Motion-Onset Visual Evoked Potentials for Gaming: A pilot study

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Abstract − This paper details a pilot study for a motion onset Visual Evoked Potential (mVEP) based Brain Computer Interface (BCI) controlled game. mVEP is a type of VEP that uses visual responses from the dorsal pathway of the visual system allowing elegant visual stimuli to elicit different brain patterns depending on the motion and position of the stimuli. The study here was conducted to determine the most appropriate methods, parameters and EEG setup to use in order to extract reliable information when classifying responses on up to five different stimuli. Initial offline results show that 80% accuracy can be achieved by averaging stimuli over 5 seconds when discriminating target versus non target. This was achieved by the use of simple averaging techniques and support vector machines. The initial results are encouraging, showing that mVEP may be used as a control system within a computer game. Details of the proposed games are also included.

Keywords − mVEP, BCI, Game, Virtual Environment

I INTRODUCTION

Many people with motor impairments cannot use conventional control devices such as a mouse, keyboard or game controller. Individuals with no motor control cannot rely on interfaces such as mouth sticks; eye tracking or electromyogram (EMG) switches (a switch that can convert electronic signals on the skin into signals that can be used in assistive equipment). Brain Computer Interfaces (BCIs) have the potential to enable these users to control and interact with devices and technology using directly measured brain activity. An EEG-based BCI measures voltage fluctuations resulting from ionic current flows within the neurons of the brain via electrodes placed upon the scalp, translating these signals into commands for a program to execute [1]. Recently there has also 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 [2] [3] [4].

In recent years the application of BCI for interacting with computer games has become increasingly popular across many BCI research studies. BCI games are often used to test paradigms or train users how to use BCI and have become increasingly more advanced; utilising 3D environments, multiple user objectives and hybrid control systems which incorporate both conventional input devices and multiple BCI techniques[14] [15].

Visual Evoked Potentials (VEPs) have frequently been used in BCI systems, with the brain signals in response to visual stimuli such as flashing lights (P300) or pattern reversal (SSVEP) being utilised to elicit signals from the primary visual cortex. Recently however BCI studies [9] [10] have focused upon 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. This paper focuses on testing a number of mVEP classification techniques, investigating the most appropriate signal processing techniques and parameters to use, for classifying up to five different stimuli from a minimal number of EEG electrodes. The focus is on how mVEP-BCI might be used as control methodology in a new computer game. A short review of VEP based BCI is as follows.

II VEP

A VEP (Visual Evoked Potential) is an electrical potential recorded after a subject is presented with a type of visual stimulus. There are several types of VEPs. Steady-State Visually Evoked Potentials (SSVEPs) use potentials generated by exciting the retina using visual stimuli modulated at certain frequencies. SSVEPs stimuli are often formed from alternating checkerboard patterns [5] and at times simply use flashing images [6] [7]. 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 [7].

Motion Onset Visual Evoked Potential is a type of VEP that uses visual responses from the dorsal pathway of the visual system which allows more elegant visual stimuli than the aforementioned types of VEP (P300 and SSVEP) [9]. Among all visual motion related VEPs mVEP displays the largest amplitudes and the lowest inter- and intra-subject variability rendering it suitable for use within a BCI application. Motion-onset VEP is typically composed of three main peaks: P1, N2 and P2. The negative N2 peak, with a latency of 160-200ms, is motion specific. The positive P2 peak has a latency of around 240ms and is increased with more complex visual stimuli. These clear and robust temporal features make mVEP a promising EEG component for information encoding and decoding within a BCI system.

As flash or pattern reversal VEP based BCIs use a high contrast or bright luminance of visual stimuli they can cause notable visual fatigue of the BCI user. It is therefore important to consider these factors given knowledge about the end use of BCI as many of these VEPs depend upon environments without poor target contrast or fluctuant luminance such as a user's home or a clinical bedside. In contrast mVEP is elicited entirely by the motion behaviour of the visual object and is not sensitive to the contrast and the luminance of the object or the area around it [9].

The first notable use of mVEP was within a simple testing BCI environment [9] 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 Figure 1) elicited the mVEP. The EEG data segment taken was aligned to the motion onset of the chosen target and contained prominent motion related VEP features. The spatio-temporal pattern of mVEP in this paradigm was investigated by using EEG data from 15 subjects. 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 was enhanced. The stimulus producing the largest N2/P2 component was 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 [9].

mVEP has also been used within n200 spelling applications [10]. The n200 speller uses the same rectangular symbols used within [9], 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 91.5% using a single channel compared to the P300 speller using a single channel which achieved a mean accuracy of 72%.

As it has been established that mVEP represents an appropriate VEP for use as a control signal within a BCI-game framework, the objectives of this study are to create a BCI game that tests the mVEP paradigm in a computer game environment where the user interacts with the game directly using their EEG. This paper outlines a pilot study undertaken with two subjects to initially test the use of mVEP for a BCI. A computer game environment that will enable thorough testing of the robustness of the mVEP BCI in several different game situations is also described.

III METHODS

An initial recording setup included a 15 channel montage. Two participants with some prior BCI experience (sensorimotor rhythm BCIs) were used for this pilot study across two recording runs each in a single session.

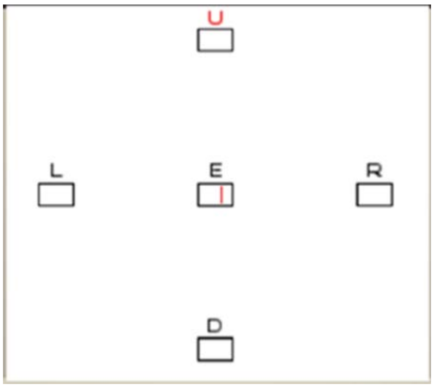

Figure 1: The Virtual Keyboard used within the game. In this figure it shows the virtual keyboard with the target letter U highlighted. This tells the participant to gaze at the symbol below U. E is active in this example with the red horizontal line in the symbol moving from right to left; the participant will ignore this symbol movement.

a)Paradigm

The proposed mVEP BCI game comprises of several different components both physical and software based. The commercial game engine Unity 3D [11] was used to develop the game and present all the visual stimuli to the user. As Unity 3D renders the visual stimuli to the screen data packets describing these stimuli events are transmitted to Matlab Simulink® [16] over a User Datagram Protocol (UDP). UDP was selected as the communication protocol as it allowed Unity 3D to transmit messages without requiring special transmission channels or data paths. Upon receiving a UDP packet the Matlab Simulink® component processes the game event data and user EEG signals in real-time.

This pilot study tests a virtual environment for presenting stimuli in a training MVEP paradigm that includes the same setup as used in [9]. During the offline testing the participant is instructed to concentrate upon the stimuli with a red letter above it [Figure 1].

Visual stimuli were displayed on a white board within the game environment and viewed on a 17 inch LCD monitor within a 60Hz refresh rate. Each symbol is a small rectangle of 1.24° by 0.76°. The rectangles when active contain a red vertical line with a 0.66° visual angle appearing in the right side of the vacant rectangle and is moved leftward at a velocity of 3.10° before it disappears (this process of motion took 140ms) e.g., see symbol E in Figure 1.

Each symbol had a letter placed above it, the letter would dictate what symbol the user is required to look at. When the letter is highlighted red the user must focus on the symbol. These symbols or buttons form a virtual games controller U/L/E/R/D, representing Up/Left/Enter/Right/Down commands, respectively.

The timing scheme of the stimuli followed the scheme set in [6] with a single block consisting of 15 trials taking 24s, when a block is complete each symbol within the block will have moved 15 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.

For training, in each block the subject is asked to focus on one symbol (letter highlighted). 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) Figure 2 shows the proposed timing scheme [6]. For offline testing each run lasts approximately 12 minutes and consists of 30 blocks with each block containing 15 trials each.

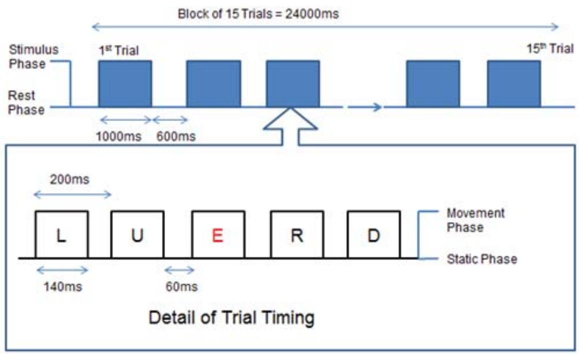

Figure 2: The timing protocol of one data acquisition period (one block): each block consists of 15 trials Each trial is subdivided into five stimulus periods dedicated to the five virtual buttons respectively. SOA (stimulus-onset asynchrony) was 200 ms. The motion stimuli indicating the five buttons appear in random order, with one button (E in this case) designated as the target. This is based on the timing paradigm proposed in [9].

b) Data acquisition

Two male participants with some prior BCI experience (sensorimotor rhythm BCIs) ages 24 and 30 were used for this pilot study across two recording runs each in a single session. Data was recorded using 16 channels on a EEG montage according to the International 10/20 system [Figure 3] recorded using a g.BSamp [13], digitized using a cDAQ 9171[12] and oversampled at 2KHz then average down sampled to 125Hz. g.GAMMAsys active electrodes[13] were used. Subjects sat in front of a 17 inch LCD monitor being viewed at a distance of 50cm. As in [9] visual angles to stimuli where taken into account, with symbols having a length of 1.24° and a height of 0.76°. The entire visual keyboard subtends a square field of 15° x 15° on a white background [Figure 1].

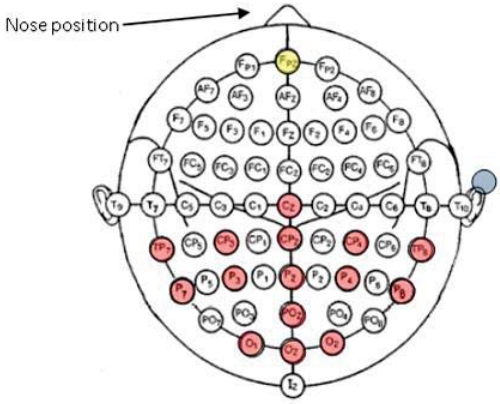

Figure 3: 16 Channel setup used for recording the trials using a standard EEG cap and G.GaNNAsys active electrodes [13].

The participant was informed via onscreen prompts to focus attention on the desired symbol and mentally count the number of times the red vertical line appears in the highlighted symbol (this task was called "counting"[9]). During one acquisition period of 15 trials the participant was instructed to keep their sight and focus upon a single target symbol. For each subject a total of 30 blocks was recorded and the corresponding EEG data was logged.

c). Data pre-processing Methods

A total of 450 trials were recorded from each subject (15 trials per block, 30 blocks). The raw EEG data in each individual data set was downsampled to 125Hz. Data epochs from each channel between 200ms preceding the movement stimulus to 1,000ms resulting in triggered trial data of 1,200ms for each stimulus. All single trials were baseline corrected with respect to the mean voltage over the 200 ms preceding motion onset.

d) Channel selection, feature extraction and classification

Optimizing the EEG translation algorithm involves subject-specific parameter selection to maximise the accuracy in detecting which symbol or target stimuli the user intents to use.

Stimulus vs Non-stimulus analysis

Leave one out cross validation (LOOCV) was employed to identify the channels and features required for MVEP control. Initially LOOCV accuracy was assessed using all of the stimuli epochs in association to all non-stimuli epochs. For each EEG channel in the subset a 1,000ms segment of data following each motion onset stimulus was extracted. The data epochs chosen where originally 150 samples of data taken from 16 channels. Channel selection was performed by finding the classification accuracy of each channel alone and then combining the best of the single channels. After the best channels where selected feature selection was conducted, finding the best section of data for classification.

It was found that channels Tp7, P8, and TP7 produced the best signals for subject one and channels Cz CP3 and O1 for subject 2. The section of 100ms to 500ms was selected for use as a feature vector. To reduce the dimension of the feature vector the EEG epochs were filtered at 1-10HZ and resampled at 20 HZ this yielded nine points for the 100 to 500 ms period of each epoch. The resulting nine point epochs were then concatenated by the channel for each stimulus; this created a single feature vector of 27 points. Each individual data set was divided into a training set that contained an equal number of target and non-target vectors. LOOCV was then conducted on all stimulus trials in comparison to all non-stimulus trials. Classification accuracy's for 3 channels 27 point feature vector were assessed.

After gaining an understanding of what accuracy's can be achieved using a single sample (27 point feature vector over 3 channels taken from single stimuli), an averaging procedure was conducted over different samples. A number samples from the same target stimuli were averaged and LOOCV conducted on the averaged stimuli and non-stimuli averaged vectors.

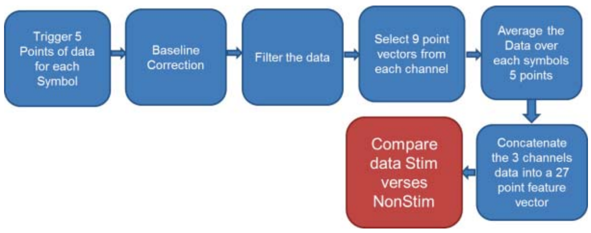

Figure 4: Process of finding the accuracy using LOO

Two class assessment

Support vector machines (SVM) have been used in an online mVEP system previously [10]. SVM was applied offline to investigate the possibility of SVM use in an online system. SVM's principle is to seek the maximal margin between 2 or more classes, to form a hyper-plane with the best generalization capabilities.

Data was separated into 2 classes (one for stim and one for non-stim). The best channels and feature extraction setup derived from the stim vs non stim analysis were used in the SVM analysis. Again LOOCV was used to determine the achievable accuracy when averaged over different number of trials. Ideally a single trial classification would be best.

Offline analysis was performed using customized code and the Biosig and LIBSVM toolboxes [17] [18].

V RESULTS AND DISCUSSION

a) MVEP analysis

For initial inspection the data epochs for both experimental conditions (viewing stimuli and not viewing stimuli) were averaged for each subject [Figure 5]. When averaged over all trials the data epochs for the selected sample areas were noticeably different for each subject Analysis of the grand average evoked potentials for subject one in response to target stimuli revealed a sharp negative deflection (the N2) with a latency of 200 to 300ms, this was then followed by a sharp positive deflection between 300 and 400ms after the motion onset. Yet subject 2 showed a sharp positive N2 and a sharp negative deflection between 280 and 340, this did not affect target detection. It should also be noted that some latency difference between subjects was noticed with subject 2's N2 being earlier than subject 1's.

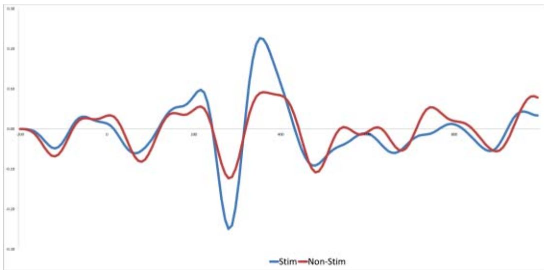

Figure 5: Subject 1's average responses to Stimulus and Non Stimulus over all 450 samples collected using channels Tp7, P8, and TP7. Table shows the 1200ms in a data epoch.

b) Accuracy

Initial results were calculated by using all the stimulus epochs in comparison to all, non-stimulus data epochs. It was found that when using the 3 best channels accuracy's of 80% could be achieved, this resulted in a 27 point data epoch being selected for each trial. Note that the accuracies were found using 25 data epochs recorded over 5 seconds [Figure 6].

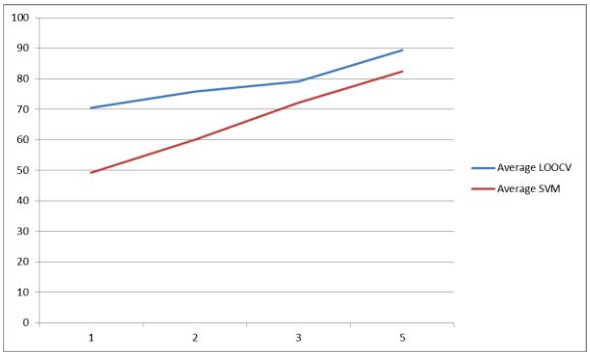

Figure 6: The averages of the 2 different methods over all sessions used to test accuracy.

Table 1: The number of trials averaged over using the best 3 electrodes for each subject, a good accuracy was achieved when using 5 trails (% accuracy).

Averaged Epochs:	1	2	3	5	7	9	10	15
Subject 1 Session 1 LOOCV	71.11	76.67	81.11	91.11	90.00	96.00	98.89	100
Subject 1 Session 2 LOOCV	72.00	76.89	81.33	90.56	91.67	96.00	97.78	98.33
Subject 2 Session 1 LOOCV	68.78	75.56	77.33	88.89	94.17	95.00	96.67	98.89
Subject 2 Session 2 LOOCV	70.11	74.00	77.00	86.67	90.00	88.00	97.78	98.33

Table 1 shows the mean detection accuracies for each session and subject after analysis with LOOCV. The accuracy rises significantly when averaging between 1 and 5 trials. When averaging 5 trials together the detection accuracy was above 85% for both subjects, this suggests that after only 5 trials reasonable accuracy could be achieved based on the evidence from leave one out cross validation. When averaging over 15 trials 100% accuracy was achieved for subject one.

The use of the SVM on averaged results when simulating online use of the paradigm was then investigated. This simulated online application allowed for testing of the stimuli as if they are being received by the system online by sending raw subject data into the system and processing it as if the system was online. This system compares each symbol with the four other symbols, allowing for the system to detect the one selected symbol from the rest. It was found that when averaging over 5 trials accuracy's above 80% where achievable [Table 2].

As a good accuracy could be achieved within only 5 trials (5 trials = 5 seconds) this suggests that mVEP could be used as a computer game control type especially in slower paced games such as strategy or puzzle games.

Averaged Epochs using 3 channels:	1	2	3	5
Subject 1 Session 1 SVM	52.22	63.33	79.67	88.89
Subject 1 Session 2 SVM	53.33	62.22	77.78	83.33
Subject 2 Session 1 SVM	37.78	60.00	66.67	80.00
Subject 2 Session 2 SVM	53.33	54.44	64.44	77.78

Table 2: The number of trials averaged when using the best 3 electrodes and SVM (% accuracy).

To compare results with [10] trials using only a single electrode where analysed. [10] Allowed for accuracy's of 83% within 2.3 trials in comparison with this test scoring 65% in 3 trials. Yet the analysis in [10] was conducted over 12 subjects each in a single session as opposed to 2 in 2 sessions. Further optimisation may allow for improved online accuracy's with use of a single electrode.

As a reasonable accuracy can be reached in 3 trials with the use of 3 electrodes (72% average) it may be possible to use only 3 seconds of participant input to control a game. This would allow for the option of faster paced games with slightly less accurate user control.

VI THE PROPOSED GAME

As the initial offline results are encouraging and that stimuli presented in the games platform elicit the desired EEG response an online setup of the game and BCI is currently being developed. The game will include a complex environment incorporating several different game scenarios and real time mVEP processing. The game will use mVEP as a control mechanism for a selection of tasks; each task will test aspects of different game genres. This will allow for an understanding of what genres and game environments can be used most efficiently with the mVEP paradigm.

As before Unity 3D will be used to render the game environment and transmit signals detailing the movement of stimuli to Real-Time signal processing Module (RTM) (in Matlab) for detailed online analysis in real-time. The online signal processing system will allow data to be analysed and accurately used for classification in an online setting. The game will send triggers detailing when the motion stimuli are active, then within the (RTM) the signals will be segmented, filtered, analysed, averaged and classified. The RTM will send the results of the signal analysis back to Unity via UDP which will in turn update the game environment based on the player's mVEP.

Testing of mVEP in multiple genres and game environments will allow the paradigm to be thoroughly analysed as a games control method.

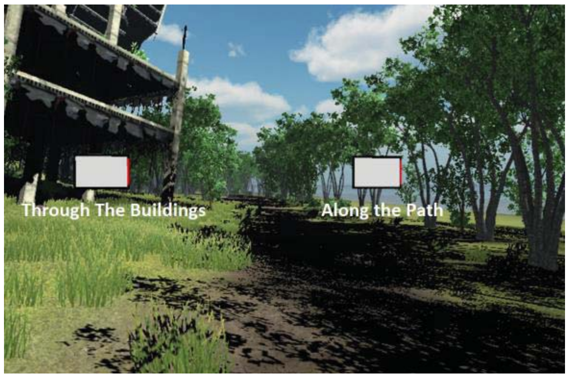

Figure 7: Concept of a detailed virtual environment to be used within the full game. This includes dynamic lighting, moving objects in the subject's peripheral vision and other textured models in the game.

VII CONCLUSIONS

This paper describes the offline test of a BCI control paradigm in a virtual environment. In a 2 class configuration mVEP was evoked by using a small visual field allowing the display of multiple targets in a virtual environment. Robust N2 and P2 components of mVEP were detected and selected as noticeable features of the brain response to the attended on screen target. The combination of N2 and P2 features over 3 channels combined with a simple averaging procedure gave encouraging results for the use of the paradigm in a computer game.

In comparison with existing BCI VEP games, mVEP requires no sudden change of luminance or a high contrast of visual objects, thus allowing for subjects to experience less visual fatigue when playing a BCI game for longer periods.

After testing mVEP presenting in a 3D gaming environment successfully offline it was decided that mVEP in a computer game must be tested in a more comprehensive manner online. mVEP provides high offline accuracy a when averaging over five trials. Five trials is approximately five seconds, this would allow the paradigm to be used in slower paced games (puzzle, adventure, or strategy genres). As an accuracy of 72% can be reached in only 3 trials the use of the paradigm in faster action or sports games may be possible after further investigation and optimisation.

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