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# A Physiological Approach to Affective Computing

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## 1. Introduction

Psychologists, cognitive scientists and neuroscientists have studied emotion for more than a century (Darwin, 1872). Only recently has computer science research shown an increasing interest in incorporating emotion into computers (Picard, 1997; Whang *et al.*, 2003). Given that the computers are built to operate logically and computing work is intended to be rational, however, this interest is rather challenging and controversial (Hollnagel, 2003). As technological developments progress at a rapid pace, computers are ubiquitous and disappearing. They become regarded even as 'social agents' rather than just a machine (Marakas *et al.*, 2000). As a result, it is deemed that communication with computers should be more natural and friendlier than the traditional one chiefly relying on hand driven movement using the mouse or the keyboard. Efforts are underway to improve the interface with more intrinsic medium through voice, face expression or gesture and computers are getting human-like (Marsic *et al.*, 2000). Even so it is still far short of what is needed.

What we feel conveys an essential context in the human-human communication and computers with the capability to recognize and express the emotion is definitely friendlier and more of human-like. There exist some theoretical foundations what brings up certain emotion and somatic changes. It is certain, however, that emotion naturally arises in our daily life when we encounter a certain situation or make a risky decision. Emotion affects many different aspects of human behavior, cognition and decision making (Cowie *et al.*, 2001), often leading to some heuristic shortcuts and cognitive biases (De Martino *et al.*, 2006). Surely it is a challenging task to build computers to serve the users mechanically, intelligently or even further emotionally. Recent research has reported some cases where emotion aware computing may be useful. For example, people like to signal their emotional state in email or SMS with so-called emoticons (Curran & Casey, 2006). Emotion recognition also has a part to play in tutoring, remote education (Nasoz & Lisetti, 2006) and computer entertainment such as game (Mandryk & Atkins, 2007).

Despite the role of emotion that has been shown in the literature, it is not clear the effect of emotion on the human computer interaction (HCI). Many studies have analyzed the artificial data that were taken from the subjects off-line and used them to recognize what emotional states they were in. On the other hand, our approach is made with on-line data that were read from the sensors attached on the mouse. This physiological data were

processed to build an algorithm to enable the computers to understand the emotion in real-time. What we aim is to build an emotional computer which is more sympathetic with the computing work and behave more intelligently in recognizing users' emotion and responding to it in an appropriate manner.

## 2. Related literature on emotion recognition

Emotion is not a simple phenomenon. The term emotion, despite being much used in our daily life, is still controversial in academia (Forgas, 1989). In the context of affective computing, however, the exact definition may not be consequential as the focus is pointed to the automatic recognition of the expressed emotion or feelings. We will use the term emotion to include both affect and mood. Emotion and mood are related but distinct phenomena in terms of cause, duration, control, experience, and consequences (Beedie *et al.*, 2005). The term emotion will be used to refer to a relatively intense state that has been induced for a short duration and involves a definite cause (Forgas, 1992). Given this definition, an emotion differs from a mood because the former is typically about something specific, its onset/offset time-course is more rapid and it is more intense at its peak.

Research has shown that emotion impacts upon human behavior and decision processes in a variety of ways and its effects can occur in the perception, storage and use of information. For instance, affect can influence the processes of search, acquisition and retrieval of information (Bower, 1981) and the selection of decision strategies for a task (Isen & Means, 1983). It may be contrary to the view that emotion can lead to irrational thinking of human and thus should be inhibited. Rather emotion can help people act more intelligently and choose more rational choice (Bechara & Damasio, 2005). This argues that people would behave differently what emotional state they are in. More relevant to affective computing, emotion, as an important medium of expression, plays a crucial role in human-human communication.

Among the theories for categorizing or structuring emotions, two main views include either discrete or dimensional. The former claims the existence of universal 'basic' emotions. One of the typical perspectives was from Ekman (1993), who empirically showed six basic emotions of anger, disgust, fear, joy, sadness and surprise. An alternative view on emotion is a dimensional approach, assuming the existence of two or more major dimensions which describe different emotions and distinguish between them (Russell, 1980). There is still debate on which view best captures the structure of emotion even though some attempts have been made to merge the two (Russell & Barrett, 1999). Both perspectives have received little unanimous support from physiological studies (Cacioppo *et al.*, 2000).

Here introduced is a brief overview of computing approaches to automatic human affect recognition. The references in Table 1 are representative of existing empirical studies and are by no means exhaustive. More details on the automatic recognition of human emotion as well as more complete lists of references can be found in Picard (2000). Table 1 shows primarily two approaches to automatically recognizing human emotion based on audio or visual cues that are expressed through linguistic or paralinguistic channels. Machines need to be trained to learn the patterns that signal emotion as contained in speech, face, bodily movements or in combination. Unfortunately, none of the studies perfectly estimate human emotion embedded in these channels. This may be attributed partly to the fact that pattern learning algorithms are imperfect to learn the properties of the human emotion. Data may get noised due to sensing capability or be subject to vulnerable to unwanted thoughts

during data capturing. An alternative explanation could be related to the nature of emotion expression and regulation, often hidden and contextually dependant (Ekman & Friesen, 1975). Some studies (see for a review Murray & Arnott (1993) & Scherer (2003)) have empirically investigated acoustic and prosodic characteristics such as pitch variables and speaking rate, which are taken into emotion recognition models and this approach has shown varying detection rates (Devillers *et al.*, 2005). Table 1 shows some of the recognition accuracy of empirical evidence in the range of between 50% (Nakatsu *et al.*, 2000) and 83.5% (Grimm *et al.*, 2007). It should be noted that the accuracy may be dependent on the number of emotional states attempted in the studies. Facial expressions and movements such as a smile or a nod (Essa & Pentland, 1997; Fasel & Luettin, 2003) have been also extensively used to map into emotion (see Fasel & Luettin (2003) for a review). Due to delicate face muscle movements, however, some emotional states (e.g., happiness) seem to be easier to recognize than others (e.g., fear). Motion captured data with markers placed on human body are collected and analyzed to recognize emotion (Bianchi-Berthouze & Klemsmith, 2003; Castellano *et al.*, 2007). Or an attempt has made to analyze images of body gestures. The problem for this method is related to separating the movement from the background. People may have to wear a certain colored dress or need to be trained for some manual initial markings (see for a review Wang et al. (2003)). Thus some research tends to take a multimodal approach in consideration of the importance of non-verbal cues (Kapoor *et al.*, 2007; Zhihong *et al.*, 2007). Interestingly enough, in communicating feelings, non-verbal cues (e.g., 38% for voice tone & 55% for gestures) often carry more informative messages than do verbal ones (7%) (Mehrabian, 1971).

| Approaches | Recognition Rates |
|---|---|
| Vocal | 50% (Nakatsu et al., 2000),73% (Lee et al., 2006), 83.5% (Grimm et al., 2007) |
| Facial | 98% (Essa & Pentland, 1997), 86% (Anderson & McOwan, 2006), 78% (Ioannou et al., 2005) |
| Body gestures | 84-92% (Kapur et al., 2005),44-90% (Castellano et al., 2007), 60% (10% noise added) (Bianchi-Berthouze & Klemsmith, 2003) |
| Physiological | 61.2% (Kim et al., 2004), 70-90% (Lisetti et al., 2003), 81% (Picard et al., 2001) |
| Multimodal | 31-98% (voice, face & speech) (Fragopanagos & Taylor, 2005), 91.1% (face & gestures) (Gunes & Piccardi, 2007)72% (face & speech) (De Silva & Pei Chi, 2000) |

Table 1: Some of the empirical approaches to emotion recognition

Of the above mentioned approaches, a physiological approach is promising in that inner bodily changes are reflected in autonomous nervous systems and thus, integrally related to human emotion (Picard et al., 2001; Lisetti et al., 2003; Zhihong et al., 2007). For example, there is empirical evidence that physiological activities in face, finger, and body (e.g., EMG, PPG, EEG) are related to emotions. Thus, measuring these somatic activities would make it possible to obtain information about the emotional states. Research has been recently growing in the discipline of human–computer interaction to study the emotion-related physiological signals. Kim et al. (2004) employed pattern learning algorithms to recognize

four types of emotions (sadness, anger, stress & surprise) from four physiological signals (ECG, SKT, EDA & PPG). Considering the large number of subjects participated in their study, recognition rates were relatively high in the range of 78.4% for three and 61.8% for four emotions. Lissetti et al. (2003) have made an attempt to recognize some basic emotions such as anger, fear, sadness and frustration and the recognition accuracy was varied depending upon the emotional states from 70% to 90% (70% for frustration, 80% for anger & fear, 90% for sadness). Picard et al. (2001) used a single subject design methodology and instead more number of emotions were put into machine learning techniques. GSR, EMG (jaw), BVP and respiration signals were taken from a subject repeatedly over many days and the accuracy was comparatively high. Some of the issues worthy attention in physiological studies include obtrusiveness (e.g., sensors and gel), noise and environmental context that may pollute data. Given the alternative approaches discussed by thus, it is hard to compare results across studies or to draw any conclusion about the applicability of emotion recognition due to different techniques used in the studies. Techniques used in the studies are varied as to the way emotion is defined, elicited and controlled.

## 3. Automatic emotion recognition: an experiment

As discussed, the most pertinent agenda for affective computing would be understanding what emotional state one is in. The authors have been studying this issue in three aspects of emotion modeling, recognition and adaptive interaction. We report here mainly as to our physiological approach to affective computing with individualization capability.

### 3.1 Physiological measurement
Autonomic parameters were chosen for emotion recognition with discretion in full consideration of easiness and convenience of measurement. Electrodes were applied to the fingers and palm region of the hand. Photoplethysmogram (PPG), galvanic skin response (GSR) and skin temperature (SKT) were representative parameters of autonomic nervous responses. GSR was measured as an indicator for sympathetic activity (Boucsein, 1992), skin temperature (SKT) for parasympathetic activity and PPG for arousal and orienting. GSR, as one of electrodermal responses, is low in frequency. Its amplitude measures the degree of arousal as calculated by the difference in conductance level between the tonic and the peak of the response. SKT is slower in frequency and represents a state of relaxation. PPG as measured at the fingertips is relatively faster in frequency with a peak every 0.8 and is a useful index for orienting response. Therefore, the physiological parameters were analyzed from the amplitude of PPG and GSR, and the slope of SKT and mapped with subjective emotional states for emotion recognition.

### 3.2 Emotional computer
The specially designed mouse was constructed as shown in Figure 1 to record three measures that signal the most salient aspects of autonomic activities. It was optimally shaped for a firm contact between skin and sensors of PPG, GSR and SKT in order to avoid measurement noise. Ten curvatures were designed on the mouse in reference to the Korean anthropometric data collected from the 20- year-old subjects in 1992. The mouse was 9-10 cm in width and 18-19cm in length.
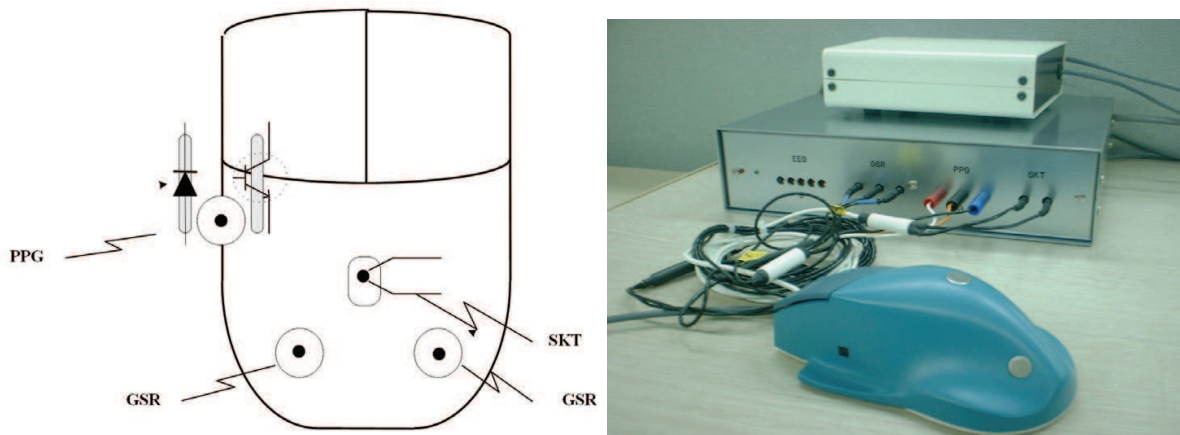
Figure 1: Emotional mouse with sensors for PPG, SKT & GSR.

As the mouse is capable of estimating human emotion, we named it as 'emotional mouse.' The emotional mouse was developed as shown in Figure 1. PPG signals were collected from the thumb, the GSR from the low part of the palm and the SKT from the center of the palm respectively. Three curvatures as depicted in Figure 1 according to the natural profiles of a right hand were designed to prevent noise signals, which may occur due to any unstable contacts between sensors and skin. Included were the thenar-hypothenar curvature for GSR (Boucsein, 1992) and the curvature of the inner palm for SKT. Both the curvature of the thumb and a special wing were modeled for PPG to minimize any movement effect.

The data acquisition board was specially configured to filter, amplify and digitally convert analog signals produced from three data channels simultaneously. The prototype for the board was produced separately from the mouse as seen in Figure 2. This was later reduced in size and stacked in a multi-layered structure to fit into the emotional mouse. It supports the RS 232 or the USB port.

Attention was paid to the chance of overloading due to incoming data from the emotional mouse, which may slow down the computer. This study has taken the client-server architecture to tackle any possible system delay. The client-side computer was given the role of data acquisition and display while the server was responsible for more demanding jobs such as data processing, emotion analysis and evaluation. The measurements along with user profiles were put into the data base for a more personalized service. The emotional mouse hooked up to the client side computer read the physiological data (PPG, GSR & SKT) and transmitted them to the server. The server then processed and analyzed the data to evaluate the emotion based on the inference algorithm (to be discussed in a following section). The results were transferred back to the client computer to be made available what emotional state was in.

### 3.3 Emotion inference

The term emotional computer is designed to operate emotionally as the term denotes, which may sound illogical. The inference algorithm was designed in this study to have emotion as background intelligence. The procedure required to assess the physiological data and map them to the emotional states is depicted in Figure 2. As discussed earlier, the dimensional emotion model as proposed by Larsen and Diener (1992) was adopted and PPG, GSR and SKT were analyzed into two dimensional measurements such as arousal and valence. In most of the time, however, users were in a neutral state of emotion, which was not defined

in the theoretical dimensional model. The neutral emotion refers to a state that is free from any emotional influence and thus set as a reference state in the course of assessing the emotional state. Each physiological signal of PPG, GSR, and SKT needs setting a neutral band based on subjective evaluation of the emotional states. As a result, the four categories (i.e., (1) pleasantness-arousal, (2) pleasantness-relaxation, (3) unpleasantness-arousal, and (4) unpleasantness-relaxation) were added with neural states. This resulted in nine categories of emotional states with five more states added; that is, (5) pleasantness-neutral arousal, (6) unpleasantness-neutral, (7) neutral pleasantness-arousal, (8) neutral pleasantness–relaxation, and (9) neutral pleasantness-neutral arousal.
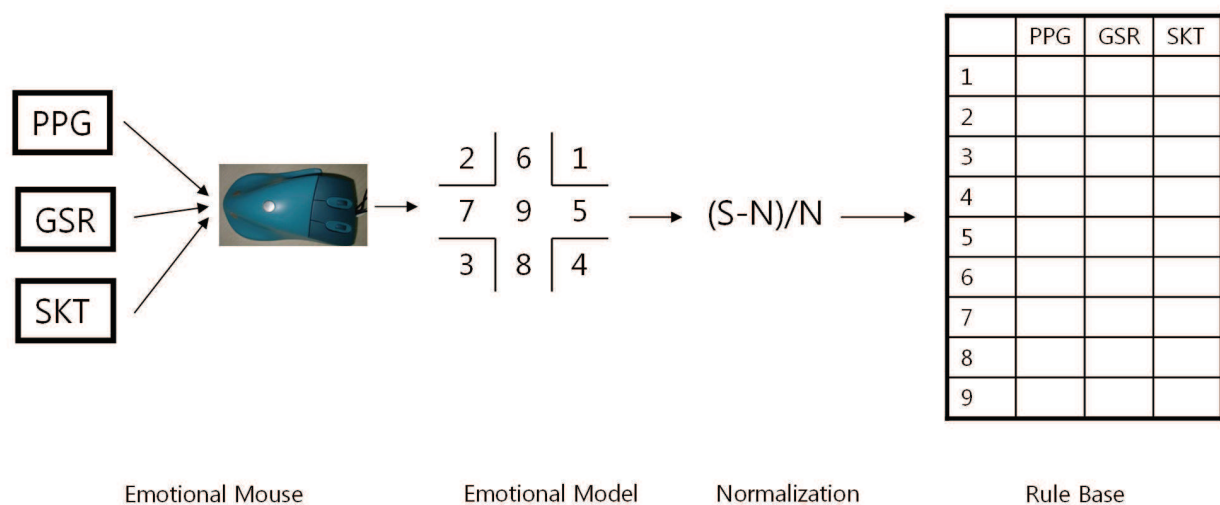


Figure 2: Process to assess the emotional states

The neutral state of emotion was not identical across individuals due to their physical and psychological characteristics. This certainly leads to variations in individual emotional experience, which was manifested for both within and between subjects. This problem has been also reported in literature and some (Picard et al., 2001) used one subject over long period of time. To overcome the hurdle of individualization, the neutral band was introduced and automatically decided in reference to the subjectively assessed values of self-emotion to accommodate some likely individual differences.

The neutral band was used to normalize physiological data. As shown in Equation 1, E refers to the percent changes of physiological signals and is computed as the difference between stimulated state (S) and neutral state (N) divided by neutral state (N). Thus, normalization values should lie in the range of between 0 and 1.

$$E = (S-N)/N \qquad (1)$$

Each physiological signal was normalized and assigned into one of the three states, i.e., increase, decrease and no variation. The three possible states for three physiological signals yielded 27 cases. Individual difference was also taken into account in developing the rule base. The rule set was defined for each individual with individualistic neutral band and responses to emotional events. This algorithm was updated by mapping subjectively assessed scores of valence and arousal states to incoming physiological signals. The recognition accuracy of the emotional computer was empirically validated. Five university students participated in 100 repetitive experiments for three consecutive days. Their

subjectively reported self-emotions were compared to the one estimated according to the inferential algorithm. The recognition rates were 70-90%. Higher accuracy was found for arousal than for valence of the emotion.

## 4. Conclusion

Emotion is one of the intellectual traits that may distinguish human beings from computers (Picard, 1997; Oatley, 1998). Despite considerable efforts over the past decades, computers are far from understanding the delicacy of human emotion and this would certainly lead users to perceive computers being challenging and inhumane. This study has shown that the computer may be capable of recognizing emotion in an automatic way with the physiological signals such as PPG, GSR, and SKT. The computers were designed to be equipped with some devices that evaluated the emotional state of computer users and could trigger appropriate actions adaptively depending upon the changes in emotion. In this context, the physiological data of users were read into the signal processor of emotional computers to assess the state of users' emotion. It should be, however, noted that there may be a number of factors that could contribute to the accuracy of emotion evaluation. Accuracy may be greatly related, among others, to data measurement and preprocessing of measured data and mathematical models to classify the state of human emotion. Also, there have been very few studies which evaluated 'live' emotion. Most studies captured the signals and analyzed them off-line. Physiological computing raises the issue of obtrusiveness. The size and number of sensors required for the collection of physiological data may be obtrusive. The time and chemicals to affix sensors onto human body may also be cumbersome. Individual differences should also be taken into account that emotion may not be necessarily consistent over individuals and over days. Our approach with on-line physiological data would be valuable to provide insights into the notion of emotional computers and further research is required in this respect.

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**Affective Computing**

Edited by Jimmy Or

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This book provides an overview of state of the art research in Affective Computing. It presents new ideas, original results and practical experiences in this increasingly important research field. The book consists of 23 chapters categorized into four sections. Since one of the most important means of human communication is facial expression, the first section of this book (Chapters 1 to 7) presents a research on synthesis and recognition of facial expressions. Given that we not only use the face but also body movements to express ourselves, in the second section (Chapters 8 to 11) we present a research on perception and generation of emotional expressions by using full-body motions. The third section of the book (Chapters 12 to 16) presents computational models on emotion, as well as findings from neuroscience research. In the last section of the book (Chapters 17 to 22) we present applications related to affective computing.

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