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DESIGNING INTERACTIVE VIRTUAL ENVIRONMENTS WITH FEEDBACK  
IN HEALTH APPLICATIONS

By  
Yi Li  
M.S. in Computer Science, 2012

A Dissertation  
Submitted to the Faculty of the  
J.B. Speed School of Engineering of the University of  
Louisville  
in Partial Fulfillment of the Requirements  
for the Degree of

Doctor of Philosophy  
in Computer Science and Engineering

Department of Computer Science and Engineering  
University of Louisville  
Louisville, Kentucky

May 2018

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Dissertation approved on

April 6, 2018

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## DEDICATION

This dissertation is dedicated to my wonderful parents

Mr. Xiangping Li

and

Mrs. Zhifen Xie

who love me the most in this world.

## ACKNOWLEDGMENTS

I owe my gratitude to all those people who have made this dissertation possible and have guided me towards my goal.

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## ABSTRACT

# DESIGNING INTERACTIVE VIRTUAL ENVIRONMENTS WITH FEEDBACK IN HEALTH APPLICATIONS

Yi Li

April 6, 2018

One of the most important factors to influence user experience 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 satisfactions. Testing and training for user emotional competence is meaningful in healthcare field, which has motivated us to analyze immersive affective games using emotional feedbacks. In this dissertation, a systematic model of designing interactive environment is presented, which consists of three essential modules: affect modeling, affect recognition, and affect control. In order to collect data for analysis and construct these modules, a series of experiments were conducted using virtual reality (VR) to evoke user emotional reactions and monitoring the reactions by physiological data. The analysis results lead to the novel approach of a framework to design affective gaming in virtual reality, including the descriptions on the aspects of interaction mechanism, graph-based structure, and user modeling. Oculus Rift was used in the experiments to provide immersive virtual reality with affective scenarios, and a sample application was implemented as cross-platform VR physical training serious game for elderly people to demonstrate the essential parts of the framework. The measurements of playability and effectiveness are discussed. The introduced framework should be used as a guiding principle for designing affective VR serious games. Possible healthcare applications include emotion competence training, educational softwares, as well as therapy methods.



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# CHAPTER I

## INTRODUCTION

In recent years, portable virtual reality has become very popular in the market, the best models include Oculus Rift, HTC Vive, Sony PlayStation VR, and Google Daydream View. This emerging technology with hardware improvement provides solutions to family entertainment and more serious, scientific applications. Research related to virtual reality can trace back for decades, but most applications were limited in laboratory, medical, or military training usage, due to the cumbersome equipment required to host virtual reality scenes. Now with much lighter headsets and more seamless immersive environment, researches could turn to more fun directions and be concerned with less environment requirement such as space limit or power supply.

A wide variety of applications could be developed with virtual reality besides pure entertainment, here are a list of some examples:

- Healthcare
- Scientific visualization
- Training
- Education
- Media

- Telecommunication

Many tools or frameworks related to designing virtual reality environments are available, yet still needed to be explored or tested with newest technologies. It is very promising to make use of these methods and let virtual reality better serve human beings.

## 1 Background

Emotional Intelligence is believed to be increasingly importance in affecting people in daily life, and may arguably weigh more in measuring individual success than mathematical and verbal intelligence [2]. On the other hand, the ability to recognize and interpret different emotions correctly is not only a long-lasting challenge for human social needs especially for persons with social impairment, but is also expected to be contained in intelligence machines such as robots, virtual assistance *etc.* One may argue that technologies or machines have been contributed so many years to modern human society without the ability of emotional perception. Given that artificial intelligence can be even more advanced than human brains in certain fields, being completely rational may be a good virtue for machines. However, it is hard to deny that how eagerly human beings desire to communicate with machines(*e.g.* see the pleasure Siri has brought us). Naturally, people would prefer to interact with someone who cares people's feelings, with which their emotions can be understood and react accordingly, rather than having to deal with impersonal pre-scripted machines(*e.g.* imagine Siri could sense your tone and react accordingly to soothe your

anger). Therefore, starting from the end of last century, affective computing was introduced by Picard[3] at MIT laboratory as a new interdisciplinary study area, and soon became emerging technology.

Affective computing is one of the most active and challenging research topics because it involves many fields not just computer science, but also engineer, psychiatry, sociology, cognitive science, psychophysiology, and even more. Emotions are generally complex and hard to measure, there's no determinate method or metrics to calculate emotions through numbers. Although, more and more experiments have been conducted towards the goal, emotion recognition is not as mysterious as it sounds any more. Several physiological measurements have been proved to be related to emotional reactions, and it is also convincing that behaviors, including facial expressions and body movements, can reveal more or less emotions. All in all, affective computing leads to an improvement in e-learning, e-training, and e-therapy, which will provide better user experience and more customized features that balance purposes and individual emotions, such as playing calming music when user presents anxiety, or reducing difficulty level when user shows frustration.

## **2 Motivation**

Not surprisingly, many people think games are distracting and only for killing time. It is undeniable that entertainment is needed by human nature. One would easily crave for relaxation rather than hard working, no matter it is in ancient time after hunting or in modern time after high pressure work. However, carefully-designed games can be used in a broader field to let people learn or benefit more willingly in a relaxing



situation. For example, in the concept of serious games, they can be educational applications, where their entertainment features can draw users' attention, while the educational elements let users gain knowledge at the same time. The products in game industry has evolved from 2D to 3D texture, and then virtual reality, from PC standalone games to online social games, but there is not yet big breakthrough on emotional interactions. Although, with the existing hardware and technologies, it is feasible to design such an interactive environment that takes human emotional reactions as feedback to control the game. In this way, the games become emotionally adaptive and will surely improve user experience.

In addition to the needs of emotional communication in human-computer interaction, some special group of people who suffer from impairment of social skills, such as children on autism spectrum disorder (ASD), are also in need of training or therapy to help improve their emotional competence. Games designed for children on ASD often aim at their communication skills or activities of daily living. However, their lack of ability on emotional competence, including emotional recognition and expression, is hardly targeted. VR provides a very important feature that suits perfectly for children on ASD - safely controlled environment. Not only that, but in general, a 3D VR immersive environment can provide more presence, which leads to more user emotional responses for measurement. Applications with dynamic adaptiveness based on user emotional states will be beneficial and helpful. This is one of the major reasons that motivated this project.

Oculus Rift and HTC Vive are two of the most popular tools on the market that provide portable and affordable VR reality. They are easy to be integrated with

game engines such as Unity using compatible drivers and SDKs for game development. With the precise, low-latency positional tracking, the immersive presence and inexpensive prices, the Oculus and Vive are suitable for all kinds of VR applications as well as serious VR games. Our work is based on an open-source VRTK tool that provides useful tool kits for multi-platform VR integrity and VR simulation. Not many research projects have been reported so far for immersive affective environments. In the present research, experiments are done with Oculus, but the demo application is multi-platform compatible.

Most related works on affective computing relying on self-reporting questionnaires to label different user emotional reactions and then train advanced classification models upon them. The advantage of this conventional way is that it is able to categorize emotions into more specific status, *e.g.* being able to differentiate happy or excited, angry or scared. The disadvantage is that it relies too much on subjectivity and also memory. Memories could be easily distorted by the series of events that keep stimulating users. Furthermore, in some cases, the user might deny the fact that he/she was scared or upset by some horror scenes subconsciously. This motivated us to find a more objective way to evaluate user's emotional reactions.

The main purpose of this research is to study human emotions that can be evoked by game scenarios, build a model that is more objective to recognize user emotional states, and then introduce an interaction mechanism with feedbacks on user emotions based on customizable user models. The outcome of this present research will lead to a new approach of designing immersive affective serious VR games, the applications include therapy or training toward children on ASD.

### 3 Aims and Objectives

As stated, the general idea is to learn how user emotions are evoked by 3D VR emotional context, and then bring up a novel mechanism of designing serious VR games that accommodate to user emotional reactions. This research has been carried out in four phases. Each phase described in following paragraphs has achieved its objective, thus leading to a multi-modal affective gaming application implemented in a healthcare theme.

- Phase 1: Preliminary affective study

During the first phase, we reviewed and extended previous studies using traditional methodologies, including audio-visual experiment, music experiment, and video experiment. Most of them were conducted in comparison between autistic children group and typically developing children group. The results in this phase has provided evidence for choosing VR contents to be used in later phases.

- Phase 2: Preliminary VR experiment

During the second phase, we chose several emotion-laden VR scenes to be shown in experiment, and started recruiting volunteers to interact with the VR context and recorded their physiological reaction data. These data were then analyzed offline and served as benchmark for model checking and verification in later phases.

- Phase 3: Establish affective computing training model and testing

During the third phase, the interactive model for affective environment gaming design was established. More experiments were conducted using various VR contents with labeled and unlabeled events as stimuli to induce emotional reactions. The labeled data served as training data and unlabeled data served as testing data. Several classifiers were trained and compared. The model was then verified by the testing data. From the results, we found that constructing customizable user model would be more reasonable than building a common classification model over different users. Up till this phase, all data were analyzed offline, and the model was tested by running data as game simulation.

- Phase 4: Adaptive VR environment framework and application

In the last phase, we were finally ready to bring up the theoretical game design framework and implement into demonstrative application. The framework is generic and can be applied into many fields. In the present project, we chose physical training healthcare application as an example of implementation with essential modules. The game is written in C# with Unity game engine and is a cross-platform application, so that it is able to be hosted on multiple popular VR devices. The application connects physiological monitoring device, game engine, and the VR helmet. Finally, we brought up several metrics to evaluate the presented system, in order to measure the importance aspects of the framework. More summary on the unique features of this framework is given in the next section.

## 4 Interactive Affective Environment Design Model and Game Application

In this research, a game design model of immersive affective serious game with biofeedback is introduced. 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
- Training customized model for different user groups
- Interacting with user emotional states
- Multi-modal: Real-time adaptiveness based on biofeedback or offline analysis
- Being able to be extended to more sub-categories of emotion recognition
- Suitable for applications in many fields such as physical training for therapy purpose

When a user is playing, the back-end receives data from sensor, running affective recognition and adaptively changes game scenarios based on the biofeedback, so that the whole game is adaptive to user emotional states in real time.

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.

## **5 Dissertation Organization**

The structure of my dissertation is listed as follows:

- Chapter II Literature Review

Psychology experiments have shown that many human reactions are related to emotions such as physiological signals, body movements and facial expressions, and thus data can be collected and studied to learn emotions. Since the sympathetic and the parasympathetic nervous system are not easily controlled by awareness, they can become direct and robust measures for affect recognition. Chapter II provides literature view of related works on serious games, affective computing, and most recent studies on affective VR.

- Chapter III Experiments

Chapter III performs phase 2 and phase 3 experiments. In order to train the affect recognition module and get more useful information of human emotions, several experiments have been conducted. Different sources of stimuli were used to induce emotions: affective sounds, music, visual picture, 2D video clips, and 3D VR scenarios. The results have shown VR provides 3D immersive environment that has more impact on user emotion reactions than regular 2D videos. Phase 3 experiment with unlabeled emotion-laden events is an extension to the phase 2 experiment, where the data are used to testify the trained classification

model and to build up a customizable user model, details are also discussed in this chapter.

- Chapter IV Affective Game Design and Application

Chapter IV builds up a user model that contains more useful information aiming to improve affect control mechanism. The chapter also describes a novel graph-based game structure and explains the interaction mechanism and physiological monitoring used for affect recognition. A healthcare application is implemented based on this model as an example to show the promising usage of serious affective VR gaming.

- Chapter V Discussion

Chapter V contains discussion and evaluation of the proposed model and its applications. It refers to heuristic evaluation on playability of a game, and provides several metrics to assess multiple aspects of the model effectiveness.

- Chapter VI. Conclusion and Future Work

Finally, Chapter VI concludes the research and points out a few future directions to better improve the framework, and also provides suggestions for its applications.

## CHAPTER II

### LITERATURE REVIEW

#### 1 Games

Tracing back to ancient time, gaming has been a very important part of human lives because of the needs of leisure and entertainment. In fact, with the rise of the video games industry in past decades, there is no doubt that gaming would have impact on a whole generation.

There are lots of good reasons that games are attractive to a large population, such as the satisfaction of mastery, the feeling of fairness in life, and the social needs, of course. One of the important factors is the extraordinary human-computer interaction nowadays in new gaming technology. Users get immediate and concrete feedback each time they take an action, hit a trigger, and succeed or fail in a task. A positive feedback such as adding bonus points will lead to user satisfaction and the gain of self-confidence. When the user gets negative feedback, he/she will analyze the reason and adjust the strategy immediately. These reflections happen in a habitual way, where one may not realize the stream of thoughts. The whole process makes the user feel excited, and also makes them feel like the center of attention.

Most people would be concerned that gaming is harmful to the young generation, which may lead to violence or addiction. However, there are also other opinions



that value the benefits of playing games. For instance, Granic *et al.* [4] summarized possible benefits of games to the young generation in four domains: cognitive, motivational, emotional, and social experiences. Designing games focusing on benefits to human beings leads to the concept of serious games. The current research mainly considers the emotional domain that games can benefit human beings.

### **1.1 Serious Games**

Serious games can be defined as a gaming technology that is used for the purpose of education, training and information, other than mere entertainment [5]. The ultimate goal of this research project is to develop healthcare applications with the ability to monitor and interact with users' emotional states, in order to achieve better medical purposes. In fact, the presented framework is fully capable of being implemented to educational or training games.

### **Education**

As people are spending more and more time playing games, ideas of education-entertainment are brought up. Games designed for education provide multimedia approaches and interactive ways of learning, which allow users to gain knowledge while having much more fun than traditional class-based learning.

One of the good examples for educational serious games is language learning [6, 7]. Some serious games were designed to teach children knowledge in a certain topic, such as math, science, engineering [8] and more.

## **Training**

Since technology allows vivid simulation of realism, games are adopted in many fields for training purposes, such as in military use. Games designed for training provide simulated conditions that may not be easily accessed or constructed in real life.

Besides the use in military training, games can also be designed for sports training such as football[9]. There are also training for special skills, e.g., medical professions such as surgical skills training[10].

## **Health**

With the continuous improvement of living standards, the public has gained more awareness of healthcare. Serious games designed for health purposes become good platforms for people to gain knowledge, get carefully controlled treatment, or get mental healthcare. Examples include health informatics [11], and therapy sessions for specific development disorders [12].

### **1.2 Game Design**

A good game design is not just about writing a story; there are many other aspects to be considered in designing a game. One of the most important parts is the structure of the game [13].

There are many classic ways to design a game: storyboard, flowchart and state transition diagrams, and so on. Storyboarding, as it describes what will be going on in a sequence of drawings, is one of the classic ways of designing games[14, 15]. The process of storyboarding has been well-established in visual-storytelling media such

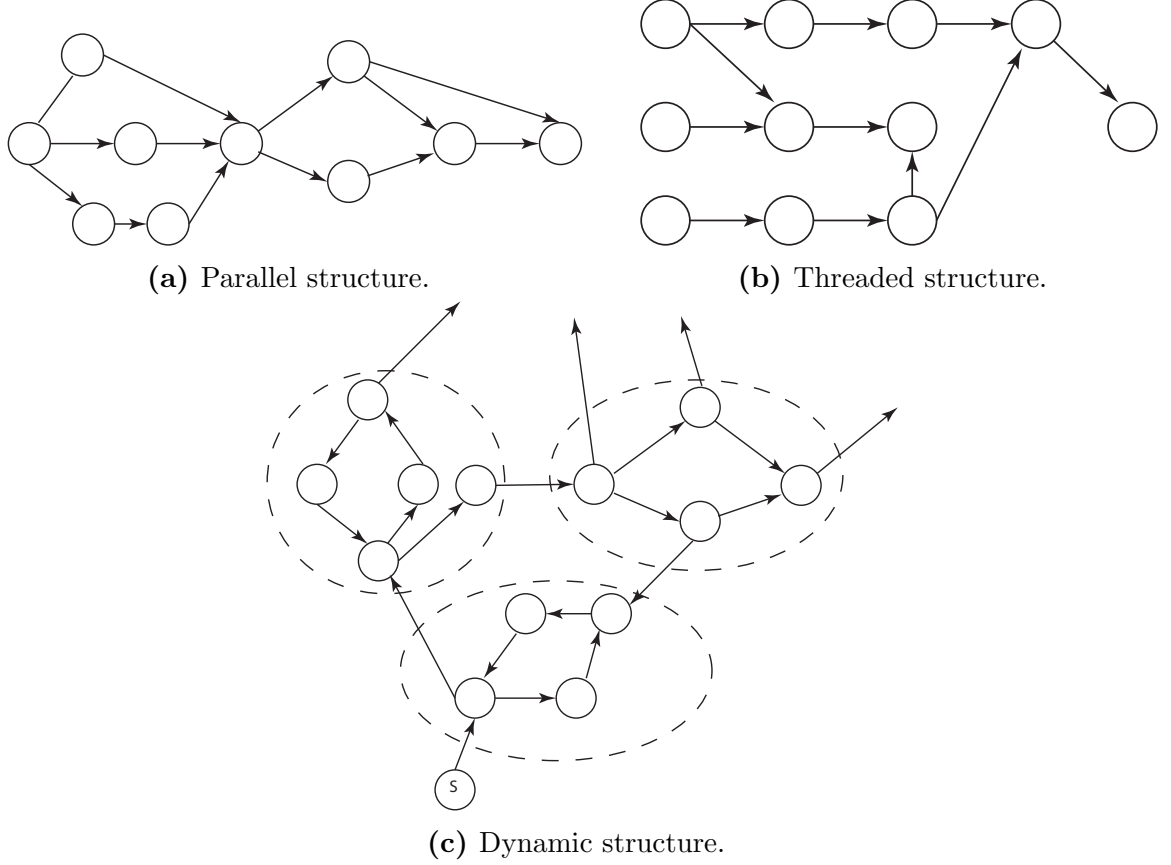
as movies and television programs. Even though storyboards can easily depict what it is in the plan, the drawback of applying storyboards in serious games is that it is highly dependent on the tool, and the requirement for art talent makes it difficult to use under scientific lab conditions.

Creating flowcharts is another classic way of designing a game. It helps to present the logic of a game more clearly, so that the communication between all involved persons is easier. The problem is that when the logic itself is complex, the flowcharts become cumbersome and even worse for understanding.

In the book *Tricks of the Windows game programming gurus* [16], state transition diagrams and decision trees are recommended for game design. This approach explicitly defines all possible states and transitions between them. It is formal and efficient when the system is relatively small, but when the system gets larger, having to define all possible states would be impractical.

Naturally, game structures can be represented by directed graphs, as a pair  $(V, E)$ , where  $V$  is the vertex set representing game states, and  $E$  is a set of transition paths directed from one game state to another game state.

Structures in game design can be described as linear or nonlinear graph [17]. Linear structure has a simple timeline, with only one path to go from the beginning state to the very end. There is no option to involve interactions 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



**Figure 1.** Commonly used game structure graphs in game design

game design structures are parallel and threaded mechanisms, as shown in Figure 1a and 1b, respectively. The parallel structure keeps the option of 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 a combination of choices. The complexity can be kept down if strategies are carefully designed.

In 2010, Park *et al.* [18] proposed a graph-based representation to drive game scenarios. Efforts were made to work on a better understanding between the game designers and game developers. Three graph forms were introduced: Event graph, State graph, and Action graph. In addition, six types of events were defined, and all

scenarios were eventually categorized into one of those types. It has the ability to consider game anomaly and event causality.

The game *Façade* utilizes a methodology called Dynamic Object-Oriented Narrative [19]. The graph of this structure is shown in Figure 1c. 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.

In this dissertation, a novel graph-based game design methodology is introduced on the basis of the Dynamic Object-Oriented model, in which it defines different nodes in sub-graphs. The transitions are decided by a user model that considers not only the current user emotional state, but also user preference and other user profile information, as well as a controllable system mode.

## **2 Emotions**

Emotional intelligence (EI) is defined as constituting "self-awareness, self-management, social awareness, and social skills at appropriate times and ways in sufficient frequency to be effective in the situation" [20](pp. 345). It plays an important role in the evaluation of social assessment on individuals. Emotional Competence Inventory (ECI) 2.0 [20, 21] clusters EI into four clusters, including 18 emotional competencies.

Human emotions are complicated to study, as human brains have evolved in changing environments through our long history. In general, emotions can be classified into different categories. A simplified perspective on various emotional states and their



**Figure 2.** Various emotional states

description is shown in Figure 2 (Source: [22]), while other concepts may have even more categories. In the figure, emotions are divided into six groups; three of them can be considered positive (Happy, Excited, Tender), and the other three can be considered negative (Sad, Angry, Scared). In the present research, emotions are grouped into neutral, positive, and negative for generic affect recognition.

## 2.1 Emotional stimuli

Typically, one person's emotions can be affected by all kinds of stimuli, from outside to inside factors. Here we look at the most common stimuli that can be used for inducing emotions under lab conditions.

## **Acoustic stimuli**

Affective sounds and music are both potential stimuli, capable of inducing a variety of emotions. It is well known that listening to affective sounds or music elicits emotional responses, but research on the physiological responses elicited during exposure to affective sounds has yielded varying results. Various psychological and physiological experiments have shown that musical excerpts can evoke specific emotions [23, 24, 25], and some studies have successfully used music as an affective stimulus to induce a variety of emotional states [26, 27, 28], based on the notion that emotions elicited by acoustic stimuli are fundamentally the same as other emotions[29]. Consequently, these emotions can also be differentiated on a dimensional level by placing them on the arousal-valence dimensions [24, 30].

Unlike affective sounds that only last for several seconds, one of the many issues in measuring emotional responses to music is the fact that music changes over time, so that what one is feeling at one moment is not necessarily the same as that at the next moment. Since emotional states can change over the duration of a piece of music, it is feasible and preferable to measure subjective psychological and physiological reactions continuously. The Continuous Response Digital Interface (CRDI) device was used to measure subjects' responses to music nonverbally in a continuous mode [31].

## **Visual stimuli**

Visual stimuli include facial expression picture and videos. Videos contain both dynamic visual and auditory stimuli. Therefore, videos are often used as stimuli to

induce emotions for studies. Some studies focus on facial emotion recognition[32], in which the facial expression is in response to video clips. Internet video advertisement is used as stimuli in[33]. Movies generally have full narrative structures, and they have contrasting emotional-laden scenarios in different clips, so they form a good source for emotion elicitation.

### **Virtual reality (VR)**

Virtual reality has been around for decades before stepping into everyday life. Traditionally, it required complicated device mounting at unaffordable prices, and thus the access to VR applications was limited. Only in recent years, the technology became prevalent in both research and commercial markets. The steady development of growth in the hardware lets the price go down, and also make devices more portable than ten years ago. The most outstanding feature for VR applications [34] is that it provides the feel of presence with full three-dimensional visual immersion. In addition, VR has the advantage to imitate and create systematic testing, training and treatment environments that could meet the high requirement of precise control[35].

Besides the use in pure entertainment, VR applications have been used in research projects as an exposure method in multiple fields. For example, the applications have been used to expose subjects in VR scenarios to induce craving in treatment for addiction, including smoking [36], alcohol dependence[37], and cocaine dependence[38]. Commonly used methods are VR exposure with functional magnetic resonance imaging, Quantitative electroencephalography and autonomic nervous variables. Some other examples of VR exposure experiments are phobia-related training, such as spi-



der phobia[39], acrophobia[40], and agoraphobia[41]. What is more, PTSD (post-traumatic stress disorder) and anxiety were also addressed using VR exposure as treatment.

The present research makes use of the fully immersive feature of VR to provide affective scenarios. With the inexpensive and relatively portable equipment to host VR, the system can be easily applied to daily life usage and hence to reach the needs of the general public. Moreover, other than being only an exposure environment, we focus on interactive mechanisms that could form a real game. By studying users' multiple possible emotional reactions that are induced by specific stimuli of the interactive environment, serious games on VR can be designed for special purposes.

## **2.2 Affective Computing**

Starting from the end of last century, affective computing was introduced by Picard [3] as a new interdisciplinary study area. There are plenty of affect recognition publications in the literature [42, 43]. The most commonly used methods are speech affect recognition [44, 45], facial affect detection [32, 46, 47], body gesture recognition [48], and physiological monitoring [49]. They may be combined with each other to form a more sophisticated system.

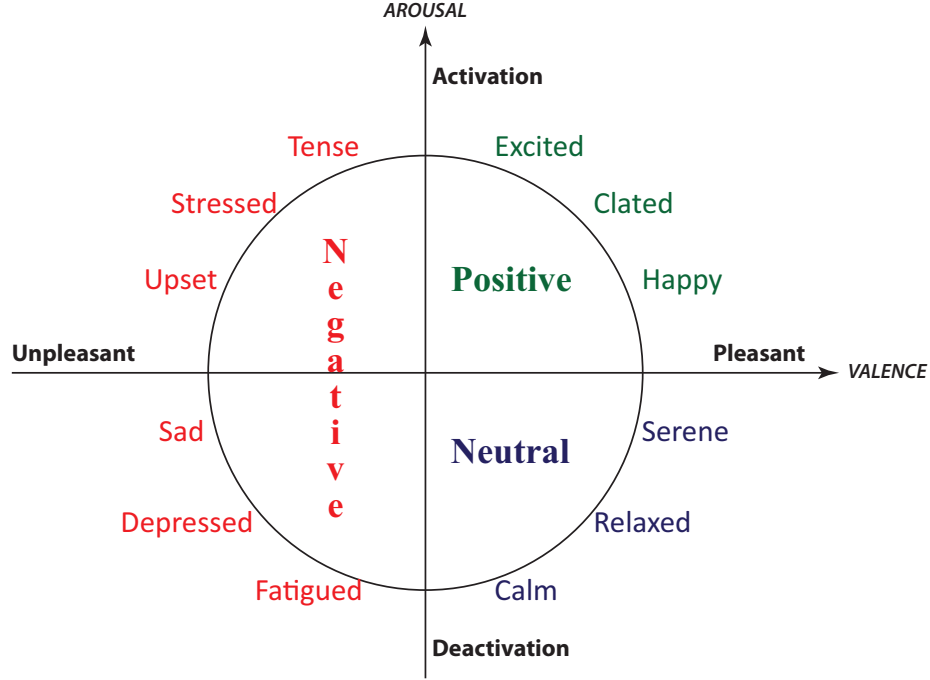
Physiological responses are believed to be more reliable and more truthful, for the reason that they can hardly be controlled by awareness. For example, one may hide his emotions by changing his facial expression, body gestures as well as his vocal tones intentionally. Although recording physiological variables can be environment-dependent and very sensitive to surrounding conditions, research found them reflect-

ing cues of true emotions from subjects.

Picard *et al.* [50] presented and discussed algorithms for human-computer interaction machines to be able to recognize emotions by measuring affective physiological states. Given four types of physiological signals, they learn the patterns for eight emotional states, and reach 81% as the highest recognition accuracy. A set of new features along with classic statistic features are proposed for feature extraction, selection, and transformation. The project is based on data collected from one specific subject daily for a relatively long time period. It also concludes that physiological states are day-dependent due to the condition of the sensors, temperature, and even different gels that the same subject uses on different days. Two methods are used to avoid this day-dependent situation; one is to add day matrix to the existing features, and the other is to use neutral emotion as a baseline for calibration.

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 be adjusted in real time according to users' responses.

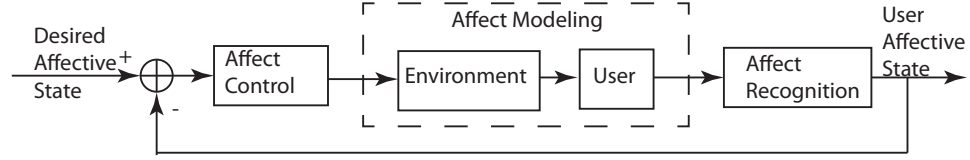
Psychologists believe that emotions can be decomposed and mapped into coordinates and thus quantified. Several mapping models have been created in emotion investigation. Among those models, the three dimensions of affect [51] are fairly standardized and generally accepted: Valence (pleasant or unpleasant), Arousal (activated or deactivated) and Dominance (potency). Although dominance has been proved to be as important as the other two dimensions, due to the subtle behaviors it often connects to such as control, influence, autonomy and more, it was paid less interest in research. Figure 3 shows an example of a psychology model with valence



**Figure 3.** Two-dimensional coordinates of emotions

and arousal axes and color-coded emotion categories.

Wu et al. [52] made efforts to implement one of the closed-loop affective computing systems using Virtual Reality Stroop Task (VRST) scenarios from the Virtual Reality Cognitive Performance Assessment Test. Figure 4 shows their closed-loop affective computing system model. The paper performs affect recognition by assessing the arousal states for 18 subjects. Physiological signals from subjects are recorded along with three different VRST scenarios. Each of the scenarios is intended to induce different levels of arousal. An optimal arousal level is identified for each subject following Yerkes-Dodson Law [53] and set as the goal towards which the users are guided by the games. Features are selected and extracted using sequential forward selection, then a support vector machine (SVM) is trained to classify them into three arousal levels.



**Figure 4.** A closed-loop affective computing system

Two years later, Wu [54] summarized four applications of affective computing in the last decade. Furthermore, he reviewed fuzzy sets (FS) and fuzzy logic systems (FLS), pointing out that they have more advantages for reducing both intra-personal uncertainty and inter-personal uncertainty than other existing methods. Type-2 FSs and FLSs are also believed to be suitable for all three components of the closed-loop affective computing systems: affect recognition, affect modeling and affect controlling.

Moghim el at. [55, 56] has done quality work in an on-going research project that is planned to implement a physiological feed HCI system, which is very related to our research. They first conducted VR exposure experiments [55] to test users' emotional reactions to various of VR contents, and analyzed the recorded physiological data with self-report questionnaires answered by users. A database was constructed to store the stimuli VR events and corresponding physiological reactions, as well as self-reported scaled emotional states. To analyze features being extracted and selected from the data [56], they compared and evaluated four different machine learning algorithms that are applicable in emotion classification. We referred to their results in III.4 and built our model based on that. As this is highly-related on-going research, and according to their phase plan, it is predictable that they will be designing adaptive VR game applications in their next step. We will keep updated to their progress.

## 2.3 Affective Gaming

In the 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. With the use of feedback on user emotional states as an extra dimension of game feedbacks, games will surely provide different aspects of user experience and be more attractive. Sykes [57] stated that affective gaming can benefit and even lead to the evolution of game-based learning.

### Games with biofeedback

Serious games with biofeedback are valuable in the sense of utilizing physiological signals and sending them back to impact the game, to achieve either therapeutic or training purposes. Typically, the devices to process physiological signals are cumbersome and hard to mount. Thus, the applications on medical-related games are not commonly used. Nowadays, with the development of portable sensors and effective algorithms, researchers started developing more affective games using biofeedback.

Wang *et al.* [58] 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 [59]. Another game was designed to enhance the horror scale of zombies in real time by detecting skin

conductance response and heartbeat[60].

### **Games with other feedback**

As mentioned in Affective computing, there are many mechanisms to be used in affect recognition. Likewise, rather than using biofeedback, other forms of feedback can also be used in affective games. They can be one of the future works to extend the current proposed model.

The force of each button pressed on a gamepad was studied and found to be related to the user's state of arousal [61], which indicates a single dimension of user emotional states. Similarly, error rates, button pressure, gamepad grip, gamepad tilt, vibration and swing were assessed to detect user frustration [62]. Eye gaze, head pose, and facial expression were also proposed to be used in affective games [63]. In addition, affective body movement was reported to be automatically recognized in a video game scenario [64].

Li et al. [47] proposed a multimodal game framework using Microsoft Kinect for behavioral analysis on autism. Emotions are recognized by analyzing the 3D facial data and skeleton motion captured by Kinect, integrating with audio and text affect recognition modules.

In a very recent study [65], facial expression recognition has been used to develop a VR platform named FACETEQ. The sensors are attached to a VR helmet to detect facial expression, which is sent to the game scene as an input for interaction with VR to influence user experience.

### 3 Applications

#### 3.1 Health Applications

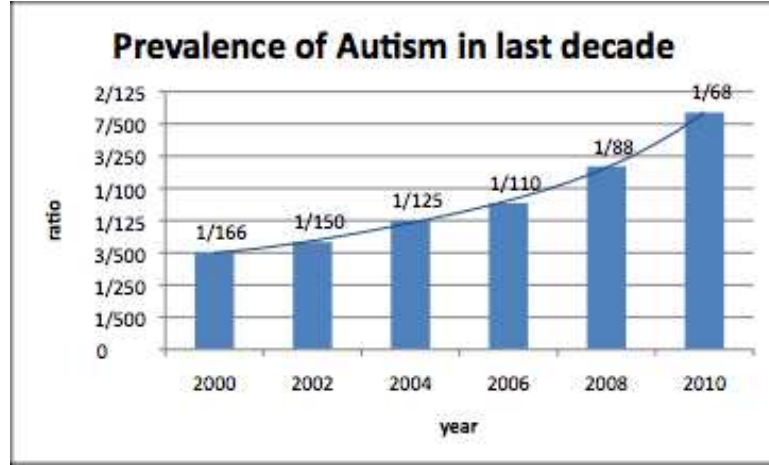
This proposed serious game model is designed for health purposes. It combines advantages of VR and reliable biofeedback, in order to create immersive environments that interact with users' emotional states. Particularly, games applying this model could be used as training or therapy sessions for subjects with emotional impairment such as autism spectrum disorder (ASD).

A preliminary experiment has been done on autistic children to explore the feasibility of designing VR games for conditioned emotional intervention for ASD. The aim of this experiment is to characterize differences in autonomic reactivity between these two groups and select more usable measures for functional reactivity assessment and training targets. The results of the preliminary experiment will be discussed in Chapter III.

#### **VR applications related to ASD intervention**

One in 68 U.S. children has an ASD, which has increased by 30% compared to two years ago. The public awareness of autism is also growing fast in the past decade. Figure 5 shows an estimated prevalence of autism since 2000 by the CDC [66].

Children on the ASD, even those diagnosed as high-functioning autism, suffer from impairment in social skills, emotion recognition and expression, and are at high risk of anxiety. However, along with the behavior therapy and medication targeting specific symptoms, clinical researchers are still seeking suitable therapeutic methods



**Figure 5.** Estimated prevalence of autism since 2000 by CDC

to help them make progress in developing social communications skills and improving emotional reactivity.

VR is proven to be effective in a wide range of treatment sessions, such as exposure therapy for patients with addiction or social anxiety disorders. There are also training protocols utilizing VR equipment to train children with high-functioning autism social skills.

It is very likely that the standard emotional response to the same VR scenarios between children with ASD and typical developed persons would be different. Therefore, it is a reasonable approach to measure the differences in physiological responses during VR environment immersion, in order to design VR-based emotional reactivity diagnostic, training or therapy sessions best suitable for children with ASD.

Diagnostic criteria for ASD (DSM-V, American Psychiatric Association, 2013) and several other assessment tools all suggest that children and adolescents with ASD are suffering from impairment of emotional competence. Research in this area has been emerging in recent two decades. Begeer *et al.* [67] reviewed recent findings



in emotion impairments of children with ASD.

Experiments on using biofeedback as treatment for ASD have been conducted along many years [68]. Some serious games aimed at face recognition skills training on ASD[69], and some aimed at communication skills[70]. Although, combining the existing affect recognition methods into technology such as VR as well as affective gaming is a relatively new trend, especially for emotional competence training purposes.

It is worth noting that in [71], Parsons *et al.* reviewed two papers about potential advantages for using VR for learning of children with ASD and some related experiments. While being supportive that this approach has some distinct benefits, they also brought up questions and challenges. One thing is about the trade-off between the realistic representation of 3D scenes and the most comfortable environment, considering the scenarios may be perceived differently by children with ASD.

Moreover, Grynszpan *et al.* [72] examined computer-based interactive training, which states that the executive dysfunction in autism affect the interactive method. That is to say, special consideration of designing the interactive interface and gaming strategy should be dedicated to autistics needs.

## **Rehabilitation training applications**

Little work related to rehabilitation training applications using VR with emotional intelligence were reported so far, although it has been discussed since the prevalence of VR devices. An example is a study on stroke rehabilitation [73]. It reported significant improvement in recreational therapy groups after participating in the VRWii

game.

Implementations of rehabilitation or physical training affective games help turn boring physical movements into interesting VR context, and help monitor users' emotional states along the way to control the challenge intensity. One big constraint for implementation is the space limitation. Most VR devices on the market are constrained in one room with wired cables, which is inconvenient for more complex movements. Another hardship to overcome is the tracking of body motion; unfortunately most VR devices can only track eye gaze and hand gestures but no body or limb detection. Integrating with Microsoft Kinect or similar products that track skeleton movements could possibly solve this problem. Despite the temporary limitations of VR technology, applications for this purpose are surely needed. With the fast speed of VR hardware evolution, there is huge potential of applications in this field without a doubt. Our current research introduced generic designing framework for affective gaming, which could be implemented in not only this direction but also other fields. A simple demo application for rehabilitation training is developed to elaborate the concept.

### **3.2 Training applications**

Nasoz *et al.* [74] reported their VR application with the focus on driving safety. The VR device they were using was not a small helmet as what we are using today, but with a car-shaped machine that users can sit in to simulate driving. They managed to record similar physiological data such as skin conductance, heart rate and temperature to recognize drivers' emotional states. By designing the VR context to elicit

users' panic/fear, frustration/anger, and boredom/fatigue emotions, the application aims to train drivers with possible incidents on the road to improve driving safety. This paper has introduced a driver's modeling using Bayesian Belief Network, which is used as a reference in the present dissertation, where the customizable user modeling is derived.

### **3.3 Educational applications**

Another promising field of adaptive VR serious games would be educational applications. Books in the cognitive and education field [75] point out emotions are very important parts in school context, including both teacher and student emotions. A review on educational affective games [76] summarized three key elements of cognition that these games would have impact on: attention, memory storage and retrieval, and decision making.

In daily life, it is obvious that positive or negative emotions would influence differently in the effectiveness of learning. It is not just negative emotions that may affect learning productivity; even too much excitement may become distraction and end up with bad influence. On that account, if an adaptive educational VR game is able to detect user emotional states correctly and timely intervene during their learning process, it would make the learning process both fun and effective.

### **3.4 Affective gaming application evaluation**

Upon all kinds of implementations of affective gaming systems, there should be a few measurements to evaluate them.

Knoé *et al.* [77] introduced a high-level energy model to estimate the energy consumption and the performance of emotion detection systems mainly using physiological signals. A few matrix were derived and an application scenario was introduced to consider all constraints of healthcare systems. The influence of sampling frequencies and communication protocols on the system's autonomy were also discussed.

Ng *et al.* [78] reviewed numerous types of evaluations in literature on user-centered design for video games. The subject is not VR applications, but the summary of different assessments are useful. Evaluations on interfaces, methods, user feedback methods, and other methods like heuristics evaluation are all summarized. A table of heuristics evaluation questions [79] is adopted in the present work to evaluate the playability of the proposed gaming system.

## CHAPTER III

### EXPERIMENTS

#### 1 Physiological Parameters

The Autonomic Nervous System (ANS) consists of the sympathetic and the parasympathetic nervous system that control and regulate most human organs' functions in competing and opposite ways. The ANS is believed to be associated with basic emotions [80]. In the proposed system, the ANS variables are detected during the game scenarios by sensors attached to subjects and recorded by monitoring device. The corresponding emotional states are analyzed and used as feedback to interact with the game scenarios. In the current experiments, emotional states are generally divided into neutral, negative and positive groups, which later can be extended to more specific groups, such as joy, excitement, fear, sadness, anger, *etc.*

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

##### **Electrodermal Activity**

Electrodermal activity, also known as skin conductance response (SCR), or galvanic skin response (GSR) in slightly older terminology, is commonly used to measure human ANS activity, which records continuous electricity changes on the skin, and shows the activity of only sympathetic system. SCR is believed to be not under

conscious control [81], and is highly related to emotional arousal, as mentioned in literature, which is one of the three dimensions of the emotion mapping model. Thus, when exposed to certain stimuli, SCR is an important indicator of user emotional reactions.

In this research, we are measuring different parameters under skin conductance, including skin conductance level (SCL), SCR peak average, i.e, the average of local maximum of SCR, SCR number per minute, i.e., non-specific SCR frequency (NS.SCR freq.), which is measured as number of SCRs in 1 min.

### **Cardiovascular Activity**

In the medical field, Heart rate variability (HRV) is normally measured by EKG or ECG, which requires several electrodes to be attached to a human body. As we aim to find portable devices for the whole adaptive system, we mainly rely on monitoring and recording blood volume pulse(BVP) to calculate heart rate and all its dependent HRV measurements. The ProComp BVP sensor we are using in this research is one single sensor that could be taped to a person's thumb.

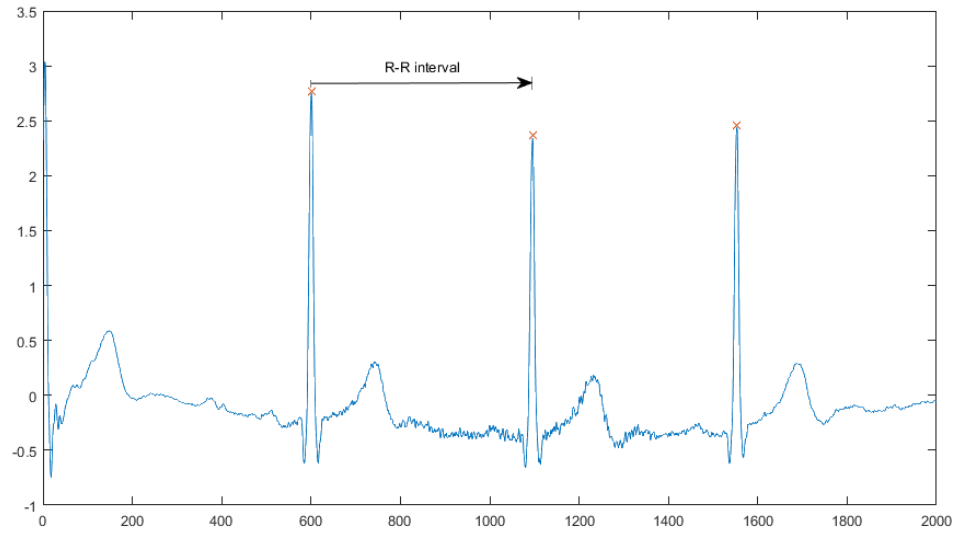
HRV, calculated as cardiac autonomic control measures, can be analyzed in both time and frequency domains. In time domain, RR interval is the time between successive heart beats, and Figure 6 shows an example of RR interval in a typical ECG image. The statistics of the RR intervals are reliable measures: mean value of RR intervals, standard deviation of RR intervals(SDNN(ms)), root mean square of successive differences(RMSSD(ms)) [82].

In frequency domain, we look at high frequency (HF) components (0.15 to 0.40

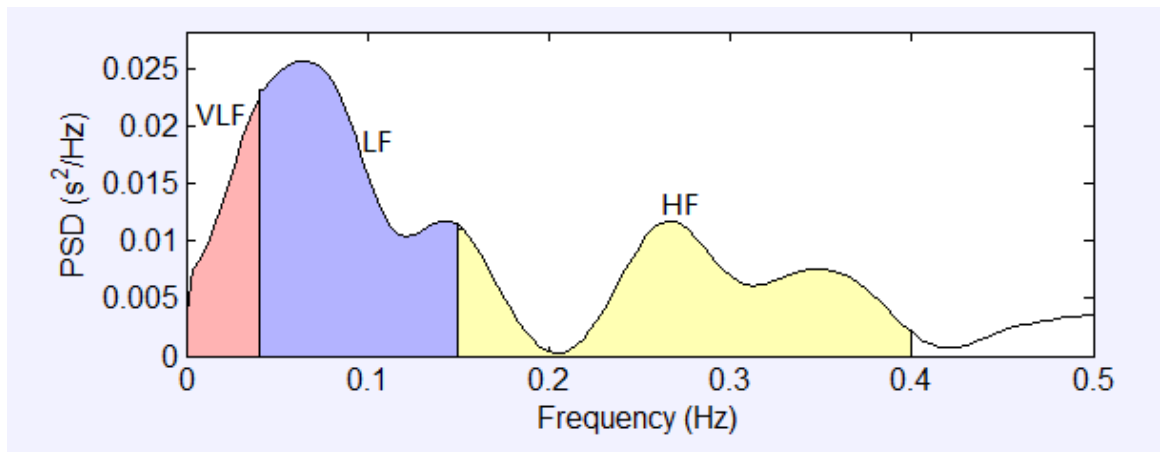
Hz), low frequency (LF) components (0.04 to 0.15 Hz), and LF/HF ratio. See Figure 7 as an example of these three components in frequency domain. The very low frequency (VLF) (under 0.04Hz) has not shown much physiological evidence related to emotional reactions, though some may claim that it reflects deficit energy states [83]. Since it is still awaiting more experiments and proof, we chose not to include this measure in our analysis. HF component is generally believed to show the activity of the parasympathetic system, while the LF component is argued to be a general indicator of aggregate modulation of both the sympathetic and parasympathetic branch of ANS [84]. LF/HF ratio was originally believed to be measuring sympatho-vagal balance and was widely used as an indicator of stress in some earlier studies. However, in recent decades, there are studies arguing that as a univariate parameter, LF/HF ratio lacks evidence to interpret physical and mental stress. Despite this controversy, we still extracted LF/HF ratio as a feature, and let the feature selection process decide whether to keep it or not.

### **Fingertip Temperature (FTT)**

Fingertip temperature is another popular parameter in physiological signals. Research projects [85, 86] have shown that if one person is comfortable, his/her blood vessels are dilated and thus the FTT should be relatively warmer. On the other hand, if this person is highly irritated or terrified, the vessels will be constricted, so the FTT will drop. By analyzing the variation of temperature, it should reflect a user's emotional reactions to stimulating events. In our experiments, the temperature sensor was taped to fingers and directly exposed to the environment taking place in



**Figure 6.** An example of RR interval in typical ECG image



**Figure 7.** An example three components in HRV frequency domain



a normal computer science laboratory, where the room temperature was controlled by a service center. The collected data are in Fahrenheit.

## 2 Preliminary Experiments Using Traditional Media

In order to gain more data of emotional responses in physiological monitoring measure for biofeedback training, a series of experiments were conducted as preliminary studies before using virtual reality contents. These experiments are aimed to analyze emotions induced by traditional media, including: affective audio, music, visual expression pictures and videos. Some of the experiments were conducted for other related projects and yielded quality publications. Most of the experiments included children with ASD as subjects. Children with ASD often suffer from emotional impairment, and thus the “standard” emotional responses of autistic groups are expected to be different from typically developed persons.

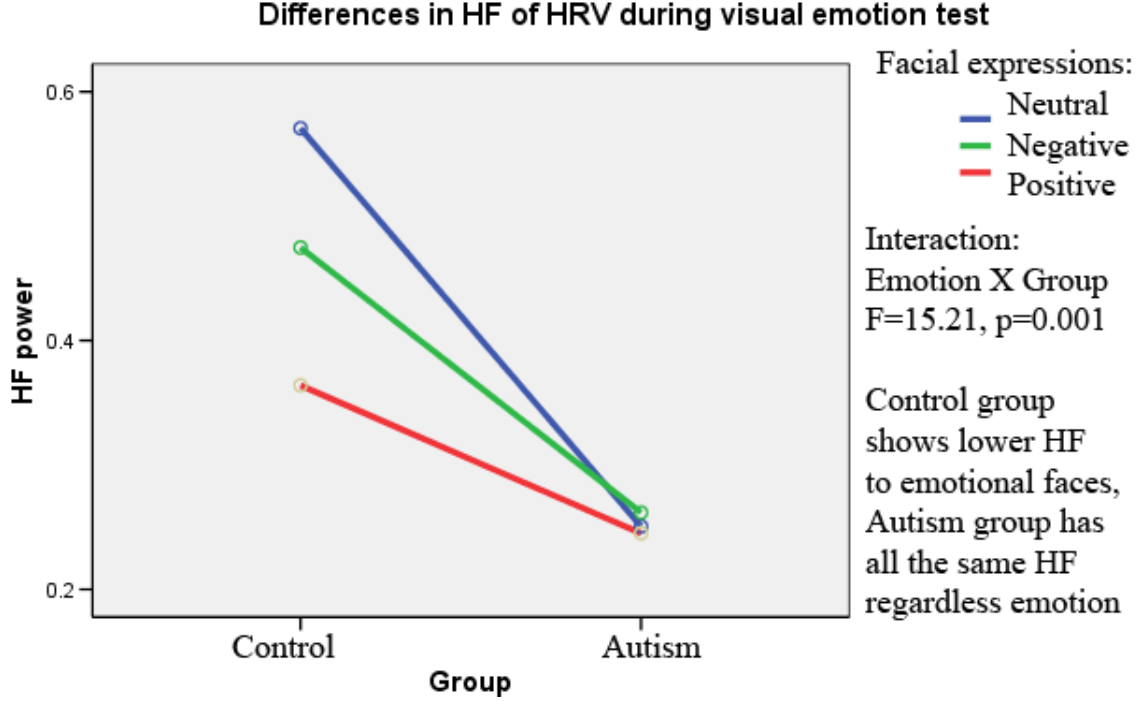
### 2.1 Audio-visual Experiment

Base level of autonomic activity were investigated in 19 children with ASD (mean age  $12.9 \pm 1.8$  years) and 21 typically developing subjects ( $16.8 \pm 5.2$  years). Analysis of autonomic measures during 5 minutes long resting baseline revealed higher HR ( $93.5 \text{ beats/min} [bpm]$  in ASD vs.  $80.4 \text{ bpm}$  in controls,  $F=5.95$ ,  $p=0.019$ ), higher SCL ( $7.3 \mu S$  vs.  $4.4 \mu S$  in controls,  $F = 4.74$ ,  $p = 0.036$ ), and a tendency ( $F=3.93$ ,  $p=0.056$ ) of lower power in the HF component of HRV in autism. High basal tonic SCL and accelerated HR in association with lower HRV index found in children with autism are indicators of excessive sympathetic and reduced parasympathetic activation in

ASD.

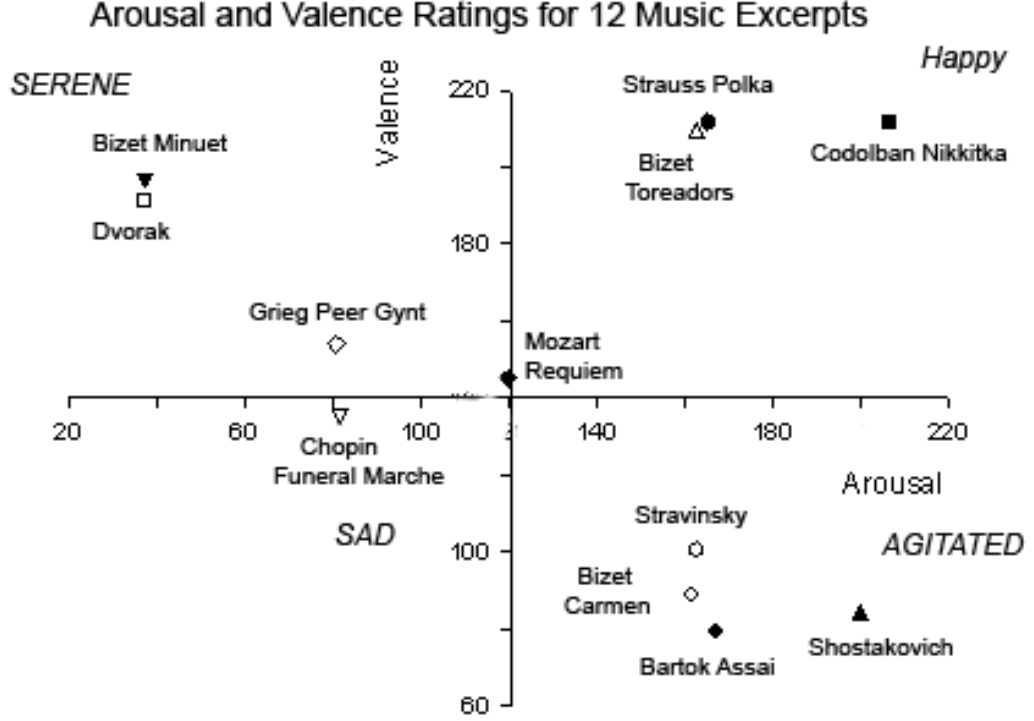
Affective sounds were chosen from the International Affective Digital Sounds (IADS)[87] database that provides international affective digitized sounds. The effects of affective sounds were investigated in eight children with ASD (12.5 years) and six age-matched controls. Children with ASD showed higher HR in response to both emotional and neutral six second long sounds (e.g., negative, 96.8 vs. 67.4 bpm in controls,  $F = 13.75$ ,  $p = 0.004$ ; neutral, 97.4 vs. 66.7bpm in controls,  $p = 0.003$ ) and higher SCL (positive,  $8.05\mu S$  in ASD vs.  $4.4\mu S$  in controls,  $F = 5.43$ ,  $p = 0.04$ ; negative,  $8.21\mu S$  vs.  $4.48\mu S$ ,  $F = 5.34$ ,  $p = 0.04$ ; neutral,  $8.04\mu S$  vs.  $4.2\mu S$ ,  $F = 6.15$ ,  $p = 0.03$ ). The children with ASD showed less pronounced phasic HR deceleration (4 sec post-stimulus vs. baseline) in response to sounds than controls. Though HRV variability measures did not show significant statistical differences, the HF component of HRV in the autism group was lower and non-reactive to stimulation, thus demonstrating decreased responsiveness of the parasympathetic control of HR in this group.

The same group of children participated in the autonomic reactivity test for facial stimuli. Forty-eight facial expression stimuli were selected from Matsumoto & Ekman[88] and presented on a monitor. The order of presentation was as follows: positive, negative, and neutral. Affective facial stimuli were presented in blocks with eight images of the same emotional content per block. Stimulation was repeated with the same order to assess habituation effects. Stimuli were presented for five seconds with one second long inter-trial interval. This visual stimulation test takes around 20 minutes to complete. Typical children demonstrated a marginal trend to higher



**Figure 8.** Differences in HF of HRV during visual emotion test

phasic HR deceleration across negative facial expressions than children with autism (mean  $2.76 \pm 0.38$  vs.  $-0.61 \pm 1.3bpm$ ,  $p = 0.057$ ). Phasic HR and SCR responses to neutral and happy facial expressions did not show any statistical difference. The most pronounced group differences in a form of *Emotion*  $\times$  *Group* interaction were found in HRV measures: VLF( $F = 6.62, p = 0.01$ ), LF( $F = 4.92, p = 0.03$ ), and HF( $F = 15.21, p < 0.01$ ). The most significant effect (i.e., power of HF component of HRV) can be described as lower and emotion-irresponsive cardiac parasympathetic response(i.e., respiratory sinus arrhythmia) in autistic group shown in Figure 8, and higher but less differentiated sympathetic response to negative facial images in the autistic group. Therefore, the group of children with autism demonstrated lower parasympathetic and higher basal sympathetic tones during visual affective stimulation in this test.



**Figure 9.** Arousal and valence ratings for 12 music excerpts

## 2.2 Music Experiment

This experiment combined physiological variables with subjective measures collected using CRDI during exposure to emotion-inducing musical excerpts to explore the correlation of subjective and physiological variables. Thus, the physiological measures of ANS activity was combined with self-reports of emotions using CRDI measurements. The experiment included music that was expected to induce four emotions (happiness, serenity, sadness, or agitation). The musical excerpts used by Nyklicek *et al.* [30] were played for a sample of 14 healthy subjects. These music excerpts are placed on the arousal-valence dimensions to be differentiated on a dimensional level as in Figure 9. The figure was first reported in [89].

The results showed significant difference in subjective report measures between

positive and negative emotional music (i.e., between sad-happy,  $-42 \pm 33$ ,  $t(13) = 3.56$ ,  $p = 0.003$ ; sad-serene,  $-33 \pm 35$ ,  $t(13) = 3.43$ ,  $p = 0.004$ ; agitated-happy,  $56 \pm 36$ ,  $t(13) = 6.04$ ,  $p > 0.001$ ; and agitated-serene,  $49 \pm 54$ ,  $t(13) = 3.37$ ,  $p = 0.005$ ), but not between musical pieces of the same emotional valence (i.e., happy-serene, sad-agitated).

Higher heart rate (HR) responses differentiated happy and agitated music conditions vs. serene and sad conditions (happy vs. agitated, happy vs. sad, agitated vs. serene, agitated vs. sad), while respiration rate responses were higher in happy and agitated conditions as compared to serene conditions (happy vs. serene, agitated vs. serene). At the same time, skin conductance responses to these 2 conditions (happy and agitated) were lower than in serene music conditions (happy vs. serene, agitated vs. serene) and showed less correlation with subjective reports of pleasantness. Skin temperature differentiated only serene vs. sad music conditions (serene vs. sad).

The HF component of HRV differentiated sad and agitated conditions as being lower during sad music ( $-0.5 \pm 0.06$ ,  $t(13) = 2.86$ ,  $p = 0.013$ ). The power of HF component tended to positively correlate with subjective scores of pleasantness during agitated conditions ( $r = 0.43$ , correlation significant at the 0.05 level, one-tailed). The LF component of HRV showed a strong negative correlation ( $r = -0.68$ ,  $p = 0.007$ , 2-tailed) with subjective reports of pleasantness during exposure to serene music.

### 2.3 Video Experiment

In an experiment on 18 children with ASD (13.9 yrs, 5 females) and 8 age-matched typical children, emotional reactivity to episodes from the "Lion King" (Disney) is

investigated using autonomic measures. All children were exposed to 8 minutes of the movie. Children with ASD showed higher HR as compared to controls ( $94.6 \pm 16.1$  vs.  $78.1 \pm 8.5bpm$ ,  $F = 6.57$ ,  $p = 0.017$ ), with a higher power of the LF component of HRV ( $F = 5.34$ ,  $p = 0.032$ ). Skin conductance level, another measure of sympathetic arousal, also tended to be higher in ASD ( $14.8 \pm 7.4\mu S$  vs.  $10.2 \pm 6.2\mu S$ ,  $F = 3.74$ ,  $p = 0.066$ , n.s).

### 3 Experiments Using Virtual Reality

Different emotionally laden VR scenarios are designed and chosen to induce different emotions. Two experiments were taken, one for training analysis, and the other one for extended testing and verification. In both experiments, users sit in front of a desk and explore different VR scenarios, which are chosen based on the experience of the above research projects using traditional media. The training experiment included three scenarios to induce three general emotional states: neutral, negative and positive. It served as a benchmark for more emotion labeling. The extended experiment took place later, using continuous non-labeled VR contents which can be grouped into 16 scenarios with different events. It was conducted purposefully, cross-verifying the data in the training experiment. These events were then labeled to be in any one of the general emotions and then used in later game design. Physiological data were recorded by a monitoring device that have sensors attached to users' fingers during all experiment sessions, and features were extracted and analyzed for both experiments.

- **ProComp Infiniti or ProComp+ with a BVP sensor:**

	Input B <i>BVP</i>	Input C <i>EMG</i>	Input D <i>EMG</i>	Input E <i>SC</i>	Input F <i>Temp</i>	Input G <i>Resp</i>	Input H <i>Resp</i>
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**Figure 10.** ProComp channels

### 3.1 Instruments

The hardware to host VR is an Oculus Rift Development Kit 2, and the software platform is Unity 5.3.3 Pro by Unity Technologies (San Francisco, CA) with C# as developing language. In preliminary experiments that are used to determine the feasibility, SASS was used in statistical analysis. Matlab 2015b 32-bit is used to analyze data, train classifiers and emotion recognition.

Different physiological parameters are measured and recorded by a monitoring device that have sensors attached to subjects simultaneously with the VR scenes. The monitoring device used in experiments are ProComp Infiniti, and the software to collect and store data is the BioGraph Infiniti produced by Thought Technology Ltd (Montreal West, Quebec, Canada). Figure 10 shows different channels provided by ProComp hardware. We are using its B, E, F channels: blood volume Pulse, skin conductance, and temperature, respectively.

### 3.2 VR Contents

#### 1. Training Experiment

Three VR scenarios were chosen and labeled generically as neutral, negative, and positive context:

- Neutral scenario is simply exploring VR environment, wandering around



**Figure 11.** An example of VR scenarios

on the terrain. This VR content is chosen to make user slightly excited than baseline, but not enough to trigger tremendously distinct emotions.

- Negative scenario makes use of affective audio and a series of events that causes fear, annoyance, disgust, and other uncomfortable experiences. Contents including spiders, flies, a dinosaur, darkness and more were presented to users, expecting to get dramatically negative emotions.
- Positive scenario is a collection of happy scenes, including interesting toys and smiling people, with harmonious music. Positive emotions are expected to induce more arousal level than those in neutral scenario.

Figure 11 shows one example of the VR scenarios.

## 2. Testing/Verification Experiment

A clip of VR, around 13 minutes in length, with multiple continuous scenarios was presented in this experiment. The clip length varies slightly each time, depending on how fast the user triggers the next scene by exploring. The clip can be roughly categorized into 16 scenarios, including outdoor scenery,



**Table 1.** Example of scenarios in extended experiment time range

Scene	Base	Instruction	Turn off lights	Particles	Grass/Dark
Time	0:01-0:59	1:56-2:36	2:53-3:12	3:13-3:58	3:59-4:15
Scene	Butterfly/Bright	Birds/Tower	Flowers/Trees	Fog/Crow/Building	Thunderstorm
Time	4:16-4:23	4:24-4:44	4:45-5:12	5:18-5:33	5:38-6:01
Scene	Car accident	Food	Space Narrowing	Rocks explosion/Universe space	Net
Time	6:02-6:16	6:45-6:58	7:28-8:18	8:22-10:25	10:27-11:15
Scene	Look down from high	Drop from high			
Time	11:17-11:56	11:56-12:19			

in-room, street, universal space, high building, and others. It is expected to induce different emotions, which are still subject to the three general categories: neutral, negative, and positive.

Table 1 summarizes scenarios in short terms and an example of their time ranges recorded from one of the volunteers.

### 3.3 Participants

Participants are individuals between the ages from 9 to 66 without any reported emotional disorders. The total number of volunteers who participated in at least one of the experiments is 50. Among them, 40 were involved the training experiment, 30 participated in the extended experiment, and 20 were involved in both. There was one volunteer who reported feeling dizzy after the session. Almost all volunteers expressed huge interest in the current sessions and the willingness to participate in any future VR-related experiments.

### 3.4 Procedures

- Training Experiment



**Figure 12.** Experiment session

In the training experiment, one session requires exploration of all three scenarios and a one-minute baseline data recording. One scenario takes around five minutes for subjects to explore, which add up to 20 minutes in total, including configuration and mount time. Figure 12 shows a picture of an experiment session. Researchers follow these steps to conduct the experiment:

1. Equipment installation.

A subject is instructed to adjust the Oculus Rift helmet, sit in front of a desk and relax. Physiological sensors are attached to the subject's fingers. A simple VR room is presented on the helmet screen to help calibrating.

2. Baseline testing.

Before starting the VR exposure, a subject is asked to record at least one minute baseline data in resting status. No VR scene is presented during this time. The subject is told to relax without verbal communications

during this time.

### 3. Scenarios exploration

After the baseline testing, VR scenes are presented on the helmet screen, which are 360 degree immersive, and with stereo background music. The order of VR exposure is from neutral scenario, then negative scenario, and positive scenario at the end.

The neutral scenario serves as an introduction of VR, in order to eliminate the variation of first exposure. A subject would use his/her unoccupied hand to navigate through the scene and wander anywhere in the scene until time is up.

The other two scenarios mainly require subject to sit and explore by turning around his/her body. There is no input or oral communication needed from the subject. Researchers monitor the scenarios by streaming the screen of Oculus, instruct as needed, record both physiological data and screen, and mark event labels for synchronization purposes.

### 4. Data synchronization and analysis

The recorded data are then analyzed along with the synchronized events and trigger from VR scenes. At this stage, all data are processed and analyzed offline, in order to get better evidence for emotion recognition in later real-time affective games. The analysis result is separated in next section.

- Testing/Verification Experiment

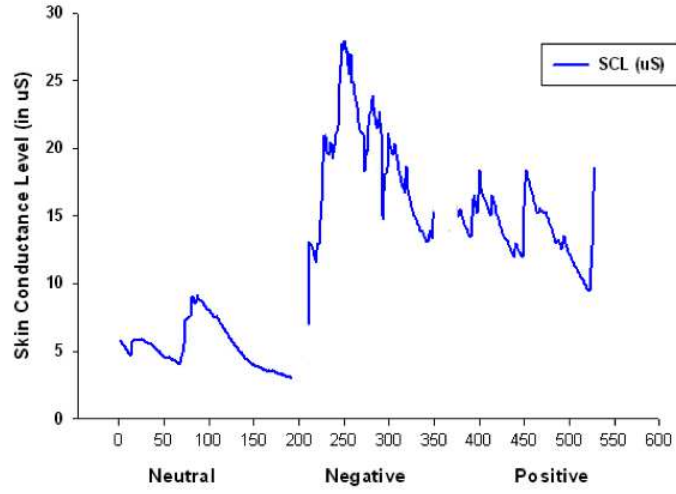
This experiment takes the same steps as in the training experiment except step 3, where in this case the VR content has been changed to a clip with multiple continuous scenarios. Similarly, the subject needs to sit and turn around to explore the content and trigger the next scenario. Due to different reaction times and style of exploration, the time to complete this experiment varies from 12 to 15 minutes.

The event markers are labeled when different scenarios are triggered. The synchronization is more difficult in this experiment since the duration of each scenario is flexible depending on the subject's reaction, while the training session has fixed length on each scenario except slight differences in the negative one.

### **3.5 Initial Results with Small Sample**

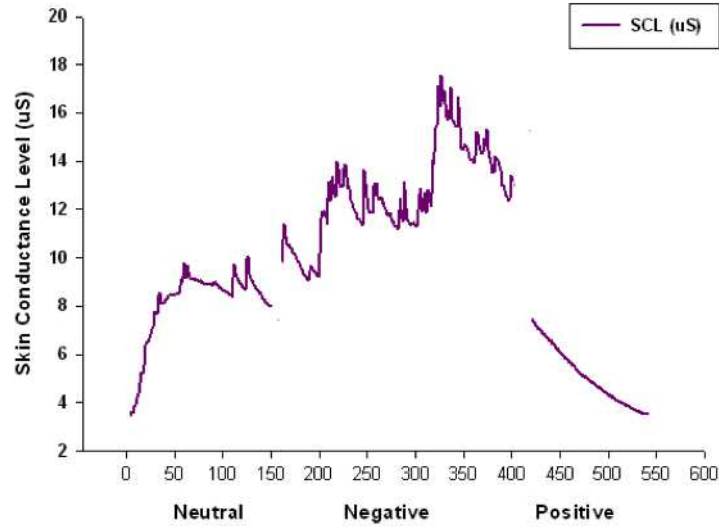
In order to testify the assumption of using physiological data to differentiate user emotional reactions toward VR contents and that VR contents are generally better stimuli than traditional media, an initial experiment using the same VR content with a small sample of participants was conducted, including four children with ASD and twenty typically developed children and adults. The data were analyzed with traditional statistical methods using software tools such as SPSS and Kubios for HRV analysis. The results served as an evidence showing prospective in emotional recognition with VR and the significant difference between ASD and the control group. Due to IRB policy, the initial data were excluded from the analysis on follow-up experiments, *i.e.*, training and verification experiments. The extended training experiment was conducted with a different group of individuals without emotional

SCL during exposure to 3 emotional VR scenarios in subject C. (ASD group)



(a) SCL from ASD group.

SCL during exposure to 3 emotional VR scenarios in control subject H.



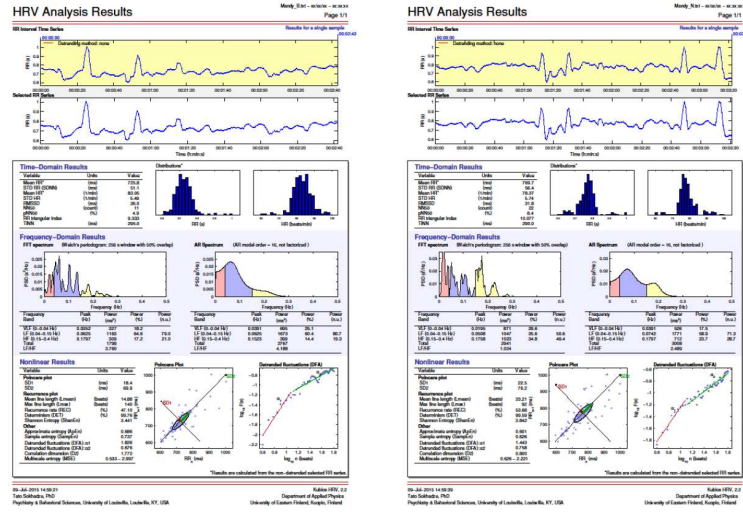
(b) SCL from control group.

**Figure 13.** Samples of skin conductance level (SCL) of two subjects [1]

disorders.

Figure 13-Figure 18 were previously reported in publication [1].

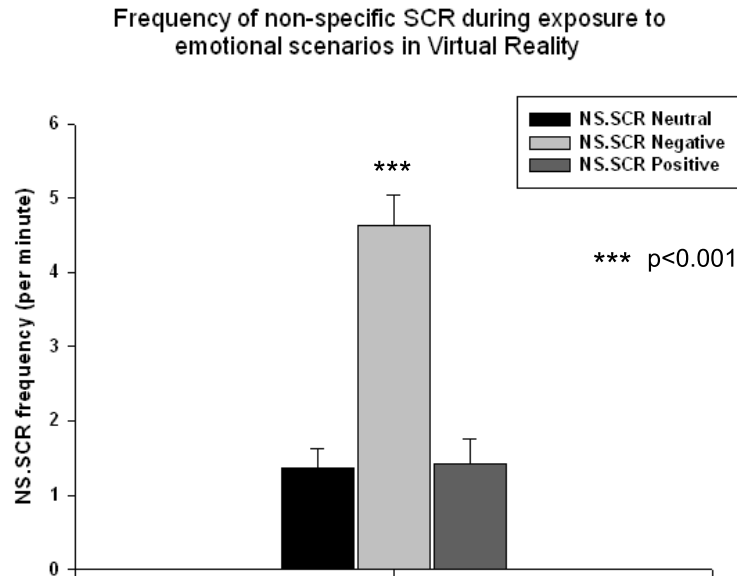
Figure 13 shows some samples of skin conductance level during the experiment session. The samples show common patterns as expected that SCL is low for neutral



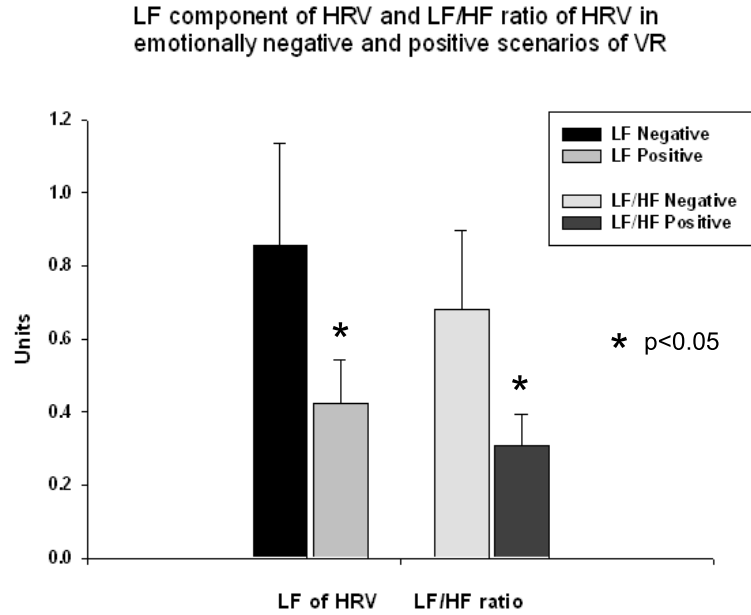
(a) Neutral scenarios

(b) Negative scenarios

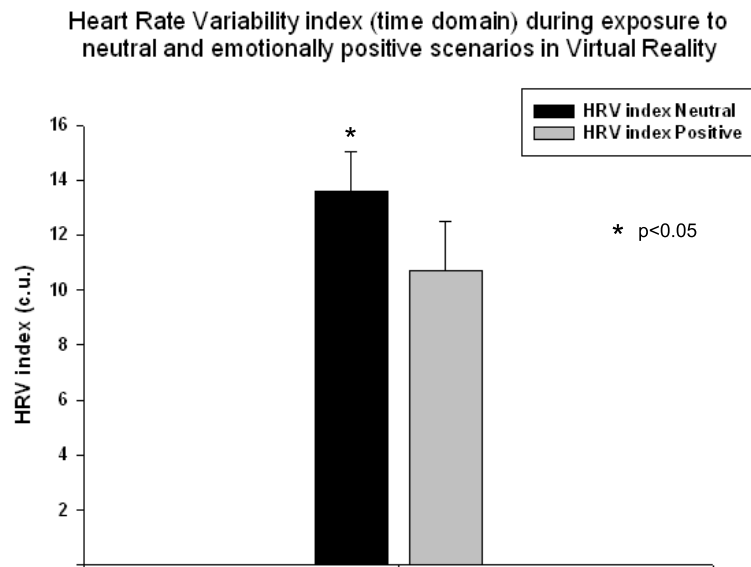
**Figure 14.** Sample of heart rate variability (HRV) analyses for one subject in control group under different scenarios [1]



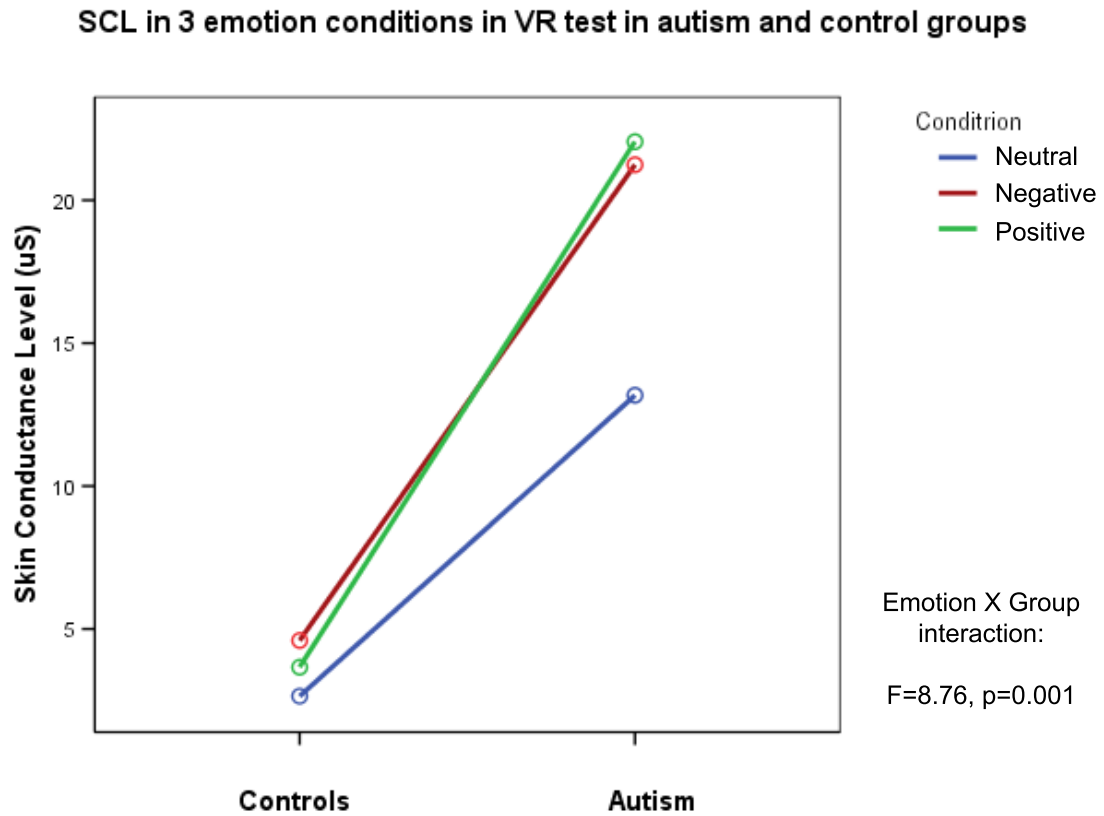
**Figure 15.** Frequency of non-specific SCR during exposure to emotional scenarios in VR



**Figure 16.** Frequency of non-specific SCR during exposure to emotional scenarios in VR



**Figure 17.** Heart Rate Variability (HRV) in emotionally neutral and positive scenarios of VR



**Figure 18.** Frequency of non-specific SCR comparison between autism and control groups

scenarios, and high for negative scenarios. The major difference is that the autism group shows higher responses across three scenarios. Note that scales on y-axis are different in the two samples for the purpose of displaying.

Figure 14 shows samples of heart rate variability analyses for one subject in the control group. Dependent variables are extracted from the results to be analyzed within each group by different emotions.

Figure 15 - 18 show significant statistic results for differentiating emotional states as reaction to VR scenarios. In Figure 15, 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 16 demonstrates that both the LF component of HRV and LF/HF ratio are capable of distinguishing significant difference between negative and positive scenarios. On the other hand, Figure. 17 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 systems for children with ASD. Therefore, a comparison was made between children with ASD and normally developed individuals, originally reported in [90]. Figure 18 compares SCL results between two groups. Generally, children with ASD have higher SCL responses for all three themes. It is also worth noticing that the trend for responses to positive and negative themes are different between the two groups. In fact, we are aware of the needs for gathering more data from those groups like children with ASD to build specialized models or databases for dedicated applications. However, due to the difficulties of getting IRB approval, we discontinued experiments on children with ASD after the preliminary experiment, only focusing on adults without emotional disorder for the rest of experiments.

With the results of the initial experiment on VR contents, it is feasible to use physiological reaction data to differentiate different emotions, as well as differentiate groups of people. What is more, by comparing the results with traditional media, VR contents trigger stronger emotional reactions in both experimental and control groups and thus could be a better medium to use in treatment intervention in special groups of people.

## 4 Analysis and Results

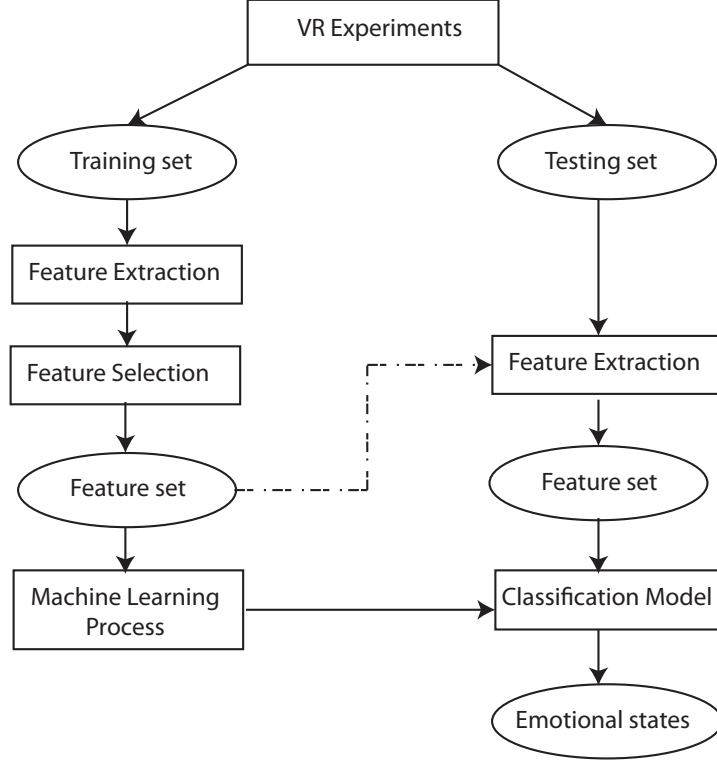
To achieve better understanding and interpretation of user physiological reactions in order to build a reasonable model for affective gaming systems, analysis upon the VR experiments was originally done by following classic machine learning steps as the flow chart shows in Figure 19. First of all, numerous features were extracted from raw data collected from the training experiment. Secondly, the extracted features were sent for feature selection method, where it eliminates redundancy and reduces the feature set into its optimal subset. Three labels were used to train the classification model: Neutral, negative, and positive. The result of analysis on training sets served as a benchmark for extended set classification. Similarly, the data from the extended set were sent through the same feature extraction module. In this case, features extracted from different scenarios were categorized based on the results generated from the training set. Lastly, by applying the classification model on the feature set from the extended experiment, we get the result of user emotional states.

### 4.1 Feature extraction

First of all, for any time domain parameters, we normalize them before extracting features using Equation 1, here  $V$  is used to denote any variable needed to be normalized:

$$V_{norm} = \frac{CurrentV - BaselineV}{BaselineV} \quad (1)$$

- Skin conductance



**Figure 19.** Conventional flow chart of classification modeling

Raw SCR data were recorded from the experiment by taping two sensors from the ProComp device to users while they were doing experiments, including resting status as baseline data for normalization. The raw data were first normalized as in Equation 1 and then sent for feature extraction. A few features can be extracted from here: SCL; SCR peak average as in Equation 2, in which  $I$  is a function that evaluates to 1 if its argument is true or to 0 if not; and NS.SCR frequency as in Equation 3. Moreover, statistical features are calculated from each of the parameters: minimum, maximum, mean, and standard deviation.

$$SCR_{Pavg} = \frac{\sum SCR_{peak}}{\sum I(SCR_{peak})} \quad (2)$$

$$NS.SCR = \frac{\sum_{SCR} SCR}{minutes} \quad (3)$$

- Temperature

As stated in a previous section and from literature, the change of temperature can reveal certain patterns of user emotion reactions. Similar to SCR, statistic features can also be extracted from temperature data: minimum, maximum, mean, and standard deviation.

- Heart rate variability

As stated in Section 1, there are a good number of parameters that can be derived from HRV data. We picked a few trending features, which are believed to have high correlation to emotional states.

First of all, in time domain, the mean value of RR intervals (ms) and mean Heart Rate (bpm) are calculated as in Equation 4 and Equation 5, respectively:

$$\overline{RR} = \frac{1}{N} \sum_{j=1}^N RR_j \quad (4)$$

$$\overline{HR} = \frac{1}{\overline{RR}} \quad (5)$$

SDNN is calculated as:

$$SDNN = \sqrt{\frac{1}{N-1} \sum_{j=1}^N (RR_j - \overline{RR})^2} \quad (6)$$

RMSSD represents the square root of the mean squared differences of successive RR intervals, which is also a good statistical measure in time domain. It is calculated as in this equation:

$$RMSSD = \sqrt{\frac{1}{N-1} \sum_{j=1}^{N-1} (RR_{j+1} - RR_j)^2} \quad (7)$$

Furthermore, maximum, minimum and standard deviation of heart rate were also extracted or calculated as time domain features.

On the other hand, since the power spectrum of HRV in frequency domain has also shown importance in analyzing affective factors, we would like to include frequency domain features in the analysis. Based on one of the commonly used frequency domain analyses on HRV, Welch's periodogram [91], we split the RR interval into M data segments of length L, with overlapping of O data points (overlapping=50% if O=L/2; overlapping=0 if O=0). Then we apply a discrete Fast Fourier Transform (FFT) on the overlapped data segments to calculate the Power Spectral Density (PSD) of RR interval. A weighted window such as Hamming window or Turkey window can also be added here to avoid Spectral Leakage effect [56]. As explained in an earlier section, the HF spectral power, LF spectral power, and LF/HF ratio were extracted as features of frequency domain.

Table 2 summarizes the numbers of features extracted from different parameters and their total count.

**Table 2.** Summary of extracted features

Skin conductance					
$f_1$	$f_2$	$f_3$	$f_4$	$f_5$	$f_6$
peak average	NS.SCR frequency	average	standard deviation	maximum	minimum
Temperature					
$f_7$	$f_8$	$f_9$	$f_{10}$		
average	standard deviation	maximum	minimum		
Heart Rate					
$f_{11}$	$f_{12}$	$f_{13}$	$f_{14}$		
average	standard deviation	maximum	minimum		
Heart Rate Variability					
$f_{15}$	$f_{16}$	$f_{17}$	$f_{18}$	$f_{19}$	$f_{20}$
RR average	SDNN	rmSSD	LF	HF	LF/HF ratio

## 4.2 Feature Selection

Our experiments aim to analyze user physiological reactions, where the results serve to form a portable adaptive VR gaming model with biofeedback. That is to say, keeping the dimension of feature set as low as it could be but still adequate enough to predict user emotion reactions would help the model to be portable, even with fewer or less precise sensors. In order to train an efficient model with a minimum subset of significant features, we applied a few feature selection methodologies to get the best subset. The methods we used include manual pre-exclusion for unreliable data, running through filter methods, and running wrapper methods. As a result, we have reduced the size of features from 20 to 9 of the most important factors. To simplify the description and focus more on mathematics, we name the extracted features as  $f_1, f_2, \dots, f_{20}$  from this point.

### a. Observation and pre-exclusion on temperature

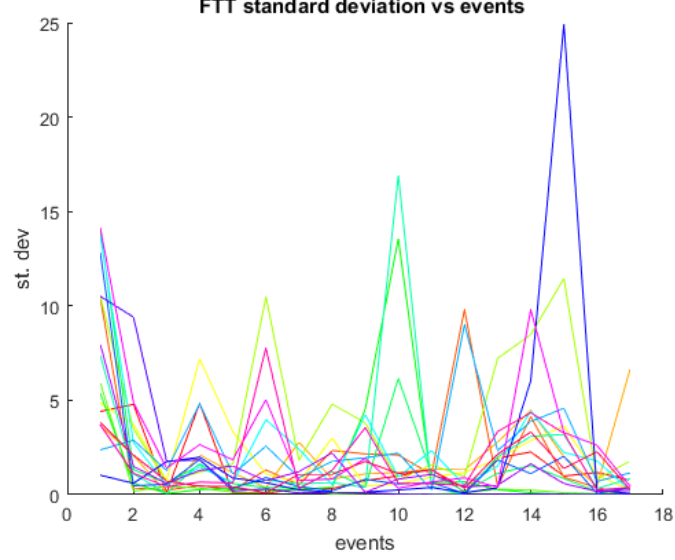
In our experiments, unlike the other sensors that are made with finger tapes, the temperature sensor is exposed directly to the environment. The outside environment

affected significantly the accuracy of detecting skin temperature, especially when the subject’s base FTT is low and the variation is too little, in which case the temperature line tends to be flat. There is also a case where room temperature interfered with sensors picking up the FTT correctly. This research lasted more than a year, through winter to summer, as recruiting and pausing for analysis were taking place alternatively. After looking over the temperature data recorded and running through a few preliminary analyses, we found that the FTT data in our specific research was not controlled well in experiments, therefore they were not reliable enough to serve in classification model construction. For example, Figure 20 shows the standard deviation of FTT for each subject with regard to different events in the extended experiment. Many of them are close to zero across several events, which means the temperature was not collected properly with some subjects and thus lost track of its variation. Unfortunately we had to exclude FTT measurement and all of its dependent variables. That is to say,  $f_7$ ,  $f_8$ ,  $f_9$ ,  $f_{10}$  were eliminated from the feature set.

## **b. Filter methods**

After manually excluding unreliable FTT data, the remaining features were running through a filter method to calculate their correlation coefficients in order to eliminate redundancy in data representation.

Principal component analysis (PCA) [92] was the most intuitive thought when thinking about dimension reduction methods. However, the class labels lost their meanings after PCA, while in our case it is very important to maintain the original



**Figure 20.** Fingertip temperature (FTT) standard deviation (different colors represent different subjects)

physical meanings of the measures, so that we keep track of what sensors to use. Also considering the expandability of the proposed system model, it is good to reserve the options as introducing new sensors/features based on the fast-paced hardware development industry.

Pearson’s Correlation was used here to calculate the linear correlation among features. The algorithm itself is to find correlation between two variables  $X$  and  $Y$ , defined as the following Equation [93]:

$$\rho_{X,Y} = \frac{cov_{X,Y}}{\sigma_X \sigma_Y}, \quad (8)$$

where the *cov* denotes the covariance and  $\sigma$  the variance. On the other hand, when applying to a sample,  $r_{X,Y}$  is normally used to denote the correlation coefficient, and



**Table 3.** Highly correlated features

Groups	Features
Group 1	$f_1, f_3, f_5, f_6$
Group 2	$f_{12}, f_{16}, f_{17}$
Group 3	$f_{18}, f_{19}$

can be estimated by calculating:

$$r_{X,Y} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (9)$$

The estimated  $r$  value will be in range between  $[-1, 1]$ , where  $+1$  means the two variables are positively linear correlated,  $-1$  negatively, and  $0$  no linear correlation. From the result of this step, we found out highly related features ( $|r_{X,Y}| > 0.8$ ) listed in Table 3. The result follows intuition that features extracted from the same category are more likely to be highly correlated, *e.g.*, the group 1 falls in skin conductance features, the group 2 falls in time domain statistics of heart rate variability, the group 3 falls in frequency domain of heart rate variability. From the list, we can choose one or more features from each group and generate several feature subsets by permutation to run through the next step for further feature subset refinement and classification model training.

### c. Wrapper methods

By using wrapper methods, we basically are choosing a subset of features and actual training models using them. Features were added or dropped in each iteration depending on the performance of last run, until there's no more significant improvement on performance or an acceptable tolerance has reached. Commonly used wrapper

methods are forward feature selection, backward feature elimination, recursive feature elimination, and so on. A forward selection starts with no feature in the subset and keeps adding more features in each iteration until the finish condition; while a backward elimination starts with all the features as one subset and keeps removing the least significant features in each iteration until reducing more features will cause significant performance drop; a recursive elimination is a greedy optimization algorithm that explores all possibilities by creating different models in each iteration and ranks the models by their performance.

Here we used backward elimination and trained different models by subtracting highly correlated features in each iteration until an essential subset has constructed. The classification methods and the training results will be discussed in detail in the following subsection III.4.4.3. These two steps are overlapping, since the classification models were actually trained at the same time as we try to find the optimal feature subset. One thing worth noticing is that wrapper methods may cause the issue of overfitting as compared to the feature subset result of filter methods. Therefore, we wrapped features and trained with K-nearest neighbor classifier, Linear Discriminant Analysis (LDA), and Linear Support Vector Machine (SVM), and compared the result among them. The reason a filter method is run beforehand is to reduce the possible subsets to be wrapped and trained with classifiers. A traverse selection of feature subsets of each size  $k$  to get the best candidate would cost polynomial time on  $O(n^k)$ , while searching for the best subset from filtered subsets only depends on polynomial time on much smaller sizes than  $n$ . We also trained on KNN classifier using traverse searching to compare with the best combination from filter method. They show

similar accuracy with very little difference in features being selected, while they used significantly longer time to finish training, which supported our choice of feature selection methods.

As a result, the feature subset being chosen is  $\{f_1, f_4, f_5, f_{11}, f_{15}, f_{18}, f_{20}\}$ . It underlines the filter methods step where there is exactly one feature from each group of the highly related features from Table 3. To recapitulate, the physiological meanings of selected features are: SCR peak average, SCL standard deviation, SCL maximum, HR average, RR interval standard deviation, HRV LF component, HRV LF/HF ratio.

### 4.3 Classification

#### Techniques

In the literature review, we mentioned there are some popular machine learning techniques being adopted in related affective computing projects: K-nearest Neighbor classification, Support Vector Machine, Discriminant Analysis, Marquardt Backpropagation Algorithm, and Decision Trees. Moghimi *et al.* [56] did a great job in exploring and evaluating the performance among them in affective and emotion label classification. Their research results indicated that KNN and SVM generally reached better accuracy in any windowing size than other methods, and each of these two has advantage and disadvantage under certain conditions. In our research, we mainly implemented KNN and LSVM classifiers because their performance are proved to be one of the best classifications in the emotional classification. In order to avoid feature

overfitting, we also compared the accuracy of the chosen feature subset with LDA, then chose the classifier with the best performance.

### *K-nearest Neighbor (KNN)*

KNN is a non-parametric supervised learning algorithm, which memorizes the training set of labeled objects and predicts the new input by calculating its  $k$  nearest neighbors and counting their majority vote to which class they belong. The  $k$  is usually a small integer and when  $k = 1$ , the new object is assigned to the class of its nearest single neighbor. In our implementation, the goal is to find a function  $h$  that maps from feature vector set to class space  $\mathbf{X} \rightarrow \mathbf{Y}$  follows these steps:

1. Denote feature vector as  $x$ , each with a number  $N$  of features, and choose an integer  $k$  as the number of nearest neighbors to vote for classification. The training phase is done by storing the whole training set  $\mathbf{T}$  with all the feature vectors and class labels.
2. Calculate a chosen type of distance  $d$  between  $x$  and each feature vector in  $\mathbf{T}$ , and put  $k$  nearest neighbors in set  $\mathbf{K}$ . The distance  $d$  could be applying any of the popular distance measures: Euclidean Distance, Hamming Distance, Manhattan Distance, and Minkowski Distance. Here we use Euclidean Distance:

$$d(x, x') = \sqrt{\sum_{j=1}^N (x_j - x'_j)^2} \quad (10)$$

3. Estimate conditional probability for each class  $c$  by calculating the fraction of feature vectors in  $\mathbf{K}$  labeled as class  $c$ , here  $y$  is used to denote output which forms set  $\mathbf{Y}$ , and  $I$  is a function that evaluates to 1 if its argument is true or

to 0 if not:

$$P(y = c|X = x) = \frac{1}{k} \sum_{i \in K} I(y^i = c) \quad (11)$$

### *Discriminant Analysis (DA)*

DA is a supervised algorithm that can be used in both feature selection and classification. In the present research, we are simply using linear discriminant analysis (LDA) to train the classification model with selected feature subset and compare with KNN algorithm. An LDA is basically looking for linear combinations of feature variables to form a set of discriminant functions:

$$\mathbf{z} = \mathbf{w}^T \mathbf{x}, \quad (12)$$

that project samples onto hyperplanes and find the best one that maximizes the separability of classes. A pair-wise classification for binary classes was trained based on Fisher's LDA[94] that maximizes between class means and minimizes within-class means. Let  $\mu_i$  be the mean vector of class  $i$  in  $f$  space, and  $\Sigma_i$  be the covariance of class  $i$  in  $f$  space, we seek to maximize the criterion function:

$$J(w) = \frac{\sigma_{between}^2}{\sigma_{within}^2} = \frac{|(\mathbf{w}^T(\mu_1 - \mu_2)|^2)}{\mathbf{w}^T(\Sigma_1 + \Sigma_2)\mathbf{w}}, \quad (13)$$

### *Support Vector Machines (SVM)*

SVM is also a supervised classification algorithm. The goal of SVM is to find a hyperplane that separates binary classes with the largest margin and under certain constraint. SVM can use different kernel functions to substitute the linear dot product and thus being able to fit the hyperplane in a transformed higher-dimensional feature space. In the present analysis, we used the basic linear kernel function. Suppose we

are training the Linear SVM pair-wisely for binary classes labeled as  $y_i \in \{-1, +1\}$  for all training data  $\mathbf{x}_i$ , now the hyperplane could be decided by

$$\mathbf{w} \cdot \mathbf{x} + b = 0, \quad (14)$$

which has a same dimension as the feature set. The hyperplane to be chosen should have the largest margin for best separation, by minimizing  $\frac{1}{2} \|\mathbf{w}\|^2$ :

$$\min_{w,b} \Phi(w) = \frac{\|\mathbf{w}\|^2}{2}, \quad (15)$$

under the constraint

$$y_i(\mathbf{x} \cdot \mathbf{w} + b) = 1 \geq 0, \forall_i \quad (16)$$

Now this becomes a Quadratic Programming (QP) problem, the surface of which is a paraboloid with one global minimum. This can be solved by standard techniques, *e.g.*, Lagrangian multiplier method [95], by substituting  $\mathbf{w}$  and  $b$  to get a maximizing problem only depending on inner products of  $\mathbf{x}$ . The final function to be optimized is a dual function:

$$L_d = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i \cdot \mathbf{x}_j), \quad (17)$$

where  $K(\mathbf{x}_i \cdot \mathbf{x}_j)$  represents kernel function. The linear kernel function is the inner product of  $\mathbf{x}_i \cdot \mathbf{x}_j$ , which can be replaced by other non-linear ones. Other commonly used kernel functions including polynomial, radial basis function, and sigmoid, are outside of our research scope.

## Subset Refinement and Training Results

As stated in feature selection wrapper methods, the classification methods are used to train models with feature subsets, in order to choose an essential feature set with

reasonable reduced size, while still keeping good performance for emotion recognition. Feature subsets are generated randomly based on the results of filter method that calculates correlation coefficient, by choosing one or more representations at a time from each category from Table 3. Training data are randomly divided into five datasets with roughly equal size, four of them are used for training and one for validation. Each training process repeats 5 times for the purpose of cross-validation. All three classification models are trained repeatedly on different subsets, and for each size, the feature set with the best performance is selected to represent the training result on that size. Figure 21 shows the training results. We can see that all three methods show acceptable prediction accuracy due to the categories of emotions are generic, and the number of features is relatively small.

Figure 21a shows the result of KNN vs different numbers of variables, Figure 21b show the result of LDA, and Figure 21c shows that of LSVM. From the figures, we can notice that from size 3 to size 13, the accuracies of three methods are all above 90%. The best accuracy drops dramatically when there are not enough features. Likewise, adding more highly correlated features to the feature size does not help improve the model. They perform even worse than smaller sets, possibly due to the training sample size not being large enough for the feature dimension.

Figure 21d compares the results among the three classifiers. Even though they are all not bad, we can still see that LDA performs slightly worse than the other two in the middle range of the size. The KNN and the LSVM are almost equally good; they even share some precision scores in the middle range. The difference is when the number of features grow, *i.e.*, with more highly correlated features, the LSVM tends

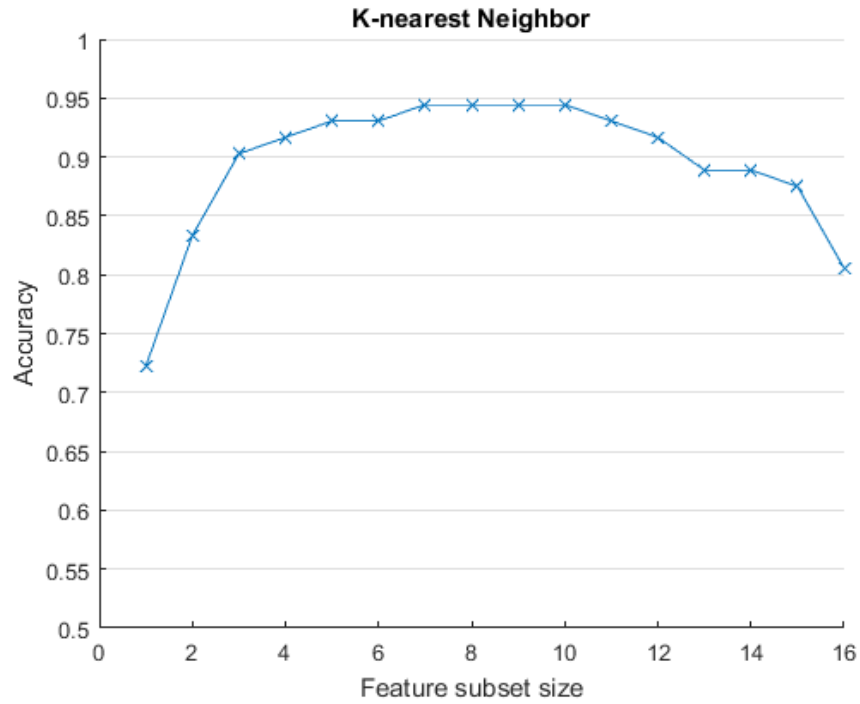
to be more stable. It kept accuracy above 90% while the accuracies of the other two methods declined sharply from size 12 on.

In the present research, we are looking to train a classification model essentially with a feature set as small as possible while having relatively good performance. Through observations of the training result, we decided to choose the size of features as 7. And since the three methods do not show significant difference at size 7, choosing any one model from them should not be a big concern. Considering the possibility of expanding feature dimensions to allow more user information as input, LSVM model with features of size 7 was chosen in our present project for all the following classification steps. Here more user information refers to not only physiological signals but also other aspects of a user that help detect emotional states, details to be discussed in the next chapter. Those seven features used to train LSVM classifiers that will be used to classify unlabelled emotions are  $\{f_1, f_4, f_5, f_{11}, f_{15}, f_{18}, f_{20}\}$ . They are SCR peak average, SCL standard deviation, SCL maximum, HR average, RR interval standard deviation, HRV LF component, HRV LF/HF ratio, respectively. They are easy to be calculated from the raw data collected by sensors. With the fast speed of hardware development in industry, it is reasonable to believe that sensors will be more portable and could be easily attached to a human body, or integrated in a wireless VR system, in the near future.

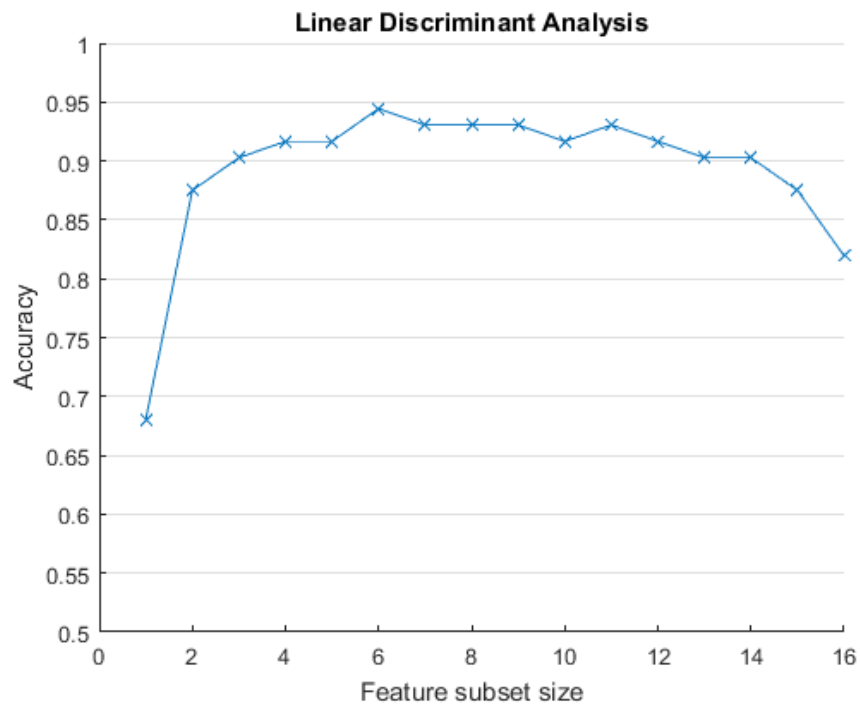
#### **4.4 Emotion Recognition on Extended Experiment Data**

The extended experiment was conducted with more complex events that are unlabeled, since there is no clear evidence which emotion might be triggered by the events.



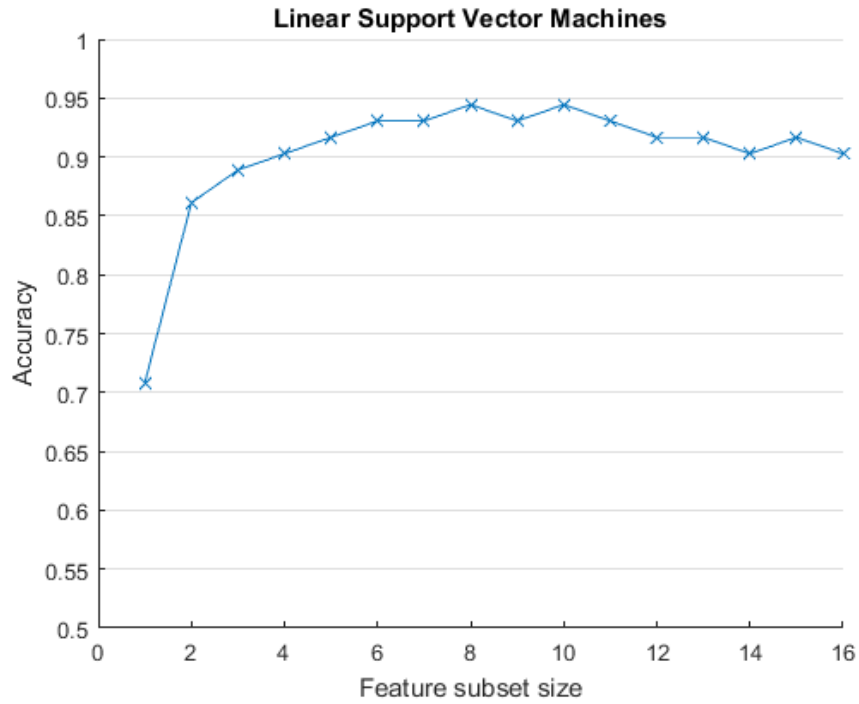


(a) KNN training results

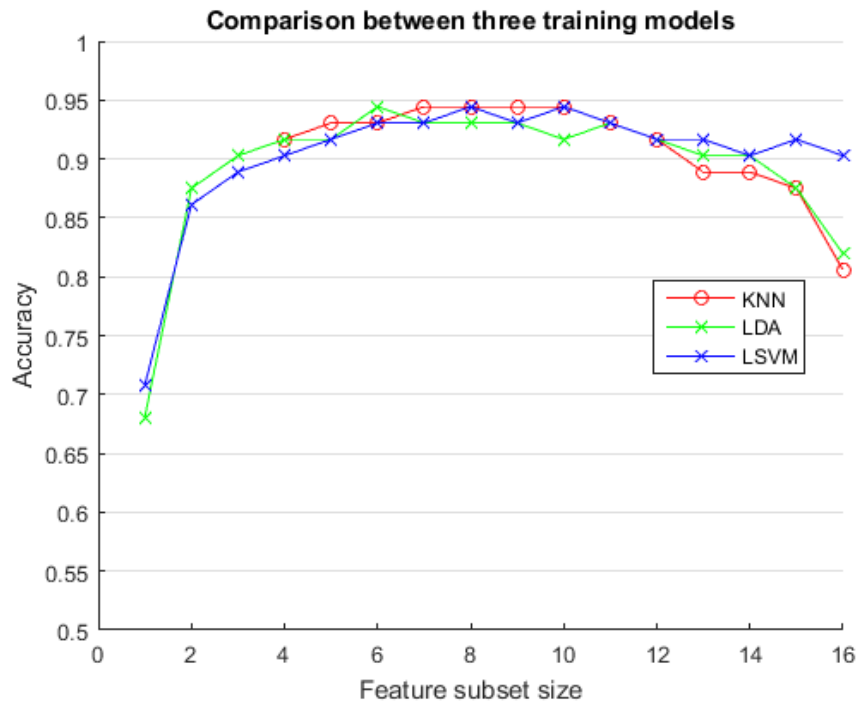


(b) LDA training results

**Figure 21.** Classification models training results



(c) LSVM training results



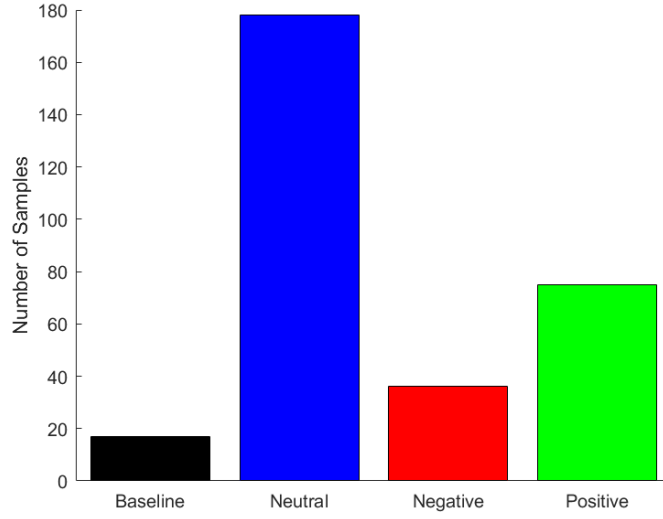
(d) Comparison among classifiers

**Figure 21.** Classification models training results

As discussed in Figure 19, a same set of features based on the feature selection step were extracted and collected from volunteers. Statistic features were extracted with same window length from different scenes. Then the trained LSVM classifier was applied on the feature samples.

Figure 22 displays the histogram of all recognized emotion states over different users and different events. It indicates that during the extended VR experiment, the majority of the VR events do not trigger intensive emotions on users. Users are relaxed and staying in neutral states until some stronger stimuli. More positive emotions are triggered than negative emotions, which aligns with our assumptions on chosen clips, where no terrifying scenes or super disgusting creatures are presented in the immersive environment.

Figure 23 shows the emotion recognition results on each event. From event 2 to event 12, the dominating emotion state is neutral, which makes sense that most of the scenes are about scenery or weather: although there is bad weather or a car accident that may make fewer people feel uncomfortable. One surprising result is the event 12, in which the player is sitting in front of a dining table, where roasted chicken and ham are sizzling. Most volunteers had neutral feelings with this scenario, while a few felt negative, but no positive feelings were recognized in our current dataset. One possible guess is that they may feel bad when they are in front of food but it is not accessible to eat, or the food being presented is not attractive. The events 13-15 are in the universe looking at stars and earth, and it is reasonable that most volunteers feel positive while some might be scared. Events 16 and 17 are more terrifying as the volunteers are sitting on the top of a building under construction with the risk of



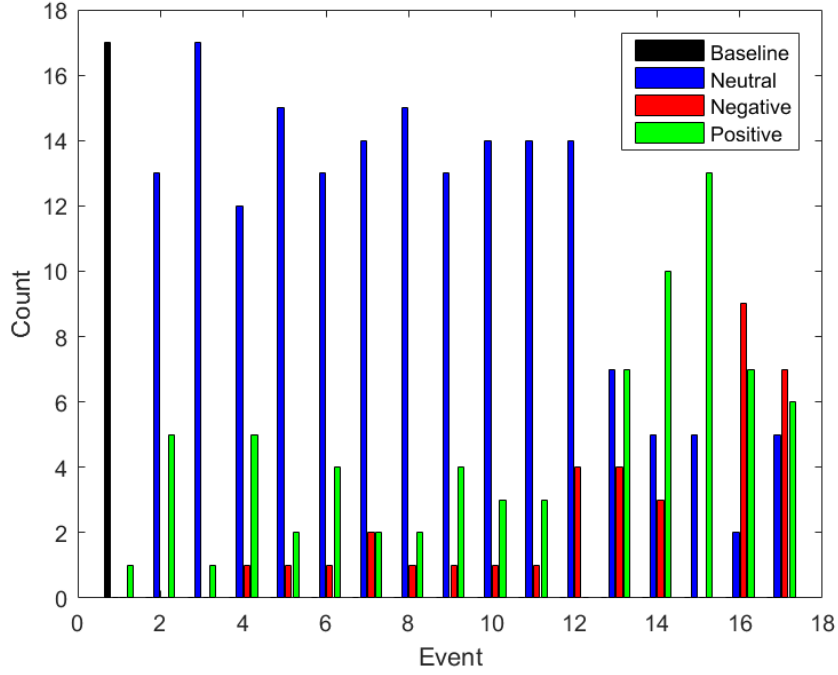
**Figure 22.** Emotion recognition histogram of emotion states

falling; although, a few may feel neutral because they know the danger not real, and some may feel excited by nature.

#### 4.5 Discussion

So far, we have been doing conventional ways to select feature sets, train classification models and apply on new incoming data to predict the user's current emotional state. The classification models have shown promising accuracy with such a small feature set, which could lead to our goal of building portable VR environments with adaptivity to real-time user emotional biofeedback. However, there arose a problem to be solved if we are going to design games that can adapt its scenario as feedbacks to user emotional states.

The problem is, even though we are already using generic categories of emotions, *i.e.*, neutral, negative and positive, with a new-coming unlabeled scenario, different



**Figure 23.** Emotion recognition on each event

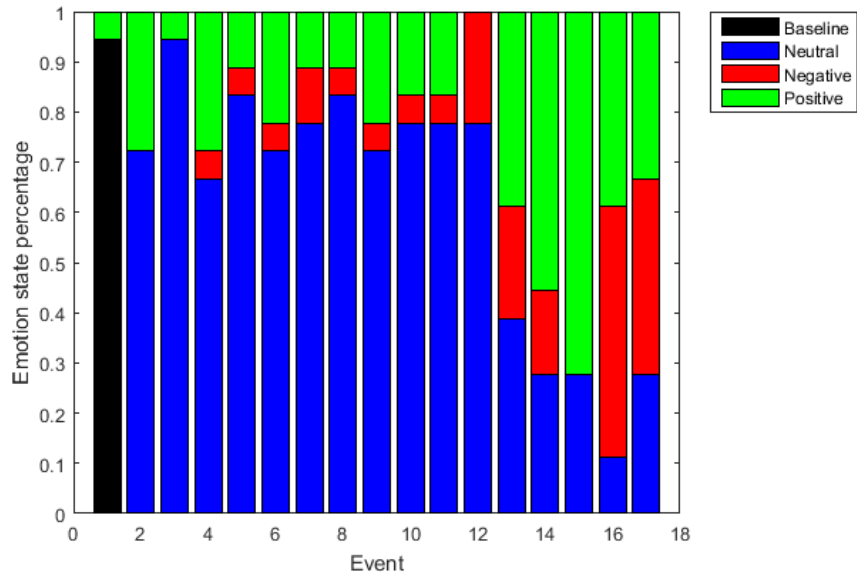
users may have different reactions to it. For example, someone might think of riding a roller coaster as scary experience, but the ones who love adventure would think it is exciting. We did not have to worry about this in training the model because training scenarios are chosen to be simple, straightforward, uncontroversial VR stimuli. This does not apply to more complex scenarios anymore. Upon observing the user data, we can see the chosen feature subsets yield similar patterns to training scenarios, while the patterns to the extended experiment is rather vague. In fact, if we look at the classification results toward the same events among different subjects, there could be more than one answer.

To tackle the problem, there are two directions: adopting mechanisms on how to label the new scenes or making decision based on the individuals.

On the first matter, as mentioned in motivation and literature, the traditional way to label a scene is to ask subjects to fill out a survey after experiments, which is subjective and relying heavily on subjects' memory on their feelings after several minutes of an emotional session. We are looking at using unsupervised learning and categorizing similar scenes. Instead of just labeling one unknown scene to be one specific emotion state by selecting the most voted one, but keeping a set of weighted possible emotions and generating new scenes based on the probability makes more sense and may make the game less predictable and more fun.

In the present research, we summarized the events in the extended experiments by letting the results of user emotional states vote for the scene, and recorded the percentage of each. Now that the events are stored with probability labels instead of fixed ones, this helps us in the next step on how to generate the next scene based on the current recognized emotional state. The concept is shown in Figure 24.

The second direction is based on that a user could have very much different emotional reactions depending on one's age, gender, personality and so on. Nevertheless, possible factors that can affect one's emotional reactions are their previous experience, or even what happened just earlier that day, or the weather. These are the factors very difficult to quantify and serve as features in the classification training model. We will discuss in the next chapter to possibly form a user model that can let the gaming system continuously learn and adjust to an individual, then being able to give feedback in game scenarios more precisely targeted. With the small dataset we have, we can start with generic user models that cluster users into groups, and make decisions based on similar patterns shown in data analysis. Later on as



**Figure 24.** Emotion state stored with percentage

the dataset grows bigger, parameters could be learned more clearly, models could be build in more customized ways, and be dedicated to a single person, which will provide unique gaming experiences to each user and thus make serious games even more beneficial and meaningful.

## CHAPTER IV

### AFFECTIVE GAME DESIGN AND APPLICATION

#### 1 Game Design

After the analysis on the preliminary experiment, training experiment, and extended experiment, the next step is to construct a gaming model to serve as a guideline for adaptive game applications that interact with user emotions. Both game modeling and user modeling are described in this chapter.

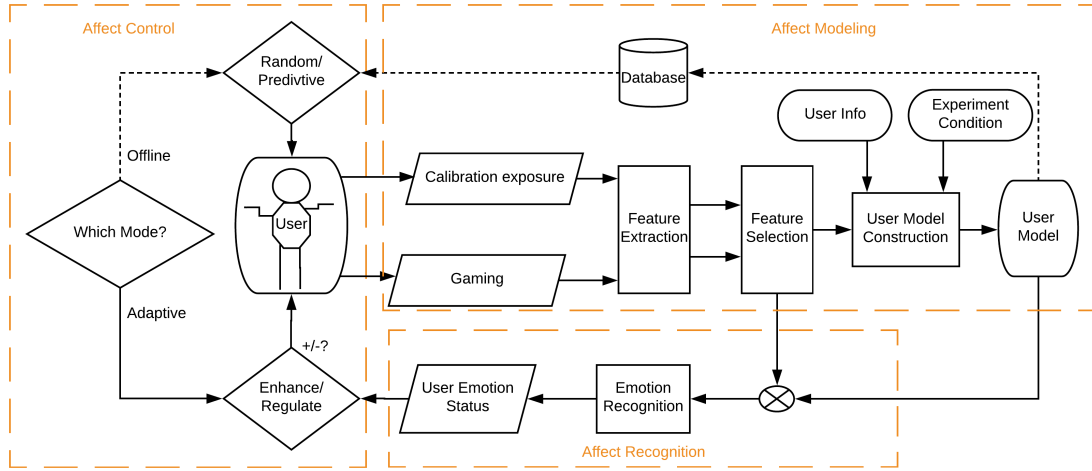
##### 1.1 Game Interaction Modeling

Based on this concept, our current work presents an extension of Wu's model [35] of a closed-loop affective computing system, shown in Figure 25. This closed-loop affective game system consists of three essential modules: affect modeling module, affect recognition module, and affect control module. The dashed line indicates the optional offline path just to differentiate from the main loop.

##### **Affect modeling module**

The affect modeling module is mainly collecting user data from all measures and extrapolating out to construct user models. Features can be extracted from speech, body gestures, facial expressions, physiological signals, and so on. The previous chap-





**Figure 25.** A closed-loop affective gaming system

ter focused on using traditional classification models to train classifiers on recorded physiological data, which achieves acceptable cross-validation results. In this chapter, we are going to talk about constructing user models, and possible improvement as the dataset grows larger.

### Affect recognition module

This module is mainly applying the learned user model to recognize user emotional states. After a possible calibration process, a user could be categorized into user model presets or a dedicated model. The same set of features as the constructed model are extracted during game sessions, then going through the recognition process. The results of recognition could be within a range of confidence, and can either be sent offline to further improve the user model if offline mode is selected, or sent to generate feedback game scenario for real-time adaptivity.

## **Affect control module**

This module changes environment according to user emotional states. The environment includes any one or combined methods to induce user emotional states, such as visual exposure (picture, video or 3D VR scenarios), and audio exposure (affective sounds or music). In our preliminary and extended experiments, each of the methods is studied to learn its efficiency.

This module should have the option to choose either real-time adaptive or off-line mode. Real-time adaptive mode means changing game scenarios immediately when emotion changes are detected. It also includes decision making on whether to enhance the current emotion intensity, or reduce emotion intensity for training purposes. Offline mode can either be randomly choosing the next scenario or running through a predictive path based on the off-line dataset. Either way the user data are collected and used to feed the user model construction.

If the desired emotional states are known beforehand, this framework 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.

As summarized by the previous chapter, every single individual may have different emotional reactions toward the same emotion stimuli. Therefore, in order to adapt the game scenarios to accommodate emotions, there is a need to take a look at user preference and construct user models to better understand the current emotional states and lead to the decision of how to apply the adaptivity mechanism on it. It is nearly as important as designing adaptivity mechanism from the game point of view

to control the interactive environment based on the user models.

The user modeling and adaptivity mechanism are discussed in following two subsections in detail to illustrate this affect control module.

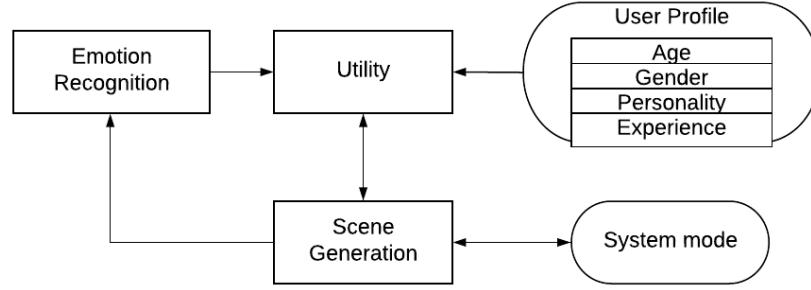
## 1.2 User Modeling

Besides the emotion recognition done by the last chapter, some users may follow similar patterns in their physiological reactions. We can cluster them into different groups to learn the pattern, and to develop representation as the first step of constructing user models, especially when the dataset is not large enough.

As a simple example, K-means clustering algorithm is selected in present research to roughly categorize user groups. K-means is an unsupervised learning algorithm. It aims at minimizing the objective function

$$\operatorname{argmin} \sum_{j=1}^k \sum_{i=1}^n (\|x_i - c_j\|)^2, \quad (18)$$

where  $(\|x_i - c_j\|)^2$  is a chosen distance measure, *e.g.*, Euclidean, to calculate the distance between every data point  $x_i$  and each cluster centroid  $c_j$ . It repeatedly calculates this distance and assigns the current data point to the nearest centroid, and then calculates new cluster centroids after one iteration until centroids do not move any more. In this case, the data points are features extracted from physiological data, and the result cluster centroids are then stored to be representations of user groups. New users can get a few minutes of the same calibration VR exposure to place themselves in one group, then the adaptivity mechanism will be able to control game scenarios depending on the user model and the current user emotions.



**Figure 26.** A Bayesian Belief Network user model

To extend user models more specific to individuals, a learning system can include more user profile information such as user preference, personality, previous experience of VR, as well as the current experiment condition. A Bayesian Belief Networks [96] (BBN) can be adopted in finalizing the model, for the reason that its capable of handling uncertainty, and extending to more variables when feasible. A typical BBN model consists of a bunch of nodes that represent optional parameters that are related to the gaming experience, directed arcs between nodes that represent direct causal dependencies of the connected parameters, and conditional probabilities of arcs that represent the weight of dependencies between nodes.

In the present research case, an example of BBN user model is shown in Figure 26. A list of parameter nodes that can be chosen are:

- Emotion Recognition (e), including current recognized emotion and recognition accuracy;
- User Profile (p), as a combination of any known information like user age, user gender, user personality, the user group assigned using clustering methods *etc.*;
- System Mode (m), whether to enhance or reduce current emotion intensity;

- System Utility (U), to calculate the system utility and affect decision making for next scene generation;
- Scene Generation (s), including possible changing scenarios and their probability of inducing emotions.

User personality can be estimated by a quick questionnaire before the game, or based on user selections on a few scenario branches as options in the VR environment. Different models of describing personality types should be discussed; commonly used models can be four types, eight types, or 16 types. We use three generic types to represent our present model: enthusiastic, distressed, and quiet.

There are three possible values of the system mode:

- -1 (reduce emotions)
- 0 (do nothing)
- +1 (enhance emotions)

The system mode can be adjusted dynamically during the game, or follow pre-game settings. Positive or negative 1 indicate enhancing or reducing the current emotion intensity by changing the next generated scene towards the chosen direction from possible context alterations. If the system mode is 0, the system is equivalent to offline mode, where it does not adapt to user current emotional state, but still can consider other parameters to generate the next scenario dynamically, or completely random scene generation in a special case.

Scene generation is to generate the next scene in either neutral, negative or positive context, which is decided by the system mode and utility. Possible alterations are referring to the result of the extended experiment, where events were stored with probability to each emotion it may stimulate.

From the model figure, utility of each scene can be estimated by deriving a function  $f(e, s, p)$  over current emotion recognition results, current scene and any known user profile information. The function can be learned through regression once user profile is quantified.

$$U_i = \alpha f(e, s_i, p) \quad (19)$$

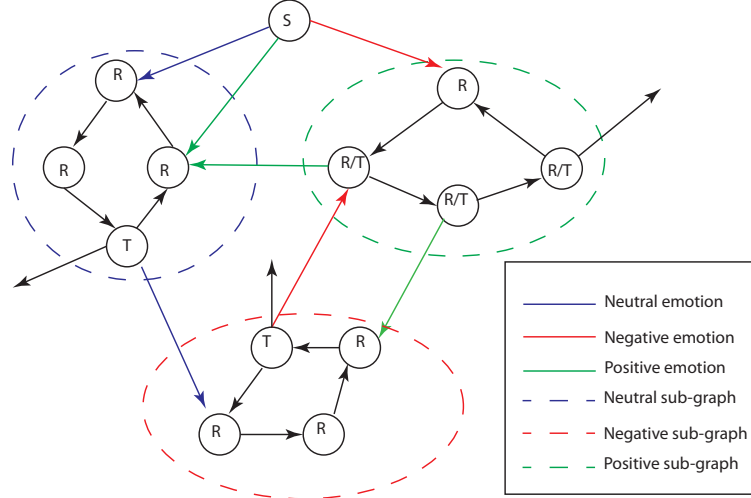
Specially, when all other information is unknown,  $U_i$  is simply dependent only on  $e$  and  $s_i$ . A linear relationship can be written as  $U_i = \beta e + \gamma s_i$ . Once there is any user profile information collected, it can be quantified and inserted into the expression.

The posterior probability of scene generation can be given by:

$$P(s_i|U, m) = \frac{P(U, m|s_i)P(s_i)}{P(U, m|s_1)P(s_1) + P(U, m|s_2)P(s_2) + P(U, m|s_3)P(s_3)} \quad (20)$$

### 1.3 Graph-based adaptivity game structure

To be able to adapt game scenarios depending on users' emotional reactions as a new type of game feedback, a carefully designed adaptivity mechanism is necessary. The Bayesian Belief Network described in the last section provides a solution for how to integrate known information to calculate the probability that each possible scene could be generated. Besides that, we need to look at the big picture of the gaming structure.



**Figure 27.** Proposed biofeedback structure.

**Table 4.** Types of key scenario nodes

Notation	Representation	Action(s)
$S$	Source node	Test which emotional sub-graph to begin the game
$R$	Interactive node	Stimuli that either enhance or reduce current emotional intensity
$T$	Testing node	Decide whether to switch to another sub-graph or stay in current sub-graph

As stated in the literature review, based on a Dynamic Object-Oriented methodology [19], our novel biofeedback structure is described as in Figure 27. Key scenarios are denoted as nodes in the figure, while emotional states indicated by biofeedback are coded by colored arrow. Sub-graphs represent different types of scenario sub-graphs that induce different emotions. Blue represents neutral sub-graph or emotional state, while green represents positive and red represents negative. Table 4 explains different types of key scenarios and their actions.

The work flow of the Dynamic Biofeedback Structure is described below:

1. Let  $S$  be the source point of the game. Randomly assign one of the starting key scenarios from three sub-graphs.

2. For each  $r_{i,j} \in \mathbf{R}_j$ , where  $i \geq 0$  represents nodes, and  $j \geq 0$  represents sub-graphs. Apply affective stimuli based on the current sub-graph to enhance or reduce the emotional state, then move to a next node  $r_{i+1,j}$ . 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  $r_i, \dots, r_{i+m}$  nodes, where  $m$  is a non-negative integer. If emotional state has changed during the period, decide whether to go to the corresponding sub-graph or stay at the same sub-graph by referring to the BBN model for next scene generation.
4. Continue looping previous steps, until either time is up or it reaches a desired emotional state, that is, the end node of the entire game.

The structure interacts with emotional states induced by key scenarios, and initiates dynamic switch among key scenarios under constraints. A key scenario contains several VR attributes to stimulate a certain kind of emotion; stimuli are selected referring to the experiment outcomes of events voting.

Notably, in this presented design, there are a few reasons that the  $T$  nodes occur every fixed amount of time and analyze all factors during that range, and then make decisions based on BBN model. First of all, for recorded experiments (usually with screen capture videos), it is relatively easy to sort out the time range when events begin to happen or finish, while real-time gaming will not have a clear timing for what is happening. Calculating emotions in every node in absolute real time dramatically



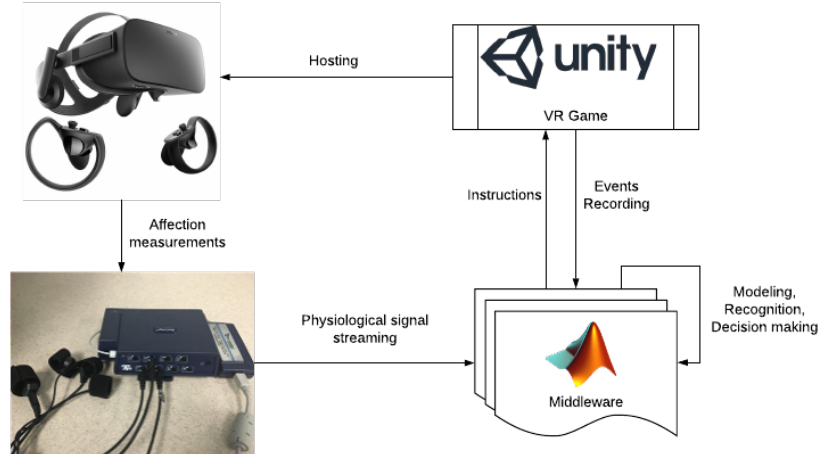
adds calculation complexity, which is not a good idea for the purpose of designing a portable gaming system. Meanwhile, a time window is needed anyway to calculate statistic features in order to recognize the current emotional state: too short a window will decrease the accuracy. The length of window is adjustable, and can be either fixed or relative. Moreover, making decisions based on every node lead to jumping around different sub-graphs too soon, which is a bad experience to be avoided, since it may confuse users and get undesirable bad looping.

In reality, any games, including serious games or normal entertainment games, can make use of the above user model and adaptivity mechanism, since it is one extra dimension of feedback. The storyline may or may not be subject to changes of emotions depending on the design needs. Sub-graphs could be affecting the main storyline, changing the surroundings, or leading to different side quests.

## **2 Game Application**

In order to demonstrate this interactive game framework, a simple VR game application was developed, which consists of all essential modules described in previous chapters and sections. Figure 28 shows the essential parts of the game and their work flow.

A middleware was implemented with Matlab to form the affect recognition and affect control module. It connects ProComp sensors, reads real-time psychophysiological data, processes affect recognition, analyzes the user model and then sends instructions to Unity, where the VR game scenarios are hosted and will be adaptively changed to coordinate with the affection status change.



**Figure 28.** VR rehabilitation training game.

The demonstrative application is roughly a rehabilitation/physical training game for older people, where it changes scenarios, tasks, backgrounds and music according to user emotion reactions while requiring physical movements to achieve health goals. For example, one of the game scenes requires a user to stretch his/her arm to draw some specific pattern. While the user is doing exercise, the environment, including sky, the background, the audio, and the particles that show the drawing trail will be subtly changing colors or textures according to the change of the user's emotional states. In most cases, the atmosphere of the game will be leading to positive scenarios if the system detects the user in a bad mood or too relaxed; but if the user is feeling too excited, the atmosphere will try to use soothing music and corresponding scenes to calm the user down.

The game is able to show the basic concept of the introduced framework, but is still in need of further polish in regards to art design and intensity levels.

## CHAPTER V

### DISCUSSION

Despite the functionality and purpose of a product, user experience is increasingly important nowadays in designing web apps, software, games, or anything related to human-computer interactions. It does not only affect the users' awareness and understanding of the products, but also directly leads to user acceptance and thus market success, even if the market strategy aims to specific groups of people. Therefore, when designing new gaming models, one should always keep in mind to ensure the basis of user-centered design, which leads to the need of evaluating the games by their playability as well as effectiveness.

#### **1 Measuring playability of affective gaming system**

The most traditional way of evaluating the playability of a system is through user testing and feedback, usually involving interviews or surveys, and also bug reports. Although self-report method is often subjective and hard to scale, it does reveal insights from the user side that might differ from game designers' original thoughts.

In the earlier stage of a game development, Heuristic Evaluation for Playability (HEP) is widely accepted in assessing an HCI system. Article [79] provided a comprehensive table of HEP with description that considers four categories of a game:

game play (problems and challenges), game story (characters and narratives), game mechanics (interactions), and game usability (interface and control). They all apply to our present research. Generally, HEP is able to find more issues that need improvement than user testing cases can find.

## 2 Measuring effectiveness of affective gaming system

Besides the generic heuristic evaluation that applies to almost all types of games, our gaming system that interacts with user emotional states should also be evaluated in a quantitative way, where the manipulation and alterations of emotions should be considered. Several metrics are derived to measure different aspects of the effectiveness of a VR affective gaming system.

The system keeps track of the path that users take to complete the game, including the order of nodes visited and each transition between sub-graphs. Let  $i \in \{1, 2, \dots, N\}$  represent different emotion categories,  $s_i$  represent sub-graph that induce emotion  $i$ , and  $e_i(t)$  represent the current user emotional state  $i$  at time  $t$ . In the present case,  $N = 3$  since we categorize emotions generally into neutral, negative and positive states.

### Effectiveness of sub-graphs

In each sub-graph, before a user changes his/her emotional state  $e_j$  as reaction to the current sub-graph  $s_i$ , we record that  $m$  nodes have been visited, then the effectiveness

of sub-graph  $i$  can be calculated as:

$$E_i = \frac{m}{\|R_i\|}, \quad (21)$$

where  $\|R_i\|$  is the total number of Interaction nodes in that subgraph  $s_i$ .

### **Effectiveness of emotion transition**

Of all system-controlled change of scenarios, how many of them have achieved the goal? There might be failure when the system tries to guide the user from one emotional state to another, but instead the user jumps to another unintended emotion. Staying in the same emotional state and then transitioning within a certain amount of nodes  $m_j$  still counts as success. Therefore, the effectiveness of emotion transition is evaluated by the probability of the change of emotional state from  $i$  to  $j$  given the current user emotional state is  $i$  and the scenarios are under sub-graph  $s_j$ .

$$E_{inducing} = P(e_j(t+m)|s_j, e_i(t)), \quad (22)$$

where  $i \neq j$ .

### **Effectiveness of interaction**

For each  $t_j \in \mathbf{T}$  node, there is a test to determine transition. Let  $n_{i,j}$  count how many times the transition from sub-graph  $S_i$  to  $S_j$  happens during the game, so  $n_{i,j} = \sum_t etr_{i,j}(t)$ . 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:

$$E_{interaction} = \frac{\sum_{i=1}^N n_{i,i}}{\sum_{i=1}^N \sum_{j=1}^N n_{i,j}(i \neq j)}, \quad (23)$$

### **Effectiveness of game design**

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

The effectiveness of game design can be calculated as below:

$$E_{design} = \frac{\# \text{ of success in training}}{\# \text{ of total user trials}} \quad (24)$$

## CHAPTER VI

### CONCLUSION AND FUTURE WORK

In this dissertation, a novel approach for designing affective VR environments with feedback to user emotions is introduced based on the results of a series of VR exposure experiments. The interactive model combines advantages of portable VR devices and reliable physiological sensors along with affective computing, in order to create immersive environments that interact with users' emotional states. The implementation of the system can either be applied to general emotional response testing, or used to extend one extra dimension of feedback to variety of game applications, such as designing rehabilitation training for older people. Evaluations on playability and metrics to calculate effectiveness are also described, in order to assess different aspects of gaming applications to better serve its designing purpose.

It is not the end of the research; there are a few directions for future work to further improve the model or its applications:

Currently, three generic emotion categories are recognized and used to yield affective control of the game scenario. It will definitely bring more interesting user experience to extend the categories to include more detailed states, as in Figure 2, so that more sub-graphs will be used to stimulate different emotions.

In the laboratory experiments, we are using professional physiological sensors ProComp 5 series. As the purpose of the presented framework is to implement portable games so they can be widely used in healthcare and other fields, looking for less expensive wireless sensors with acceptable accuracy as replacement is also a need. With the reduced size of required feature set, a smart watch or wristband may serve the needs. The VR hardware is developing very fast in recent years. It is promising to see more portable VR systems on the market; some probably will come with built-in sensors.

Besides collecting data from physiological sensors to train emotional classification models, another direction of future work could be extending the current affect modeling module to include other features such as behavioural analysis using Kinect or Leap Motion, in order to increase accuracy of recognition and provide options for cross verification.

Furthermore, building up robust user models needs more experiment data and information collection. More advanced machine learning or data mining methodologies can be used in the affective recognition module as well as the affective control module.

Last but not least, the game needs to be polished with art design and better narratives. We are collaborating with therapist experts from the healthcare field to learn more about realistic needs for therapy and physical training and thus to include meaningful storylines and scenarios, which will make our current physical training game more suitable for real world application and make it ready to help people.



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# CURRICULUM VITAE

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## EDUCATION

Aug. 2012 - May. 2018	Ph.D. Computer Science and Engineering, University of Louisville, KY, USA
Aug. 2010 - May. 2012	M.S. Computer Engineering and Computer Science, University of Louisville, KY, USA
Sep. 2006 - Jun. 2010	B.S. Optical Information of Science and Technology, Communication University of China, Beijing, China

## PROFESSIONAL EXPERIENCE

Aug. 2014 - May. 2018	Graduate Teaching Assistant, Department of Computer Engineering and Computer Science, University of Louisville
Aug. 2010 - May. 2012	Graduate Research Assistant, Department of Computer Engineering and Computer Science, University of Louisville
Sep. 2008 - Jun. 2010	Project Leader, Research on Popular New Optical Film, Communication University of China

## AWARDS

Apr. 2018	CECS Doctoral Award(For the Computer Science outstanding PhD students)
Sep. 2015	Recipient of Student Travel Award, 2015 ISNR Conference, Denver, CO
Mar. 2015	Recipient of Graduate Research Fund, GSC Executive Committee, University of Louisville
Jul. 2014	Second Place in TCSIM IEEE Best Student Paper Award, CGames USA 2014 Conference
Aug. 2012 - Jul. 2014	Provost Fellowship Recipient from University of Louisville (The most prestigious university-wide scholarship at UofL)
Apr. 2012	CECS Master of Science Award(For the Computer Science graduate who has attained the highest cumulative scholastic standing in the departmental Master of Science program)
Oct. 2009	Third Grade Scholarships for Outstanding Undergraduates, Communication University of China
Oct. 2008; Oct. 2007	Second Grade Scholarships for Outstanding Undergraduates, Communication University of China
Oct. 2008; Oct. 2007	“Three Goods” Student Award, Communication University of China

## PUBLICATIONS

- Li, Y., Elmaghraby, A. S., El-Baz, A. S., Casanova, M. F., & Sokhadze, E. M. (2016, December). *“Virtual Reality as a Tool for Investigation of Autonomic Reactivity in Autism”*. In APPLIED PSYCHOPHYSIOLOGY AND BIOFEEDBACK (Vol. 41, No. 4, pp. 444-444). 233 SPRING ST, NEW YORK, NY 10013 USA: SPRINGER/PLENUM PUBLISHERS.
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- Li, Y. (2012, July). *“Multi-scenario gesture recognition using Kinect”*. In Computer Games (CGAMES), 2012 17th International Conference on (pp. 126-130). IEEE.
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