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Personalized Coaching Systems to support healthy behavior in people with chronic conditions

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Abstract
Chronic conditions cannot be cured but daily behavior has a major effect on the severity of secondary problems and quality of life. Changing behavior however requires intensive support in daily life, which is not feasible with a human coach. A new coaching approach – so-called Personal Coaching Systems (PCSs) – use on-body sensing, combined with smart reasoning and context-aware feedback to support users in developing and maintaining a healthier behavior. Three different PCSs will be used to illustrate the different aspects of this approach:

1. Treatment of neck/shoulder pain. EMG patterns of the Trapezius muscles are used to estimate their level of relaxation. Personal vibrotactile feedback is given, to create awareness and enable learning when muscles are insufficiently relaxed.

2. Promoting a healthy activity pattern. Using a 3D accelerometer to measure activity and a smartphone to provide feedback. Timing and content of the feedback are adapted real-time, using machine-learning techniques, to optimize adherence.

3. Management of stress during daily living. The level of stress is quantified using a personal model involving a combination of different sensor signals (EMG, ECG, skin conductance, respiration).

Results show that Personal Coaching Systems are feasible and a promising and challenging way forward to coach people with chronic conditions.

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1. Introduction

The burden on healthcare services in the Western world is increasing substantially during the past decades. Both the quality and quantity of the care has to increase to meet the demands, especially for people with chronic conditions. The demand for an increase in quality is due to the aging western population and an increase in prevalence of chronic diseases. Life expectancies have increased yearly with a rate of 0.24 years over the past century in the United States, Europe and Japan (Christensen et al., 2009). This increase in life expectancy however has hardly resulted in more healthy life years; in contrast, these additional life years are years with chronic conditions. This is becoming especially apparent now as the baby boom generation is reaching the age of retirement, also an age at which many chronic conditions are becoming more prevalent. These trends make that in the near future, we have to cope with a growing population in need of chronic care, during longer periods of time and on the other hand a smaller workforce that is able to pay and deliver the care. Consequently, healthcare services have to be innovated towards more automated services that are scalable and limit the need for trained healthcare professionals.

The need for such drastic innovation is most evident when considering people with chronic conditions. Their chronic conditions cannot be cured but their behavior has a major impact on further progression of the disease, quality of life and the occurrence of secondary health problems. It is becoming more evident that actual and perceived health can be influenced positively by creating awareness of adverse behavior and developing a sustainable healthy behavior. Regular physical activity reduces the risk of (chronic) diseases like coronary heart disease, type II diabetes and some cancers (Kohl et al., 2012; Lee et al., 2012). For example, in Chronic Obstructive Pulmonary Disease (COPD) patients avoid physical activities due to their symptoms, which cause a downward spiral towards lower physical condition and quality of life. Stress has also a substantial impact on health; it is a major cause of sickness absences (EC, 2010) and is strongly related to burn-out and depressions (Leka and Jain, 2010). Chronic neck/shoulder pain has often no clear cause and is often associated with a downward spiral of experienced pain and changes in behavior. Behavioral
approaches for the interventions are most successful, although success rates are rather low; below 50%.

So, changing behavior into a more healthy behavior can contribute substantially to a better health, but changing behavior is for us humans quite difficult, requiring substantial feedback when adverse behavior occurs and encouragement when progress is being made. It requires also that the feedback is given during the daily activities of living, so changes can be easily integrated. These considerations make adequate coaching important but make also clear that solving this by using human coaches is not feasible and not scalable to the required level.

The recent developments of small on body sensors, powerful smartphones and knowledge on behavioral changes have opened the way to the development of an artificial coach.

The concept of such an artificial coach, a so-called Personal Coaching System (PCS) is shown in Fig. 1. This coach is able to provide intensive and timely persuasive feedback to its user. Targeted physiological variables are measured on-body that are relevant and valid for the health aspect that we want to influence. These signals are processed and used as input for the intelligent module. This module is capable of using these variables and relevant context information to generate a personal advice to the user for that specific moment. The third module takes care of the presentation of the actual feedback to the user in the most persuasive way.

This paper summarizes our work in the area of Personal Coaching Systems (PCSs). This will be done using three cases, illustrating research on the different aspects:

1. The pain coach. This concerns a PCS for the treatment of people with chronic neck shoulder pain. It involves the use of surface EMG electrodes embedded in a garment to measure the EMG patterns of the upper trapezius muscles.
2. The Activity coach. This concerns a PCS designed to stimulate people towards a more active and healthy activity behavior. Sensing is done by a dedicated activity sensor.
3. The stress coach. This concerns a PCS to assess and feedback mental stress. It involves the use of several wearable physiological sensors to assess stress level.

These PCSs start from the same concept but have different approaches in terms of the sensing, the reasoning and the feedback, dedicated to the specific application area they were designed for. They are also in different stages of development. The pain coach was the first system that was developed and it has gone through all the different phases of development. It is a relatively simple system with respect to its reasoning component, but it is also the most mature one with respect to its implementation and validation. It was extensively evaluated in a large European project (Myotel). The research concerning the activity coach has been focused on the reasoning part; how and when should feedback be provided in order to be as persuasive as possible in getting people to develop and maintain a physically active lifestyle. Several studies were carried out in different pathologies to investigate the specific activity patterns. The stress coach is most recently developed and research is especially focused on how to measure stress using multiple sensors and how to develop a personalized model from the recorded data that drives the feedback.

2. The neck pain coach

2.1. Introduction

Chronic pain is long standing pain that persists beyond the usual recovery period. In many cases pain is non-specific pain meaning that the cause is unknown (Manek and MacGregor, 2005). In Europe 19% of the people suffer from moderate or severe pain for more than 6 months (Breivik et al., 2006). With a self-reported point prevalence of 21% for neck pain and 21% for shoulder pain, neck and shoulder pain is one of the most common musculoskeletal complaints. Costs related to chronic pain are high; not only due to medical costs but also due to sick leave and loss of workability. A significant amount of patients with severe pain is not able to work, those working have 8 times higher absenteeism and absenteeism increases with pain intensities (Holtermann et al., 2010). The costs related to lost working days due to chronic pain are estimated to nearly 34 billion Euros for 500 million lost working days each year. Chronic pain seriously affects patients in performing their daily activities like participation in social, sports and work activities (Breivik et al., 2006). As a result, interventions focusing on improving a patient’s functional level like physical and behavioral interventions have an important share in the treatment of patients with chronic pain. However, in the way currently provided these treatments are insufficiently effective as effects are small and just 30–50% of the patients really benefit. Factors related to this hampered effectiveness are that treatments are too generic, not sufficiently targeted at the individual patient, insufficiently focused to support self-management and that patients experience difficulties in translating the learned skill to everyday life.

One way to overcome these issues is by making use of personal health systems that focus on the patient’s individual response mechanism. Experimental studies for patients with chronic neck pain have shown that these patients show deviating muscle responses compared to asymptomatic controls (Nederhand et al., 2003, 2000). This is reflected in a prolonged activation of their muscles after a task, i.e. a decreased ability to relax their muscles. Patients may not be aware of this, because prolonged activation often occurs at rather low levels. According to the Cinderella hypothesis these low levels of activation may contribute seriously to the development and maintenance of chronic pain, when occurring during long periods of time (Hägg, 1991). Besides being an explanation for the development of muscle pain, the Cinderella hypothesis also provides an important starting point for a Personal Coaching System. The concept is that by monitoring and providing subjects feedback on their lack of sufficient muscle relaxation they are able to recognize during which situations insufficient relaxation occurs and are able to learn to perform the tasks in these situations in different ways.

2.2. Methods

A Personal Coaching System, called the Pain PCS, has been developed consisting of the following building blocks; a sensing part, a feedback part and an ICT infrastructure (Bults et al., 2010).

2.2.1. Sensing

Starting points for the design of the sensing were that (1) the EMG signals of the left and right upper trapezius muscles had to be recorded by bipolar surface electrodes in a reliable, reproducible way, (2) the recording should be done in such a way that the person is not hindered in his activities of daily living and (3) that the person is able to put the system on and take it off independently.

A special garment was designed, in which two EMG sensors are embedded to record the EMG from the left and right upper Trapezius muscles (Fig. 2). The embedding of the EMG sensors is such that the placement of the electrodes follows as good as possible the Seniam recommendations (Hermens et al., 2000).

Special dry surface electrodes were designed and tested extensively. The rubber casing was shown to enable a rather fixed placement on the skin whereas the silver/silver chloride coating enabled a good stable contact. The garment was tested extensively with over 50 subjects and it was shown that after training the subject...
was able to don and doff the garment independently and that the garment did not hinder the subject during his activities of daily living. EMG recordings showed a sufficient quality, especially after 10 min and maintained at that level for up to 12 h of use. To estimate relative rest both amplitude and time related variables were investigated. The amplitude related variables were shown to be much more sensitive to displacement of the EMG sensors compared to the time related variables, making them less suitable for use in the PCS or requiring an additional normalization procedure. The relative rest time (RRT) defined as the relative time the EMG activity (Root Mean Square) is below a certain threshold appeared to be less sensitive for electrode placement and does not need standardization procedures appeared to be more suitable (Hermens and Vollenbroek-Hutten, 2004). The threshold setting for muscle relaxation was chosen to be true when the RMS is below 10 μV for at least 0.12 s. All processed signals were sent from the EMG processing unit to the smartphone using Bluetooth. From there the processed signals were sent to a server and stored in a database. Privacy, authentication and security were established by using pin codes between the devices, encrypted data streams and password protection of the database and web portals.

2.2.2. Reasoning and feedback

The concept of the pain coach is that by means of feedback to the patient on their lack of sufficient muscle relaxation patients are able to recognize during which situations insufficient relaxation occurs and are able to learn to perform the tasks in these situations in different ways. In the Pain PCS, feedback is given to the person in 3 different ways. First, the processing unit that is connected to the electrode garment gives sensory feedback by means of vibration after each 10 s interval when the relative duration of muscle relaxation in that particular interval was below 20%. This threshold was chosen based on the work of Hagg and Aström (1997).

Secondly, the processing unit is connected by a Bluetooth link to a smartphone. The application running on this phone allows the patient to start and stop a measurement session and to receive personalized feedback on the processed sEMG signals; i.e. it shows graphs of the Root Mean Square (RMS) and relative rest times (RRT) of both the left and right trapezius muscle. Thirdly, a web portal was developed in which both the patient and the health care professional have access to the data anytime, anyplace. The web portal allows the healthcare professional to register a new patient, access and edit patient treatment information, access patient diaries and visualize the measurement data. The patient can look at the same visualizations of the data and simultaneously discuss the progress with the clinician; look at specific events and decide together about the next steps in the treatment.

Before starting to use the Pain PCS, patients receive training from a healthcare professional on how to use the system and how to interpret the RMS–RRT graphs.

2.3. Evaluation

The Pain PCS was developed and evaluated in various studies using the DeChant framework (DeChant et al., 1996) and its results are described in various papers (Huis in’t Veld et al., 2008; Kosterink et al., 2010; Sandsjo et al., 2010). DeChant et al. (1996) proposed a framework, a staged approach, for telemedicine evaluation studies in which the type of assessment is tailored to the development life cycle of the technology. Stage 1–2 evaluations are considered the starting point of evaluation and aim at proving the technical efficacy and evaluating the primary objectives of the service in domains of access, quality or cost. Stage 3 and 4 evaluations are larger scale evaluations with multiple outcome measures focusing mainly on effectiveness or cost-effectiveness. Huis in’t Veld et al. (2008) performed a stage 1–2 evaluation with a focus on technical feasibility and user experience. The Pain PCS was used by ten female workers suffering from neck–shoulder pain related to computer work for four weeks. Their results show that in 78% of the remote counseling sessions between the therapist and the patient sufficient amounts of data were available at the server for the therapist to make an assessment of muscle tension needed for the remote counseling sessions. Subjects reported high satisfaction with the usefulness and ease of use of the remote counseling. However, they were less satisfied with the technical functioning of the myofeedback system. Eighty percent of the subjects reported a reduction in pain intensity and disability directly after end of treatment. Kosterink et al. (2010) and Sandsjo et al. (2010) performed a large scale randomized controlled trial into the Pain PCS for patients with non-specific neck and shoulder pain and work related musculoskeletal neck shoulder pain, respectively. Kosterink included 71 subjects (36 in the PCS group and 35 in the conventional care group) and showed that the Pain PCS was at least as effective clinically as conventional care. Pain intensity and disability decreased after 4 weeks of treatment in both groups and part of the effect remained at 3 months’ follow-up. The telerehabilitation also increased efficiency for therapists by almost 20% and patients experienced the benefits of less travel time and travel costs by remote consultation. Sandsjo et al. (2010) included 65 females with neck–shoulder pain at work (33 in the PCS group and 32 in the control group continuing on-going traditional care). Results showed an improvement in terms of pain and work ability for both groups with no differences found between them. The time saved in relation to traditional care was mainly from reduced travel time, which was recorded to be 41 min per teleconsultation. They concluded that the Pain PCS allowed employees to take part in muscle relaxation training while performing their regular work. The clinical evaluation indicates the PCS service to be on par with traditional care but without the efforts and time losses associated with regular visits to the clinic. Both studies concluded that the Pain PCS has the potential to ensure more efficient treatment for patients with non-specific neck and shoulder pain.

3. The Activity Coach

3.1. Introduction

Physical inactivity has been identified as the fourth leading risk factor for global mortality causing an estimated 3.2 million deaths globally (WHO, 2010). Regular physical activity is related to better health, and reduced risk of (chronic) diseases like coronary heart disease, type II diabetes and some cancers (Kohl et al., 2012;
Lee et al., 2012). The promotion of a physically active lifestyle is especially important in chronic disease management, as it can increase active life expectancy by limiting the development and progression of chronic disease and disabling conditions (Chodzko-Zajko et al., 2009). The importance of an active lifestyle is underlined by studies that show lower daily activity levels in patients with chronic diseases as well as a skewed distribution of activity compared to healthy controls (Evering et al., 2011; Tabak et al., 2012; van Weering et al., 2009). However, reviews show that programs that aim to reduce inactive behavior and increase physical activity are only marginally effective (Cindy Ng et al., 2012; Conn et al., 2011; Hillsdon et al., 2005). As such there is an emerging need for interventions that aim at sustainable lifestyle change characterized by increased physical activity and a more equally distributed activity pattern. Personal Coaching Systems could be used to shift the intervention to the daily environment, to help patients manage their disease in everyday life.

One of the envisioned PCS solutions is the Activity Coach – consisting of an activity sensor and a smartphone – to support people with chronic conditions in developing and maintaining an active and balanced lifestyle, either independently or supervised remotely by their healthcare professionals. The smartphone shows the measured activity cumulatively in a graph in relation to the activity goal: the reference activity line. In addition, the patients automatically receive time-based motivational cues, for awareness and extra motivation. These cues are based on the difference between the measured activity and the reference line and consist of (1) a short summary of activity behavior and (2) an advice on how to improve or maintain the activity behavior.

We performed several studies to investigate the potential value of applying the Activity Coach for treating patients with chronic low back pain (CLBP) (van Weering et al., 2012) chronic fatigue syndrome (CFS) (Evering, 2013) and Chronic Obstructive Pulmonary Disease (COPD) (Tabak et al., 2014a,b,c). The motivational cues have shown to be a valuable component in changing daily activity behavior with significant responses in activity level on both encouraging and discouraging cues. In addition, the Activity Coach could change the daily activity of CFS patients towards their goal and could reduce pain intensity levels of CLBP patients. Furthermore, higher usage of the Activity Coach was significantly associated with improvement in activity levels in COPD patients. However, changes in activity behavior seem to diminish after few weeks of use (Tabak et al., 2014a,b,c) and compliance to the feedback decreases over time (Evering, 2013). In these studies, a reference line was used that was (partly) based on the mean activity line of healthy persons. Our monitoring studies already showed the large and significant difference in activity levels between healthy persons and patients with chronic conditions (Evering et al., 2011; Tabak et al., 2012; van Weering et al., 2009). The goal could be considered too difficult to reach and a more individual goal setting that resembles the capacities of the individual patient could provide a better fit. Besides, the responses of the patients to the motivational cues were not clearly related to the cue- or context variables such as the contents of the cue (Tabak et al., 2014a,b,c), as the patients seem to respond very differently to the cues. This suggests that the response and compliance could be better when the Activity Coach is more tailored to its individual user. Therefore, the next step towards a truly personal PCS was the development of an intelligent Activity Coach that uses individualized goal-setting and tailored feedback. Improvements towards tailoring the Activity Coach are described in the sections below.

3.2. Methods

In the following sections we describe the improvements made to the Activity Coach PCS, starting with an overview of the PCS Platform (Section 3.2.1) and introductory research into tailoring physical activity coaching systems (Section 3.2.2). Based on our research into tailoring, three improvements to the Activity Coach were developed: automatic message timing (Section 3.2.3), tailored message content (Section 3.2.4) and adaptive goal setting (Section 3.2.5). A small-scale, longitudinal trial was executed, targeting physical activity in COPD patients, in which the automatic message timing and a first version of the adaptive goal setting was evaluated.

3.2.1. The PCS platform

The Activity Coach is part of a Telemedicine platform developed at Roessingh Research and Development that is described in detail in (op den Akker et al., 2012). The most relevant components related to the Activity Coach are the sensor and smartphone. The sensor used is a ProMove-3D wireless activity tracker, developed by Inertia Technology and was designed to provide a trade-off between performance, computational and storage resources, wireless capabilities, low-power operation and wearable form factor (Bosch et al., 2009). The sensor node contains a 3D-accelerometer for daily physical activity tracking (as well as a 3D gyroscope and 3D magnetic compass for more advanced body tracking), and communicates wirelessly over Bluetooth to the smartphone. An algorithm to convert the raw accelerometer values to IMA units (Bouten et al., 1997) – a unit that is demonstrated to correspond with daily energy expenditure – is implemented on the sensor’s micro controller.

The smartphone application receives the activity data from the sensor, shows the activity data in a graph to the patient, and can trigger motivational cue messages as well as questionnaires for the user to answer. Fig. 3 shows the graphical user interface for the Activity Coach smartphone application. Based on an extensive requirements elicitation phase, the software architecture developed was designed to form a flexible framework in which various types of applications can be defined by linking together various modules that support e.g. different sensors or user interface functionalities. Each module performs a typically small, clearly defined task and delivers its output to a central communication module, or Hub. Other modules can subscribe to this information and are notified when new output becomes available. For example: a BluetoothModule is charged with the task of opening, maintaining...
and closing Bluetooth connections within the device (but knows nothing about specific communication protocols). As output it delivers a stream of data coming from the sensor, as well as updates regarding the status of the connection. The Graphical User Interface, implemented in a GIModule can subscribe to the status messages and provide the user with a warning if a Bluetooth connection is lost. Software developers are free to develop their modules without specific limitations and can communicate with other modules by passing messages through the Hub, to which other modules can subscribe.

All measured data (e.g. questionnaire results, activity data, message logs) can be synchronized to a central server that can store this data in a dedicated database. The server provides an Application Programming Interface (API) through which other applications, such as web portals can request data and provide more complicated views for patients as well as healthcare professionals. More details regarding the server, web portals, platform evaluations as well as discussions can be found in (op den Akker et al., 2012).

3.2.2. Tailoring physical activity coaching

The Activity Coach with its modular architecture provides a convenient platform for developing and testing new coaching methodologies. In previous studies, the need for new coaching methods was identified, in particular methods that better target individual users. Tailoring, or the process of adjusting the system’s behavior to individuals in a specific context, is an emerging topic of interest within the field of physical activity coaching. In order to explore the possibilities of tailoring in physical activity coaching applications, we conducted an extensive survey of the literature (op den Akker et al., 2014a,b). The survey was used to create a conceptual framework of tailoring. In our definition of tailoring we state that tailoring can be applied to communication to the user, and that each communication instance can be seen as having four distinct properties: timing, intention, content, and representation. From the literature survey, and building on previous attempts to define tailoring (Hawkins et al., 2008), we identified seven tailoring techniques – feedback, inter-human interaction, adaptation, user targeting, goal setting, context awareness, and self-learning – that can be applied to each of the four communication properties. Various combinations of tailoring techniques can be used, and the model defined in (op den Akker et al., 2014a,b) shows how each tailoring concept relates to each other and to the communication instance properties. As such, the model can be used for designers of activity coaching systems, by following certain paths through the model, and exploring different tailoring approaches. Improvements to the Activity Coach PCS were made by exploring some of the opportunities identified in the model.

3.2.3. Automatic message timing

One of the first issues we aimed to address through tailoring was the delivery of motivational messages, and in particular the timing of such messages. Previous studies used a fixed timing schedule in which users were sent a message every hour (or every two hours) to encourage more activity (“Please go for a walk!”), or discourage excessive activity (“Why don’t you sit down for a while?”). Although, overall these messages seemed to have a positive effect on activity, the compliance to the individual messages was only 60.35%, over a set of 2769 messages.

In an attempt to increase the compliance to individual messages a system was developed that could automatically decide on an optimal moment to notify the user by applying context-awareness and self-learning (op den Akker et al., 2014a,b). The smartphone application constantly evaluates the context of the user and uses machine learning to classify situations as suitable moments for delivery of motivational coaching. The first phase — the cold start phase, in which no data for the current user is known — uses a k-nearest-neighbor classifier trained on historical data. In the second phase, real-time prediction and self-learning takes place by means of a Support Vector Machine implementation which is automatically generated on the smartphone and which is re-trained periodically. The system was evaluated by means of a three-month longitudinal trial with patients with COPD (see Section 3.3).

3.2.4. Optimizing message content

Once a suitable timing has been chosen for a motivational message, the next step is to determine what to say exactly – or what is the intention and content of the message. In previous studies, motivational messages were selected randomly from a list of predefined messages. After some period of using the Activity Coach, the messages would start to repeat and become predictable. Also, through random message selection there is a high probability that the message content does not match the user’s current context (e.g. “Go for a walk”, when it rains outside).

To address these issues we looked again at the available tailoring techniques. In op den Akker (2014a), we developed a model of motivational messages based on the analysis of literature and a large collection of motivational messages used in previous studies. We presented the decomposition of a motivational message into the four high level communication aspects of timing, intention, content and representation, each of which are further deconstructed and modeled in detail. The result is a theoretical model of messages that takes into account the relevant concepts identified in literature, and provides a link to the seven key tailoring concepts.

A practical framework was developed that demonstrates the sequential process of generating each of the four message components. In each step of the process, simple tailoring rules can be implemented. For example, in the process of generating the message intention, a decision rule can be defined based on user knowledge regarding e.g. stage of change (Prochaska and diClemente, 1986) to decide whether or not the user should be told about the benefits of physical activity. The idea here is that users who are only contemplating their physical activity behavior change would benefit from such a message component, while users who are trying to maintain their newly adopted healthy lifestyle would not. Similar decision making constructs are implemented for each step of the message generation process, every time drawing on different tailoring rules and different user or context information. By including a factor of randomness in the decision making process and by including many different surface representations of the messages, the system reduces the repetitiveness introduced in previous message generation methods.

3.2.5. Adaptive goal setting

As earlier studies with the Activity Coach showed a mismatch between the reference (target) activity line and the user’s activity, we aimed to tailor the goals to individual users. In our longitudinal trial with COPD patients described below (Section 3.3) the involved physiotherapist was instructed to change the reference line weekly. The reference line was adapted to every patient’s abilities and changed based on the previous performance of the patients as follows. First, patients performed a baseline measurement. From this measurement the mean daily activity level is calculated and distributed per day part according to the distribution of daily activities in healthy individuals: 40% in the morning, 30% in the afternoon and 30% in the evening (Waschki et al., 2012). After the baseline, every week, the reference line is increased with 10% above the mean of the past measurement weeks.

With the method described, both the end goal (total activity at the end of the day), and the distribution of activity over the day is taken into account. To reduce the burden on the physiotherapist, a new automatic version of the procedure was developed and
described in a paper by (Cabrita et al., 2014). At the end of each measurement day, the system would automatically update an internal set of parameters describing the user’s average activity at the end of the mornings, afternoons, and evenings for each separate day of the week. Then, an automatic reference line is generated on the smartphone, targeted specifically at the weekday (e.g. Tuesdays). The new reference line is automatically set to be somewhere in-between the user’s current activity pattern and a predefined ideal activity pattern (e.g. 10,000 steps per day, 40% in the morning, 30% in the afternoon and 30% in the evening).

3.3. Evaluation

The most recent evaluation of the Activity Coach was conducted in the context of the European AAL-project IS-ACTIVE (www.is-active.eu). This version of the coach included two of the tailored coaching mechanisms: the automatic message timing (Section 3.2.3) and the preliminary version of the adaptive goal setting mechanism (Section 3.2.5). The system under evaluation would automatically decide the timing of providing feedback messages, while the reference goal lines were adjusted according to the described schedule every week. The goal of the evaluation was twofold: (1) to evaluate the overall effect on daily levels of physical activity, and (2) to evaluate the process of the self-learning feedback timing component and the effect on compliance to individual feedback messages.

To investigate the changes in activity behavior by using the Activity Coach, we applied the intervention in a small group of patients with COPD (n = 10) for 3 months (Tabak et al., 2013). From the 10 patients, 8 were included in the analysis for effect on physical activity levels. For such a highly individualized intervention, a single-case experimental design was used. The main outcome parameter was objectively measured activity behavior; which was measured for one week before the intervention (A1: baseline phase), during the 3-month intervention (B: intervention phase), and for one week three months after the intervention (A2: follow-up phase).

In total, 464 measurement days were analyzed. The study showed that intervention was effective in 5 patients in terms of increasing activity levels and 4 patients of improving activity balance from baseline to the end of the intervention, which seems an improvement compared to the time-based Activity Coach (Tabak et al., 2014a,b,c). This suggests that the tailoring we applied might contribute to better treatment effectiveness.

Our study showed that the increased activity levels of the individuals were not maintained at follow-up and only two patients maintained their improved activity balance. This suggests that the patients were not able to maintain their change in activity behavior after the intervention ended.

The self-learning feedback timing component was evaluated by looking at the compliance to individual motivational messages (or cues). Fig. 4 shows the average compliance to individual cues from all study participants after receiving increasing numbers of cues. These statistics are gathered for the adaptive timing system ‘Kairos’ (op den Akker et al., 2014) (thick black line) as well as for historical data including COPD, CFS, CLBP and obese subjects (thin black line). Compared to a previous study with COPD patients (dotted line), the compliance to individual cues generated by the Kairos system is significantly higher in the period of receiving the 41st and 105th cue (62.70% compliance versus 56.00% for the historical COPD dataset on average in this period).

4. The stress coach

4.1. Introduction

More than half of the European workers experience work-related stress to be common in their workplace and 4 out of 10 workers think that stress is not handled well in their organization (EU-OSHA, 2012). Of sickness absences of one month or more, 25% is caused by stress, depression or anxiety (EC, 2010). Chronic work-related stress can cause several mental and physical health problems. These problems include (Leka and Jain, 2010):

- Burnout and depression
- Difficulty in concentrating
- Drug and alcohol abuse
- Cardiovascular disease
- Musculoskeletal problems

Given the physiological reaction to stress, assessing stress by measuring physiological parameters seems feasible. Various physiological signals are potentially useful for this purpose, including: Heart rate and heart rate variability, Blood pressure, Respiration, Skin conductance, Muscle activation and Skin temperature. Many
researchers investigated the relation between mental stress and physiological parameters (see for example (Hjortskov et al., 2004; Lundberg et al., 1994; Peters et al., 1998). Most of these studies involved a specific, short-term, stressor in a controlled environment. However, there is no conclusive evidence that stress in the real world induces the same physiological response as the response that is induced by these short-term and controlled stressors (Kamarck and Lvallo, 2003). Also, there is evidence that different persons react differently to stress (Lacey and Lacey, 1958), so a personalized model would be needed for reliable detection of the stress response.

The PCS solution we envision is a wearable sensor system that measures multiple signals and uses personalized models for reliable stress assessment in real-world environments. The information about stress level is subsequently used to give adequate feedback to the user and to help the user to manage his or her stress level. So far our studies focused on finding the best way to detect mental stress. The next step towards a PCS would be to provide accurate and relevant feedback to the user. This could be done using graphs and messages using a smart phone application or web application, or by using other modalities such as light or sound to influence a person’s mood and behavior.

4.2. Methods

It can be concluded from the above that there are two main issues regarding the state of the art of physiological stress research: the controlled test environments in which most of the studies were executed so far and the need for personalization of the data analysis to address the different reactions of different persons to stress. In our studies we address both issues. Details of the studies will be discussed in the next section.

4.2.1. Test environments

In our first study we designed a protocol that mimics office-like stress situations. Our second study was performed in the real world: subjects were performing their daily job routine while participating in the study.

4.2.2. Personalization

In our first study we normalized the physiological data for every subject separately before putting the data in the classification algorithm. In our second study, we performed the analysis of our data for every subject individually to determine a personal stress model. In both studies we recorded multiple parameters to make sure we captured all aspects of the stress response even though different subjects show different reactions.

4.3. Evaluation

4.3.1. Quantitative assessment of stress in a simulated office environment

Our first study was set up in a controlled environment. We designed a protocol with three different stress conditions that were invented to resemble office-like stress situations. The first condition was the Norinder test, a mathematical test that required some effort to solve a number of small calculation problems. The second test was a logical puzzle test, which required thinking a problem through and finding the solution as quick as possible. The third and last stressor was a memory test that required remembering a set of pictures. The subjects were told that the results of this test would be communicated to colleagues. All three tests were done under time pressure and while hearing distracting sounds (news fragments). Rest periods were scheduled in between the stress tests and at the end of the protocol to ensure that subjects would return to baseline stress level. Subjects could indicate their current stress level after every rest and stress condition on a Visual Analogue Scale (VAS). A detailed description of the protocol can be found in (Wijsman et al, 2013a,b,c).

During the protocol we measured four physiological signals:

- Electrocardiogram (ECG) to derive heart rate and heart rate variability features
- Respiration
- Skin conductance from the fingers
- Electromyogram (EMG) from the upper trapezius muscles in the shoulders

We first analyzed just the EMG signals because these signals are not as commonly used in stress research as the other signals. We wanted to investigate the potential benefits of measuring EMG apart from the other physiological parameters. The results were as expected: EMG amplitude increased during the stress conditions and the relative time with EMG gaps decreased during the stress conditions. Also, EMG mean and median frequency decreased during stress. We found a positive correlation between the RMS of the EMG signal and the VAS values and a negative correlation between the relative time with EMG gaps and the VAS values. A more detailed description of the data analysis and the results can be found in (Wijsman et al., 2013a,b,c).

Our next step was to analyze all four physiological signals and to use the features that could be derived from these signals for classification between the rest and the stress conditions of the protocol (Wijsman et al., 2011, 2013a,b,c). We reduced our feature set of 19 features by using feature selection and Principal Component Analysis. Using various classification methods we achieved a classification accuracy of 75–79% between the rest and stress conditions. The automated feature selection algorithm selected features from all four physiological signals. This is an indication that recording multiple parameters is useful because every parameter provides information to the classifier.

Finally, we proposed a way to indicate not just a classification into a rest or stress condition, but a stress level on a continuous scale. We used a 2-min sliding window to calculate the physiological features and normalized the feature values. On one hand, we used the stress and rest conditions as given by the protocol and built a classifier to classify the data points into one of these two conditions. We applied this classifier to the feature values coming out of the sliding window and used the probability determined by the classification algorithm to express a continuous level of stress. On the other hand, we used the self-reported stress levels by the subjects to build a linear regression model that could estimate the stress level based on the physiological feature values. Again, we used the feature values coming out of the sliding window to calculate a continuous stress level estimation. An example of stress level estimations over the various rest and stress conditions of the protocol is shown in Fig. 5 (Wijsman et al., 2012).

4.3.2. Stress estimation in real-world conditions

Starting from the results of the lab studies, we recently conducted a study that ran for multiple days in a real-world office environment.

Ten subjects, who were researchers, continued their normal job activities during their participation in the study. Five physiological signals were recorded during five working days, only during working hours. Four signals are the same as in our previous study (ECG, respiration, skin conductance, EMG). We added skin temperature to this list. We used the wireless body area network system developed in Holst Centre/imec (Eindhoven, The Netherlands) to record the signals. The ‘ECG necklace’ (see Fig. 6) was used for ECG, respiration and EMG recording. Both skin conductance and skin temperature were recorded from the wrist using the wrist sensor shown
5. Discussion

In this paper we presented the concept of Personal Coaching Systems and our experience with three different realizations of such a system. The Pain PCS utilizes a new way of myofeedback and has gone through many interactive cycles of development and was demonstrated in a large international trial with many subjects suffering from chronic neck/shoulder pain. It was also the first PCS that involved the use of streaming EMG data and real-time feedback. The Activity PCS is illustrating how artificial intelligence technology can contribute to a smart personalization of the PCS in order to improve the adherence to the coaching advices given. The stress PCS illustrates the use of multiple sensors and the use of individually optimized models to obtain variable that is representing the health aspect to be coached.

5.1. Sensing

Non-obtrusive sensing of relevant physiological variables is the first key element of the PCS. During the past years an amazing progress has been made with the availability of sensors, especially involving inertial sensors that are able to quantify the amount of movement. Nowadays many small, cheap activity sensors are available, like Nike (www.nike.com) and fitbit (www.fitbit.com). Most of them are able to communicate with a smartphone, so enabling an Activity Coach. Some critical remarks have to be made however. A well accepted standard to filter and process the sensor signals from the inertial sensors is still missing, which makes a comparison of the different studies difficult. Another more important issue is that the amount of activity is strongly influenced by the place where the sensor is worn on the body. The original thought was that the sensor should be placed very nearby the center of mass at a stable place to make an estimate of the amount of mechanical energy possible. Bouter showed in his double labeled food experiment that the sensor should be placed very nearby the center of mass.

In Fig. 6, Subjects indicated their stress level on a VAS in a smartphone application every 30 min. They also entered context information about physical activity, posture and consumption of food, drinks and cigarettes in the application. Furthermore, four saliva samples were taken every day for analysis of the concentration of the stress hormone cortisol. More details of the protocol and data collection can be found in (Wijsman et al., 2013a,b,c).

We used forward multiple regression to select the relevant physiological features to model the general stress reaction of all subjects together and the personal stress reaction of every subject separately. We used the self-reported stress levels as dependent variable and the physiological features as independent variables. See Table 1 for the selected features and resulting $R^2$ value of the general model and two examples of personal models.

These preliminary results show that we can model the stress reaction to a certain extent. However, a general model performs substantially worse than personalized models. The general model (based on the average data of all subjects) showed a very low $R^2$ value compared to the individual models of subjects 6 and 7. This is an indication that individual stress detection models improve the accuracy of the estimated stress level, compared to a general model. Therefore it seems necessary to adapt a stress detection algorithm to the user to achieve the most reliable estimation of stress level.

![Figure 5](image.png)

**Fig. 5.** Examples of continuous stress level estimations using logistic regression (top) and linear regression (bottom). Green areas indicate the rest conditions, red areas indicate the stress conditions. The blue line indicates the continuous estimation of stress level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

![Figure 6](image.png)

**Fig. 6.** ECG necklace sensor able to record and process ECG and EMG signals and the wristband sensor to record skin conductance and skin temperature (Holst Centre, Imec).

<table>
<thead>
<tr>
<th>Subject</th>
<th>Selected features</th>
<th>Adjusted $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>- Heart rate</td>
<td>0.112</td>
</tr>
<tr>
<td></td>
<td>- High frequency heart rate variability</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Skin conductance response rate</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>- Heart rate</td>
<td>0.481</td>
</tr>
<tr>
<td></td>
<td>- Static load of EMG signal of right trapezius muscle</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>- Skin temperature</td>
<td>0.223</td>
</tr>
<tr>
<td></td>
<td>- Skin temperature</td>
<td></td>
</tr>
</tbody>
</table>
is the European Interaction project (http://cms.interaction4stroke.eu/drupa). The aim of the project is to develop a sensing system that is able to monitor all interactions a person has with its environment and involves muscle activation patterns, posture and 3D forces on the foot. It is used to relate the performance of a stroke subject in his daily activities to his functional capacities and use this information to guide therapeutic interventions.

For applications such as the Stress Coach it is very important to sense not only the physiological parameters, but also context measures. These measures include physical activity, consumption of food, coffee, cigarettes, etc. All of these factors influence the physiology and will influence the parameter of interest: mental stress. If these context factors are sensed they could be accounted for or data that is influenced by these factors (e.g. just after a cup of coffee) could be excluded from the analysis.

5.2. Intelligence

The second element of the PCS, the intelligence, concerns the conversion of the sensing into a personal timely advice that is feasible and persuasive. This is probably the most challenging part of the system with many options to realize it. It is probably also the most complex one in the sense that it requires substantial input from other disciplines such as computer science to enable the reasoning and behavioral science to obtain a persuasive advice for a specific person. The framework that was developed for the Activity Coach is a very general one, suited for all PCS’s and provides a good starting point to research the different components separately before integrating them in a single PCS. It shows the four components of communication: intention, timing, content and representation, which together define the communication.

There are two ways forward to develop a persuasive coach. One way is to use a statistical model of likely behavior and use reasoning with the model, based on the sensing and contextual data to create persuasive communication. The human responses are taken into account to adapt the model and generate in a dynamic way the most persuasive advices to the person. The second way is to use behavioral models from psychology to generate the most persuasive advices. The best example of such a model is the Stages of Change (Prochaska and diClemente, 1986). This model describes four different stages in which a user can be with respect to his ambition to change his behavior: precontemplation, contemplation, action and maintenance. Based on the current stage of the user, coaching to the individual user can be tailored in various ways.

It is our intention to combine both approaches. A way forward could be that using a questionnaire beforehand, several relevant personality aspects can be determined and used in a user model, avoiding cold start problems. An example of this approach concerns the work of (Achterkamp et al., 2013), who defined 8 typical users, with relevant differences in responses, based on their stage of change as well as their level of self-efficacy. Interacting with the user regularly about his preferences and state of mind could adjust the parameters of the user model throughout the period of use of the system.

5.3. User interaction

The third element of a PCS concerns the user interaction. In our present systems the interaction with the user is done in the form of graphs to display physical activity, and text messages to convey the motivational coaching. As academics, the use of graphs may seem obvious to display data over time, but this may be unsuitable for a majority of people who are not used to such representations. Especially in the area of activity coaching, many examples exist of more imaginative and maybe more intuitive presentations. The Ubifit garden, a smartphone based system that displays the progress of daily activity through a flowering garden, may be the most well-known example (Consolvo et al., 2008).

An alternative could be to incorporate gaming technologies to include more fun elements into the feedback strategy of the Activity Coach, to obtain a positive effect on motivation and engagement (Lange et al., 2009). Gaming enables advanced awareness and personalization which are important aspects in behavioral change (Prochaska and diClemente, 1986) and enables engagement in using an intervention by applying game mechanics. As such mobile games could have an added value in changing daily activity behavior.

Another aspect of user interaction concerns the device to be used. It seems obvious that during the day, on the go, a smartphone is the best choice. But the average user interacts with many different devices during the day (e.g. television, laptop, tablet), most of which offer much more capabilities in terms of rich feedback. Multi-device systems are systems that extend across a range of different devices, allowing the system to support the user in a range of different contexts (Segerstahl, 2008). By extending the PCS to a multi-device system, it will become easier to reach the user by providing the feedback on the nearest and most suitable device. Large screen displays can offer more detailed insights into daily behavior, and can provide video based feedback, or full screen animations through embodied agents to offer coaching through more natural interaction.

5.4. Clinical application of PCSs

The concept of the PCS is that it is able to operate independently from a professional clinician but that the clinician is always present remotely to monitor progress, to adjust goals and to assist and motivate the user when required. This is the big difference with all the apps that are presently available. These do measure physiological variables and are often able to provide feedback, but in general there is no realistic goal setting and the interpretation of the results is possible when you are a healthy person but difficult or impossible when you are someone with health problems. This is also the problem with the “quantified self” approach: it is interesting to know all these things but they are not useful and they certainly will not contribute to a sustainable change of behavior.

One can discuss the place of the PCS in the treatment phase of people with chronic conditions. It looks obvious that the PCS can be a module in the treatment and as such has to be integrated in daily healthcare. There are an increasing number of chronic studies in which PCS’s were used to change behavior. The Pain PCS has been evaluated in a considerable number of patients, showing that the PCS treatment has similar outcome as traditional treatment, but also that it achieves this outcome without the efforts and time losses associated with regular visits to the clinic (Kosterink et al., 2010; Sandsjo et al., 2010). The Activity PHS has been evaluated in several chronic patients groups, showing promising results regarding health outcomes, adherence to the motivational cues and changes in activity behavior (Evering, 2013; Tabak et al., 2014a,b,c; 2013; van Weering et al., 2012). We also succeeded in integration of the Activity PCS within a 9-month technology-supported care program for COPD, which was applied as blended care in both primary and secondary care. This program consisted of (1) the Activity Coach, (2) a web-based exercise program for home exercising, (3) self-management of exacerbations via a triage diary on the webportal and (4) teleconsultation. Results show that such an integrated program indeed has potential (Tabak et al., 2014a,b,c). In addition, the Activity Coach is currently applied in several integrated care programs for e.g. cancer treatment and in rehabilitation programs.
5.5. Conclusions

Personal Coaching Systems might be the way forward to sup- port those people who want to develop and maintain a more healthy behavior. Other ways with a great involvement of humanity seem not possible, especially not scalable up to the level that is required to serve the increasing population of people with chronic conditions. The clinical studies show that PCSs seem capable to change behavior. This makes PCS a promising way forward, but PCS is still in its infancy. A lot of challenging research is still required involving multidisciplinary teams to create mature PCSs with a serious impact on our societal challenges.

Conflict of interest

None.

References


EU-OSHA. European opinion poll on occupational safety and health: European Agency for Safety and Health at Work; 2012.


op den Akker H, Tabak M, Jones VM, Hermens HJ. Reaching Kairos: adaptive prediction of the opportune moment for stimulating physical activity 2014b [submitted for publication].


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