Visualizing User's Emotions for Enhanced Human Computer Interaction

Christine L. Lisetti, Fatma Nasoz, and Ning Yu

University of Central Florida, Computer Science Department

Orlando, FL32826

{lisetti, fatma and nyu}@cs.ucf.edu

Abstract— In this paper we describe the Affective Intelligent User Interface we created that recognizes its users emotions and visualizes them in order to give feedback to them about their affective states and to have a better human-computer interaction by responding to the users appropriately with an anthropomorphic avatar.

Index Terms—Affective Intelligent User Interfaces, Emotion Recognition

I. INTRODUCTION AND MOTIVATION

EARLIER studies have emphasized that facial expressions are universally expressed and recognized by humans [8]. In addition, the human face is considered an independent channel of communication that helps to coordinate conversations in human-human interactions [26]. 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. [27] 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 [26] 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.

Given this strong influence of facial expressions on human-human and human-computer interactions, we created our Multimodal Affective User Interface (MAUI, discussed in section II) [18] with an anthropomorphic avatar that gives feedback to the users about their affective states and interacts with them appropriately based on the context and the application.

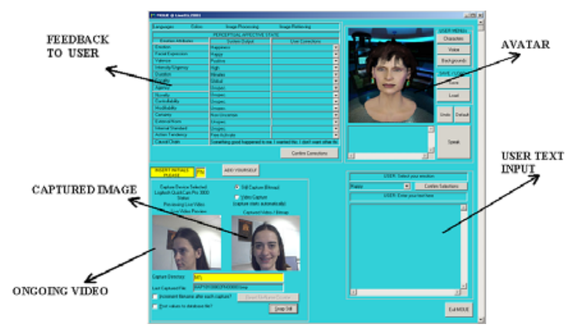

Fig. 1. MAUI: Multimodal Affective User Interface

II. MAUI

We created MAUI (shown Figure 1) to be used in various applications (such as training and telemedicine) to visualize the output of our various multimodal recognition algorithms [18] described in Section IV. The feedback given to the user is context and application dependent. For example, an interface agent for a tutoring application can display empathy via an anthropomorphic avatar who adapts its facial expressions and vocal intonation (in the future) depending on the current user's affective state.

A. Avatar

The upper right section of the MAUI displays an anthropomorphic avatar that adapts its facial expressions and vocal intonation according to the user's affective state. The avatar in our MAUI system has the ability to make context relevant facial expressions. Among the ways the avatar can be used are: mirroring users' emotions as a method to confirm their emotional states (see Figure 2); responding with socially appropriate facial expressions as users display their emotional states (i.e., avatar displays empathy when the user is frustrated by a task, see Figure 1); assisting users in understanding their own emotional states by prompting them with simple questions and comparing the various components of the states they believe they are experiencing with the system's output; and displaying the facial expressions of individuals in a text-based chat session in order to enhance communication. In addition, in order to address individual differences in user preferences, the MAUI system provides a choice of avatar portraying different ages, genders, ethnic backgrounds, skin colors, voices, hair, make-up, accessories, and backgrounds scenery. Indeed, one of our research goals is to evaluate the effect of various characters on different users, depending on the application [Lisetti et al., in press].

Fig. 2. Avatar Mirroring the Angry and Sad States of the User Respectively

We use Haptek PeoplePutty [13] to build the avatar. Haptek software provides some build-in facial expressions, which we can use directly. We chose this software because it allows creating collections of characters with different gender, skin color and ethnic background and voice and – more importantly in the context of this article – because it allows to manipulated the avatar facial expression's intensity and create some facial expression manually. It should be noted, however, that our approach currently focuses on using the avatar to visualize the user's perceived emotional state, rather than on building sophisticated animated models of the face which can be found in the works of de Rosis and Pelachaud [7, 20, 21]. However, within our software, we can control the following parameters to control the face's muscles shown in Table 1, and arrive at reasonable levels of expressiveness:

According to the user's emotion sensed intensity determined with our physiological pattern recognition algorithms described in Section IV, the avatar can adjust its expressions with different intensity. For example, in Figure 3 we show three different intensities for the happy expression.

B. *User Text Input*

The text field in the lower right hand corner of figure 1 is for users to communicate with the system via text. Users enter here the information about their own emotional states in their own words. Users' input will be used by natural language understanding algorithms for more accurate recognition of emotions.

TABLE 1.
PARAMETERS THAT WE CAN USE TO CONTROL THE AVATAR'S FACE MUSCLES

Parameter	**Portion of Face Controlled**
ExpMouthHappy	Raise_cornerlip, raise_eyebrow, lift_cheek
ExpMouthSad	Low_cornerlip, low_inner_eyelid
ExpBrowsSad	raise_inner_eyebrow, low_outer_eyelid
ExpMouthMad	Low_conerlip, squeeze_nosewing, raise_nosewing
ExpBrowsMad	Move_eyebrow_up_and_down, raise_eyelid
ExpEyesTrust	Blink_slowly, nod_head_slowly
Antitrust	Raise_eyelid
ExpEyesDistrust	Raise_bottom_eyelid
AntiDistrust	Low_mid_bottom_eyelid, low_eyelid
ExpBrowsCurious	Raise_outer_eyebrow_alternatively

(a). low intensity (b) middle intensity (c) high intensity

Fig. 3. From neutral to Happy

C. *Ongoing Video and Captured Image*

The first image in the lower left hand corner of Figure 1 displays the ongoing video of the user, which is recorded by a camera connected to user's computer. This video captured during interaction is saved in order to compare the system's interpretation of changes in user's physiological arousal and the changes in her/his facial expressions over time. The second image displays the still image of user captured at specific times for facial expression recognition.

D. *Feedback to the User*

In the upper left hand corner of Figure 1, the system displays, in a text format, its interpretation of the user's current emotional state (i.e., happy, sad, frustrated, angry, afraid, etc.) by indicating the emotion components (i.e., valence, intensity, causal chain, etc.) associated with the emotion, facial expression reading, and physiological signals. As mentioned previously, the information about the user's affective state that feeds the system is gathered by physiological measurements of arousal. These data are then interpreted through pattern recognition algorithms, which identify the user's current emotion.

III. APPLICATIONS

MAUI will be used in various applications for an enhanced human-computer interaction. Below we discuss two of these applications: Telemedicine and Learning/Training.

A. Telemedicine

Tele-Home Health Care (Tele-HCC) has been performed in United States since the early 1990's. Tele-HHC provides communication between medical professionals and patients in cases where hands-on care is not required, but regular monitoring is necessary. For example, tele-HHC interventions are currently used to collect vital sign data remotely (e.g. ECG, blood pressure, oxygen saturation, heart rates, and breath sounds), verify compliance with medicine and/or diet regimes, and assess mental or emotional status [1]][4][29]. With increasing use of Tele-HHC, it is important that the caregiver and care recipient communicate along the affective channel to allow for better assessment and responsiveness. However, formulating an assessment may be particularly difficult in tele-HHC settings where patients are treated and monitored remotely by medical professionals using multiple media devices with social and emotional cues filtered out. Social presence during patient-physician communication is indeed essential; furthermore, the rising use of Tele-HHC signifies a need for efforts aimed at enhancing such presence. Not only may appropriate emotional state assessment be a key indicator of the patient's mental or physical health status, but the power of emotions themselves over the recovery process has also been documented [5].

With the affective intelligent user interfaces, we aim to enhance human-computer interaction in telemedicine environments. For example, when the health-care provider and the telemedicine patient are communicating, the avatar (discussed in Section 3) will mimic the facial expressions of each user at both sites [17]. Furthermore, during this interaction, when our system accurately recognizes depression or sadness from telemedicine patients and forwards this information to the health-care providers monitoring them, they will be better equipped and ready to respond and this will improve the patients' health and satisfaction.

B. Learning/Training

Learning is one of the cognitive processes that is affected by one's emotional state. The emotion *frustration* leads to a reduction in the ability to learn [15]. Rozell and Gardners's [25] study points out that when people have negative attitudes towards computers, their self-efficacy toward using them reduces, which then reduces their chances of performing computer-related tasks very well (when compared to those with positive attitudes towards computers). This research also emphasized that individuals with more positive affect exert more effort on computer-related tasks.

Another emotion that influences learning is *anxiety*. According to the American Heritage Dictionary (2000), anxiety is (1) a state of uneasiness, apprehension, and/or fear resulting from anticipation of a real or imagined threatening event or situation; and, (2) impairs physical and psychological functioning. In training situations, anxiety is presumed to interfere with the ability to focus cognitive attention on the task at hand because that attention is preoccupied with thoughts of past negative experiences with similar tasks, in similar situations [19][28]. It follows that learning may be impaired when trainees are experiencing high levels of anxiety during training. Indeed, with a sample of university employees in a microcomputer class, Martocchio [19] found that anxiety was negatively related to scores on a multiple choice knowledge test at the end of training. In addition, individuals who had more positive expectations prior to training had significantly less anxiety than individuals who had negative expectations of training.

Anxiety also appears to influence reactions to training. For example, with a sample of British junior managers enrolled in a self-paced management course, Warr and Bunce [28] found that task anxiety was positively related to difficulty reactions in training. To be clear, individuals who experienced high task anxiety perceived training to be more difficult than individuals who experienced low task anxiety. In this study, interpersonal and task anxiety were assessed prior to training. Task anxiety was significantly higher than interpersonal anxiety and only task anxiety was associated with difficulty reactions. Lastly, Warr and Bunce [28] found no relationship between anxiety and learning outcomes. Finally, in their meta-analytic path analysis, Colquitt et al. [3] reported that anxiety was negatively related to motivation to learn, pre-training self-efficacy, post-training self-efficacy, learning, and training performance.

In summary, the most consistent findings are that anxiety is negatively related to self-efficacy, motivation, learning, and training performance. In addition, social anxiety may influence training outcomes when trainees are taught new tasks as a team. Furthermore, facilitating a mastery orientation towards the task may help to reduce the anxiety (e.g., attitude change) experienced during training and allow trainees to focus their cognitions on the task at hand, resulting in better learning [19].

With the affective intelligent user interfaces, we aim to enhance human-computer interaction in learning environment. For example when our system recognizes that the learner is anxious, in response, it might provide encouragement in order to reduce anxiety with the avatar and allow the individual to focus more attention on the task.

IV. EMOTION RECOGNITION FROM PHYSIOLOGICAL SIGNALS

For the interface to interact with the user appropriately it needs to know what affective state s/he is in. Many studies were conducted to understand the connection between emotions and physiological arousal [9][10][2][14][24]. We conducted our own experiment in order to map the physiological signals to emotions by implementing and testing pattern recognition algorithms. The results of this experiment will be used in our Multimodal Affective User Interface.

A. *Experiment Design*

We conducted an experiment where we elicited six emotions (Sadness, Anger, Surprise, Fear, Frustration, and Amusement) and measured three physiological signals (galvanic skin response [GSR], temperature, and heart rate). We elicited above emotions from participants by showing them movie clips. We used the results of Gross and Levenson's [11] work to guide the design of the study. The authors chose 16 of these 78 film clips 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.

For our experiment, we chose the following movie clips to elicit emotions:

- **The Champ** for sadness
- **Schindler's List** for anger
- **Capricorn One** for surprise
- **Shining** for fear
- **Drop Dead Fred** for amusement

In order to elicit frustration we used math questions.

While 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 4 (for GSR and temperature) and a chest band (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.

Fig. 4. BodyMedia SenseWear Armband

B. *Data Analysis and Results*

We implemented three algorithms to analyze the data collected and stored. These are k-Nearest Neighbor (KNN) [20], Discriminant Function Analysis (DFA) [21], and Marquardt Backpropagation (MBP) [12], which is a derivation of a back-propagation algorithm with Marquardt-Levenberg modification.

As shown in Table 2, with KNN algorithm the recognition accuracy obtained was: 67% for sadness, 67% for anger, 67% for surprise, 87% for fear, 72% for frustration, and finally 70% for amusement. As can be seen in Table 3, the results of the DFA algorithm demonstrated a similar pattern of accuracy across emotions to that of the KNN algorithm. The DFA algorithm successfully recognized sadness (78%), anger (72%), surprise (71%), fear (83%), frustration (68%), and amusement (74%). Finally, as shown in Table 4 the recognition accuracy gained with MBP algorithm was: 92% for sadness, 88% for anger, 70% for surprise, 87% for fear, 82% for frustration, and 83% for amusement. Overall, the DFA algorithm was better than the KNN algorithm for sadness, anger, surprise, and amusement. On the other hand, KNN performed better for frustration and fear. MBP Algorithm performed better than both DFA and KNN for all emotion classes except for surprise.

TABLE 2.
EMOTION RECOGNITION RESULT WITH THE KNN ALGORITHM

Recognized Emotion	Elicited Emotion					
	Sad.	Anger	Surp.	Fear	Frust.	Amuse
Sadness	67%	8%	0%	0%	0%	0%
Anger	4%	67%	0%	0%	4%	0%
Surprise	7%	4%	67%	13%	4%	4%
Fear	7%	8%	15%	87%	20%	13%
Frust.	7%	1%	9%	0%	72%	13%
Amuse.	7%	0%	9%	0%	0%	70%

TABLE 3.
EMOTION RECOGNITION RESULT WITH THE DFA ALGORITHM

Recognized Emotion	Elicited Emotion					
	Sad.	Anger	Surp.	Fear	Frust.	Amuse.
Sadness	78%	8%	0%	4%	9%	0%
Anger	4%	72%	5%	0%	0%	4%
Surprise	4%	4%	71%	9%	5%	4%
Fear	7%	8%	14%	83%	13%	9%
Frust	0%	4%	10%	4%	68%	17%
Amuse.	7%	4%	0%	0%	5%	74%

TABLE 4.
EMOTION RECOGNITION RESULTS WITH MBP ALGORITHM

Recognized Emotion	Elicited Emotion					
	Sad.	Anger	Surp.	Fear	Frust.	Amuse.
Sadness	92%	0%	0%	0%	4%	0%
Anger	8%	88%	9%	5%	9%	4%
Surprise	0%	0%	70%	8%	0%	4%
Fear	0%	8%	4%	87%	0%	0%
Frust	0%	4%	13%	0%	82%	9%
Amuse.	0%	0%	4%	0%	4%	83%

V. FUTURE WORK

Our future work will include 1) continuing to conduct experiments for better emotion recognition accuracy, 2) integrating different emotion recognition systems for various modalities such as facial expressions, vocal intonation, and natural emotion language understanding, 3) creating interaction models for the interface to adapt to the user, especially the avatar, and 4) building models of the emotional patterns of users for a more personalized adaptation of the system.

REFERENCES

[1] Allen, A. Roman, L. Cox, R. and Cardwell, B. (1996). Home health visits using a cable television network: User satisfaction. *Journal of Telemedicine and Telecare,* 2: 92-94.

[2] Collet, C., Vernet-Maury, E., Delhomme, G., and Dittmar, A. (1997). Autonomic Nervous System Response Patterns Specificity to Basic Emotions. *Journal of the Autonomic Nervous System,* 62 (1-2), 45-57.

[3] Colquitt, J.A., LePine, J.A., and Noe, R.A. (2000). Toward an integrative theory of training motivation: A meta-analytic path analysis of 20 years of research. *Journal of Applied Psychology*, 85, 678-707.

[4] Crist, T. M., Kaufman, S. B., and Crampton, K. R. (1996). Home Telemedicine: A Home Health Care Agency Strategy for Maximizing Resources*, Home Health Care Manage* Practice, Vol. 8, 1-9.

[5] Damasio, A. (1994). Descartes' Error, New-York: Avon Books.

[6] Darkins, A. W. and Carey, M. A. (2000). *Telemedicine and Telehealth: Principles, Policies Performance and Pitfalls*. New York, NY: Springer Publishing Company, Inc.

[7] de Rosis, F., Pelachaud, C., Poggi, I., Carofiglio, V. and De Carolis, B. (2003). From Greta's Mind to her Face: Modelling the dynamics of Affective States in a Conversational Embodied Agent. *International Journal of Human-Computer Studies – Special Issue on Applications of Affective Computing in HCI.* Hudlicka, E. and McNeese, M. (Eds), Vol 59.

[8] Ekman, P. (1989). *Handbook of Social Psychophysiology*, pages 143–146. John Wiley, Chichester.

[9] Ekman, P., Levenson, R.W., and Friesen, W.V. (1983). Autonomic Nervous System Activity Distinguishes Between Emotions. *Science*, 221 (4616), 1208-1210.

[10] Gross, J. J. and Levenson, R. W. (1997). Hiding Feelings: The Acute Effects of Inhibiting Negative and Positive Emotions. *Journal of Abnormal Psychology,* 106 (1), 95-103.

[11] Gross, J.J., and Levenson, R.W. (1995). Emotion elicitation using films. *Cognition and Emotion*, 9, 87-108.

[12] Hagan M. T. and Menhaj M. B. (1994). Training Feedforward Networks with the Marquardt Algorithm. *IEEE Transactions on Neural Networks*, 5 (6), 989-993.

[13] Haptek PeoplePutty: www.haptek.com

[14] Healey, J. and Picard, R. W. (2000). SmartCar: Detecting Driver Stress. In *Proceedings of ICPR'00*, Barcelona, Spain, 2000.

[15] Lewis, V.E. and Williams, R.N. (1989). Mood-congruent vs. mood-state-dependent learning: Implications for a view of emotion. *Special issue of the Journal of Social Behavior and Personality*, 4, 157-171.

[16] Lisetti, C., Brown, S. Alvarez, K. and Marpaung, A. (in press). A Social Informatics Approach to Human-Robot Interaction with an Office Service Robot. *IEEE Transactions on Systems, Man and Cybernetics – Special Issue on Human-Robot Interaction.*

[17] Lisetti, C. L., Nasoz, F., Lerouge, C., Ozyer, O., and Alvarez K. (2003). Developing Multimodal Intelligent Affective Interfaces for Tele-Home Health Care. *International Journal of Human-Computer Studies --Special Issue on Applications of Affective Computing in Human-Computer Interaction,* . E Hudlicka and M Mc Neese (Eds), Vol. 59.0

[18] Lisetti, C. L. and Nasoz, F. (2002). MAUI: A Multimodal Affective User Interface. In *Proceedings of the ACM Multimedia International Conference 2002,* (Juan les Pins, France, December 2002).

[19] Martocchio, J.J. (1994). Effects of conceptions of ability on anxiety, self-efficacy, and learning in training. *Journal of Applied Psychology, 79*, 819-825.

[20] Mitchell, T. M. (1997). *Machine Learning*, McGraw-Hill Companies Inc.

[21] Nicol, A. A. (1999). *Presenting Your Findings: A Practical Guide for Creating Tables*. Washington, DC: American Physiological Association.

[22] Pasquariello, S. and Pelachaud, C. (2001). Greta: A Simple Facial Animation Engine. In *Proceedings of the 6th Online World Conference on Soft Computing in Industrial Applications*.

[23] Pelachaud, C. and Bilvi, M. (to appear). Computational Model of Believable Conversational Agents. In Communication in MAS: Background, Current Trends and Future. Huget, MP. (Ed.), Springer-Verlag.

[24] Picard R. W., Healey, J., and Vyzas, E. (2001). Toward Machine Emotional Intelligence Analysis of Affective Physiological State. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 23 (10), 1175-1191.

[25] Rozell, E.J. and Gardner, W.L. (2000). Cognitive, motivation, and affective processes associated with computer-related performance: A path analysis. *Computers in Human Behavior*, 16, 199-222.

[26] Takeuchi, A. and Nagao, K. (1993). Communicative facial displays as a new conversational modality. In *Proceedings of the INTERCHI'93 Conference on Human factors in computing systems,* 187-193, (Amsterdam, The Netherlands).

[27] Walker, J.H., Sproull, L., and Subramani, R. (1994). In *Proceedings of Human Factors in Computing Systems*, 85-91. Reading, MA: CHI '94.

[28] Warr, P. and Bunce, D. (1995). Trainee characteristics and the outcomes of open learning. *Personnel Psychology, 48*, 347-375.

[29] Warner, I. (1997). Telemedicine Applications for Home Health Care, *Journal of Telemedicine and Telecare,* Vol. 3, 65-66.