REAL TIME ASSESSMENT OF A VIDEO GAME PLAYER'S STATE OF MIND USING OFF-THE-SHELF ELECTROENCEPHALOGRAPHY

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The focus of this research is on the development of a real time application that uses a low cost EEG headset to measure a player's state of mind while they play a video game. Using data collected using the Emotiv EPOC headset, various EEG processing techniques are tested to find ways of measuring a person's engagement and arousal levels. The ability to measure a person's engagement and arousal levels provide an opportunity to develop a model that monitor a person's flow while playing video games. Identifying when certain events occur, like when the player dies, will make it easier to identify when a player has left a state of flow.

The real time application Brainwave captures data from the wireless Emotiv EPOC headset. Brainwave converts the raw EEG data into more meaningful brainwave band frequencies. Utilizing the brainwave frequencies the program trains multiple machine learning algorithms with data designed to identify when the player dies. Brainwave runs while the player plays through a video gaming monitoring their engagement and arousal levels for changes that cause the player to leave a state of flow. Brainwave reports to researchers and developers when the player dies along with the identification of the players exit of the state of flow.

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CHAPTER 1

INTRODUCTION

The Entertainment Software Association (ESA) [3] reported that consumers in the United States spent 22 billion dollars on video games, hardware, and accessories in 2014. The ESA also found that almost half of the population in the United States plays video games. AAA games (those with the highest development costs) require several years of development and millions of dollars in funds, all of which are wasted if the consumers end up disliking the game. Developers naturally try to evaluate player experience before their game is released by letting a small group of people play the game at various points in its development, a process known as *play-testing*.

Game developers commonly employ a questionnaire to gauge subjectively how players feel about their game after play-testing. However, data from questionnaires is subject to inaccuracies from various sources, including the subject's memory, their desire to fit in, or their ability to recognize their own feelings. Physiological data provides a means for accessing in real time various states of feeling that a person experiences including engagement and boredom. Game developers have been reluctant to collect physiological data because it has historically required the use of laboratory grade or medical grade devices which have an extremely high cost and require a skilled technician to connect the equipment and interpret the data.

New advances in technology have led to the release of some inexpensive consumer-grade devices that provide easy access to physiological data. Specifically, several companies developed new brain computer interfaces that they advertised as a new means of controlling computers, games, and toys using the power of the player's mind. However, they are much more than just controllers; they are tools that provide access to the mental activity of the player. These cheap and easy to use devices therefore provide an opportunity to develop a new and practical approach to measuring player experience.

The recently released brain computer interfaces are so new to the research world that there is a lack of consensus on their resolution. Researchers continually work with these devices to discover how well these devices measure a person's neural activity. Most of the research indicates that these brain computer interfaces are adequate for capturing basic neurological information, but naturally do not have the same capabilities as medical grade devices. Until now, no research has been conducted using off-the-shelf devices to measure gamer experience.

The main advantages of using physiological data to measure player experience is that the data can be gathered in real time during gameplay using a real-time application, the development of which presents us with three major hurdles. Firstly, we must gather information about the neural resolution of the brain computer interface when used during gameplay. Secondly, we must devise a methodology for processing the captured data, since there is no set standard on how to process neurological information from off-the-shelf brain computer interfaces. Thirdly, we need to devise a way to report the processed data in a designer-friendly way. Game developers need information about how specific game events affect the player's experience, for example, how often the player dies and how this affects them. Developers also need data about any fluctuations in player experience as they move throughout a level without engaging with any specific game event.

1.1. Current Evaluation Methods

While knowledge of the player's state of mind is imperative to the design of a successful video game (Norman [58]), the current evaluation methods employed by developers to assess player state of mind are costly, antiquated and ineffective. Game developers and researchers most commonly employ questionnaires for this purpose. Schwarz [68] found that when used in isolation, self-report data is highly susceptible to influences from the questionnaires' wording, context, and format. Questionnaires also induce a timing issue, since asking the player to answer the questions while playing the game affects their experience causing negative feedback (Berta et al. [10]). Chiang et al. [17] learned that asking the player after completing the game leads to missed and/or false information. To help supplement the questionnaire, developers and researchers sometimes record game play so that they can play it back later to help evaluate player experience; however, the only benefit of replaying game play footage is that it shows were the players struggled the most within the game, which is not a true measure of player experience.

1.2. Affective Computing

Affective computing is a term given to the process of computationally measuring a human's state of feeling, commonly referred to as *affect* (Tao and Tan [75]). Affective computing systems work by collecting data from humans and interpreting that data to find patterns that associate to human affect. The systems collect data using various inputs such as cameras and microphones. A camera can be used to interpret the meaning behind facial expressions and body language while a microphone can be used to detect variations in a person's voice that may signify changes in mood. Current research is directed at developing affective computing system that respond in a rational and strategic fashion to real-time changes in user engagement (Wu et al. [79]), neurocognitive performance (Parsons et al. [59]), and arousal (Fairclough et al. [30]).

1.2.1. Psychophysiological Metrics

Psychophysiological metrics are measures of physiological signals produced by humans interacting within their environment. Psychophysiological metrics are excellent sources of input for affective computing systems, the most common devices being used are electroencephalogram (EEG), electromyogram, galvanic skin response, and electrocardiograph.

The *electroencephalogram* is a monitoring tool used to look for variation in electrical activity in the brain. By placing EEG electrodes on the scalp, scientists can monitor the brain's voltage fluctuations over a period of time to identify neural oscillations, commonly known as *brainwaves* which are typically broken down into five bandwidths: alpha, beta, delta, gamma, and theta. Each bandwidths represent the states of activity of a person's mind. The alpha band primarily indicates that a person is in a relaxed state of mind. The beta band is predominate when a person is active and engaged in cognitive tasks. During deep sleep, while not dreaming, the delta band becomes the prevailing signal. gamma is commonly associated with higher levels of brain activity such as memory processing or the formation of ideas. The theta band indicates extreme relaxation or a light sleep where the brain is still active and processing information. Combined, these bandwidths create a picture of a person's mental activity while engaged in processing information. For example, a person engaged in a difficult task would produce a strong beta rhythmic activity with some alpha activity to help keep them in a calm state. Over a period of a study, the brainwaves begin to form patterns that correspond to specific tasks a person completes. For instance, every time a person blinks the brain tells the different parts of the eye what to do. The signal generated to start an eye blink is the same every time and becomes uniquely identifiable in a person's brainwave signature. Identifying and decoding other patterns generated by the brain gives researchers a non-invasive method to identify human affect.

An *electromyogram* is a monitoring tool designed to measure electrical activity generated by muscle movement. When a person wants to move, their nervous system sends a small electrical signal to the muscle that requires movement. An electromyogram records the electrical activity allowing researchers to identify electrical signals that correspond to specific muscles. Using an electromyogram in affective computing allows the system to monitor the human face for expressions, which can correlate to affect. However, electromyograms lack the capability to measure neurocognitive performance.

Galvanic skin response is the monitoring of the skin conductance between two different body parts. Skin conductance changes with the amount of sweat generated, which changes with arousal level. Current galvanic skin response devices typically measure skin conductance between two fingers on the same hand. Measuring on the fingers proves to be a problem for video game players, who need the use of their fingers to operate game controls. Some other locations are available for measuring galvanic skin response, but these alternate locations often introduce artifacts from muscle movement.

An *electrocardiograph* is a monitoring tool that measures the electrical activity of the human heart. Electrocardiograph electrodes placed on a person's chest measure the electrical activity generated by the heart and report the number of times the heart beats per minute, commonly referred to as *heart rate*. As a person experiences increases in arousal levels, their nervous system compensates by increasing their heart rate to send more blood throughout the body. An affective computing system can use this information to determine whether a person is in an anxious or exicted state. Electrocardiographs are very effective at measuring arousal but lack the ability to measure engagement and neurocognitive performance.

Psychophysiological metrics afford researchers and developers a way to obtain information about a players experience that would otherwise be quite difficult to gather from self-report data (Kivikangas [47]). The psychophysiological signal is continuously available for developers to collect information from their players. This continuous feeback offers several key advantages over self-report data when used it to measure player experience. The first advantage, as describe by Gilleade et al. [33], is that it allows for greater understanding of how any stimulus in the gaming environment impacs the gamer, not just the parts of the game designed to produce behavioral responses. The second advantage is that psychophysiological signals allow for the collection of data without interrupting the player allowing for true immersion into the game. Finally, as reported by Slater et al. [71], psychophysiological measures may uncover stimuli in the gaming environment that caused a break in the player's sense of reality within the game, commonly referred to as presence. Psychophysiological responses occur without the gamer's conscious awareness, creating an objective measure of the gamer's state, which can include measures of cognitive workload (Berka et al. [9], Brookings et al. [16], Kobayashi et al. [42]), varying stress levels (Branco and Encarnacao [15], Fairclough and Venables [29]), task engagement (Pope et al. [63], Seery et al. [69]), and arousal (Bradley and Lang [14], Cuthbert et al. [23] [24]).

1.3. Off-The-Shelf Electroencephalography

Electroencephalography (EEG) provides a means of accessing and recording neural activity, thus allowing a computer to retrieve and analyze information from the user's brainwave patterns. Until recently, Birbaumer [12] points out, the brain computer interfaces were developed as communication tools to allow a person to integrate with external devices. As an example, a person with paralysis could use a brain computer interface to operate computers, prosthetic limbs, and motorized chairs. Research conducted by Zander and Kothe [82] demonstrated that these same brain computer interfaces have the capability for near real-time decoding of a person's neurocognitive or affective state, opening up a whole new way to collect data from individuals.

Affective computing has recently seen great advancement due to the improvements in off the shelf EEG brain computer interfaces, which allow researchers from all areas of study an inexpensive alternative to laboratory-based systems. The primary function for these EEG devices, until now, is as an input for players to interact with video game characters in the next generation games commonly referred to as neurogaming. Neurogames map specific neural activity to various game controls, so as the player reproduces these neural patterns they have the ability to interact with the game without the use of a controller. Recent studies demonstrated the potential of neurogaming applications for interfacing with well-known games such as Pacman (Reuderink et al. [64]), Tetris (Pires et al. [62]), and World of Warcraft (Van et al. [76]).

Neurogaming platforms use a gamer's psychophysiological metrics to complete tasks or alter the mood of the game. However, the research design, data logging, and the control algorithms found in neurogaming are not systematic and studies to support their use remain limited. The growing trend in neurogaming literature is to recognize a user's cognitive and affective states in real time. While establishing the optimal relationship among frequency bands, task engagement, and arousal states is one of the main goals of neurogaming, these indices are typically developed in isolation and do little to take into account cognitive and affective information. Currently there is no standardized method for measuring a person's cognitive and affective information in real time.

A popular EEG-based brain computer interface used for research is the Emotiv EPOC, a compact, wireless headset that requires comparatively little effort to set up and allows much greater flexibility and mobility than traditional EEG. The EPOC was aimed at the gaming market and is not classified as a medical device though a few researchers Cinar and Sahin [18], Rosas et al. [65], and Vi and Subramanian [77] have adopted it for a variety of applications including detecting facial movements, emotional states, and imagined motor movement.

Sourina and Liu [73] used the EPOC to measure a user's affective states while they watched film. Researchers have also investigated different EEG processing algorithms, with the EPOC, to assess classification of positive and negative emotion elicited by pictures (Jatupaiboon et al. [38], Pham and Tran [61]) and evaluation of cognitive workload (Anderson et al. [2]). Esfahani and Sundararajan [28] used the EPOC to investigate different EEG processing algorithms to assess classification of shapes that the participants were thinking about. The goal of their research is to develop a way to use brain computer interfaces within a computer aided design program. Although their results were not the strongest, Esfahani and Sundararajan's research offers some potential uses for the Emotiv EPOC EEG headset.

Although the Emotiv EPOC EEG headset does not have the fidelity of a laboratory EEG device it still offers the ability to measure a gamer's brain wave signature. Duvinage et al. [26] compared the Emotiv headset (Cost: 750.00) to the Advanced Neuro Technology (ANT) (Cost: 50,000.00) acquisition system during a run with the P300 speller system. The results from this research showed that the data recorded by the Emotiv EPOC headset was not as precise as the ANT system. Duvinage et al. indicated that the measurement taken from Emotiv had far above chance classification rates concluding that Emotiv was measuring EEG. Although the Emotiv headset did not match the accuracy of the ANT system (a medical grade device), it was able to capture EEG signal at a successful level that was deemed adequate for game psychophysiological testing. With the benefit of being non-invasive to the wearer, the Emotiv is a tool that is practical for use by game developers and researchers.

1.4. Electroencephalography to Measure Player Experience

The Emotiv EPOC offers an opportunity to gather data about the users-state during game play, where currently little work is done to use EEG to measure player experience while playing video games. The limited research that does exist uses laboratory grade EEG devices, which is impractical for use by game developers. Salmin and Ravajja [66] used EEG to isolate specific game events from the EEG data. Using Super Monkey Ball 2 as their test platform, they were able to detect changes in the brainwave bands as different event occurred during game play. Research by Murthy and Fetz [52] and Steriade [74] show that beta rhythmic activity increases with attention and tasks requiring vigilance. Salmin and Ravajja found this to be true as well during video game play.

Nacke et al. [55] showed that EEG data can determine a player experience across entire game levels. Using a Half Life 2 modification Nacke and colleagues captured the EEG signature of players as they played through three different levels designed to induce boredom, immersion, and flow. Nacke's data showed significant fluctuation in brainwave activity as the player moved across the three different levels, specifically an increase in the theta band during the immersion level. In other research, Nacke [54] and Wirth et al. [78] discovered a relationship between beta and gamma brainwave activity attributed to spatial presence of the player within virtual gaming environments. Berta et al. [10] used EEG and other physiological signals to assess a player state by using game levels designed to induce boredom, flow, or anxiety. Using machine-learning algorithms, Berta classified player EEG data into one of the three categories, achieving a correct classification rate of 67 percent. The work performed by Nacke and Berta focuses on measuring a player's experience across an entire game level versus measuring changes throughout the level. Averaging player experience across an entire level does not allow for the identification of specific game events that affect the player's experience negatively.

1.5. Player Experience

No standardized descriptions exist that best explain player experience. This is due to the large number of factors that contribute to the way a person feels about a video game. For example, some players may not like a game because it is too hard or too easy. If a person thinks the game has too much repetition they may become bored. Individuals will invariably have different reactions to a given video game, so developing a method to measure player experience requires looking at the changes to an individual person's affect as they play a video game.

1.5.1. Flow in Video Games

According to Csikszentmihalyi [20], [21], [22], the general understanding of "flow" is as an optimal state of consciousness that is best characterized by a state of concentration so focused that it results in complete immersion and absorption within an activity. In video games, flow or immersion is a state in which the player is in a preferred level of both engagement and arousal. If the player is either too engaged or aroused they are in a state of stress where if it is too low, the player is in a state of boredom. Figure 1.1, adapted from Csikszentmihalyi [20], illustrates the flow channel which is used to keep the player in complete immersion. As game play constantly shifts, flow channels are required to adjust over the course of the game. When a player starts playing a new game their skill level is lower, requiring lower intensity and complexity. However, as the player's ability level and familiarity with the game increases, the intensity and complexity must increase or the risk increases that the player will become bored. This works in reverse as well, if the game starts off with too much intensity and complexity for a player's skill level they become frustrated or stressed. This makes it important to be able to find a players optimal engagement and arousal levels to keep them in the flow channel.

1.5.2. Electroencephalography for Establishing Indices of Engagement

The first part to measuring player experience requires knowing the player's level of engagement while they play the video game. Currently, no research exists that utilizes off-the-shelf EEG tools to measure a person's engagement level. However, several studies conducted with medical grade EEG devices have demonstrated the successful ability to determine a person's engagement levels from neural activity. Pope et al. [63] built an automation task that fluctuated based upon the user's engagement level. As the operator's engagement level would increase the system would perform more of the operator's duties. As their engagement level decreased the system would do less of the operator tasks. Freeman et al. [31] expanded on this same system by evaluating the performance of each task along with using absolute values of engagement versus just looking at increasing and decreasing engagement. Task engagement and mental workload are areas that Berka et al. [9] explored as a way to

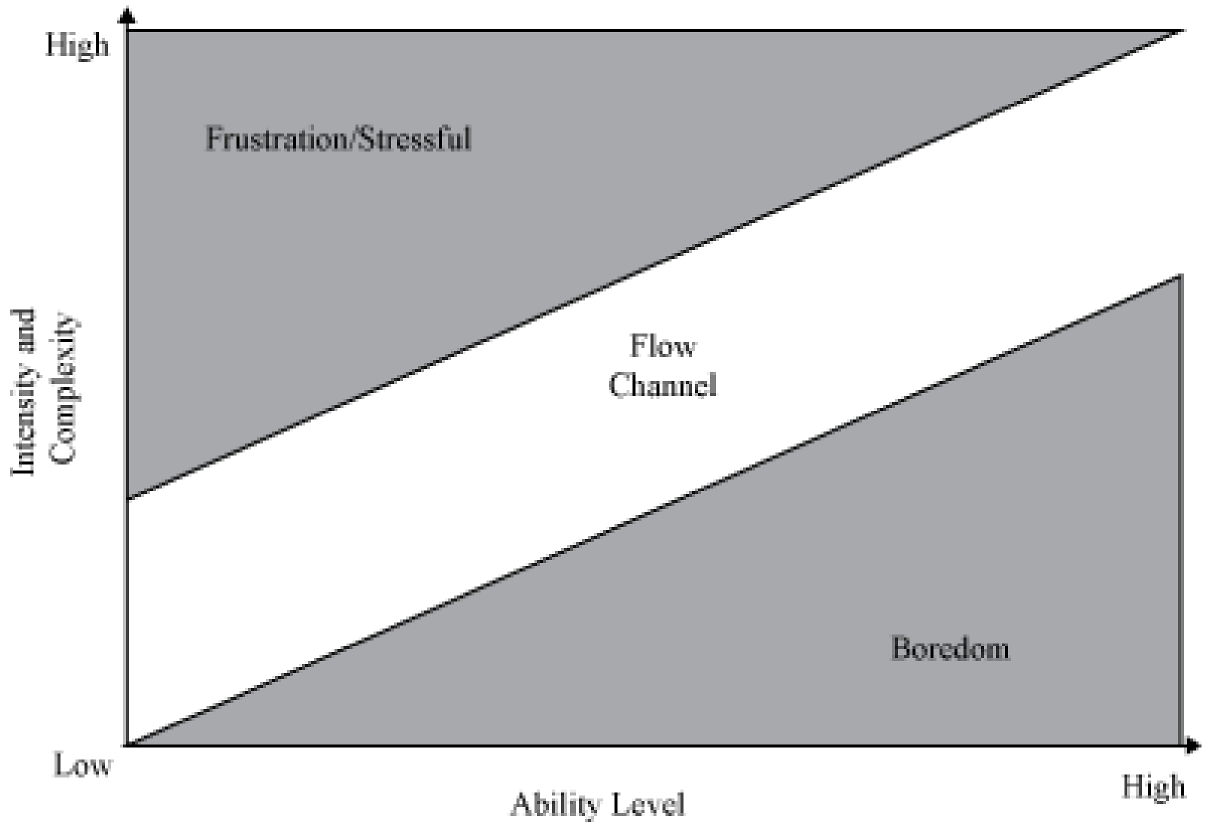

FIGURE 1.1. Two-dimension representation of the flow channel for video games, the figure depicts the need for video games to increase intensity and complexity to keep a player in a state of flow as their ability level increases.

help identify more accurate and efficient methods for people to interact with technology with the possibility of developing more efficient work environments that increase motivation and productivity. Their results suggest that EEG measurement reflects information gathering, visual processing, and attention allocation.

Smith and Gevins [72] used a flight simulator to subject participants to low, moderate or high difficulty tasks to see how players' brains responded. The results from their study showed an increased frontal theta response along with reduced parietal alpha during demanding tasks. Work conducted by Fairclough et al. [30], Holm et al. [37], and Nassef et al. [56], produced similar results indicating that an increase in theta and a decrease in alpha correlated with an increased number of tasks along with amount of time a person is awake. Yamada [81] measured frontal theta activity along with eye blinking and found that children playing video games had higher theta activity along with a high degree of blink inhibition. Recently, Kamzanova et al. [39] compared the sensitivity of various EEG engagement indices during time-on-task effect and cueing to determine which index was most effective for detecting reduced alertness linked with a decline in vigilance.

1.5.3. Electroencephalography for Establishing Indices of Arousal

The second part of measuring player experience requires knowing the player's arousal levels while playing a video game. Kim et al. [41] performed a review in which they found fluctuation in various brain wave frequency bands provides an excellent tool for assessing arousal and affect. Miskovic and Schmidt [50] exposed participants to highly arousing images while they were connected to an EEG device in hopes of isolating variations in neural activity. They found an increase in the overall EEG coherence, specifically in the beta band. Several studies performed by Balconi and Lucchiari [5], Aftanas et al. [1], and Sammler et al. [67] found theta power event-related synchronization during transitions between affective states. In addition to spectral power and waveforms, Wyczesany et al. [80] found interactions between pairs of neural oscillations, such as phase synchronization and coherence, which commonly implies affective states of hedonic arousal.

Nie et al. [57] suggested that higher brain wave frequency bands may have greater contribution to arousal response than lower brain wave frequency bands. Often, researchers emphasize the potential of alpha power variance with the negative and positive valence states (Balconi and Mazza [7]) or with discrete affective states such as happiness, sadness, and fear (Balconi and Lucchiari [5]). Davidson [25] reported finding alpha power frontal asymmetry as a steady correlation of valence. Gothlib [35] expanded on this idea suggesting that frontal alpha asymmetry may reflect the approach/avoidance aspects of emotion. Other research by Balconi and Lucchiari [6], Keil et al. [40], and Muller et al. [51] found that gamma power event-related synchronization and de-synchronization related to affective states such as happiness and sadness. Martini et al. [46] saw an increase in the gamma phase synchronization index when they introduced unpleasant visual stimuli to participants.

1.6. Manuscript Outline

The following outline offers a framework for a real-time method of measuring player experience. Chapter 2 describes the procedures, apparatus, and measures used in the study. Further, a description of participants is included. Chapter 3 describes the EEG power spectral bands drawn from the Emotiv EPOC, the testing of multiple EEG engagement indices, discusses the use of arousal-valence indices, and the mixing engagement and arousal indices to build a flow model. Chapter 4 describes the implementation of machine learning techniques to identify game events. Chapter 5 discusses implementation of the framework. Chapter 6 is the future work and conclusion.

CHAPTER 2

METHODOLOGY[1]

Developing a program that measures players experience using EEG first requires knowing how to process and analyze the data that the EEG collects. There is no established framework for analyzing EEG data collected while playing video games and the minimal availabel research using EEG to measure player experience was conducted with medical grade EEG equipment. Given this, the first part of developing a framework requires collecting more information about the off-the-shelf EEG equipment. Specifically, how it gathers data and how effective and accurate when measuring video games. Answering these questions requires collecting EEG data from people as they play video games, then analyzing their data to standardize measuring player experience.

2.1. Participants

A study was conducted of thirty people (66 % female, mean age = 20.87, range 18 to 43). Participants were recruited from undergraduate and graduate schools; education levels ranged from 13 to 20 years (See Table section 2.1). Ethnicity was as follows: Caucasian (n=20), African American (n=1), Hispanic (n=4), Native American (n=1), and Asian Pacific (n=4). Participants reported they used a computer at least once every day with 30 % saying they used the computer several times a day. 66 % participants rated themselves as experienced, 27 % rated themselves as somewhat experienced, and 7 % rated themselves as very experienced when ranking their computer competency. Homogeneity of the sample was found in that there were no significant differences among participants relative to age, education, ethnicity, sex, and self-reported symptoms of depression. Strict exclusion criteria were enforced to minimize possible confounding effects of comorbid factors known to adversely impact cognition, including psychiatric conditions (e.g., mental retardation, psychotic disorders, diagnosed learning disabilities, attention deficit/hyperactivity disorder, and bipolar

[1]Parts of this chapter have been previously published, either in part or in full, from T. McMahan, I. Parberry, and T. D. Parsons, "Modality Specific Assessment of Video Game Player's Experience Using the Emotiv", *Entertainment Computing*, Vol. 7, pp. 1-6, March 2015, with permission from Elsevier B.V.

disorders, as well as substance-related disorders within 2 years of evaluation) and neurologic conditions (e.g., seizure disorders, closed head injuries with loss of consciousness greater than 15 minutes, and neoplastic diseases). All participants were right handed and had at least average computer skills. Game playing skills ranged from casual cell phone games to playing every day on a personal computer or a game console. The participants received class credit for their participation in the study.

2.2. Apparatus

2.2.1. Super Meat Boy

Super Meat Boy [49] is a platform game in which players control a small, dark red, cube-shaped character named Meat Boy (See Figure 2.1). The participant played a cube of meat jumping around the level to avoid saw blades to reach their goal of rescuing bandage girl. This game requires the minimum amount of keys to play (arrow keys and space bar) thus making it easy for any level of gamer to achieve success. As the player progresses through the game the levels get increasingly difficult by adding more saw blades and large jumps. A goal of the game is to get through each level as fast as possible. The core gameplay requires fine control and split-second timing (Egenfeldt et al. [27]). Primary game events used for this study included: 1) Death Events; and 2) General Game Play. The "Death events" occurred when the participant's character died. Although there are a number of possible ways for a character to die in a game (e.g., the character gets sliced to pieces, or falls into acid, or gets skewered on needles), samples for Death Events came from the character falling into acid. The "General Game Play" was differentiated from "Death Events" in that General Game Play are periods in which the player had not experienced any death events for 1 minute before or after "General Game Play" sampling.

2.2.2. Two-Picture Cognitive Task

Participants saw a pair of color pictures of a landscape (See Figure 2.2), and were given the evaluative task of identifying any differences between the pair. Unknown to the participants, the pictures were identical.

FIGURE 2.1. Screen shot from Super Meat Boy.

FIGURE 2.2. Two-Picture Cognitive Task presented to participants.

FIGURE 2.3. Venomous head crab used in the Spider Jump Arousal Stimulus.

2.2.3. Spider Jump Arousal Stimulus

The Spider Jump Arousal stimulus was first storyboarded and designed on paper. A 3-D model of a venomous headcrab was taken from the Half-Life 2 game [19] (See Figure 2.3). The venomous headcrab leaps with incredible speed while releasing an angry squeal when a suitable host is in a clear line of sight. The participants encountered the Spider Jump Arousal Stimuli without any cue or knowledge that it would occur.

2.2.4. Game Experience Survey

Participants answered a series of questions assessing their prior videogame experience and other personal characteristics (See Appendix A and Table 2). Participants reported the number of hours they spent playing video games on their cell phones (M = 3.47), on their computer (M = 3.47), and on their game console (M = 2.3). 20 % of the participants reported playing video games more than 20 hours per week. The participants also reported whether or not they classified themselves as "gamers", 33 % responded as being part of this category. An interesting finding from the survey was that a portion of women played games

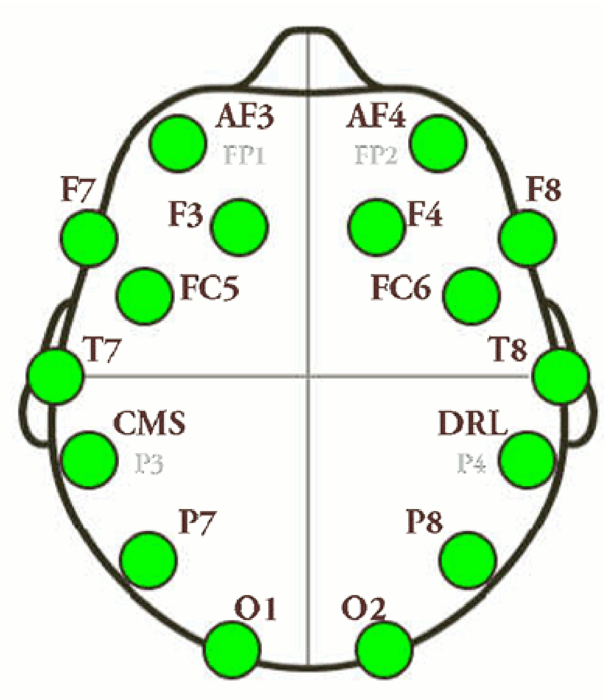

Figure 2.4. Emotiv EEG sensor locations.

on their cell phone an average of 4 hours a week which is higher than males and females who classified themselves as gamers, yet did not classify themselves as gamers.

2.2.5. Emotiv EPOC EEG

This Emotiv EPOC EEG headset has 14 electrodes (saline sensors) locating at AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2 (see Figure 2.4) and two additional sensors that serve as CMS/DRL reference channels (one for the left and the other for the right hemisphere of the head). The Emotiv EEG's 14 data channels are spatially organized using the International 10–20 system. The Emotiv EPOC headset does not require a moistened cap to improve conduction. The sampling rate is 128Hz, the bandwidth is 0.2–45Hz, and the digital notch filters are at 50Hz and 60Hz.

2.3. Procedure

Upon arriving at the testing office, the participants read and signed an informed consent (See Appendix B). Included in the informed consent was a waiver to allow recording of the participant during the study. The participants were then seated in a comfortable

FIGURE 2.5. Chair specifically designed to for participants to sit in with keyboard, sound and comfort.

chair (see Figure 2.5) and given a keyboard and mouse to complete a questionnaire about their computer and game experience. The game was displayed on a Samsung 60 inch plasma screen (see Figure 2.6). The participants sat in a chair with a built in keyboard tray, along with a speaker system and USB port around head level to minimize the distance between the Emotiv headset and the receiver/transmitter. A member of the study combed the participants' hair on the left, mid-line, and right sides of their scalp firmly in order to reduce electrode impedances (Mahajan and McArthur [45]). After cleaning the relevant areas on the face and mastoids, the study member positioned the Emotiv EEG headset on the participant's head. The examiner confirmed impedances in connections between each electrode and the participant's scalp.

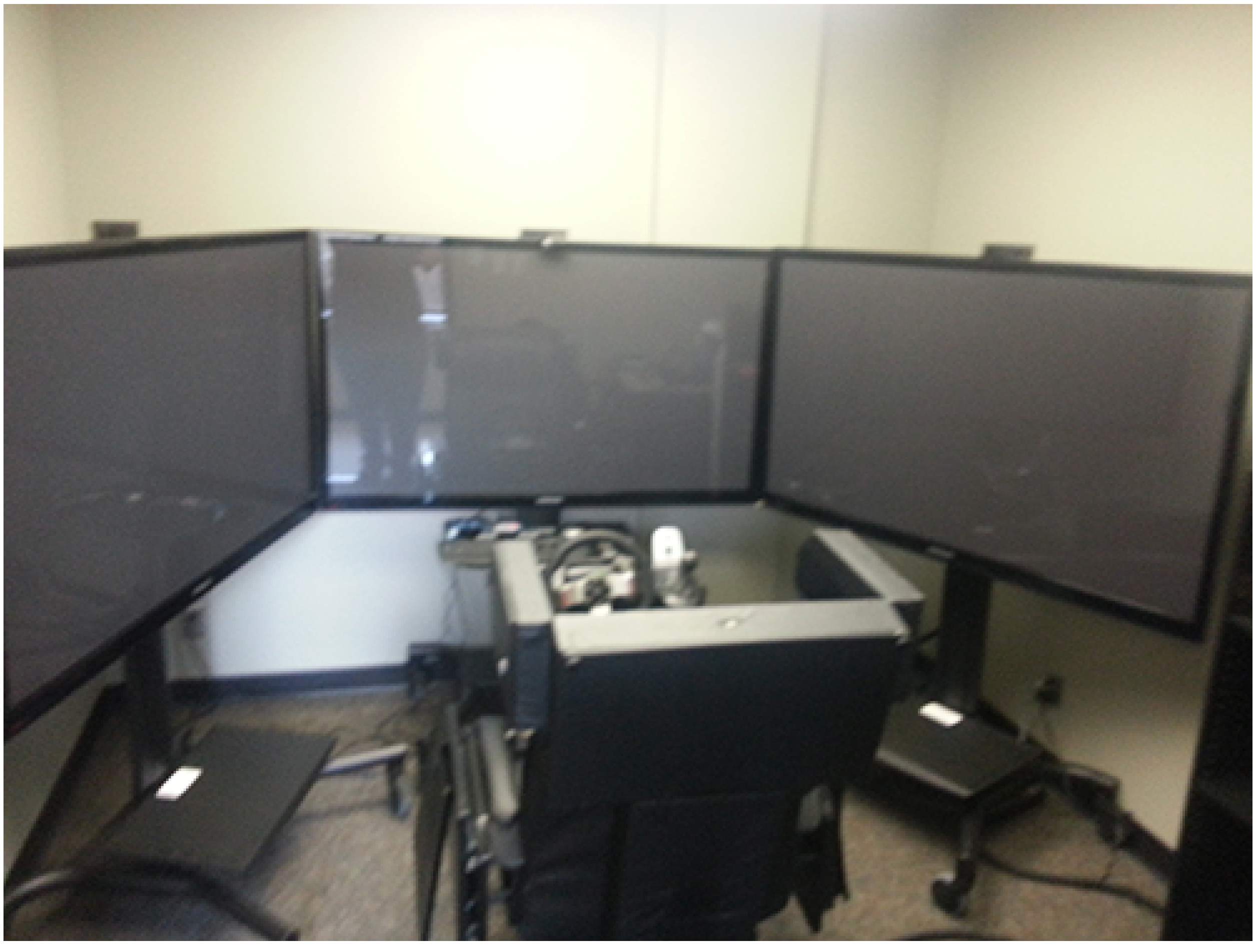

FIGURE 2.6. Testing environment.

Participants first watched a video designed to establish a baseline. During the video the participants were told “to relax and try not to think about anything”. In the video the screen was blank for two minutes to establish a minimum brain wave activity. Next, the participant completed the Two Picture Cognitive Task, which required them to compare two pictures to determine the difference between them. After a set amount of time passed, the spider jump arousal stimulus displayed and startled the participant. This allowed for the establishment of a brain wave signature for basic cognitive processing and arousal. After the spider jump arousal stimulus the participants were presented with 90 seconds of blank screen viewing to allow them to return to a steady state. During the Super Meat Boy Task the researcher aided the participant with the first few levels to allow the player to acquaint themselves with the rules and game controls. The experimenter informed the participants

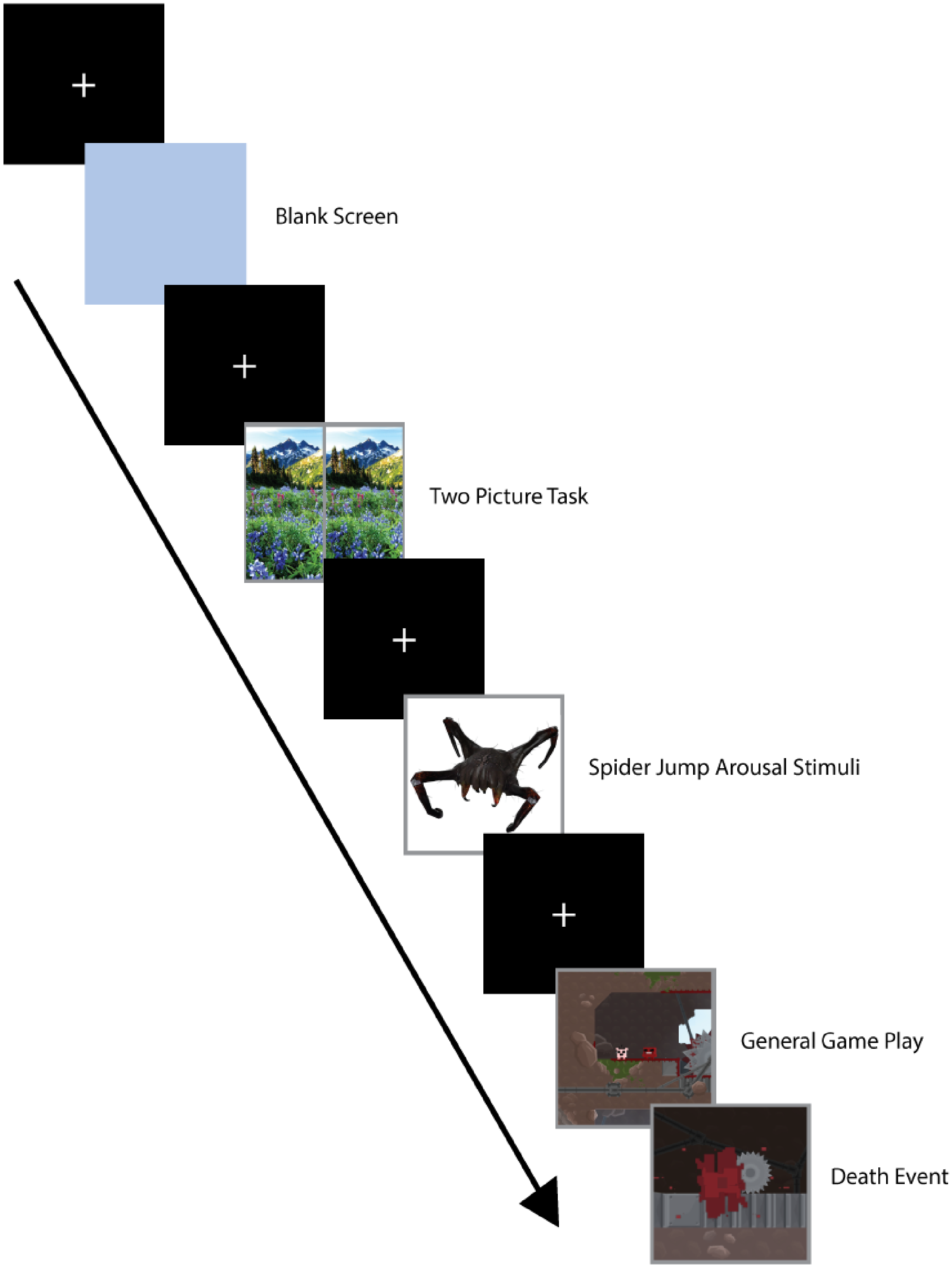

FIGURE 2.7. Chronological orders of events that participants encountered.

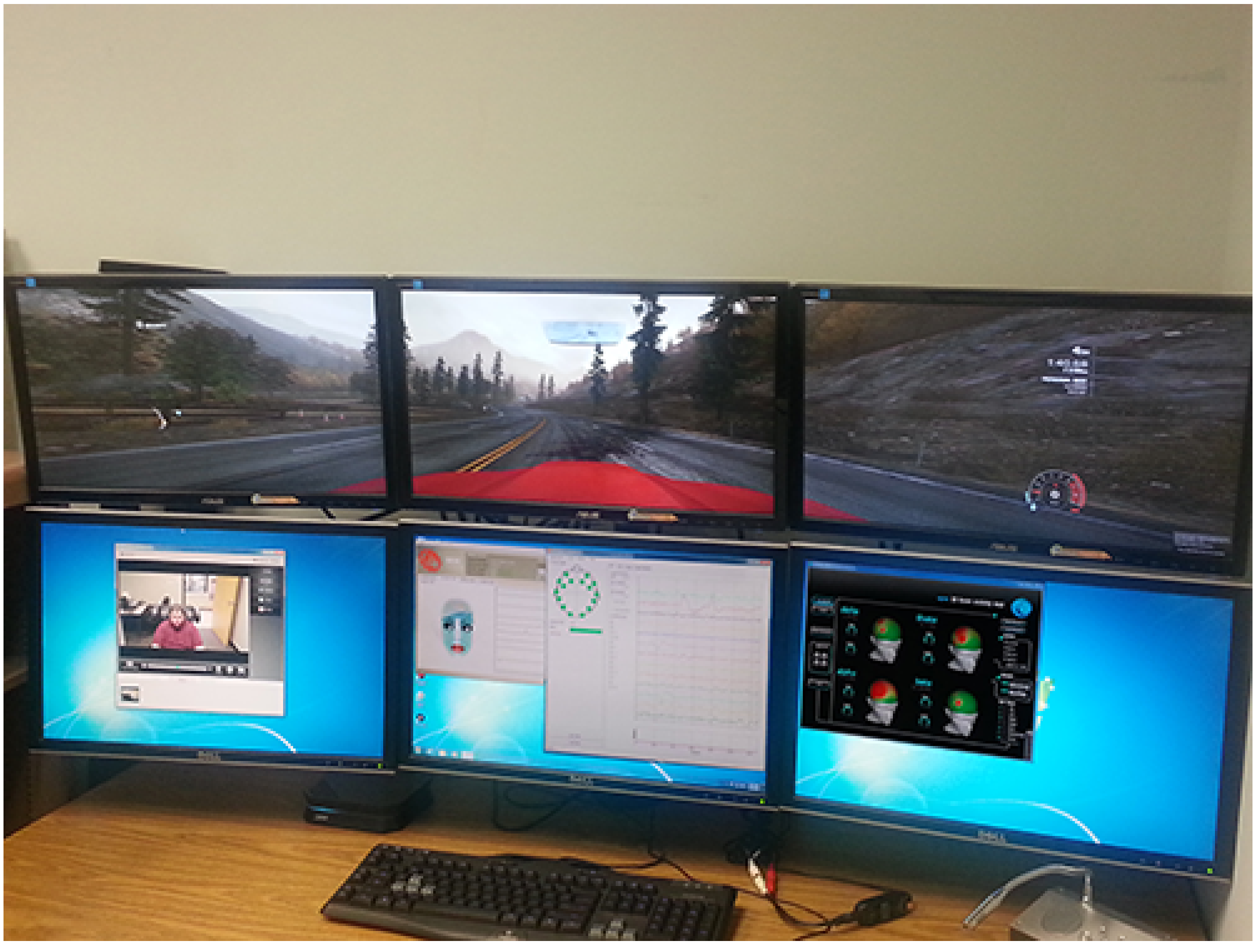

Figure 2.8. Image of recording setup.

that they would play Super Meat Boy for 15 minutes and that they were to advance as far as they could in the game. The participants played the game with the lights turned off to help immerse the player into the game and reduce glare from overhead lights.

The examiner captured each participant's game play footage in 1080p HD (60 frames per second) using a Hauppauge video capture device. This allowed for the synchronization of the participants game play to their EEG data (See Figure 2.8). Each participant was also recorded using a Logitech 9000 HD webcam to help isolate events (facial or body movements) that may affect the EEG data. The experiment required the use of two computers. The first computer captured EEG and video data, with all non-essential programs closed to ensure minimal disruption. The participant played Super Meat Boy on the second computer. Using two computers alleviated the problem of other programs interfering with the capture of EEG data. OpenViBE drift correction allowed the capture of EEG data at 128 Hz sample rate, minimizing any syncing issues between the EEG data and the video recording of game play. Syncing all video recordings with EEG recording software involved the use of screen captures before and after every section of the study (baseline video and game play). Each screen shot produced a time stamp for EEG data and video to establish the location of the start and end of each section. The screen shots were saved to reference later during the data analysis phase.

2.4. Preprocessing EEG Data

Before analysis of the EEG data begins, it must first undergo some basic preprocessing. The data needs to have noise and artifacts removed, as well as a transformation applied to convert it out of the raw electrical signal. Performing this preprocessing has been established and is common in most research involving EEG.

Artifacts such as blinking, head movements, or body movement can cause unwanted data in the EEG signal. Most EEG analysis requires removal of these artifacts to help identify medical issues. However, this is not necessarily a detrimental issue when used for game play analysis. Research performed by Bos et al. [13] found that eye blinking, head movements, and body movements are common in games and can suggest a person's current state of feeling. Bianchi et al. [11] took it further and was able to show that body movement and other artifacts can actually signify engagement. As each participant ran through the study, the researcher annotated the times any visibly noticeable deflection of the EEG equipment or body movement occurred. The Emotiv SDK automatically detects and records eye blinks which allows for an easier way to identify the events within the EEG data.

The next step in preprocessing EEG data is to segment the data into equal length time intervals, commonly referred to as epochs. The epochs required for this research broke down into 5 different modalities: 1) baseline—staring at a blank screen; 2) Two-Picture Cognitive Task; 3) Spider Jump Arousal Stimulus; 4) General Game Play; and 5) Death Events. The epochs for each modality consisted of 100 ms before the onset of each event (0 ms), and ended 750 ms after the onset of the same event. After sub dividing the data, the

EEG data passes through a low-pass filter and a high-pass filter. The low pass filter removes unwanted noise commonly caused by changes in skin conductance. The low pass filter is set to cutoff any frequency above 50Hz. The high pass filter removes noise caused by muscle electrical activity. The high pass filter is set to cutoff any frequency below 1Hz.

The final step in preprocessing EEG data is to apply a transformation that converts the data from the time domain into the frequency domain commonly referred to as calculating the power estimates (μV^2). Applying a 1 second Hamming window with no overlaps and then a fast Fourier transform (FFT) to the data, allows for the acquisition of the various brainwaves delta (1 – 4 Hz), theta (4–7 Hz), alpha (7–13 Hz), beta (13 – 25 Hz) and gamma (25 – 43 Hz). All 14 sensors locations on the Emotiv EPOC headset produce their own measure for each bandwidth. Typically in EEG studies, the number of channels (e.g., 32, 64, 128, or 256 EEG channels) ranges from 32 channels (for routine exams) up to 256 channels (for source estimation) and the systems are able to sample at up to 1000Hz. Given that the Emotiv has only 14 channels and the data sample rate is only 128Hz, along with the individual measurement from each sensor, the average was calculated across all 14 sensors to obtain a global average for each frequency band. Following Anderson et al. [2], the baseline and stimulus signals were transformed to determine the power change and frequency shift induced by the task. These values calculate the cognitive processing experienced at each of the 14 sensors for a given task. The spatial averaging of the 14 values gives a single measurement for analysis. Applying the natural logarithm to the resulting EEG data normalizes the data for further analysis.

Variables	Total (N = 30)	Percentage
Gender		
Female	20	66.67 %
Male	10	33.33 %
Age		
18–19	17	56.67 %
20 – 21	8	26.67 %
22 – 24	2	6.67 %
28 – 43	3	10.0 %
Ethnicity		
African American	1	3.33 %
Asian	4	13.33 %
Hispanic	4	13.33 %
American Indian	1	3.33 %
Caucasian	20	66.67 %
Highest Level of Education		
High School Diploma	1	3.33 %
Some College	24	80.0 %
Associate Degree	2	6.67 %
Bachelor's Degree	3	10.0 %
Computer Compentency		
Somewhat Experienced	8	26.67 %
Experienced	20	66.67 %
Very Experienced	2	6.67 %
Computer use Frequency		
Several Times a Day	9	30.0 %
Every Day	21	70.0 %

Table 2.1. Demographics of participants.

	Female	Male	Gamer	Non-Gamer
N	20	10	10	20
Gamer	4	6		
Non-Gamer	16	4		
Age (SD)	19.9 (2.30)	22.9 (7.71)	19.5 (1.84)	21.6 (5.80)
Ethnicity				
African American	1	0	0	1
Asian	3	1	0	4
Hispanic	3	1	0	4
American Indian	1	0	0	1
Caucasian	12	8	10	10
Game Use (Hours)				
Cell Phone (SD)	4.0 (3.13)	2.4 (3.06)	3.0 (2.98)	3.7 (3.28)
Computer (SD)	2.2 (1.98)	6.1 (3.48)	6.1 (2.92)	2.2 (2.37)
Console (SD)	1.7 (2.32)	3.6 (3.10)	4.0 (3.20)	1.5 (2.04)

TABLE 2.2. Demographics males versus females and gamer versus non-gamer.

CHAPTER 3

EXPLORING THE EMOTIV EPOC HEADSET[1]

There is no set standard on how to process neurological information that comes from the Emotiv EPOC headset. So to develop a framework that measures player experience we first need to explore the headset's capabilities. The major goal while evaluating the Emotiv headset is to find methods that will work in real time. Most research involving EEG data uses post processing techniques that will not work in real-time. Thus our focus will be on systems that can be implemented in real time. The first step in the evaluation is looking at the raw data from the headset. Knowing that the Emotiv EPOC meets the minimum need for this type of research, we can apply EEG algorithms designed to extract specific information about the neural activity of a person. Finally, we must find a way to combine this information so that it reports meaningful information for our program.

3.1. Emotiv EPOC Neural Resolution

The Emotiv EPOC measures the electrical signal produced by the human brain and records the data in the form of voltage measurements. Applying a fast Fourier transform (FFT) to the raw voltages allows us to convert the data into the power spectrum and extract the various brainwaves. Evaluating these brainwaves for changes will help determine the Emotiv's resolution, specifically the changes in brainwaves during the different measured modalities (Two Picture Cognitive Task, General Game Play, and Death Events). Being able to find changes in the EEG data during each modality will confirm the headset has the basic capabilities to provide measurable date of player experience.

3.1.1. Comparing Individual Power Estimates

Individual power estimates were compared using a repeated-measures analysis of variance (ANOVA) for the assessment of the following modalities: 1) Two Picture Cognitive

[1]Parts of this chapter have been previously published, either in part or in full, from T. McMahan, I. Parberry, and T. D. Parsons, "Modality Specific Assessment of Video Game Player's Experience Using the Emotiv", *Entertainment Computing*, Vol. 7, pp. 1-6, March 2015, with permission from Elsevier B.V.

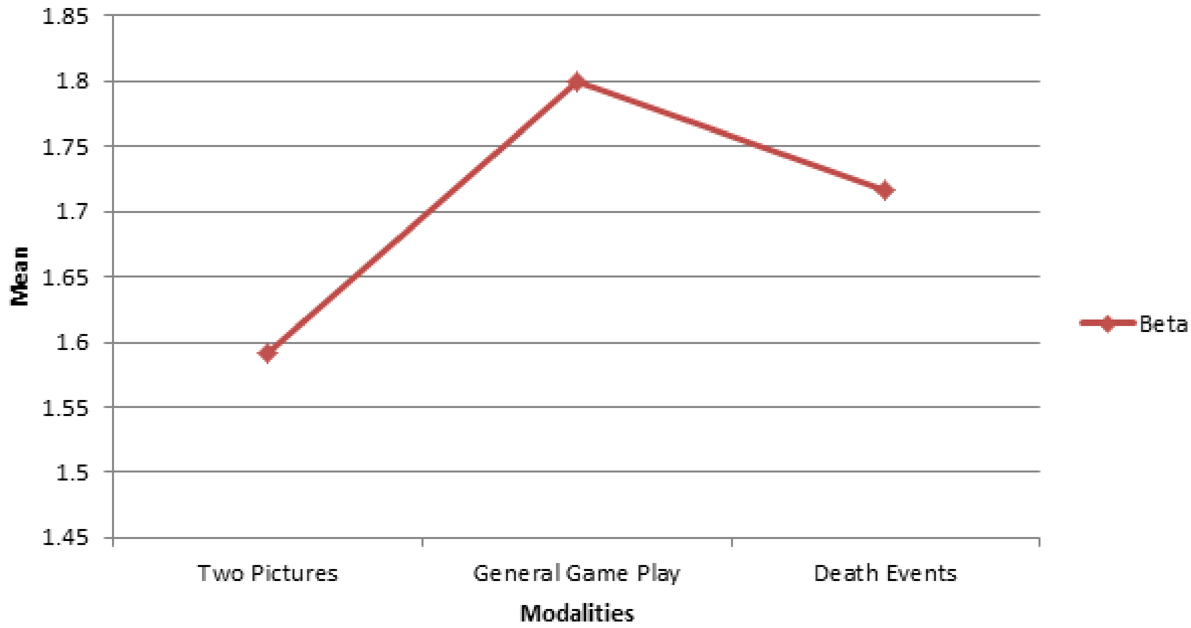

FIGURE 3.1. EEG beta power mean values ln[μV^2] for differences between baseline and each modality that was tested.

Task; 2) simple game play (General Game Play) using Super Meat Boy; and 3) complex game events (e.g., Death) using Super Meat Boy. Results from the repeated measures ANOVA using modalities as a within-subject factor for dependent variables delta (1-4 Hz), theta (4-7 Hz), alpha (7-13 Hz), beta (13 – 25 Hz), and gamma (25 – 43 Hz; ln[μV^2]) revealed a significant difference for beta ($F(2, 28) = 6.213$, $p = 0.004$, partial eta^2= 0.18) (see Figure 3.1), delta ($F(2, 28) = 4.698$, $p = 0.01$, partial eta^2 = 0.14)see Figure 3.2), and gamma ($F(2, 28) = 8.875$, $p = 0.0001$, partial eta^2 = 0.23)(see Figure 3.3) power estimates was found during the different modalities (See Table subsection 3.1 for descriptive).

Follow-up tests of repeated within-subject contrasts revealed that modalities had differing impacts on power estimates. Beta power was significantly increased during the Death Event in comparison with the Two-Picture Cognitive Task ($t(1, 29) = 2.97$, $p < 0.006$; see Figure 3.4). Gamma power was also significantly increased during the Death Event in comparison with the Two-Picture Cognitive Task ($t(1, 29) = 2.99$, $p < 0.006$; see Figure 3.6). Interestingly, there were no significant difference between General Game Play and the Two-

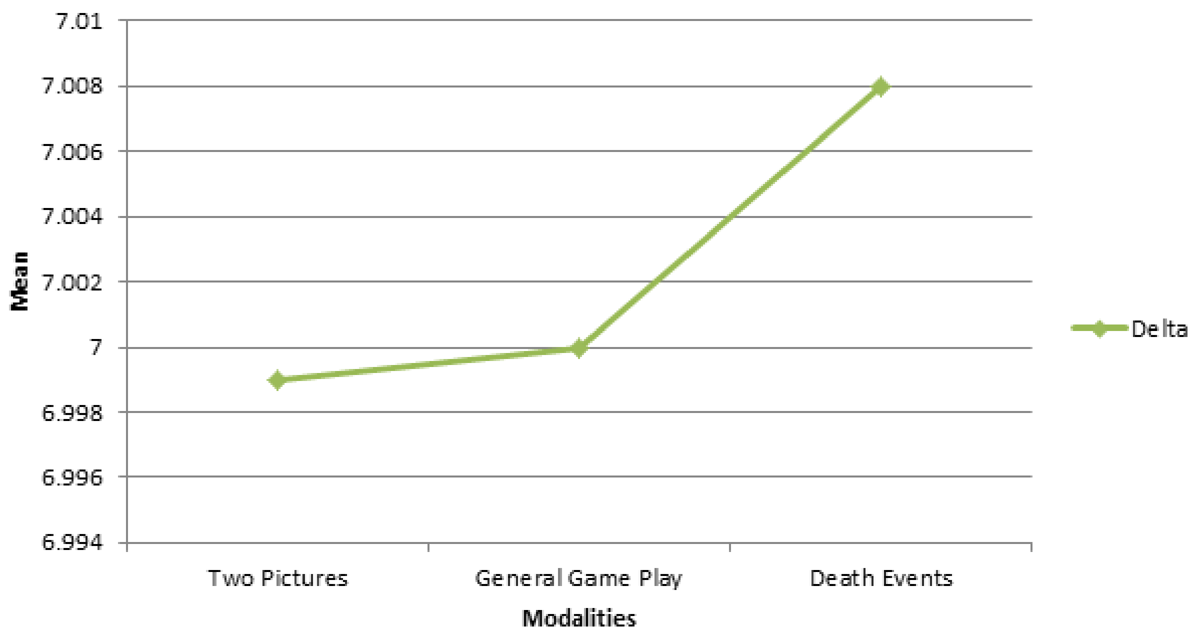

FIGURE 3.2. EEG delta power mean values $\ln[\mu V^2]$ for differences between baseline and each modality that was tested.

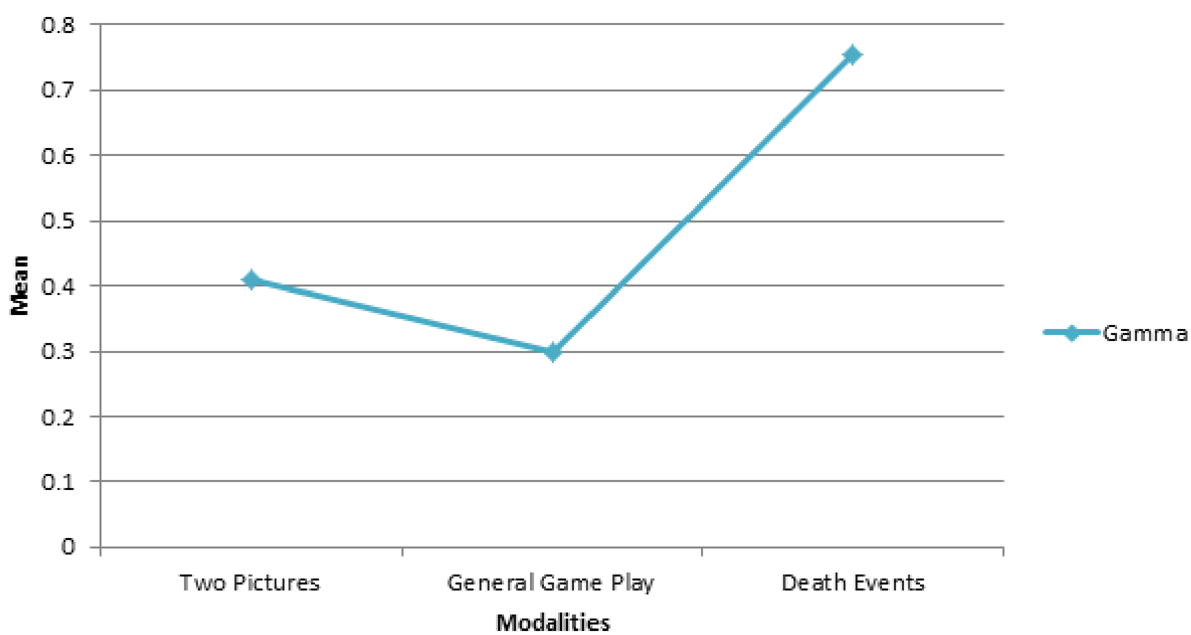

FIGURE 3.3. EEG gamma power mean values $\ln[\mu V^2]$ for differences between baseline and each modality that was tested.

	Mean	Std. Deviation	Std. Error Mean
Two Picture Task			
Alpha	3.167	0.066	0.012
Beta	1.592	0.126	0.023
Delta	6.999	0.014	0.003
Theta	6.997	0.014	0.003
Gamma	0.409	0.232	0.042
General Game Play			
Alpha	3.033	0.183	0.033
Beta	1.800	0.407	0.074
Delta	7.000	0.000	0.000
Theta	7.000	0.000	0.000
Gamma	0.300	0.466	0.085
Death Events			
Alpha	3.219	0.202	0.037
Beta	1.717	0.232	0.042
Delta	7.008	0.034	0.006
Theta	7.001	0.027	0.005
Gamma	0.756	0.451	0.082

TABLE 3.1. Description of the three modalities.

Picture Cognitive Task.

Comparison of low intensity (General Game Play) gaming events with high intensity (e.g., Death events) using repeated within-subject contrasts revealed that beta power was significantly increased during the Death Event in comparison with the General Game Play ($t(1, 29) = 2.536$, $p = 0.01$; see Figure 3.4). Delta power was also significantly increased

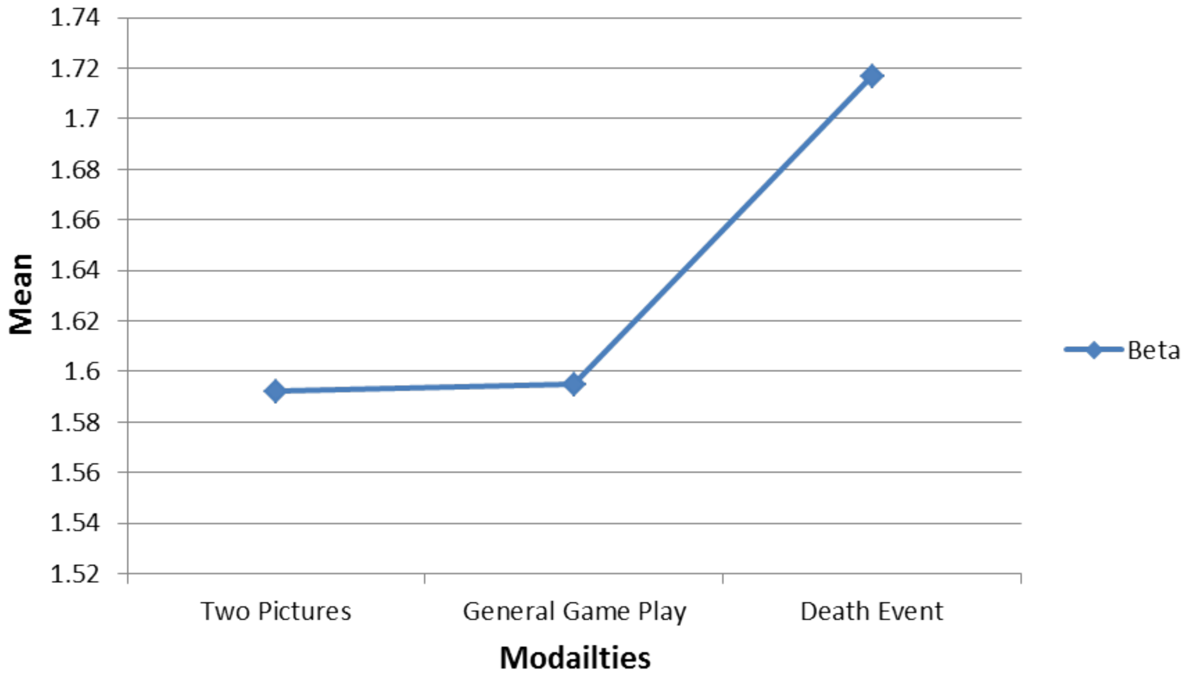

FIGURE 3.4. EEG beta power mean values $\ln[\mu V^2]$ for comparisons between each modality that was tested.

during the Death Event in comparison with the General Game Play (t(1, 29) = 2.438, p = 0.02; see Figure 3.5). Further, gamma power was also significantly increased during the Death Event in comparison with the General Game Play (t(1, 29) = 3.372, p = 0.002; see Figure 3.6).

3.1.2. Overview of Findings

The primary results were: (a) a significant difference was found among different gaming modalities (Two-Picture Cognitive Task; General Game Play; Death events) for beta and gamma; (b) gaming modalities had differing impacts on power estimates, with beta and gamma power being significantly increased during the Death Event in comparison with the Two-Picture Cognitive Task; and (c) comparison of low intensity (General Game Play) gaming events with high intensity (e.g., Death events) revealed that beta and gamma power were significantly increased during the Death Event in comparison with the General Game Play. Interestingly, there were no significant difference between General Game Play

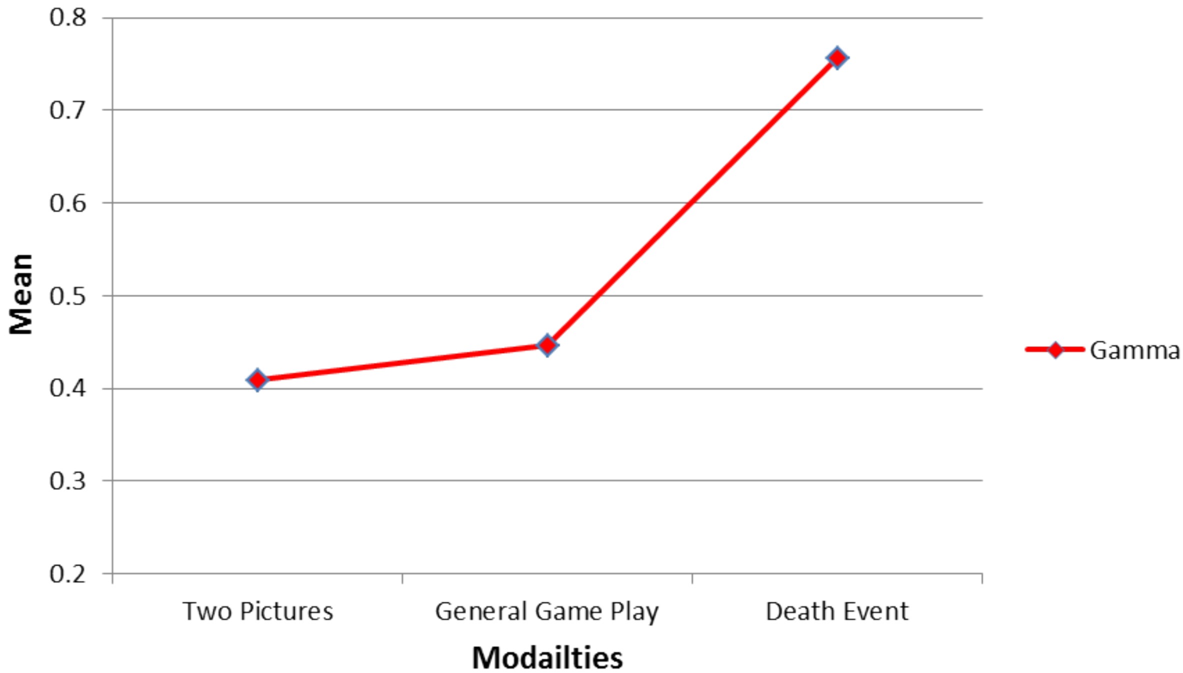

FIGURE 3.5. EEG delta power mean values $\ln[\mu V^2]$ for comparisons between each modality that was tested.

and the Two- Picture Cognitive Task.

3.1.3. Gaming Modalities had Differing Impacts on Power Estimates

Modality type was found to have differing impacts on power estimates. Beta power was significantly increased during the Death Event in comparison with the Two-Picture Cognitive Task. Activity in the beta range is known to be important for attention and motor processing (Gross [36]). Given that Death Events require increased attention, these results are not surprising. Beta rhythm has been shown to increase with attention and vigilance in general (Murthy and Fetz [52], Steriade [74]) and during video game play specifically (Salminen and Ravaja [66]). For example, Salminen and Ravaja [66] found that different events in the platform game Super Monkey Ball 2 evoked oscillatory responses in beta. Likewise, gamma power significantly increased during the Death Event in comparison with the Two-Picture Cognitive Task. Gamma oscillations commonly signify the brain's ability to integrate various aspects of a stimulus into a coherent whole. Further, Engel et al. en-

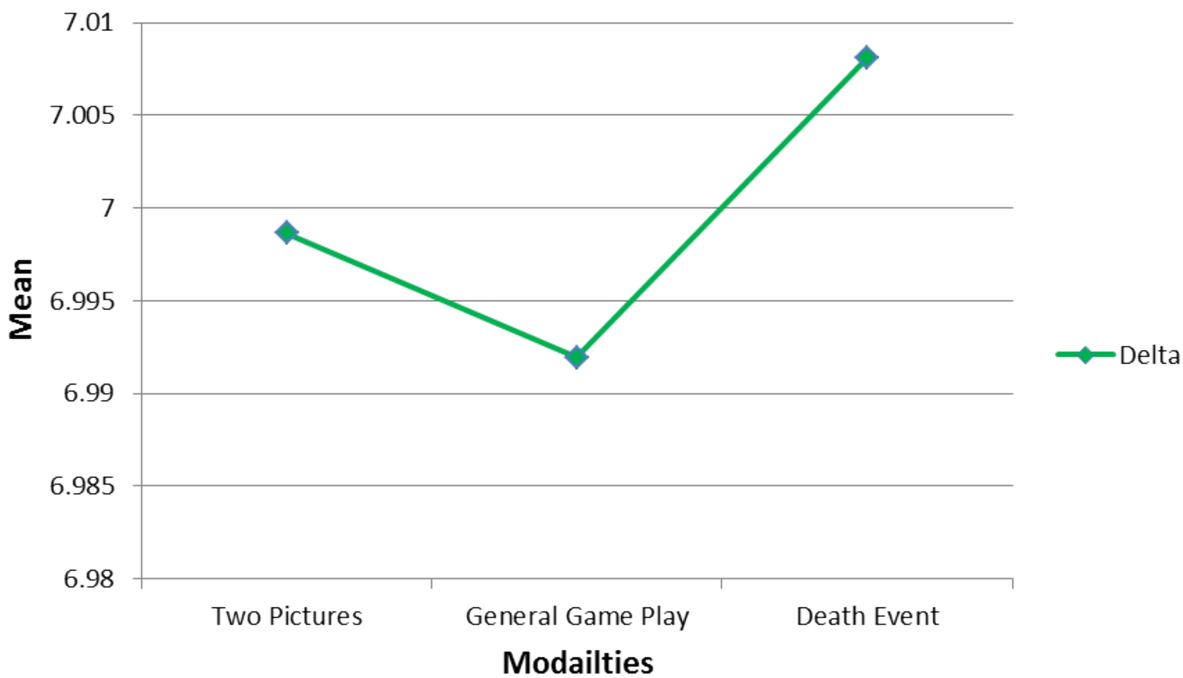

FIGURE 3.6. EEG gamma power mean values $\ln[\mu V^2]$ for comparisons between each modality that was tested.

gel2001dynamic found gamma changes in a host of other cognitive processes: attention, arousal, object recognition, and top-down modulation of sensory processes. The increased beta and gamma between Death Events and the Two-Picture Cognitive Task reflect findings in the literature that suggest a link between EEG beta activity, gamma activity and perceived action possibilities in a virtual gaming environment (Nacke [54], Wirth et al. [78]).

Interestingly, there were no significant difference between General Game Play and the Two- Picture Cognitive Task. This may reflect a lack of differences in the cognitive resources needed for the two tasks. The cognitive processes needed for the Two-Picture Cognitive Task involve those needed for staring at two pictures and performing a visual search for any differences. This is a low arousal and simple cognitive search task. Likewise, General Game Play is low in arousal and requires the participant to simply scan the viewable play area for safe areas to jump. Changes in beta and gamma occur when the participant moves from a low intensity search process to a high threat and high intensity Death event.

Comparison of low intensity (General Game Play) gaming events with high intensity (e.g., Death Events) using repeated within-subject contrasts revealed that beta and gamma were significantly increased during the Death Event in comparison with the General Game Play. As mentioned above, the beta and gamma results are consistent with expectation.

3.1.4. Individual Power Estimates for Gamer Versus Non-Gamer

Using a series of one-way analysis of variances (ANOVAs) tests were performed to compare the EEG signatures between gamers and non-gamers during each modality (Blank Screen, Two Picture Task, Spider, Game Play, and Death Event). Table subsection 3.2 shows the means and standard deviation for each modality. The Levene's test was not significant for any of the modalities (Blank Screen Levene's $F(1, 28) = 1.31$, $p = 0.261$; Two Picture Task Levene's $F(1, 28) = 0.59$, $p = 0.450$; Spider Levene's $F(1, 28) = 0.72$, $p = 0.405$; Game Play Levene's $F(1, 28) = 0.48$, $p = 0.493$; Death Event Levene's $F(1, 28) = 0.40$, $p = 0.531$), meaning equal variance can be assumed. The results from the one-way ANOVAs indicate that there are no significant difference between gamer and non-gamer in any of the different modalities (Blank Screen $F(1, 28) = 0.002$, $p = 0.963$; Two Picture Task $F(1, 28) = 0.297$, $p = 0.590$; Spider $F(1, 28) = 0.665$, $p = 0.422$; Game Play $F(1, 28) = 0.049$, $p = 0.826$; Death Event $F(1, 28) = 1.431$, $p = 0.242$). The results suggest that there is not a distinguishable difference in the EEG signatures during each modality between gamers and non-gamers. EEG signatures may not be able to be used to help identify gamers from non-gamers. However, this does suggest that player experience does not have an impact when comparing across the different modalities.

3.2. Measuring Engagement with the Emotiv EPOC

There is no established outline for measuring player experience. One solution is to develop a framework that follows the concept of flow. Keeping a person in an adequate flow state requires that they always have the appropriate levels of engagement and arousal. Too much deviation in engagement or arousal leads to the person being in possible states of stress or boredom. The first part of implementing the flow model requires the Emotive EPOC headset to be able to measure a person's engagement levels. Various EEG algorithms

	N	Mean	Std. Deviation
Blank Screen			
Gamer	10	0.154	0.009
Non-Gamer	20	0.154	0.013
Two Picture Task			
Gamer	10	0.159	0.009
Non-Gamer	20	0.156	0.015
Spider Jump Arousal Stimulus			
Gamer	10	0.182	0.031
Non-Gamer	20	0.193	0.036
Gerneral Game Play			
Gamer	10	0.157	0.011
Non-Gamer	20	0.156	0.015
Death Event			
Gamer	10	0.161	0.026
Non-Gamer	20	0.171	0.020

TABLE 3.2. Gamer versus non-gamer performance.

exists that measure a person's engagement level, however these algorithms have only been implemented with laboratory grade EEG devices and require further testing with the Emotiv to validate its compatibility.

3.2.1. EEG Engagement Indices

Measuring engagement level is one part of determining a player's experience while playing a video game. Pope et al. [63] and Freeman et al. [31] have shown that an engagement index can be calculated by taking the ratio of beta / (alpha + theta) [Index 1] EEG bands (see Table 3.3). Berka et al. [9] was able to show that the engagement index reflected a person's process of information-gathering, visual scanning and sustained attention. Gevins and Smith [32] introduced a different task engagement indicator that looks at the ratio of frontal midline theta activity to parietal alpha locations (theta/alpha) [Index 2]. A third index was identified by Yamada [81] that looks at activity at the frontal theta [Index 3] sites which indicate increased attention. Kamzanova et al. [39] compared these indices across time-on-task effects and workload manipulation with their findings indicating that there is a difference between tasks that are queued versus non-queued tasks.

Indices	Brainwave Bands	Notes
Index 1	$\frac{beta}{alpha+theta}$	Averaged across all sensor locations [9, 31, 63].
Index 2	$\frac{theta}{alpha}$	Average frontal midline theta and average parietal alpha [72, 32].
Index 3	$theta$	Averaged frontal theta [81].

TABLE 3.3. EEG indices.

An example of brain activity during General Game Play and an example of a Death Event can be seen in Figure 3.7. This shows higher levels of theta and beta during the death event compared to General Game Play.

- Index 1 (beta/(alpha + theta)) was calculated for each participant using the single measurement from all sensors.
- Index 2: (frontal theta/parietal alpha) was calculated by using the theta average at frontal lobe locations F3, F4, FC5, FC6 and dividing them by the alpha averages at the parietal locations P7, P8.
- Index 3: (frontal theta) was calculated using the average of the following frontal lobe locations: AF3, AF4, F3, F4, F7, F8, FC5, FC6.

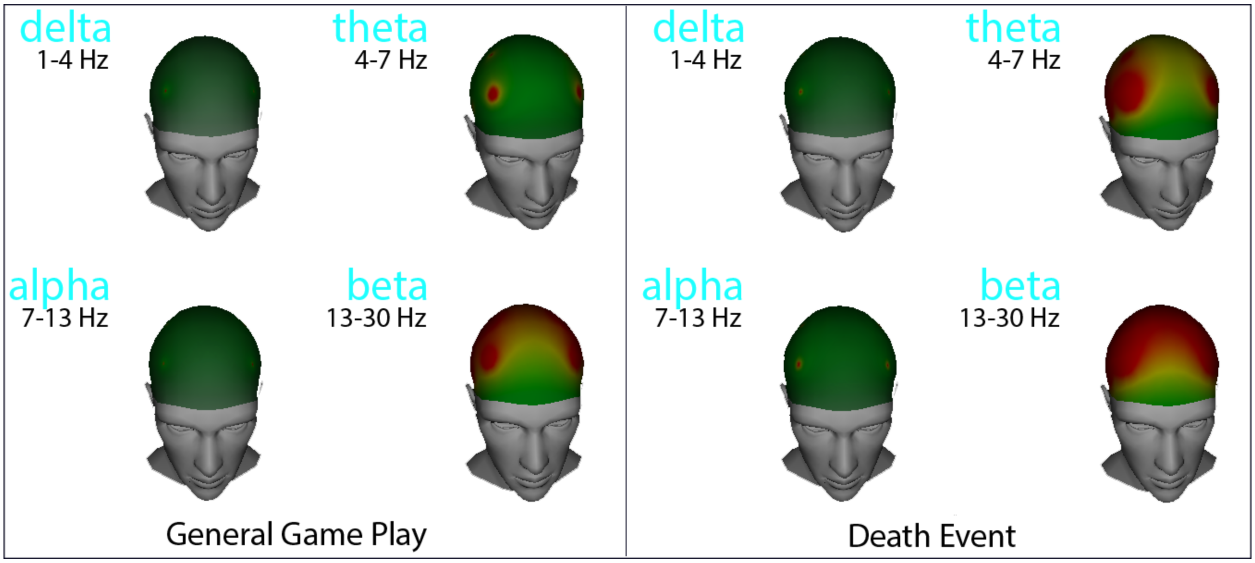

FIGURE 3.7. Brain activity during General Game Play and Death Events.

Each index calculation produced an engagement level for each modality specifically focusing on General Game Play and Death Event.

3.2.2. Engagement Comparison Results

Repeated-measures analysis of variance (ANOVA) was used for assessment across the 3 indices: 1) Index 1 (beta / (alpha + theta); 2) Index 2 (frontal theta/partial alpha); 3) Index 3 (frontal theta); and General Game Play and Death Events from Super Meat Boy (See Table 3.4). Results from the repeated measures ANOVA using indices as the within-subject factor for dependent variables General Game Play and death events revealed a significant difference for the main effect ($F(2,28) = 17.5$, $p < 0.001$, partial $eta^2 = 1.0$). These results represent the difference in the formulas used to calculate the index of engagement ratio.

Follow-up tests of repeated within-subject contrasts revealed differences between General Game Play and Death Events within each index. Index 1 engagement levels during Death Event was significantly increased in comparison to General Game Play ($t(1,29) = 2.720$, $p = 0.011$). Index 3 also showed increased engagement levels during death events in comparison to general game play ($t(1,29) = 2.485$, $p = 0.019$). Index 2 did not yield any significant results between general game play and death events.

Indices	Mean	Std. Deviation	Std. Error Mean
Index 1			
General Game Play	0.327	0.148	0.027
Death Event	0.449	0.238	0.044
Index 2			
General Game Play	0.816	0.197	0.036
Death Event	0.815	0.186	0.034
Index 3			
General Game Play	0.315	0.075	0.014
Death Event	0.421	0.207	0.038

Table 3.4. EEG descriptive for each index.

3.2.3. General Overview of Comparison Findings

The goal was to assess various engagement indices using EEG to determine which is most compatible with the Emotiv EPOC headset. The aim was to analyze difference in response in engagement levels between specific game events (General Game Play and Death Events). The primary result were: (a) a significant difference among the three different indices due to the difference in the equations used; (b) Increased engagement levels during Death Events compared to General Game Play Events when using Index 1 and Index 3.

3.2.4. Findings from Assessment of Engagement Indices

The findings suggest that Index 1 (beta / (alpha + theta) is an adequate algorithm for calculating the engagement levels of players playing video games. The results suggest that the Emotiv headset may not have the resolution to support individual sensor measurements that Index 2 uses to calculate engagement levels. Higher levels of engagement during Death Events when compared to General Game Play may suggest the user is not more engaged when their character dies, but rather they have entered a more stressful state which has increased their attention [9, 81, 39]. Putting thresholds on individual players engagement levels based upon their base-line results would help identify when players have entered a stressful state and identify from their EEG signal when a death event has occurred.

3.3. Measuring Arousal with the Emotiv EPOC

The second part to the flow model is measuring the arousal level of a player. Again there is no existing methodology for measuring arousal using an off-the-shelf EEG. Various methods and algorithms exist for measuring arousal, all which have used laboratory grade EEG devices, but which have not been tested with the Emotiv EPOC.

3.3.1. Arousal – Valence Indices

Measuring arousal levels is an important part of determining a player's experience while playing a video game. Arousal has been shown to be measurable by using (betaF3 + betaF4) /(alphaF3 + alphaF4) and valence using (alphaF4 / betaF4) - (alphaF3 / betaF3) by Giraldo and Ramirez [34]. Similar to the engagement indices, arousal and valence level was calculated for each participant during General Game Play and Death events.

A repeated-measures analysis of variance assessment (ANOVA) was completed across the index of engagement, the arousal index and the valence index to verify the existence of differences between General Game Play and Death Events. Results from the repeated measures ANOVA using the indices as the within subject factor for dependent variable General Game Play and Death Events revealed a significant different in the main effect ($F(2,28) = 183.22$, $p < 0.001$, partial $eta^2 = 0.68$). These results represent the difference in the formulas used to calculate each index.

Follow-up testing of repeated within-subject contrasts revealed differences in General Game Play and Death Events within each index. The engagement level during Death Events was significantly increased in comparison to General Game Play ($t(1,29) = 2.720$, $p = 0.011$). The arousal was also significantly increased during Death Events in comparison to General Game Play ($t(1,29) = 3.959$, $p < 0.001$). The valence index did not yield any significant differences between General Game Play and Death Events. However, it did yield an interesting trend that valence usually decreased during Death Events when compared to General Game Play events (see Table 3.5).

Indices	Mean	Std. Deviation	Std. Error Mean
Arousal Index			
General Game Play	0.22	0.262	0.005
Death Event	0.25	0.398	0.007
Valence Index			
General Game Play	0.70	0.682	0.124
Death Event	0.45	0.545	0.099

Table 3.5. EEG descriptive for arousal and valence indices.

3.3.2. Overview of Arousal Index Results

Higher levels of arousal and engagement were measured during Death Event when compared to General Game Play. Higher levels of engagement during Death Events when compared to General Game Play may not suggest the user is more engaged or aroused when their character dies, but rather may reflect that they have entered a more stressful state which has increased their vigilance [9, 61]. Putting thresholds on individual players engagement levels based upon their results would help identify when players have entered a stressful state and identify from their EEG signal when a death event has occurred.

3.4. Flow Model

The previous sections demonstrated the capability of the Emotiv to measure engagement and arousal levels. A flow model can be established by combining "Engagement" data with "Arousal" data. Using the data from the model we can establish upper and lower thresholds to indicate when the player had left a state of flow. Using these thresholds along

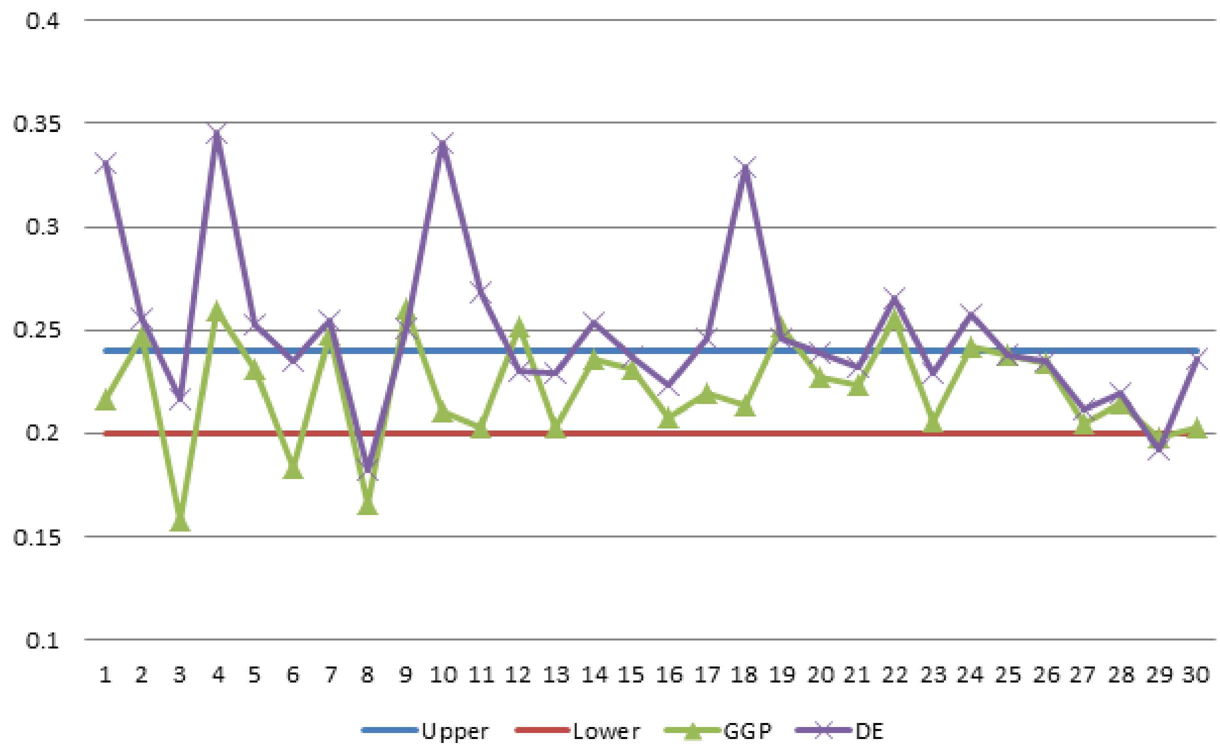

Figure 3.8. Arousal index results with thresholds applied.

with combining Engagement and Arousal measurement allows for the development of rules which indicate when the player is in a state of flow while playing a video game.

3.4.1. Applying Thresholds to Indices

There are several potential ways to establish thresholds for the flow model. An optimal (though difficult to achieve) method involves the use of data collected from the baseline video to represent individual limits for each person. The most difficult aspect is finding an adequate lower limit. To establish baseline brainwave activity, the participants were asked to stare at a blank screen and told not to think about anything. There was a great deal of variance in the data from some participants. Future work should address this issue and identify a better methodology for inducing minimal brainwave activity.

Using data during game play presents an alternative to establishing threshold levels using the baseline video. Accomplishing this required dividing the engagement data and arousal data from both General Game Play and Death Events into their own quartiles,

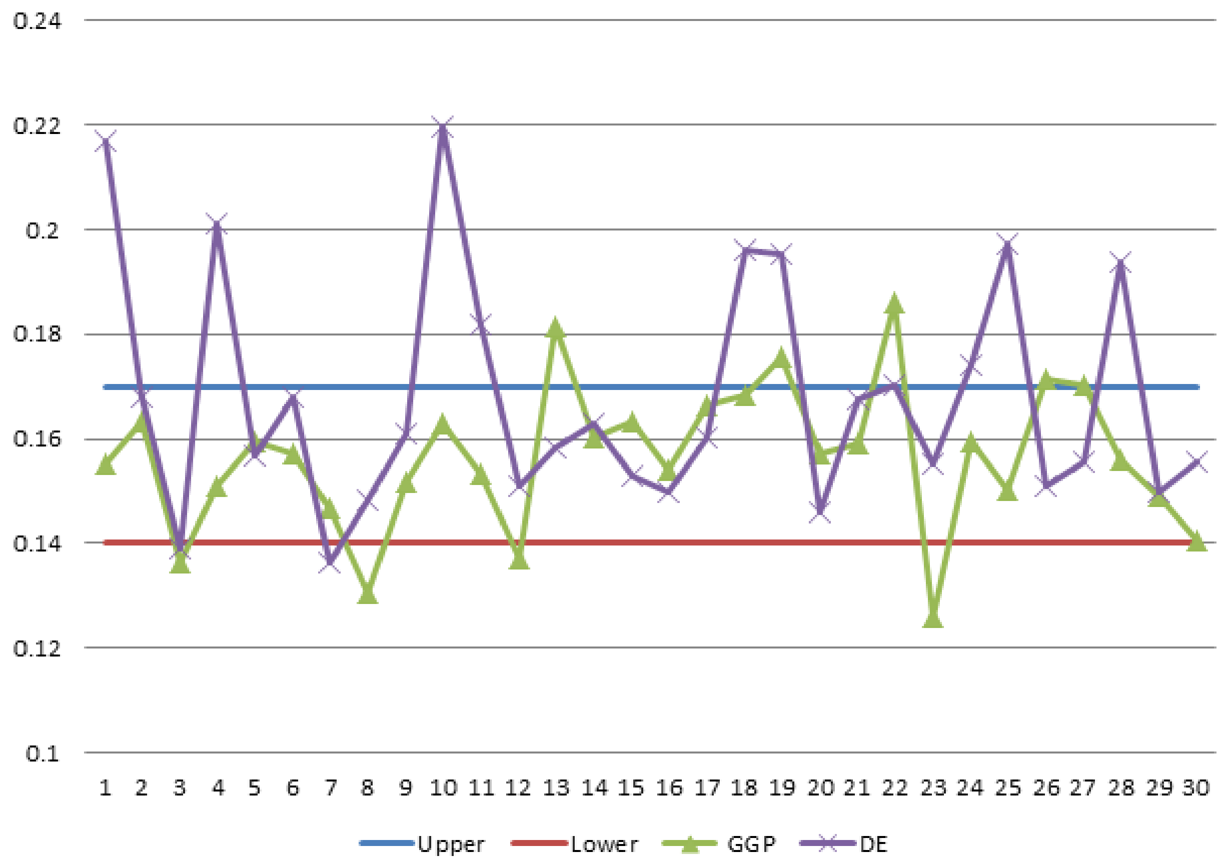

FIGURE 3.9. Engagement results with thresholds applied.

which allowed me to establish upper (Task Engagement = 0.17, Arousal = 0.24) and lower (Task Engagement = 0.14, Arousal = 0.20) thresholds to indicate when the player has left a state of flow. Figure 3.8 and figure 3.9 show that both the arousal levels and engagement levels are mostly within the threshold levels during General Game Play. During death events participants leave the threshold levels indicating flow has been disrupted.

3.4.2. Flow Discussion

The findings suggest that using the Emotiv with the engagement index (beta / (alpha + theta) and the arousal index ((betaF3 + betaF4) / (alphaF3 + alphaF4)) can measure the immersion levels of players in video games. Establishing threshold levels is a complicated task due to variability in the EEG data. Threshold levels are not fixed factors and will need to be adjusted as more player data is incorporated. However, using the principles of thresholds in this study along with combining Task Engagement and Arousal-Valence a set of rules to indicate when the player is in a state of flow can be determined.

(1) If engagement levels fall below the lower threshold, then the game needs to become more complex

(2) If engagement level rises above the upper threshold, then the game needs to become simpler

(3) If arousal level falls below the lower threshold, then the game play needs to be more stimulating

(4) If arousal level rises above the upper threshold, then the game play needs to become less arousing.

These rules can be applied to any method or variation in the threshold levels. These are a fundamental set of rules that can be expanded on as the game becomes more complex. It will be up to game designers to determine how to make adjustments to the game to keep the player in flow. In the future, the rules could be expanded to adjust for the different types of games. For example, in a first person shooter the amount of enemy the player is engaging at any time can affect the engagement and arousal levels. So the rules could be transformed to include specific details about the amount of enemy to send against the player at any given time. This will require fine tuning by testing on players with different skill levels to validate the rules still work for players of any skill level.

CHAPTER 4

CLASSIFICATION OF PLAYER EVENTS

There are a number of potential game events that a player may experience while playing a game. For example, some game events in a first person shooter might include dying, winning, picking up an item, or killing an enemy. The dying game event will occur frequently as the player progress through the game. This is especially the case in Super Meat Boy. Player commonly leaves a state of flow or come close to leaving the state of flow when they die. Automatically identify these common game events will allow researcher and game developers the ability to focus more on the other parts of the game that are causing the player to leave the flow state. Classification using machine learning techniques provides a solution to identify these common events. The best machine learning algorithm to use is not presently a well-established concept when it comes to using the Emotiv EPOC headset. Most previous research has focused on the use of a support vector machine (SVM), naïve bayes (NB), and k-nearest neighbor (kNN). This is why it is the most practical to start with these three classifiers to identify game events.

4.1. Data Organization

Figure 4.1 shows a flow chart of the process used to obtain the data and results for the classification process. User datasets were analyzed together aiming to verify the possibility of building a generalizable model. Time epochs were split into corresponding signals alpha, beta, theta, gamma, Engagement Index, and Arousal Index, which are used as the predictors for each class. The corresponding epochs are assigned to 2 different classes game event and dying event. The first class is trained using data captured from the Two Picture Cognitive Discrimination Task. The second class is trained using data gathered from the Spider Jump Arousal Stimulus. Each class contains 30 data samples to train the classifier. Data for testing the classifier was captured from general game play and death events from all of the subjects. Each class in the testing data contains 30 data samples. Given that it was a 50/50 dataset, cross-validation was irrelevant and it was not used.

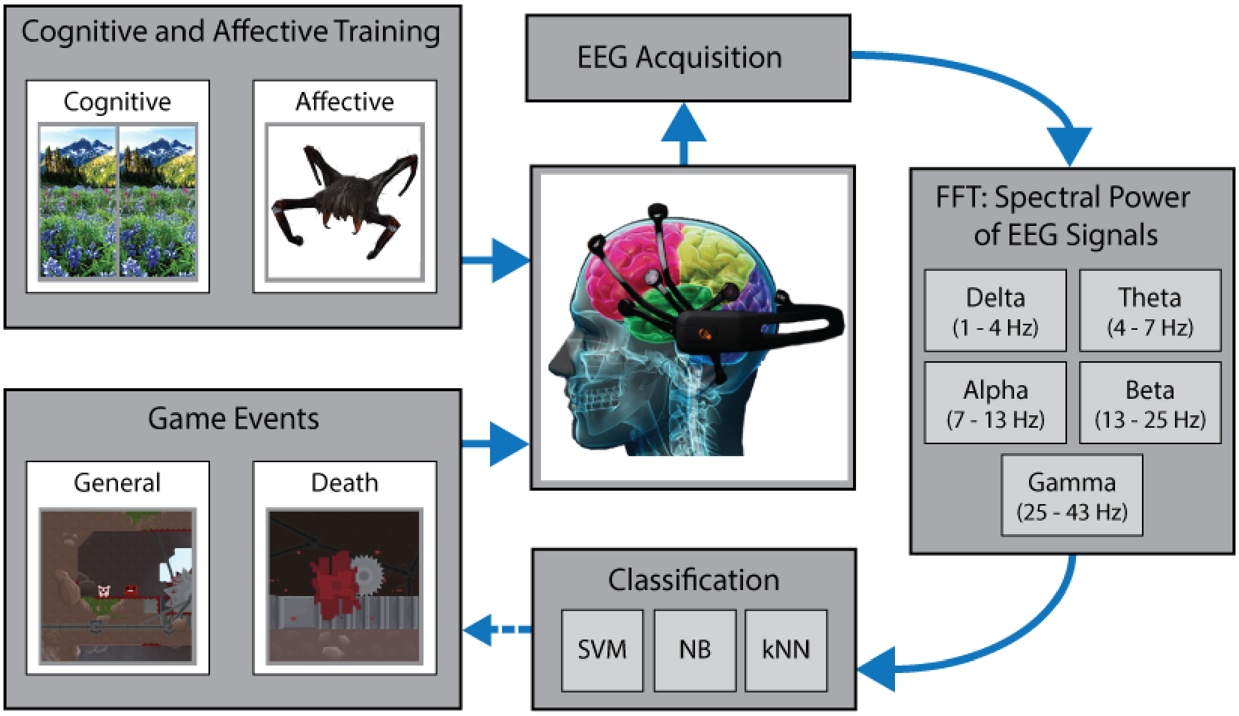

FIGURE 4.1. Flow chart depicting the procedure used to obtain results. The dashed line between classification and game events signifies the eventual use of a closed loop system.

4.2. Support Vector Machine

To classify a set of binary labelled data, the SVM algorithm uses a hyper plane to separate the data into two classes. During the training process of the SVM takes in data belonging to each category and maps them into a higher dimensional space with the goal of creating a hyper plane with the maximum difference. The training process can use different types of kernels (linear, polynomial, or radial basis function) to achieve a better hyper plane. During the testing process test new data is run through the SVM and placed into one of two categories based upon which side of the hyper plane the new point falls following training of the algorithm on a given dataset, the discriminate hyper plane is optimized and selected based on the maximum margins between the hyper plane and the data. This is accomplished via transformation of the data from the input space into feature space (in which linear classification is achievable). This is achieved through outlier accommodating and error allowance during training [8]. The SVM technique has been used for arousal state estimation and results revealed a recognition accuracy of 83 percent could be achieved [60]. Herein the Classification SVM Type 2 was implemented in the libsvm library using 0.5 nu-SVM classification with radial basis function kernel. Gamma was set to 0.008 and the maximum number of iterations 1000. A stop error of 0.001 was utilized.

4.3. Naïve Bayes

The NB Classifier technique is based on Bayes theorem and is appropriate when the dimensionality of the inputs is high. This classifier computes the probability that some data points belong to a specific class. To perform the classification, the algorithm chooses the class with the highest probability, as its result. When event related potentials are included as a feature, the NB has been used to classify emotions in two classes (low valence and high valence) with a classifying accuracy of 56 percent [70]. In a related analysis, NB has been found to provide recognition accuracy of 70 percent for two classes (as reviewed in Nie et al. [57]). The NB is an efficient supervised learning algorithm used to classify data into different groups based upon a calculated probability of new data belonging to that group. The NB classifier makes the assumption that each input is independent from every other input. During the training phase the classifier takes the inputs and builds feature vectors for each category. When new data is presented to the NB classifier it uses the maximum likelihood estimates to find place that data into the correct category. The NB classifier has an added benefit of not requiring large sets of training data to be effective at classification.

4.4. k-Nearest Neighbor

kNN is a supervised learning algorithm that classifies data into different groups based upon how closes it is located to a category. During training the classifier stores each category data into a feature vector. New data is then classified based upon the training sample that has the shortest distance to the new data point. An issue that can arise from the kNN classifier is if the data does not have an even distribution causing the classifier to favor one category over the other. In a study of arousal state estimation Lin et al. [44] extracted

Machine Learning	Mean	Std. Deviation	Min	Max
SVM	57.5	4.44	50.0	63.3
NB	70.0	6.56	58.6	75.9
kNN	57.9	11.15	44.5	76.0

Table 4.1. Overall classifier percentages.

power spectrum density of different EEG subbands as features during an emotion induction (listening to music) protocol. They found a classification accuracy of 82 percent for four emotions. In another study using the kNN technique for two different sets of EEG channels (62 channels and 24 channels), an accuracy of 82.87 percent was found for the 62 channel data set and 78.57 percent for the 24 channel dataset for five emotions [53].

4.5. Classification Results

Each participant's results from the Two Picture Cognitive Discrimination Task and Spider Jump Arousal Stimulus were used to predict General Gameplay Events and Death Events using a Support Vector Machine (SVM), a Naïve Bayes (NB) classifier, and a k-Nearest Neighbor (kNN) classifier (see Table 4.1). Having thirty participants in the study allowed for a total of 60 data points (30 for the Two Picture Cognitive Discrimination Task and 30 for the Spider Jump Arousal Stimulus) to train each classifier and 60 data points to test each classifier (30 for the General Gameplay Events and 30 for the Death Events). The Engagement Index (beta / (alpha + theta); Pope et al [43] and Freeman et al [60], Arousal Index (betaF3 + betaF4) / (alphaF3 + alphaF4) and Valence Index (alphaF4 / betaF4) - (alphaF3 / betaF3; [106]), as well as alpha, beta, theta, and gamma bands were all individually tested to identify the strongest signals for classification (see Table 4.2 and Table 4.3).

4.6. Machine Learning Classifiers and EEG Power Spectral Bands

Figure 4.2 shows the overall accuracy for each classifier using the different signals. From Figure 4.2 it is apparent that the strongest classifier was NB especially when using

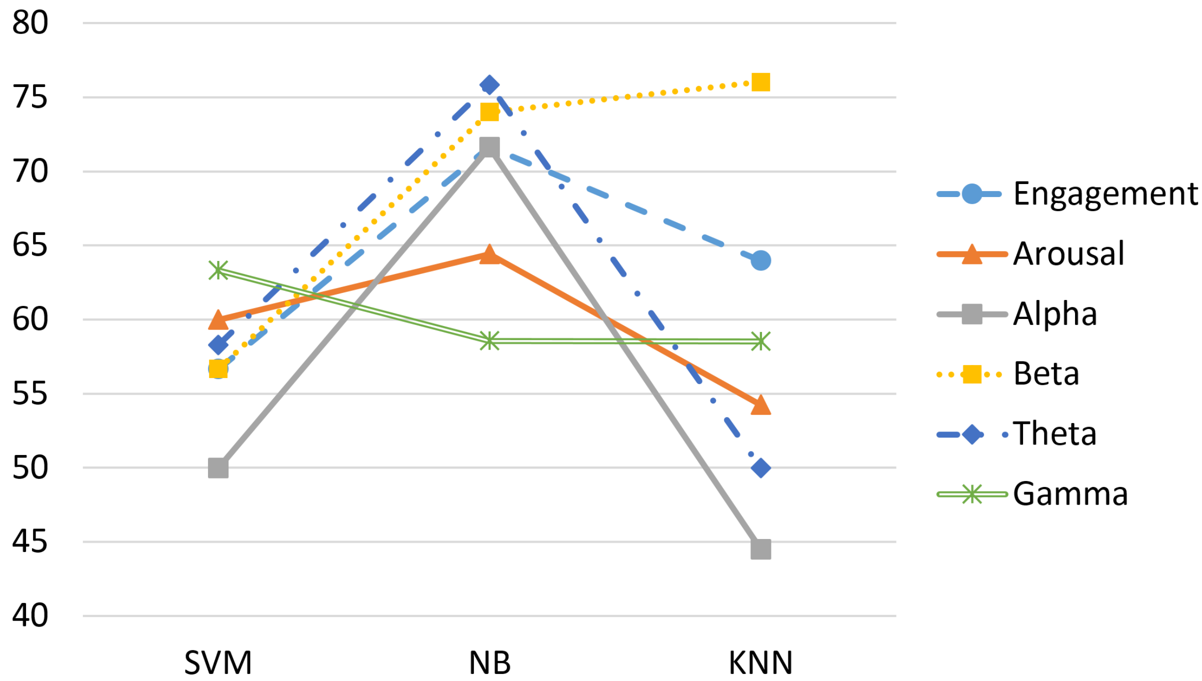

FIGURE 4.2. Overall classifier results for each machine learning algorithm.

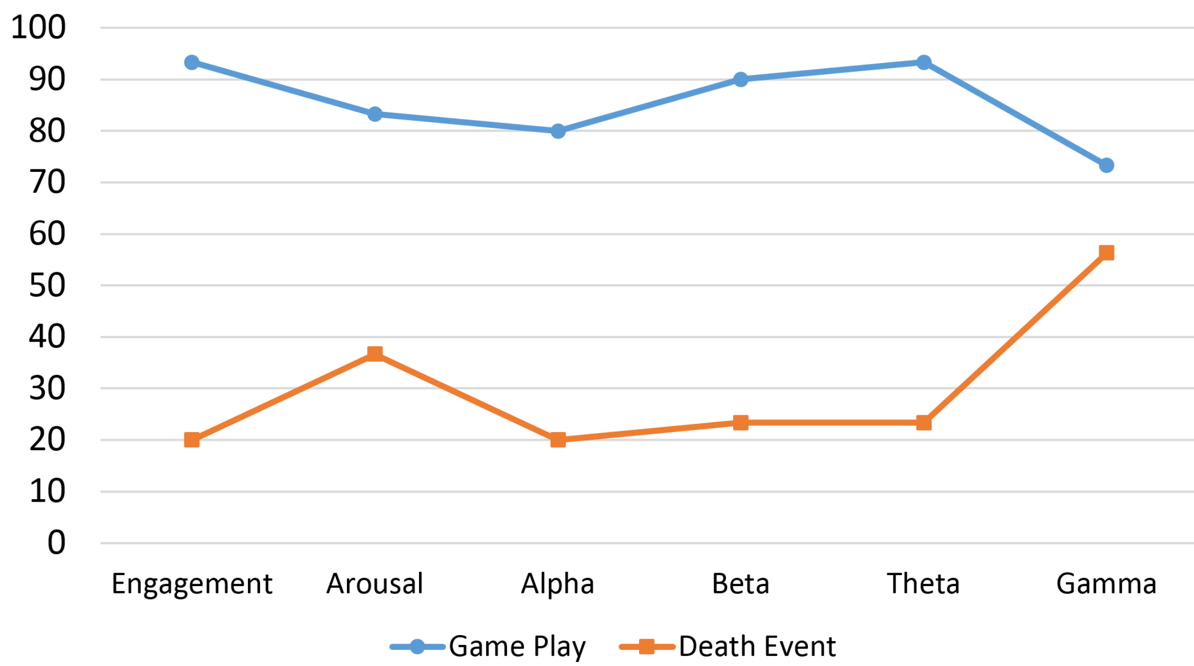

FIGURE 4.3. SVM classifications percentage across each signal for General Game Play and Death Events.

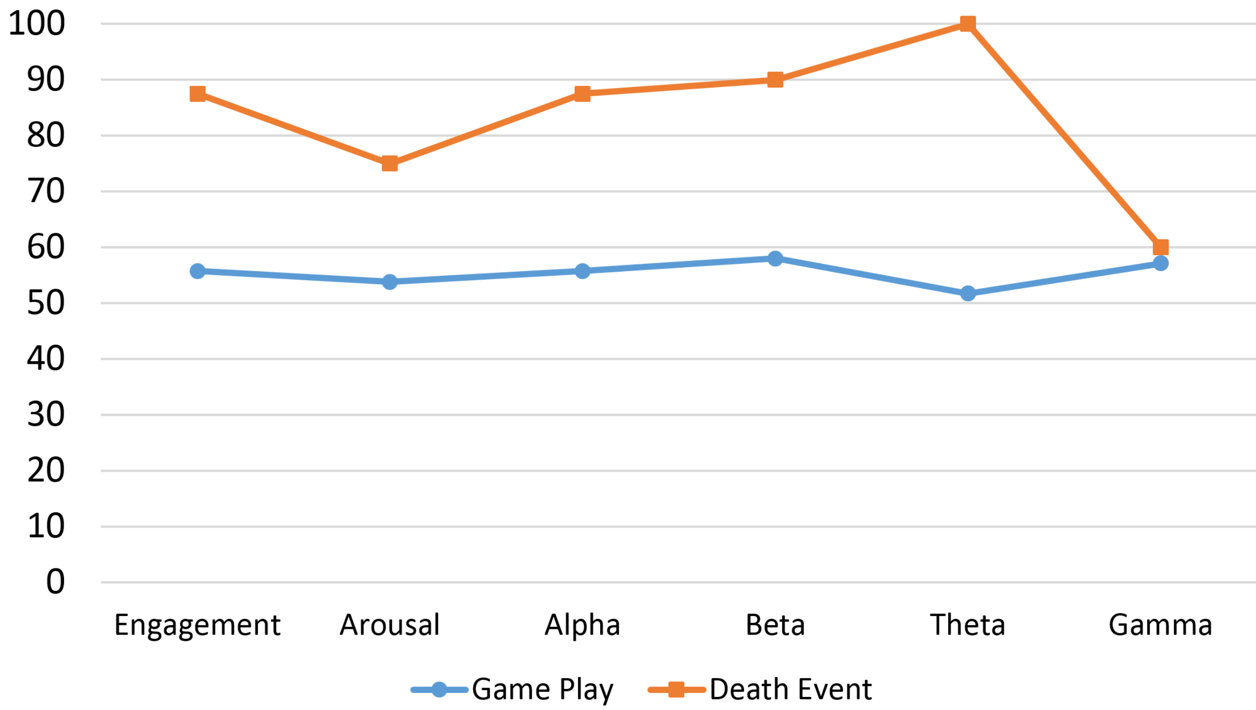

FIGURE 4.4. NB classification percentages across each signal for General Game Play and Death Events.

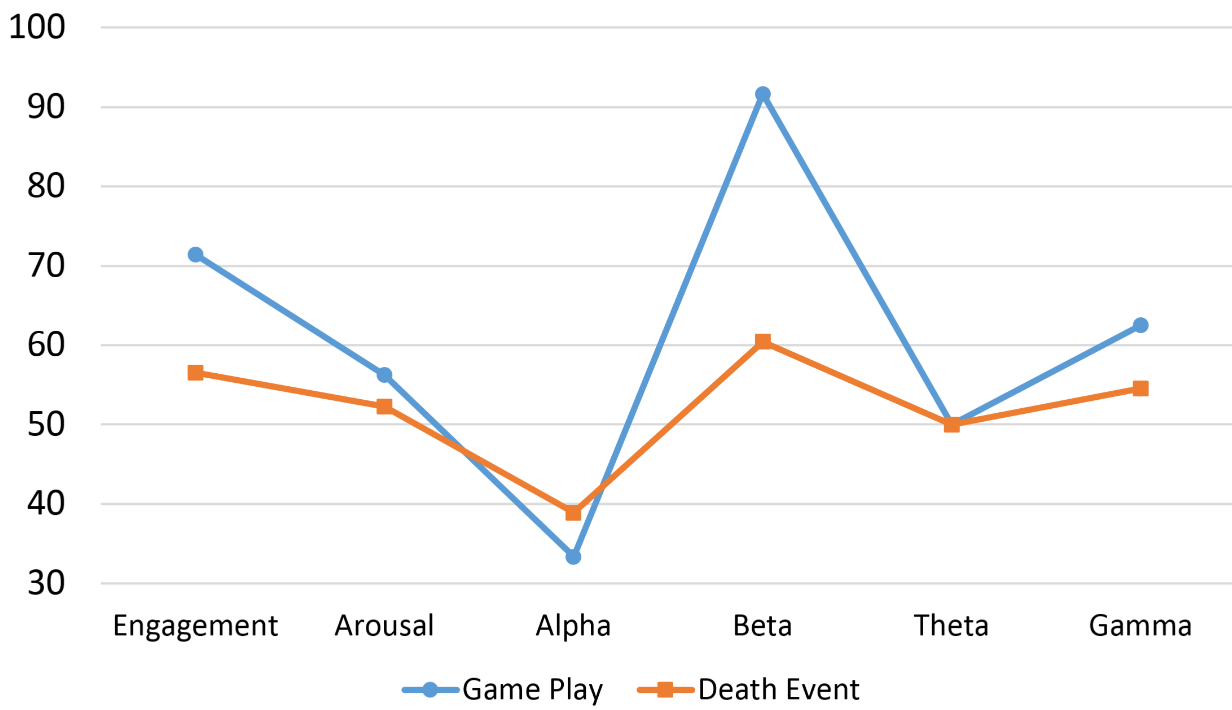

FIGURE 4.5. kNN classification percentages across each signal for General Game Play and Death Events.

Machine Learning	Mean	Std. Deviation	Min	Max
Engagement	64.1	7.50	56.7	71.6
Arousal	59.6	5.10	54.3	64.4
Alpha	55.4	14.34	44.5	71.6
Beta	68.9	10.64	56.7	76.0
Theta	61.4	13.20	50.0	75.9
Gamma	60.1	2.76	58.5	63.3

Table 4.2. Signal classifications percentages.

Signal	SVM	NB	kNN
Engagement	56.7	71.6	64.0
Arousal	60.0	64.4	54.3
Alpha	50.0	71.6	36.1
Beta	56.7	74.0	76.0
Theta	58.3	75.9	50.0
Gamma	63.3	58.6	58.5

Table 4.3. Individual classification percentages.

the theta and beta signals. The NB classifier had an overall average of 70 percent correct classification. Although the kNN classifier produced the highest accuracy rate with the beta signal when compared to other classifiers, it performed poorly with the alpha signal. Gamma turned out to be the strongest predictor in the SVM classifier. The beta band wave was the strongest predictor followed by theta, the Engagement Index, and then alpha.

4.7. Distinguishing between General Game Play and Death Events

Figure 4.3 illustrates that using the Two Picture Cognitive Discrimination Task and the Spider Jump Arousal Stimulus to train the SVM classifier did a better job overall classifying General Gameplay Events over Death Events. The strongest signals again were beta, theta, and the Engagement Index. The gamma band showed the most potential with this classifier as it did the best job in classifying Death Events.

Figure 4.4 shows that the NB classifier did the best job classifying Death Events from the training data. The strongest signals were theta and beta followed by alpha and the Engagement Index. While gamma performed well for the SVM classifier, the gamma band performed the worst for NB. The overall trend of the NB classifier reveals it as being the most steady and reliable in distinguishing between General Gameplay Events and Death Events.

Although the kNN classifier had the greatest variance in terms of signal was being used for classification, it did a better job overall with General Gameplay Events (see Figure 4.5). The beta signal was the strongest predictor for the kNN classifier for both General Gameplay Events and Death Events. Although alpha was the weakest predictor, it performed better in predicting Death Events then General Gameplay Events. The overall trend of the kNN classifier was erratic but revealed potential when using the beta signal.

4.8. Overview of Classification Results

While various neurogaming platforms use machine learning to model a gamer's EEG indices, the research designs, data logging of game-based psychophysiological signals, and the control algorithms found in neurogaming are not systematic and studies to support their use remains limited. As neurogaming systems increase in use, new properties will need to be taken into consideration. A common difficulty encountered in this research area is the dearth of published objective comparisons among classifiers. Although there have been growing efforts in the neurogaming literature to recognize a user's cognitive and affective states in real time using EEG bands, these studies do little to take into account both cognitive and affective information. While establishing the optimal relation among frequency bands, task engagement, and arousal states is one of the main goals of neurogaming, a standardized method has yet to be established. Herein the aim is to test classifiers within the same context, users, feature extraction methods, and protocol [94]. Specifically, the EEG signals from users were logged as participants experienced various stimulus modalities aimed at assessing cognitive and affective processing. Given the emphasis upon neurogaming, the commercial Emotiv EPOC headset was used. The EEG data were then filtered to get separate frequency bands to train cognitive-affective classifiers with three classification techniques: Support Vector Machines, Naïve Bayes, and k-Nearest Neighbors.

4.9. Machine Learning Classifiers and EEG Power Spectral Bands

The beta band wave was the strongest predictor followed by theta, the Engagement Index, and then alpha. This was not surprising given that beta EEG coherence has been found to increase when participants viewed highly arousing stimuli [50]. Further, McMahan et al. [48] found significant difference in the beta band among various stimulus modalities. The Naïve Bayes classifier had an overall average of 70 percent correct classification. Further, NB was found to be the strongest classifier when using the theta and beta signals. These findings are consistent with findings that NB has been found to have a good classification for two classes [70]. Although the kNN classifier produced the highest accuracy rate with the beta signal than any other classifier, it performed poorly with the alpha signal. For the SVM classifier, gamma turned out to be the strongest predictor.

4.10. Cognitive and Affective Training

Using the Two Picture Cognitive Discrimination Task and the Spider Jump Arousal Stimulus to train the SVM classifier did a better job overall classifying General Game Play over Death Events. These results support findings that the SVM technique is useful for classifying arousal state and has been found to have a recognition accuracy of 83 percent [60]. Again, the strongest signals were beta, theta, and the Engagement index. The gamma band showed the most potential with the SVM classifier as it did the best job in classifying Death Events. The gamma band has been shown in previous research to find changes in emotion [43], however this research looked at a gamma band ranging from 30-100 Hz which was far outside the range of the Emotiv (has a cut off of 45 Hz).

4.11. Distinguishing Between General Game Play and Death Events

The NB classifier did the best job classifying Death Event from the training data. The strongest signals were theta and beta followed by alpha and the Engagement index. Unlike in the SVM classifier the gamma band performed the worst. The overall trend of the NB classifier shows it being the most steady and reliable in distinguishing between General Gameplay Events and Death Events. The kNN classifier varied more upon which signal was being used to classify, but overall did a better job with General Gameplay Events. The beta signal was the strongest predictor in for the kNN classifier for both General Gameplay Events and Death Events. The alpha signal was the weakest predictor, however it did perform better in predicting Death Events than General Gameplay Events. Although the overall trend of the kNN classifier was erratic, potential was observed when using the beta signal.

CHAPTER 5

IMPLEMENTATION

One of the goals of this research is to develop a proof-of-concept program, which we will call `BrainWave`, for use by researchers and game developers to analyze player experience. `BrainWave` takes raw EEG signals from the Emotiv EPOC headset as input and outputs text to a window. `BrainWave` is designed to satisfy the following criteria:

(1) It must run in real time. Since games and game development tend to move at a fast pace, being able to evaluate a player in real time while they are playing would lead to the developer being able to make changes to the game faster and more effectively.
(2) It must be able to collect data with minimal interference to the player's experience. Utilizing physiological data allows the player to be uninterrupted while they play as well as provide immediate feedback to the researchers.
(3) Its output must be user-friendly, that is, presented in terms familiar to the average game developer who is not an expert in EEG usage. Most raw physiological data consists of voltage or impedance fluctuations, which usually requires an expert to interpret and understand.

5.1. Design

Figure 5.1 shows the process of using `BrainWave` which is broken up into 5 steps: data capture, data processing, training, testing, and analysis. Each of these is addressed below. See Appendix C for `BrainWave` pseudocode.

5.1.1. Data Capture

Figure 5.2 shows the process of data capture. Data capture begins with a successful connection to the Emotiv EPOC headset. Utilizing Emotiv's dynamic link library (DLL), we call a function that creates and returns a handle to the headset. Once the handle is created and the connection state verified, data capture can begin. As the EPOC headset measures raw data, it stores it into a buffer. The size of the buffer determines the amount of

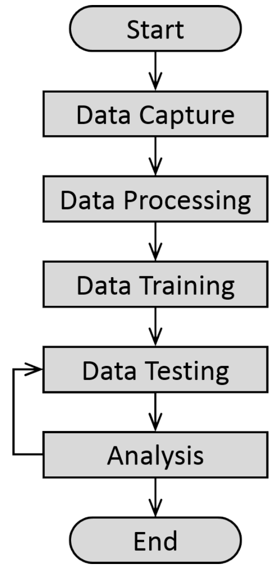

FIGURE 5.1. High-level flowchart for the process of measuring player experience. Flowcharts for each of the five steps represented by the boxes Data Capture, Data Processing, Data Training, Data Testing, and Analysis are given in Figure 5.2 and Figures 5.5–5.9, respectively.

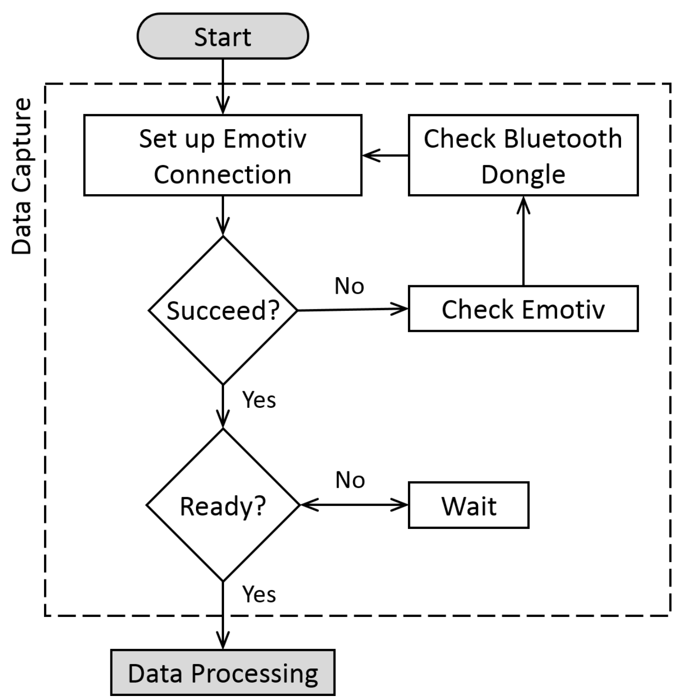

FIGURE 5.2. Flowchart for the Data Capture box in Figure 5.1.

Time	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
1	raw	EEG	data											
...														
...														
128														

FIGURE 5.3. The Array of struct that the Emotiv EPOC headset use to store all the raw EEG data. The size of the data structure is 128×14.

data that is collected before it is accessible. The buffer size is determined by the number of epochs the user chooses to collect at one time. `BrainWave` will analyze EEG data once per second, thus we need a buffer that will hold exactly one second worth of EEG data. Once the buffer is full, the Emotiv returns the buffer to the user in the form of an array of structs. The array is made up of all the data from each sensor that is collected during the epoch. Because the headset collects 128 samples a second and has 14 sensors it creates an array that is 128×14 (see figure 5.3). This array provides an efficient way to access the collected data so that processing can begin.

5.1.2. Data Processing

Figure 5.4 shows the process of data processing. For each full buffer, the following four steps are performed, as shown in Figure 5.5.

(1) Remove the potential for noise to affect the data. EEG works by measuring electrical activity at the scalp, however in the process of measuring the electrical activity it can introduce what is known as direct current (DC) noise. This noise comes from the battery that is powering the headset and the radio transmitter. Removing this noise requires applying a high pass filter to the data that will remove any frequency less than 1 Hz and a low pass filter that removes any frequency over 50 Hz. The noise must be removed from each sensor location.

(2) Calculate the average voltage across all of the sensors. This is accomplished by adding all of the values from each sensor and dividing it by 14, the number of

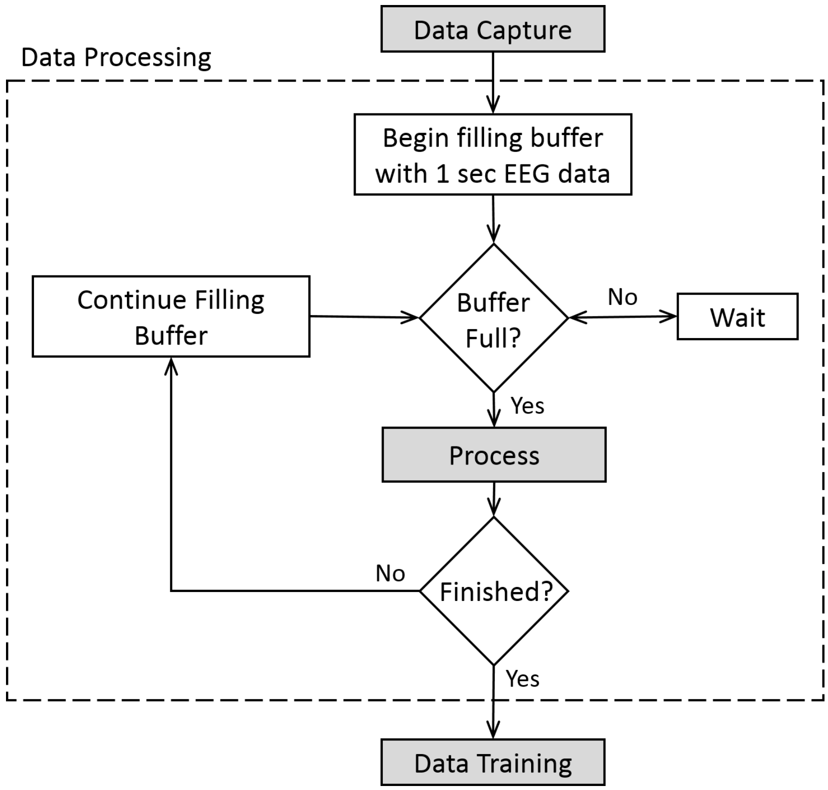

FIGURE 5.4. Flowchart for the Data Processing box in Figure 5.1. The Process box is described in Figure 5.5.

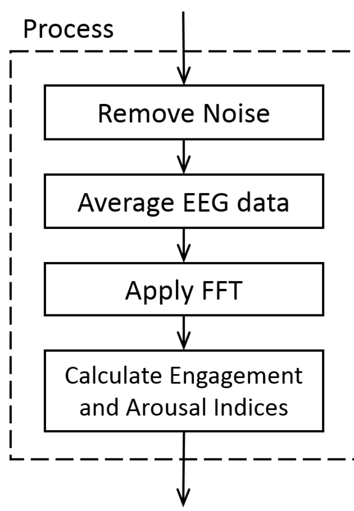

FIGURE 5.5. Flowchart for the Process box used in Figure 5.4 and Figure 5.7.

sensors. This calculation is performed for each individual measurement that the headset takes. Averaging the sensor data allows for a global overview of the changes the user is experiencing. It also helps in eliminating any potential outlier data caused by sensor malfunction.

(3) Apply the Fast Fourier Transform (FFT) to the data. This step makes the EEG data more meaningful by converting it from time-domain to frequency-domain. The amplitudes for each frequency are calculated by squaring each individual frequency this is also known as calculating the power estimates. Figure 5.6 shows an example of an epoch of data that has undergone this process. The figure demonstrates how the individual brain wave bands are extracted from the processed data. The average is taken of all the frequencies in each band. The resulting value give the overall power level of the band for the current epoch.

(4) Use the band data to calculate the engagement and arousal indices. This is done by simply plugging the data into the appropriate equation that were tested in the previous chapters. All of the above steps are repeated each time an epoch of data is gathered by the headset.

5.1.3. Data Training

Figure 5.7 shows the process of data training. Gathering the data to train the machine learning algorithm first requires gathering the data at the right time. Using a video to collect user baseline data for training allows the program to know which data it need to save. The program knows when to collect the training data by simply knowing how many seconds after the video starts that each stimulus is presented to the player.

The program then begins using the data to train the three machine learning algorithms. The program utilizes a Naïve Bayes (NB) classifier that trains under the assumption that the data has a Gaussian distribution. During the training phase the mean and variance it calculated and stored for all of the training data. The training of the k-nearest neighbor (k-NN) algorithm requires storing the data into vectors representing the various classes. The support vector machine (SVM) plots the training data to find the best possible linear hyperplane that provides the maximized margin between the data.

The engagement and arousal levels are also calculated from the training data. Utilizing the middle base line the program calculated the upper and lower threshold for both

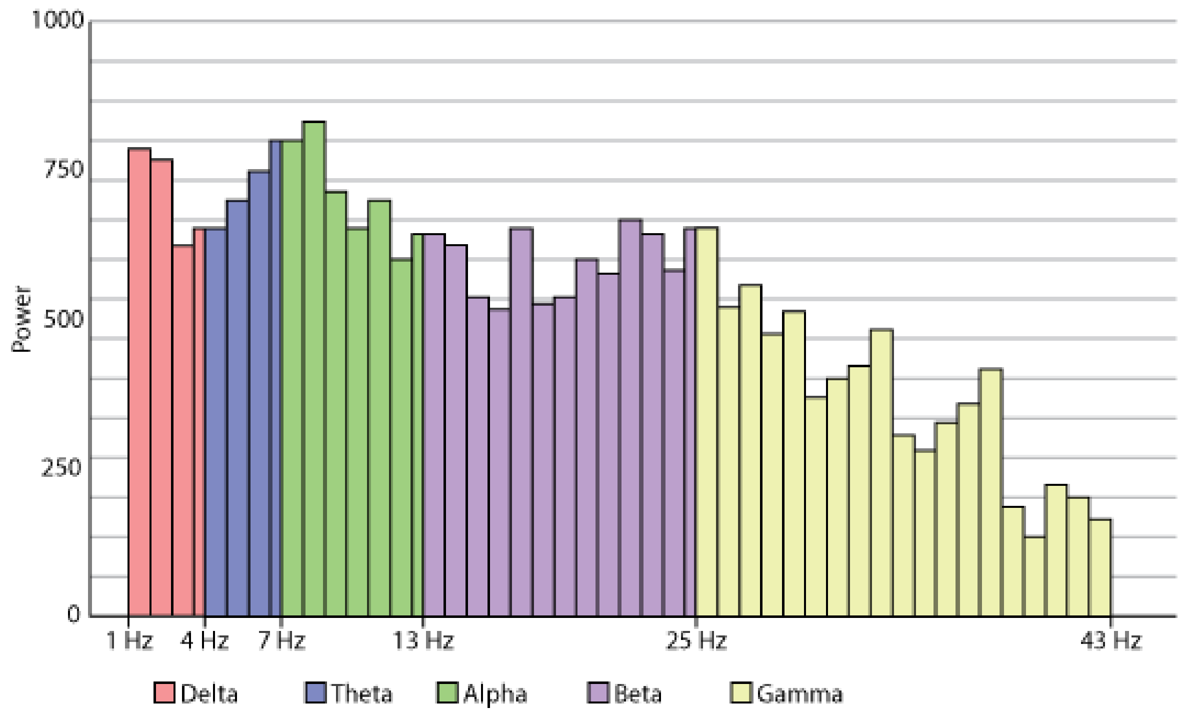

FIGURE 5.6. FFT applied to raw EEG data. The data is converted from the time-domain to the frequency domain allowing access to the individual amplitudes for each frequency.

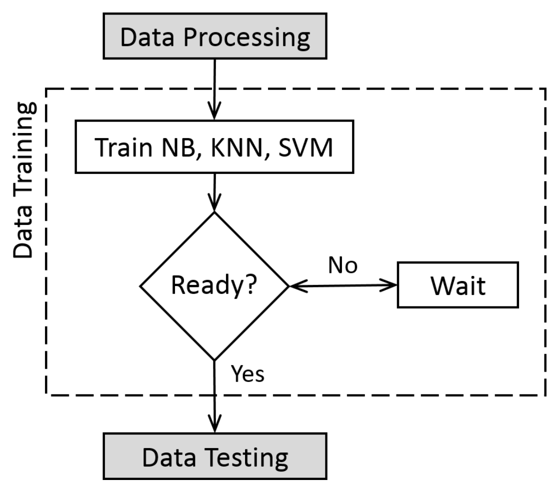

FIGURE 5.7. Flowchart for the Data Training box in Figure 5.1. The Process box is described in Figure 5.5.

engagement and arousal. These thresholds will be used during testing time to determine if the player has left a state of flow while playing a video game.

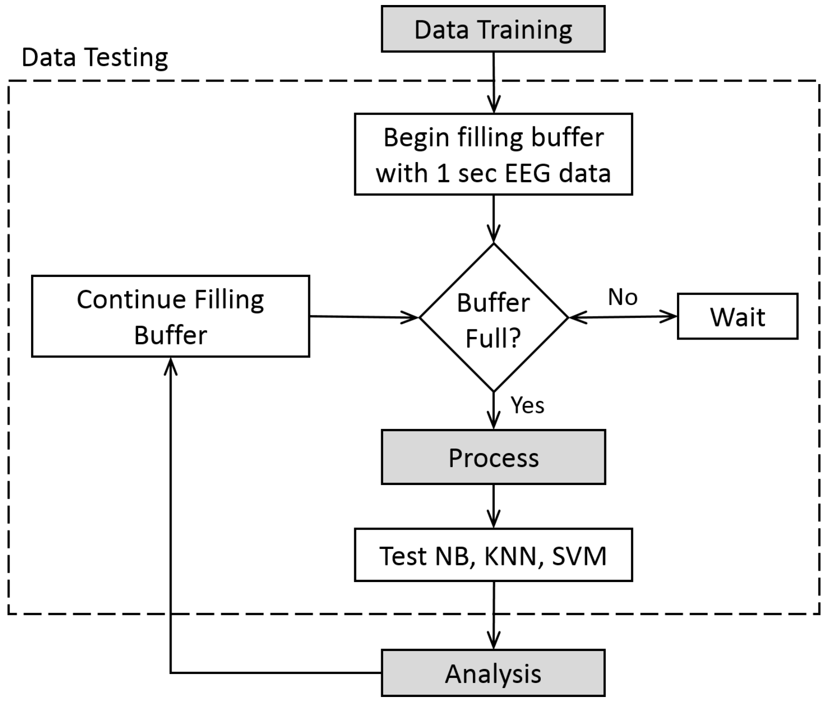

Figure 5.8. Flowchart for the Data Testing box in Figure 5.1.

5.1.4. Data Testing

Figure 5.8 shows the process of data testing. After training the classifier, `BrainWave` switches into testing mode where the player is playing the game. During the testing phase all of the data collected from the headset is processed the same way as described above. As the program finishes processing each epoch of data it send the data to the classifiers to determine if the player is playing the game or has died in the game. For the NB classifier the program uses the mean and variance calculated from the training data to compute the probability that the current epoch of time belongs to a game event or a death event. Depending on which probability is larger the program selects the appropriate class.

To test using the k-NN the program puts the current epoch of data into a vector. The k-NN classifier then calculates a distance between the test data, game training data, and death training data. The classifier chooses which class to pick based upon the shortest calculated distance. Finally the SVM tests the data by placing in into the hyperplane it found during the training phase. The SVM picks the class it thinks the current epoch belongs to

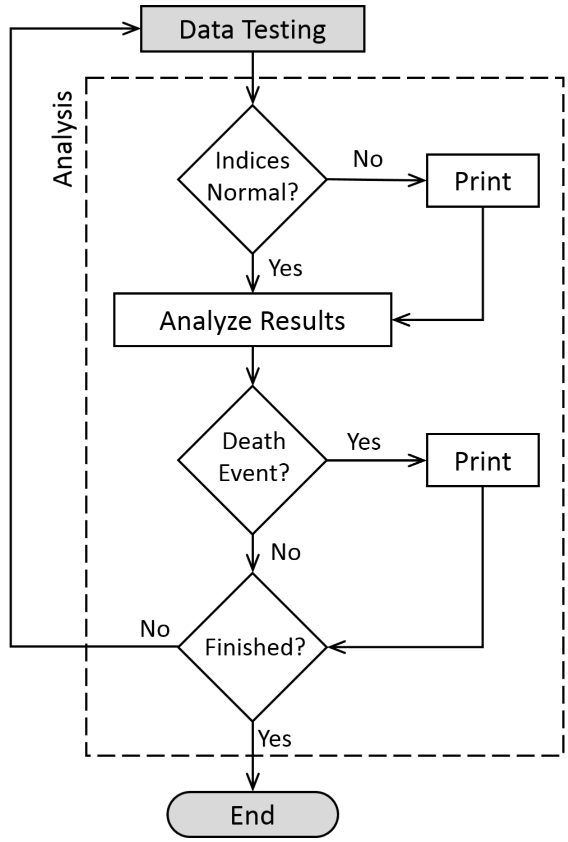

FIGURE 5.9. Flowchart for the Analysis box in Figure 5.1.

by knowing which side of the hyperplane the data lands.

5.1.5. Analysis

`BrainWave`'s final task is to analyze the results from the classifiers. Each classifier picks which class the current epoch belongs. Initially each classifier is independent of each other so if one classifier thinks a death event has occurred then the program outputs a time stamp along with an indication message. In a different iteration of the program the classifiers are dependent on each other. The program requires that they must all agree that a death event has occurred before the program will output that a death event has occurred. The program then calculates if the player has left a state of flow by comparing the currents epoch engagement and arousal level to the upper and lower thresholds. If the player goes above or below the threshold the program timestamps and indicates that this has occurred.

FIGURE 5.10. A screen shot of the video playing while `BrainWave` collecting training data from the two picture at the correct designated time.

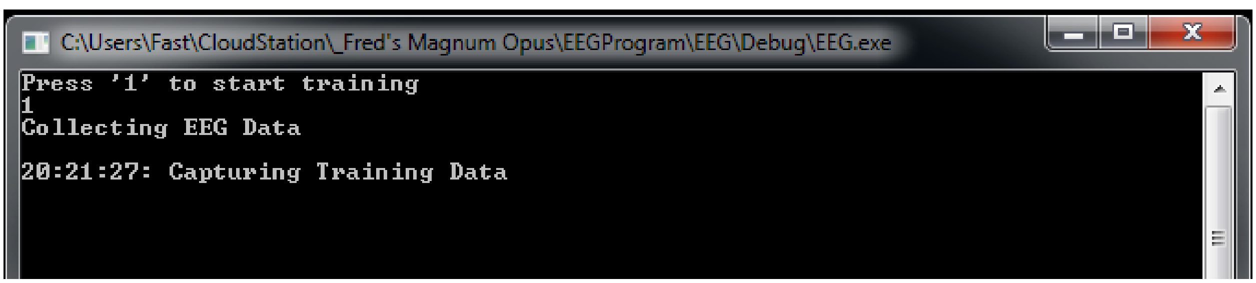

FIGURE 5.11. A screen shot of `BrainWave` collecting training data from the two picture at the correct designated time.

5.2. User Testing

To validate `BrainWave`, two participants wore the Emotiv EPOC headset and played Super Meat Boy. Unlike the first study conducted, all of the data processing was completed by `BrainWave` in real time. Each participant first watched the same video from the previous study to establish their base line (see Figure 5.10 and 5.12) and collect the training data (see Figure 5.11 and 5.13). They then were instructed to play Super Meat Boy for 10 minutes.

The first participant went through the first iteration of the program which kept the

FIGURE 5.12. A screen shot of thevideo playing while `BrainWave` collecting training data from the spider jump at the correct designated time.

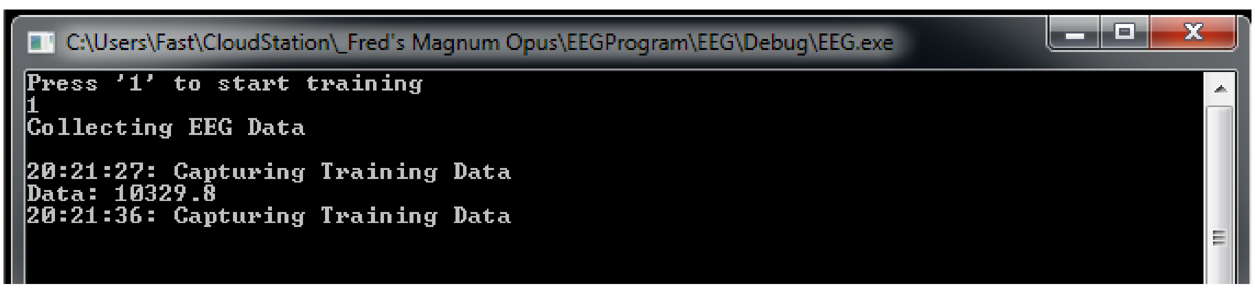

FIGURE 5.13. A screen shot of `BrainWave` collecting training data from the spider jump at the correct designated time.

classifiers independent of each other. This iteration was able to achieve a 83 percent correct classification of death events that the player experienced (see table 5.1). This was achieved by both the k-NN and SVM classifiers (see Figure 5.14 and 5.15). The NB classifier did not fare as well as it was more sensitive to the player's frustration while playing. One particular instance of this was when the player said out loud "I am going to die" he did not die but the NB classified this epoch as a death event. Figure 5.16 and 5.17 shows that the NB classifier was able to correctly identify death events. An interesting observation was that 75% of the

Machine Learning	Correct	Incorrect	Missed	Percentage
SVM	25	5	6	83
NB	23	20	8	53
kNN	25	5	6	83
All 3	28	16	4	64

TABLE 5.1. Program classification results.

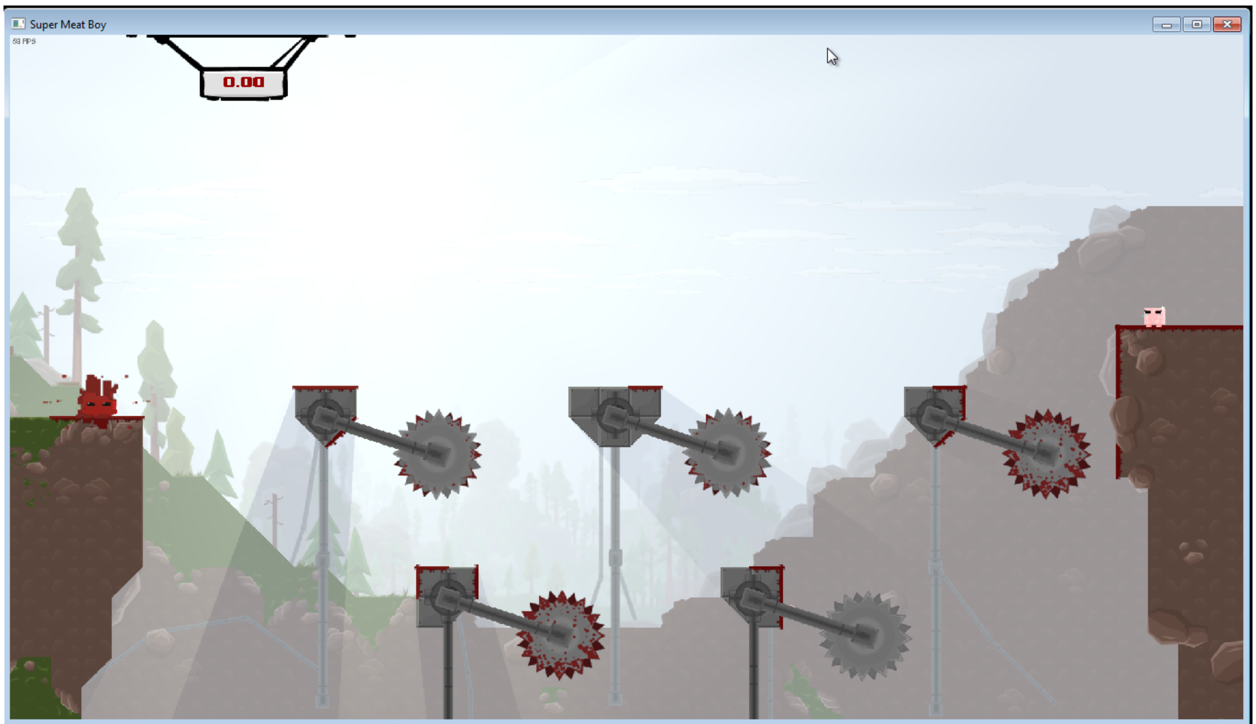

FIGURE 5.14. Screen shot of Super Meat Boy dying and `BrainWave` showing that it correctly classified a death event using the k-NN classifier.

time all of the classifiers agreed that a death event occurred (see Figure 5.18 and 5.19).

Throughout game play the player moved into and out of flow continuously. From visual and audible observation of the player this constant fluctuation in engagement and arousal could be attributed to frustration. Figure 5.15 shows several times stamps that represent the constant fluctuation in engagement and arousal in this particular level the player had died 9 times and was very upset with himself.

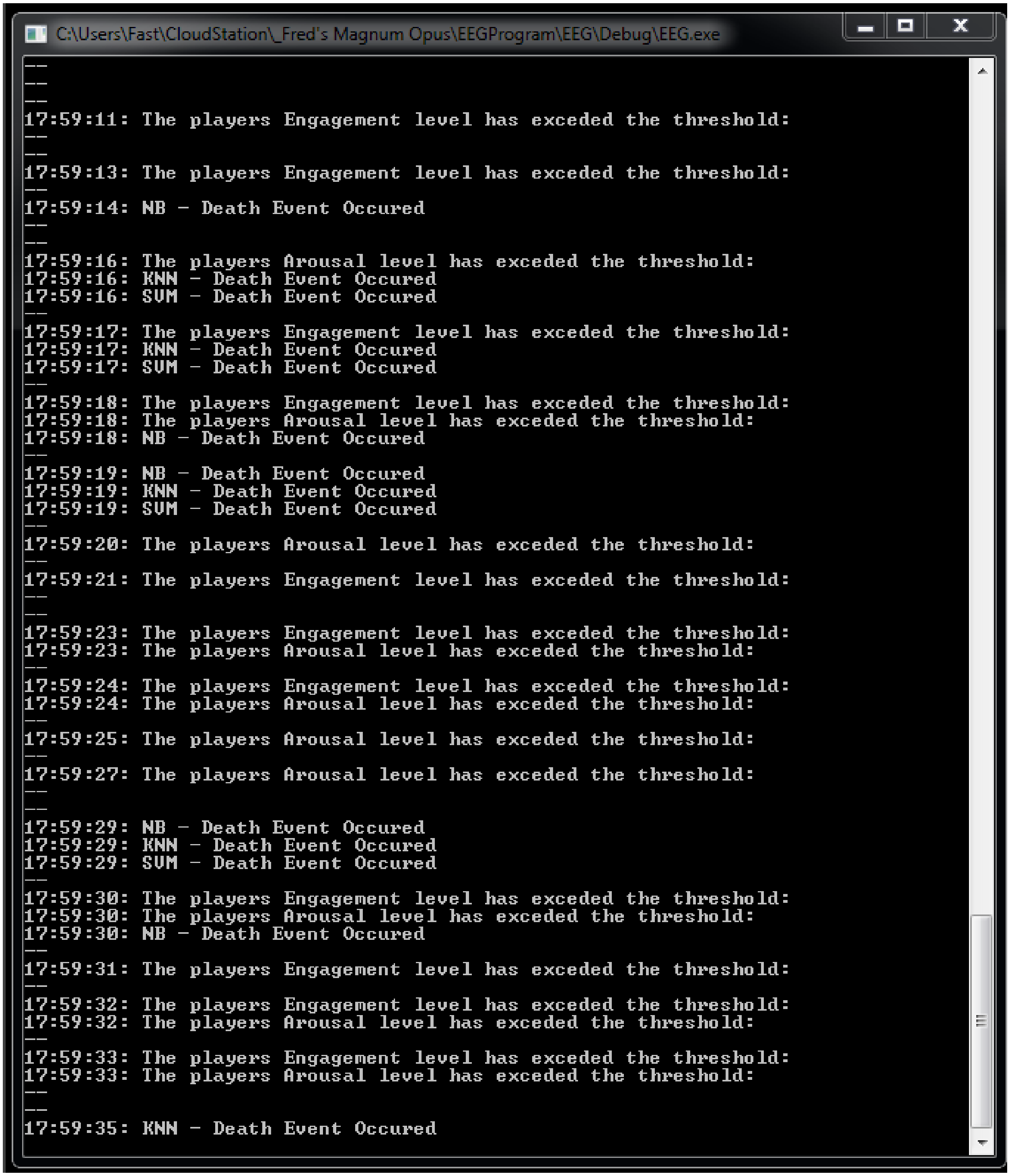

FIGURE 5.15. Screen shot of `BrainWave` showing that it correctly classified a death event using the k-NN classifier.

FIGURE 5.16. Screen shot of Super Meat Boy dying and `BrainWave` showing that it correctly classified a death event using the NB classifier.

The observation that the classifier agreed 75 percent of the time led to the creation of a second iteration of the program. In this iteration all of the classifier had to agree a death event had occurred before the program thought it had occurred. The second participant used the new iteration of the program during their session. The program was able to obtain a correct classification percentage of 64 percent of the time (see table 5.1). This demonstrates that currently the best choice for classifying is either the k-NN or the SVM algorithms.

The second participant was visually and audibly more calm while playing super meat boy. This was reflected in his flow during the game. He left the state of flow significantly less than the first participant, which is seen in the smaller number of time stamps in figure 5.21. The majority of the times that the player did leave the state of flow occurred right before or after dying.

FIGURE 5.17. Screen shot of `BrainWave` showing that it correctly classified a death event using the NB classifier.

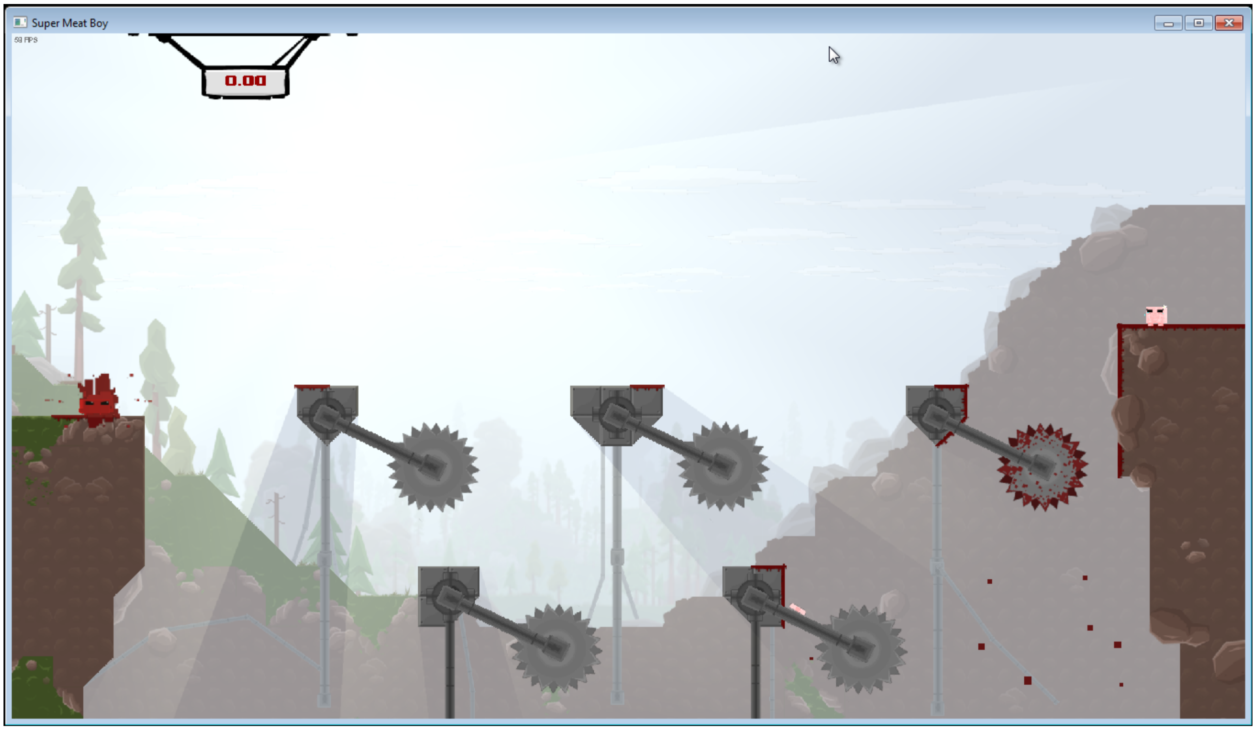

FIGURE 5.18. Screen shot of Super Meat Boy dying and `BrainWave` showing that the classifier used in the application commonly agreed that a death event had occurred.

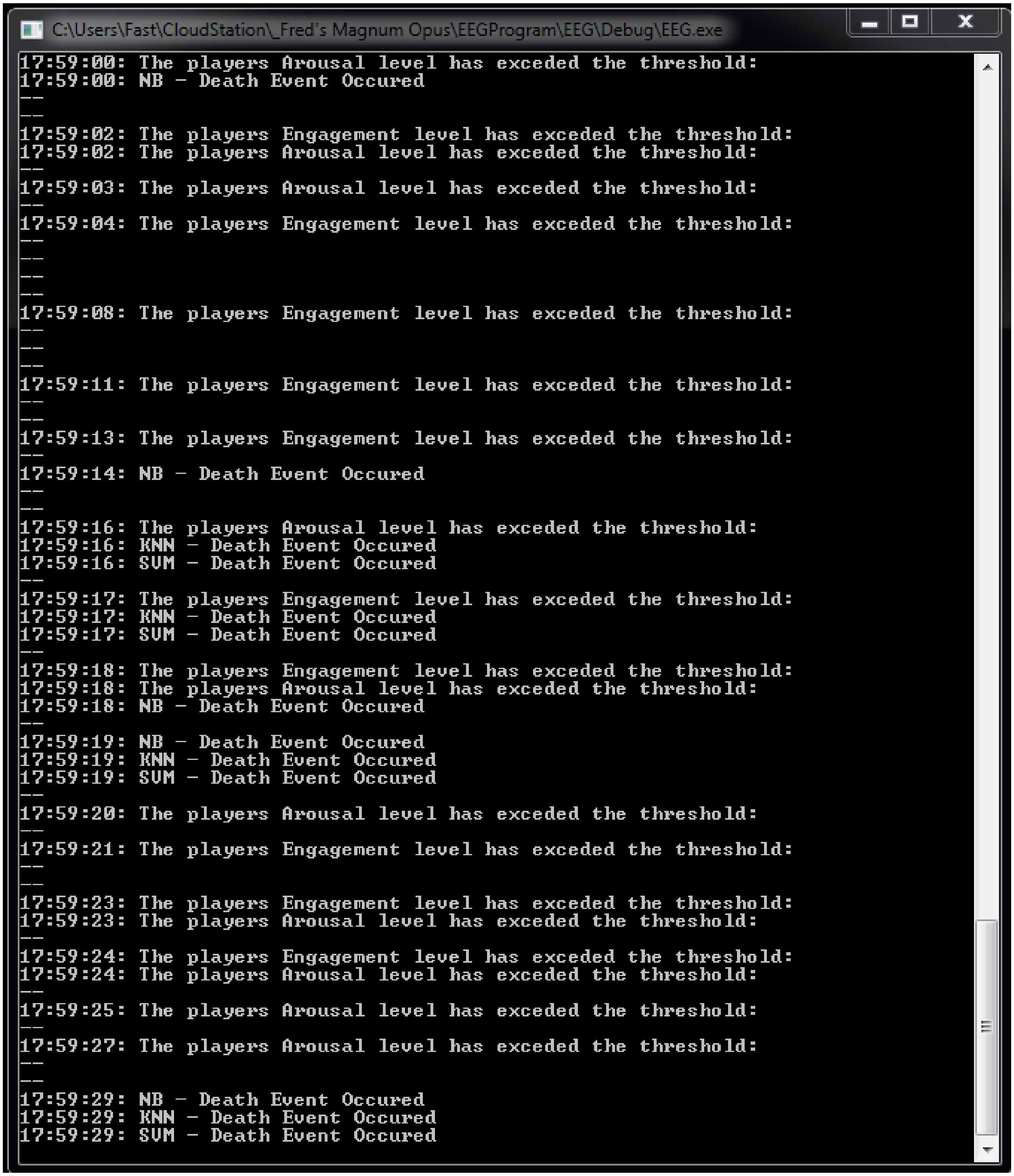

FIGURE 5.19. Screen shot showing that the classifier used in the application commonly agreed that a death event had occurred.

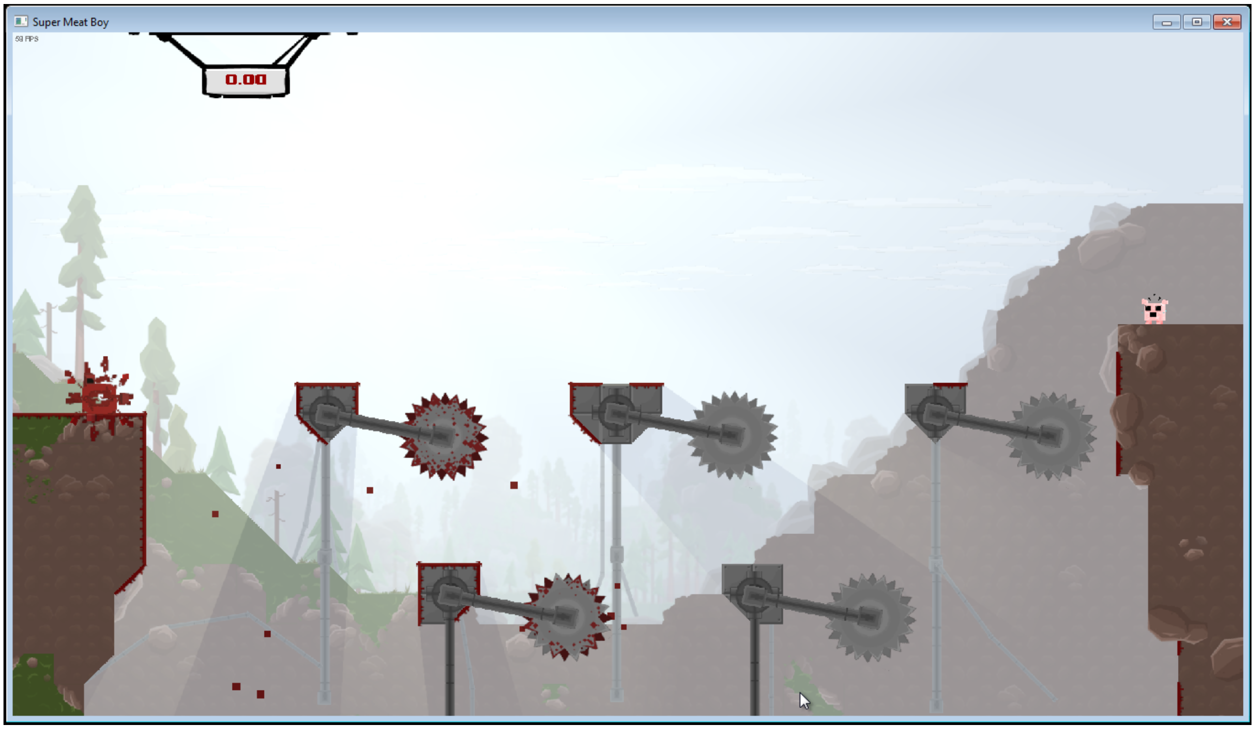

FIGURE 5.20. Screen shot of Super Meat Boy dying and `BrainWave` showing that all 3 classifier used in the application agreed that Participant 2 character died.

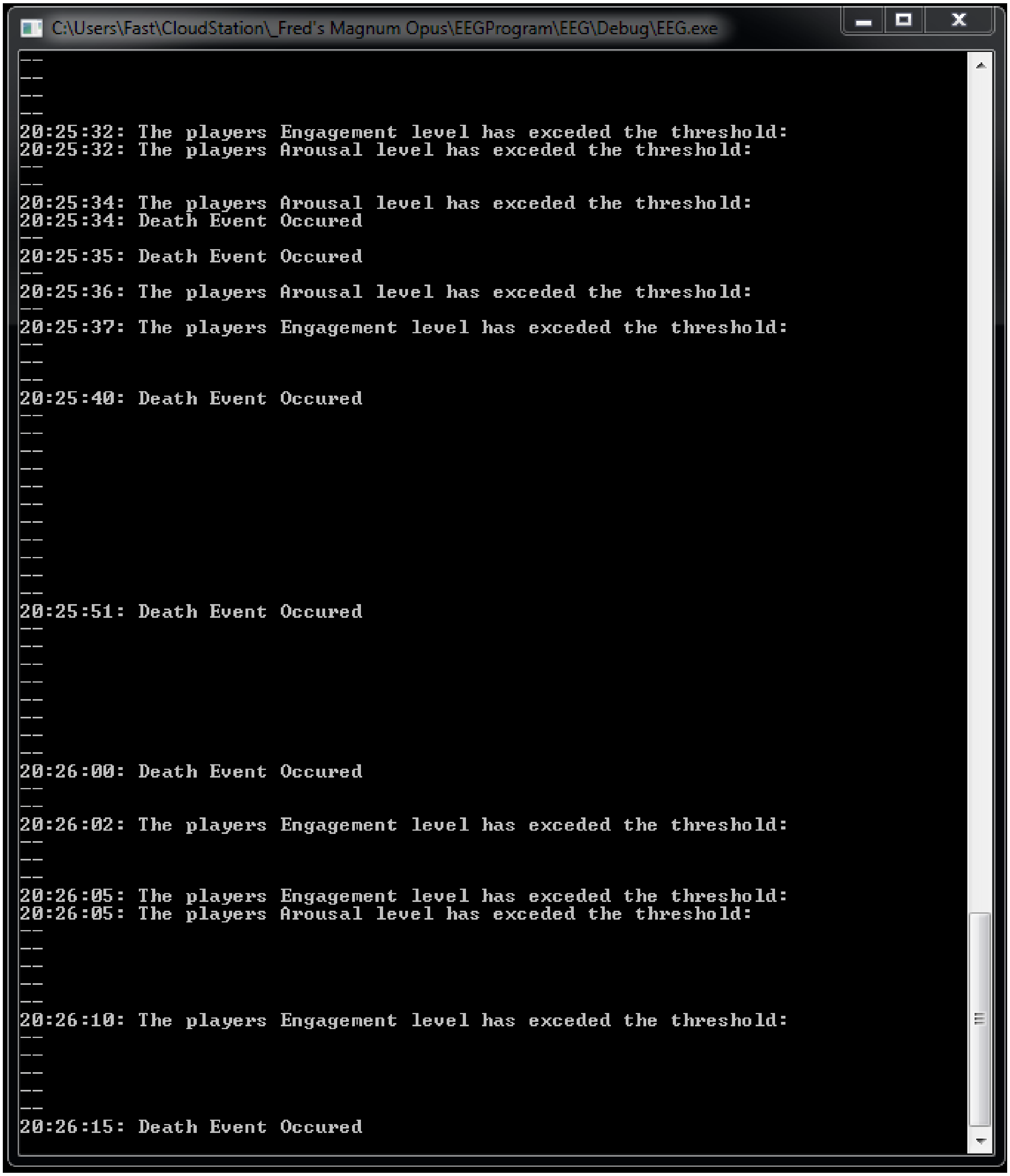

FIGURE 5.21. Screen shot showing `BrainWave` correctly classifying participant 2 death events.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1. Conclusion

The goal of this research was to utilize a low cost EEG device to develop a new tool that game developers and researcher could use to evaluate a player's state of mine while playing a game. Specifically, the work reported herein reflects the following: 1) the viability of the off-the-shelf Emotiv EPOC was tested to find its resolution; 2) various engagement indices were evaluated to identify the most effective one for use with the Emotiv; 3) an arousal – valence index was evaluated to determine if the Emotiv can affectively differentiate between video game events; 4) engagement and arousal indices were combined to produce a model for determining whether a player is in a state of flow; and 5) machine learning algorithms were used to identify events that cause the player to exit a state of flow; 6) the development of an application that can measure player experience in real time.

The development of the real time application first required knowing the neural resolution of the Emotiv EPOC headset. EEG data was collected from 30 people while they played the video game Super Meat Boy. Once the data was processed, it was analyzed to determine if the Emotiv EPOC was able to measure a difference between three different modalities (Two-Picture Cognitive Task; General Game Play; Death Events). Comparing the Two-Picture Cognitive Task to Death Event showed a significant increase in beta and gamma power during the Death Event. beta and gama power also increased significantly when the player died as compared to General Game Play. These results indicate that the Emotive EPOC headset measures EEG fluctuations correctly as player's experience various stimulus. This further supports the idea that a player's experience can be measured utilizing a low cost EEG headset.

The next step in the development of the real time application was to find a way to measure the engagement level of a player. Various EEG indices exist that provide a way for calculating a person's current engagement level. These engagement indices were never implemented using data from the Emoitv EPOC. This means that the indices must first be validated to confirm that they work with the Emotiv EPOC correctly. The engagement levels were calculated using each index and then compared to one another to find which one produces the best results. Index 1 (beta/(alpha + theta), which used an average band wave from all sensors, proved to be the most effective in measuring engagement. A significant increase in engagement was found in the player's Death Event compared to their General Game Play. These results reflect the idea that higher levels of engagement mean the players has entered a state of stress or frustration. Index 1 proved to be the best choice to use with the Emotiv EPOC because it requires a lower overhead to implement compared to the other two indices which requires accessing individual sensor locations. Using the averaged band wave approach also help in reducing noise that may come from individual sensors.

The third step in the development of the real time application was to find a way to measure the arousal level of a player. Like engagement, an arousal index ((beta F3 + beta F4) / (alpha F3 + alpha F4)) exist that calculate a person's level of arousal. The arousal index was authenticated the same way that the engagement indices where done. A significant increase in arousal was found during Death Events when compared to General Game Play. These results correspond to the idea that the player has entered a state of stress or frustration when their character dies in the video game.

The fourth step required Coordinating "Task Engagement" data with "Arousal-Valence" data to establish a flow model. Completing the flow model requires knowing when the player had left the state of flow. Thresholds were established for the player's engagement and arousal levels. Developing thresholds is a difficult task because they are different for every person. Using the low level and high level from the baseline video was the first idea used to calculate the thresholds. This proved to be unsuccessful because to measure the low level of a player required them to relax and not think about anything which is quite difficult for a person to accomplish. The low level measured from the baseline video did not always adequately reflect a person low engagement and arousal level. An alternative solution to using the low and high from the baseline video was to utilize the mid measurement (Two-Picture Cognitive Task) from the baseline video. Treating the Two-Picture task as the midpoint allowed for the data to be split into quartiles. The lower threshold being represented by the first quartile and the high threshold being represent by the third quartile.

Having engagement and arousal threshold allowed for the creation of the following rules to determine what to do when a player leaves a state flow. 1) If engagement levels fall below the lower threshold, then the game is to become more complex; 2) If engagement level rises above the upper threshold, then the game is to become simpler; 3) If arousal level falls below the lower threshold, then the game play is to be more stimulating; and 4) If arousal level rises above the upper threshold, then game play is to become less arousing. These rules can be applied to any method or variation in the threshold levels.

The fifth step in the development of the real time application was to find a way to automatically detect when player's encountered specific game events. The problem with this is that we never know when an event is going to occur which makes it difficult to train machine learning algorithms with event data. The baseline video created in the research offers a way to know when a particular event is going to occur. The research results have indicated that the Two-Picture Cognitive Task and the Spider Jump Arousal Stimulus correspond to General Game Play and Death Events. This suggested that machine learning algorithms could be trained with data from the Two-Picture Cognitive Task and the Spider Jump Arousal Stimulus. Once trained the classifier would be able to classify General Game Play Events and Death Events.

Using the base line video for training data was tested using Support Vector Machine (SVM), Naïve Bayes (NB), and k-Nearest Neighbor (kNN). The beta, theta, alpha, gamma, engagement, and arousal signals were used as the predictors for each classifier. The machine learning algorithms used the predictors from the Two-Picture Cognitive Task and the Spider Jump Arousal Stimulus to train. They then attempted to classify General Game Play and Death Events. The beta band wave was found to be the best predictor for both NB and kNN achieving an average of 75 percent correct classification of death events. These results support the idea that the data collected from the Two-Picture Task and the Spider Jump

Arousal Stimulus are capable of classifying General Game Play and Death Events.

The final goal of this research was the development of an application that analyzes player experience in real time. The `BrainWave` application establishes a connection and captures data measured by the Emotiv EPOC headset. It then converts the raw EEG data in the into meaningful brainwave band frequencies. `BrainWave` records training data while the player watches the baseline video. The collected data is then used to train the SVM, NB, and kNN classifiers. After training the program runs while the player plays the video game. `BrainWave` monitors the player's engagement and arousal levels as they play. Any time the player goes above or below their calculated thresholds the program outputs this so the reasoning can be determined.

The `BrainWave` program also attempts to classify whenever the player dies. The SVM and kNN classifiers were able to achieve an 83 percent correct classification of death events. While `BrainWave` was not able to identify all of the Death Events that occurred it caught the majority of them. The ones that `BrainWave` did correctly classify allow researchers and developers the ability to focus on other events that cause the player to leave a state of flow.

The results from the work performed in this study have shown that the Emotiv is an efficient measuring tool for evaluating player experience as well as supporting the idea of using it as a low-cost solution for game companies to use for player testing. This framework does not only provide a method for measuring gamer experience but also provides a new concept of dynamic gaming. As sensor technology becomes better, EEG sensor soon could be placed in new devices such as headphone or virtual reality headsets. As player play games using these devices the game can have an ever changing environment that adapts to the player's current state of mind. This framework could also be expanded to work in other areas of computer science as a tool for programmers to use to gain instantaneous feedback about the user's experience, providing a new method for programmers to evaluate their programs along with find area of the program that cause users the most frustration.

The findings should be understood in the context of some limitations. These findings are based on a fairly small sample size. As a necessary next step, the reliability and validity of the Emotiv EEG needs to be established using a larger sample of participants to ensure that the current findings are not an anomaly due to sample size. Further, findings need further validation through straightforward comparison of Emotiv EEG results with those of standard laboratory-based EEG assessment technology. It is important to note, however, that the Emotiv has been favorably compared to a laboratory-based research EEG system (Neuroscan). Badcock et al. [4] found that the Emotiv EEG system can prove a valid alternative to laboratory ERP systems for recording reliable late auditory ERPs over the frontal cortices. While some interesting results were found, it is important to emphasize that these are very preliminary there are not currently well-established methodologies for examining the impact of game levels on players. Nevertheless, there is an increasing body of literature suggesting that game impact can be measured via EEG [Nacke et al. [55], Salmin and Ravajja [66]]. Future studies will be needed to expand these results into methodological approaches to quantifying video game based EEG assessment in general and Emotiv based EEG assessment of various games in particular.

6.2. Future Work

Super Meat Boy was the game used in the study because of its simple learning curve along with it abilities to induce frustration in the player. As a jumping puzzle game, it is just one of several different game genres. Future work should focus on testing this frame work on other games. Specifically, the framework needs to be tested and expanded to include games with more events players encounter such as picking up items or level exploration.

30 participants were used to build and evaluate this framework. In future work, the reliability and validity of the Emotiv EEG needs to be established using a larger sample of participants to help expand and refine the framework. When expanding the sample size, special attention needs to be taken to include an equal number of people who consider themselves gamers. As this framework continues to expand it must continue to be validated by testing is on players with different skill levels to ensure that it is effective regardless of the level of the player.

The baseline video was extremely effective in measuring cognitive work load and arousal stimulus. However, improvement could be made in the staring at a blank screen task. This task was designed to find a person minimal EEG activity but this turns out to be quite difficult as there is no way of knowing if the person is actively thinking about something. In the future, a better procedure should be developed to induce lower brain wave activity. This could include expanding the amount of time a person looks at a blank screen, or finding some other mechanism that can induce boredom.

`BrainWave` was designed to be a standalone program outside of any game. The downside to this is that the `BrainWave` does not know when specific game events occur. Being able to add `BrainWave` into a video game will allow for the game to be able to tell when a player experience events. This intern will allow `BrainWave` to train on true game event data instead of the baseline video. Training on event data will allow for more events to be able to be identified as well as provide a clearer picture of the player's current state of mind

APPENDIX A

COMPUTER AND VIDEO GAME QUESTIONNAIRE

Computer And Video Game Questionnaire

1. I have avoided computers because they are unfamiliar and somewhat intimidating to me.
   - Strongly Agree
   - Agree
   - Neither Agree Nor Disagree
   - Disagree
   - Strongly Disagree

2. How would you rate your computer competency in terms of knowing how to use a computer?
   - Completely Inexperienced
   - Inexperienced
   - Somewhat Experienced/Inexperienced
   - Experienced
   - Very Experienced

3. Indicate the average number of hours a week you do the following computer activities	Average Number of Hours										
	0	1	2	3	4	5	6	7	8	9	10+
Word Processing	○	○	○	○	○	○	○	○	○	○	○
Programming	○	○	○	○	○	○	○	○	○	○	○
Playing Games on my Cell Phone	○	○	○	○	○	○	○	○	○	○	○
Playing Games on my Computer	○	○	○	○	○	○	○	○	○	○	○
Playing Games on my Game Console	○	○	○	○	○	○	○	○	○	○	○
Data Entry/Processing	○	○	○	○	○	○	○	○	○	○	○
Graphic Design/Art	○	○	○	○	○	○	○	○	○	○	○
Surfing the Internet	○	○	○	○	○	○	○	○	○	○	○
Emailing	○	○	○	○	○	○	○	○	○	○	○
Other	○	○	○	○	○	○	○	○	○	○	○

4. I play videogames for 20 or more hours per week:

- ○ Yes
- ○ No

5. I read videogame magazines.

- ○ Strongly Agree
- ○ Agree
- ○ Neither Agree Nor Disagree
- ○ Disagree
- ○ Strongly Disagree

6. I consider myself a "Gamer":

- ○ Yes
- ○ No

Submit

APPENDIX B

IRB LETTER

UNT

A green light to greatness.

OFFICE OF RESEARCH INTEGRITY AND COMPLIANCE

November 12, 2013

Supervising Investigator: Dr. Thomas Parsons
Student Investigator: Timothy McMahan
Department of Psychology
University of North Texas

Re: Human Subjects Application No. 13534

Dear Dr. Parsons:

As permitted by federal law and regulations governing the use of human subjects in research projects (45 CFR 46), the UNT Institutional Review Board has reviewed your proposed project titled "Using EEG to Measure Engagement and Arousal While Playing Video Games." The risks inherent in this research are minimal, and the potential benefits to the subject outweigh those risks. The submitted protocol is hereby approved for the use of human subjects in this study. **Federal Policy 45 CFR 46.109(e) stipulates that IRB approval is for one year only, November 12, 2013 to November 11, 2014.**

Enclosed is the consent document with stamped IRB approval. Please copy and **use this form only** for your study subjects.

It is your responsibility according to U.S. Department of Health and Human Services regulations to submit annual and terminal progress reports to the IRB for this project. The IRB must also review this project prior to any modifications. **If continuing review is not granted before November 11, 2014, IRB approval of this research expires on that date.**

Please contact Shelia Bourns, Research Compliance Analyst at extension 4643 if you wish to make changes or need additional information.

Sincerely,

P. Kaminski, PhD

Patricia L. Kaminski, Ph.D.
Associate Professor
Department of Psychology
Chair, Institutional Review Board

PK/sb

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University of North Texas Institutional Review Board

Informed Consent Form

Before agreeing to participate in this research study, it is important that you read and understand the following explanation of the purpose, benefits and risks of the study and how it will be conducted.

Title of Study: Using EEG to Measure Engagement and Arousal While Playing Video Games

Student Investigator: Timothy McMahan, University of North Texas (UNT), Department of Computer Science.

Supervising Investigators: Thomas D. Parsons, PhD

Purpose of the Study: We are asking you to take part in a research study because we are trying to learn more about how brain waves change while playing different stages of a video game.

Study Procedures: You will be asked to do the following things:

1. The examiner will ensure you are eligible to participate by asking you some brief health-related questions. You will then be asked to complete a brief test of attention and reaction time. This is expected to take no more than 5 minutes.
2. You will then be asked to complete some computer-based tasks of attention and reaction time. This is expected to take no more than 25 minutes.
3. Participants will then be given an "emotive" headset (that records EEG data) and will complete a cognitive task.
4. Finally, the investigator will remove the emotive and debrief you about the study, communicate the hypotheses and experimental design of the study, and answer all of your questions. Debriefing is expected to take no more than 5 minutes.
5. Your overall time commitment for this session is expected to last about one hour.

Foreseeable Risks: This study has minimal risks to the participants. The participants may experience eye fatigue towards the end of the session. Please let the research assistant know if you are feeling fatigued or distressed at any time during the simulation, and would like to discontinue your participation.

Benefits to the Subjects or Others: This study is not expected to be of any direct benefit to you. However, your participation in this study may help us learn about how brain wave recordings can be used in the future for testing and developing videogames. It is our belief that the possible knowledge that will be gained as a result of these experimental procedures will outweigh any potential risks.

Compensation for Participants: Participants will receive class credit from participating in the study. 1 credit for each ½ hour of participation

APPROVED BY THE UNT IRB
FROM 11/12/13 TO 11/11/14

Procedures for Maintaining Confidentiality of Research Records: Participants will be assigned a study ID. No Identifying information will be kept about the user. The confidentiality of participant information will be maintained in any publications or presentations, and all data analyses will be conducted at the group level.

Video Image Release: Part of this study requires us to record your facial movements and body movements to help isolate any artifacts that may occur in the EEG signal. The videos will be maintained on a password protected computer and only accessible by Dr. Thomas Parsons and Timothy McMahan. The recordings will be kept for no more than 3 years then destroyed. We may decide to use the imagery from the videos in future publications. However, no identify information will be associated with the imagery.

Please indicate below, by initialing next to your selection, if you agree to allow use of the video imagery in any future publications.

______I agree that segments of the recordings made of my participation in this research may be used for future publications.

______I do not want segments of the recordings made of my participation in this research to be used for future publications.

Segments cannot be used for purposes beyond those detailed and consented to in the informed consent form.

Questions about the Study: If you have any questions about the study, you may contact Timothy McMahan at fred.mcmahan@unt.edu.

Review for the Protection of Participants: This research study has been reviewed and approved by the UNT Institutional Review Board (IRB). The UNT IRB can be contacted at (940) 565-3940 with any questions regarding the rights of research subjects.

Research Participants' Rights:

Your signature below indicates that you have read or have had read to you all of the above and that you confirm all of the following:

- A research assistant has explained the study to you and answered all of your questions. You have been told the possible benefits and the potential risks and/or discomforts of the study.
- You understand that you do not have to take part in this study, and your refusal to participate or your decision to withdraw will involve no penalty or loss of rights or benefits. The study personnel may choose to stop your participation at any time.
- You understand why the study is being conducted and how it will be performed.
- You understand your rights as a research participant and you voluntarily consent to participate in this study.

APPROVED BY THE UNT IRB
FROM 11/12/13 TO 11/11/14

- You have been told you will receive a copy of this form.

____
Printed Name of Participant

______________________________ ____________
Signature of Participant Date

For the Student Investigator or Designee:

I certify that I have reviewed the contents of this form with the subject signing above. I have explained the possible benefits and the potential risks and/or discomforts of the study. It is my opinion that the participant understood the explanation.

______________________________ ____________
Signature of Student Investigator Date

APPROVED BY THE UNT IRB
FROM 11/12/13 TO 11/11/14

APPENDIX C

PSEUDOCODE

```
MAIN (argc, argv)
Event = EE_EmoEngineEventCreate()
eState = EE_EmoStateCreate()
DataHandle hData = EE_DataCreate()
task = 1
state = 0
Ready_to_Collect = false
TWP = 130
SP = 140
End_Video = 240
Train_Timer = 0
Train_Complete = false
Low_Threshold_Engagement = 0
High_Threshold_Engagement = 0
Low_Threshold_Arousal = 0
High_Threshold_Arousal = 0
EE_DataSetBufferSizeInSec(seconds)
Wait for input to start training
While NOT finished
  if Key_Pressed == Q
    finished = true
  state = EE_EngineGetNextEvent(Event)
  if state == EDK_OK
    Ready_to_Collect = false
  else
    Emotiv not ready
    return 0
  if Ready_to_Collect
```

```
Grab data out of the Emotiv buffer
SET_TO_ZERO()
for each sample in buffer
    for each channel in buffer
        Run the data through a low pass filter
        Run the data through a high pass filter
Calculate the average across all sensors
Run the data through the Fast Fourier Transform
for each result in FFT
    Square the result
    Add the result to correct Brainwave Band
if NOT Train_Complete
    if Train_Timer == TWP
        Store Values for training the classifiers
    if Train_Timer == SP
        Store Values for train the classifier
    if Train_Timer == END_Video
        DIVIDE_BY(task = 1)
        CAL_ENGAGEMENT(task= 1)
        DIVIDE_BY(task = 2)
        CAL_ENGAGEMENT(task= 2)
        Low_Threshold_Engagement = TWP Engagement - TWP Engagement * 0.5
        High_Threshold_Engagement = TWP Engagement + TWP Engagement * 0.5
        Low_Threshold_Arousal = TWP Arousal - TWP Arousal * 0.5
        High_Threshold_Arousal = TWP Arousal + TWP Arousal * 0.5
        Train Support Vector Machine
        Train Naïve Bayes
        Train k Nearest Neighbors
```

```
            Train_Complete = true
        else
            DIVIDE_BY(task = 3)
            CAL_ENGAGMENT(task =3)
            Test current EEG Data in Support Vector Machine
            Test current EEG Data in Naïve Bayes
            Test current EEG Data in K Nearest Neighbors
            if Current_Engagment >Highr_Threshold_Engagement
                Report Player engagement to high
            else if Current_Engagment <Low_Threshold_Engagement
                Report Player engagement to low
            if Current_Arousal >High_Threshold_Arousal
                Report Player arousal to high
            else if Current_Arousal <Low_Threshold_Arousal
                Report Player arousal to low
            if SVM
                Report Death Event
            if  NB
                Report Death Event
            if KNN
                Report Death Event
        Train_Timer++
        Wait until next full buffer
    return 0
```

```
SET_TO_ZERO()
    Set all variables back to zero
    return 0
```

```
DIVIDE_BY(task)
if task == 1
   Divide alpha sensor data by 7
   Divide beta sensor data by 13
   Divide delta sensor data by 4
   Divide gamma sensor data by 19
   Divide theta sensor data by 4
   Store results for TWP
elseif task == 2
   Divide alpha sensor data by 7
   Divide beta sensor data by 13
   Divide delta sensor data by 4
   Divide gamma sensor data by 19
   Divide theta sensor data by 4
   Store results for SP
else
   Divide alpha sensor data by 7
   Divide beta sensor data by 13
   Divide delta sensor data by 4
   Divide gamma sensor data by 19
   Divide theta sensor data by 4
   Store results for Game Data
return 0
```

```
CAL_ENGAGMENT(task)
if task == 1
   for each value in EEG_Sensor
```

```
        Engagment = Beta / Alpha + Theta
        Arousal = Beta F3 + Beta F4 / Alpha F3 + Alpha F4
        Store TWP engagement
        Store TWP arousal
else if task == 2
    for each value in EEG_Sensor
        Engagment = Beta / Alpha + Theta
        Arousal = Beta F3 + Beta F4 / Alpha F3 + Alpha F4
        Store SP engagement
        Store SP arousal
else
    for each value in EEG_Sensor
        Engagment = Beta / Alpha + Theta
        Arousal = Beta F3 + Beta F4 / Alpha F3 + Alpha F4
        Store Game engagement
        Store Game arousal
return 0
```

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