valence. Besides, we may also need to look for alternative parameterisation techniques for physiological values that are less demanding regarding signal quality and therefore more appropriate for real-life settings.

5 Methodology and Implementation Plan

Test persons and control groups will be recruited after an alcohol abstinence program (randomized study design). Stress parameters will be measured regularly by touching the sensors on the smart phone and visualised on the display of the smart phone by means of a visual analogue scale (VAS). For this purpose, we are planning to develop an application that evaluates the signals and translates them into graphs or any other appropriate visual form. In addition to enabling self-monitoring, the smart system will provide feedback to the test person if he or she so wishes, e.g. by giving advice on how to cope with stress, e.g. through breathing or other exercises which can be performed in everyday situations and do not require any special equipment. After doing the exercise, test persons will be requested to measure the stress parameters via mobile phone once more and to estimate craving via VAS.

The study phase will last for three months. Test persons and controls will be invited to assign their daily alcohol consumption. After six months test persons and controls will be re-assessed with regard to the outcome parameters stress regulation, craving and abstinence.

The procedure just described implies that medical assistance is a key feature of the solution. In the first phase of the project the architecture will therefore consist of the BSN, a mobile device that acts a gateway and data aggregator and a computer located in the physician's office, i.e. data are only fully displayed there. At a later stage, once we have successfully analysed and correlated the data, the physiological and contextual information will also be displayed to the patient and the medical staff.

The major steps of the implementation plan are the following:

- Identify existing tools, devices and sensors for self-monitoring
- Identify methods and parameters for modelling user emotional states
- Conduct a requirements analysis among a representative group of users with a focus on alcohol-dependent subjects
- Based on the results design relevant use case scenarios of human centred situations
- By means of rapid prototyping, iteratively develop demonstrators based on these scenarios and adapt the underlying approach, add and modify existing components based on the feedback

To increase the acceptance of the final product, the solution should make use of components that are affordable and as widely available as possible. We should look to the entertainment and fitness industries, in particular, because they tend to develop products that are not only easy to use but actually fun to use and therefore enhance people's motivation.

As Simons and Hampe (2010) rightly point out, openness is an important asset for future growth and health care provider integration. This is why the mobile solutions tested and validated by Pereira and his colleagues (2010) will serve as a good starting point. They allow data retrieval, storage, and analysis in a single solution, can run on a Java and Bluetooth enabled phone and have been implemented on the major operating systems for mobile devices (Symbian, Android, Windows Mobile and iPhone) and should be easy to set up and use.

6 Contributions in Terms of Information and System Quality

Referring to the criteria suggested by Simons and Hampe (2010) to explore the potential and evaluate the impact of mobile health solutions, we would like to summarize the potential contributions as follows:

Accuracy and objectivity	Potentially very high due to the use of sensors that measure physiological parameters such as skin conductance and heart rate, but accuracy will eventually depend on how sensor accuracy interacts with context information evaluation, which is difficult to estimate in advance.
Relevance	Very high given the connection to everyday behaviour and the highly personalised approach
Timeliness	Feedback can be given immediately or whenever considered relevant (alerts at defined thresholds)
Completeness	Very high because of correlation of sensor data streams with contextual and environmental data which together provide a comprehensive picture
Representation	Depends on designing suitable GUIs (see below)
Accessibility	Information or applications on mobile phones are accessible any time and anywhere

Table 1: Information quality of proposed mobile solution

As far as suitable user interfaces are concerned, we will investigate how best to present the information to the user. Should notification or alerts be in visual, tactile and/or audio form?

We will explore different ways of presenting feedback, e.g. via a face showing emotions or using different colours or colour combinations to reflect a person's mood or state of mind, or graphs with timelines that illustrate a person's progress over time.

With regard to system quality criteria, we can measure and summarize the improvements of the proposed solution as follows:

Integrated health management (across care providers and patients)	The solution brings together self-monitoring, specialist physician care and health coaching and can be integrated into the overall action plan of the patient and the workflow of the clinic.
System flexibility	Solution will conform to open standards so as to be independent of mobile platforms or operating systems; the basic approach can be easily adapted to other health scenarios and user groups
Accessibility	Implementation on mobile devices allows access at any time and at any place.
Integration (interoperability)	At the prototype stage, data will be sent to the medical and IT experts for analysis. Later on, integration with other personal data and relevant support groups is feasible.
Effectiveness, efficiency and ease of use	The solution is expected to add value to the care process, esp. by providing after-care service, which is often lacking.

Table 2: System quality of proposed mobile solution

7 Conclusion and Outlook

We expect that by combining psycho-physiological data with contextual data we will be able to accurately recognise sources of stress including emotional states, which in turn will allow individuals to either avoid stress-inducing factors or develop appropriate coping strategies. Correlating physiological signals as well as activity and environmental data and drawing the right conclusions goes well beyond the current state-of-the art in integrated support for stress management and will help improve overall quality of life.

The outcome of the project will be a prototype implemented on mobile devices using biofeedback as a tool for self-monitoring one's psycho-physiological state and learning how to better cope with stress. In turn, this should contribute to a significant reduction in stress-related symptoms (palpitation, skin conductance) and in craving, and consequently improve the abstinence rate in alcohol-dependent subjects.

Although in this project we will restrict ourselves to stress reduction with alcohol dependent subjects, the basic approach can be easily transferred to other health problems such as stress-induced over-eating, smoking, depression, sleeping problems, or inability to concentrate, which may require different biomarkers and user interfaces.

Besides, we expect that after successful completion of the project, the prototype will be exploited by suppliers of healthcare applications who will provide appropriate back-ends for data analysis.

References

- Barr, C.S., Dvoskin, R.L., Gupte, M., Sommer, W., Sun H., Schwandt, M.L., Lindell, S.G., Kasckow, J.W., Suomi, S.J., Goldman, D., Higley, J.D. and Heilig, M. (2009). Functional CRH variation increases stress-induced alcohol consumption in primates. *Proc Natl Acad Sci USA*. 2009; 25; 106(34): 14593-8. Epub 2009 Aug 17.
- Chaffey, D. and Wood, S. (2005). *Business Information Management*. London: Prentice Hall.
- Ciccocioppo, R., Gehlert, D.R., Ryabinin, A., Kaur, S., Cippitelli, A., Thorsell, A., et al. (2009). Stress-related neuropeptides and alcoholism: CRH, NPY, and beyond. *Alcohol*. 2009; 43(7): 491-8.
- Clarke, T.K. and Schumann, G. (2009). Gene-environment interactions resulting in risk alcohol drinking behaviour are mediated by CRF and CRF1. 2009; 93: 230-6. Epub 2009 May 3.
- Clarke, T.K., Dempster, E., Docherty, S.J., Desrivieres, S., Lurdsamy, A., Wodarz, N., Ridinger, M., Maier, W., Rietschel, M. and Schumann, G. (2010). Multiple polymorphisms in genes of the adrenergic stress system confer vulnerability to alcohol abuse. *Addict Biol*. 2010 Nov 11.
- Clifford, G.D. (2007). ECG Statistics, Noise, Artifacts, and Missing Data. In: Acharya, R.U., Suri, J.S., Spaan, J.A.E., Krishnan, S.M. (eds.) *Advanced Methods and Tools for ECG Data Analysis*, pp. 55--100. Artech House, Boston (2007)
- Dawson, M.E., Schell, A.M. and Filion, D.L. (1990). The Electrodermal System. In: Cacioppo, J.T., Tassinary, L.G. (eds.) *Principles of Psychophysiology*, pp. 295--324. Cambridge University Press, Cambridge (1990) 6.
- Duffy, E. (1972). Activation. In: Greenfield, N., Sternbach, R. (eds.) *Handbook of Psychophysiology*, pp. 577--622. New York: Holt, Reinhart and Winston.
- Lee, Y., Strong, D., Hahn, B., and Wang, R. (2002). AIMQ: a methodology for information quality assessment. *Information and Management*, 40, 133-146.
- Legendre, A. and Harris, R. (2006). Exaggerated response to mild stress in rats fed high-fat diet. *Am J Physiol Regul Integr Comp Physiol*, 291(5), R1288-1294.
- Lowery, E.G. and Thiele, T.E. (2010). Pre-clinical evidence that corticotropin-releasing factor (CRF) receptor antagonists are promising targets for pharmacological treatment of alcoholism. *CNS Neurol Disord Drug Targets*. 2010; 9: 77-86.
- Maier, E. (2009). HCI in the Wild. In: *Proceedings of HCII09, San Diego 19-24 July 2009*.

- Maier, E., Reimer, U., Guttormsen, S. and Zimmermann, Ph. (2010). SEMPER. A Web-Based Support System for Patient Self-Management. In: Proc. 23rd Bled eConference, June 20 - 23, 2010, Bled, Slovenia.
- Maier, E. and Kempter, G. (2007). Increasing psycho-physiological wellbeing by means of an adaptive lighting system. In: Cunningham P. & Cunningham M. (eds.) *Expanding the Knowledge Economy - Issues, Applications, Case Studies*. Amsterdam: IOS Press, 529-536.
- Mandryk, R.M. and Atkins, M.S. (2007). A fuzzy physiological approach for continuously modelling emotion during interaction with play environments. *International Journal of Human-Computer Studies*, 6(4), 329-347.
- Pereira, O., Caldeira, J.M.L.P. and Rodrigues J.J.P.C. (2010). *Body Sensor Network Mobile Solutions for Biofeedback Monitoring, Mobile Network Applications*.
- Picard, R.W. (2010). Emotion research by the people, for the people. *Emotion Review*, Volume 2, Issue 3 (July 2010).
- Plant, J.A. (2007). *Your life in your hands: understand, prevent and overcome breast cancer and ovarian cancer (updated ed.)* London: Virgin Books.
- Poh, M.Z., Swenson, N.C. and Picard, R.W. (2010). A Wearable Sensor for Unobtrusive, Long-term Assessment of Electrodermal Activity. *IEEE Transactions on Biomedical Engineering*, Vol.57, No.5, pp.1243-1252, May 2010.
- Reimer, U., Maier, E., Streit, S., Diggelmann, Th. and Hoffleisch, M. (2011) *Learning a Lightweight Ontology for Semantic Retrieval in Patient-Centered Information Systems*. *International Journal of Knowledge Management*.
- Ritter, W. (2009). *Measuring Psychophysiological Signals in Every-Day Situations*. In: *Proceedings of HCII09, San Diego 19-24 July 2009*.
- Simons, L.P.A. and Hampe, F.J. (2010). Exploring e/mHealth Potential for Health Improvement: A Design Analysis for Future e/m Health Impact. Proc. 23rd Bled eConference, June 20 - 23, 2010, Bled, Slovenia.
- Stull, W., Snyder, D. and Demark-Wahnefried, W. (2007). Lifestyle Interventions in Cancer Survivors: Designing Programs that Meet the Needs of this Vulnerable and Growing Population. *J Nutr*, 137, 243S-248S.
- Verschuren, P. and Hartog, R. (2005). Evaluation in Design-Oriented Research. *Quality and Quantity*, 39, 733-762.
- Vossel, G. and Zimmer, H. (1998). *Psychophysiologie*. Stuttgart: Verlag W. Kohlhammer.