Using the EMFi chair to measure the user's emotion-related heart rate responses

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The research reported here is part of a multidisciplinary collaborative project that aimed at developing embedded measurement devices using electromechanical film (EMFi) as a basic measurement technology. The present aim was to test if an unobtrusive heart rate measurement device, the EMFi chair, had the potential to detect heart rate changes associated with emotional stimulation. Six-second long visual, auditory, and audiovisual stimuli with negative, neutral, and positive emotional content were presented to 24 participants. Heart rate responses were measured with the EMFi chair and with earlobe photoplethysmography (PPG). Also, subjective ratings of the stimuli were collected. Firstly, the high correlation between the measurement results of the EMFi chair and PPG, $r = 0.99$, $p < 0.001$, indicated that the EMFi chair measured heart rate reliably. Secondly, heart rate showed a decelerating response to visual, auditory, and audiovisual emotional stimulation. The emotional stimulation caused statistically significant changes in heart rate at the 6th second from stimulus onset so that the responses to negative stimulation were significantly lower than the responses to positive stimulation. The results were in line with previous research. The results show that heart rate responses measured with the EMFi chair differed significantly for positive and negative emotional stimulation. These results suggest that the EMFi chair could be used in HCI to measure the user's emotional responses unobtrusively.

Keywords: Affective computing, Emotion, Psychophysiology, Heart rate, Physiological user interfaces, Wireless monitoring, Human-computer interaction.

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1. Introduction

Affective computing is an emerging field of research that studies emotions in human-computer interaction (HCI). Emotions were long regarded as distracting factors to reason and intelligence. Thus, emotions that blur clear reasoning were thought of as something that should be avoided and they were not considered to be important in HCI. Today, however, it is widely acknowledged that emotions are important factors for both an intelligent and a meaningful life [Cacioppo & Gardner, 1999]. Accordingly, contemporary psychological research emphasizes the importance of emotions in human behavior and emotions are also being studied in the context of HCI.

Research has shown that emotions have a significant influence on human interaction and communication, cognitive processes, others' emotions, and motivation [Hietanen *et al.*, 1998; Isen *et al.*, 1987; Lang *et al.*, 1992; LeDoux, 1995; Surakka & Hietanen, 1998; Zajonc, 1980]. We begin to communicate emotions nonverbally immediately after birth with our first cry. Emotional communication forms the first and important interaction between an infant and a caregiver long before, for example, verbal communication. Also later on in our lives, emotions are important in social interactions. According to Zajonc [1980] practically all social phenomena involve emotions in some important way. Emotional communication helps to communicate intentions and behavioral tendencies to others. For example, emotions are important in the regulation of interaction. They show whether the interaction is going well or whether adjustments need to be made to improve the interaction [Oatley & Jenkins, 1996, p. 173]. Also, emotional expressions can have a significant effect on other people's emotions. For example, seeing another person smile spontaneously and genuinely may cause changes in the observer's physiology and emotional experience [Surakka, 1998; Surakka & Hietanen, 1998]. Thus, emotions can be contagious so that we experience similar emotional reactions as other people.

In respect to the interplay with cognitive processes, emotions are significantly involved in, for example, attention, perception, learning, memory, problem-solving, decision-making, and creative thinking [Davidson & Cacioppo, 1992; Isen, 2000; Oatley & Jenkins, 1996, pp. 251-284; Schulkin *et al.*, 2003; Zajonc, 1980]. Affective processing and cognitive processing are intertwined so that both have influences on each other. What is interesting, however, is that affective processing can have primacy over cognitive processing and, therefore, affective judgments can precede cognitive ones [Zajonc, 1980]. Affective and cognitive processing complement each other: emotions provide fast, rough, and sometimes automatic processing whereas cognition allows more precise processing when there is time for it.

Why should emotions, then, be considered in HCI? Firstly, HCI evokes emotions in the user. Affective reactions such as preferences, liking, or affective judgments on aesthetics influence our interaction with the computer. There is considerable evidence that HCI events have effects on the user's experienced emotions as well as physiology [Aula & Surakka, 2002; Klein *et al.*, 2002; Partala & Surakka, 2004; Scheirer *et al.*, 2002]. Studying these relations is important to gain understanding on emotions in HCI. Then, we can aim at designing information systems that take into account the effects that the systems have on the user's emotions.

Secondly, HCI involves information processing. Many cognitive processes are needed during the interaction with a computer. For example, attention and perception are needed to perceive objects on the screen. Then, higher cognitive processing is needed to make sense of what has been perceived. Learning and memory functions are also essential to maintain and extend the knowledge related to computer usage. Affective and cognitive processing influence each other and both contribute to information processing [Surakka *et al.*, 1999; Zajonc, 1980]. Thus, to understand human information processing the interaction of both cognition and emotion must be examined. At the moment, cognitive factors in human information processing are, at least to some extent, covered in HCI. In addition, the influences of emotions in information processing should also be considered.

Finally, by definition, HCI is about interaction and emotions are central in human interaction. Importantly, human interaction involves emotions even when the interaction partner is a computer. Various studies have shown that users communicate social behaviors, such as emotions, also to computers [Nass *et al.*, 1994; Reeves & Nass, 1996]. For example, users treat the computer with politeness and respond to a computer's flattery, apologies, and humor in a social manner similar to human-human interaction [Fogg & Nass, 1997; Morkes *et al.*, 1998; Nass *et al.*, 1999; Tzeng, 2004]. Thus, human-computer interaction involves also emotional communication between the user and the computer. However, traditionally the computer has not been very active in emotional communication. To sum up, emotions are important in human interaction, cognition, others' emotions, and motivation. All of the above are present also in the context of HCI. Therefore, it is important to study the effects that HCI has on the user's emotions and the effects that the user's emotions have on the interaction.

The starting point for affective computing is that emotion-related information must be acquired from the user in some way. One promising alternative is the use of psychophysiological measures. The advantages of using physiological measures are that physiological measures can reveal also involuntary emotional responses and information on the user's physiology is continuously available. However, traditional technologies for the measurement of physiological activity can be too obtrusive to be used in HCI. Therefore, measurement technologies that are unobtrusive, comfortable, and reliable need to be developed to make physiological measurements a feasible alternative for HCI and affective computing.

Through my work in the Research Group for Emotions, Sociality, and Computing I have been involved in a multidisciplinary collaborative project, funded by the National Technology Agency (Tekes), that developed embedded measurement methods based on electromechanical film (EMFi) technology. Our group's interest in the project was in methods that can be used to detect emotion-related physiological changes in the user. The EMFi chair, which was developed in the project, is an example of technology that enables unobtrusive measurement of heart rate. The aim of my research was to test if the EMFi chair could detect emotion-related changes in heart rate. If this technology proved reliable, it could be used in HCI to perceive information on the users' emotions together with other physiological and behavioral measures.

2. What are emotions?

Emotions are complex psychological, physiological, and social phenomena. They include changes at neurophysiological, neuromuscular, phenomenological, and behavioral levels. There is no one absolute definition of emotions but various definitions that describe the different aspects of emotions. There are also several theoretical approaches to emotions and the definitions of emotions vary partly according to the different theoretical approaches. Some theories stress the evolutionary functions of emotions, while others focus on cognitive processing of the emotion-eliciting situation (i.e. appraisal process), and yet others see emotions as social and cultural constructs. However, there are also similarities across the different definitions of emotions and the definitions are not mutually exclusive. Here, I will concentrate on the similarities and outline the essence of what defines an emotion.

Most emotion researchers agree that emotions involve components of physiology, experience and behavior [Keltner & Gross, 1999; Oatley & Jenkins, 1996, pp. 95-132; Zajonc, 1980]. Emotions are comprehensive phenomena that include changes in our neural systems and also in the musculature of our body. In addition to physiology, emotions have impacts on the phenomenological level. We experience, for example, joy, anger, fear or disgust. Furthermore, emotions cause changes in the behavioral level. For example, we may approach a pleasant situation or withdraw from an unpleasant situation. Also, emotions are very short-termed phenomena. Emotions last from seconds to a few minutes at the most [Oatley & Jenkins, 1996, pp. 124-125]. The short duration is one aspect that distinguishes emotions from moods and feelings. Unlike emotions, moods and feelings can last for hours, days or weeks.

According to Nesse [1990], biological systems are often described through their functions. Consequently, his definition of emotions is based on the evolutionary functions of emotions [Nesse, 1990, p. 268]:

> ”The emotions are specialized modes of operation shaped by natural selection to adjust the physiological, psychological, and behavioral parameters of the organism in ways that increase its capacity and tendency to respond adaptively to the threats and opportunities characteristic of specific kinds of situations”

A central function of emotions is their role in adaptation to environmental changes and the maintenance of equilibrium. From an evolutionary perspective, the essential function of emotions is to rapidly direct our actions and thereby adapt us to changing environments. Evolutionarily, it has been especially important for the survival of an individual that emotions are evoked rapidly. For example, threatening stimuli are processed fast and roughly via an affective pathway to make fast reactions possible [LeDoux, 1995]. The affective pathway does not involve the slower higher-order cognitive processing that takes place in our cortex. Instead, the processing is done more rapidly in the deeper parts of the brain, mainly in the limbic system. The limbic system is an inner brain structure that is evolutionarily older than the cortex and also more primitive species have similar structures. When threatened, cognitive reasoning would be too slow, and instead, emotions are needed to guide the behavior rapidly. It would be impossible to rationally scan through all possible alternatives. Emotions help us to instantly skip some alternatives that are not worth a closer consideration and direct us towards other alternatives that are more preferable [Zajonc, 1980].

It has been argued that a change in action readiness and a change in behavioral tendency essentially define emotions [Frijda, 1986; Frijda *et al.*, 1989]. For example, in a situation that is evaluated as threatening fear guides our behavior. Our body starts to prepare us for "fight or flight" behavior by regulating our metabolism and hormonal levels. Also, our cognitive processing is modified, for example, our attention gets narrower to enable us to focus on the cause of the alarm reaction [Surakka *et al.*, 1998]. Thus, emotions can bias cognitive processing by activating or inhibiting the processing of specific stimuli. When a stimulus is judged to be threatening we may start running to escape the threat, and thus, our behavior has changed.

Also, emotions are closely linked to motivation. Emotions can be both motivating (cause of motivation) and motivated (consequence of motivation) [Averill, 1980; Frijda, 2000]. Emotions are strong motivating factors for human behavior. The action readiness involved in emotions "arouses behavior and drives it forth" [Frijda, 2000]. However, emotions can also be motivated. For example, emotions are often elicited by a motivation to achieve a certain goal. Thus, motivation can become actualized as an emotion when an event promises the satisfaction or frustration of the motivation [Frijda, 2000]. For example, if you are motivated to accomplish a certain goal, anger is easily evoked when something comes in the way to interfere your progress towards the goal.

However, human emotions are more complicated than merely hard-wired responses to possibly threatening or favorable situations. We evaluate events in our environment and pick up the ones that are significant and meaningful. Then, we categorize the events as favorable or unfavorable. These evaluative judgments are called appraisals [Arnold, 1960; Frijda *et al.*, 1989]. Some researchers argue that appraisal is necessary for all emotions. According to Arnold [1960, p. 174] the appraisals are direct, immediate, and automatic processes. What is specific about human behavior is the extent to which learning and cognitive processing affect the appraisals [Cacioppo & Gardner, 1999]. According to social constructivists, culture and learned social rules shape the content of the appraisals and, thus, emotions are also culturally defined [Cornelius, 2000].

Finally, there is a broad agreement that emotions are social phenomena that often include expressive components [Keltner & Haidt, 2001]. We communicate our emotions to others, for example, through facial expressions, gestures, and speech. It has been argued that the meaning of emotion and the present functions of emotions (as opposed to the evolutionary functions) will be found at a sociocultural level [Averill, 1980].

As emotions involve changes at multiple levels, they should also be measured in multiple ways to get information on the changes at different levels. Neurophysiological and neuromuscular changes can be measured with psychophysiological signals, phenomenological effects can be measured by ratings of the subjective experiences of emotions, and behavioral changes can be measured, for example, by observing behavior.

2.1. Structure of the affective space

The relations between different emotions have been widely studied. There are two main approaches to understanding emotions. One approach is the discrete model of emotions and the other is the dimensional model of emotions. The discrete and dimensional models are not mutually exclusive. It is possible that discrete emotions locate in specific areas of the dimensional model [Christie & Friedman, 2004; Izard & Ackerman, 2000].

According to the discrete model of emotions there is a set of discrete primary emotions that are also referred to as basic emotions. All other emotions can be defined though these basic emotions [Ekman 1992, 1999]. There is some variation between emotion researchers in what they consider to be basic emotions and how many basic emotions there are. According to Ekman and his colleagues [1983], the set includes anger, fear, disgust, happiness, sadness, and surprise. Basic emotions are accompanied by distinctive universal signals that are expressed and recognized in the same way in all, even isolated, cultures [Ekman, 1999]. Also, basic emotions are thought to have distinctive patterns of autonomic nervous system and central nervous system activation [Ekman, 1999; Ekman *et al.*, 1983].

In the dimensional model of emotions, emotions are defined by an affective space that consists of two or more dimensions. Bradley and Lang [1994] proposed three dimensions: valence, arousal, and dominance. Out of these, valence and arousal are the most commonly used dimensions. The valence dimension represents the pleasantness of emotional experience ranging from unpleasant to pleasant. The arousal dimension represents experienced arousal ranging from calm to excited. The valence and arousal dimensions are thought to represent underlying appetitive and aversive motivational systems that guide us to approach or withdraw from different stimuli [Lang *et al.*, 1992]. This kind of affective categorization and responding is so critical that with certain kinds of stimuli there are primitive, hard-wired processes for it [Cacioppo and Gardner, 1999].

Bradley, Lang, and their colleagues have accumulated evidence for the dimensional model of emotions in a series of studies [Bradley *et al.*, 1996; Bradley & Lang, 1994; Bradley & Lang, 2000; Cuthbert *et al.*, 2000; Ito *et al.*, 1998; Lang, 1995; Lang *et al.*, 1990; Lang *et al.*, 1993]. They have used psychophysiological and neurophysiological measures and collected evaluations of the subjective emotional experiences. These data have provided support for the dimensional model of emotions and the motivational tendencies behind the model. They have also developed sets of visual and auditory stimuli called the International Affective Picture System (IAPS) and the International Affective Digitized Sounds (IADS) [Bradley & Lang, 1999; Lang *et al.*, 1999]. The IAPS and the IADS stimulus sets provide a standardized set of emotionally provocative stimuli that are well studied and categorized on the dimensions of valence and arousal.

There is also a standardized way of collecting subjective evaluations of the emotional experiences evoked by the dimensionally organized stimuli [Bradley & Lang, 1994]. Subjective experiences are commonly measured with rating scales that represent the valence and arousal dimensions. In the theoretical background of the dimensional model, emotions are linked to motivational tendencies of approach and withdrawal. However, subjective ratings of the motivational tendencies associated with emotions have rarely been collected. Therefore, in addition to valence and arousal ratings, also approach-withdrawal ratings should be collected.

3. Affective computing

Picard [1997] defined affective computing as "computing that relates to, arises from, or deliberately influences emotions". Affective computing involves studying what kind of effects emotions have in HCI and how emotions can be implemented into interaction design. For example, what kind of influences the interaction has on the users' emotions and how users' emotions can be recognized and regulated by interaction design.

Affective interaction has two sides. On one hand, it involves the user communicating emotional information to the system and the system recognizing and using that information and, on the other hand, it involves the system expressing emotional information to the user and the user understanding that information. A computer can recognize emotions, for example, from facial expressions, voice, physiological signals, or self-report measures [Brave & Nass 2003; Picard, 1997, p. 50-55]. A computer can express emotions, for example, through the emotional content of messages or the acoustic qualities of speech [Johnstone & Scherer, 2000]. In the case of embodied agents, also nonverbal cues such as postures, gestures, and facial expressions can be used [Brave & Nass, 2003; Hudlicka, 2003; Picard, 1997, p. 55-60].

There are several reasons why emotions should be taken into account in HCI. One reason is that HCI events evoke emotions in the user causing changes in the user's experienced emotions and physiology [Aula & Surakka, 2002; Klein *et al.*, 2002; Partala & Surakka, 2004; Scheirer *et al.*, 2002]. It is important to study how different user interfaces and interaction techniques affect the user's emotions to be able to improve them on the part of the emotional experience. The emotional responses related to software use may also have health outcomes. For example, the results of Dennerlein and others [2003] suggest that interface designs that frustrate the users can increase the exposure to physical risk factors. There is considerable evidence that stress and negative emotions have an effect in the development of diseases such as the coronary heart disease [Leventhal & Patrick-Miller, 2000]. Also, there is evidence that positive emotions may help in recovering from negative emotions [Fredrickson & Levenson, 1998; Fredrickson et al., 2000]. Thus, it is of importance what kind of emotions user interfaces evoke in the user.

Klein *et al.* [2002] studied the effects of affective support on users' experienced emotions and interaction behavior. The participants played a computer game. For half of the participants the game included pre-programmed delays during which the character froze on the screen preventing the user from playing the game. The game session was immediately followed by an interactive questionnaire containing text and buttons. In one condition, the users received emotional support in the form of empathy and sympathy. In another condition, the users got to "vent" their emotions, meaning that they got to report what they felt, but they did not receive any kind of emotional support. In the last condition, the users' emotions were completely ignored. They found that, among the users who experienced frustrating delays during the game, the users who received affect-support were willing to continue the interaction significantly longer than the users in the other two groups. This result suggests that emotional regulation by an interface agent could relieve negative emotions that are caused by problematic interaction [Klein *et al.*, 2002].

Another reason is that it is clear that HCI involves also cognitive processing. Therefore, it is essential to acknowledge the interaction between emotional and cognitive processes, which means that emotions affect our cognitions and vice versa. Through this interaction, emotions can enable or prevent the optimal use of human potential [Cacioppo *et al.*, 2000]. For example, Isen and her colleagues [Isen *et al.*, 1987; Isen, 2000] have found that emotional state influences creative problem-solving. They have conducted a series of experiments involving tasks that are generally thought to require creative problem solving. In one of their experiments, the participants were provided with a candle, a box of tacks, and a book of matches and they were asked to fix the candle to the wall so that it will burn without dripping wax on the floor. In one condition, the participants viewed five minutes of a comedy film and in the other condition they viewed five minutes of a neutral film before the problem-solving task. The participants in the positive-affect condition produced significantly more solutions than participants in the neutral condition [Isen *et al.*, 1987].

In another experiment, the participants were asked to perform the Remote Associates Test [Isen *et al.*, 1987]. In the test, three words are presented to the participant who should discover a fourth word that relates to each of the given three words. The items were pre-tested and categorized into easy, moderate, and difficult according to the percentage of participants who were able to invent the correct solution. The experiment included items of three difficulty levels: easy, moderate, and difficult. In a positive-affect condition, the experimenter thanked the participants for coming and gave a bag of candy before beginning the experiment. In a neutral-affect condition, no such efforts were made. The results showed that in the easy items there were plenty of correct solutions and in the difficult items very few subjects had given correct answers. In the moderate items, the participants in the positive-affect condition gave significantly more correct answers than the participants in the neutral-affect condition [Isen *et al.*, 1987]. Creative thinking and problem-solving are often needed also in HCI. Thus, to enhance creative thinking we can aim at evoking more positive emotions in the user.

Similar results of the beneficial effects of positive emotions on problem-solving have also been found in the context of HCI. Aula and Surakka [2002] studied the effects of emotional feedback on subjects' cognitive performance, psychophysiology, and experienced emotions. Emotional feedback was given with a speech synthesizer in a computerized problem-solving task. The feedback was emotionally negative, neutral, or positive and it was given independently of the actual performance. They found that task times were significantly shorter after positive than after negative feedback. The feedback did not affect error rates. They also found that pupil size returned back to baseline significantly faster after positive feedback than after negative feedback indicating a beneficial effect on the user's physiology.

Recently, Partala and Surakka [2004] studied the effects of affective interventions that were given after the users had been exposed to pre-programmed mouse delays in an interactive problem-solving task. After the users encountered these delays, they were provided with either emotionally positive or emotionally negative interventions or no interventions at all. The interventions were given with a speech synthesizer. They found that problem-solving performance was significantly more successful after positive interventions than after negative interventions or no interventions at all. Also, smiling activity measured with facial muscle electromyography (EMG) was significantly higher during positive interventions than during negative interventions or no interventions at all. Furthermore, after the positive interventions smiling activity was significantly higher and frowning activity (i.e. knitting one's eyebrows) was significantly more decreased than after the no intervention condition. Thus, emotions have a significant effect on cognitive processing in HCI.

A third reason why emotions are important in HCI is that emotions are central in all human communication and interaction. Nass and his colleagues [Nass *et al.*, 1994; Reeves & Nass, 1996] have shown that human-computer interaction is fundamentally social and that users regard the computer as a social actor. The users express social behaviors, including emotions, also to computers although the users know that the computer is not a living being with feelings or other human qualities [Nass *et al.*, 1994]. Several effects found in human-human interaction (such as social responses to flattery, apologies and humor) have been found to hold also in human-computer interaction [Fogg & Nass, 1997; Morkes *et al.*, 1998; Nass *et al.*, 1994; Reeves & Nass, 1996; Tzeng, 2004]. For example, it is known that interviewees will give socially desirable responses that are biased in the favor of the interviewer. Thus, if a human interviewer asks questions of him- or herself, the respondents will give more positive answers than if the questions are asked by an outside party. In a study by Nass and his colleagues [1999] users performed a task with a computer and then were interviewed about the performance of that computer. They found that users gave more positive evaluations of the computer's performance when the same computer conducted the interview as opposed to when identical interviews were conducted by another computer or in a paper-and-pencil format. This result was observed both in text-based and speech-based interaction with the computer. Thus, a social rule found in human-human interaction applied also when interacting with a computer.

Emotions are an important part of human interaction, even when interacting with computers. It is important to take into account, on one hand, the effects that HCI has on the user's emotions and, on the other hand, the effects that the user's emotions have on the interaction. With knowledge on the user's emotions we can study, for example, how systems should adapt their functioning according to the user's emotions or how user's emotions can be regulated by interface design. One aim of emotion regulation is that by providing affective support and feedback we can aim at reducing the drawbacks that negative emotions cause on cognitive performance. However, it should be remembered that negative emotions are not only harmful but they are important, too. For example, it has been argued that conflicts and failure are an important part of the learning process [Aïmeur *et al.*, 2001]. Thus, the goal of affective computing is not to avoid negative emotions but to help users deal with them and recover from the physiological activation associated with them. Computers can pursue this aim, for example, by providing the user with affective support and interventions [Klein *et al.*, 2002; Partala & Surakka, 2004].

4. Measuring the user's emotions

Measuring the user's emotions is valuable for several approaches to affective computing. First, these measures can be used as an interaction technique to adapt system functionality. Recently, there has been considerable effort, in HCI in general, to transfer the burden of adaptation from the user to the system. In addition, there has been a shift in thinking about the computer as a tool to thinking about the computer as a partner who might even have social intelligence [Hudlicka, 2003]. Emotionally intelligent systems recognize the user's emotions and adapt their functioning during the interaction according to interpretations of the user's emotional state and the current context [Picard, 1997]. For example, Scheirer *et al.* [2002] measured blood volume pulse (BVP) and skin conductivity to make inferences about the user's state of frustration caused by malfunctioning software. The participants played a computer game where they completed puzzles as quickly and accurately as possible to win a cash reward. At random intervals, the mouse was jammed to evoke frustration in the participants. They used Hidden Markov Models to analyze the physiological responses and were able to recognize a frustrated state from a non-frustrated state better than by random guessing.

Emotional intelligence is not necessary for all systems, but there are some application types that may benefit from it. Especially socially interactive applications such as embodied conversational agents need to infer the user's emotions to be able to engage in social interaction using, for example, emotion regulation strategies [Picard, 1997]. Another example of an application area where emotional intelligence might be of value is learning applications [Picard, 1997, p. 93-97]. As emotions significantly influence cognitive processes, such as learning, taking the user's emotions into account might improve learning outcomes and subjective learning experiences.

Second, it is important to study what kind of effects different interaction techniques or interaction events have on the user's emotions. With this kind of understanding the interaction can be developed in a direction that has beneficial effects on the user's emotions and cognitive performance by the means of emotion conscious interaction design. Measuring the user's emotions can also be beneficial in affective evaluation of interfaces as an extension of regular usability testing [Cockton, 2004; Norman, 2002; Reeves & Nass, 2003]. The competitiveness of software products is not only dependent on the efficiency and effectiveness of a product but it involves also user satisfaction in which delivering positive user experiences plays a central role. The non-productive values of a product can be evaluated by measuring the user's emotions - not by measuring the user's performance.

Currently, information on the user's emotions is mostly collected with self-report measures either during the experimental session or immediately after the session. However, both alternatives have problems. Collecting emotional reports during the session will seriously interfere with the tasks that are being performed as well as the emotional experience itself [Brave & Nass, 2003, p. 91]. Retrospective reports, on the other hand, may be biased because of forgetting and responding in a socially desirable way [Brave & Nass, 2003, p. 91; Ericsson & Simon, 1993]. Objective measures of the user's emotions during the session along with post-session subjective measures would improve the reliability of the results. One way to get objective information is the use of physiological measures. The use of physiological signals also enables perceiving emotion-related information which the user is not even conscious of and which, thus, could not be obtained, for example, by subjective evaluations. Therefore, objective measures of emotions, such as physiological measures, might be profitable in both affective computing research and applied usability testing.

To sum up, measures of the user's emotions can be used to adapt the interaction according to the user's emotional states. Also, physiological and subjective measures of emotions are important tools in studying emotions in HCI. Finally, measures of the users' emotions can extend usability evaluations to examine also the emotional experiences related to software use.

4.1. Emotion-related physiological measures in HCI

One way to measure the users' emotions is to use physiological signals. The most commonly used measures of human physiology include those that measure central nervous system activity (for example, electroencephalography, EEG), autonomic nervous system activity (for example, cardiorespiratory measures, skin conductivity measures, and pupil size measures), and the electrical activity of muscles (for example, electromyography, EMG) [Cacioppo *et al.*, 2000].

The human nervous system is divided into central nervous system (CNS) and peripheral nervous system (PHS) and furthermore, the PHS is divided into somatic nervous system (SNS) and autonomic nervous system (ANS) [Cacioppo *et al.*, 2000]. The SNS controls, among other things, voluntary muscle innervations and sensory information coming from the body. The ANS controls, among other things, vital functions such as the innervations of the heart and the digestive system. The physiological responses controlled by the ANS are partly involuntary and reflex-like but they are also subject to voluntary control and learning (e.g. operant conditioning such as biofeedback)

[Frijda, 1986, p. 145]. Therefore, information on the user's spontaneous activity can also be obtained with measures of ANS activity.

Hence, the use of physiological signals in HCI can be divided into two classes. First, physiological signals can be utilized for voluntary interaction as a deliberate input method. For example, physiological signals can be used as a pointing technique in which voluntarily directed gaze is used for moving the cursor and voluntary facial muscle activation is used for making selections [Partala *et al.*, 2001; Surakka *et al.*, 2004]. Second, physiological signals can be used to measure the user's spontaneous activity, that is, activity that is not voluntarily controlled. This means that a system can react to the user without the user's deliberate voluntary input. When used in this way, physiological signals extend the interaction beyond voluntary control [Allanson, 2002].

There are several advantages and disadvantages in using physiological measurements to obtain information on the user's emotions. As said before, physiological measurements have the advantage that some physiological reactions are partly involuntary. Thus, information on spontaneous reactions can be obtained more reliably when using physiological signals than when, for example, modeling facial expressions that are under social control [Surakka and Hietanen, 1998]. Another advantage of using physiological signals is that the information is continuously available [Wilson & Eggemeier, 1991]. Continuous access to information is essential because information on the user's emotional state is needed throughout the interaction, not only at the point when, for example, subjective evaluations are asked.

Furthermore, the use of physiological measures need not disturb the primary task [Wilson & Eggemeier, 1991]. By monitoring emotion-related physiological changes, information on the user's emotional state can be obtained without interrupting the task and the flow of the interaction. For example, if a researcher or the system itself would ask: "Did you like this function", the primary task would be interrupted. However, a disadvantage of the traditional sensors used in measuring physiological reactions is that they are intrusive and may cause distractions to the user. This is probably one of the reasons why physiological measures have not been so widely adopted in HCI research. However, recent advances in sensor technologies have made it possible to measure physiology without interrupting the interaction [Harland *et al.*, 2002; Picard & Healey, 1997].

One challenge in the use of physiological measurements is the large variability in physiological signals. There is variation between individuals and variation within the same individual even during the same day. Factors such as temperature, posture, smoking, time of the day, or time from the last meal may cause variations in heart rate [Siddle & Turpin, 1980, p. 154]. Therefore, it is difficult to make reliable inferences from physiological signals on an individual level. Rather, inferences are based on several observations that are averaged over several individuals. Even averaged information is valuable when studying users' emotions as a dependent measure in affective computing or usability research. However, when using physiology to control the interaction, inferences need to be made on an individual level. This problem is alleviated by the fact that affective applications can be taught to recognize the physiological changes and typical features of one specific individual [Picard *et al.*, 2001]. Also, when studying responses to HCI events, we calculate the physiological response that is relative to a baseline period before the event.

Another issue in physiological measurements is that physiological signals are sensitive to artifacts. Artifacts are changes that are caused, for example, by body movements. To overcome the difficulties in making inferences from physiological data efficient methods for signal processing are needed so that artifacts can be detected in real time and the variations in the signal can be dealt with [Wilson & Eggemeier, 1991]. Also, emotion recognition is more reliable when multiple physiological signals are used together instead of using only one signal. If one signal has artifacts, the other signals may still provide valid data. In HCI, the information that is acquired with physiological measures should also be complemented by subjective and behavioral information as well as information on the current context.

5. Heart rate measures and emotions

Cardiac activity is a very common physiological measure and it has been used in scientific research for a relatively long time. There are various measures that indicate cardiac activity and one of them is heart rate. Heart rate is a promising physiological measure for HCI because it can provide information on the user's spontaneous reactions: it cannot be controlled as easily as, for example, respiration or facial activity such as smiling or frowning. Heart rate is generally associated with autonomic nervous system activation [Brownley *et al.*, 2000]. It has been found that ANS activation is related to emotional processing, and thus heart rate measures can be used to make inferences about emotions.

The ANS is further divided into the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS prepares the body for quick action in emergency situations and the PNS takes care of conservation of energy when the emergency is over. The activation of the ANS is a result of covarying activation of the sympathetic and the parasympathetic parts [Brownley *et al.*, 2000]. In general, the sympathetic part is more active during emotions and when the emotional reaction fades out the parasympathetic part regains control normalizing the organism's physiology. Thus, when sympathetic activation dominates heart rate accelerates and when parasympathetic activation dominates heart rate decelerates.

It has been argued that specific emotions can be recognized from specific patterns of physiological activation [Levenson, 1992; Ekman *et al.*, 1983]. This means that different emotions and different patterns of physiological activation are somehow related. When physiology is examined in the framework of the dimensional emotion model, we seek to discriminate emotions on the basis of valence and arousal dimensions. Heart rate has been found to reliably discriminate between pleasant and unpleasant emotions [Bradley at al., 1996; Bradley & Lang, 2000; Lang et al., 1993; Palomba et al., 1997]. There is evidence that heart rate has a general tendency to decelerate in response to visual and auditory emotional stimulation. Furthermore, heart rate has shown a sustained deceleration in response to unpleasant stimuli [Bradley at al., 1996; Bradley & Lang, 2000; Hare *et al.*, 1971; Lang et al., 1993; Palomba et al., 1997].

Why, then, is a sustained cardiac deceleration observed during negative stimulation? Basically, aversive, possibly threatening stimuli cause an alarm reaction that may result in overt behavior – a fight or flight response. When a new stimulus is perceived, heart rate decelerates slightly at first as a result of parasympathetic activation. Heart rate deceleration becomes larger and prolonged if the stimulus is perceived arousing and negative. During this period resources are allocated to focused attention. This period may also include freezing, which means that movement is sustained [Lang *et al.*, 1997]. On the contrary, if the stimulus is perceived to be neutral or positive, heart rate begins to recover from the initial mild deceleration. Fight and flight behaviors associated with negative stimuli require an acceleration in heart rate as well as in respiration so that the body will be prepared for the quick action. Heart rate deceleration during the attentive phase will eventually turn into sympathetically driven heart rate acceleration only immediately before the actual fight or flight behavior [Lang *et al.*, 1997]. In threatening situations of the real-life we may attack or escape. However, such overt defense behavior is never or very rarely observed in response to media [Lang *et al.*, 1997].

Emotions can be induced in various ways and the induction method affects the physiological responses. Emotions can be evoked in participants by presenting pictures, sounds, or videos that have a varying emotional content. A decelerating heart rate response is observed in such emotional perceptual tasks [Bradley *et al.*, 1996; Bradley & Lang, 2000; Coles 1984; Hare *et al.*, 1971; Lacey & Lacey, 1970; Lang et al., 1993; Lang et al., 1997; Palomba et al., 1997]. Instead, heart rate has shown different patterns in studies where emotions have been evoked, for example, by asking participants to relive past emotional experiences or by using directed facial action task. In the directed facial action task, participants voluntarily produce facial expression prototypes of different emotions muscle by muscle according to instructions [Ekman et al., 1983; Levenson et al., 1990; Levenson et al., 1992]. These tasks differ in their nature from an emotional perception task that is relatively passive and requires focused attention. When performing a directed facial action task or reliving past emotional experiences, heart rate responses have been mostly accelerating [Ekman et al., 1983; Levenson et al., 1990; Levenson et al., 1992]. It has been argued that effort-related changes in respiration due to the production of facial expressions result in accelerating heart rate [Boiten, 1996].

5.1. The EMFi chair

In HCI, one of the essential issues in perceiving physiological information from the user is that it should not distract the interaction. Traditional heart rate measurement methods can, in some cases, be too obtrusive to be used in HCI. For example, the use of electrocardiogram (ECG) requires that wired electrodes are attached to the user. Thus, the use of this technology can cause distraction and discomfort for the user. Although wireless technologies decrease the distraction and enable mobility, the trouble of attaching the electrodes still remains. While traditional measures can be useful for many types of HCI related research, it would be ideal if no sensors at all were attached to the user.

Thus, methods for unobtrusive measurement of, for example, heart functioning are very much needed. Recent advances in sensor technologies have enabled more unobtrusive and comfortable measurement of the users' physiological changes than before. The advancements have made it possible to embed various sensors into different objects in the environment or to develop sensors that need not be in contact with the user [Harland *et al.*, 2002; Picard & Healey, 1997]. Such developments are essential for physiological measurements to become a feasible alternative. Recently, our research group has been involved in the development of one example of embedded technology for physiological measurements. The EMFi chair[1] is a device prototype for unobtrusive heart rate measurement (Figure 1).

Figure 1. The EMFi chair.

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[1] The EMFi chair has been developed in a multidisciplinary collaborative project funded by the Finnish National Technology Agency (Tekes). It was developed by Jukka Lekkala's research group at the Technical Research Centre of Finland, VTT Information Technology. The signal analysis algorithms were developed by Alpo Värri's research group at the Digital Media Institute of Tampere University of Technology.

The EMFi chair is a regular office chair that is embedded with sensors of electromechanical film (EMFi) in its seat, backrest, and armrests. EMFi is a low-cost cellular polypropylene film that senses changes in pressure [Paajanen *et al.*, 2000] making the calculation of heart rate possible. Heart rate measurement with the EMFi chair is based on ballistocardiography (BCG), which measures the recoil that spreads through the body as a result of a heartbeat.

In a workstation environment, the chair is a natural choice for sensor placement because the user is sitting on the chair most of the time allowing continuous access to heart rate data. Furthermore, sensors embedded in a regular office chair will not attract the user's attention and thereby will not cause distractions to the interaction. A chair has been used as an underlaying for sensors previously for measuring postural changes to detect the user's interest [Kapoor *et al.*, 2001; Tan, 2000].

I was interested in the possibility of using the EMFi chair in affective computing. So, the present aim was to test if the EMFi chair had the potential to detect emotion-related heart rate variations reliably. Thus, emotional responses to negative, neutral, and positive emotional stimulation were studied with the EMFi chair technology. Another objective was to compare the measurement results obtained with the EMFi chair with results that were obtained by a more traditional heart rate measurement method, namely, earlobe photoplethysmography (PPG). Visual, auditory, and audiovisual stimuli with negative, neutral, and positive emotional contents were presented to participants while their heart rates were measured with the EMFi chair and with earlobe PPG. After the experiment, the participants rated the subjective emotional experiences evoked by the stimuli with valence, arousal and approach-withdrawal dimensions.

6. Methods

6.1. Participants

Twenty-six voluntary participants took part in the experiment. The participants were recruited from the university campus area and by e-mail from Computer Science students' mailing list at the University of Tampere. There were 15 women and 9 men with a mean age of 26.7 years ranging from 19 to 58 years. Data from two participants was excluded due to poor signal to noise ratio and due to a misunderstanding in the use of the arousal scale in the subjective ratings. Thus, the statistical analyses were based on the data from 24 participants.

6.2. Stimuli

The experiment consisted of visual, auditory, and audiovisual stimuli selected from the International Affective Picture System (IAPS) and from the International Affective Digitized Sounds (IADS) stimulus sets [Bradley & Lang, 1999; Lang *et al.*, 1999] (see Appendix 1 for further information). The IAPS and IADS stimulus sets include picture and sound stimuli, respectively. The audiovisual stimuli were simultaneously presented combinations of pictures and sounds that were contextually similar, for example, the picture and the sound of a laughing baby.

Three stimulus categories were used. They were negative arousing (e.g. a picture and a sound of a laughing baby), neutral (e.g. a picture and a sound of an office), and positive arousing (e.g. a picture and a sound of an attack). The stimuli were chosen based on their IAPS and IADS mean ratings of valence and arousal so that the positive and negative stimuli were equally arousing and the neutral stimuli were neutral both on the valence and on the arousal dimension (Table 1). In table 1, valence and arousal values for audiovisual stimuli are estimates that were obtained by calculating a mean from the mean rating of the IAPS picture and the mean rating of the IADS sound.

Table 1. The IAPS and IADS mean ratings of valence and arousal for the selected stimuli.

	Modality	Negative	Neutral	Positive
Valence ratings	Visual	2.4	3.5	7.4
	Auditory	2.7	3.7	7.5
	Audiovisual	2.5	5.0	7.4
Arousal ratings	Visual	7.0	6.2	6.6
	Auditory	6.8	5.9	6.3
	Audiovisual	6.6	4.7	6.5

6.3. Equipment

Continuous heart rate (beats/min) was measured with the EMFi chair and with Tunturi earlobe photoplethysmography (PPG). PPG measures the pulsatile component of skin blood flow in peripheral circulation which has the same frequency as heart rate [de Trafford & Lafferty, 1984]. The PPG sensor is a pair of an infrared-transmitting diode and a phototransistor that detects the light. It can be attached, for example, to an earlobe. The diode emits infrared light that penetrates the earlobe. However, when a blood pulse fills the capillaries of the earlobe, the amount of infrared light that passes through the earlobe decreases [de Trafford & Lafferty, 1984]. Heart rate can then be calculated from these blood pulse volume changes.

The sampling rate of the EMFi chair was 500 Hz. The EMFi signal was digitized with a Quatech DAQP-16 digitizing card to a PC computer with a Windows XP operating system. The stimulus presentation during the experiment and the rating of the stimuli after the experiment were controlled by E-Prime© experiment generator [Schneider *et al.*, 2002] running on a PC computer with a Windows 98 operating system. The visual stimuli were presented on a 15″ Nokia 500 Xa LCD display in a 1024×768 resolution at a distance of approximately 100 cm from the participant's eyes. The auditory stimuli were presented through loud speakers at a comfortable constant volume level.

6.4. Procedure

First, the laboratory was introduced to the participant. Then, the participant was seated on the EMFi chair and the ear sensor was attached to the right earlobe. As a cover story the participant was told that the ear sensor measured changes in skin temperature. The participant was asked to sit still and watch and listen to the stimuli carefully. S/he was also asked to keep his or her eyes on the screen. When everything was ready, the experimenter left the room. Then, the participant sat still for half a minute before the stimulus presentation was begun.

The experiment consisted of three stimulus blocks: visual, auditory and audiovisual. The three stimulus blocks were presented in subsequent sessions lasting approximately four minutes each and separated by a one minute resting period. The experiment was counterbalanced by varying the order of visual, auditory, and audiovisual stimulus blocks across the participants. Each block consisted of five negative, five neutral and five positive stimuli. Thus, the total number of stimuli in the experiment was 45. The order of the stimuli within each of the three blocks was randomly varied for each participant. All stimuli were 6-second long and they were separated with 10-second interstimulus intervals. The display was black during the intervals.

After the experiment, the participant rated the stimuli. Each stimulus was rated on three nine-point (1-9) scales. The scales included valence, arousal, and approach-withdrawal scales, where the end points represented unpleasant – pleasant, calm – arousing, and a tendency to withdraw from the stimulus – a tendency to approach the stimulus respectively. In all of the scales, the middle of the scale represented a neutral experience. The scales appeared on the display and the ratings were given with the digit keys of the keyboard. The use of the scales was explained to the participant who first rated three practice stimuli that were not used in the actual experiment. Each stimulus was first rated on the valence, then on the arousal, and finally on the approach-withdrawal scale. Each stimulus was repeated three times so that one of the three scales appeared after each presentation. When the participant gave a rating, the scale disappeared and a beep indicated that the rating had been recorded. Visual, auditory, and audiovisual stimuli were rated in separate blocks. The order of the blocks and the order of stimuli within a block were randomly varied for each participant. Finally, the participant was debriefed about the actual purpose of the study and the EMFi chair. The experiment lasted approximately one hour.

6.5. Data analysis

First, artifacts were detected from the EMFi chair data and the PPG data by an algorithm developed at the Digital Media Institute of Tampere University of Technology. Artifacts are erroneous measurements results that physiological data inevitably include. For example, larger body movements cause artifacts in heart rate measurements. The detected artifacts were then coded as missing values. As a result, 4.13 % of the EMFi chair data and 2.50 % of the PPG data were discarded.

Then, a Pearson correlation was calculated between the EMFi chair data and the PPG data to compare the similarity of the measurements obtained by the two methods. Both of the data included over 12,000 values. The correlation was significant, $r = 0.99$, $p < 0.001$, suggesting that the two methods measured heart rate nearly identically. Thus, further statistical analyses were performed only to the EMFi chair data.

Second, the EMFi chair data was baseline corrected using a 2-second pre-stimulus baseline. In the baseline correction, a baseline value, which is, for example, a mean of a two-second period before stimulus presentation, is subtracted from all subsequent values. This procedure is necessary because of the great variation in physiological measurements that makes the comparison of absolute values inappropriate. For the statistical analyses, stimuli that included ≥ 50 % of missing values (due to artifact removal) during the baseline period or during the stimulus presentation period were discarded from further analysis. As a result, 9.9 % of the EMFi chair data was left out from the statistical analyses.

Then, the EMFi chair data was categorized into three groups according to the emotional content of the stimuli (negative, neutral, and positive). A mean value of all the stimuli within a category was calculated for each participant and each time point. Thus, each category contained six mean values (1…6 seconds from stimulus onset) for each participant. The EMFi chair data was analysed so that a one-way repeated measures ANOVA and associated post hoc pairwise comparisons were performed separately for each second. All the reported *p*-values in post hoc pairwise comparisons were Bonferroni corrected.

To analyze how the individual mean responses fit to the overall mean responses, averaged heart rate responses to negative and positive stimulation were calculated and plotted for each participant. The plotted individual graphs were visually examined and classified according to criteria that are defined in detail in the next chapter.

7. Results

7.1. Heart rate measures

In general, the response to emotional stimulation was decelerating (Figure 2). Heart rate decelerated the most in response to negative stimulation. The deceleration was also more prolonged in response to negative stimulation than in response to positive or neutral stimulation. Responses to positive stimuli were decelerating only during the first two seconds and after that the heart rate began to return towards the baseline. Thus, the recovery to baseline was faster during positive stimulation than during negative or neutral stimulation.

To test whether there were differences in the heart rate responses associated with negative, neutral, and positive stimuli six one-way repeated measures ANOVAs (i.e. one ANOVA per each second) with emotional content (negative, neutral, positive) as a factor were performed. The ANOVAs showed a significant effect at the last second of the six-second long stimulus presentation period, $F(2, 46) = 4.27$, $p < 0.05$. Post hoc pairwise comparisons showed that at the 6th second the responses to negative stimuli were significantly lower than the responses to positive stimuli, $t(23) = 3.23$, $p < 0.05$. There were no significant differences between responses to positive and neutral emotional stimulation or between responses to negative and neutral emotional stimulation.

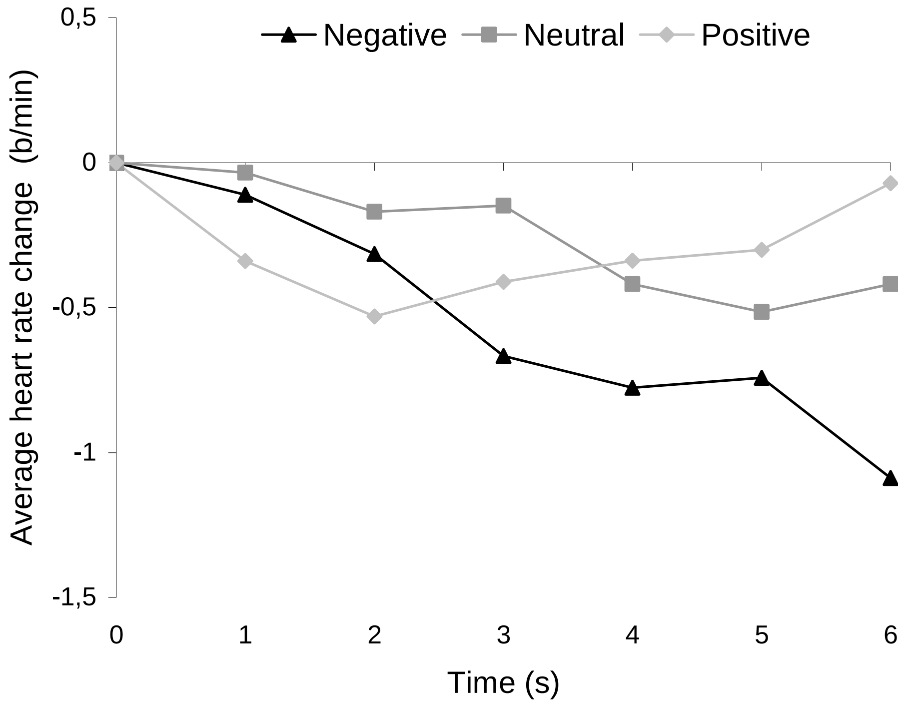

Figure 2. Averaged heart rate responses to negative, neutral, and positive stimuli.

The match between individual mean responses and the overall mean responses, in Figure 2, was also compared. The individual mean responses to negative and positive stimuli were visually examined and classified using the following criteria. If the responses to positive and negative stimuli differed so that the negative graph was below the positive graph at least half of the time, and if the positive graph was clearly above the negative graph at the stimulus offset, then the match was defined as good. If one of the two criteria, but not both, was met, then the match was defined as adequate. In the case that the positive and negative responses could not be clearly differentiated from each other then the responses were defined to be overlapping. Otherwise the match was defined to be conflicting.

In example (a), in Figure 3, the negative graph is below the positive graph all the time and the positive graph is also clearly above the negative graph at the stimulus offset and, thus, the match is good. In example (b), the positive graph is clearly above the negative graph at the stimulus offset but the positive graph is below the negative graph most of the time making it an adequate match. In example (c), the positive graph is mostly below the negative graph and at the stimulus offset the positive graph is not clearly above the negative graph and, thus, the match is conflicting. In example (d), the positive and negative graphs do not clearly differ by a visual examination and, thus, the responses are overlapping by the previous definition.

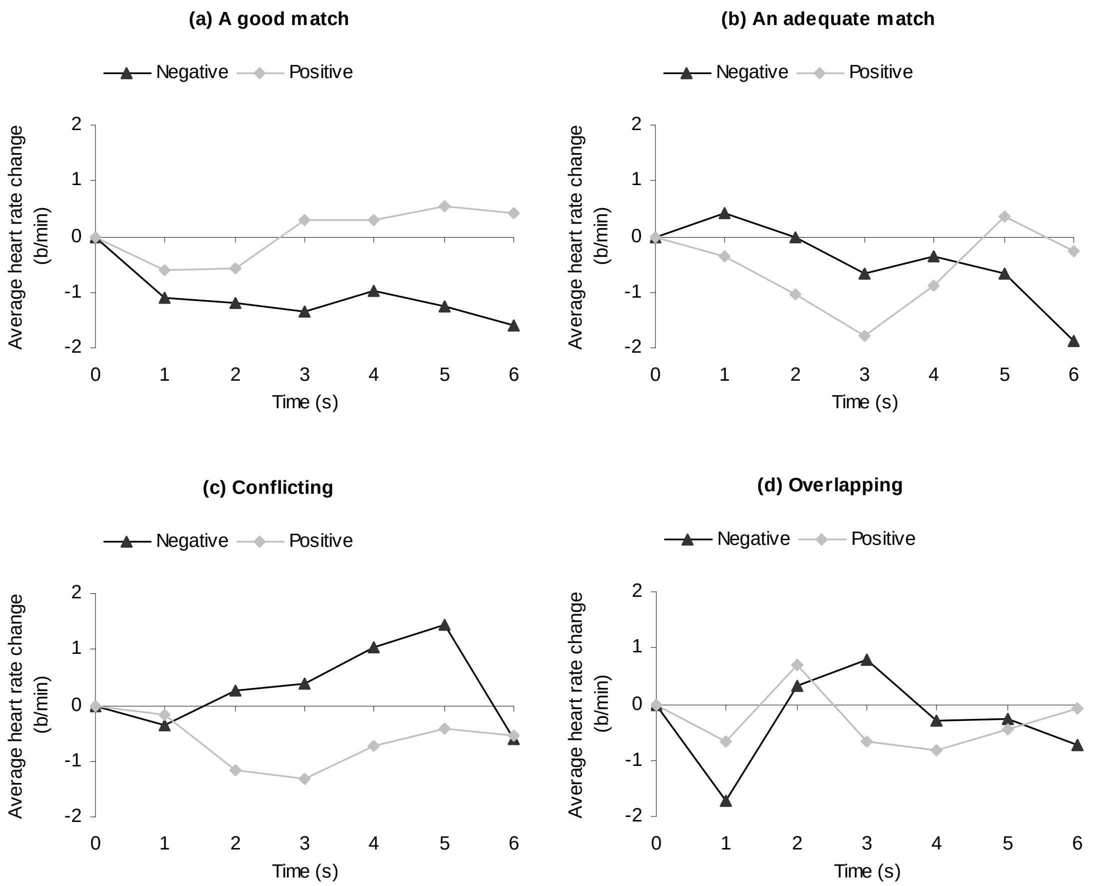

Figure 3. Examples of individual mean responses.

The examination of the individual mean responses to positive and negative responses revealed that 45.8 % of the individual mean responses were well in line with the overall mean responses and 16.7 % were adequately in line with the overall mean responses. Together, these two classes make up 62.5 % of all cases. In 20.8 % of the cases, the positive and negative responses in the individual mean profiles were in conflict with the overall mean response. In 16.7 % of the cases, the positive and negative responses were overlapping.

7.2. Subjective ratings

To test whether there were differences between the subjective ratings of negative, neutral, and positive stimuli in the valence, arousal, and approach-withdrawal ratings, three separate one-way repeated measures ANOVAs were performed. The ANOVAs showed a significant effect in the valence ratings, $F(2, 46) = 328.51$, $p < 0.001$; in the arousal ratings, $F(2, 46) = 65.72$, $p < 0.001$; and in the approach-withdrawal ratings, $F(2, 46) = 167.08$, $p < 0.001$. The mean ratings of the stimuli are presented in Figure 4.

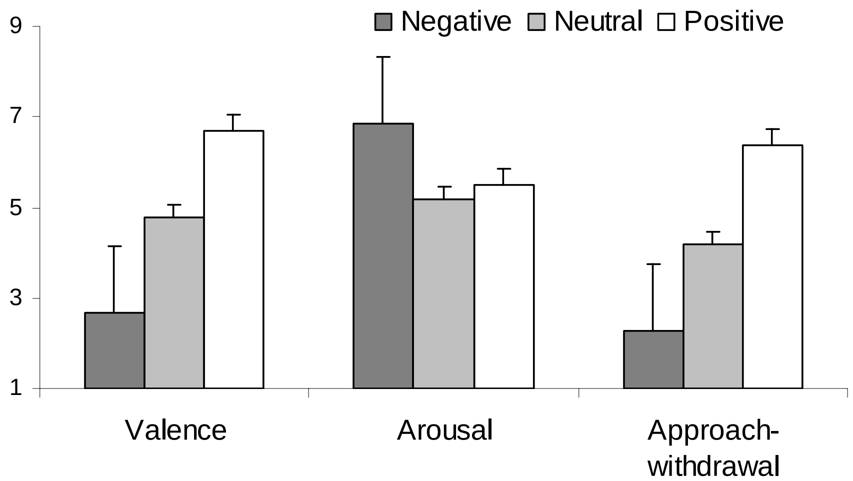

Figure 4. Mean ratings and standard errors of mean (S.E.M.) of all stimuli.

Post hoc pairwise comparisons of the valence ratings showed that positive stimuli were rated significantly more positive than negative stimuli, $t(23) = 22.03$, $p < 0.001$. Further, the ratings of positive stimuli were significantly more positive than the ratings of neutral stimuli, $t(23) = 14.87$, $p < 0.001$. Also, neutral stimuli were rated significantly more positive than negative stimuli, $t(23) = 13.59$, $p < 0.001$.

Post hoc pairwise comparisons of the arousal ratings showed that negative stimuli were rated significantly more arousing than positive stimuli, $t(23) = 8.56$, $p < 0.001$. Also, negative stimuli were rated significantly more arousing than neutral stimuli, $t(23) = 12.04$, $p < 0.001$. Arousal ratings for positive and neutral stimuli did not differ significantly.

Post hoc pairwise comparisons of the approach-withdrawal ratings showed that positive stimuli were rated significantly more approachable than negative stimuli, $t(23) = 16.86$, $p < 0.001$. Also, positive stimuli were rated significantly more approachable than neutral stimuli, $t(23) = 10.94$, $p < 0.001$. Finally, neutral stimuli were rated significantly more approachable than negative stimuli, $t(23) = 8.39$, $p < 0.001$.

8. Discussion

Firstly, the results showed that the measurement results of the EMFi chair were nearly identical with the measurement results of earlobe PPG as suggested by the significant correlation between them. Secondly, the results showed that heart rate had a general tendency to decelerate in response to visual, auditory, and audiovisual emotional stimulation. Heart rate decelerated the most in response to negative stimuli. At the last second of the six-second long stimulus presentation, the difference between responses to negative and positive stimulation was statistically significant. Heart rate response to positive stimulation recovered near to the baseline at the end of the stimulus presentation period whereas heart rate response continued to decelerate during the whole period of negative stimulation. Thus, heart rate showed distinctive responses to positive and negative emotional stimulation. The results are in line with previous research showing a decelerating heart rate response to visual and auditory emotional stimulation and a greater deceleration in response to negative stimulation [Bradley *et al.*, 1996; Bradley & Lang, 2000; Palomba *et al.*, 1997]. Together, these results suggest that the EMFi chair could be used to reliably detect the user's emotion-related heart rate responses.

The match between the individual mean responses and the overall mean responses to negative and positive emotional stimulation was also analyzed. In

62.5 % of the cases, the individual mean responses were well or relatively well in line with the overall mean responses to negative and positive stimulation.

The results of the subjective ratings of the stimuli showed that negative, neutral, and positive stimulation induced emotional experiences in the participants as expected. The emotional experiences related to stimuli with positive, negative, and neutral emotional contents differed significantly. Valence and approach-withdrawal ratings were significantly different for all emotional contents. However, for arousal ratings there were significant differences between ratings of positive and negative stimuli and between ratings of negative and neutral stimuli. Arousal ratings of positive and neutral stimuli did not differ significantly. The results of the subjective ratings are mostly in line with the IAPS and IADS ratings [Bradley & Lang, 1999; Lang *et al.*, 1999]. Thus, the subjective ratings showed that positive, negative, and neutral emotional stimulation caused distinctive emotional experiences and behavioral tendencies. The negative stimuli evoked an emotional experience with high negative valence, high arousal, and a clear tendency to withdraw away from the stimuli. On the contrary, the positive stimuli evoked a highly positively valenced, somewhat less arousing emotional experience and a clear tendency to approach the stimuli.

According to the results of the subjective ratings, the participants experienced the negative stimuli as significantly more arousing than the positive stimuli. However, according to the IAPS and IADS mean ratings [Bradley & Lang, 1999; Lang *et al.*, 1999] the mean arousal levels of the selected stimuli were nearly equal: 6.50 for the positive stimuli and 6.80 for the negative stimuli. In the subjective ratings results of the present experiment, the mean arousal levels were 5.49 for positive stimuli and 6.86 for negative stimuli. Thus, the experienced mean arousal of the positive stimuli was lower than expected. One possible explanation is cultural differences between the American participants of the IAPS and IADS studies and the Finnish participants of the present study. Because of the difference in experienced arousal between negative and positive stimuli, the present results might not result purely from the difference in valence between positive and negative stimuli but to some extent also from the difference in arousal between positive and negative stimuli.

The results also suggest that heart rate recovered towards the baseline faster after positive emotions than after negative emotions. During positive emotional stimulation, heart rate decelerated only during the first two seconds and then began to revert back towards the baseline. During negative emotional stimulation, heart rate continued to decelerate during the whole stimulus presentation period. Brosschot and Thayer [2003] have found similar results that indicate a prolonged cardiovascular activation after negative emotions. They did not use emotional stimulation to evoke emotions in the participants but asked the participants to report the emotions they were experiencing in real life at certain time points. They collected subjective evaluations of the current emotional state (i.e. ratings of valence and arousal), reports of the current amount of physical activity, and heart rate recordings that were measured with a sports heart rate meter. These three measures were reported on eight occasions during one day. On each occasion, entries of all measures were given three consecutive times at five-minute intervals (i.e 0, 5, 10 minutes). When negative emotions were experienced during the first time point, a prolonged heart rate response five minutes later was likely, even if the negative emotion was, then, not experienced anymore. The result shows a prolonged heart rate response after negative emotions.

In the context of HCI, Aula and Surakka [2002] observed similar results indicating prolonged pupillary responses after negative affective feedback. They studied the effects of affective feedback on cognitive performance and psychophysiology in a computerized problem-solving task. During the task, the users received emotionally negative, neutral, and positive feedback that was given by a speech synthesizer independently of the actual performance. They found that pupil size reverted back to the baseline significantly faster after positive affective feedback than after negative or neutral affective feedback.

Thus, the present findings and the results of Aula and Surakka [2002] and Brosschot and Thayer [2003] support each other and suggest that recovery from autonomic arousal is faster after positive than after negative emotions. Brosschot and Thayer [2003] argued that a prolonged physiological activation after negative emotions could be a significant link between negative emotions and somatic disease.

In respect to generalizing the present results to real HCI use scenarios, there are some limitations. Firstly, in the present experiment, the analyses were made offline after averaging the results over all participants and all stimuli with the same emotional content. Also, the individual responses were averaged over all stimuli with the same emotional content. However, in real use the user's physiological responses should be detected in real-time and from single responses to different HCI events. Thus, further research is needed to make real-time inferences on a single user in a more realistic HCI setting and also over longer time periods than six-second long stimuli. In a recent study, Partala, Surakka, and Vanhala [2005] showed that it was possible to estimate the participant's emotional experiences on the basis of electrical facial muscle activity in real-time. They were able to categorize emotionally negative and positive experiences with a reasonable accuracy using relatively simple algorithms.

Secondly, it should be noted that the significant changes occurred only at the last second of the stimulus presentation although it was a tightly controlled laboratory experiment with a number of participants and a number of stimulus repetitions. It is difficult to make inferences on psychological events based on physiological signals in settings other than tightly controlled laboratory experiments where the observed changes are attributable to the controlled variable because careful steps are taken to ensure that other variations are eliminated as far as possible. For example, Ward and Marsden [2003] measured software induced changes in the user's physiology in more loosely controlled settings comparable to usability testing and they concluded that significant changes were observed in response to some major interface events, such as the sudden appearance of a pop-up window, but not in response to more subtle events.

More research is needed to be able to conclude whether the EMFi chair could be used to distinguish heart rate responses to negative and positive events when interacting with software. It should be remembered, however, that being able to recognize the user's emotions in real use scenarios is not the only goal but conducting research in controlled software usage situations in a laboratory setting is also valuable to get information on the user's emotions while they interact with software. Then, we can learn what kind of effects HCI events have on the user's physiology and experienced emotions and how these effects could be regulated through emotion-conscious interface design. One of the ultimate goals of affective computing is that we would be able to recognize the user's emotions in real use situations in real-time. To get there, we need basic research that is conducted in controlled laboratory experiments to understand which signals respond the best to certain HCI events and to expand the knowledge on how to interpret the signals. The EMFi chair offers an unobtrusive method for heart rate measurement, thus, adding to the repertoire of possible emotion-related physiological sensing.

In general, unobtrusive measurement methods pose ethical concerns due to the possibility that the person who is being measured is unaware of the measurement that is taking place. However, unobtrusiveness does not demand full invisibility. Invisibility is required and can be justified only to the extent that is needed for the measurement technology not to distract the user. In an HCI setting, it is important that the user is always informed about measurements that are taking place. To inform the user about the augmented nature of an appearingly normal object, a device such as the EMFi chair could, for example, be equipped with a visible logo. Another alternative for providing the information to the user is using ethical contracts as suggested by Reynolds and Picard [2004]. These contracts provide the users with information on what is being measured, who has access to the measurement data, and how that data is used. Also, when using embedded sensors, it is possible to leave the control over the measurement to the users by providing a possibility to easily switch off the measurement when they wish to do so. In respect to ethical issues, sensors that require physical contact may be experienced as less invasive for privacy than, for example, video recording, which reveals the user's identity [Scheirer *et al.*, 2002].

To sum up, emotions should be taken into account in HCI because HCI events evoke emotional responses in the users and because emotions are central in human interaction, cognition, motivation, and health. We need to measure the user's emotions to get information on what kind of emotions the user is experiencing. One way to get information on the user's emotions is to use physiological measurements. As emotions are increasingly brought into HCI unobtrusive measurement methods for measuring the user's emotions are essential.

The findings of this study showed that the EMFi chair offers a possibility for reliable and unobtrusive heart rate measurement. The advantages of the EMFi chair are that it does not draw the user's attention to the measurement and in the workstation environment the user is nearly constantly in contact with the chair. Besides the workstation environment, the EMFi chair could also be used, for example, in different rehabilitation situations where heart rate measures would be useful but the visibility of medical instruments would harm the intended atmosphere. Also, a device like the EMFi chair could be used for physiological sensing in automobiles to make inferences, for example, on driving safety.

The use of physiological measures in affective computing seems promising and, although more research is needed, the present results suggest that the EMFi chair could be used in HCI to make inferences on the user's emotional responses. In the present experiment, heart rate responses measured by the

EMFi chair differed significantly for positive and negative emotional stimulation. Measures of the user’s heart rate can be used as an interaction technique or as a dependent measure in affective computing research or in applied usability testing together with other physiological measures, behavioral measures, and relevant contextual information on the state of the interaction. If we can make inferences on the user’s emotions, we can design interfaces that regulate the user’s emotions and minimize the harmful effects that negative emotions can have on the user’s cognitive performance, use experience, and physiology.

9. Summary

As emotions are increasingly brought into HCI, it is essential that the user's emotional responses could be measured unobtrusively without interrupting the interaction. Emotion-related heart rate responses were measured with unobtrusive EMFi chair technology during emotionally provocative visual, auditory, and audiovisual stimulation. The emotional content of the stimuli was negative, neutral, and positive. Heart rate responses measured by the EMFi chair differed significantly for positive and negative emotions. In general, the heart rate responses were decelerating. Heart rate decelerated significantly more in response to negative than in response to positive or neutral emotional stimulation. This result is in line with previous research. The findings of this study suggest that emotion-related heart rate responses could be measured reliably with the EMFi technology.

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Appendix 1: The experimental stimuli

The IAPS and IADS mean ratings of valence and arousal for the stimuli used in the experiment are listed in tables 1, 2, and 3.

Table 1. Ratings of the visual stimuli.

	IAPS #	IAPS Name	Valence	Arousal
Positive	8080	Sailing	7.73	6.65
	8185	Skydivers	7.57	7.27
	5470	Astronaut	7.35	6.02
	8180	Cliff Divers	7.12	6.59
	8400	Rafters	7.09	6.61
Mean			7.37	6.63
Neutral	2220	Male Face	5.03	4.93
	3550_2	Coach	4.92	5.13
	7560	Freeway	4.47	5.24
	8060	Boxer	5.36	5.31
	1390	Bees	4.50	5.29
Mean			3.50	6.16
Negative	6230	Aimed Gun	2.37	7.35
	3150	Mutilation	2.26	6.55
	6550	Attack	2.73	7.09
	6350	Attack	1.90	7.29
	9250	War Victim	2.57	6.60
Mean			2.37	6.98

Table 2. Ratings of the auditory stimuli.

	IADS #	IADS Name	Valence	Arousal
Positive	220	Boy Laugh	7.64	6.14
	226	Laughing	7.32	6.37
	353	Baseball	7.66	6.63
	601	Colonial Music	7.17	5.95
	820	Funk Music	7.58	6.52
Mean			7.47	6.32
Neutral	101	Cat	4.72	4.76
	105	Puppy Cry	4.76	5.44
	325	Traffic	5.12	4.98
	425	Train	4.93	4.78
	704	Touchtone	5.10	4.22
Mean			3.73	5.93
Negative	626	Bombs	2.70	7.44
	116	Wasp	2.74	6.84
	627	Howling Rain	2.74	7.32
	501	Plane Crash	3.16	6.38
	502	Engine Fails	2.30	6.25
Mean			2.73	6.85

Appendix 1 continued.

Table 3. Ratings of the audiovisual stimuli.

	IAPS #	IAPS Name	Valence	Arousal	IADS #	IADS Name	Valence	Arousal
Positive	2050	Baby	8.20	4.57	110	Baby Laugh	7.92	6.04
	8370	Rafting	7.77	6.73	815	Rock N Roll	8.02	7.25
	8490	Roller Coaster	7.20	6.68	360	Roller Coaster	6.90	7.36
	8030	Skier	7.33	7.35	352	Sports Crowd	7.36	6.91
	5450	Liftoff	7.01	5.84	415	Countdown	6.38	6.62
Mean			7.50	6.23			7.32	6.84
Neutral	7550	Office	5.27	3.95	320	Office	4.83	5.04
	7211	Clock	4.81	4.20	311	Crowd	5.44	4.52
	9411	Boy	4.63	5.37	410	Helicopter	5.19	5.50
	1313	Frog	5.65	4.39	171	Country Night	5.49	4.51
	6930	Missiles	4.39	4.88	699	Bomb	4.46	5.07
Mean			4.95	4.56			5.08	4.93
Negative	3500	Attack	2.21	6.99	286	Victim	2.03	7.35
	2800	Sad Child	1.78	5.49	261	Baby Cry	2.84	6.49
	6312	Abduction	2.48	6.37	290	Fight	2.59	6.22
	3250	Open Chest	3.78	6.29	287	Cardiac Arrest	1.90	7.38
	6510	Attack	2.46	6.96	730	Glass Break	3.10	6.49
Mean			2.54	6.42			2.49	6.79