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Modality specific assessment of video game player's experience using the Emotiv ☆

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ABSTRACT

A growing body of literature has emerged that focuses upon cognitive assessment of video game player experience. 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 games. In this study, we assessed various stimulus modalities and gaming events using an off-the-shelf EEG devise. A significant difference was found among different stimulus modalities with increasingly difficult cognitive demands. Specifically, beta and gamma power were significantly increased during high intensity events when compared to low intensity gaming events. Our findings suggest that the Emotiv EEG can be used to differentiate between varying stimulus modalities and accompanying cognitive processes.

1. Introduction

Video games represent an immersive activity that is rapidly increasing in popularity. According to the Entertainment Software Association [1], 72% of the general population and 97% 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 [3–6]. 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 impact of the video game immersion on the user is often difficult. Numerous studies exclusively employ subjective response questionnaires to draw conclusions about what the participant is experiencing while immersed in virtual environments [7–10]. 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

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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 [21–23], varying stress levels [24,25], task engagement [26,27], and arousal [28–30] 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 interactive 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]. Beta rhythm has been shown to increase with attention and vigilance in general [35,36] and during video game play specifically [37]. Salmin and Ravaja [37] 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. [38] 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. 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 [39]. Beta activity, gamma activity and perceived action possibilities have been found in studies of virtual gaming environments [40,41].

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. 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 [42–44]. Using the EPOC, researchers can detect facial movements, emotional states, and imagined motor movement.

A number of researchers have used the Emotiv EEG recordings for assessment of cognitive processes. Researchers have investigated different EEG processing algorithms to assess classification of shapes being thought about [45], detection of hand movement intentions on the same side of the brain as the hand [46], classification of positive and negative emotion elicited by pictures [47–49], and evaluation of cognitive workload [50].

It is important to note that some have questioned "what" the Emotiv EEG is actually measuring [51], and it is known that the Emotiv sensors detect EMG along with EEG data. Nevertheless, the system has been found to work well for detecting events when the participant is told to picture various stimuli [45,52]. 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. [53] 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 the impact of various stimulus modalities on participants using the Emotiv EEG. Specifically, we aimed to (1) assess the impact of various stimulus modalities on participants; and (2) isolate video game events (e.g., death of a character) using the collected EEG data from the Emotiv Headset.

2. Methods

2.1. Participants

EEG data was collected from 30 healthy participants (66% female, mean age = 20.87, range 18–43). Participants were recruited from undergraduate 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 min, 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 [54] 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 level is timed 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 [55]. 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), 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 min before or after "General Game Play" sampling.

2.2.2. 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.

2.2.3. 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 h per week. The participants were also asked if they would classify themselves as "gamers", 33% responded as being part of this category.

2.2.4. 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 Fig. 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 128 Hz, the bandwidth is 0.2–45 Hz, and the digital notch filters are at 50 Hz and 60 Hz.

2.3. 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 in. 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 [56]. 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 min to establish a minimum brain wave activity. Next, the participant completed two tasks: the Two Picture Cognitive Task and Super Meat Boy task. Task presentation order was counter-balanced across participants. After the initial task (either Two Picture Cognitive Task or Super Meat Boy) the participant was presented with 1:30 s of blank screen viewing to allow the participant to return to a steady state. During the Two-Picture Cognitive Task they compared two pictures to determine the difference between them. This allowed for the establishment of a brain wave signature for basic cognitive processing. 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 min 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.

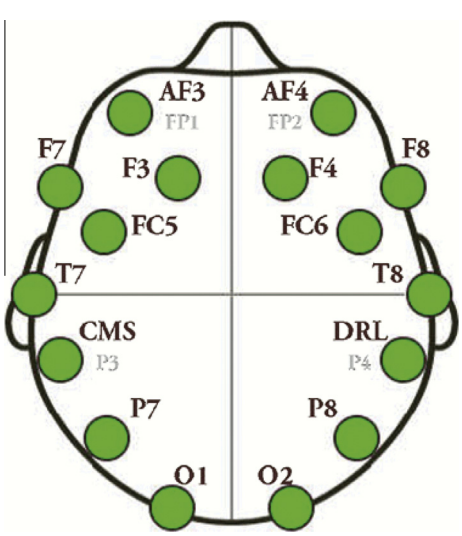

Fig. 1. Sensor placement of the 14 data channels in the Emotiv EEC.

2.4. 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 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 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 [57,58]. These artifacts can actually be used for further analysis as body movement or other movement can signify engagement [59]. The EEG artefact data was annotated as artefact 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 [60], 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. [61] 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 (μV^2) were found using a fast Fourier transform (FFT) and a 1 s 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 typically 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 1000 Hz. Given that the Emotiv has only 14 channels and the data sample rate is only 128 Hz, the average was calculated across all 14 sensors to obtain a global average for each frequency band. Following Anderson et al. [50] 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. Finally the data was normalized with the natural logarithm (ln).

2.5. 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. Given that epochs were 0.85 s, 3.5 Hz is the lowest frequency that can be estimated with some reliability, since it still contains 3 periods. As a result, estimates of power for the delta and theta band were not included because of their low reliability (see Table 1). Results from the repeated measures ANOVA using modalities as a within-subject factor for dependent variables 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 eta2 = .18), and gamma ($F(2,28) = 8.875$, $p = .0001$, partial eta2 == .23) power estimates was found during the different modalities.

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 Fig. 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 Fig. 3). 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 Fig. 2). 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 Fig. 3).

Table 1
Descriptives for the three modalities.

	Mean	Std. deviation	Std. error mean
Two picture			
Beta	1.592	.126	.023
Gamma	.409	.232	.042
General game play			
Beta	1.800	.407	.074
Gamma	.300	.466	.085
Intense events			
Beta	1.717	.232	.042
Gamma	.756	.451	.082

3. Discussion

3.1. General overview of findings

Our goal was to assess various cognitive tasks within gaming environments using an off-the-shelf EEG devise. 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 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 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 [62]. 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 [35,36] and during video game play specifically [37]. For example, Salminen and Ravaja [37] 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

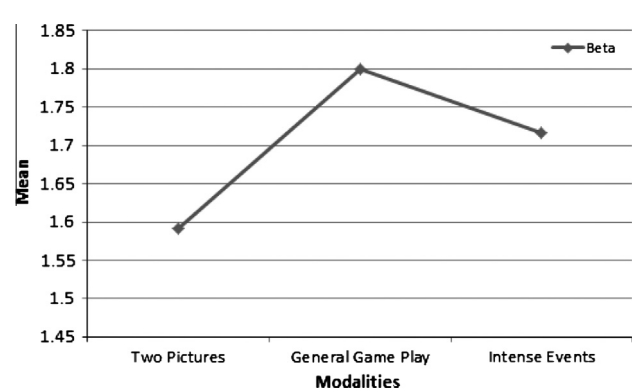

Fig. 2. EEG beta power mean values ln[μV2] for each modality that was tested.

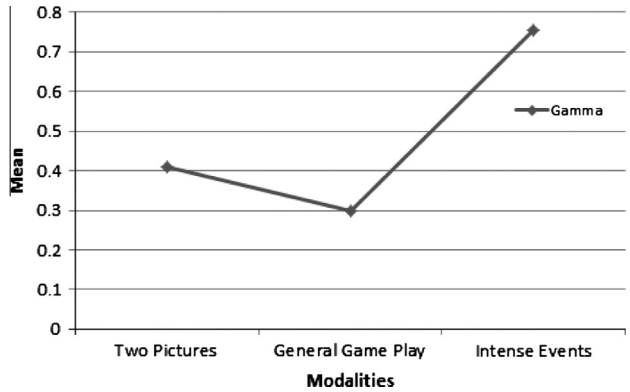

Fig. 3. EEG gamma power mean values ln[μV2] for each modality that was tested.

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 [39]. 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 [40,41].

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.

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.

3.3. 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. [63] 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 [38,64,37,65]. A further limitation is that we only compared two tasks in this study; and only one of these tasks was a video game. 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.

4. Conclusions

We have presented findings from a study aimed at assessing the impact of various stimulus modalities on participants using the Emotiv EEG. 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 assess differences in frequency bands when persons are experiencing various stimulus modalities using off-the-shelf EEG-based gaming technology. 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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