

# Emotion Recognition from Physiological Signals for User Modeling of Affect

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## Abstract

In this paper, we describe algorithms developed to analyze physiological signals associated with emotions, in order to recognize the affective states of users via non-invasive technologies. We propose a framework for modeling user's emotions from the sensory inputs and interpretations of our multi-modal system. We also describe examples of circumstances that these systems can be applied to.

**Keywords:** Emotion recognition, affective intelligent user interfaces, user-models of emotions.

## 1. Motivation

Conventional user models are built on what the user knows or does not know about the specific context, what her/his skills and goals are, and her/his self-report about what s/he likes or dislikes. The applications of this traditional user modeling include student modeling (Barker et al., 2002; Millan & Perez-de-la-Cruz, 2002; Corbett et al., 2000; Selker, 1994), news access (Billsus & Pazzani, 2000), e-commerce (Fink & Cobsa, 2000), and health-care (Warren et al., 2002).

However, none of these conventional models includes a very important component of human intelligence: *affect* and *emotion*.

Emotions are essential for human cognition and they influence different aspects of people's lives including:

- **organization of memory and learning:** we recall an event better when we are in the same mood as when the learning occurred (Bower, 1981);
- **perception:** when we are happy, our perception is biased at selecting happy events, likewise for negative emotions (Bower, 1981);

- **categorization and preference:** familiar objects become preferred objects (Zajonc, 1984);
- **goal generation, evaluation, and decision-making:** patients who have damage in their frontal lobes (cortex communication with limbic system is altered) become unable to feel, which results in their complete dysfunctionality in real-life settings where they are unable to decide what is the next action they need to perform (Damasio, 1994). Normal emotional arousal, on the other hand, is intertwined with goal generation and decision-making;
- **strategic planning:** when time constraints are such that quick action is needed (as in fear of a rattle snake), neurological shortcut pathways for deciding upon the next appropriate action are preferred over more optimal but slower ones (Ledoux, 1992);
- **focus and attention:** emotions restrict the range of cue utilization such that fewer cues are attended to (Derryberry & Tucker, 1992);
- **motivation and performance:** an increase in emotional intensity causes an increase in performance, up to an optimal point (inverted U-curve Yerkes-Dodson Law);
- **intention:** not only are there positive consequences to positive emotions, but there are also positive consequences to negative emotions - they signal the need for an action to take place in order to maintain, or change a given kind of situation or interaction with the environment (Frijda, 1986);
- **communication:** important information in a conversational exchange comes from body language (Birdwhistle, 1970), voice prosody

and facial expression revealing emotional content (Ekman & Friesen, 1975), and facial displays connected with various aspects of discourse (Chovil, 1991);

- **learning:** people are more or less receptive to the information to be learned depending their liking (of the instructor, or the visual presentation, or of how the feedback is given). Moreover, emotional intelligence is learnable (Goleman, 1995).

Given the strong interface between affect and cognition on the one hand, and given the increasing versatility of computer agents on the other hand, the attempt to enable our computer tools to acknowledge affective phenomena rather than to remain blind to them appears desirable.

In the last five years, there has been a significant increase in number of attempts to build user models that include emotion and affect at some level in the user model. Conati's (to appear) probabilistic user model, which is based on Dynamic Decision Network, represents the emotional state of the user interacting with an educational game, as well as her personality and goals. ABAIS, created as a rule-based system by Hudlicka and McNeese (2002), assesses pilots' affective states and active beliefs and takes adaptive precautions to compensate for their negative affects. Klein et al.'s (2002) interactive system responds to the user's self-reported frustration during an interaction with a computer game. All these systems are created to adapt to the user's affective state based on the current context, however none of them performs any emotion recognition stage. Our multimodal system that recognizes the emotional state of the user will be a good complement to these systems and other systems that model user's emotions.

Maybury (2001) defines the purpose of human computer interaction as enabling users to perform complex task more quickly, with more accuracy and improving user satisfaction. New interfaces can dynamically adapt to the user, the current context and situation (Maybury, 2001).

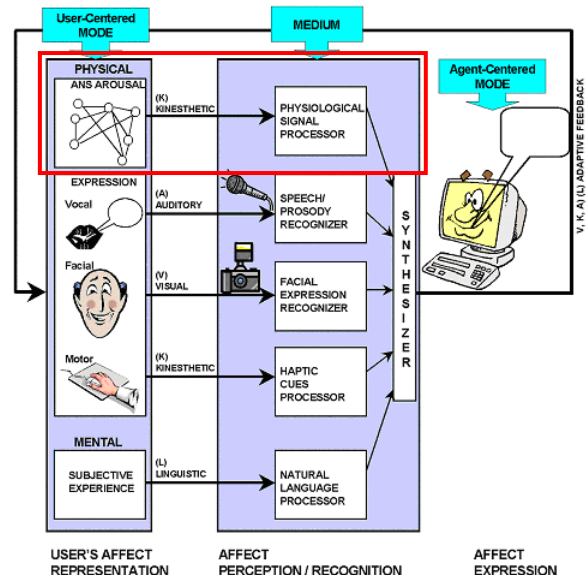
We aim at creating intelligent systems that achieve the goals of human-computer interaction defined by Maybury (2001) by developing algorithms for real-time emotion recognition. For example, when our system recognizes a learner's frustration, confusion or boredom and adjusts the pace of the training accordingly, the learning task will be improved. Similarly, when our system recognizes the anger or rage of a driver and takes action to neutralize her

negative emotions, the driving safety will be enhanced. Furthermore, when our system recognizes the depressive patterns of sadness telemedicine patients might experience in their homes and communicates these to the health-care providers monitoring them, the patients' satisfaction will improved from the better treatment received.

## 2. Our Approach

The first step in our approach to model the emotional state of the user focuses on recognizing the user's emotional state accurately. Our system is shown in Figure 1 and is designed to (Lisetti & Nasoz, 2002):

- gather multimodal physiological signals and expressions of a specific emotion to recognize the user's emotional state;
- give feedback to the user about her/his emotional state;
- adapt its interface to the user's affective state based on the user's preferences of interaction in the current context or application.



**Figure 1: Human Multimodal Affect Expression matched with Multimedia Computer Sensing**

Currently, we are working on recognizing the users' emotions by interpreting the physiological signals (temperature, heart rate, galvanic skin response) and mapping these physiological signals to their corresponding emotions (shown in Figure 1 in the red rectangle).

### 3. Related Work on Emotion Elicitation and Recognition

#### 3.1 Emotion Recognition from Physiological Signals Previous Research

Both manual analysis and statistical analysis of physiological signals collected during emotional experience have been implemented to understand the connection between emotions and physiological arousal.

##### 3.1.1 Research with Manual Analysis

Ekman et al.'s study (1983) used manual analysis to interpret the physiological signals (finger temperature, heart rate and skin conductance, muscle tension) that occurred when anger, fear, sadness, happiness, disgust, and surprise were elicited. The results demonstrated that anger, fear, and sadness increased the heart rate more than happiness and surprise did, while disgust decreased the heart rate. Anger increased left and right finger temperatures more than happiness and sadness did, while fear surprise, and disgust decreased the finger temperature.

In Gross and Levenson' (1997) study amusement, neutrality, and sadness were elicited by showing films. Skin conductance, inter-beat interval, pulse transit times and respiratory activation were measured. The results showed that inter-beat interval increased for all three states, but for neutrality it was the least. Skin conductance increased after the amusement film, decreased after the neutral film and stayed the same after the sadness film.

##### 3.1.2 Research with Statistical Analysis

In Collet et al.'s (1997) study, the participants were shown naturally and emotionally loaded pictures to elicit happiness, surprise, anger, fear, sadness, and disgust and skin conductance, skin resistance, skin potential, skin blood flow, skin temperature, and instantaneous respiratory frequency were measured. Statistical comparison of data signals was performed pair-wise, where 6 emotions formed 15 pairs. Out of these 15 emotion-pairs, electrodermal responses distinguished 13 pairs, skin conductance ohmic perturbation duration indices separated 10 pairs, and conductance amplitude could distinguish 7 pairs successfully.

Healey and Picard conducted a study (2000) in which physiological signals (electrocardiogram, electromyogram, respiration, and skin conductance) of the drivers were measured in order to detect their

stress level. SFFS (sequential forward floating selection) algorithm was used to recognize pattern of drivers' stress and the intensity of driver's stress was recognized by 88.6% accuracy.

Picard et al. conducted another study (2001) by showing emotion specific pictures to elicit happiness, sadness, anger, fear, disgust, surprise, neutrality, platonic love, and romantic love. The signals measured were galvanic skin response, heartbeat, respiration, and electrocardiogram. The algorithms used to analyze the data were SFFS, Fisher Projection, and hybrid of these two. The best classification achievement was gained by the hybrid method, which resulted in 81.25% accuracy overall.

#### 3.2 Emotion Elicitation with Movie Clips

Gross and Levenson (1995) conducted a study to find an answer to the question of whether movie clips could be used to elicit emotions. Based on five years of research, the authors reported their findings of the most effective films to elicit discrete emotions. 78 movie clips were shown to 494 subjects in the study. 16 of these 78 film clips were chosen as being the best films based on discreteness and intensity for eight target emotions (amusement, anger, contentment, disgust, fear, neutrality, sadness, and surprise), 2 best films for each emotion. The study showed that these 16 film clips could successfully elicit the above 8 emotions (Gross & Levenson, 1995).

Amusement, disgust, and sadness movie clips were most successful in producing the target emotion. The more difficult emotions to elicit were anger, contentment, and fear. Upon further analyses, the authors reported that contentment films elicited high degrees of happiness; anger films were affiliated with a host of other emotions, including disgust; and fear films were confounded with tension and interest. The authors concluded that "With films, it appears that there is a natural tendency for anger to co-occur with other negative emotions ... we are becoming increasingly convinced that elicitation of *discrete* anger with brief films is going to be extremely difficult, if not impossible" and "perhaps the co-occurrence of fear, tension, and interest is a natural one" (p. 104). However, if the goal is to elicit one emotion more intensely than others, films are a viable choice.

Since in Gross and Levenson's study (1995) these 16 movie clips were validated to elicit these emotions successfully, we used their results to guide the design of our experiment described in the next section.

## 4. Recognizing Emotions From Physiological Signals

We designed experiments where we elicited emotions from participants via multi-modal input and measured their physiological signals. We analyzed these physiological signals by implementing and testing pattern recognition algorithms.

### 4.1 Designing Our Experiment

In order to map physiological signals to certain emotions we designed an experiment in which we elicited six emotions, and measured three physiological signals.

**Emotions Elicited:** Sadness, Anger, Surprise, Fear, Frustration, and Amusement.

**Movie Clips Used:** Before choosing the movie clips we used in this experiment we conducted a panel study to measure how effectively they elicited emotions according to the reports of the participants. The chosen movie clips are from the following movies:

- **The Champ** for sadness [same as one of the sadness movie clips from Gross and Levenson (1995)]
- **Schindler's List** for anger [different from Gross and Levenson's (1995) since Schindler's List gained higher agreement in our panel study]
- **Capricorn One** for surprise [same as one of the surprise movie clips from Gross and Levenson (1995)]
- **Shining** for fear [same as one of the fear movie clips from Gross and Levenson (1995)]
- **Drop Dead Fred** for amusement [although the movie clip from When Harry Met Sally from Gross and Levenson (1995) gained the same agreement, we chose not to use it since most of the participants experienced embarrassment as well as amusement]

**Body signals Measured and Equipment Used:** While the above emotions were elicited, participants' galvanic skin response (GSR), heart rate, and body temperature were measured with the non-invasive wearable computer BodyMedia SenseWear Armband shown in Figure 2 (for GSR and temperature) and a chest strap (for heart rate) that works in compliance with the armband. Since the armband is wireless and

non-invasive, it can easily and efficiently be used in real life scenarios without distracting the user.



Figure 2 BodyMedia SenseWear Armband

**Participants:** The sample included 31 undergraduate students from different genders, age groups and ethnicities who enrolled in a computer science course.

**Procedure:** One to three subjects participated in the study during each session. After signing consent forms, the armband was placed on the subjects' right arm. As the participants waited for the armband to detect their physiological signals, they were asked to complete a pre-study questionnaire. Once the armband signaled it was ready, the subjects were instructed on how to place the chest strap. After the chest straps were activated, the in-study questionnaire was placed face down in front of the subjects and the participants were told the following: 1) to find a comfortable sitting position and try not to move around until answering an item on the questionnaire, 2) to wait for the slide show to instruct them to answer questions on the in-study questionnaire, 3) to please not look ahead at the questions, and 4) that someone would sit behind them at the beginning of the study to time the armband.

The 45-minute computerized slide show was then activated. The study began with a slide asking the subjects to relax, breathe through their nose, and listen to soothing music. The following slides were pictures of the ocean, mountains, trees, sunsets, and butterflies. After 2.5 minutes, the first movie clip played (sadness). Once the clip was over, the next slide asked the participants to answer the questions relevant to the scene they watched. Starting again with the slide asking the subjects to relax while listening to soothing music, this process continued for the anger, surprise, fear, frustration, and amusement clips. The frustration segment of the slide show asked the participants to answer analytical math

problems without using paper and pencil. The movie scenes and frustration exercise lasted from 70 to 231 seconds each.

The in-study questionnaire included 3 questions for each emotion. The first asked, “Did you experience SADNESS (or the relevant emotion) during this section of the experiment?”, and required a yes or no response. The second question asked the participants to rate the intensity of the emotion they felt on a 6-point scale. The third question asked participants if they had experienced any other emotions at the same intensity or higher, and if so, to specify what that emotion was on an open basis.

## 4.2 Analyzing the Data

We segmented the collected data, according to the emotions elicited at corresponding time frames (for example, although the movie clip shown for surprise was 68 seconds, we only used the data from the time frame when the actual surprising event happened, which was 7 seconds). Then we stored the data in a three dimensional array of real numbers. The three dimensions are 1) the subjects who participated in the experiment, 2) the emotion classes (sadness, anger, surprise, fear, frustration, and amusement), and 3) the physiological signal types (GSR, temperature, and heart rate).

Each slot of the array consists of the normalized average value of one specific data signal belonging to one specific participant while s/he was experiencing one specific emotion. (e.g. a slot contains the normalized average skin temperature value of participant #1 while s/he was experiencing anger). The values of each data type were normalized with respect to the average value of corresponding data collected during the relaxation period for the same participant. For example, equation 1 shows how we normalized the GSR values:

$$\text{normalized\_GSR} = \frac{(\text{original\_GSR} - \text{relax\_GSR})}{\text{relax\_GSR}}$$

We normalized the data for each emotion in order to calculate how much the physiological responses changed as the participants go from a relaxed state to the state of experiencing a particular emotion. Normalization is also important for minimizing the individual differences of participants in terms of the physiological responses they give while experiencing a specific emotion.

We used two different algorithms to analyze the data we collected. One of them is the *k-Nearest Neighbor* (KNN, henceforth) Algorithm (Mitchell, 1997). The algorithm uses two data sets: (1) training data set; (2) test data set. Training data set contains instances of GSR, skin temperature, and heart rate values and the corresponding emotion class. Test data set is similar to the training data set, except that it does not have the emotion information. In order to classify an instance of a test data into an emotion, KNN calculates the distance between the test data and each instance of training data set. For example, let an arbitrary instance  $x$  be described by the feature vector

$$\langle a_1(x), a_2(x), \dots, a_n(x) \rangle,$$

where  $a_r(x)$  is the  $r^{\text{th}}$  feature of instance  $x$ . The distance between instances  $x_i$  and  $x_j$  is defined as  $d(x_i, x_j)$  where,

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^n (a_r(x_i) - a_r(x_j))^2}$$

The algorithm then finds the  $k$  closest training instances to the test instance. The emotion with the highest frequency among  $k$  emotions associated with these  $k$  training instances is the emotion mapped to the test data.

The other algorithm developed is based on *Discriminant Function Analysis* (DFA, henceforth) (Nicol, 1999), which is a statistical method to classify data signals by using linear discriminant functions.

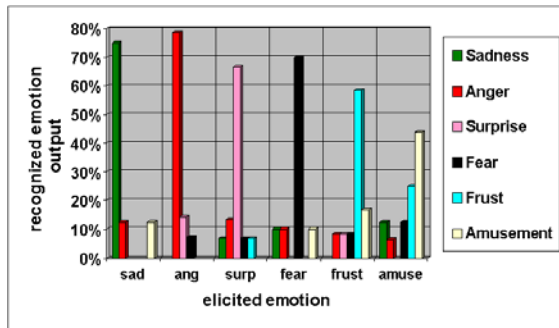
Let  $x_{\text{data}}$  be the average value of a specific data signal, the functions that we are going to solve the coefficients of will be,

$$f_i(x_{\text{gsr}}, x_{\text{temp}}, x_{\text{hr}}) = u_0 + u_1 * x_{\text{gsr}} + u_2 * x_{\text{temp}} + u_3 * x_{\text{hr}}$$

The coefficients of these functions are calculated from the covariance matrices of the data matrix. Data labeled with emotions are entered into the discriminant function and as a result a new data set clustered by emotions is obtained. By using the  $k$ -nearest neighbor algorithm with these emotion clusters, the input signals are mapped to the corresponding emotions.

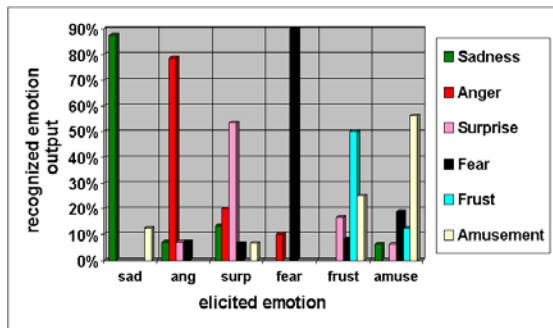
### 4.3 Results

As shown in Figure 3, with KNN algorithm the recognition accuracy we obtained was: 78.58% for anger, 75.00% for sadness, 70.00% for fear, 66.67% for surprise, 58.33% for frustration, and finally 43.75% for amusement.



**Figure 3 Emotion Recognition Results with KNN Algorithm**

Similarly, Figure 4 shows the results of accuracy we gained with DFA. The DFA algorithm recognized fear with 90.00%, sadness with 87.50%, anger with 78.58%, amusement with 56.25%, surprise with 53.33%, and frustration with 50.00% success rates.



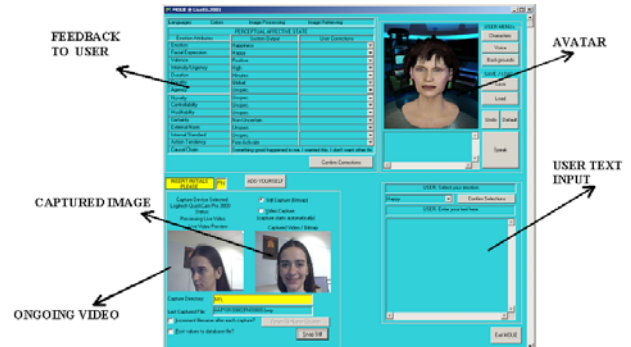
**Figure 4 Emotion Recognition Results with DFA Algorithm**

The accuracy we gained with our DFA algorithm is better than the KNN Algorithm for fear, sadness, anger, and amusement while KNN performed better for frustration and surprise.

### 5. Visualizing User's Emotional States

Finally, we designed MAUI (Lisetti & Nasoz, 2002), a prototype multimedia affective user interface shown in Figure 5, to visualize the output of our various multimodal recognition algorithms.

The mode of feedback given to the user is context and application dependent. For example, whereas an interface agent for a car could automatically adjust the radio station or roll down the windows if the driver is falling asleep, an interface agent for a tutoring application can display empathy via an anthropomorphic avatar that adapts its facial expressions and vocal intonation according to the user's affective state (see Figure 5 upper right).



**Figure 5: MAUI – Multimedia Affective User Interface**

Earlier studies have emphasized that facial expressions are universally expressed and recognized by humans (Ekman, 1989). In addition, the human face is considered an independent channel of communication that helps to coordinate conversations in human-human interactions (Takeuchi & Nagao, 1993). In human-computer interactions, research suggests that having an avatar as part of an interface helps to increase human performance. For example, Walker et al. (1994) reported that subjects in an interview simulation spent more time, made fewer mistakes, and wrote more comments when interacting with an avatar than the subjects being interviewed with a text-based interface. In another study, Takeuchi and Nagao (1993) gave participants ten minutes to ask a series of questions regarding functions and prices of computer products. Individuals interacting with the avatar successfully completed the interaction more often than individuals interacting with a text-based program.

The avatars we created can be used to

- assist the user in understanding his/her emotional state by prompting the user with simple questions, comparing the various components of the states he/she believes to be in with the system's output (since self-report is often self-misleading)

- mirror the user's emotions with facial expressions to confirm the user's affective state (Figure 6)
- animate a previously text-only internet-based chat session showing empathic expressions



**Figure 6 Avatar is Mirroring User's Angry and Sad States Respectively**

## 6. Discussion and Future Work

We made substantial progress toward recognizing emotions accurately by mapping them to physiological signals with two different algorithms (KNN and DFA). We proposed a way to use this affective knowledge to model the user's affective state.

We are aware of the fact that generation of emotions in humans is very complex and it is very hard to detect fine-grained human emotions. That is why we do not try to recognize each of these fine-grained emotions and instead we choose smaller subset of emotions for various applications and deal with this small subset (e.g. anger, fear, and sleepiness for driving safety, sadness, depression, and happiness for telemedicine patients, and frustration, boredom, or interest for learners).

Furthermore, we also know that it is hard to recognize emotions very accurately only with one modality. For this reason we also plan to conduct studies on facial expression recognition and on integrating these two modalities (see the last paragraph of this section). Although currently our research focus is on physiological signals and facial expressions, once they are integrated, we plan on including more modalities such as vocal intonation and natural language processing for increased accuracy.

We are well aware that these kinds of systems will only be applicable to real use in telemedicine, driving safety, and learning once the research is fully mature and results are completely reliable within restricted domains and appropriate subsets of emotions.

Our future work will include 1) designing and conducting more experiments and measuring the

physiological signals with different equipment; 2) analyzing the collected data with different pattern recognition algorithms; 3) integrating the different modalities of emotion recognition with recognition from physiological signals including facial expression recognition, vocal intonation recognition, and natural language understanding; and 4) adapting the interface to the user appropriately with respect to the current application, e.g. soldier training, driving safety (Nasoz et al., 2002), and telemedicine (Lisetti et al., to appear).

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