The Emotion Mouse

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1 Introduction

One goal of human computer interaction (HCI) is to make an adaptive, smart computer system. This type of project could possibly include gesture recognition, facial recognition, eye tracking, speech recognition, etc. Another non-invasive way to obtain information about a person is through touch. People use their computers to obtain, store and manipulate data using their computer. In order to start creating smart computers, the computer must start gaining information about the user.

Our proposed method for gaining user information through touch is via a computer input device, the mouse. From the physiological data obtained from the user, an emotional state may be determined which would then be related to the task the user is currently doing on the computer. Over a period of time, a user model will be built in order to gain a sense of the user's personality. The scope of the project is to have the computer adapt to the user in order to create a better working environment where the user is more productive. The first steps towards realizing this goal are described here.

2 Emotions and computing

Rosalind Picard (1997) describes why emotions are important to the computing community. There are two aspects of affective computing: giving the computer the ability to detect emotions and giving the computer the ability to express emotions. Not only are emotions crucial for rational decision making as Picard describes, but emotion detection is an important step to an adaptive computer system. An adaptive, smart computer system has been driving our efforts to detect a person's emotional state.

An important element of incorporating emotion into computing is for productivity for a computer user. A study (Dryer & Horowitz, 1997) has shown that people with personalities that are similar or complement each other collaborate well. Dryer (1999) has also shown that people view their computer as having a personality. For these reasons, it is important to develop computers which can work well with its user. By matching a person's emotional state and the context of the expressed emotion, over a period of time the person's personality is being exhibited. Therefore, by giving the computer a longitudinal understanding of the emotional state of its user, the computer could adapt a working style which fits with its user's personality. The result of this collaboration could increase productivity for the user.

One way of gaining information from a user non-intrusively is by video. Cameras have been used to detect a person's emotional state (Johnson, 1999). We have explored gaining information through touch. One obvious place to put sensors is on the mouse. Through observing normal computer usage (creating and editing documents and surfing the web), people spend approximately 1/3 of their total computer time touching their input device. Because of the incredible amount of time spent touching an input device, we will explore the possibility of detecting emotion through touch.

3 Theory

Based on Paul Ekman's facial expression work, we see a correlation between a person's emotional state and a person's physiological measurements. Selected works from Ekman and others on measuring facial behaviors describe Ekman's Facial Action Coding System (Ekman and Rosenberg, 1997). One of his experiments involved participants attached to devices to record certain measurements including pulse, galvanic skin response (GSR), temperature, somatic movement and blood pressure. He then recorded the measurements as the participants were instructed to mimic facial expressions which corresponded to the six basic emotions. He defined the six basic emotions as anger, fear, sadness, disgust, joy and surprise.

From this work, Dryer (1993) determined how physiological measures could be used to distinguish various emotional states. Six participants were trained to exhibit the facial expressions of the six basic emotions. While each participant exhibited these expressions, the physiological changes associated with affect were assessed. The measures taken were GSR, heart rate, skin temperature and general somatic activity (GSA). These data were then subject to two analyses. For the first analysis, a multidimensional scaling (MDS) procedure was used to determine the dimensionality of the data. This analysis suggested that the physiological similarities and dissimilarities of the six emotional states fit within a four dimensional model. For the second analysis, a discriminant function analysis was used to determine the mathematic functions that would distinguish the six emotional states. This analysis suggested that all four physiological variables made significant, nonredundant contributions to the functions that distinguish the six states. Moreover, these analyses indicate that these four physiological measures are sufficient to determine reliably a person's specific emotional state.

Because of our need to incorporate these measurements into a small, non-intrusive form, we will explore taking these measurements from the hand. The amount of conductivity of the skin is best taken from the fingers. However, the other measures may not be as obvious or robust. We hypothesize that changes in the temperature of the finger are reliable for prediction of emotion. We also hypothesize the GSA can be measured by change in movement in the computer mouse. Our efforts to develop a robust pulse meter are not discussed here.

4 Experimental Design

An experiment was designed to test the above hypotheses. The four physiological readings measured were heart rate, temperature, GSR and somatic movement. The heart rate was measured through a commercially available chest strap sensor. The temperature was measured with a thermocouple attached to a digital multimeter (DMM). The GSR was also measured with a DMM. The somatic movement was measured by recording the computer mouse movements.

4.1 Method

Six people participated in this study (3 male, 3 female). The experiment was within subject design and order of presentation was counter-balanced across participants.

4.2 Procedure

Participants were asked to sit in front of the computer and hold the temperature and GSR sensors in their left hand, hold the mouse with their right hand and wore the chest sensor. The resting (baseline) measurements were recorded for five minutes and then the participant was instructed to act out one emotion for five minutes. The emotions consisted of: anger, fear, sadness, disgust, happiness and surprise. The only instruction for acting out the emotion was to show the emotion in their facial expressions.

4.3 Results

The data for each subject consisted of scores for four physiological assessments [GSA, GSR, pulse, and skin temperature, for each of the six emotions (anger, disgust, fear, happiness, sadness, and surprise)] across the five minute baseline and test sessions. GSA data was sampled 80 times per second, GSR and temperature were reported approximately 3-4 times per second and pulse was recorded as a beat was detected, approximately 1 time per second. We first calculated the mean score for each of the baseline and test sessions. To account for individual variance in physiology, we calculated the difference between the baseline and test scores. Scores that differed by more than one and a half standard deviations from the mean were treated as missing. By this criterion, twelve score were removed from the analysis. The remaining data are described in Table 1.

Table 1: Difference Scores.

		Anger	Disgust	Fear	Happiness	Sadness	Surprise
GSA	Mean	-0.66	-1.15	-2.02	.22	0.14	-.1.28
	Std. Dev.	1.87	1.02	0.23	1.60	2.44	1.16
GSR	Mean	-41209	-53206	-61160	-38999	-417990	-41242
	Std. Dev.	63934	8949	47297	46650	586309	24824
Pulse	Mean	2.56	2.07	3.28	2.40	4.83	2.84
	Std. Dev.	1.41	2.73	2.10	2.33	2.91	3.18
Temp	Mean	1.36	1.79	3.76	1.79	2.89	3.26
	Std. Dev.	3.75	2.66	3.81	3.72	4.99	0.90

In order to determine whether our measures of physiology could discriminate among the six different emotions, the data were analyzed with a discriminant function analysis. The four physiological difference scores were the discriminating variables and the six emotions were the discriminated groups. The variables were entered into the equation simultaneously, and four canonical discriminat functions were calculated. A Wilks' Lambda test of these four functions was marginally statistically significant; for lambda = .192, chi-square(20) = 29.748, $p < .075$. The functions are shown in Table 2.

Table 2: Standardized Discriminant Function Coefficients.

	Function			
	1	2	3	4
GSA	0.593	-0.926	0.674	0.033
GSR	-0.664	0.957	0.350	0.583
Pulse	1.006	0.484	0.026	0.846
Temp.	1.277	0.405	0.423	-0.293

The unstandardized canonical discriminant functions evaluated at group means are shown in Table 3. Function 1 is defined by sadness and fear at one end and anger and surprise at the other. Function 2 has fear and disgust at one end and sadness at the other. Function 3 has happiness at one end and surprise at the other. Function 4 has disgust and anger at one end and surprise at the other.

Table 3: Functions at Group Centroids.

EMOTION	Function			
	1	2	3	4
anger	-1.166	-0.052	-0.108	0.137
fear	1.360	1.704	-0.046	-0.093
sadness	2.168	-0.546	-0.096	-0.006
disgust	-0.048	0.340	0.079	0.184
happiness	-0.428	-0.184	0.269	-0.075
surprise	-1.674	-0.111	-0.247	-0.189

To determine the effectiveness of these functions, we used them to predict the group membership for each set of physiological data. As shown in Table 4, two-thirds of the cases were successfully classified.

Table 4: Classification Results.

		Predicted Group Membership						Total
	EMOTION	Anger	Fear	sadness	disgust	happine	surprise	
Original	anger	2	0	0	0	2	1	5
	fear	0	2	0	0	0	0	2
	sadness	0	0	4	0	1	0	5
	disgust	0	1	0	1	1	0	3
	happiness	1	0	0	0	5	0	6

	surprise	0	0	0	0	1	2	3

5 Conclusions

The results show the theory behind the Emotion mouse work are fundamentally sound. The physiological measurements were correlated to emotions using a correlation model. The correlation model is derived from a calibration process in which a baseline attribute-to-emotion correlation is rendered based on statistical analysis of calibration signals generated by users having emotions that are measured or otherwise known at calibration time.

Now that we have proven the method, the next step is to improve the hardware. Instead of using cumbersome multimeters to gather information about the user, it will be better to use smaller and less intrusive units. We plan to improve our infrared pulse detector which can be placed inside the body of the mouse. Also, a framework for the user modeling needs to be develop in order to correctly handle all of the information after it has been gathered.

There are other possible applications for the Emotion technology other than just increased productivity for a desktop computer user. Other domains such as entertainment, health and the communications and the automobile industry could find this technology useful for other purposes.

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7 References

Ekman, P. and Rosenberg, E. (Eds.) (1997). *What the Face Reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS).* Oxford University Press: New York.

Dryer, D.C. (1993). Multidimensional and Discriminant Function Analyses of Affective State Data. Stanford University, unpublished manuscript.

Dryer, D.C. (1999). Getting personal with computers: How to design personalities for agents. *Applied Artificial Intelligence, 13*, 273-295.

Dryer, D.C., and Horowitz, L.M. (1997). When do opposites attract? Interpersonal complementarity versus similarity. *Journal of Personality and Social Psychology, 72*, 592-603.

Johnson, R.C. (1999). Computer Program Recognizes Facial Expressions. EE Times www.eetimes.com, April 5.

Picard, R. (1997). *Affective Computing.* MIT Press: Cambridge.