Emotion Detection as a Design Opportunity for Wellness Applications

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Abstract
Our attitudes and moods may greatly effect on our everyday life experiences, perception, behavior and mental wellbeing. Emotion recognition and ability to detect e.g. positive or negative thinking offers a novel perspective for designing for wellness and behavior change. Especially, we are interested in utilizing nervous system as a data source. In this work-in-progress paper, we present our ongoing work in the domain and discuss it in the perspective of the workshop.

Author Keywords
Human behavior, emotion recognition, psychophysiological measurements. affective computing, electrothermal activity, heart rate, physiological signals.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

Introduction
So far emotions are one of the main differentiators between human beings and machines such as computers and robots. Emotions are interesting but challenging area for user experience (UX) design. Our emotions can have an effect on our performance e.g. in learning and completing tasks, and in interaction tasks,

nervous or frustrated people both behave as well as perceive things differently than calm and delighted users. Emotions are thus linked both to the utilitarian and hedonistic side of the holistic user experience [7], and form an interesting viewpoint for technology and application design.

Emotion recognition has traditionally used quite complex sensor or machine vision based technologies and has typically required robust and not mobile set-ups. However, the development in sensor technology and signal recognition is now increasingly overcoming these limitations and enabling shifting the emotion recognition from laboratories to real life context. This paves way for developing new applications, which can take into account the emotional state of the user as an input *in situ* or record it for later purposes.

In this paper, we present one example case from our work on emotion recognition and discuss it in the perspective of HCI. During the workshop, we wish to discuss the opportunities for utilizing emotion recognition in designing for wellness and behavior change.

Emotion Recognition

Human-computer interaction, ubiquitous computing and affective computing are all quite new and popular human-centered research areas which can all exploit automatic emotion recognition. Several applications already exist where emotion recognition has been used. Examples include medical applications in situations where person's ability to tell his/her emotions is reduced such as new born, aged people, patients with autism. Other examples include, e.g., a psychologist and a patient whose data is monitored during appointment, learning situations either in a classroom or online, and gaming applications [3,6,11].

Several theories to classify emotions exist depending on the field of the research. One widely used model (see Figure 1.) that majority of researchers accept is developed by psychology James Russell in 1977 [12]. This model describes the emotions by two dimensions: arousal and valence. The dimension of valence ranges from highly positive to highly negative or pleasantness to unpleasantness, whereas the dimension of arousal ranges from calm to excited. For instance, happy is very positive in valence and moderately in arousal while bored is moderately negative in valence and very low in arousal.

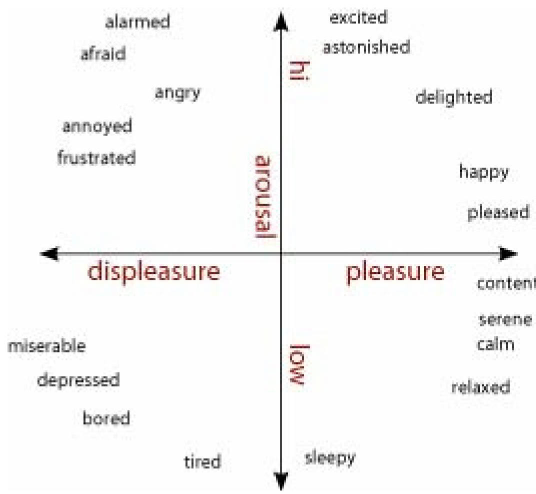

Figure 1. The two dimensions of emotion accorging to Russel's model [Russel]

Emotion can be expressed in humans by physiological, behavioral, verbal and/or neural mechanisms. Thus several methods in order to recognize emotions have been used such as facial expression from images or videos, gesture, speech and many physiological signals. Facial and speech expression were the first methods used to recognize emotions. Their performance is reasonable, even though they suffer from the user dependency meaning that, e.g. culture, gender and age may affect. In addition lighting conditions, eyeglasses and auditory noise induces their own challenges. Basically, it is easier to recognize arousal than valence using these methods. Yet, one major problem is that a person may try to hide his/her true emotions which can then result in wrong interpretation of the measurements.

Utilizing autonomic and/or central nervous system measurements for detecting emotions provides interesting means for affective computing. If the challenges of this approach, such as sensitivity to motion artifacts and difficulties in the interpretation, can be overcome, we could have an access to a data source which is more objective and where the person him/herself has no control over.

Physiological Signals for Affective Computing

Electrodermal activity (EDA) measures emotional arousal by measuring skin conductance, i.e. electrical changes in the skin. Skin is the only organ in humans that is mainly innervated by the sympathetic nervous system (SNS) which is known to activate during the so called fight-or-flight response. Interestingly, SNS is also activating e.g. during positive emotions or during the anticipation of something exciting [4]. Heart rate is highly regulated by the autonomic nervous system. The parasympathetic nervous system decreases the heart rate while sympathetic nervous system increases it. Thus it is obvious that emotions affect the heart rate and heart rate variability. From heart rate variability signal we can further calculate indexes describing the autonomic nervous system function [13]. In addition we can calculate the respiration rate that is related to arousal. Respiration is important in maintaining the physiological homeostasis and thus co-exists with emotions [8].

Case Study: Public Dissertation

In our experiments, we have recorded PhD students (n = 4) during their public dissertation in University of Oulu, Finland. For the PhD candidate, the event is a great personal milestone filled with strong emotions, containing stress, nervousness, even the fears of failure and finally relief with positive emotions if the dissertation is accepted. The dissertations in Finland are very formal situations and usually all closest family members, friends and faculty members attend. The sensors where put on at 10.30AM, the dissertation started at 12AM and the sensors were taken off after the post-dissertation coffee break. The total amount of data is four to six hours.

EDA was acquired using wrist-worn Affectiva Q™Sensor products (Affectiva Inc., Boston, United States), one for each wrist. The heart rate was measured using a Polar S810i (Polar Electro, Kempele, Finland) heart rate monitoring system that includes the chest band and a wrist-worn monitor. In addition, the dissertation was videotaped for further analysis and PhD students were interviewed before and after the dissertation for subjective experiences. In the analysis phase, the data were further processed for additional analysis but the details are however out of the scope of the workshop and not described here.

In Figure 2. we show an example of the EDA and heart rate signals measured in the dissertation day. Basic features of EDA include EDA level and EDA response amplitude, rate, rising time and recovery time. The EDA level is the smooth trend of the EDA curves (right hand EDA = blue curve and left hand EDA = green curve) it can easily see in the upper plot.

From electroencephalogram (EEG) measurements it is known that positive emotions are associated with increased activity in the left prefrontal cortex while negative emotions are associated with increased brain activity in the right side. Also stress has been connected with increased activity in the right prefrontal cortex [5,9].

According to Figure 2 there is asymmetry between the right and left hand EDA. The left brain hemisphere is responsible for controlling the right side of the body and the right brain vice versa. In the current example, the person is obviously suffering from stress and valence is more negative due to the increased level of his left EDA (right brain hemisphere is activated). There are some labels presenting the 1) start time of the dissertation, 2) the first question of the opponent and 3) the end of the dissertation with congrats and coffee and cake. The first question seems to induce a huge peak in the data for example. Before the dissertation PhD candidate was having a little panic attacks because he forgot to bring the thesis books to the lecture hall and had to do that in a hurry. This is easily seen from the figure.

The heart rate is about 140beats/min right before the dissertation (lower plot). It can be seen that heart rate decreases during the dissertation and rises quickly up when the coffee and cake is starting.

Discussion

The data shown in the previous example illustrates how today’s off-the-self wearable sensors provide the interesting information of the user’s emotional state in the everyday life use context. This offers interesting further opportunities for designing for wellness and behavior change.

Earlier examples of user interfaces that aim for increasing awareness of one’s behavior typically rely either on completely non-physiological device data, such as presented in [10] for detecting personal communication behavior patterns, or data the user manually enters to the device, e.g. in [1]. Physiological data enables detecting emotional information without a mediating technology. Emotion recognition technology can facilitate the opportunity to become aware of one’s emotional state, which can lead to conscious efforts for changing negative emotions to more positive ones. The awareness of the emotional state can also help the user to recognize (and, consequently, cope with or avoid) conditions which agitate him/her. One important application is also stress management. Stress is sometimes difficult to recognize and it is known to be harmful if a person is exposed to stress for a prolonged period of time.

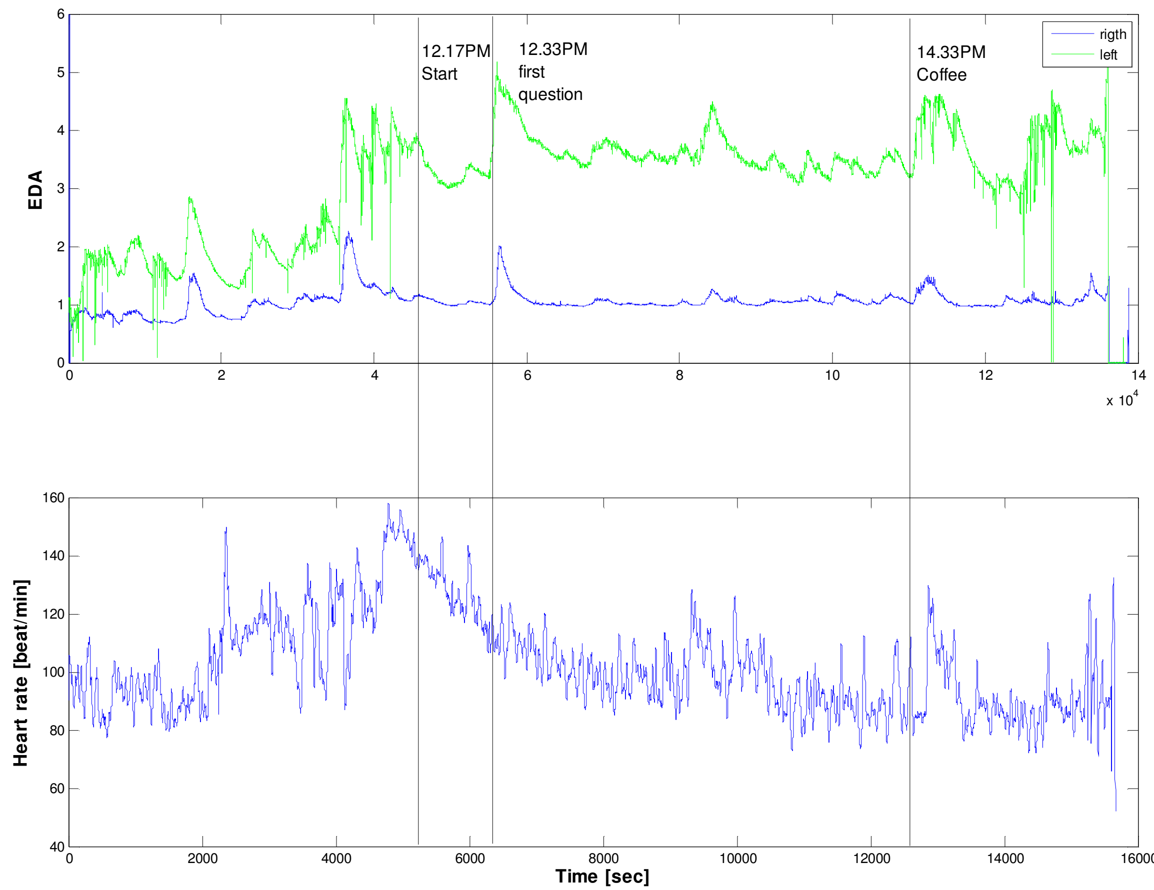

Figure 2. Physiological signals during PhD candidate's dissertation day. Electrodermal activity (EDA) in the upper plot, green curve presenting left and blue right wrist data. Heart rate is shown in the lower plot.

Our future work includes developing algorithms to detect different emotions of a person from physiological signals. Presently, we are including also other modalities such as facial expressions, speech and EEG. We are interested in utilizing the data in application or user interface design. In the workshop, we wish to discuss with other participants the possibilities and challenges related to using this approach in design for self-awareness and behavior change.

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