Using Physiological Signal Analysis to Design Affective VR Games

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***Abstract*—One of the most important factors in human-computer interaction is the user emotional reaction. Interactive environments including serious games that are responsive to user emotions improve their effectiveness and user acceptances. Testing and training for user emotional competence is meaningful in health care, which has motivated us to analyze immersive affective games using feedback. In this article, a systematic model of designing interactive environment is presented, which consists three modules as affect modeling, affect recognition, and affect control. For affect control module, a graph-based structure is described to control the game scenarios dynamically by analyzing user emotional states. The affect recognition module makes use of physiological signal analysis such as autonomic nervous system variables to evaluate user emotional reaction to different stimuli, then send it as biofeedback to affect control module. The analysis should be used as a guiding principle for designing affective serious games. Oculus Rift DK2 is used in experiments to provide immersive virtual reality with affective scenarios. The experiments demonstrate the ability to induce measurable and distinguishable emotions from physiological signals. The measurement of effectiveness is discussed. Possible applications include emotion competence training for children with autism spectrum disorder.**

Keywords*—*physiological signals, biofeedback, affective game, virtual reality, Oculus Rift

I. Introduction

In a interesting TED talk, McGonaigal [1] is very convincing that "Gaming can make a better world." Since gaming is needed by human nature, carefully-designed games can be used in a broader field rather than pure entertainment. For example, in the concept of serious games, they can be educational or health-related applications. Naturally, one would prefer to interact with machines in a friendly way that the users' emotions can be understood and react accordingly, rather than impersonal pre-scripted manner. However, even though the gaming industry has evolved from 2D to 3D texture, from video vision to Virtual Reality (VR), from PC games to on-line games, there is not yet big breakthrough on emotional interactions.

Scientists have shown that many physiological measures are related to emotions, and nowadays the technology makes them easier to be collected and studied. Since the sympathetic and the parasympathetic nervous system are not easily controlled by awareness, they can become direct and robust measures for affect recognition. Related works will be reviewed in Section II.

Virtual reality(VR) provides 3D immersive environment that can provide more presence, and thus it has more impact on user emotion reactions than regular 2D videos. Oculus Rift Development Kit 2 (DK2) [2] is one of the most popular tools on the market that provides portable and affordable VR reality. Little research has been reported so far with Oculus for immersive affective environments.

Therefore, the main purpose of this article is to study human emotions that can be evoked by game scenarios, and then introduce an interaction mechanism using biofeedback produced by physiological signal analysis. It is based on a dynamic graph structure and a closed-loop affective computing system, and its effectiveness is assessed by several metrics.

This model has several key features:

- Capable of recognizing user emotions by physiological analysis
- Interacting with user emotional states
- Multimodal: Real time training or off-line analysis
- Being able to extend to applications in many fields such as training for autism

The model provides new approach to human-computer interaction, which makes use of features of VR, combined with biofeedback self-adaptation. It can be applied to a variety of applications in serious games. For example, a testing system to analyze user's emotional responses, or a training system for emotional impaired persons to improve their response to different stimuli. This work expands on earlier experience in designing immersive environments with biofeedback [3].

II. Background

Starting from the end of last century, affective computing was introduced by Picard [4] as a new interdisciplinary study area. There are plenty of affect recognition in the literature [5], [6]. The most commonly used methods are speech affect recognition [7], [8], facial affect detection [9]–[11], body gesture recognition [12], and psychophysiological monitoring [13]. They may be combined with each other to form a more sophisticated system.

Psychophysiological responses are believed to be more reliable and more truthful, for the reason that they can hardly be controlled by awareness. For example, one may hide his emotions by changing his facial expression, body gestures as well as his vocal tones intentionally. Although recording psychophysiological variables can be environment-dependent and very sensible to surrounding conditions, researches found them reflecting cues of true emotions from subjects.

Adaptive environments in serious games are discussed in the current decade, as it is very helpful in training or therapy when the gaming environments are able to adjust in real-time according to users' responses.

Wu *el al.* [14] are making efforts to implement one of the closed-loop affective computing systems using a Virtual Reality Stroop Task(VRST) scenarios from the Virtual Reality Cognitive Performance Assessment Test. In addition, Wu [15] summarized four applications of affective computing in last decade. Type-2 FSs and FLSs are also believed to be suitable for all three components of the closed-loop affective computing systems: affect recognition, modeling and controlling.

In recent decade, researchers started to design games considering interactions with user emotions. Designing interactive games responsive to user emotions improves their effectiveness and user acceptances. Sykes [16] stated that affective gaming can benefit and even lead to evolution of game-based learning.

1) Games with biofeedback: Serious games with biofeedback are valuable in the sense of utilizing autonomic signals and send back to impact the game, to achieve either therapeutic or training purposes. Wang *el al.* [17] has proposed a game design system based on EEG signals to identify concentration status. While users are playing games, EEG signals are extracted and analyzed through fractal dimension algorithm. After this, brain state is decided to be either concentrated or distracted, then the system gives reward points for concentration or cuts penalty points for distraction. Skin conductance response was used to design a game in [18]. Another game was designed to enhance the horror scale of zombies in real-time by detecting skin conductance response and heartbeat [19].

2) Games with other feedback: There are many mechanisms to be used in affect recognition. Likewise, rather than using biofeedback, other form of feedback can also be used in affective games. They can be one of the future works to extend the current proposed model.

III. Methods

A. Emotion mapping

In the literature of psychological, there are several models of defining and measuring emotions. One of the commonly used model is Pleasure, Arousal, and Dominance(PAD). Similarly, in [20], three numerical dimensions of affect are stated as Valence, Arousal and Dominance. The dominance indicates the ability to harm another person, thus it is not yet included in the current experiment.

Based on Russells circumplex model [21], we map emotional states into a 2-dimensional circular space as shown in Figure 1. In the preliminary experiment, emotional states are generally mapped into neutral, negative and positive groups, according to the extent they locate in the two dimensions. Blue represents neutral emotional state, while green represents positive and red represents negative. Later the system can be

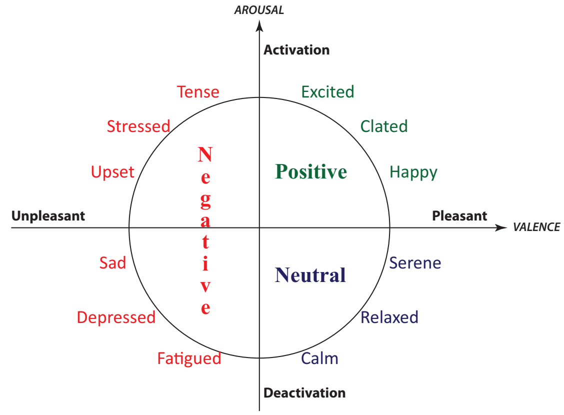


Fig. 1. Emotion Mapping

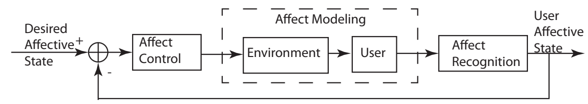


Fig. 2. A closed-loop AC system

extended to recognition of more specific groups as shown in the figure, such as happy, serene, sad, upset, etc.

B. Physiological signals

The Autonomic Nervous System (ANS), which consists of the sympathetic and the parasympathetic nervous system, is believed to be associated with basic emotions [22]. Heart rate variability has been studied for emotion recognition as well [23], [24]. In the proposed system, the ANS variables are measured during the game scenarios by sensors attached to subjects. The corresponding emotional states are analyzed and used as feedback to interact with the game scenarios.

Here are the physiological parameters recorded and analyzed in this paper:

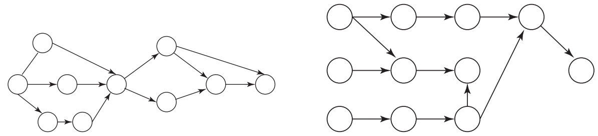
1) Electrodermal activity: Skin conductance level (SCL), skin conductance response magnitude (SCR-M, i.e., sum of all SCR with amplitude more than 0.05 μS in 1 min epoch), SCR number per minute, i.e., non-specific SCR frequency (NS.SCR freq.) which is measured as number of SCRs in 1 min.

2) Cardiovascular activity: Heart rate, Hear rate variability (HRV), high frequency (HF) components (0.15 to 0.40 Hz), and low frequency (LF) components (0.04 to 0.15 Hz), and LF/HF ratio of HRV are calculated as cardiac autonomic control measures.

C. Interaction Mechanism

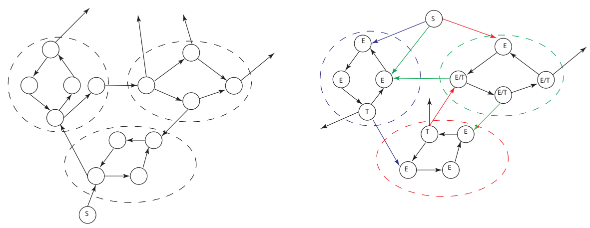
Wu *et al.* [25] proposed a closed-loop affective computing system as shown in Figure 2. The current work is based on an adaptation of this model, which consists of three essential modules:

1) Affect recognition module: Using any one or combined features to recognize user emotional states, such as speech, body gesture, facial expression, and physiological signals. Here biofeedback is used as described in previous section III-B.



(a) Parallel structure (b) Threaded structure

Fig. 3. Commonly used game structure graphs in game design



(a) Dynamic structure (b) Biofeedback structure

Fig. 4. Dynamic structure and proposed biofeedback structure

2) Affect modeling module: Using any one or combined methods to induce user emotional states, such as visual exposure (video or 3D VR scenarios), audio exposure (affective sounds or music). In the preliminary experiments, each of the methods is studied to learn its efficiency, in order to build enhancing nodes that will be described in following subsection.

3) Affect control module: Controller that changes environment according to user emotional states. It should have the option to choose either real-time or delayed control mode, where real-time control means changing game scenarios immediately, delayed control means changing next level of game based on the analysis of current level.

If the desired affective states are known beforehand, this model could be applied to a training system; otherwise it is self-adaptive, to be used as a testing system to keep track of changes of users' emotional states.

The real-time control mode is described as dynamic graph-based biofeedback structure in next subsection.

D. Graph-based Design

Park [26] presented a graph-based representation of game scenarios, looking to reduce the communication gap between game designers and game programmers.

Structures in game design can be described as linear or nonlinear graph [26]. As one would imagine, linear structure has a simple time line, with only one path to go from the beginning state to the very end. There is no option to involve interaction with linear structure. An easiest way to turn it into interactive game is to add choices in each game state, which will lead to an exponential growth of variability. The disadvantage is that the complexity is also exponentially increased, as scripts should be written for all possible endings after each choice . Other than these two, the most commonly seen game design structures are parallel and threaded mechanisms, as shown in Figure 3. The parallel structure keeps the option of

TABLE I
TYPES OF KEY SCENARIO NODES

Notation	Representation	Action(s)
S	Source node	Test which emotional sub-graph to begin the game
E	Enhancing node	More stimuli to enhance current emotional sub-graph
T	Testing node	Test whether to switch to another sub-graph or stay in current sub-graph

choices, while the main script could remain the same, with minor modifications according to different choices. On the other hand, the threaded structure provides more storyline, in which users can reach different endings with combination of choices. The complexity can be kept down if strategies are carefully designed.

In the game *Façade*, it utilizes a methodology called Dynamic Object-Oriented Narrative [27]. The graph of this structure is shown in Figure 4a. The structure graph consists of a group of several sub-graphs; sub-graphs can be self-contained and thus relatively independent to each other, with limited connection paths based on conditions. In this case, the game structure is not necessary to be linear, i.e., no specific order between scenarios and no definite ending.

Based on this methodology, a novel structure is described as in Figure 4b. Key scenarios are denoted as nodes in the figure, while emotional states indicated by biofeedback are coded by colored arrow. Sub-graphs represent different type of scenario sub-graphs that induce different emotions. To make it consistent with Figure 1, blue represents neutral sub-graph or emotional state, while green represents positive and red represents negative. Table I explains different types of key scenarios and their actions. Notably, the T nodes occur at fixed amount of time to simplify the calculation for psychophysiological signals.. The scale of stimuli in enhancing nodes is ranked by game levels.

The structure interacts with emotional states induced by key scenarios, and initiates dynamic switch among key scenarios under constraints. A key scenario contains several stimuli to induce a certain kind of emotion; stimuli are selected according to outcomes of preliminary studies.

Dynamic biofeedback structure:

1) Let **S** be the starting point of the game. Randomly assign one of the starting key scenarios from three sub-graphs.
2) For each $e_{i,j} \in \mathbf{E_j}$, where $i \leq 0$ represents nodes, and $j \leq 0$ represents sub-graphs. Apply affective stimuli based on the current sub-graph to enhance the emotional state, then move to a next node $e_{i+1,j}$. Keep track of enhancing time, node type and affective scale.
3) When a $t_j \in \mathbf{T}$ node occurs, test the current user emotional state by analyzing the psychophysiological signals collected during the time of past consecutive $e_i, ..., e_{i+m}$ nodes, where m is a non-negative integer. If emotional state changes, go to the corresponding sub-graph or stay at the same sub-graph.
4) Keep on looping previous steps, until either time is up or reaching a desired emotional state, that is, the end node of the entire game.

(a) (b)

Fig. 5. Examples of VR scenarios.

IV. Experiments

A. Instruments

Three emotionally laden VR scenarios are designed and chosen specifically to induce general emotion states in neutral, negative, and positive context. The scenarios are chosen based on the experience of above researches, and are generally divided into three categories:

- Neutral scenario is simply exploring VR environment.
- Negative scenario makes use of affective audio and a series of events that causes fear, disgust, and other uncomfortable experience.
- Positive scenario is a collection of happy scenes, including interesting toys and smiling people, with harmonious music.

Figure 5 shows two examples of the VR scenarios.

The hardware to host VR is an Oculus Rift Development Kit 2, and the software platform is Unity 4.6 Pro by Unity Technologies(San Francisco, CA) with C# as developing language.

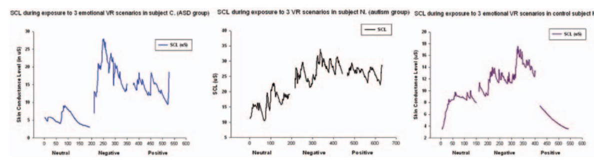
Physiological signals are measured and recorded by sensors attached to subjects simultaneously with the VR scenes. The sensors are ProComp Infiniti, and the software to collect and store data is the BioGraph Infiniti produced by Thought Technology Ltd(Montreal West, Quebec, Canada).

Matlab and SPSS are used for signal analysis. Dependent parameters based on skin conductance and heart rate variability are calculated and applied on one-way ANOVA, paired t-test, etc., in order to find best suitable combination for assessment.

B. Procedures

The order of VR exposure is from neutral scenario, to negative scenario, and positive scenario at the end. The neutral scenario serves as introduction of VR and baseline, in order to eliminate the variation of first exposure. One scenario takes around three minutes for subjects to explore; one session requires exploration of all three scenes, which takes 20 minutes in total, including configuration and mount time. Researchers are able to monitor the scenario by streaming the screen of Oculus to a working computer, in order to take actions when needed. Then the recorded data are analyzed along with the synchronized events and trigger from VR scenes. Figure 6 shows a picture of an experiment session.

Fig. 6. An experiment session



(a) ASD group (b) ASD group (c) Control group

Fig. 7. Samples of skin conductance level(SCL) of two groups.

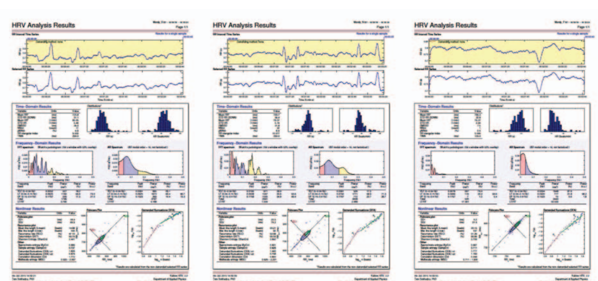
C. Participants

The subjects consist of a group of six high functioning children and adolescents with ASD between the ages from 9 to 14. As a control group and for general data collection, twenty typical developed individuals were recruited to take same sessions to record series of ANS data.

D. Results

Figure 7 shows some samples of skin conductance level during the experiment session. The samples show common pattern as expected that SCL is low for neutral scenarios, and high for negative scenarios. The major difference is that autism group show higher responses across three scenarios. Noticeably, scales are different in three samples for the purpose of display.

Figure 8 shows samples of heart rate variability analyses for one subject in control group. Dependent variables are extracted



(a) Neutral scenario (b) Negative scenario (c) Positive scenario

Fig. 8. Sample of heart rate variability (HRV) analyses for one subject in control group.

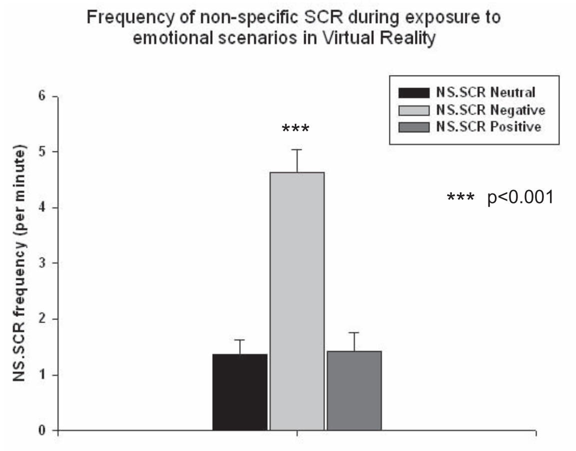


Fig. 9. Frequency of non-specific SCR during exposure to emotional scenarios in VR.

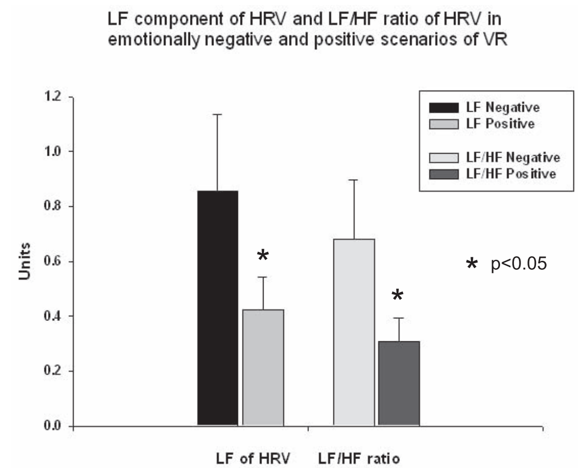


Fig. 10. LF and LF/HF ratio in emotionally negative and positive scenarios of VR.

from the results to be analyzed within group by different emotions.

Figure 9-11 show significant statistic results for differentiating emotional states using 3D VR scenarios. In Figure 9, using non-specific SCR signals, it is easy to distinguish negative emotions from neutral and positive emotions, while neutral and positive emotions are not significantly different from each other. Similarly, Figure 10 demonstrates that both LF component of HRV and LF/HF ratio are capable of distinguishing significant difference between negative and positive scenarios. On the other hand, Figure 11 indicates that by using HRV in time domain, it is able to differentiate neutral and positive emotions.

As mentioned in the previous sections, one possible application this system model can be applied to is emotional training system for children with ASD. Figure 12 shows result of preliminary experiments on children with ASD. Generally, children with ASD have higher responses for all three themes in SCL. In addition, the trend for responses to positive and negative themes are different between two groups. More data have to be collected for training purposes.

E. Measuring system effectiveness

Several metrics can be used to measure different aspects of the effectiveness of the system.

The system keeps track of the path that a user takes to complete the game, including the order of nodes visited and each transition between sub-graphs.

1) Effectiveness of emotions: Between each switch of emotional state, we record that m nodes have been visited, and let j represents sub-graphs, i.e., themes. Then the effectiveness of emotion j can be calculated as:

$$E_j = \frac{m}{\|E\|}, \tag{1}$$

where $\|E\|$ is the total number of enhancing nodes.

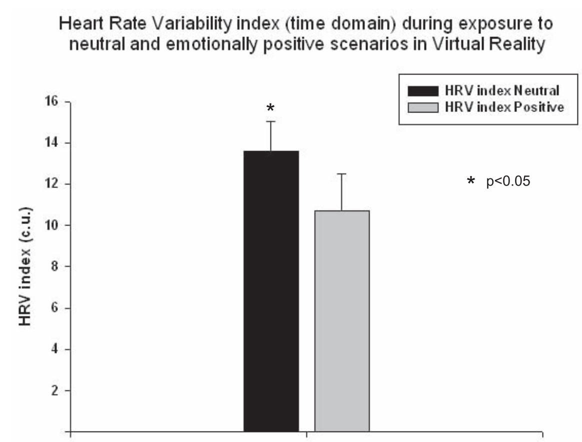


Fig. 11. Heart Rate Variability (HRV) in emotionally neutral and positive scenarios of VR.

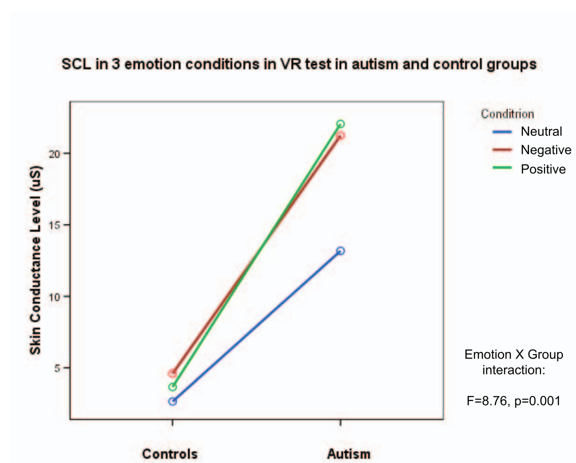


Fig. 12. Frequency of non-specific SCR comparison between autism and control groups

2) Effectiveness of interaction: For each $t_j \in \mathbf{T}$ node, there is a test to determine transition. Let N be the matrix that record all transitions, where $n_{i,j}$ counts how many times the transition from sub-graph S_i to S_j happens during the game. When $i \neq j$, it represents an external transition, i.e, a transition from the current sub-graph to another sub-graph; when $i = j$, it represents an internal transition, which means the user emotional state did not change in between two testing nodes. The effectiveness of interaction is calculated by the equation below:

$$E_{interaction} = \frac{\sum_{i=1}^{N} n_{i,i}}{\sum_{i=1}^{N}\sum_{j=1}^{N} n_{i,j}} \tag{2}$$

3) Effectiveness of game design: Data of each user could be collected throughout testing or training. If a user completes a game level with desired emotional path, then this trial is counted as success.

The effectiveness of game design can be calculated as below:

$$E_{design} = \frac{\#\text{ of success in training}}{\#\text{ of total user trials}} \tag{3}$$

V. Conclusion

In this article, an expanded approach for designing affective VR environments with biofeedback is introduced. Applications of this model combine advantages of VR and reliable physiological signal analysis, which allows us to send analysis results as biofeedback to interact with users' emotional states. Applications can be used for therapeutic purposes, including social skills training for people who suffer from lack of emotional competence, such as children with ASD.

For future work, the next step is to implement the system framework into dynamic affective games. During the game, the E nodes will be generated automatically along with current user emotional state. By using discrete calculation and cross verification on more sensors, the analysis will be able to reach approximately real-time.

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