Evaluating Electroencephalography Engagement Indices During Video Game Play

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ABSTRACT

Given the growing popularity of video gaming and off-the shelf electroencephalographic (EEG) devices like the Emotiv, there is a growing need for methods of measuring gamer experience in real-time. Engagement indices developed to monitor human engagement have yet to be implemented with the Emotiv. In this study, we compared three different engagement indices during various video game modalities using the Emotiv device. EEG data was collected from 30 participants during video game play of Super Meat Boy. Two EEG indices (frontal theta and the ratio of beta to alpha+theta) showed a significant difference in engagement level among the different gaming modalities with the increasingly difficult cognitive demand. Our findings suggest that the Emotive EEG can be to measure a player's varying levels of engagement as they play a video game.

1. INTRODUCTION

Given the growing popularity of video gaming, there is a growing need for a novel approaches to measure player experience to thoroughly keep persons immersed in video games. One area that is gaining popularity rapidly in the gaming community is affective computing because it has great potential in the next generation of human-computer interfaces [45, 59]. One goal of affective computing is to design a computer system that responds in a rational and strategic fashion to real-time changes in user engagement [63], neurocognitive performance [42, 43] and arousal [21, 43, 62].

1.1 Assessing gamer experience

Currently the most common tool used for assessment is a questionnaire given to player asking about their experience after they have played a game. It also has been a common practice in literature to use questionnaires to draw conclusions about what the participant is experiencing while immersed in games and virtual environments [12, 27, 47, 61]. Self-report data, when used in isolation, are highly susceptible to influences outside the participant's own targeted attitudes [53]. Other issues with questionnaires are that wording, context and format can affect the responses from the participant [55]. Further, questioning the player while they are playing the video game affects their experience during the video game [6]. While asking them after playing the game can lead to missed information and/or false information [13]. Knowledge of the user-state during exposure to the video game is imperative for development and assessment of video game design [40].

Psychophysiological metrics provide a number of advantages over self-report for enhanced assessment of video game experience [35, 41]. The psychophysiological signal is continuously available allowing for greater understanding of how stimuli in the gaming environment impact the gamer without a break in the gamers sense of presence [1, 25, 56]. It is also important to note that psychophysiological responses can be made without the gamer's conscious awareness, creating an objective measure of the gamer's state which can include measures of cognitive workload [5, 11, 33], varying stress levels [10, 20], task engagement [46, 54], and arousal [9, 15, 16]. Multiple channels of psychophysiological data can be gleaned from various sensors continuously allowing for increased experimental control so that one measure alone is not the sole basis for design decisions [26].

1.2 Using EEG to measure gamer experience

Recent approaches to psychophysiological computing have applied psychophysiological modeling to interactive video games [43]. Electroencephalography (EEG) provides a means of accessing and recording neural activity, allowing a computer to retrieve and analyze information from the brainwave patterns produced by thought. EEG has been shown to have the capability to measure player experience [62, 63]. Beta rhythm has been shown to increase with attention and vigilance in general [36, 58] and during video game play specifically [51]. Salmin and Ravajja [51] used EEG to isolate specific game events from the EEG data. Nacke et al. [37] also showed that EEG data could be used to determine player experience across entire level designs. Whilst there are many beneficial EEG applications, much of this technology has yet to leave the research lab because the majority of current research uses medical EEG devices which are expensive, bulky, and require skilled technicians to operate them.

New technology has resulted in inexpensive consumer-grade devices that are designed for novice user to be able to use. An example of this 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 have since adopted it for a variety of applications [14, 48, 60]. Researchers have investigated different EEG processing algorithms to assess classification of shapes being thought about [19], detection of hand movement intentions on the same side of the brain as the hand [22], classification of positive and negative emotion elicited by pictures [29, 30, 44], and evaluation of cognitive workload [2]. The system has been found to work well for detecting events when the participant is told to picture various stimuli [19, 32].

Although the Emotiv EEG does not have the fidelity of a laboratory EEG it still offers the ability to provide a gamer's brain wave signature. Duvinage et al. [17] compared the Emotiv headset to the Advance Neuro Technology (ANT) acquisition system during a run with the P300 speller system. Although the Emotiv headset was not found to be as accurate as the ANT system (a medical grade device), it was able to capture EEG signal at a successful level that was deemed adequate for games. With the benefit of being noninvasive to the wearer, it is a tool that is practical for use by game developers.

1.3 Measuring Engagement from EEG

Using EEG to measure task engagement is not a new concept. It has been widely used with medical grade EEG devices. Pope et al. [46] built a system to control the level of task automation based upon the whether the operator had increasing or decreasing engagement. Freeman et al. [23] expanded on this same system by evaluating 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. [5] explored as a way to 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 engagement reflects information-gathering, visual processing, and attention allocation.

Smith and Gevins [57] used a flight simulator to subject participants to low, moderate or high difficulty tasks to see how the brain responded. The results from their study showed an increased frontal theta response along with reduced parietal alpha during demanding tasks. Other work [21, 28, 38] had similar results indicating that an increase in theta and a decrease in alpha was correlated with increased number of tasks along with amount time a persons is awake. Yamada [64] 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. These results suggest that interesting tasks result in higher frontal theta activity while the task inhibits eye blink activity. Recently, Kamzanova et al. [31] compared the sensitivity of various EEG engagement indices during time-on-task effect and cueing to detect which index was most effective for detecting reduced alertness linked with vigilance decline in performance.

Few studies have approached measuring player engagement with off-the-shelf technology while playing video games. The current study aimed to assess user engagement while playing video games using the Emotiv EEG. Specifically, we aimed to 1) compare three engagement indices during video game modalities to show which one the Emotiv is most compatible with; and 2) compare video game events (e.g., death of a character) to analyze changes in player engagement levels.

2. METHODS

2.1 Participants

EEG data was collected from 30 healthy participants (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. 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 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[1] is a platform game in which players control a small, dark red, cube-shaped character named Meat Boy (see Figure 1) jumping around the level avoiding saw blades to reach their goal of rescuing bandage girl. This game requires a minimal amount of keys to play (arrow keys and space bar) thus making it easy for any level of gamer to achieve success. Major events in the game include successfully completing a level and death. Death can occur from many sources including running into spinning saw blades, falling into fire, falling into acid, or getting skewered on needles. As the player progresses through the game the levels get increasingly difficult through the addition of more saw blades and large jumps. Each level is timed. The player must get through each level as fast as possible.

The core gameplay requires fine control and split-second timing [18]. 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, we sampled from death events related to the character falling into acid. The "General Game Play" was differentiated from "Death events" in that general game play was sampled during periods in which the player had not experienced any death events for 1 minute before or after "General Game Play" sampling.

[1] `http://supermeatboy.com/`

Figure 1: Screen shot from Super Meat Boy

2.2.2 *The Game Experience Survey*

Participants answered a series of questions assessing their prior videogame experience and other personal characteristics. Participants were asked to report the number of hours they spent playing video games on their cell phones (M = 3.47), playing games on their computer (M = 3.47), and playing games on their game console (M = 2.3). 20% of the participants reported playing video games more than 20 hours per week. The participants were also asked if they would classify themselves as "gamers", 33% responded as being part of this category.

2.2.3 *The Emotiv EPOC EEG*

This Emotiv 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) and two additional sensors that serve as CMS/DRL reference channels (one for the left and the other for the right hemisphere). 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.

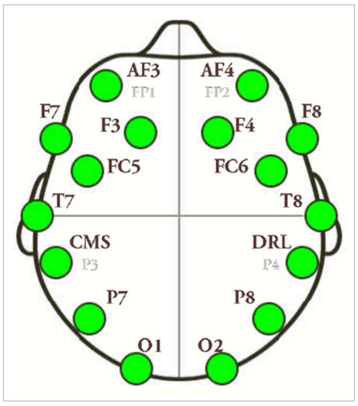

Figure 2: Sensor locations on Emotiv headset.

2.3 Procedure

Upon arriving at the testing office, the participants were given an informed consent form to read and sign, including a waiver to record the participant during the study. The participants were then seated in a comfortable chair and given a keyboard and mouse to complete a questionnaire about computer and game experience.

For the actual assessment, each participant played the game in the same room location. The game was displayed on a Samsung 60 inch plasma screen. The participants sat in a chair that has 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.

While the participant played the game the lights were turned off to help immerse the player into the game and reduce glare from the overhead lights. The experimenter combed the participants on the left, mid-line, and right sides of their scalp firmly in order to reduce electrode impedances [34]. After the relevant areas on the face and mastoids had been cleaned, the Emotiv EEG headset was positioned on the participant's head. The examiner verified impedances in connections between each electrode and the participant's scalp.

During the Super Meat Boy Task the researcher aided the participant with the first few levels to allow the player to become acquainted with the rules and game controls. Next, participants were informed that they would play Super Meat Boy for 15 minutes and that they were to advance as far as they could in the game.

Each participant's game play was captured in 1080p HD (60 frames per second) using a Hauppauge video capturing device allowing the game play to be synced the EEG data. 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. EEG data and video data were recorded on the same computer with all non-essential programs closed. Using OpenViBE drift correction, a 128 Hz sample rate was achieved 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 Data Analytics

All data were analyzed using SAS version 9.1. Descriptive statistics were calculated for participant demographics and for EEG results (see Table 1). Missing data were imputed by either mean substitution or last case carried forward.

Table 1: EEG Descriptive for Each Index

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

The Emotiv Epoc headset was used to capture the EEG data from each participant. Emotiv TestBench and OpenViBE were used to capture the raw EEG output from the headset. The EEG data was segmented into epochs that started 100 ms before the onset of each stimulus (0 ms), and ended 750 ms after the onset of the same stimulus. Epochs were calculated for General Game Play and Death events.

Artifacts such as blinking, head movements, or body movement can cause unwanted data in EEG data. Most EEG analysis requires removal of these artifacts to help identify medical issues. However this is not necessarily a detrimental issue when using for game play analysis. These types of artifacts are common in everyday game play [8, 39]. They can actually be used for further analysis as body movement or other movement can signify engagement [7].

The EEG data was annotated as artifact where visually noticeable deflection in the EEG was observed at the times that participants performed movements. Artifacts related to eye blinks and other muscle movements in addition to physical movements of the sensors themselves were removed before the EEG traces were processed. The Emotiv SDK automatically detects and records eye blinks. Given that muscle contraction and control are generally governed outside of the frequency range of interest [49], we were able to use frequency band limiting procedures such as low-pass, high-pass and notch filters to adequately remove these signal components.

As Anderson et al. [3] describe, after removing EEG artifacts the researcher may assess whether the energy densities of the alpha or theta frequency bands are changed by more than 20% of their original values. If so, the trial should be removed from all further analysis. In this study, we did not need to throw out any of the trials due to excessive signal degradation from movement or excessive change in spectral densities.

The power estimates (μV2) were found using a fast Fourier transform (FFT) and a 1 second Hamming window with no overlap for Delta (1 – 4 Hz), Theta (4- 7 Hz), Alpha (7 -13 Hz), Beta (13 – 25 Hz) and Gamma (25 – 43 Hz) for all 14 sensor location on the Emotiv headset. In typical EEG studies the number of 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, 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 are used to 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.

Measuring engagement level is one part of determining a player's experience while playing a video game. Pope et al. [46] and Freeman et al. [23] have shown that an engagement index can be calculated by taking the ratio of the (Beta/(Alpha + Theta) [Index 1] EEG bands (see Table 2). Berka et al. [5] was able to show that the engagement index reflected a person's process of information-gathering, visual scanning and sustained attention. Gevins and Smith [24] introduced a different task engagement indicator that looks at the ratio of frontal midline theta activity to parietal alpha locations Frontal Theta/Parietal Alpha [Index 2]. A third index was identified by Yamada [64] that looks at activity at the Frontal Theta [Index 3] sites which indicate increased attention. Kamzanova et al. [31] compared these indices across time-on-task effects and workload manipulation with their findings indicating that there is a difference between tasks that are cued versus uncued tasks.

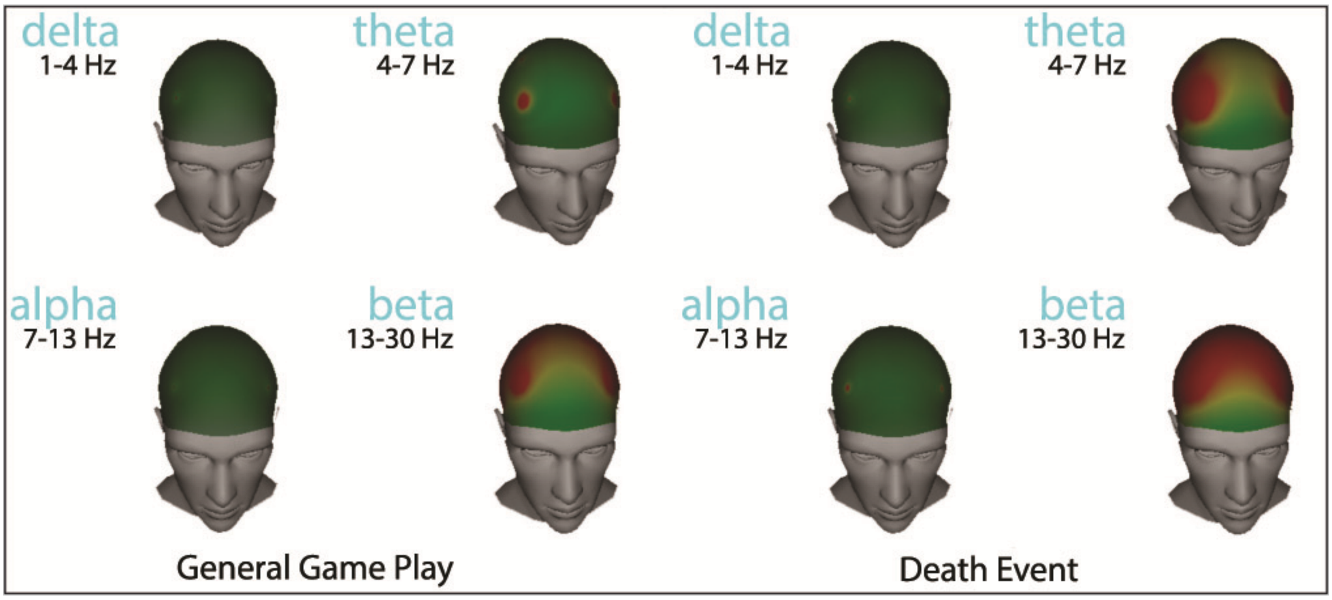

Figure 3: Brain activity during general game play and death events.

Table 2: EEG Indices

Indices	Brainwave Bands	Notes
Index 1	$\frac{Beta}{Alpha+Theta}$	Averaged across all sensor locations [5, 23, 46].
Index 2	$\frac{Theta}{Alpha}$	Average frontal midline theta and average parietal alpha [24, 57].
Index 3	$Theta$	Averaged frontal theta [64].

An example of brain activity during general game play and a death event can be seen in Figure 3. 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 form 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.

Each index calculation produced an engagement level for general game play and death events.

2.5 Results

We completed a repeated-measures analysis of variance assessment (ANOVA) across the 3 indices and general game play and death events from Super Meat Boy. 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 ($F(2,28) = 1755982.48$, $p < 0.001$, partial eta2 = 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 difference in 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.

3. DISCUSSION

3.1 General Overview of findings

Our goal was to assess various engagement indices drawn from the off-the shelf Emotiv during video gameplay. We aimed to ascertain which index is preferable given time for calculation and prediction of game events. Specifically, we used the Emotiv to analyze differences in engagement levels between specific game events (general game play and death events). The primary results were: (a) significant differences were found among the three indices; (b) significantly increased engagement levels were found during death events compared to general game play events when using Index 1 (Beta/(Alpha + Theta)) and Index 3 (Frontal Theta).

3.2 Engagement indices finding

Our findings suggest that when using the Emotiv EEG headset Index 1 (Beta/(Alpha + Theta)) is the preferred algorithm for calculating the engagement levels of players playing video games. Using Index 1 comes with a lower overhead compared to the other two indices. This is primary due to the fact that Index 1 allows the use of global band waves from all the sensor channels that the headset produces, whereas the other two indices require calculations based on data from specific individual sensors. The global band wave approach has another added benefit that it will reduce noise that may come from an individual sensor location when using Index 2 or Index 3. Furthermore, The Emotiv sensors may not have the resolution to support individual sensor measurements that Index 2 requires for calculating engagement levels.

Higher levels of engagement during death events when compared to general game play may not suggest the user is more engaged when their character dies, but rather may reflect that they have entered a more stressful state that has increased their vigilance [5, 31, 64]. Putting thresholds on individual players engagement levels based upon their baseline results would help identify when players have entered a stressful state and identify from there EEG signal when a death event has occurred.

3.3 Limitations and future directions

Our findings should be understood in the context of some limitations. The first is that they 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 small sample size.

Our findings need further validation through straightforward comparison of Emotiv EEG results with those of standard laboratory-based EEG 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 be a valid alternative to laboratory ERP systems for recording reliable late auditory ERPs over the frontal cortices.

While we have found some interesting results, it is important to emphasize that these are very preliminary. Although there are not currently well-established methodologies for examining the impact of game levels on players, there is an increasing body of literature suggesting that game impact can be measured via EEG [37, 50, 51, 52]. Future studies will be needed to expand these results into methodological approaches to quantifying videogame based EEG assessment in general and Emotiv–based EEG assessment of video games in particular.

4. CONCLUSION

We have presented finding from a study aimed at comparing different engagement indices with the use of the Emotiv EEG headset. We also aimed to analyze engagement levels between specific game events (general game play and death events). We were able to find significant higher levels of engagement during death events when compared to general gameplay suggesting a higher level of arousal. Our findings suggest the Emotiv EEG can be used to assess varying levels of engagement as game players experience varying gaming events. Using an averaged band wave from all sensors within Index 1 (Beta/(Alpha + Theta)) provided the best solution as it has lower overhead for implementation along with the benefit of mitigating noise from individual sensor locations.

It is important to note that these findings are based on a fairly small sample size and future studies will be needed to expand these results into methodological approaches to quantifying videogame based EEG assessment in general and Emotiv–based EEG assessment of various games in particular. Nevertheless, these results support the idea that the Emotiv EPOC headset is a low-cost tool that has the potential to assess player experience during game play.

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