Physiological Signals to Real-Time Modelling of Emotion During Interaction with Play Technologies

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ABSTRACT
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Categories and Subject Descriptors
B.4.2 [**Input/Output and Data Communications**]: Input/Output Devices—*Channels and controllers*; C.3 [**Computer System Organization**]: Special-Purpose and Application-based Systems—*Real-time and embedded systems, Signal processing systems*; H.1.2 [**Models and Principles**]: User/Machine Systems—*Human factors, Human information processing*; H.5 [**Information Systems**]: Information Interfaces and Presentation—*Input devices and strategies*; H.5.2 [**User Interfaces**]: Input devices and strategies—*mouse, keyboard*; H.5.2 [**User Interfaces**]: Interaction styles—*commands, menus, forms, direct manipulation*

General Terms
Algorithms, Measurement, Performance, Experimentation, Human Factors

Keywords
Affective Computing, , Biometrics, Emotion Recognition, Valence and Arousal, Play, Games, Physiology, GSR, EMG, HR, Fuzzy Logic

1. INTRODUCTION
Since computers are playing a significant role in our daily life, the need for a more friendly and natural communication interface between human and computer has continiously increased. Making computers capabale of perceiving the situation in terms of most human specific factors and responding dependent to this perception is of major steps to acquire this goal. If computers could recognize the situation the same way as human does, they would be much more natural to communicate.

Emotions are of important and mysterious human attributes that have a great effect on people's day to day behavior. Researchs from neuroscience, psychology, and cognitive science, suggests that emotion plays critical roles in rational and intelligent behavior [19]. Apparently, emotion interacts with thinking in ways that are nonobvious but important for intelligent functioning [19]. Scientists have amassed evidence that emotional skills are a basic component of intelligence, especially for learning preferences and adapting to what is important [16, 8]

People used to express their emotions through facial expressions, body movement, gestures and tone of voice and expect others understand and answer to their affective state. But sometimes there is a distinction between inner emotional experiences and the outward emotional expressions [18]. Some emotions can be hard to recognise by humans, and inner emotional experiences may not be expressed outwardly [9].

Recent extensive investigations of physiological signals for emotion detection have been providing encouraging results where affective states are directly related to change in inner bodily signals [9]. However whether we can use physiological patterns to recognise distinct emotions is still a question [19, 4].

Although the study of affective computing has increased considerably during the last years, few have applied their research to play technologies [24]. Emotional component of human computer interaction in video games is surprisingly important. Game players frequently turn to the console in their search for an emotional experience [21]. There are numerous benefits such technology could bring video game experience, like: The ability to generate game content dynamically with respect to the affective state of the player, the ability to communicate the affective state of the game player to third parties and adoption of new game mechanics based on the affective state of the player [24].

This work concentrates on developing a real-time emotion recognition system for play technologies which can quantify player instant emotional state during a play experience The rest of the paper is organized as follows: in Section 2 we outline different emotion recognition theories with an overview of physiology sensors. In Section 3 we demonstrate some implementation details of the system. We then describe the experimental setup in Section 4 before giving our results in Section 5. Finally, we give conclusions in Section 6.

2. BACKGROUND

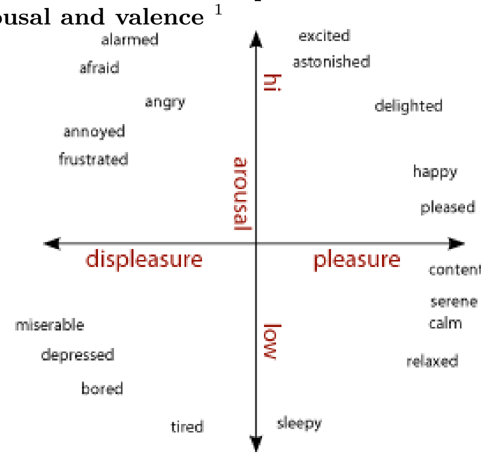
Using emotional responses to increase the level of users interaction with a real-time play technology requires an effective technique to identifying specific emotion states within an emotional space. Major existing emotion models in the psychology literture includes: basic emotion theory [7, 6] , dimensional emotion theory [10, 22] and models from appraisal theory (e.g.,[20]) [26]

Basic emotion theory identifies anger, disgust, fear, happiness, sadness, and surprise [17] as the consice set of primary emotions. These are actually the least six universal categories researchers agreed upon [25]. It also claims these primary emotions are distinguishable from each other and other affective phenomena [5]. On the other hand dimensional emotion theory argues that all emotional states reside in a two-dimensional space, defined by arousal and valence.

While there are various opinions on identifying emotional states, classification into discrete emotions [5], or locating emotions along multiple axes [23, 10], both had limited success in using physiology to identify emotional states [3].

Lang used a 2-D space defined by arousal and valence (pleasure) (AV space) to classify emotions [10]. Valence can be described as a subjective feeling of pleasantness or unpleasantness while arousal is the subjective state feeling activated or deactivated [1]. Using an arousal-valence space to create the Affect Grid, Russell believed that arousal and valence are cognitive dimentions of individual emotion states. Affect is a broad definition that includes feelings, moods, sentiments etc. and is commonly used to define the concept of emotion [18]. Russell's circumplex model has two "axes" that might be labeled as displeasure/pleasure (horizontal axis) and low/high arousal (vertical axis) It is not easy to map affective states into distinctive emotional states, However these models can provide a mapping between predefined states and the level of arousal and valence [25], Figure 1.

Figure 1: Russell's circumplex model with two axes of arousal and valence [1]



Both mentioned models for identifying emotions convey some practical issues in emotion measurement. In a HCI context, the stimuli for potential emotions may vary less than in human-human interaction (e.g., participant verbal expressions and body language) [26] and also the combination of evoked emotions [17]. However with help of physiological signals and the fuzzy logic in the model we are going to use, such issues with our dimentional emotion models would be minimized. Though it is anticipated to observe different range of evoked emotions while interacting with play technologies compared to interacting with other humans in daily life. [26]. However our dimensional emotion models suffers some other problems. One problems is that arousal and valence are not independent and one can impact the other [13]. Continuously capturing emotional experiences in this applied setting is of its other halmarks. Subjective measures based on dimensional emotion theory, such as the Affect Grid [23] and the Self-Assessment Manikin [2], allow for quick assessments of user emotional experiences but they may aggregate responses over the course of many events [26]. This work uses Mandryk et al. version of AV space [13].

[1]Photo credit: http://imagine-it.org/gamessurvey/

2.1 Recognising emotion

Heart rate (HR), blood pressure, respiration, electrodermal activity (EDA) and galvanic skin response (GSR), as well as facial EMG (Electromyography) are of physiological variables correlated with various emotions most. Interpreting physiological measures into emotion state can be defficult, due to noisy and inaccurate signals, however recent on-going studies in this area by Mandryk and Atkins [13] presented a method to continuously identifying emotional states of the user while playing a computer game. Using the dimentional emotion model and the fuzzy logic, based on a set of physiologcial measures, in its first phase, their fuzzy model transforms GSR, HR, facial EMG (for fowning and smiling) into arousal and valence variables. In the second phase another fuzzy logic model is used to transform arousal and valence variables into five basic emotion states including: boredom, challenge, excitement, frustration and fun. Their study successfully revealed self-reported emotion states for fun, boredom and excitement are following the trends generated by their fuzzy transformation. The advantage of continiously and quantitatively assessing user's emotional state during an entire play by their fuzzy logic model is what makes their model perfect to be in incorporated with real-time play technologies. Therefore exposeing user's emotional state as a new class of uncontious inputs to the play technology.

3. SYSTEM IMPLEMENTATION

This project has developed a real-time emotion detection system which can continiously detect and recognise user's emotional state. The system uses Blood Volume Pulse (BVP), Galvanic Skin Response (GSR) and Electromyography (EMG; for frowning and smiling), to classify human affective states in 2-dimensional valence/arousal space, Figure 2.

The system has three modules, Figure 4:

The Blood Volume Pulse (BVP) signal is a relative measure of the amount of blood flowing in a vessel. From BVP we calculated heart rate and heart rate variability. The heart rate is known to reflect emotional activity and has been used to differentiate between both negative and positive emotions as well as different arousal levels [12]

The Galvanic Skin Response (GSR) sensor to measure the

Figure 2: Modeling arousal and valence from physiological data. The number of membership functions applied to that input or output follows the input/output labels. Within each input and output, there is a schematic representing the location and form of the membership functions. Fig. 4 through Fig. 7 show the membership functions in more detail. The system used 22 rules to transform the 4 inputs into the 2 outputs.

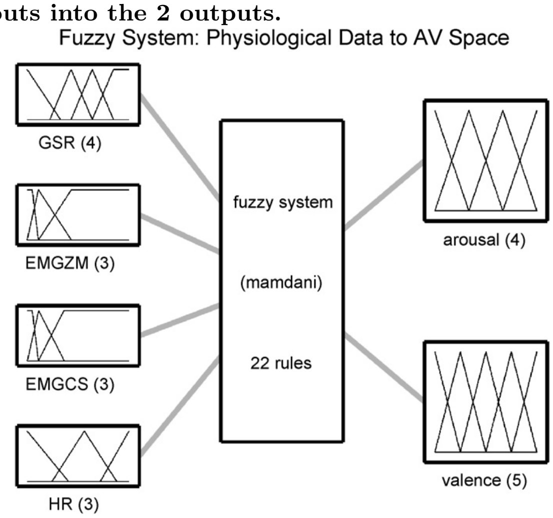
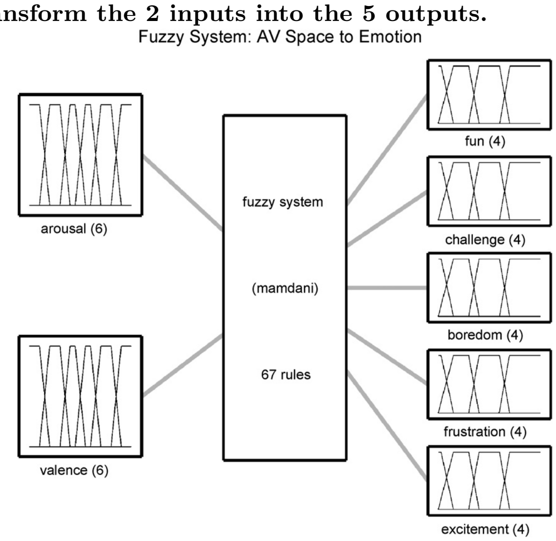


Figure 3: Modeling emotion from arousal and valence. The number of membership functions applied to that input or output follows the input/output labels. Within each input and output, there is a schematic representing the location and form of the membership functions. All membership functions were trapezoidal, exhibited by the flat ceilings, rather than the peaked ceiling of a triangular membership function. The system used 67 rules to transform the 2 inputs into the 5 outputs.



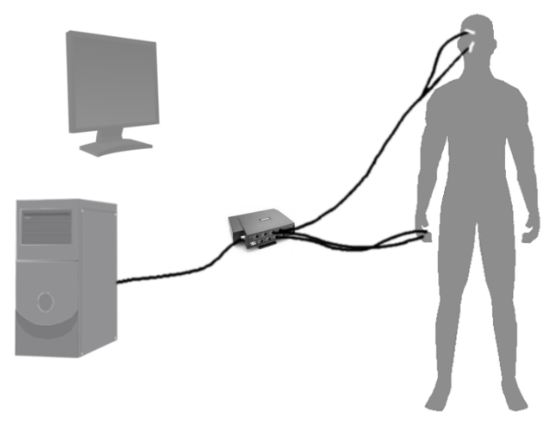
skin's conductance (between two electrodes and is a function of sweat gland activity and the skin's pore size). As a person becomes more or less stressed, the skin's conductance increases or decreases proportionally [18].

Figure 4: System Modules

The sensor module includes a Thought Technology ProComp Infinity encoder [12] connected to PC with a USB cable.

SensorLib is the basic module which receives and filters raw physiological inputs. Then filtered signals are fuzzified by the use of 22 fuzzy rules in the first phase of transformation. Then generated arousal and valence values are transformed into emotion values using another 67 fuzzy rules in the second pass [13]. Appliactions such as games can easily integrate the system where emotion recognition can offer adaptive control to maintain user interest and engagement. Once connected via sensors to the emotion recognition system, the affective state of the user can be captured continuously and in real-time and it can be monitored on a displayed 2-dimenstional graph of valance and arousal, Figure 1.

Figure 5: System Implementation



4. EXPERIMENTATION AND TEST DATA

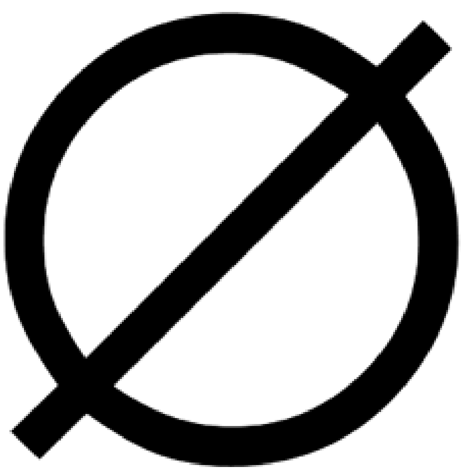
In this study we want to investigate wheather this system is responsive enough to be incorporated with real-time play technologies. We use developed framework to transform normalized physiological inputs of GSR, HR, EMGsmiling, and EMGfrowning, and generate emotion values for boredom, challenge, excitement, frustration, and fun.

We would study 12 participants (6 female, 6 male, aged 20-35) by wiring them to the sensor module which recordes samples of GSR and EMG at 32 Hz, BVP at 256 Hz and therefore HR is computed at 4 Hz. Participant would be asked which hand he/she prefers to use for rating pictures, therefore the opposite hand is used for capturing GSR and HR signals, Figure ??. This hand (with sensors attached) should be as still as possible to avoid any noise from the sensors.

20 images assembled from the International Affective Picture System (IAPS) [11], viewed to participants as a slideshow. [The order of showing pictures is not decided yet]. IAPS consists of a collection of pictures designed to induce emotions in people. Each picture is viewed for 15 seconds. after which there is a 5 seconds for manual rating and participants are asked to conduct their own subjective rating of how the picture made them feel. Pictures are organized in three groups, each of which aimed to generate a specific change in values for boredom, challenge, excitement, frustration, and fun. [should picture be pre-rated for valence and arousal?] Before each group, participant rests for 5 min. The resting period helps the participant with returning to baseline levels of physiological measures. Experiments showed the act of subjective rating or communicating with the experimenter alteres the physiological signals [14, 15]. The resting periods corrected for these effects. Participant were left alone during the session which lasts for about 40 min.

Physiological data were gathered using the ProComp Infiniti system and sensors, and SensorLib from University of Saskatchewan incorporated with an in-house application used for participants to rate their emotion, Figure 6.

Figure 6: Application for subjective rating of participants emotion level



Based on the Self-Assessment Manikin (SAM) affective rating system devised by P. J. Lang [11] the rating system consists of a 5-point scale for each emotion with 1 corresponding to a "Very Low" and 5 corresponding to a "Very High" level, giving a total of 3125 possible combinations. All ratings are stored in a database for investigation of how the participants felt when viewing the picture [should they be correlated with any initial ratings?]. [does the system needs any training?] [The experiment is conducted in an office at University of Saskatchewan.]

5. SYSTEM EVALUATION AND PERFORMANCE

5.1 Fuzzy modeling

5.2 Evaluation

6. CONCLUSIONS

This paragraph will end the body of this sample document. Remember that you might still have Acknowledgments or Appendices; brief samples of these follow. There is still the Bibliography to deal with; and we will make a disclaimer about that here: with the exception of the reference to the LaTeX book, the citations in this paper are to articles which have nothing to do with the present subject and are used as examples only.

7. ACKNOWLEDGMENTS

Thanks to GRAND, NSERC and the University of Saskatchewan for funding the study. Also, thanks to Dr. Kevin Stanley, Dr. Regan Mandryk and special thanks to Michael Kalyn for helping me with the SensorLib and TEVA libraries.

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