Interacting with Multiple Game Genres using Motion Onset Visual Evoked Potentials

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***Abstract*— Motion Onset Visually Evoked Potentials (mVEPs) allow users to interact with technology using non-visually fatiguing stimuli in a Brain Computer Interface (BCI). This study employs mVEP in an onscreen controller and evaluates players' ability to use mVEP for online gameplay with games from three different genres namely action, puzzle and sports. The onscreen controller consists of five mVEP stimuli that are presented as buttons to allow the participant to choose from five different actions in each game. The performance was assessed based on online BCI accuracy and game score for each game. Results indicate that the players could control the games with an average online accuracy of 71% (5 class classification chance accuracy is 20%). The results also suggest that the use of the mVEP controller with a detailed environment and stimulating feedback in the form of an action game helped to attain the highest online accuracy (75%).**

Keywords*— Brain Computer Interface; Games; Motion onset visual evoked potentials; Controller; Genre.

I. Introduction

Traditional computer games employ a variety of high precision control methods for example joysticks, gamepads, motion controllers and touch controls. In recent years the emergence and player acceptance of new control methods in computer games has become common with major hardware manufactures releasing new control techniques in order to attract new consumers to their products and gain a competitive edge over competitors through innovation. Brain computer interfaces have recently been used as a control device by several commercial systems for controlling computer games [1] [2] and represent a highly innovative and exciting new control systems for games.

Brain-computer interfaces (BCIs) have the potential to enable individuals to control and interact with devices and technology using directly measured brain activity [3] [4] [5]. An electroencephalography (EEG) based BCI measures voltage fluctuations resulting from ionic current flows within the neurons of the brain via electrodes placed upon the scalp and translates these signals into commands for a program to execute [6]. Recently there has been interest in the application of BCI's for able-bodied users across a number of application domains such as the automotive and entertainment industries [7]. Movement-free interaction with computer games has become increasingly popular in BCI research studies [9] [10] as games offer engaging environments to test BCI paradigms. In recent years BCI based computer games have become increasingly more advanced; utilizing 3D environments, multiple user objectives and hybrid control systems which incorporate both conventional input devices and multiple BCI techniques [8] [9].

Visual Evoked Potentials (VEP) represent an electrical potential recorded after a subject is presented with a type of visual stimulus and have been used extensively in BCI interfaces for computer games. There are several types of VEPs. Steady-State Visually Evoked Potentials (SSVEPs) use potentials produced by exciting the retina using visual stimuli modulated at certain frequencies. SSVEPs stimuli are often elicited from alternating checkerboard patterns [11] and at times simply use flashing images [12] [13]. Another type of VEP used with applications is the P300 evoked potential. The P300 event-related potential is a positive peak in the EEG that occurs at roughly 300ms after the appearance of a target stimulus (a stimulus for which the user is attending or seeking) or oddball stimuli [13].

Recently however BCI studies [17] [18] have focused on VEPs that do not incorporate such alternating stimuli. Motion-onset Visual Evoked Potentials (mVEP) is a promising paradigm for VEP BCI due to its large amplitude, low inter- and intra-subject variability and the use of elegant and simplistic stimuli to elicit an mVEP. This paper focuses on assessing mVEP as part of an on screen games controller across a range of computer games genres.

Visual evoked potentials have been used in a wide range of game genres. For example a Simple action games to control a characters balance. In "MindBalance" [14] a player must balance an onscreen avatar across a tightrope using SSVEP symbols. P300 event-related potentials have also been widely used in VEP BCI's. For example in the "Mindgame" [15], a player cuts down trees within a 3D game board. The player's task is to strategically control the avatars path from tree to tree. The player must choose the quickest or shortest route between the trees as the players "confidence" or the measure of the quality of the P300 affects the number of steps the avatar takes between trees.

SSVEP has recently been used as an onscreen control interface for a commercial product; the "intendiX-SOCI" [16] by g.tec. The system uses SSVEP on an onscreen module that allows

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people to control different games. Users can send commands to the game just by paying attention to different items on the monitor, the system can also detect the “no-control” state in which the user is not paying attention to any stimulus. This system is a good example of how a commercial BCI system can use an onscreen control interface to control a game.

As flash or pattern reversal VEP based BCI stimuli use high contrast or bright luminance of visual stimuli they can cause visual fatigue on the BCI user over a relatively short period of time. It is therefore important to consider these factors given knowledge about the end use of BCI as many of these VEPs depend upon environments that are have good target contrast and free from fluctuant luminance such as a user’s home or a clinical bedside. In contrast mVEP is elicited entirely by the motion behavior of the visual object and is not sensitive to the luminance of the object or the area around it [17].

MVEP incorporates neural activity from the dorsal pathway of the visual system, which allows more elegant visual stimuli than flash or pattern reversal BCI stimuli (P300 and SSVEP) [17]. Among all visual motion related VEPs mVEP displays the largest amplitudes and the lowest inter- and intra-subject variability’s rendering it suitable for use in a BCI application. Motion-onset VEP is typically composed of three main peaks: P1, N2 and P2. The negative peak (N2) is motion specific with a latency of 160-200ms. The positive P2 peak is increased with more complex visual stimuli and has a latency of around 240ms. These clear and robust temporal features make mVEP a promising EEG component for BCI.

The first notable use of mVEP was within a simple testing BCI environment [17] where a virtual keyboard was used to enable the recording of data from a subject in both offline and online testing. The subject gazed at the desired onscreen button (an mVEP symbol); the brief motion of the symbol (a bar moving from left to right) elicit the mVEP. The EEG data segment taken was aligned to the motion onset of the chosen target which contains prominent motion related VEP features. N2 and P2 components of mVEP from temporo-occipital and parietal electrodes are selected as salient markers of brain responses to the attended target. By averaging aligned mVEP signals from multiple trials for each moving object, the time-locked response of the attended target is enhanced. The stimulus producing the largest N2/P2 component is identified as the intended target. Besides a simple feature extraction of N2/P2 area calculation, the widely used stepwise linear discriminant analysis (SWLDA) in a P300 speller was adopted to assess the target detection accuracy of a five-class mVEP BCI. Within this trial a mean of 98% accuracy was achieved when averaging over 10 trials using 15 subjects [17].

mVEP has also been used within n200 spelling applications [18]. The n200 speller uses the same rectangular symbols used in [17], however in this study the symbols were incorporated within a matrix of 36 virtual onscreen buttons (much like the P300 speller). The user was required to focus their attention toward the button labelled with the letter to be communicated. The computer then determined the target letter by identifying the attending row and column respectively. Ten users had a mean accuracy of 91% using a single channel and an average of 4.1 trials compared to the P300 speller using a single channel which achieved a mean accuracy of 72%.

Before conducting this research a pilot study evaluating the paradigms usage within the three games was conducted [19]. This study employed mVEP for brain controlled computer games and evaluated players’ ability to use mVEP for online gameplay with games from three different genres namely action, puzzle and sports. The performance was assessed based on offline and online BCI accuracy and game score. The results indicate that the players could control the games with reasonable online accuracy (65% average for 5 class classification, with an average training accuracy of 74%). The study consisted of a single session where the participants where trained initially in a separate training game environment and then tested within the three games. The buttons in this study were also contained within the game environment [Fig. 1], this meant that the area around the stimuli in which the user would be focused may have distracting visuals or movement.

Fig. 1: mVEP symbols inside the game environment several subjects commented upon movement in the background distracting them when playing the games. In this instance the characters where moving behind the symbols.

In this paper we present results based on improvement to three aspects of the pilot study, namely:-

1. This study focuses on training and testing participants in the same game environment, where each session is dedicated to one game genre.
2. This study involves locating the stimuli in an onscreen control space with white background.
3. The pilot study only allowed players limited time to actually play the games (8 control instances), this study allows the player 24 control instances to achieve the highest score.

With improvements made to the experimental paradigm, the objectives of this study were to create BCI games that test the mVEP paradigm across several game genres. Several enhancements were made to the games from the initial study including the removal of visual destractions around the stimuli, testing over multiple sessions to avoid user fatigue and extending gameplay sessions to provide players with more time to learn the gameplay mechanics.

II. Methods

To test the system three sessions were conducted each testing a separate game. The order of the games was randomized to prevent the possible impact of BCI habituation within the results. The sessions consisted of three BCI recording periods; training in the game, testing accuracy in the game with online feedback where commands are dictated within the game and playing the game with online feedback (where the user is free to play and use any command deemed necessary).

A. Visiual stimuli games conrtoller

The visual stimuli and game environment were displayed on a 22 inch LCD monitor with a 60Hz refresh rate. Visual stimuli where displayed on the white on screen bar with the game environment below them. Each symbol on the onscreen HUD was a small rectangle of 1.24° by 0.76° visual angle. The rectangles when active contain a red vertical line with a 0.66° visual angle appearing in the right side of the vacant rectangle which moves leftward at a velocity of 3.10° before it disappears (this process of motion took 140ms).

The timing scheme of the stimuli followed the scheme presented in [17] yet was significantly shorter with a single block consisting of 5 trials taking 8 seconds as opposed to 15 trials in a block taking 24 seconds [17], when a block is complete each symbol within the block will have moved 5 times (one for each trial). In a trial each symbol is activated once, this is randomly designated with no overlap. The stimulus onset asynchrony (SOA) between two motion stimuli is 200ms.

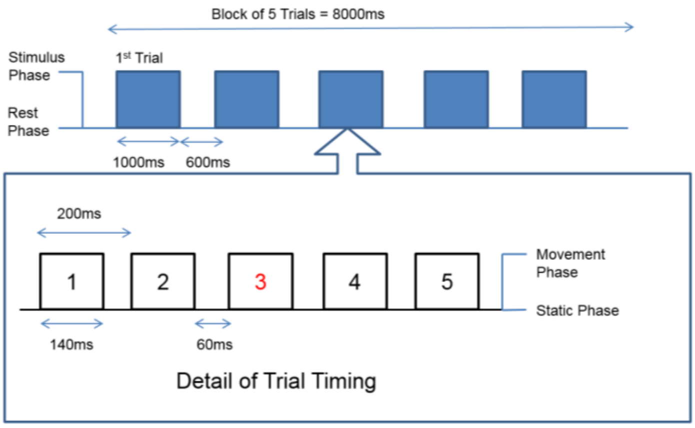

Fig. 2: The timing protocol of one data acquisition period (one block): each block consists of 5 trials. Each trial is subdivided into five stimulus periods dedicated to the five virtual buttons respectively. SOA (stimulus-onset asynchrony) was 200ms. The motion stimuli indicating the five buttons appear in random order, with one button (button 3 in this case) designated as the target. This is based on the timing paradigm proposed in [17].

B. Training

Within each training stage the player was instructed to concentrate on the stimuli with the target displayed below it. The target was indicated by an arrow pointing toward the correct symbol in each game during both the training and online testing stages of the games. The arrow was placed below the stimuli so the player could identify the correct command and then concentrate on the stimuli above to carry out the correct command.

Each trial consists of each symbol moving for a period of 140ms then a static phase of 60ms, after which the next randomly selected stimuli is initiated. This is repeated until all 5 symbols have completed their animation (therefore lasting 1,000ms). Fig. 2 shows the timing scheme used within the study. For offline training each run lasts approximately 8 minutes and consists of 30 blocks with each block containing 5 trials each. Using the data collected in each training session the system is able to identify the correct parameter data for use in the three games.

C. Testing

After collecting training data a classifier was trained on the data. The parameter data and classifier was then tested online in both a BCI accuracy test and a test in which the player plays the games.

Three games of contrasting genres were developed, an action game, a puzzle game and a sports game. Each game contained the same stimuli placed on the mVEP control bar. The mVEP control bar consisted of the symbols being placed on the in game cameras GUI (Graphical user Interface). Within games this type of GUI is referred to as a Heads Up Display (HUD). A HUD in typical video games shows the player information about their state in game for example health, points or time. Within these games presented here the HUD displays the stimuli the player needs to use to control the games. The mVEP HUD remains the same throughout all games, giving the player a consistent screen position to concentrate on when in a control instance. The HUD also keeps the training, testing and playing stages of the game similar by keeping the on screen stimuli on the same background throughout.

1) Online Accuracy

The online accuracy test consisted of 40 blocks within each game. This lasted approximately ten minutes. This stage allowed us to gauge the online accuracy of the system while playing each of the three games.

In this stage of the sessions the arrow guides the subject to the target stimuli and online feedback is provided based on real time detection of the user's response. Within the bowling and puzzle games a ball dropping from below the chosen stimuli represents the visual feedback. In the bowling game the ball is initially placed by the player in one of five positions [Fig. 3]. In the puzzle game the ball drops from one of five tubes below the stimuli. The action game gave more stimulating feedback with an on screen character falling over as if he was shot. The player's ability to control the game via the stimuli was recorded and an online accuracy result established (percentage correctly classified out of forty).

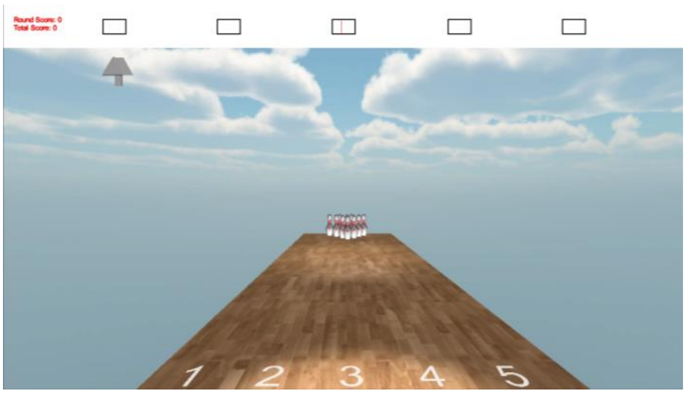

Fig. 3: The mVEP HUD within the bowling game. The arrow detailing what stimulus the player should be concentrating on is below the first stimuli. The 3rd stimuli is currently active with the red bar being approximatley mid-animation.

2) Game Testing

Within game testing section of the session the player was asked to simply play the game using their basic knowledge of the games mechanics to achieve the highest score possible. Each game had 24 control instances allowing each of the scores for each genre to be compared. In each game during the control period the symbols are placed on the mVEP HUD and sized exactly the same as within the training and accuracy testing phases.

a) Action game

The action game allowed the player to move through a detailed virtual environment automatically whilst performing tasks and interacting with the games using the mVEP HUD. The game environment included graphical aspects found in most modern games such as dynamic shadows, reflections, particle effects and animated characters [Fig. 4].

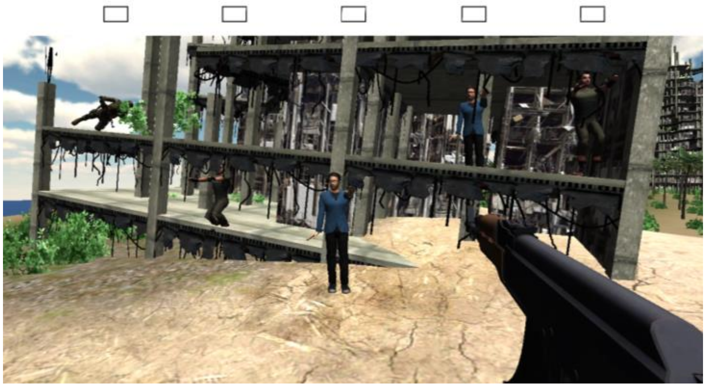

Fig. 4: In the action game the player is tasked with shooting the enemy with a weapon. In this figure the player has successfully eliminated the enemy (pictured top left).

The sections of the action game that allowed for player control are hostage situations with the player's objective being to target the hostage taker and free the captives. The player is presented with five different options with only one option being correct. As the game is an action game the player is given a short time (three seconds) to decide what character to target and what stimuli to choose to attack the character who is the only character with a weapon. The game consists of 24 different stages each slightly more complex. For example, in certain stages the hostage taker is camouflaged or the camera must firstly zoom to show the characters positions. Even with the slight difficulty increase throughout it is still obvious which target the player should choose.

b) Puzzle game

A simple physics based puzzle game was created to allow testing of the puzzle genre using the mVEP HUD. The puzzle genre was deemed most appropriate for use of VEP's within [9]. The game involved a ball being dropped from five locations and traveling through obstacles with the objective placing the ball in a green basket. This game emulates games such as the physical "coin drop" games found in arcades.

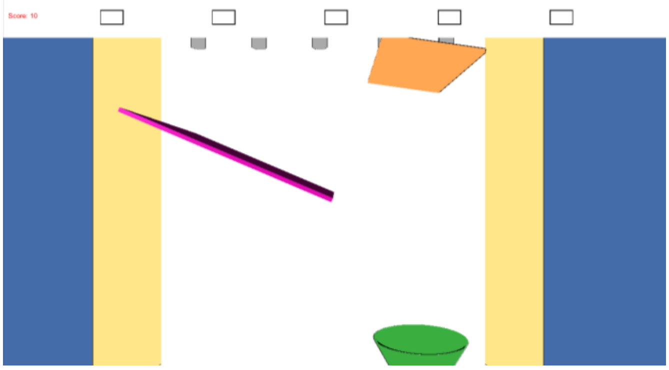

Fig. 5: One of the puzzle games later levels, the player must drop the ball from position one bounce on the bouncy pink material and drop into the green basket.

The player is given a longer time to decide what stimuli to concentrate on (ten seconds) as is common with most slower paced puzzle games. The puzzle game consists of 24 stages throughout these stages the difficulty is progressively increased with the usage of different obstacles that have different physical properties [Fig. 5].

c) Sport game

A sports game based around ten pin bowling was created. This game allows the player to participate in six rounds of bowling with control over the balls bowling position and direction. This allows the player a maximum possible score of 60. The player is presented with a typical bowling alley with ten bowling pins to knock over within two shots. The player must firstly choose the balls position and then from that position choose the bowling direction using one of five options.

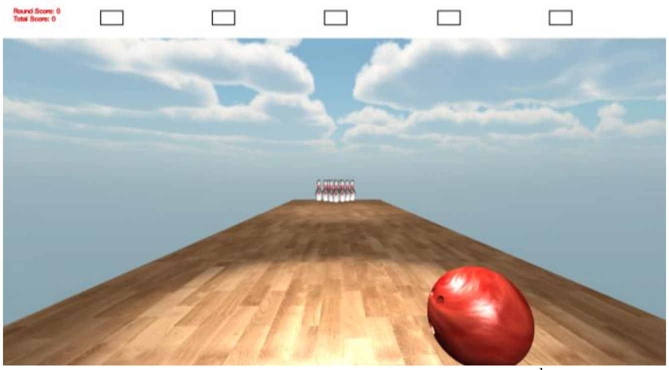

Fig. 6: The bowling game. The player has chosen the 4th position and is about to choose their bowling direction. In this case the player would choose either button one or two to hit the pins and score.

As the sports game required two decisions, the player was given five seconds to make each decision. The player is firstly shown the pins from a top view allowing them to judge where to aim. Then the player must decide what position to bowl from and choose it using the mVEP stimuli. Once the symbols have cycled and the BCI system has supplied an answer the bowling ball is dropped in the selected position [Fig. 6]. The player is then allowed five seconds to decide what direction to bowl the ball before they need to concentrate on the selected stimuli. This allows the player to make corrections if the selected bowling position was incorrect. After the pins have been knocked over the player will either have another shot to knock down the remaining pins or be taken to their next round. The games difficulty remains balanced throughout this game with the player becoming more experienced as they play.

Using the games coupled with the mVEP GUI we aimed to identify what genre the player achieves the highest accuracy/score in and improve results from pervious sessions. Using two performance metrics enables a more detailed analysis of the mVEP GUI control scheme usage in multiple game genres.

D. System

This mVEP BCI system comprises of several different components. The commercial game engine Unity 3D [20] was used to develop and present the games and visual stimuli to the user. Unity 3D renders the visual stimuli to the screen and sends timing data describing the stimuli events to Matlab [21]. User Datagram Protocol (UDP) was selected as the communication protocol to transmit the timing data as it allowed Unity 3D to transfer data without requiring special transmission channels or data paths. Upon receiving the UDP packet a session-based interface in Matlab processes the game event data and user EEG data segment in real-time.

E. Data Acquisition

One female and fourteen male participants took part in this study. Six of these subjects had previous BCI experience and the other subjects were BCI naïve. Participants were seated on a comfortable immobile chair and placed in front of a 22-inch LCD monitor, approximately 50cm away (appropriate distance to maintain visual angles). Each of the three sessions lasted approximately an hour in which a participant would train and test within a single game genre. During setup the EEG cap was placed over the participant's head, with the electrodes on the cap covering the occipital areas using a 12-channel montage [Fig. 7] according to the international 10-20 system of electrode placement [22]. This montage placement was the same as used in [19]. The electrodes cover the optimal area for classifying mVEPs. The left mastoid was used as a reference and FPz as the ground.

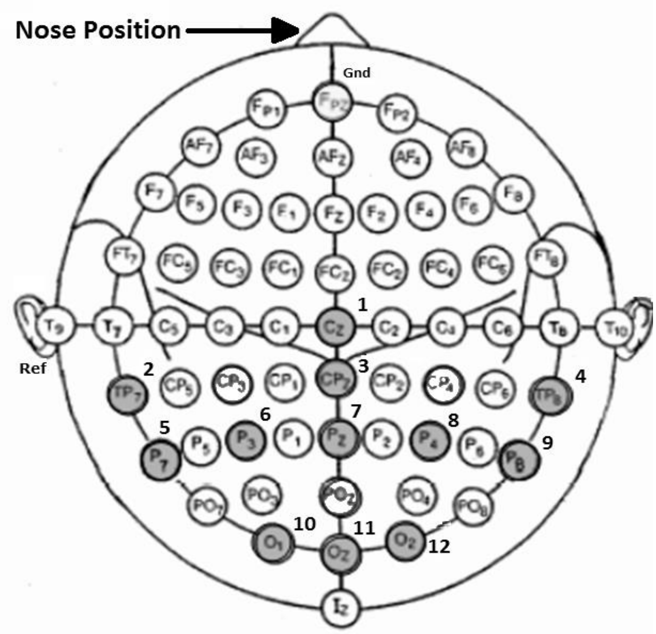

Fig. 7: The 12 channel electrode montage used, covering occipital areas (electrodes shown in grey).

EEG data was collected using a g.BSamp amplifier [23] and g.Gammasys [24] active electrode system. The data was over sampled at 250Hz, then average down sampled to 125 Hz.

F. Data preprocessing Methods

A total of 30 blocks were recorded from each subject during the training period. Data epochs were derived in association with each motion-onset stimulus, beginning 200ms prior to the motion onset and lasting 1200ms. All single trials were baseline corrected with respect to the average voltage over the 200ms preceding motion onset. Data was digitally filtered using a low-pass Butterworth filter (order 5, with cut of at 10Hz) and subsequently resampled at 20 Hz. Features were extracted between 100ms and 500ms post stimulus (the epoch that normally contains the most reactive mVEP components e.g., N200, P300), yielding nine features for each channel. Data was averaged over 5 trials yielding 6 feature vectors per stimulus. Since mVEP is time locked and phase locked to the motion-onset stimulus, mVEP induced from the motion stimuli could be obtained through the above simple processing procedure. Data was split into target vs non-target as well as individually classed for each target stimuli. For each non-target feature vector five randomly selected non-target trials were used.

G. Channel selection

A linear discriminant analysis (LDA) classifier was trained to discriminate target vs non-target feature vectors extracted from single channels in a Leave One-Out (LOO) cross validation was performed on the data. For each of the twelve channels the average LOO Classification Accuracy (LOO-CA) was determined and channels were ranked by accuracy. The three top ranked channels were concatenated to form a new feature vector (27 features per vector) and a further LOO cross-validation was performed. A single trial test of target vs non-target is also applied on the training data (Target vs Non Target - SingleTrial).

H. mVEP classification – 5 class

Using the data from the training session a new LDA classifier was produced to classify target vs non-target data. To classify individual symbols in a single trial test each feature vector associated with each stimulus in a trial is classified as either target or non-target. The LDA classifier produces a distance value, *D*, reflecting the distance from the hyperplane separating target and non-target features (*D*>0 for target and *D*<0 for non-target). The vector that produces the maximum distance value is selected as the classified stimulus (in some cases non-target data produce a *D*>0 however the value of *D* is normally maximal among the five stimuli for target stimulus i.e., the stimulus on which the user is focused). Offline analysis was performed using customized code and the Biosig and LIBSVM toolboxes [25] [26].

I. Realtime game control and online feedback

Online control of the BCI games involves using the classifier setup from the training data and the three selected channels. The online system used a Matlab session based approach that allows for data to be collected in real time and analyzed in parallel with each of the three Unity 3D based games. In each game the user waits for the five options to become available, then the stimuli is presented five times for each button (over 5 trials), the session based interface waits until the triggers associated with the stimuli are received, averages over the five trials, and then the features are extracted as described in section II.E. The trained classifier is then applied and the stimulus is determined based on the maximal distance *D* (choosing one of 5 actions) as outlined in section II.G. The selected stimuli relating to one of 5 commands is then communicated to the game via UDP and real time feedback provided to the user. With the game testing section the user is also given a score, the user can use this to identify how well they are preforming throughout the game. An illustration of the online process is shown in [Fig. 8].

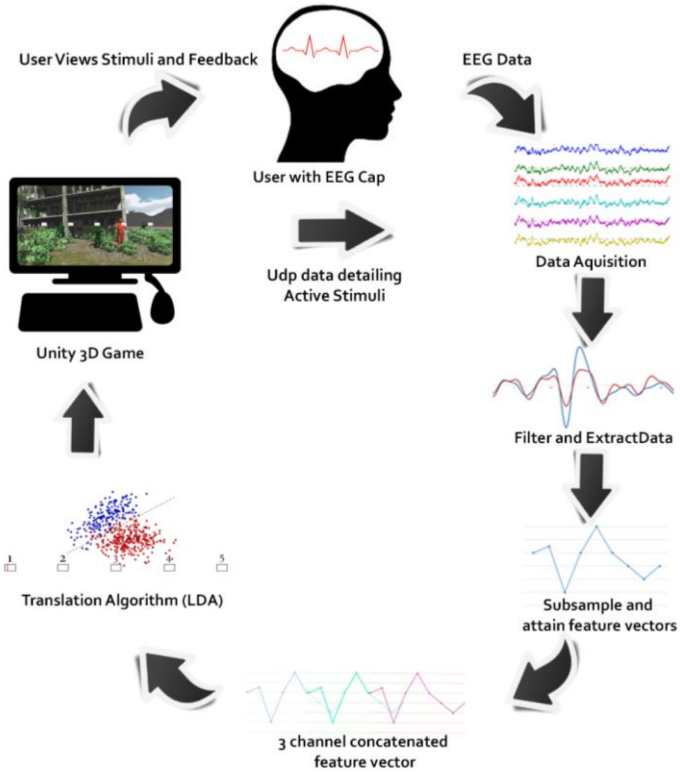

Fig. 8: The Online BCI system. Unity 3D displays the stimuli and sends timing data in relation to the stimuli movement to the Matlab session based interface to co-register with the EEG. Signal processing is then preformed in the Matlab session-based Interface to classify the EEG data segment and returns the data associated with the selected button for Unity to carry out a command.

III. RESULTS

Data recorded during both training and testing was analyzed separately. Results are presented for each game in the format; training within the game level, testing online accuracy within the game and testing the players ability to control and play the game.

A. Offline Analysis

Offline analysis was conducted over the training data and the online accuracy test data. This allowed for analysis of the online accuracy test data without the use of classification data recorded in training. Results are presented as LOO classification accuracy, Target Vs Non Target using training data and Single trial five-class detection using training data.

Table 1 shows the average LOO classification accuracy for the best 3 channels over the three games training and testing sessions. LOO classification accuracy does not vary significantly over the games. The bowling game produced 77.2% in training and 79.7% in testing on average, the puzzle game produced 80% in training and 80.4% in testing, and the action game produced 78.6% in training and 78.5% in testing. The use of LOO to find electrode placement found that the most common three electrodes selected for online use are O1, P7 and P3. These are the same electrodes selected in [19], these electrodes cover the area found in [17] to be best for leftward movement of the stimuli (the same stimuli used in this study).

The asymmetrical topography of electrode selection may be explained by the right visual field asymmetry effect on contralateral hemisphere during selective attention [27]. It may also have bearing to the hemispheric asymmetry in human motion perception, as it was found that N2 is generated by extrastriate activity and that motion stimuli are not equivalently processed in the two cerebral hemispheres [28].

Single trial five class accuracies on average where all above 83% with the puzzle game giving the highest accuracy of 89.6%. The single trial five class accuracies allowed for 8 subjects to achieve high offline accuracies >95%, yet within online tests these subjects results where degraded slightly (80%-95%). Using a single factor ANOVA (analysis of variance) on offline testing results it was found that difference between offline accuracies across game genres were not statistically significant (p= 0.433). Yet the significance value of the difference between offline accuracies across genres was found to be greater than in the previous study [19] (where p=0.914).

TABLE 1: THE AVERAGE OVER ALL SUBJECTS FOR ALL CLASSIFICATION TYPES. THE TABLE IS ORGANIZED BY WHAT WAS ASSESSED AS TRAINING DATA AND ONLINE TESTING WITH FEEDBACK. THESE ARE THEN CATEGORIZED INTO TARGET VS NON TARGET LOO CLASSIFICATION AND SINGLE TRIAL FIVE CLASS CLASSIFICATION. ONLINE ACCURACY'S WHERE ASSESSED OVER THE 40 ONLINE TRIALS WITH FEEDBACK OFFLINE TESTING ACCURACY'S USED THE FIRST 30 BLOCKS OF EACH DATA SET (TRAINING AND ONLINE DATA).

	Training Assessment		Online Testing
Data Type	**Target vs Non Target LOO Acc**	**Five Class Single Trial**	**Five Class Single Trial**
Bowling Training	77.194	83.518	-
Bowling Guide	79.685	85.259	69.167
Puzzle Training	80.018	86.037	-
Puzzle Guide	80.444	88.667	69.001
Shooting Training	78.611	85.778	-
Shooting Guide	78.518	83.148	75
Average	**79.079**	**85.401**	**71.056**

B. *Online Analysis*

Online analysis involved finding the accuracy of the player's choice when controlling the game with online feedback.

The BCI accuracy during the online testing period was measured by the percentage of correct stimuli selected. The results for each are shown in [Fig. 9]. On average participants were able to achieve 71% online accuracy. Participants accomplished the highest accuracies in the action game (75% average online accuracy). The bowling and puzzle games had very similar average online accuracies of 69.2% and 69%. Using a single factor ANOVA on online testing results it was found that difference between accuracies in games were not statistically significant (p= 0.395). Yet again the difference was greater than the previous study [19] (p= 0.537).

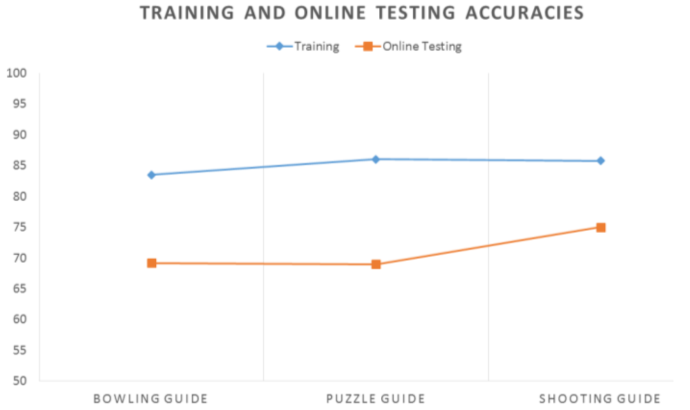

Fig. 9: Classification accuracy percentages on the training data in comparison to classification accuracy's in online testing.

Ten participants were able to achieve over 80% online accuracy in several of the games. Five participants where able to achieve over 90% online accuracy over one or more games. In comparison to the study [19] where only a single participant had the ability to achieve over 90% online accuracy.

The final section of each session allowed participants the opportunity to play the games freely. Each game had 24 control instances allowing for a more in-depth investigation than in [19].

TABLE 2: AVERAGE SCORES FOR FIFTEEN PARTICIPANTS.

Games	*Score*	*% max Score*
Bowling Game	46.4	77.3
Puzzle Game	17.2	71.6
Shooting Game	17.9	74.4

The bowling game produced the highest average game score 46.4 out of 60 (77.3%). For the bowling game players achieved an average of 69.5% BCI accuracy but allowed the players to achieve 77% of the maximum score [Fig. 10]. The bowling game allowed players to correct mistakes and so had a high game accuracy.

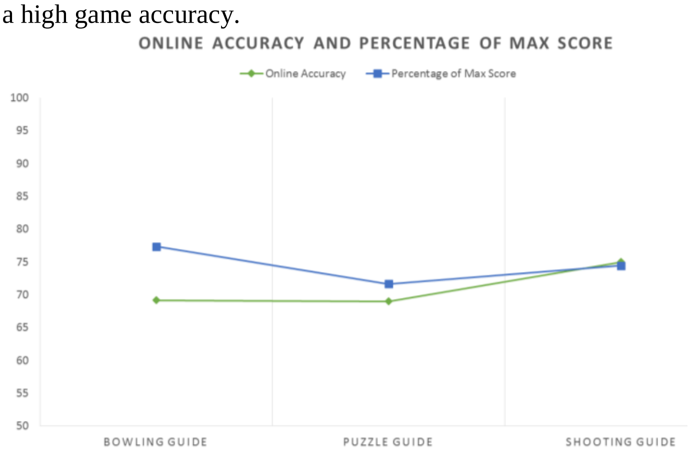

Fig. 10: Comparison of Online Accuracy Percentage and percentage of max game score.

In the action and puzzle game players need to choose a specific stimuli (the correct answer) to score a point. The player would have to use strategic thinking and target identification skills. This meant that accuracy results and scores were similar; 71.6% score to 69% accuracy for puzzle and 74.4% score to 75% accuracy for action [Fig. 10]. Using a single factor ANOVA on players percentage of maximum score over the games it was found that difference between accuracies/scores in games were not statistically significant (p= 0.5598).

IV. Discussion

The overall online control average for all games is 71.05% indicating that mVEP can be used as a control method within computer games with good accuracy. In the previous study [19] an overall average of 65.7% was achieved over all games, this suggests that the mVEP HUD has improved results as well as the use of training data recorded in the game environment [Fig. 11]. Participants showed a statistically significant increase in BCI accuracy overall games between studies (*p=0.00247*). The mVEP HUD could be used within other commercial computer games to control five actions if the mVEP HUD was employed as a screen overlay.

A. Action Game

Overall the shooting (action) game provided the highest overall online testing accuracy (75%). This was unexpected as the shooting game has a graphically rich environment, which may distract the player's attention away from the mVEP HUD. Yet the application of more stimulating feedback may have caused participants to concentrate more on the stimuli during the accuracy testing section of the game as both other games attained lower accuracy's and had similar less stimulating feedback. Participants also commented on the feedback saying it was more rewarding than in the other genres. The action game in a previous study [19] had the worst accuracy of 60.25%, in comparison to the game in this study allowing for an accuracy of 75%. This shows that using the same environment across training and testing allows for higher accuracy as well as the usage of the mVEP HUD (an improvement on average of 14.75%).

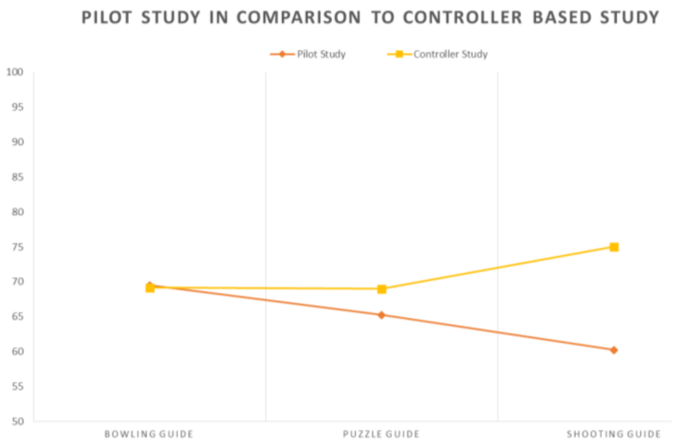

Fig. 11: Comparison of overall BCI accuracies percentages in the pilot study to this study

The mVEP HUD prevented participants from being distracted in the shooting game by the graphically rich environment of the action game. The position of the stimuli was on top of the screen meaning that the player would make their choice by looking below at the character or arrow and then divert their gaze to the mVEP HUD and the stimuli within it. The mVEP HUD kept the stimuli and the area around it consistent in comparison with the previous study [19].

The action game allowed participants to attain on average scores of 74.4%. The action game required the participant to choose a single correct answer, this meant that classification accuracy and percentage of maximum score were similar (75%/74.1). Yet participants needed to react quickly and identify the correct target and stimuli's in relation to that target in three seconds. This lead to participants selecting the incorrect target because of the short time allotted to accurately identify the enemy. Within the previous study the players on average where only able to achieve 62.5% of the maximum score. The three improvements made to this study have increased player score in the action game (mVEP HUD, training in the same environment as testing and allowing participants a longer time to play the game).

B. Puzzle Game

The puzzle game had an average accuracy of 69%. The puzzle game had relatively simplistic feedback (having a ball drop and hit some obstacles). This type of feedback is non-stimulating to participants when in comparison to the action games feedback. The puzzle game had non-distracting visuals with no on-screen movement during the active stimuli periods apart from the stimuli themselves. The use of simplistic graphical elements and the mVEP HUD led to quite a bland setting for the on screen stimuli. When in comparison with the previous session [19] the puzzle game had increased accuracy. Again the mVEP HUD prevented participants from being distracted by on screen elements such as the obstacles within the puzzle game.

The puzzle game allowed players on average to achieve an average total score percentage of 71.6%. The puzzle game had a lower BCI accuracy (69%) than total game score 71.6%. The puzzle game often had more than one correct answer, for example a player could drop the ball directly into the target basket or bounce the ball off an object to reach the basket. Yet the puzzle game relied upon trial and error with participants learning how the ball interacts with the obstacles as they play. This type of trial and error gameplay is typical in physics based puzzle games. This may have led to some participants choosing the incorrect answers but then correcting during the next turn. Again when in comparison to the previous study (66.5% of game score) this study's three improvements have allowed players to attain a higher score.

C. Sport Game

The sport (bowling) game allowed for an accuracy of 69.1%. The sport game had similar feedback to the puzzle game during the accuracy test, the bowling game having a bowling ball drop onto the alley and the puzzle game having the ball drop and hit some obstacles. Again these types of feedback are non-stimulating to participants. The sports game also had non-distracting visuals with no on-screen movement during the active stimuli periods apart from the stimuli themselves. Within the bowling game there was not a noticeable change in average accuracy when comparing studies (69.1% in this study, 69.5 in the previous). This may have been because the area around the stimuli in [19] was both static and non-graphically complex (a low resolution cloud texture).

For the bowling game players achieved an average of 69.1% BCI accuracy but allowed the players to achieve 46.4 out of 60, 77.3% of the maximum score. This is because the bowling game allowed players to correct mistakes. For example, if a player chooses the bowling position incorrectly or there is a classification error, the player can then choose to bowl the ball towards the correct pins during the spin function. Techniques such as this within games allows for players to achieve high scores even if they make mistakes because of classification errors.

Finding the ideal genre during this study proved to be difficult due to conflicting results from the accuracy and total score tests and a lack of statistically significant differences when comparing genres. It could be concluded that with the usage of the mVEP HUD, differences in game genre did not impact on results significantly. Yet accuracy improvements between this study and the previous [19] are significant, suggesting that the usage of the same testing and training environment and the mVEP HUD have a positive impact on BCI accuracy in multiple game genres.

V. LIMITATIONS

MVEP can be used with reasonable accuracy in a variety of games. Defining the ideal genre for the control method using two performance metrics has proven difficult within this study, with the sport game (bowling) achieving the highest average in game score and the action game achieving the highest accuracy. Allowing the participants more time to play the games may have allowed them to better learn the mechanics of each game genre. For example participants commented that they often misjudged how the ball would react to obstacles in the puzzle game or how long they had to identify the target in the action game. These mistakes happened early in the session as the participant was still learning the game mechanics.

The usage of the mVEP HUD significantly improved results from the previous study [19]. The purpose of the HUD was to avoid users getting distracted by the in game graphics of each genre, yet the graphics below the stimuli remained the same. This lead to the action game being in a significantly more graphically rich environment in comparison to the other two games. This may have influenced results causing participants to concentrate more on the action games stimuli. The use of a similar graphics or art style for all three genres could have helped the evaluation of the gameplay within the genres. Results also indicate no statistically significant difference in online accuracy or score when comparing game genre. The lack of statistically significant results could be due to the limited number of subjects (15) used in this study. Differences in scores and accuracies across the game genres may be clearly identifiable if a larger group of participants is used.

The mVEP HUD could also be used with commercial games of different genres, this would allow for analysis with the current state of each game genre. Much like the "intendiX-SOCI" by g.tec the mVEP HUD would only be used to control simple events in each game such as movement or simple in game selections.

VI. CONCLUSION

This study involved testing participants playing three different games of different genres using the mVEP HUD. Participants were trained in the same environment as they were tested within. The study investigated accuracy in game control and how well each of the participants could play the games.

The results from this study show that with the use of the mVEP HUD participants were able to control games of different genres to a reasonable degree (71% BCI accuracy). The study had a significant increase in overall accuracy in comparison to the previous study [19] with only changes to the game itself and session structure. As the usage of mVEP stimuli does not visually fatigue users it would be possible to achieve good accuracies over a longer period of time than most other VEP's.

This study opens up the potential for further work in mVEP based BCI controlled computer games and testing BCI controlled games genres with different control methods. A number of observations regarding the study design and a range of recommendations for future studies are outlined such as changes to the games aesthetics and gameplay as well as changes to the study itself in terms of recording length and participant numbers.

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