Modality Specific Assessment of Video Game Player's Cognitive Workload Using Off-the-Shelf Electroencephalographic Technologies

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Abstract

A growing body of literature has emerged that focuses upon assessment of video game player cognition. Given the growing popularity of video gaming and the increasing literature on cognitive aspects of video gamers, there is a growing need for novel approaches to assessment of the cognitive processes that occur while persons are immersed in video game experiences. Developers need new measuring techniques to assess gamer experience to continue producing high quality games. We assessed various cognitive tasks within gaming environments using an off-the-shelf EEG device. The Emotiv EPOC headset provides a cheap alternative to laboratory grade EEG equipment and gives us the capability to isolate video game events. A significant difference was found among different gaming modalities (Two-Picture Cognitive Task; General Game Play; Death Events) with increasingly difficult cognitive demands. Specifically, beta and gamma power were significantly increased during high intensity events (e.g., Death events) when comparison to low intensity events. Our findings suggest that the Emotiv EPOC headset can be used to differentiate between varying levels of cognitive workload presented while playing video games.

1.0 Introduction

Video games represent an immersive activity that is rapidly increasing in popularity. According to the Entertainment Software Association [1], 72 percent of the general population and 97 percent of teenagers (between the ages of 12 and 17) reported regular playing of video games. Further, video games have been found to be played more frequently and in more locations [2]. A growing body of literature has emerged that focuses upon assessment of video game player cognition [3][4][5][6]. Given the growing popularity of video gaming and the increasing literature on cognitive aspects of video gamers, a growing need is for novel approaches to assessment of cognitive processes occurring while persons are immersed in video game experiences.

1.1 Current Approaches to assessment

Assessment of the player experience, while playing video games, is often a difficult process. Numerous studies exclusively employ subjective response questionnaires to draw conclusions about the user state while immersed in virtual environments [7][8][9][10]. Self-report data, when used in isolation, are highly susceptible to influences outside the participant's own targeted attitudes [11]. The item's wording, context, and format are all factors that may affect self-report responses [12]. Further, questioning the player while they are playing the video game affects their experience during the video game [13]. While asking them after playing the game can lead to missed information and/or false information [14]. Knowledge of the user-state during exposure to the video game is imperative for development and assessment of video game design [15]. Individuals will invariably have different reactions to a given video game, and without an assessment tool that can be employed online, the researcher will experience difficulties in identifying the causes of these differences, which may lead to a loss of experimental control of the research paradigm.

1.2 Psychophysiological assessment of video game experience

Psychophysiological metrics provide a number of advantages over self-report for enhanced assessment of video game experience [16][17]. The psychophysiological signal is continuously available, whereas behavioral or self-report data may be detached from the gaming experience and presented intermittently [18]. The continuous nature of psychophysiological signals is important for several reasons. First, it allows for greater understanding of how any stimulus in the gaming environment impacted the gamer, not only those targeted for producing behavioral responses [19]. It also follows that a break in the gamer's sense of presence is not necessary, because the signal is measured continuously and noninvasively, and as Slater et al. [20] report, it is even possible that psychophysiological measures can be used to uncover stimuli in the gaming environment that cause a break in presence. 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 [21][22][23], varying stress levels [24][25], task engagement [26][27], and arousal [28][29][30] among others. Additionally, multiple channels of psychophysiological data can be gleaned from various sensors continuously, which further increase experimental control by providing a combination of measures, so that one measure alone is not the sole basis for design decisions [31].

1.3 EEG to isolate specific game events

Recent approaches to psychophysiological computing have applied psychophysiological modeling to video games [32]. 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 [33][34]. Salmin and Ravajja [35] 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 brain wave bands as different event occurred during game play. Nacke et.al [36] also showed that EEG data could be used to determine player experience across entire level designs. Using a Half Life 2 mod they measured EEG across three different levels of designed to induce boredom, immersion, and flow. The data showed that there were increased levels of brain wave activity as the player moved across the levels.

Whilst there are many beneficial EEG applications, much of this technology has yet to leave the research lab. One large factor of this is due to the EEG devices. The majority of research and medical EEG devices are expensive, bulky, and require a number of skilled technicians. As technology progresses, the cost and size will continue to decrease. Recently some inexpensive consumer-grade devices have become available. 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. Thus, providing a cheap tool that game developers can use to measure 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 [37][38][39]. Using the EPOC, researchers can detect facial movements, emotional states, and imagined motor movement.

A number of researchers have used the Emotiv EEG recordings with for assessment of cognitive processes. Researchers have investigated different EEG processing algorithms to assess classification of shapes being thought about [40], detection of hand movement intentions on the same side of the brain as the hand [41], classification of positive and negative emotion elicited by pictures [42][43][44], and evaluation of cognitive workload [45].

It is important to note that some have questioned “what” the Emotiv EEG is actually measuring [46], and it is known that the Emotiv sensors detect EMG along with EEG data. Nevertheless, the system has been found to work well on focused thoughts detected in EEG [40][47]. 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 [48] 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.

The current study aimed to assess various levels of gaming experience using the Emotiv EEG. Specifically, we aimed to 1) assess various cognitive tasks within gaming environments; and 2) isolate video game events (e.g., death of a character) using the collected EEG data from the Emotiv Headset**.**

2.0 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. Participants were comparable in age, education, ethnicity, sex, and self-reported symptoms of depression. Table 1 shows a break out of participant demographic information. 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

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. 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. Major events in the game include successfully completing a level and dying. Dying occurs from running into spinning saw blades or falling into fire. As the player progresses through the game the levels get increasingly difficult by adding more saw blades and large jumps. Each leveled is time as 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 [50]. Primary game events used for this study included: General Game Play and Death events. The “General Game Play” was differentiated from “Death events” in that general game play occurred during periods in which the player had not experienced any death events for 1 minute before or after “General Game Play” sampling.

Two-Picture Cognitive Task: Participants were shown a pair of color pictures of a landscape, and were given the evaluative task of identifying any differences between the pair. Unknown to the participants, the pictures were identical.

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.

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 1) 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.

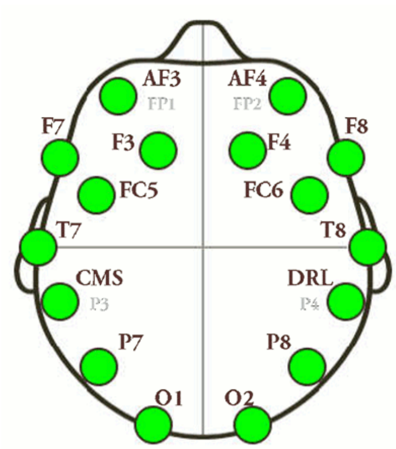

Figure 1: Sensor placement of the 14 data channels in the Emotiv EEG.

2.2 Procedure

Upon arriving at the testing office, the participants were given an informed consent to read and sign. Included in the informed consent was 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 [51]. 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.

To establish base line for each participant a video was played and were told "to relax and try not to think about anything". In the video the screen was blank for 2:00 minutes to establish a minimum brain wave activity. Next, the participants performed the Two-Picture Cognitive Task, in which they compared two pictures to determine the difference between them. This allowed for the establishment of a brain wave signature for basic cognitive processing. This was followed by an additional 1:30 seconds of blank screen viewing to allow the participant to return to a steady state. The participants were then introduced to Super Meat Boy. 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. Upon completion of the 15 minutes the headset was removed.

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. Syncing all video recordings with EEG recording software involved using screen captures before and after every section of the study (baseline video and game play). The screen shots were saved to reference later during the data analysis phase.

2.3 Data Analytics

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

The Emotiv Epoc headset was used to capture the EEG data from each participant. Emotiv TestBench was also used to capture the raw EEG output from the headset. This also allows for the data to be played back at a later date for further study. 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 4 different modalities: 1) baseline—staring at a blank screen; 2) Two-Picture Cognitive Task; 3) General Game Play; and 4) 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 [52][53]. These artifacts can actually be used for further analysis as body movement or other movement can signify engagement [54]. Since we recorded the user while they played we can compare their EEG output to make sure we are not finding one of these artifacts. In the future, these artifacts should be processed and analyzed to help determine possible engagement.

The power estimates (μV^2) were found for Delta (1 – 4 Hz), Theta (4- 7 Hz), Alpha (7 -13 Hz), Beta (13 – 25 Hz) and Gama (25 – 43 Hz) for all 14 sensor location on the Emotiv headset. The average was calculated across all 14 sensors to obtain a global average for each frequency band. Finally the data was normalized with the natural logarithm (ln).

2.4 Results

We completed repeated-measures analysis of variance (ANOVA) assessments on the following modalities: 1) Two Picture Cognitive 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 ($F(2, 28) = 6.213$, $p = .004$, partial eta^2= .18), delta ($F(2, 28) = 4.698$, $p = .01$, partial eta^2= = .14), and gamma ($F(2, 28) = 8.875$, $p = .0001$, partial eta^2= = .23) power estimates was found during the different modalities (See Table 1 for descriptives).

Table 1: Descriptives for the three modalities.

		Mean	Std. Deviation	Std. Error Mean
Two Picture	Alpha	3.167	.066	.012
	Beta	1.592	.126	.023
	Delta	6.999	.014	.003
	Theta	6.997	.014	.003
	Gamma	.409	.232	.042
General Game Play	Alpha	3.033	.183	.033
	Beta	1.800	.407	.074
	Delta	7.000	.000	.000
	Theta	7.000	.000	.000
	Gamma	.300	.466	.085
Intense Events	Alpha	3.219	.202	.037
	Beta	1.717	.232	.042
	Delta	7.008	.034	.006
	Theta	7.001	.027	.005
	Gamma	.756	.451	.082

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 ($t(1, 29) = 2.97$, $p < .006$; see Figure 2). Gamma power was also significantly increased during the Death Event in comparison with the Two-Picture Cognitive Task ($t(1, 29) = 2.99$, $p < .006$; see Figure 4). Interestingly, there were no significant difference between General Game Play and the Two-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 ($t(1, 29) = 2.536$, $p = .01$; see Figure 2). Delta power was also significantly increased during the Death Event in comparison with the General Game Play ($t(1, 29) = 2.438$, $p = .02$; see Figure 3). Further, gamma power was also significantly increased during the Death Event in comparison with the General Game Play ($t(1, 29) = 3.372$, $p = .002$; see Figure 4).

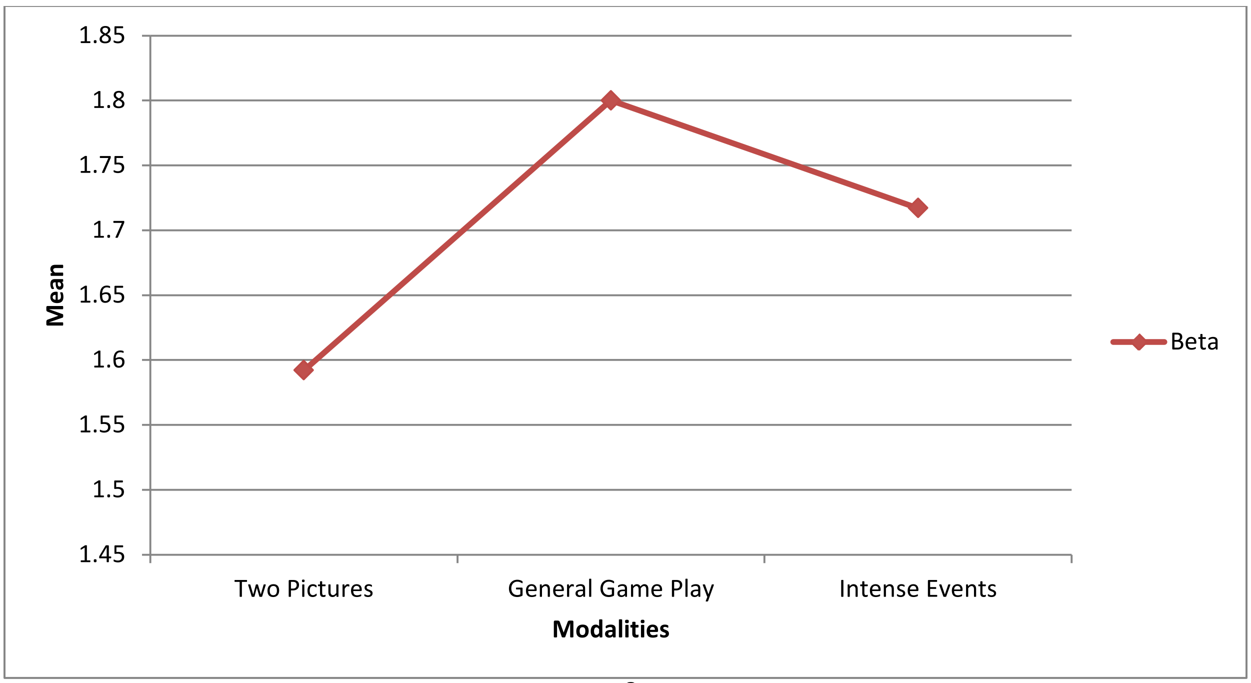

Figure 2: EEG beta power mean values ln[μV^2] for each modality that was tested.

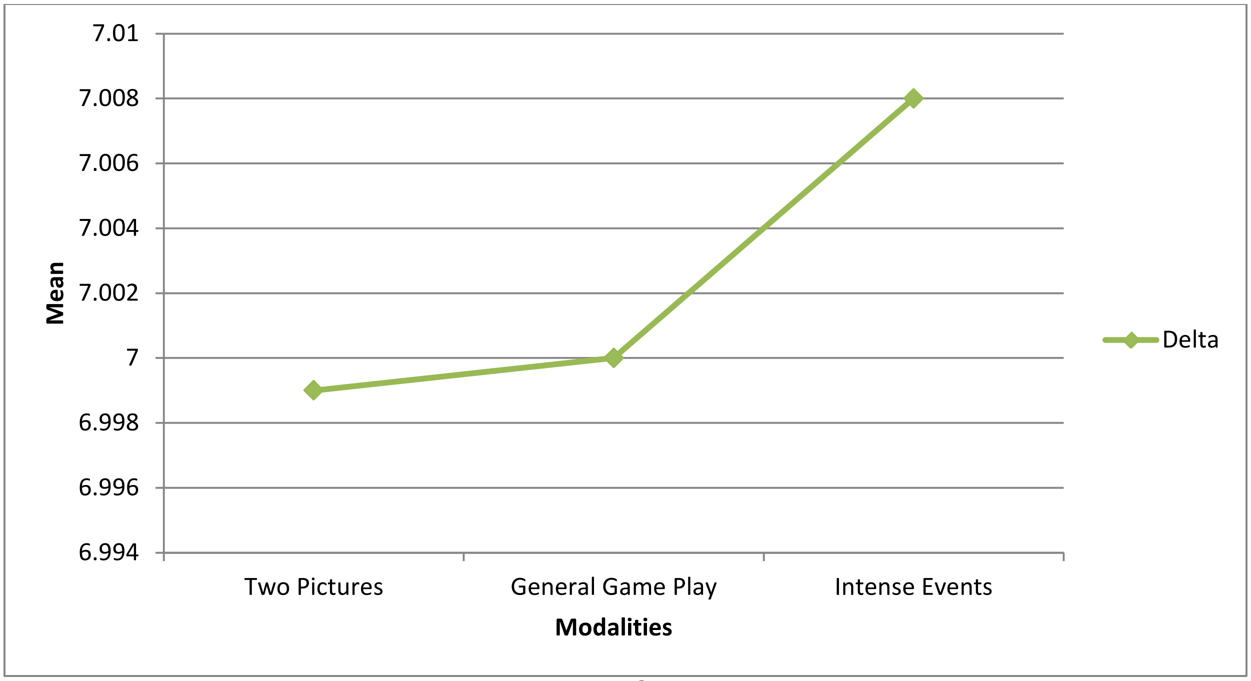

Figure 3: EEG delta power mean values ln[μV^2] for each modality that was tested.

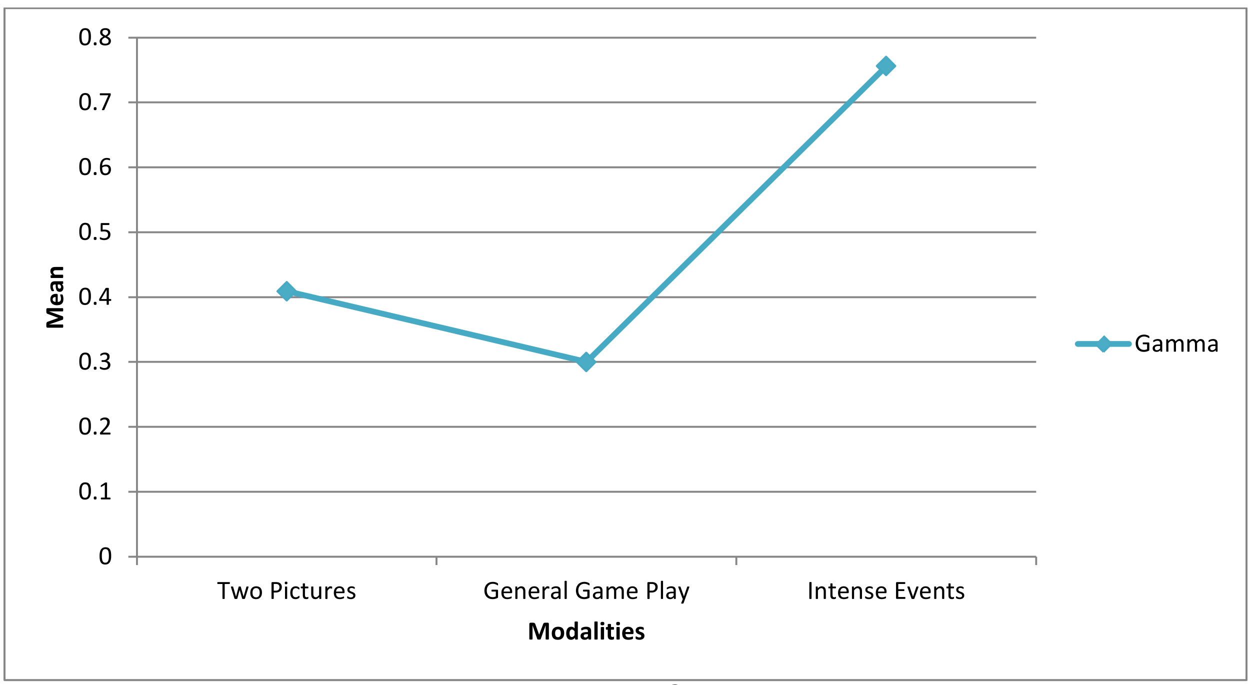

Figure 4: EEG gamma power mean values ln[μV^2] for each modality that was tested.

3.0 Discussion

3.1 General Overview of findings

Our goal was to assess various cognitive tasks within gaming environments using an off-the-shelf EEG device. We also aimed to isolate video game events (e.g., death of a character) using the collected EEG data from the Emotiv Headset**.** 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, delta, 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, delta, 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 and the Two-Picture Cognitive Task.

3.2 Gaming modalities had differing impacts on power estimates

We found that modality type had 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 [55]. 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 [56][57] (Murthy & Fetz, 1992) and during video game play specifically [35]. For example, Salminen and Ravaja [35] found that different events in the platform game Super Monkey Ball 2 evoked oscillatory responses in beta. Likewise, gamma power was significantly increased during the Death Event in comparison with the Two-Picture Cognitive Task. Gamma oscillations have been found to be significantly associated with the brain’s ability to integrate various aspects of a stimulus into a coherent whole. Further, gamma has been found to be involved in a host of other cognitive processes: attention, arousal, object recognition, and top-down modulation of sensory processes [58]. 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 [59][60].

Interestingly, there were no significant difference between General Game Play and the Two-Picture Cognitive Task. We believe that 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.

3.3 Comparison of low intensity gaming events with high intensity events

Comparison of low intensity (General Game Play) gaming events with high intensity (e.g., Death events) using repeated within-subject contrasts revealed that beta, delta, 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. It is interesting that we also found a significant difference for delta power. We could explain this with the nature of the differences between General Game Play and Death events. Death events may require more mental activity for spatial processes. Another possibility is that during the General Game Play the participants presented as drowsy (bored) when compared to Death events. This would also explain the low delta activity in the General Game Play, which was somewhat dull and thus elicited less delta activity. In a study performed by Nacke et al [59], low theta and delta EEG activity were found in more boring levels and high theta and delta EEG activity were found in the more engaging levels.

3.5 Limitations and future directions.

Our 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 [61] 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 we found some interesting results, 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 [36][62][35][63]. 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 in particular.

3.5 Conclusions.

We have presented findings from a study aimed at assessing various cognitive tasks within gaming environments using an off-the-shelf EEG device. We also aimed to isolate video game events (e.g., death of a character) using the collected EEG data from the Emotiv Headset. As our results show we were able to find significant difference in the Beta and Gamma bands between the different modalities (Two-Picture Cognitive Task; General Game Play; Death Events) of game play. We also saw an increase in the power estimates during high intensity game play (e.g., death event) when compared to low intensity general game play. Our findings suggest that the Emotiv EEG can be used to differentiate between varying levels of cognitive workload. 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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