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MAUI AVATARS: MIRRORING THE USER'S SENSED EMOTIONS VIA EXPRESSIVE MULTI-ETHNIC FACIAL AVATARS

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Abstract— In this paper we describe the Multimodal Affective User Interface (MAUI) we created to capture its users' emotional physiological signals via wearable computers and visualize the categorized signals in terms of recognized emotion. MAUI aims at 1) giving feedback to the users about their emotional states via various modalities (e.g. mirroring the user's facial expressions and describing verbally the emotional state via an anthropomorphic avatar) and 2) animating the avatar's facial expressions based on the user's captured signals. We first describe a version of MAUI which we developed as an in-house development tool for developing and testing affective computing research. We also discuss applications for which building intelligent user interfaces similar to MAUI can be useful and we suggest ways of adapting the MAUI approach to fit those specific applications.

Index Terms—Affective Intelligent User Interfaces, Emotion Recognition

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I. INTRODUCTION AND MOTIVATION

The importance of human face in human-human communication has been emphasized in various studies. The human face is considered an independent channel of communication that helps to coordinate conversations in human-human interactions [34]. Previous research studies have also suggested that facial expressions are universally expressed and recognized by all humans [8]. Human-human interactions should form the basis for the design of human-computer interfaces since it is important to facilitate a natural and believable interaction between the user and the computer. The studies in the field of human-computer interaction suggest that having an avatar (an anthropomorphic image representing a user in a multi-user reality space), which has the ability to express facial expressions, as a part of the computer interface, increases human performance. Walker et al.'s study [35] was conducted to compare the responses of the subjects who participated in a computer-based interview survey where the questions were presented either in a text format or spoken by a talking face. Experimental results showed that the participants interacted with the talking face during the survey, spent more time, made fewer mistakes, and wrote more comments compared to the participants who answered the text-based questions. In Takeuchi and Nagao's study [34], the participants interacted with a prototype computer system where they could ask about the prices and functions of computer products during a ten-minute period. While interacting with the participants the computer system either showed facial displays for each situation or it expressed the situation verbally (with short phrases). The results of this study showed that the conversations between the individuals and the system capable of facial displays were more successful than the conversations they had with the system with short phrases.

The strong influence of facial expressions on human-human and human-computer communications makes it desirable, if not necessary, to create computer systems that are capable of showing facial expressions through an anthropomorphic avatar while interacting with users. We created a generic computer system, Multimodal Affective User Interface (MAUI, discussed in section IV) [23] 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.

As it is mentioned above and discussed in Section VI, MAUI is currently in its generic state and it is widely being used as our in-house research tool. It is still under development and we are currently working on investigating the modifications that are necessary to make it suitable for various computer applications. One of the important research issues is to decide which applications should require a computer interface with a talking avatar integrated into it. The following section introduces and discusses the applications for which we think building an intelligent user interface with an affective avatar would be helpful and necessary.

II. APPLICATIONS INVOLVING SOCIO-EMOTIONAL CONTENT

With the rise of personal computers used in an increasing number of contexts, including ubiquitous ones, many applications in human-computer interactions (HCI) and computer-mediated communications (CMC) involve socio-emotional content, which need to be taken into account for natural interactions. Below we discuss two of these applications: Telemedicine and Learning/Training.

A. Telemedicine

Tele-Home Health Care (Tele-HHC) 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][6][37]. 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 both the patient and the health-care provider. When the health-care provider and the telemedicine patient are communicating through a text-based system, the avatar can mimic the facial expressions of each user at both sites [21] to enhance the quality of the communication. Furthermore, during this interaction, when our system accurately recognizes depression or sadness patterns from telemedicine patients and forwards this information to the health-care providers who are monitoring them, they will be better equipped and ready to respond to the situation and this will improve the patients' health and satisfaction. Although there is a growing progress in broadband services, and transmitting real-time videos of patients and caregivers is also an option, as of 2004 only 45% of the internet subscribers in the United States use broadband as opposed to dial-up (emarketer: Broadband Worldwide 2004: Subscriber Update)**.** Even if some day 100% of the subscribers switch to broadband and transmitting large videos is not an issue anymore, we should also take into account that some of the tele-home health care patients might want to hide their emotions and would not show them facially. Although, the patients can force themselves not to show their emotions through their facial expressions, they cannot control their physiological signals such as temperature and heart rate, which are very important indicators of emotional states and can be recognized with our intelligent system (discussed in Section III).

B. Learning/Training

Learning is one of the cognitive processes affected by one's emotional state [11]. Rozell and Gardners's [33] study pointed 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 well 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.

An emotion that affects one's learning negatively is *frustration*, which leads to a reduction in the ability to learn [19]. Furthermore, Reber defines frustration as an emotion that interferes with pursuing goals [32]. Hara and Kling's research focused on studying the frustration experienced by students who were taking a Web-based distance education course [16]. The reasons for the students' frustration were lack of prompt feedback from the instructors, ambiguous instructions on the Web, and technical problems. The results obtained in this study showed that the frustration experienced by those students with this web-based course inhibited their desire and ability to learn and it affected their educational opportunity negatively.

Since there is not a real teacher or a real classroom in an e-learning environment the students should be self-regulated and self-motivated. However, when the frustration level increases to a certain point the motivations of the students are affected negatively [18]. Moreover, frustration impedes students' ability to learn and it affects their cognitive and affective abilities [18].

Another emotion that influences learning is *anxiety*. 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 [24][36]. 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 [24] 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 [36] 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 [36] 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 [24].

With affective intelligent user interfaces, we aim to enhance human-computer interaction in an e-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. Similarly when our system recognizes the learner as being frustrated or bored it might adjust the pace of the training accordingly so that the optimal level of arousal for learning is achieved. Finally, when the system recognizes that a person is confused it might clarify the information just presented. In addition to the assistance the system will provide, an anthropomorphic avatar will adapt its facial expressions and vocal intonation according to the user’s affective state. All these adaptation techniques will improve the learner’s sense of being in a real classroom environment where a live instructor would typically recognize these same emotions and respond accordingly.

III. EMOTION RECOGNITION FROM PHYSIOLOGICAL SIGNALS

Our current approach is to capture physiological signals associated with the user's emotional states during HCI or CMC and develop machine learning algorithms to interpret the collected data in terms of signaled emotions. As shown in a later section, we aim at also visualizing the results of these interpretations via multimodal interfaces.

Many studies have been conducted to understand the connection between emotions and physiological arousal [8][12][1][17][30]. As described in detail in [21] and [22], we conducted our own experiments in order to map physiological signals to emotions by implementing and testing pattern recognition algorithms. We briefly describe the overall procedure that led to our recognition results, the main focus of this article being on linking these interpretation results to visual representations via animated 3D-graphic avatars.

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) with the non-invasive wearable computer BodyMedia SenseWear Armband shown in Figure 1 (for GSR and temperature), and with an additional 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. We elicited the above emotions from participants by showing them movie clips from different movies (*The Champ* for sadness, *Schindler's List* for anger, *The Shining* for fear, *Capricorn One* for surprise, and *Drop Dead Fred* for Amusement). Math questions were used to elicit frustration. As guided by Gross and Levenson's work [13], we conducted a panel study to choose an appropriate movie clip to elicit each emotion

.

Figure 1

B. Data Analysis and Results

Once these physiological signals were collected, as shown in Figure 2, we additionally extracted four features from each normalized raw physiological data type (GSR, heart rate, and temperature): minimum, maximum, mean, and standard deviation values. We implemented three algorithms to analyze the data collected and stored: k-Nearest Neighbor (KNN) [25], Discriminant Function Analysis (DFA) [27], and Marquardt Backpropagation (MBP) [14], which is a derivation of a back-propagation algorithm with Marquardt-Levenberg modification.

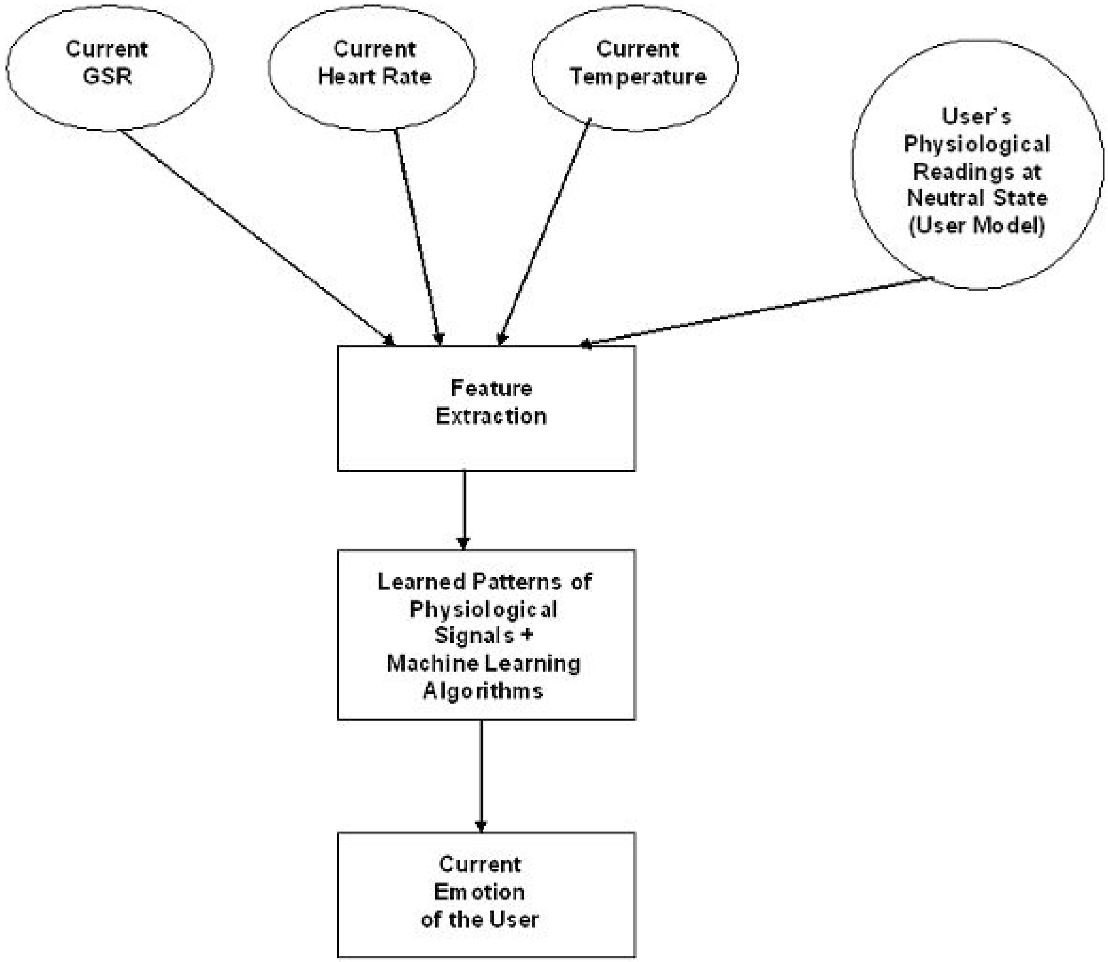


Figure 2

Detailed explanations of the algorithms and results are given in [21] and [22] and the overall results are presented in Figure 3. In summary, the recognition accuracy gained with the MBP algorithm was: 88.9% for sadness, 91.7% for anger, 73.9% for surprise, 85.8% for fear, 77.3% for frustration, and 87% for amusement. Results obtained with the other algorithms (KNN and DFA) can also be found in [21] and [22].

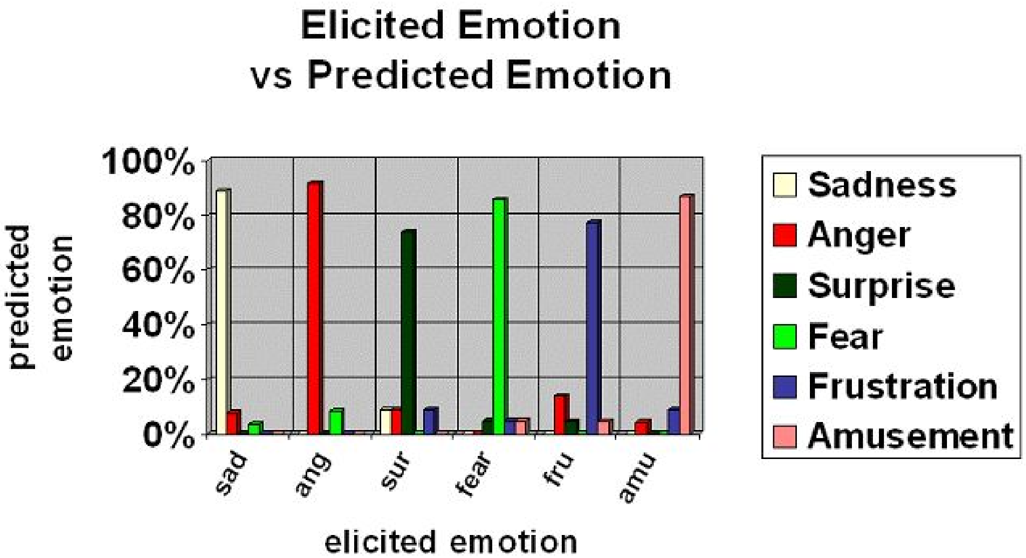


Figure 3

Each movie clip obtained a different agreement rate among the participants of our study in terms of being able to elicit the targeted emotion. The agreement rates were 56% for the sadness clip, 75% for the anger clip, 65% for the fear clip, 90% for the surprise clip, 73% for the hard math questions, and 100% for the amusement clip. For sadness, anger, fear, and surprise, agreement rates among participants were lower than the recognition rates obtained with our algorithms. This situation can be explained by the results of Feldman et al.'s study. [10] In this study, they found that individuals vary in their ability to identify the specific emotions they experience (emotion differentiation). For example, some individuals clump all negative emotions together and all positive emotions together and are thus able to indicate whether the experience is unpleasant (negative emotion) or pleasant (positive emotion), but less able to report the specific emotion. Other individuals are able to discriminate between both negative (i.e., fear versus anger) and positive (happiness versus joy) emotions and are thus able to identify the specific emotion experienced.

IV. VISUALIZING THE RESULTS via a MULTIMODAL AFFECTIVE USER INTERFACE

The results we obtained from our experiments described in the previous section and the results from our earlier experiments [22] enabled us to design our intelligent user interface. We designed and developed MAUI – Multimodal Affective User Interface – shown in Figure 4, in order to visualize the output of our recognition algorithms [23] and to provide visual feedback to users about their emotional states. As our work progresses, the interface is to be used and adapted in the future for a variety of applications such as training and telemedicine as discussed in Section II, by continuously sensing the user's emotions, updating its profile of the user, and learning appropriate ways to adapt to the user as globally depicted in Figure 5.

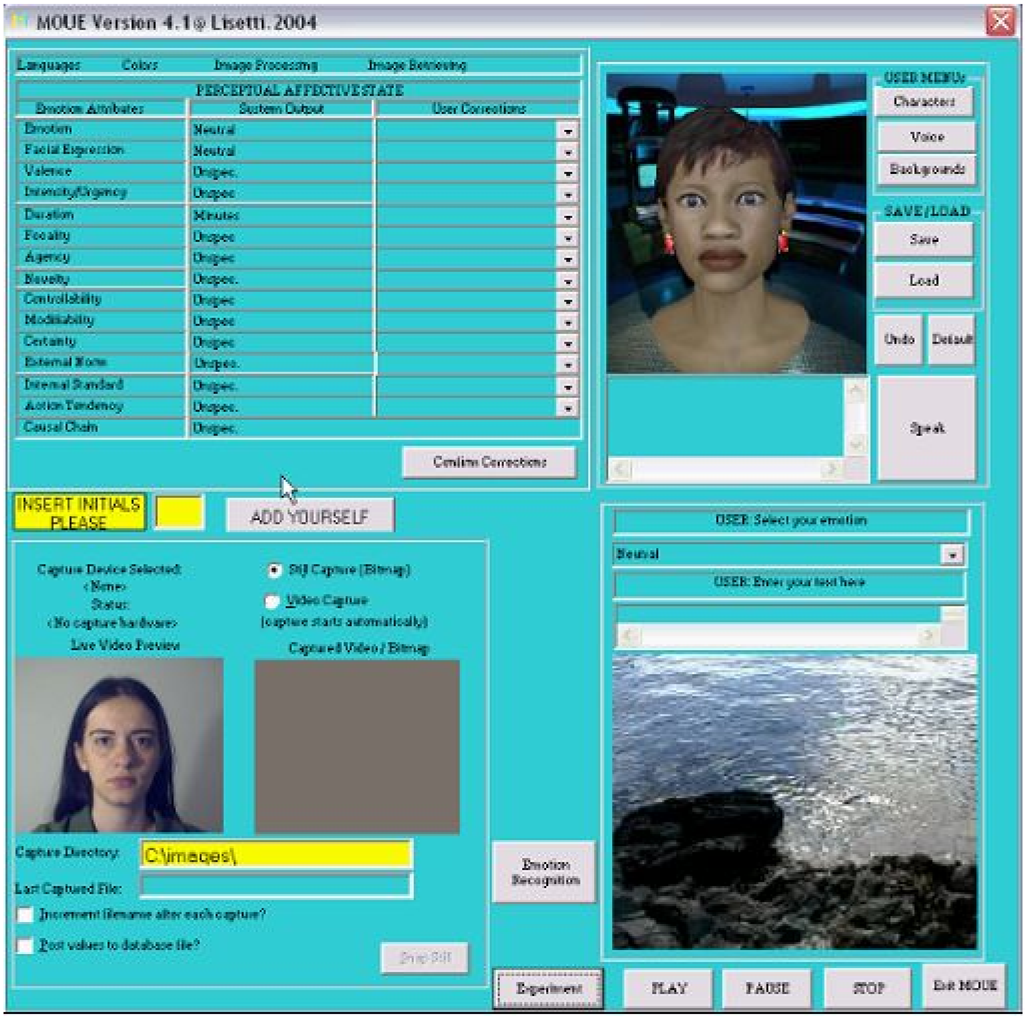


Figure 4

Examples will be given in the next section, but currently, MAUI functionalities include:

- Displaying the ongoing video of the user (as shown in the lower left hand corner of Figure 4), which is recorded by a camera connected to the user's computer. The second box next to the video (shown in black) is used to display still images of the user captured at specific, chosen time intervals (i.e. every 5 or 10 seconds) or when the user wants to take a picture of its own initiative;

- Performing face recognition of the current user from his or her facial picture. At the beginning of each interactive session with the system, the system takes a facial image and checks to see if the user belongs to its database of facial images (described later). If the user is not recognized, the system prompts him or her to enter user profile entries such as name, gender, and personality traits.

- Greeting the recognized user by name via a speaking, animated avatar shown in the upper right corner of Figure 4;

- Providing the user (via a menu) with a choice of multi-ethnic avatars to interact with, portraying different ages, genders, ethnic backgrounds, skin colors, voices, hair, make-up, styles and backgrounds (as discussed later);

- Giving the choice to the user to save his or her favorite avatar, which will then be recorded in this user profile and loaded automatically when the system recognizes the user during the next interactive session;

- Creating and saving and reloading a profile of the user currently including name, gender, personality traits, preferred avatar, and background;

- Displaying on the lower right hand side of MAUI in Figure 4, the current interaction. In this version of MAUI, the context is a slide show consisting of various eliciting stimuli for different emotions (as explained earlier and in [21] and [22]);

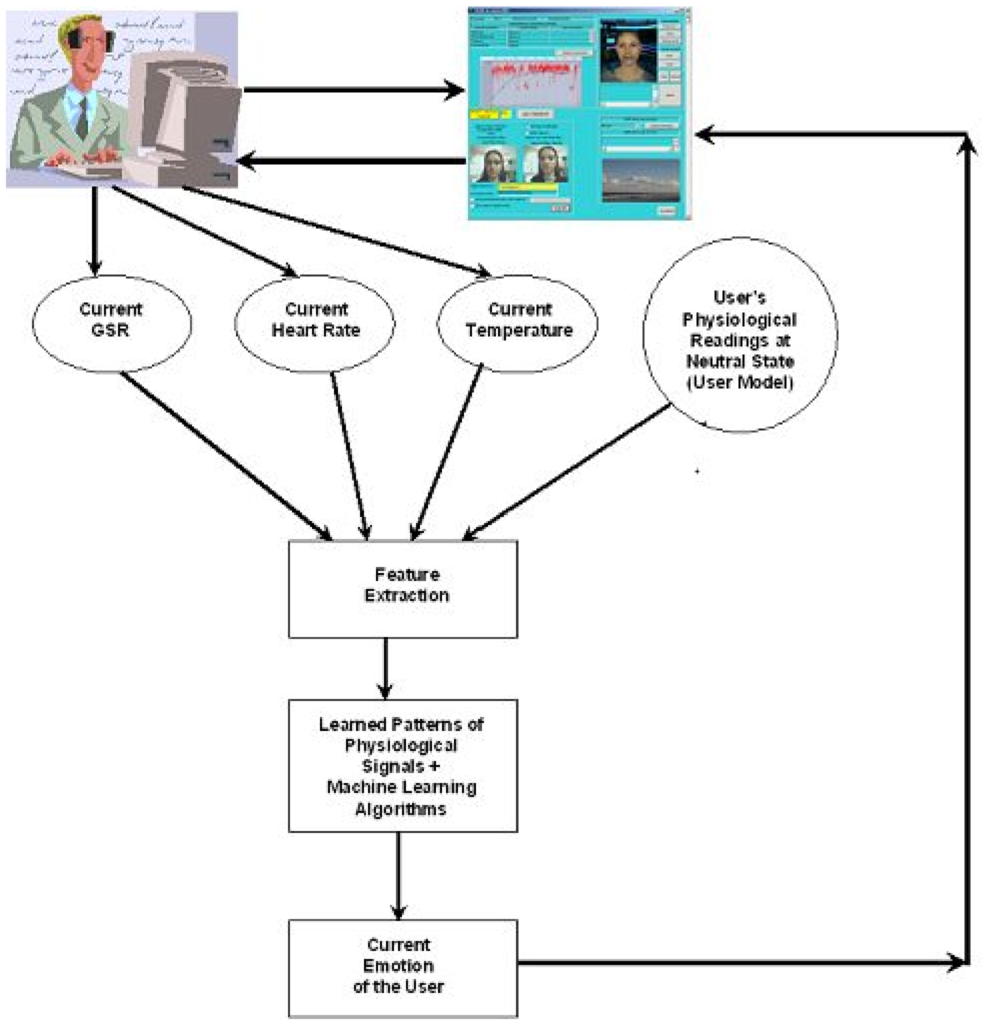


Figure 5

- Enabling the option of re-playing the eliciting videos simultaneously with the recorded facial videos of the participant. We can also display the results of the physiological signal recognition, and therefore observe the changes in the user's multi-modal expressions (physiological signals, facial expressions) simultaneously;

- Mirroring the current emotional state of the user with an animated avatar while s/he is watching the emotion elicitation movie clips (see next section);

- Capturing videos and images of the user's facial expressions while s/he is experiencing emotions, and saving this multimodal data into a web-based database called E-FERET [20];

- Displaying in a text format (shown in the upper left corner of Figure 4) the system interpretation of the user's current emotion (i.e., happy, sad, frustrated, angry, afraid, etc.), and indicating the components of the emotion associated with that emotion such as valence (*negative* or *positive*), facial expression typically associated with the emotion (*e.g.* angry, sad, neutral), causal chain (*i.e.* causes and effects of the emotion that is being experienced), and the action tendency associated with that emotion [19].

V. MAUI AVATARS

As previously mentioned, the upper right section of MAUI displays an anthropomorphic avatar that can talk to the user and adapt its facial expressions according to the user's sensed affective state.

We created our Avatar using Haptek PeoplePutty software [15], which enables changing various features of the avatar while designing it, such as its face, skin type (indicating age), skin color, voice, hair, make-up, accessories, and background. Given that people have varying preferences for the "look and feel" of their interlocutor (be it a physician, nurse, tutor, etc.) we chose a flexible technology which has enabled us to design and build a library of different avatars for people of various ethnic backgrounds, ages, and gender.

We currently have created a collection of twelve different avatars of various ages, gender and ethnic backgrounds shown in Figure 6. Users can therefore select to interact with an anthropomorphic interface agent of their choice by selecting them from a menu (Figure 4 upper right). Since MAUI also has face recognition abilities, the system remembers the user's selection from one session to the next, and sets its default value to the recognized user's preferred avatar in the next session.

As mentioned earlier, facial expressions are recognized and expressed globally [8]. Although MAUI avatars differ in their physical appearances, the way that they show facial expressions does not change. Indeed, one of our future research goals is to evaluate the effect of various characters on different users, depending on the current context and application [20].

We also chose Haptek software because it provides some built-in facial expressions, which we can use directly to encode expressions for sad, happy, surprised, and angry, each with varying degrees of intensity.

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 as seen in Zhang [38], a type of research which could complement our approach as it reaches maturity. Our approach is also different, and complementary, to approaches developing mark-up languages to control behavior of life-like characters during interaction dialogues or during web-based interactions, as with APML [7][28] [29] – an XML-based language allowing to specify the meaning of a communicative act then instantiated to an expressive communicative signal, or as with MPML [[31]] – XML-style language enabling authors to script rich web-based interaction scenarios featuring life-like characters.

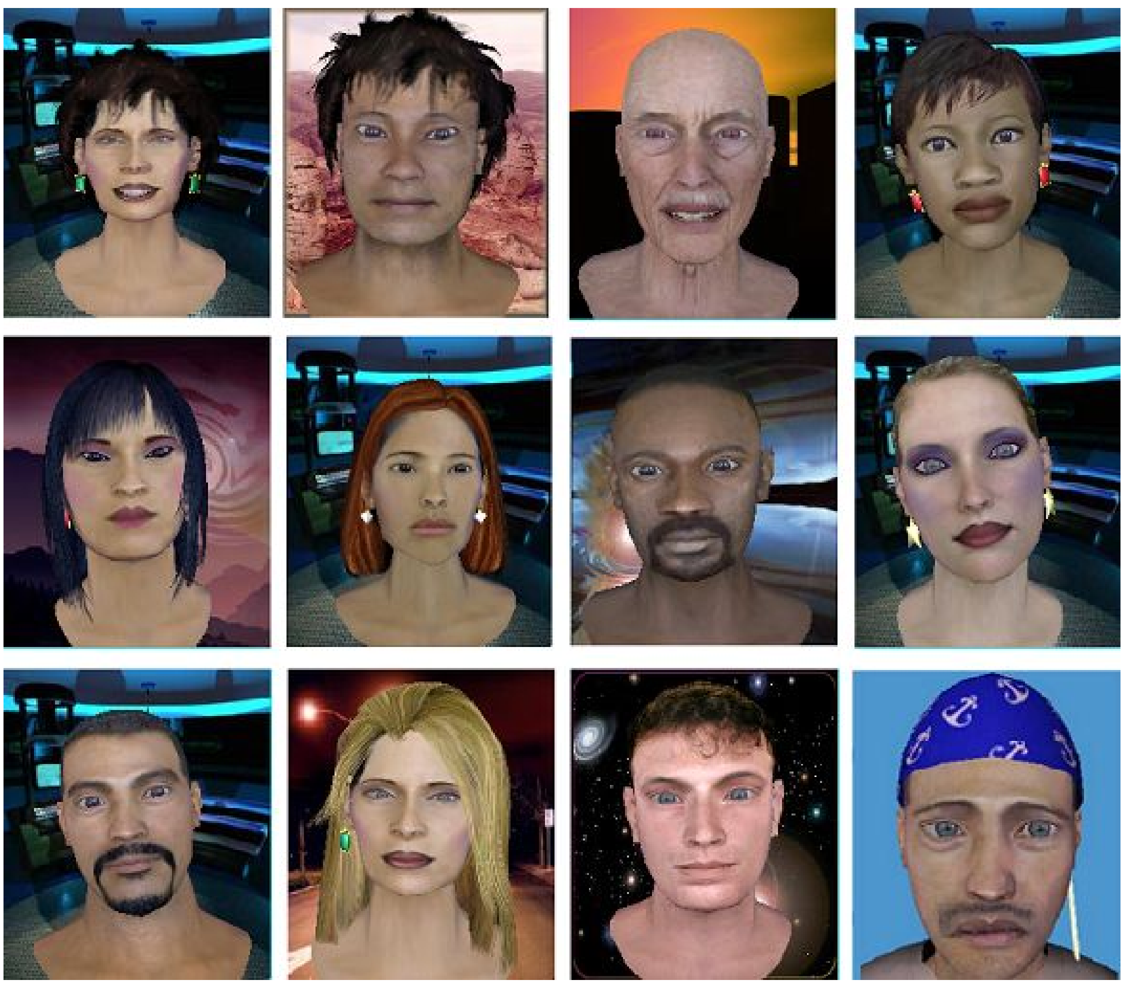


Figure 6

However, within our software, by using the software's own user interface we can control the following parameters to control the facial muscles and to create various facial expressions as shown in Table 1, and arrive at reasonable levels of expressiveness.

Table 1 Parameters 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

Furthermore, according to the user's emotion sensed intensity, it is possible for the avatar to adjust its expressions with different intensity. For example, in Figure 7 we show three different intensities for the happy expression.

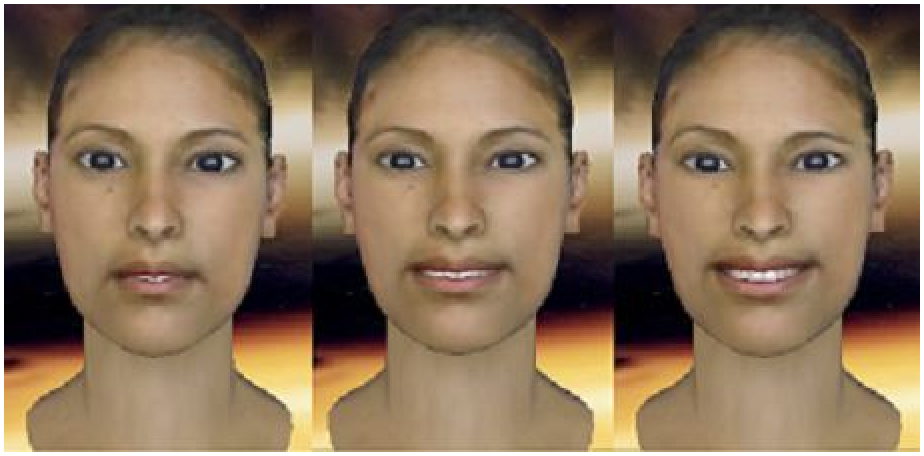


Figure 7

Our avatar's aimed functionality is three-fold: (1) it 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); (2) it can be used to mirror the user's emotions with facial expressions to confirm the user's emotions recognized by the learning algorithms mention in section III.B (Figures 8, 9, and 10); and (3) it could used to animate a previously text-only internet-based chat session showing empathic expressions (as explored in [7] in which an elaborate approach to animating affective avatars during dialogues is proposed) depending up the user's sensed emotions.

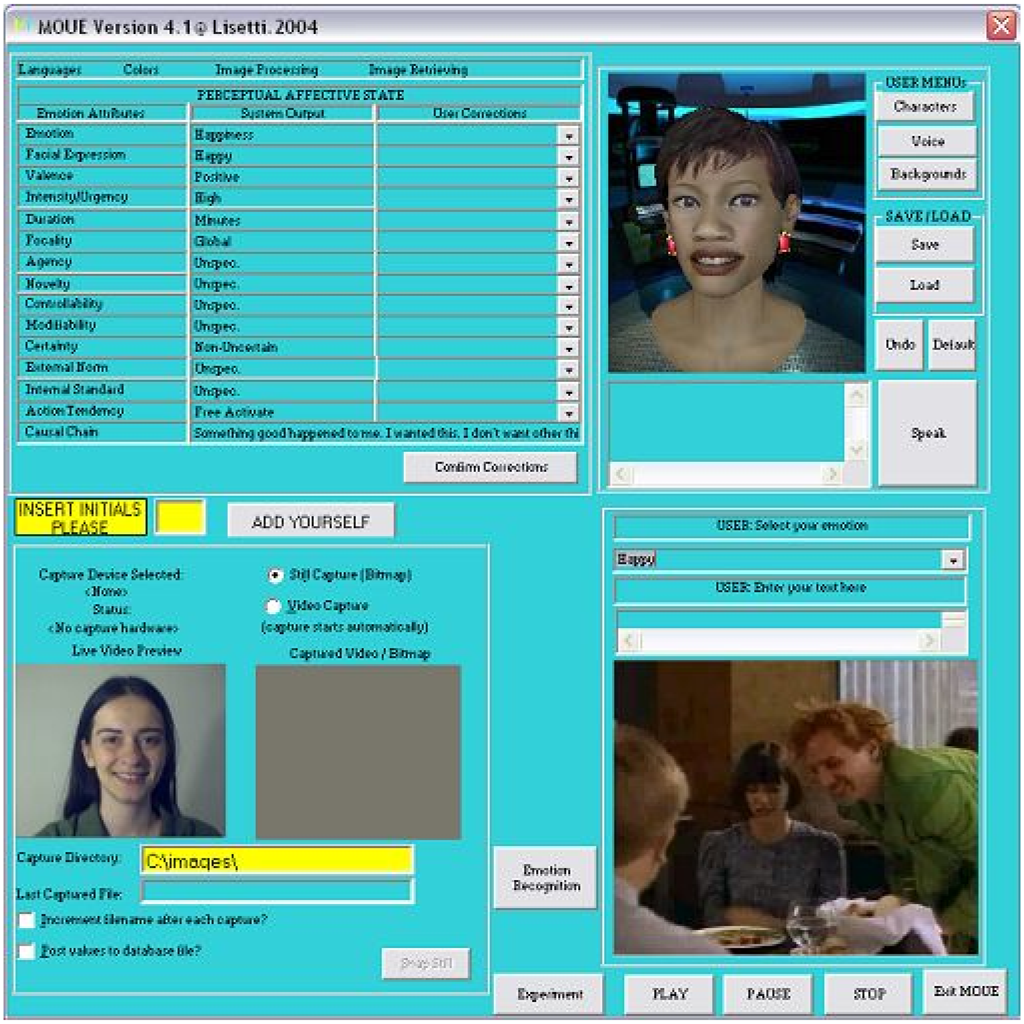
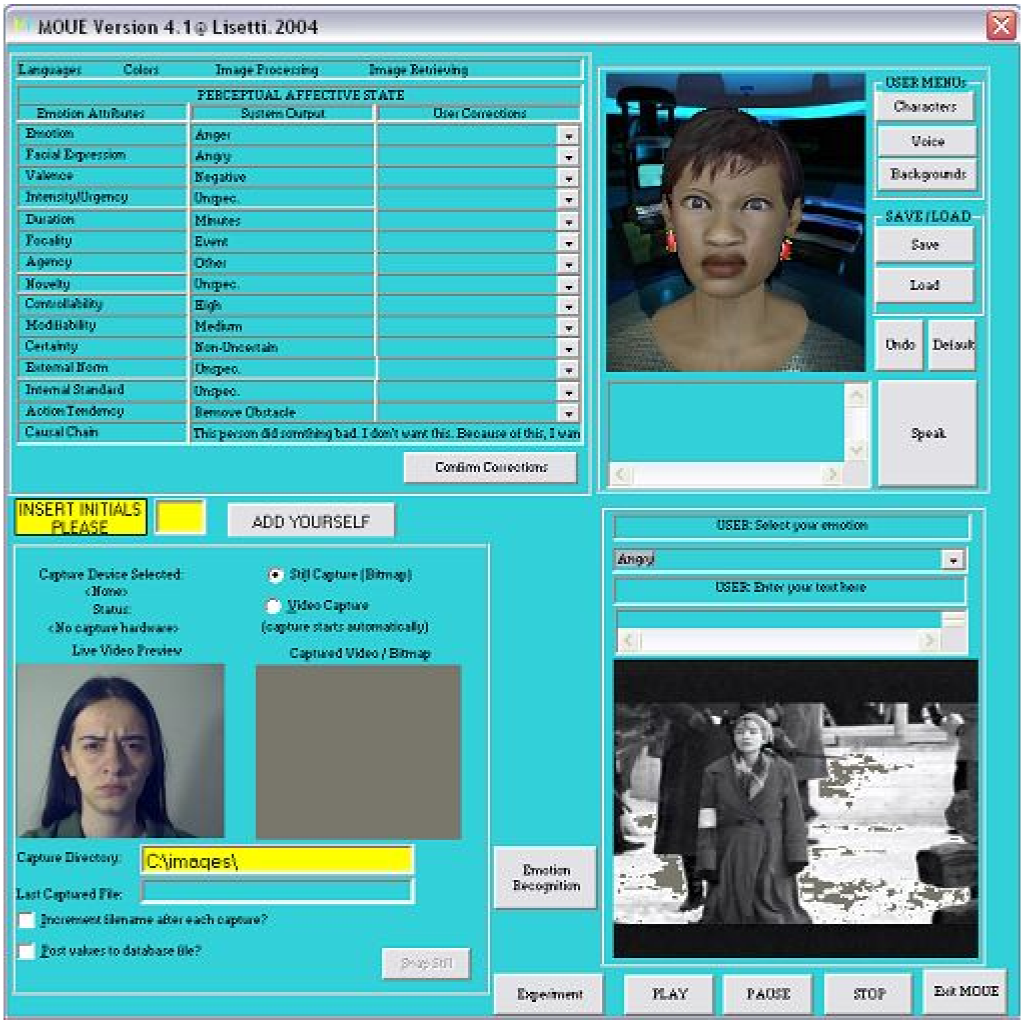

MOUE Version 4.1 @ Lisetti. 2004
Languages
Colors
Image Processing
Image Retrieving
PERCEPTUAL AFFECTIVE STATE
Emotion Attributes
System Output
User Corrections
Emotion
Happiness
Facial Expression
Happy
Valence
Positive
Intensity/Urgency
High
Duration
Minutes
Focality
Global
Agency
Unspec.
Novelty
Unspec.
Controllability
Unspec.
Modifiability
Unspec.
Certainty
Non-Uncertain
External Norm
Unspec.
Internal Standard
Unspec.
Action Tendency
Free Activate
Causal Chain
Something good happened to me. I wanted this. I don't want other thi
Confirm Corrections
USER MENUs
Characters
Voice
Backgrounds
SAVE/LOAD
Save
Load
Undo
Default
Speak
INSERT INITIALS PLEASE
ADD YOURSELF
USER: Select your emotion
Happy
USER: Enter your text here
Capture Device Selected:
<None>
Status:
<No capture hardware>
Still Capture (Bitmap)
Video Capture
(capture starts automatically)
Live Video Preview
Captured Video / Bitmap
Capture Directory:
C:\images\
Last Captured File:
Increment filename after each capture?
Post values to database file?
Emotion Recognition
Experiment
PLAY
PAUSE
STOP
Exit MOUE

Figure 8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Facial Expression
Angry
Valence
Negative
Intensity/Urgency
Unspec.
Duration
Minutes
Focality
Event
Agency
Other
Novelty
Unspec.
Controllability
High
Modifiability
Medium
Certainty
Non-Uncertain
External Norm
Unspec.
Internal Standard
Unspec.
Action Tendency
Remove Obstacle
Causal Chain
This person did somthing bad. I don't want this. Because of this, I wan
Confirm Corrections
USER MENUs
Characters
Voice
Backgrounds
SAVE/LOAD
Save
Load
Undo
Default
Speak
INSERT INITIALS PLEASE
ADD YOURSELF
Capture Device Selected:
<None>
Status:
<No capture hardware>
Still Capture (Bitmap)
Video Capture
(capture starts automatically)
Live Video Preview
Captured Video / Bitmap
Capture Directory:
C:\images\
Last Captured File:
Increment filename after each capture?
Post values to database file?
Snap Still
Emotion Recognition
USER: Select your emotion
Angry
USER: Enter your text here
Experiment
PLAY
PAUSE
STOP
Exit MOUE

Figure 9

Figure 10

VI. ADAPTING MAUI FOR DIFFERENT APPLICATIONS

As mentioned in Section I, currently, MAUI is still a work in progress and its various functionalities allow us to use it as an in-house research tool to visualize the empirical data we collect from our experiments, to run the slide shows during our experiments, to collect various facial expressions, to display emotion components, etc. We are currently focusing our research on investigating and finding the necessary modifications to be applied to MAUI in order to refine its functionalities and make it an application-specific interface. For example, currently the mirroring property of the avatar is used to display the emotion recognized by the system during an experiment; however, after the adaptation of the system for e-learning or telemedicine application, the avatar can mirror the emotional state of the user (the student or the patient) to the teacher or the health care provider. Similarly the avatar can also be used to respond with socially appropriate facial expressions as users display their emotional states. For example, an avatar can display empathy when the learner is frustrated by a task, or a tele-home health care patient is experiencing sadness patterns. Furthermore, some functionalities of MAUI such as displaying emotion components or displaying users' still images might not be necessary for the above applications. Figure 11 shows a prototype of the interface that is adapted for a learning application. As shown in the figure, the interface consists of the learning software, the student's ongoing video, and the avatar that is interacting with the student.

The avatar will interact with the student appropriately when the student is frustrated, bored, or anxious. However, each user's responses are different from the other users' while interacting with an intelligent computer system [26]. So, a socially appropriate response is going to be different for each user. This makes it necessary to build a user model that will enable the system to record relevant user information (such as preferences and personality) in order to interact with its users appropriately.

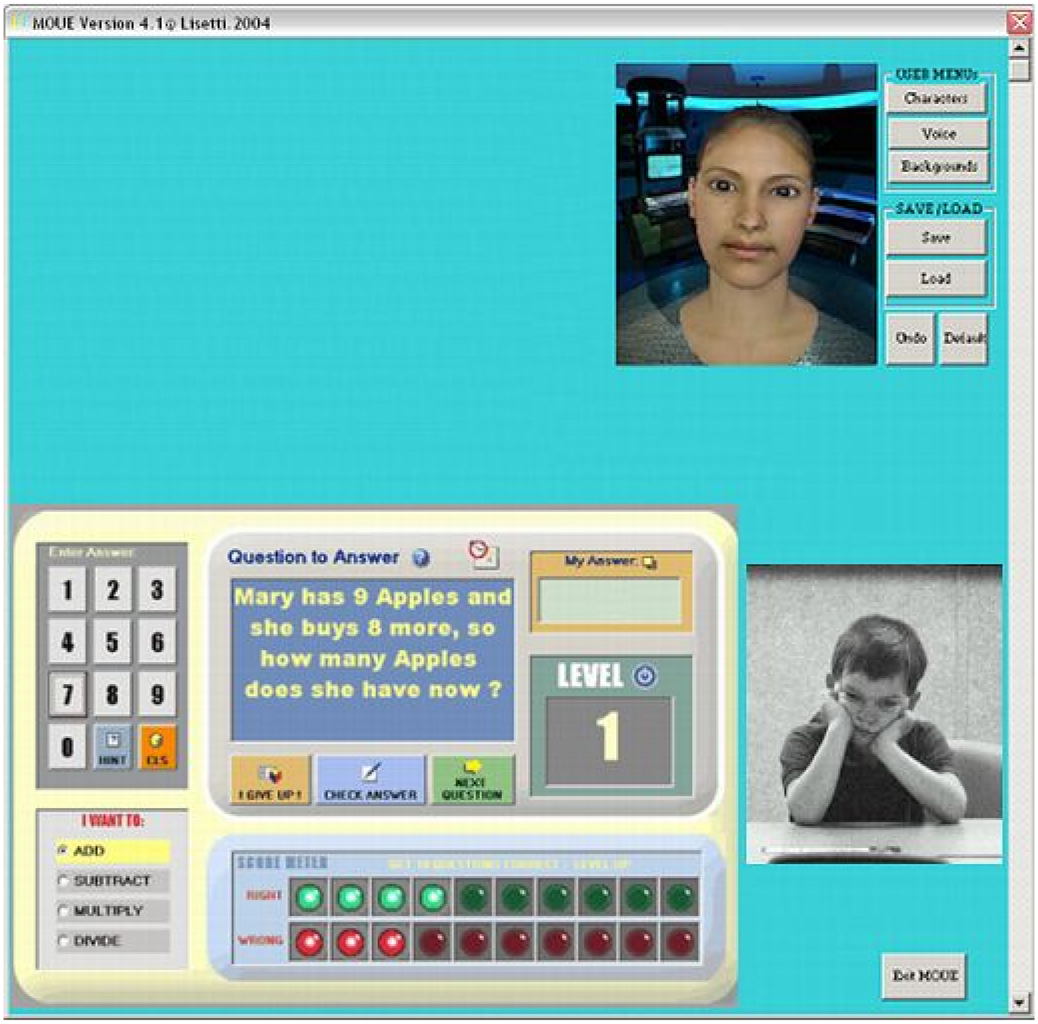

Figure 11

VII. CONCLUSION AND FUTURE WORK

In this article we showed how emotion recognition or the user's emotion can be visualized via an animated avatar in a multimodal affective user interface. We realize that much more work needs to be accomplished to render our interfaces of the future more humane, but tried to contribute a small piece of the puzzle.

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.

In particular, currently the feedback given to the user is emotion dependent, and aims in the future, to be context and application dependent. For example, an interface agent for a tutoring application could display empathy via an anthropomorphic avatar adapting its facial expressions and vocal intonation depending on the current user's affective state, personality, and cognitive learning style.

To achieve these goals, we would like to use more flexible avatar technologies which give us more control over the avatar's expressions to come closer to emotion theories on facial expressions and emotion generation.

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FIGURE CAPTIONS

FIGURE 1 BodyMedia SenseWear Armband