Psychophysiological Data Acquisition in a Virtual Environment

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Abstract

The purpose of this research was to develop a method for psychophysiological data acquisition (i.e. EEG) while the subject was immersed in a virtual environment. We specifically studied learning the neural conditions of a First-Person Shooter (FPS) game. The EEG data revealed new activity that tracked target difficulty (91%, p = .01), and that is typical of reinforcement learning (69%, p = .02).

Author Keywords

Digital Games, Electroencephalogram (EEG), Error Related Negativity (ERN), Even Related Potentials (ERP), Reinforcement Learning

1. Introduction

Andreassi (2006) defines psychophysiology as the study of the relations "between psychological manipulations and resulting physiological responses measured in the living organism." The effect that digital games have on a player's emotion and attention are examples of physiological responses to psychological manipulation. Psychophysiological measurements therefore can be used to quantify a player's experiences in a digital game. In Sweden at the Blekinge Technical Institute, the GameScience Lab has offered two classifications of psychophysiological measurements. First, context independent data is "data that can be acquired with no regard to context or content of the game." Second, context dependent data is "data that requires knowledge about key game elements or game values." Our study will focus on the second approach using electroencephalography (EEG), to obtain electrical brain wave data elicited by key events in the game.

Psychophysiological measurements represent an improvement over previous methods for recording player experiences, (i.e. the questionnaire method) Kennerly (2003) points out one flaw of the questionnaire method. He proposes that players do not accurately report their own behavior in questionnaires, but rather that a player's description is a distorted report that reflects the influence of psychological and social forces. This phenomenon is referred to as "subconscious distortion." An additional disadvantage of questionnaires is "perceptive discrepancy" that occurs after the event, giving participants the opportunity to forget important details about their experience. Automated "logging", the monitoring and recording of player-related activities during the game may circumvent both these problems.

Existing video game software does not easily accommodate real-time integration with EEG recording. A solution requires the modification of video game source code as well as software development kits that allow access to psychophysiological data acquisition hardware from custom applications. The alteration of video game source code for the integration of logging capability into digital games requires a skilled digital game computer programmer.

The goal of this study was to integrate the EEG data with the execution of a digital game. The purpose of this integration was to measure EEG data time-locked to specific events in a first person shooter (FPS) game. These EEGs may eliminate the obscuring effects of subconscious distortion and perceptive discrepancy present in survey studies. Instead researchers will be left with a record of pre-selected events that occur in the digital game followed by the brain activity associated with these events.

We hope to implement this technique to record error-related negativity (ERN) responses to artificial intelligence (AI) player death events in a FPS game. The FPS game we develop will incorporate the violation of a learning condition that we expect will elicit an ERN response. The technique we use is advantageous for this experiment because our data will record the time of AI player deaths and the EEG data will have time markers, allowing us to determine the player response in the EEG data when an AI player death occurs.

2. Literature Review

Gehring, Coles, Meyer, and Donchin (1990) first reported the observation that an ERN appears selectively on error trials in choice reaction time experiments. The ERN takes the form of a sharp, negative-going deflection of up to 10 µV in amplitude and is largest at electrodes placed over the frontal central midline of the scalp. Its onset is shortly after the onset of electromyographic (EMG) activity detected in the limb that is about to make an error, and it peaks about 100 ms following its onset. In the same year, Falkenstein, Hohnsbein, Hoormann, and Blanke (1990) confirmed this observation, independently.

Gehring, Goss, Coles, Meyer, and Donchin (1993) reveal characteristics of the ERN that make it possible for subsequent studies to detect this phenomenon. In their study, Gehring et al., varied the speed and accuracy requirements placed upon the subject to create three speed-accuracy conditions: a speed condition, an accuracy condition, and a neutral condition. Subjects received financial penalties and bonuses in such a way as to emphasize speed and/or accuracy. The authors found that the ERN increased in amplitude from speed to neutral to accuracy conditions confirming their theory that the ERN is proportional to the degree to which accuracy is important to the subject.

Additionally, subjects of the study gave their response to stimulus by squeezing zero-displacement dynamometers with either their left or right hand. Gehring et al. found the pressure of the subject's squeeze on erroneous responses to be inversely proportional to the amplitude of the ERN on the error trial. When the record of a subject's response to the same stimulus was analyzed over time, the study showed that the amplitude of the ERN on an error trial was proportional to the probability that the error would be followed by a correct response to the same stimulus on the following trial. An additional observation related to the subject's responses was that the amplitude of the ERN on an error trial was inversely proportional to the speed of the subject's response to the same stimulus on the immediately following correct trial. Taking these observations into consideration, the authors were able to conclude that the ERN "provides input to different compensatory systems … that can inhibit and correct the error as it occurs, as well as systems that control response strategies, whose effects are evident on future trials."

Finally, the timing of the ERN (at the time of an erroneous response) requires that the information the error-detection system uses to determine the accuracy of responses be available when the response is initiated. This requirement prevents the error-detection system from functioning based on sensory or proprioceptive information, but is consistent with models in which the brain retains a neural record of its motor commands which are used for the functioning of the error-detection system (Angel, 1976). These observations of Gehring et al. (1990, 1993) make it possible to recognize the ERN in psychophysiological data.

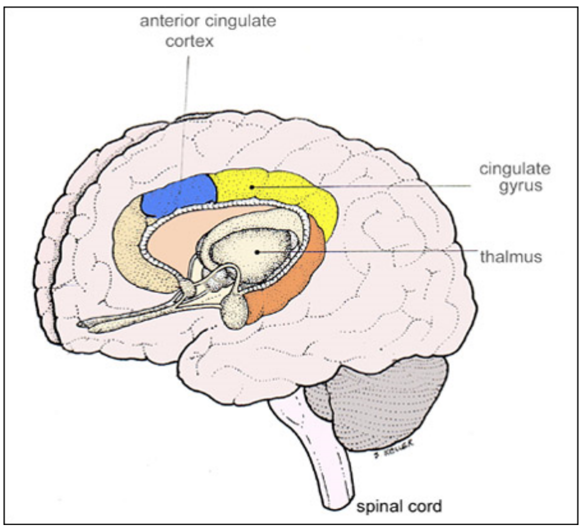

Figure 1: Anterior Cingulate Cortex (Cromie, 2004)

In a study by Miltner et. al. (1997) the ERN was measured while subjects performed a time estimation task. The study found that following feedback indicating an error, the event-related brain potentials (ERPs) became more negative. Equivalent dipole analysis procedures suggested a source for the negative scalp potential in or near the anterior cingulate cortex (ACC) indicated in Figure 1. The authors noticed a similarity between this feedback error-related negativity (the feedback ERN) and the response ERN. This similarity led the authors to propose that both ERNs were associated with the same neural and cognitive error detection process.

Nieuwenhuis et. al. (2004) noted that since the report of Miltner et. al. (1997) much progress has been made in understanding the neural basis and functional significance of the feedback ERN due to empirical studies inspired by the reinforcement learning theory of the ERN (RL-ERN theory). Nieuwenhuis et. al. (2004) outline four predictions of the RL-ERN theory.

The first prediction of the RL-ERN theory holds that the ERN reflects the outcome of an evaluation of events along a good–bad dimension, suggesting that the ERN should be sensitive to any performance-related feedback indicating favorable or unfavorable outcomes. Nieuwenhuis et. al. (2004) and Gehring and Willoughby (2002) were able to contribute the observation that the ERN evaluates events along an abstract good-bad dimension rather than in terms of correctness or gain/loss. Additionally, according to the RL-ERN theory, the ERN system can base its good–bad evaluations on different sources of information, and the choice of source can be determined by the context in which the information is provided. Additionally, Holroyd et. al. (2004) suggested on the basis of experiments conducted by Yeung and Sanfey (2004) that it might be possible that the monitoring system responsible for the error detection process scales the variance of possible outcomes so that the extreme outcomes are weighted equally irrespective of their absolute magnitude.

The second prediction of the RL-ERN theory reviewed by Nieuwenhuis et. al. is that a more negative ERN signal is elicited when the monitoring system has to revise its reward expectations for the worse. This is indicated graphically in Figure 2. (Notice that the y-axis is inverted.) The feedback ERN was in amplitude elicited when the subject revised his/her expectation for the worse. The theory further predicts that the amplitude of the ERN is proportional to the size of the prediction error, making the amplitude of the feedback ERN dependent on the difference between the actual outcome of a trial and the expected outcome of that trial. The results of two studies [Holroyd and Coles (2002) and Nieuwenhuis, Ridderinkhof, et. al. (2002)] indicate that ERN amplitude tracks the prediction error on a trial-to-trial basis. Holroyd et. al. (2002) was able to rule out the possibility that the feedback ERN is sensitive to the absolute magnitude of the reward.

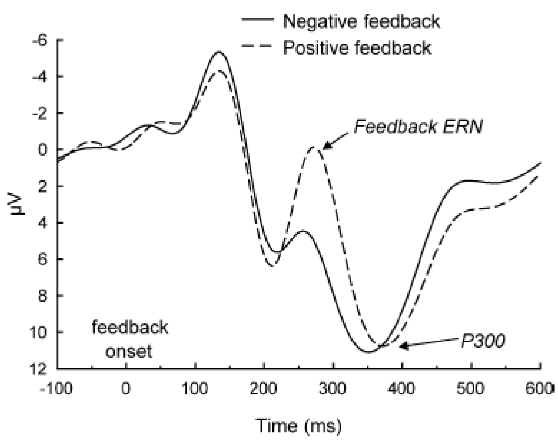

Figure 2: Feedback ERN Potential (Nieuwenhuis, 2004)

Additionally, the RL-ERN theory predicts that the ERN is elicited following the earliest predictor of negative outcome. In accordance with this prediction, Holroyd and Coles (2004) [later verified by Nieuwenhuis et. al.(2004)] showed that during the initial stages of learning the ERN is large following the feedback and absent following the response. As the predictive value of the response is learned however, the ERN propagates back from the feedback to the response. In cases where the mapping to the response is randomly determined and hence cannot be learned the ERN remains invariably high following the feedback, and does not propagate back to the response.

The final prediction of the RL-ERN theory is the generation of the ERN in the anterior cingulate cortex (ACC). All studies reviewed by Nieuwenhuis et. al. are consistent with this final prediction.

3. Methods

In our study, we developed a first person shooter (FPS) digital game. The game was developed using the Torque Game Engine Advanced. The game implemented a 3 x 2 design that had three artificial intelligence (AI) targets for the player to fire upon and two reinforcement contingencies (Table 1). Our two contingencies were differentiated by the level of difficulty for the player to kill each target. The three AI targets had a difficulty hierarchy in which each target was progressively more difficult to kill. All three targets were soldier models in different colors. The red soldier was the easiest, the white soldier was moderate, and the blue soldier was the most difficult to kill.

Type	Red	Alternate Red	White	Blue	Alternate Blue
Hits to Kill	1	10	5	10	1
Appearance in Learning	100%	0%	100%	100%	0%
Appearance in Test	70%	30%	100%	70%	30%

Table 1: Design Matrix

Learning Phase

In the first stage of the experiment subjects played the FPS game in order to learn the target difficulty. This allowed the user to establish an expectancy by learning how difficult it was to eliminate each target. The test subject was given unlimited ammo and health in order to complete the task successfully. In this phase there were 60 trials (20 trials for each target) and the AI targets were encountered individually in a random order. The following AI would not spawn until the preceding AI was eliminated.

Test Phase

In the next stage of the experiment, the contingencies were applied. The two contingencies had opposite difficulty hierarchies. The reinforcement contingencies were set up on a 70/30 basis. The thirty percent violation of this expectancy was sufficient enough to trigger the ERN from the anterior cingulate cortex (ACC). For this portion of the experiment, there were 180 trials (60 trials for each color, 15 of the 60 with alternate health values for red and blue) in the game with each trial containing each of the five different AI's (Table 1).

Incorporation of EEG

Electroencephalography (EEG) was used to measure event related potentials (ERP) associated with reinforcement learning. Our setup received information from the game data and signals a trigger in the EEG software that indicated the moment an AI was terminated. An off signal was sent when the new soldier spawns or the player completed a round of the level.

4. Results

Target Difficulty

The first analysis examined the influence of target kill difficulty on the ERP. As seen in Figure 3, target difficulty was associated with a linear decrease in ERP amplitude over the central parietal and lateral frontal regions of the scalp (91%, p = .01).

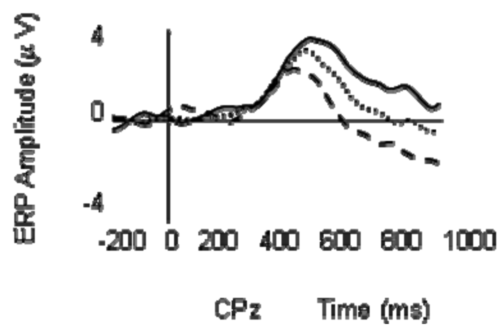

Figure 3: ERP amplitude of target difficulty (solid = red target; dotted = white target; dashed = blue target)

Expectancy

The expectancy violation had three effects on the ERPs. Between 0 and 200 ms after the kill, the alternate red target elicited a medial frontal negativity (MFN) over the frontal-central region of the scalp. However, the MFN was nearly absent for the alternate blue target (Figure 4; 69%, p = .02).

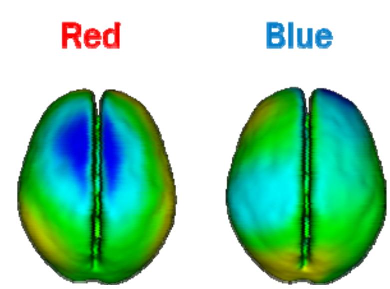

Figure 4: Medial Frontal Negativity in the first 200 ms

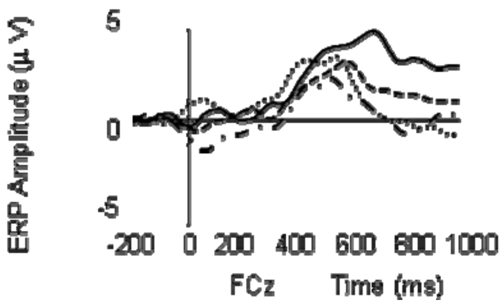

Figure 5: ERP Amplitude over the FCz electrode (dash dot = a. red target; dotted = blue target; solid = a. blue target; dashed = red target)

Beginning around 500 ms after the kill, the alternate red target was associated with slow wave activity over the left central-parietal and frontal-polar regions. In contrast, the alternate blue target elicited slow wave activity over the frontal-polar region (Figure 6; 78%, p = .001).

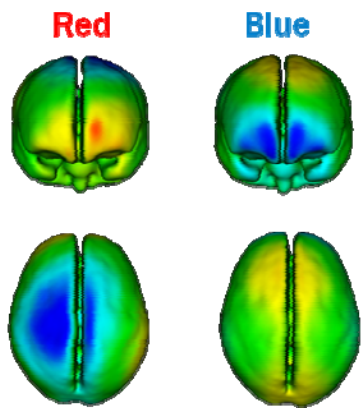

Figure 6: Slow Wave 500-1000 ms

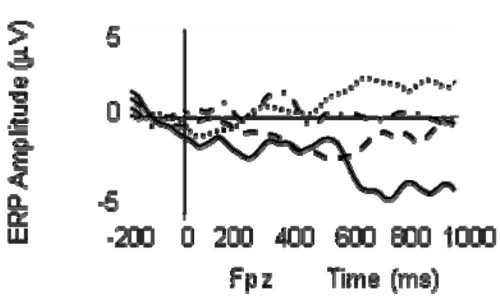

Figure 7: ERP Amplitude over the Fpz electrode (dash dot = a. red target; dotted = blue target; solid = a. blue target; dashed = red target)

5. Discussion

The purpose of this study was to integrate a digital game with EEG recordings in such a way that recordings of neural activity could be time locked to player-related activities in the game. We found that the ERPs of the subjects in our experiment differentiated between the levels of difficulty to kill the three bots in our game. Additionally, we found a medial frontal negativity (MFN) response to the elimination of an alternate red target, while the elimination of an alternate blue target failed to elicit such a response. This result is expected from current knowledge of the MFN. An alternate red kill, which is a negative outcome, is expected to elicit a MFN; an alternate blue kill, a positive outcome, does not have the same expectation. Finally, our study revealed previously undocumented slow wave activity associated with the elimination of the alternate targets. The slow wave findings for the alternate blue target was consistent with many previous positive reinforcement learning studies done on animals.

Our study offers future ability of incorporating a system that integrates the recordings of an EEG and the activity of a player in a virtual environment. A future goal of this research may include the study of the slow wave findings for the red target violation which is still unexplained. However, a broader goal may be to study other psychological phenomenon in virtual environments.

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