Quantifying EEG Measured Task Engagement for use in Gaming Applications

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Brain-Computer Interface (BCI) has the potential to revolutionize the gaming industry. However, we have little fundamental understanding of the speed and accuracy with which users can control virtual objects using only their *task engagement levels* (mental effort activity), of their brain. We present a series of studies to investigate the use of EEG techniques in the context of gaming. We first investigated the accuracy with which users could select a single target from multiple visual states. We found that users able to move quickly and effectively in both directions (increasing engagement/decreasing engagement) for up to five discrete states. In a second study, we found that users take a linearly increasing amount of time to increase and decrease their level of engagement. Finally, we investigated the practicalities of simultaneously using a traditional input device and engagement in a gaming scenario. Experienced users were more accurate in this parallel input task than novices. Based on these experimental results we discuss several engagement-based game design principles.

Keywords: brain-computer interface, gaming, input devices, non-traditional input, task engagement, electroencephalography, EEG.

Subject classification codes: include these here if the journal requires them

INTRODUCTION

Electroencephalography (EEG) kits (such as the Emotiv EEG and Neurosky headsets) are readily available off-the-shelf, allowing designers to explore novel Brain-Computer Interfaces (BCI). Applications using the EEG signals captured through non-invasive electrodes range from gaming [22] to robot control [4]. Researchers have mainly demonstrated the capability of these controllers through specific point-designs in applications such as user task classification [24] to controlling a wheelchair [25].

In these applications, EEG are commonly used to capture the affective state (e.g. relaxation [22]) of the user which can then be mapped to controlling virtual [25] or physical objects [22]. Researchers have explored a range of possibilities with sensed parameters, ranging from arousal [13] to engagement [8] and relaxation [22]. However, there exist only a limited number of generic design principles that can guide application developers in mapping a sensed parameter, such as the level of engagement, to virtual control. Answers to some of the fundamental control issues such as "*how many discrete levels of engagement can a user comfortably control?*" or "*is it easier for users to control a parameter by becoming more engaged than less engaged?*" are largely unexplored. Answers to such questions allow designers to break away from the confines of point-designs to more generic forms of mappings of EEG signals to virtual control.

Figure 1. A user wearing the EmotivTM EEG headset in the final study setup that combines engagement control and traditional input.

This paper is targeted at producing generic design principles for controlling EEG sensed parameters based on task engagement (hereafter "engagement"). According to Matthews et al. [27], engagement can be defined as the *effortful concentration and striving towards task goals* where task demands and personal characteristics may influence this pattern of processing. In another work, Matthews et al. noted that effort investments in the task would increase task engagement [28]. Studies have shown a positive correlation between EEG engagement and task demands including stimulus complexity processing and the requirement for attentional resources allocation [9, 35]. EEG engagement correlated with task loads in not only simple vigilance and memory tasks but also in complex simulation tasks such as in radar operations simulation environment [9, 10]. Consequently, if an application requires low level of engagement in using, it also requires low level of task demands, task loads, and workloads.

Commercial EEG kits (such as the Emotiv) can sense levels of engagement in real time giving interaction designers the ability to exploit this fundamental mental state as a control mechanism for various interactive activities. Previous research has derived methods to successfully measure engagement using EEG [12, 31], but the low-level questions for interactive control listed above remain unanswered.

We used an Emotiv EPOC for measuring EEG signals. Its signals quality have been validated by previous studies (e.g. detecting and classifying Event Related Potentials [11, 36], evaluating visualization effectiveness [6], exploring the nature of decision making [21], and designing a BCI controlled video game [5]). This headset is portable, easy to setup, and most users can wear it comfortably for at least an hour [14].

We implemented three experiments to generate principles for one-dimensional selection in the absence of environmental or task distractions, and a final ecologically valid experiment for controlling gaming parameters through levels of engagement.

From these experiments we observed that (a) users can comfortably control five discrete levels of cursor movement using engagement; (b) the time taken to move across levels of engagement is proportional to the distance required to displace a cursor; (c) that engagement affords bi-directional control (i.e. moving to higher and lower levels require similar amount of effort); and (d) in multi-tasking activities, engagement is a useful sensed parameter, but is mastered through repetitive task exposure.

The main contributions of this work are: 1) a systematic exploration of parameters that influence mappings of engagement to virtual cursor control; 2) quantifying the number of discrete levels that can be controlled via engagement states from EEG input; 3) a series of guidelines for designers; 4) a demonstration of the practical value of our mappings in a gaming application.

RELATED WORKS

There are many methods to detect neural signals from the human brain such as functional Magnetic Resonance Imaging (fMRI), functional near-infrared spectroscopy (fNIRS) and Electroencephalography (EEG). A brief summary of those techniques are discussed in [38]. The authors note that EEG remains a popular choice by HCI researchers due to its low cost, portability and high temporal.

A natural use of EEG sensing is for controlling interactive devices. This has led to a number of interesting applications, including new input methods for people with severe motor disabilities [15], capturing emotional and cognitive user states during computer use [23], facilitating interface adaptation based on the user's cognitive states [20], and augmenting traditional input controls with an additional emotional state, to enrich game experiences [2].

Computer games have progressed from keyboard and joystick input to rich physical movements (such as the Nintendo Wii and Microsoft Kinect). Future games are likely to take advantage of the BCI to increase user involvement. One discovery that has made BCI more interesting for gaming has been to use imaginary movements to produce similar brain signals as real movements [19]; it is then possible to create a BCI based agent which replicates the user's imagination [25].

The incorporation of BCI input technology into games can be categorized into three different groups:

- ***Traditional games with a BCI*** were originally designed for mouse and keyboard input but have been adapted to utilize BCI as the only input control for the game. Examples of these games include the walking game [26], or playing Ping-Pong using a BCI controller [1].

- ***Non-traditional games with a BCI*** afford the design of conceptually different games to those possible with traditional input mechanisms. For example, these games may utilize BCI capabilities to help players improve their mental awareness. As an example, in Brainball, gamers must relax to win the game [22].
- ***BCI assisted games*** augment BCI input with traditional controls to provide a richer experience. For example, if the user is frustrated when attempting to complete a task, the game could assist the player, or if their level of engagement is not adequate, the game difficulty could be elevated [18]. Mindflex (mindflexgames.com) is another commercial game that requires users to guide a ball through an obstacle course. The height of the ball is controlled by excitement while the movement in other directions is controlled by a knob.

One promising and highly sensitive parameter that is of interest is engagement. Pope et al. [32] present a measurement of task engagement from EEG as *beta/(alpha + theta)* at channels Cz, Pz, P3, and P4. Further studies [17, 33], with the same measure were used to show the performance quality benefits and reduced mental workload. These positive findings have been also replicated using extended periods of task performance [16] and a vigilance task [29]. This method was also used by Vi et al. [37] to evaluate the ease and interest of their dynamic photo viewing program. Interestingly, Fairclough et.al [7] raised concerns about directly applying engagement as a physiological input controller. In particular, Fairclough et. al questioned whether levels of engagement were sufficiently discriminable for input control.

In this paper we further study the discriminability of discrete levels of engagement for input control. Our study aims to provide design guidelines for the above listed styles of games. However the last experiment uses a BCI assisted gaming style to demonstrate and evaluate in an ecologically valid setting the usability of our guidelines in a gaming environment.

Factors Influencing the Design of a System using Engagement for Control

There are several factors that influence the design of EEG based systems. This section identifies four such factors: engagement discritization, selection technique, visual feedback, engagement calibration.

Engagement Discretization

EEG devices for measuring engagement provide a stream of constantly changing brain activity. Engagement can be measured as the ratio of the change in power-spectral density over a certain time window [31]. Depending on the length of the window, one can measure long-term or short-term engagement. For example, the Emotiv Epoc Neuroheadset measures short-term engagement in a short-time (overlapping) window with a step of 0.25sec and reports a number from zero to one. Continuous input control makes immediate use of this value. For example, continuous input can enhance-first person shooter games: if a player is highly engaged, small movements which make targeting easier are executed more often.

However, such measures of engagement often spike and change quickly, making on-screen parameter control difficult. To provide smoother and accurate control, the input range can be discretized into a smaller number of values or levels. This has the effect of reducing the accuracy required by users to select a specific value along a parameter range. Discretization can benefit game design, for example, by allowing the designer to alter the number of discrete levels for game balancing. There are no reported results describing how to suitably discretize this space; this is one of the central contributions of this paper.

Mapping Method

The aim of a discrete mapping is to translate a level of human engagement into one discrete command. There are at least two types of common mappings that a designer could choose: absolute or relative mapping.

Absolute mapping

Absolute mapping updates the position of the cursor regardless of the user's previous state. This can be done either linearly or non-linearly. In the former, all of the engagement states are given the same weight whereas in the latter different states afford different weights. In linear mapping, the position of the cursor is a direct one-to-one function of the current value of an emotion. Commercial games such as MindBall (www.mindball.se) and Mindflex (mindflexgames.com) use absolute mapping from relaxation level to the distance moved by a physical ball.

Relative mapping

Relative mapping positions the cursor based on the difference between the current and the previous engagement states of the user. This can be performed in different ways. One approach is to calculate the distance of two consecutive engagement states and with a function (linear or non-linear) calculate the displacement that should be applied to the cursor (e.g. this is based on the operation of the computer mouse). Alternatively, the cursor displacement can be calculated relative to a neutral state, instead of a previous engagement state.

Selection Technique

A selection technique allows users to pick a state after moving the BCI-based cursor into the required level. There are two possible ways for selection to occur on BCI systems: (1) within band, i.e. using BCI capabilities and (2) out-of-band, i.e. using a traditional input controller. Within-band capabilities include dwelling, hovering upon one state for a length of time, and changing the level of an emotion for triggering selection. Out-of-band can occur via a mouse double-click, a button press, or voice recognition. Our study employs a combination of both techniques.

Visual Feedback

This is one of the main building blocks of control systems and is especially important in Operant Conditioning based BCI systems. For example, it is a key component of P300 based systems. Buttons or objects flash over a period of time on screen and users are asked to count the number of times the interested object flashes to help them focus on the object and improve the P300 signal [39].

Different visual representations lead to different effects. For instance, Ramos et al. [34] showed in their study that users performed better with full visual feedback compared with spatial feedback. Many BCI-based outputs have been used for input control. However, there is little research that investigates how well a user can control these input states in different conditions and different forms of visual representations. We investigate the effect of visual representation on discrete state control.

Calibrating engagement

To utilize engagement as an input for a system, it is necessary to map it to a scale (i.e. 0 to 1) where the maximum and minimum values are known and used as boundaries of the scale. Although correlations exist between engagement and the power spectrum of

EEG frequency bands [12, 31], there is limited knowledge on how to find these limits. Better known is how engagement reaches low values when users close their eyes and relax, and reaches high values when users perform a three choice vigilance task (3CVT) [8]. Therefore, one solution to the mapping problem is using the values of each user obtained from the eye-closed task and 3CVT as the initial minimum and maximum values (see next section). These values can be adaptively changed during the task later. We use this approach to 'calibrate' engagement in our studies.

EXPERIMENT SETUP AND SIGNAL PROCESSING

We set out to better understand the parameters of interaction using engagement as an input for control. To do this we ran a series of experiments to understand user capabilities. This section describes the experimental setup and signal processing required; the follow sections describe individual experiments.

We used the Emotiv EPOC neuroheadset (a readily available and relatively cheap EEG based controller) in our studies. This headset collects EEG signals from 14 channels in the 10-20 international system [30]. The SDK provides access to raw EEG signals in real time. It also interprets excitement, meditation, and engagement intensities and represents those values on a scale from 0.0 to 1.0. However, the methods of extraction are 'black-box' and not revealed to researchers and consumers. To ensure the generalizability of our results we calculated the values of engagement from the raw EEG signals using the methods suggested by Pope et. al [31].

To calibrate participants perform the eyes-closed and three choice vigilance tasks (3CVT) for 5 minutes each. These values are mapped on a scale from 0 to 1 for the later control task. Participants first sat comfortably and relaxed with their eyes closed, but without falling asleep. This relaxed state was to measure the lower bound of the engagement of a participant (relaxed wakefulness state [8]). Participants then performed a three choice vigilance task (Figure 2).

The three choice vigilance task integrates features of common neuropsychological tests of vigilance. It also includes simple or choice reaction time tests and continuous performance tests [3]. It includes a primary object (presented 70% of the time) and two secondary objects. EEG signals collected from participants performing this task were used to calculate the higher bound of the engagement of each participant.

A trial started with an object appearing on the screen for 200ms; participants were asked to press the spacebar using both index fingers as soon as possible within two seconds after a primary object was shown, and do nothing with secondary objects. A message, which showed if the user performed correctly or not, was displayed for two seconds. There was a five second pause before the next trial began.

After performing the eyes-closed and 3CVT tasks, participants began the cursor positioning tasks (described later) - the on-screen cursor position was moved by users modifying their state of engagement.

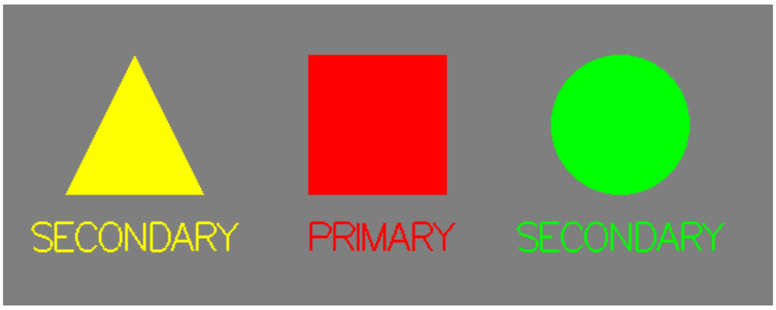

Figure 2. Three objects of the 3CVT. Objects appeared without captions in the experiment.

Signal Processing

We used an Emotiv EPOC wireless headset for measuring EEG signals. Its signals quality have been validated by previous studies (e.g. detecting and classifying Event Related Potentials [11, 36], evaluating applications [6, 37], exploring the nature of decision making [21], and designing a BCI controlled video game [5]). This headset is portable, easy to setup, and most users can wear it comfortably for at least an hour [14].

We conducted a series of steps to process raw EEG signals (see Figure 3). Raw EEG signals from the eight channels F3, F4, FC5, FC6, P7, P8, O1, and O2 were collected from the Emotiv neuroheadset. These channels were chosen because they are the Emotiv's closest to those used by Pope et. al. The signals then were filled into a two second window. The program only starts after the first window is completely filled. This window of signals was filtered through different band-pass filters to obtain β, α, and θ, the combined power in the ranges of 13-22Hz, 8-12Hz and 5-7Hz frequency.

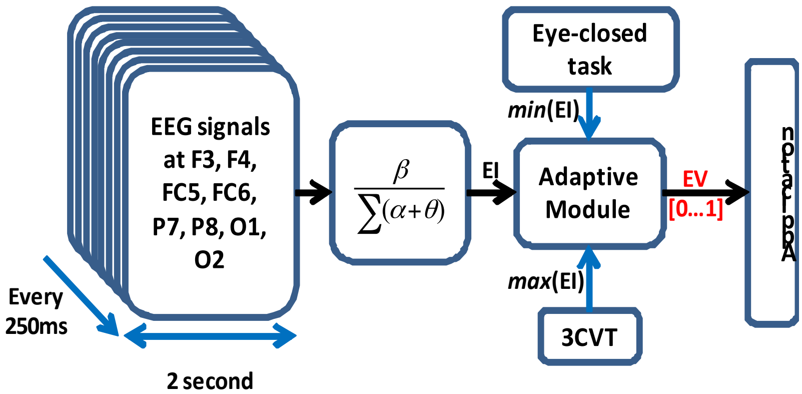

Figure 3. Signal processing procedure

The Engagement Index (EI) representing instantaneous user’s engagement was calculated by the equation (1). This formula captures best engagement [12, 31]. The window continually shifted and produced a new instantaneous Engagement index corresponding to the Emotiv’s sampling rate (128Hz). The values outputted from the closed-eye and 3CVT tasks were then averaged separately over all instantaneous engagement indices to measure lower and upper bounds of the participant. These two values were used for the third task.

For the third task, the engagement value (on [0, 1] scale) was an average of 32 instantaneous Engagement indexes (32 2-second windows). As the Emotiv has a sampling frequency of 128Hz, this also means a new engagement value is captured every 250ms. This interval is equal to the output interval of the Emotiv Affective Suite. The EI was obtained as the same as in the previous two tasks. However, the EI was mapped onto a linear scale by the formula:

$$EV = \frac{EI - \min(EI)}{\max(EI) - \min(EI)}$$

- EV = engagement value on the scale [0,1]
- EI = average Engagement Index over a 2sec window and shifted every 0.25sec
- min(EI) = minimum Engagement Index (initial value was from eye closed task)
- max(EI) = maximum Engagement Index (initial value was from 3CVT)

The maximum and minimum EI values were monitored and adapted for the user through an adaptive module that widened the engagement index band if a new EI was smaller than min(EI) or larger than max(EI). This was to cope with the case when max(EI) and min(EI) obtained from the first two tasks were not the largest and smallest EI values that the participant could obtain. The module detected and prevented noise which caused out-of-reach max and min indexes. The noise, which fell within the measured frequency bands, could be from body movement, facial actions and surrounding electrical equipments. It also smoothes the cursor movement by re-scaling the Engagement index when there was a sudden jump in EI.

EXPERIMENT 1: IDENTIFYING LEVELS OF CONTROL

The primary goal of this experiment is to establish the accuracy with which a user can manipulate their engagement levels to control an on-screen cursor. A secondary goal is to examine the suitability of different visual feedback types.

We divided this study into two parts: 1A and 1B. The experimental setup remained identical between the two parts, the conditions and participants were modified, as reported at the beginning of experiment 1B.

Experimental Procedure and Interface

The Emotiv headset was placed on the user and the experiment began when the participant was comfortable. At first, each participant performed the eye-closed task and 3CVT to get their own min and max EIs. These values were used for the following cursor control task.

In this task, the start state is shaded light green, the end state is shaded bright green, and the current state is shaded yellow (see Figure 4). To prepare the participant, a three-second countdown begins. Once the countdown ends, the user moves the cursor by changing their engagement level. The mapping was as such: being less engaged moves the cursor left (in the linear mode) or towards the center (bulls-eye mode). More engagement moves the cursor rightwards or outwards.

The participants' initial engagement level must match the start state before a trial begins. To achieve this, the participant must modify their engagement level to move the cursor into the start state, and keep it at a constant engagement for at least 200ms, at which point the trial begins. The user then adjusts their engagement level to reach the target. Once over the target, the user presses a key on a wireless remote to indicate the end of the trial. Trials are terminated if the user requires more than one minute to move and select the target. In this study, we use a one-to-one mapping of engagement level to cursor position. Participants were instructed to adjust their mental effort only. They were asked to not make body and facial movements (i.e. clenching, laughing) during the experiment. During the trials the experiment was continuously monitored to make sure participants followed our instructions.

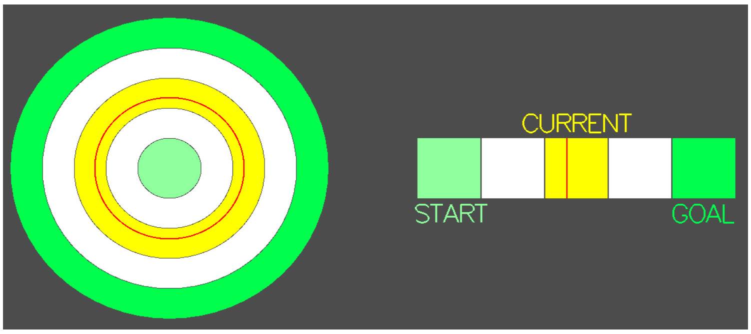

Figure 4. Bull's eye (left) and Linear (right) visualizations. The yellow circle (square) shows the user's state, the light green circle (square) shows the start state, the bright green circle/square the end state, and the red line/circle shows the cursor.

The visual interface had a size of 1280×1024 pixels and was displayed on a 19 inch widescreen monitor. Participants sat 90cm from the screen and their line of sight was perpendicular with the display. Participants were then given ample time to practice the 3CVT and control mechanism with both of the visualizations. The cursor control task consisted of four blocks of 16 trials. There was three minutes rest between blocks. The study took on average 60 minutes per participant, including practice time.

Study 1A

The experiment used a 2×4×2 within-participants design, with factors:

- ***Number of states***: 5, 10. Increasing the number of states requires users to more accurately make their selection.

- ***Distance***: +0.29, +0.59, -0.59, -0.29. Engagement is measured on a linear scale from 0 to 1. Distance is a measurement along this scale - positive distance indicates movement from less to more engaged, negative movement is the opposite.
- ***Visualization***: Linear, Bullseye. A one-dimensional matrix layout or a bullseye-like set of concentric circles (see Figure 4).

The factors visualization and number of states were counterbalanced between participants. The experiment consisted of four blocks (5B, 5L, 10B, 10L with B: Bullseye, L: Linear) of 16 trials with the presentation of distances modified between blocks. Each block contained 4 repetitions of all distances. The order of blocks was randomly assigned for each participant.

Participants

Nine participants (6 male and 3 female) between the ages of 20 and 31 volunteered for the study. All were from a local university and never had an EEG experiment before. Participants performed the eye-close task and 3CVT to obtain their minimum and maximum values of EI before performing the cursor control task.

Results

The total number of trials that were successfully completed was 552 out of 576. The average trial completion time for successful trials was 9.06sec (s.e. = 0.43sec). We carried out statistical tests using a univariate ANOVA with Tukey post-hoc pair-wise comparisons to compare the effect of *number of states* and *visualization*.

There was a significant effect of the number of states on trial completion time ($t = -5.187$, $p < 0.001$), with five states significantly faster (6.93 sec) than ten states (11.32

sec). There was also a significant effect of number of states on false target selection (t = -2.900, p < 0.05): five states had an average of 0.6 false selections, ten states 2.4. Figure 5 (left) shows the mean task completion time per state for each visualization.

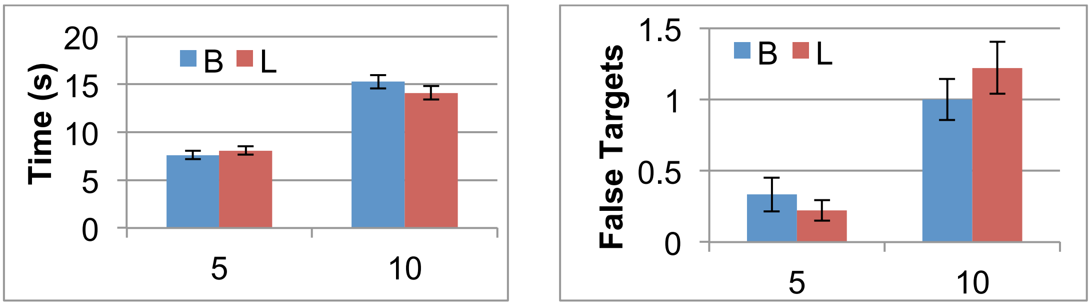

Figure 5. Task completion time in sec (left) and average number of false targets selected (right) for each state (horizontal axis) and visualizations (B / L = Bullseye / Linear Visualization) for Study 1A

We found no significant effect of visualization on trial completion time (t = -0.618, p > 0.1, linear = 8.79sec, bullseye = 9.33s) or number of false targets selected (t = 0.221, p > 0.1, linear = 1.44, bullseye = 1.33). An exit survey showed no differences in user perception of frustration (p = 0.707) or effort (p = 0.928) between the two visualizations.

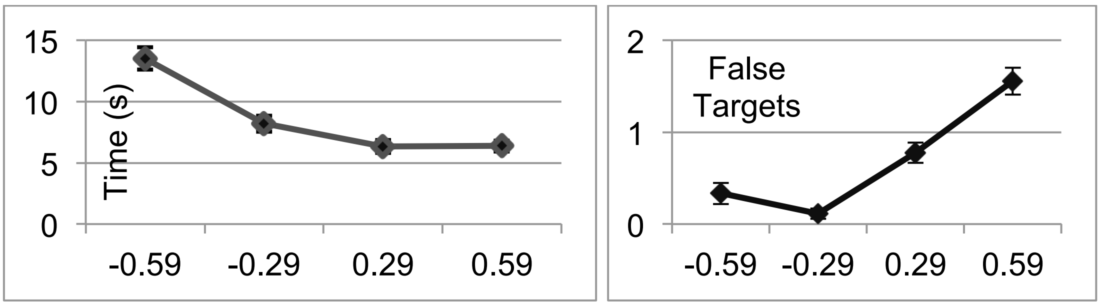

Figure 6. Task completion time in sec (left) and false targets selected (right) over distances for Study 1A

There is a significant effect of distance on trial completion time ($F_{3,25} = 13.490$, $p < 0.001$) and number of false targets selected ($F_{3,32} = 7.980$, $p < 0.001$). Post-hoc pair-wise comparisons showed users were significantly faster (p < 0.05) at decreasing their engagement than increasing it. There were significant differences in completion time within each pair: (-0.59, -0.29), (-0.59, 0.59), (-0.29, 0.59), (0.29, 0.59) (see Figure 6, left). However, there was significantly more false targets when going to 0.59 than -0.29 and -0.59. None of the other pairs showed significance.

Study 1B

In Study 1A, we observed that users were significantly faster when selecting from five states over ten and that there were less false selections using less states. Based on this result, we predicted that users should be even faster when selecting from three states over five. Study 1B tested this hypothesis. It was run with an identical setup as study 1A, with the number of states and participants differing as documented below.

Setup Differences

We modified the levels of the *number of states* factor to three and five. An additional eight participants (5 male and 3 female) between the ages of 21 and 30 were recruited for study 1B. As per experiment 1A, all had heard of an EEG headset but none of had used one before. All participants performed the eye-close task and 3CVT to obtain their maximum and minimum values of EI before performing the cursor control task.

Results

The total number of trials that were successfully completed was 501 out of 512. All false targets selected were with 5 states. The average trial completion time for successful trials was 6.08 sec (s.e. = 0.49sec). We carried out similar statistical tests for study 1A.

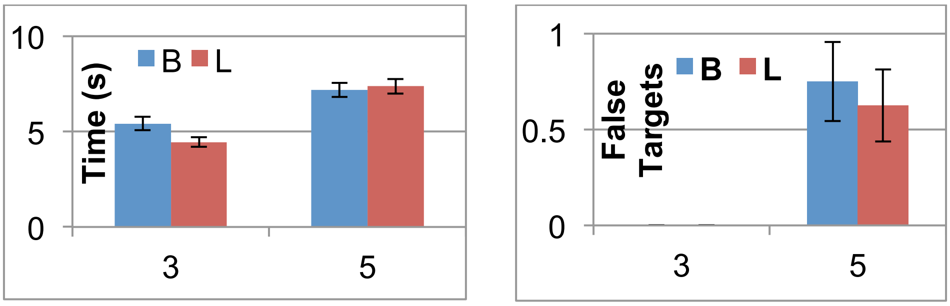

Figure 7. Task completion time in sec (left) and false targets selected (right) over number of states (horizontal axis) and visualizations (B / L = Bullseye / Linear Visualization) for Study 1B

We found a significant effect of number of states on trial completion time ($t = -3.422$, $p < 0.01$) and number of false targets selected ($t = -2.55$, $p < 0.02$). Users were significantly faster and selected fewer false targets with three states (mean 4.94 sec, 0.0 errors) than with five (mean 7.27 sec, 0.69 errors) as can be seen in Figure 7.

As with Study 1A, we found no significant effect of visualization on trial completion time ($t = -0.560$, $p > 0.5$) nor significant effect of visualization on number of false targets selected ($t = -0.221$, $p > 0.5$).

We found a significant difference between max(EI) and min(EI) measured in the eye-closed task and 3CVT over 17 participants of study 1A and 1B ($p < 0.001$). The average values of max(EI) = 0.81 (s.e. = 0.13), and min(EI) = 0.32 (s.e. = 0.02) (see 0).

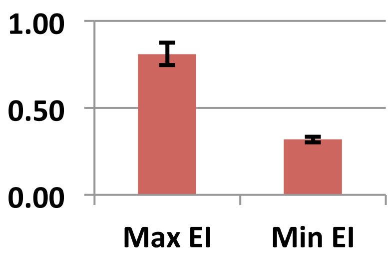

Figure 8. Average max(EI) and min(EI) measured in the first two tasks over all participants of study 1A and 1B

Discussion: Study 1A and 1B

Results from 1A and 1B reveal that the number of states is an important factor in the control of an on-screen cursor using engagement. Our studies showed that five states are preferable over ten states, and three states is significantly faster than five. However, three states offer less discretization flexibility: distances between levels must be greater than 0.33 or the start and target levels may sometimes overlap. We therefore chose five states as a comfortable range in which users can move a cursor. We use this value for our remaining studies.

Additionally, in our studies we noticed that the max and min values of the Engagement Index were similar for most participants. This might suggest that these values can be generalized to all users and can be used without calibration.

EXPERIMENT 2: ENGAGEMENT – BASED DISTANCE CONTROL

Experiment one showed that users were successfully able to move the cursor in order to select items on a one-dimensional visualization. This experiment sought to investigate the effect of engagement control direction and distance in greater detail.

Experimental Design and Procedure

The interface, design, and procedure for experiment two are identical to experiment one, except as noted below. In this study we manipulated the selection distance factor.

- ***Number of states***: From the previous two studies we saw that five states were optimal for this type of cursor movement and selection task. For this experiment, the number of states remained constant at five.
- ***Visualization***: The first experiment showed that there was no significant difference between the selection time for the two visualizations, with study 1B

finding the linear visualization was more accurate for selection. For this reason, we chose only the linear visualization.

- ***Block design***: We used four blocks with each block sampling each of the eight distances two times.
- ***Distances***: We selected four forward (increase engagement) and four backward (decrease engagement) distances: +0.2, +0.4, +0.6 +0.8 and -0.2, -0.4, -0.6, -0.8. Recall that in a five state condition a movement of 0.2 equates to shifting one state. Where possible, the start position of these distances was also varied.

Participants

Eight participants (5 female and 3 male) between the ages of 21 and 32 volunteered to participate in the experiment. All participants had heard of an EEG headset but none had used one before. They performed the eyes-closed task and 3CVT to obtain their minimum and maximum values of EI before performing the cursor control task.

Results and Discussion

The total number of trials that were successfully completed was 503 out of 512. The average trial completion time for these trials was 8.16sec (s.e. = 0.41sec).

As one would expect, an ANOVA showed that there was a significant effect of distance over trial completion time ($F_{7,49} = 5.014$, $p < 0.001$). Tukey post-hoc pair-wise comparison revealed the following pairs of distances were significant (-0.4, 0.6), (-0.4, 0.8), (-0.2, 0.6), (-0.2, 0.8), (0.2, 0.6), (0.2, 0.8).

Our results show that users are equally proficient in both directions (less to more engaged or more to less engaged state) as post-hoc comparisons did not reveal significant difference between pairs (-0.8, 0.8), (-0.6, 0.6), (-0.4, 0.4) and (-0.2, 0.2).

Figure 9 shows the mean task completion time for each distance. The graph shows an almost linear correlation between the distance moved and the time taken—R^2 values fall between 0.78 and 0.93. There are two important observations from this plot. First, the similar trend slopes indicate that the effort required for movement is similar in both directions. Second, while this was not a reciprocal tapping task, there is evidence from the plot to support the idea that Fitts' law may be a good predictor of time performance with brain-controlled movement using EEG.

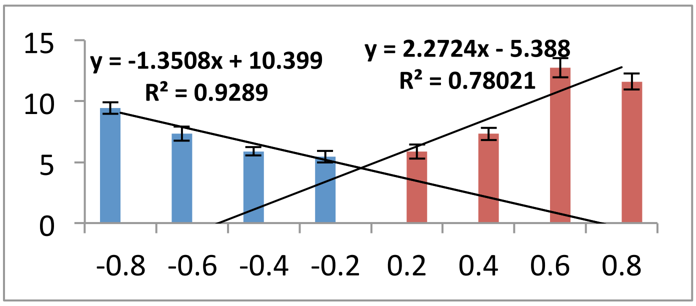

Figure 9. Mean task completion time for experiment 2; trend line shows linear correlation between time (vertical axis, in seconds) & distance (horizontal axis)

While in Study 1 participants found it easier to decrease engagement rather than to increase it, we did not find a similar affect in Study 2. In Experiments 1A, 1B and Experiment 2 the mean trial completion times for five states are similar for distances of -0.6 and 0.4. Note that Figure 9 includes the mean time for both 5 and 10 states so it cannot be directly compared to Figure 7 but it gives an indication that the data is similar. We thus believe that any difference in performance in either direction is small and less important at five states than when a higher number of states are in use.

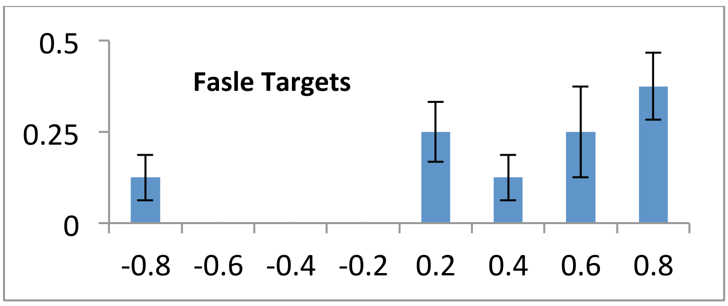

Figure 10. Mean false targets selected (vertical axis) for each distance (horizontal axis) with standard error bars for experiment two

Finally, we found no significant effect of distance on the number of false targets selected ($F_{7,56}$=1.029, p>0.05). Figure 10 shows the mean false targets selected by distance.

EPXERIMENT 3: DISTRACTIONS & MULTI-TASKING IN A GAME SETTING

With a better understanding of the low-level performance of BCI input from experiments 1 and 2, we applied our guidelines to a gaming task. The goal of this experiment was to examine users' performance in a situation that required multi-tasking.

Design

We designed a simple game that required players to complete two tasks simultaneously—one required the use of a traditional inputs (keyboard and wireless remote), the other BCI-measured engagement. The user is required to move an on-screen avatar from the start point on the left, to the end point on the right. During this task, a demon sends a fireball towards the avatar, which the player must destroy by modifying their engagement to the required level. The trial is success only if the player destroys the fireball and reaches the end point within 30sec.

Experimental Interface and Task

The experimental game interface (Figure 1 & Figure 11) was displayed on a 19 inch widescreen monitor (resolution 1280×1024 px). Participants sat 90cm from the screen.

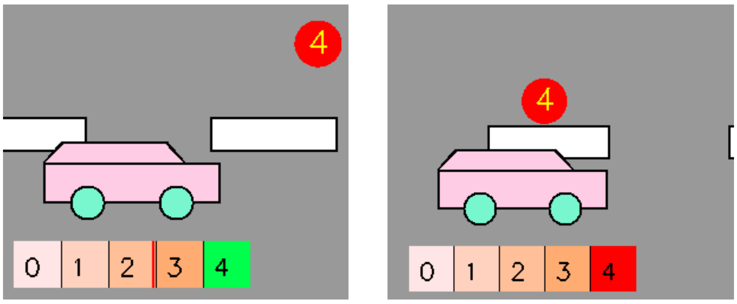

Figure 11. Visualization of the avatar (car), fireball (red circle), and engagement levels in case of not-matched (left) and matched (right)

Each trial begins when the user reaches either the maximum or minimum engagement level (on a scale from level 0 to level 4), as visually indicated on the screen. This ensures all participants begin with the same engagement level. The participant presses a key on a keyboard to move the character toward the finish line. A demon appears and fires a fireball toward the avatar as it crossed the ¼ distance position. A linear visualization with five states of engagement is attached to the character. Each state has a number inside and it is colored in a different shade of orange. The fireball has a shade of red and a number inside that matches one of the states on the visualization (Figure 11, left). When the user reaches the desired engagement level, its color on the linear visualization changes to red to indicate the matching of engagement state with the fireball's 'kill' state (right).

To destroy the fireball the user adjusts their level of engagement to match the number that is on the fireball. Once at that state, the user presses a key on the remote to destroy the fireball.

Experimental Design and Procedure

The experiment used a 2×8 between-participants design, with factors:

- ***Expertise***: Expert or novice user. Expert users had previous experience with the system through participation in either experiment 1 or 2.

- ***Distance***: +0.2, +0.4, +0.6, +0.8, -0.2, -0.4, -0.6, -0.8

The order of presentation of the distances was counterbalanced between participants. Each experiment consisted of four blocks of 16 trials. As with the previous experiments each participant was provided a full explanation of the study and given ample practice before the measured trials began. Users were encouraged to complete both tasks simultaneously - moving from one side of the screen to the other took 20 seconds, leaving only 10 seconds of extra time if the participant wished to pause to complete the engagement portion of the task (participants were informed of this). 10 seconds is about the average time we had previously observed for completing this task. Between each block the participant had three minutes of rest.

Participants

Ten participants took part in this experiment. We used five participants who had previous BCI experience from one of our prior studies (4 male and 1 female) between the ages of 20 and 29. Their max(EI) and min(EI) obtained from the previous experiment were re-used. However, these values could change adaptively during the experiment if participants reached an EI higher than current max(EI) or lower EI than current min(EI). Another five participants (4 male and 1 female) between the ages of 22 and 27 had heard of an EEG headset but had not used one before. These five people completed the eye-closed task and 3CVT, then performed the game control task. All were recruited from a local university.

Results & Discussion

With 10 participants, the system recorded a total of 640 trials. Of the 320 experienced user trials, 302 resulted in successful completion of the task. In the remaining 18 trials the users always failed to kill the demon before reaching the end. Novice users failed to complete the trial on 43 occasions, again always due to a failure to kill the demon.

The average successful trial completion time, for all users was 21.2sec. This was expected as the task was time-bound, with participants encouraged to complete the task in the time allocated. Repeated measure ANOVA showed a significant effect of distance on trial completion time ($F_{7,63}$=2.9, $p < 0.05$). Post-hoc Tukey tests (HSD=0.51, α = 0.05) showed differences between the distance pairs: (-0.4, 0.8), (0.4, 0.8), (0.6, 0.8). Repeated measure ANOVA did not show a significant effect of experience ($F_{1,8}$ = 2.434, $p > 0.05$) on trial completion time.

Repeated measure ANOVA on number of false targets selected showed no significant effect of experience ($F_{1,8}$ = 5.26, p = 0.051), a significant effect of distance ($F_{7,56}$ = 8.17, $p < 0.001$) and an interaction between the two ($F_{7,56}$=3.52, $p < 0.05$). Experienced users selected significantly fewer false targets than novices (experienced mean = 1.8, s.e. = 0.9; novice mean = 4.3, s.e. = 1.6).

We counted how frequently users stopped moving the avatar to kill the demon and measured stopping duration to see if there are any differences in how frequently and for how long experienced and novice users stopped to complete the engagement task. Univariate ANOVA did not show any significant effect of experience on either of these measures. There was also no significant difference for stop duration. Figure 12 summarizes these results.

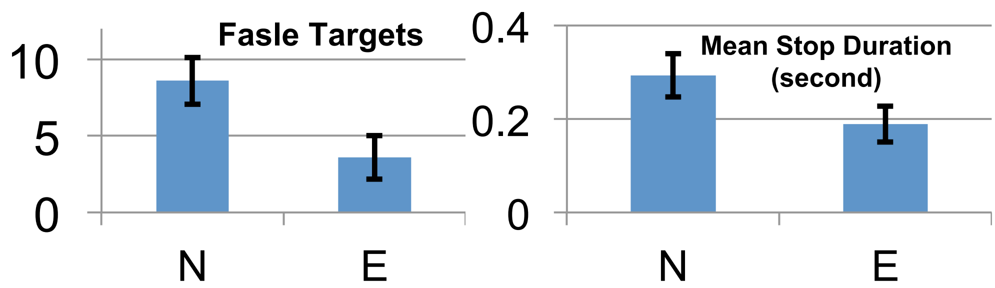

Figure 12. Number of false targets and mean stop duration for Experienced (E) and Novice (N) users

Overall Experiment 3 indicates that novice users are able to control engagement in a game like setting with similar finesse as experienced users. The biggest disadvantage is that novice users tend to select far more false targets than experienced users. One notable point is that the maximum and minimum engagement indexes can be reusable as experienced users can still perform the task well with the indexes obtained from previous studies.

DISCUSSION, IMPLICATIONS, AND APPLICATIONS IN GAME DESIGN

BCI-based input has the potential to revolutionize gaming. The results presented in this paper can guide design choices to enrich playing experiences.

Continuous vs. Discrete Input Control

Our studies have shown that users can comfortably select from a list of five items (with a proportional increase in time as the selection distance increases). By modifying the discretization of the engagement range game developers can modify the difficulty of parameter manipulation - increasing the number of levels requires more accuracy and greater practice and skill level. The studies also showed that one direction of selection is not favored over the other and that a linear mapping of engagement to cursor movement is appropriate for this type of task.

The assignment of the engagement channel to a control should also characterize the selection of continuous or discrete input. For example, weapons selection in a game would normally require discrete input control, but games with BCI could use continuous input to provide weapons that, in between discrete states, act as a morphed augmentation of two weapons. Where BCI is used as a passive parameter manipulator, the engaged or disengaged brain states could adjust the balance between armor or weapon strength; this way, users who struggle with exact parameter selection do not 'lose out' in a BCI augmented game.

It is also possible to design a game with characters adapting to different levels of engagement. For example, in a game like Warcraft Dota Allstars (www.playdota.com) where characters have intelligence, strength and agility characteristics, low engagement could increase strength; medium engagement could increase intelligence and high engagement could increase the character's agility.

Error Resilience in BCI Game Design

The swiftly changing nature of brain signals and the flickering inherent in BCI input due to this constant change makes very precise selections difficult. Unlike the common controller (keyboard, mouse) where a 'slip' error is a cause for incorrect input, BCI input is more erratic and influenced by environmental conditions. A player's emotional involvement can easily spike when triggered by an external source (for example, a friend walking into the room).

Experiment two showed that longer distance selections are more difficult (take more time) than smaller, closer selections. In these situations, developers can implement cumulative functions to let users achieve goals in small steps, rather than giant leaps. For example, a user might be able to pick up a distant sword by achieving a very high level of engagement. If they cannot reach this high level, then the sword may edge closer and closer to the user as they sustain a lower level of engagement. This choice is captured in our discussion on relative input control presented above.

Game input needs to provide error tolerance to cope with this alternative and possibly noisy input stream. Triggering actions such as firing a gun or casting a spell should not be purely based on the user's engagement level, as this could lead to unintentional actions. In this work, small scale fluctuations were smoothed by the cursor becoming thicker and combined with users indicating via a button when their engagement level was appropriate to make a selection. This latter type of mode-switching may not be appropriate for all types of gaming.

Serial vs. Parallel Interaction

There are no technical restrictions on continuously monitoring and interpreting EEG signals. However, unlike a mouse or keyboard it is unclear when input starts and ends. EEG input is 'always on', so designers must consider when to utilize this input stream. For BCI-assisted games, there are two options: serial or parallel interaction.

Serial interaction allows gamers concentrate on producing the engagement level required to complete the task - they do not need to perform mouse or keyboard input at the same time. Once their engagement level is measured they continue playing the game using more traditional input methods. Serial interaction may allow users to complete their tasks faster (as it has their full attention), but breaks the game's flow. For example, in a game like Delta Force a sniper's target aim can be relative to their level of engagement. If a player needs to aim at a small or far target he would need to bring down his level of engagement to the lowest level before firing the gun.

Conversely, parallel interaction requires the user to continue input using traditional controllers, while appropriately adjusting their engagement level to match that required by the game. Parallel input increases the number of simultaneous inputs and allows a smoother flow of game-play. However, performing other tasks using traditional inputs may distract gamers who are concentrating on controlling their level of engagement. Consequently, users may take longer or struggle to complete BCI-controlled tasks. For example, in a game like Diablo the player can move on a map and cast a spell simultaneously. The strength of the spell can be controlled by the engagement level and if the character is too close to the monster then a strong spell can also kill the player. This would encourage diligence in selecting the right spell level (encouraging control of engagement) but would also support error resilience by allowing players to kill a monster through multiple lower-level spells.

Generalizability of Results

We achieved our initial goals of providing more general guidelines for interaction with EEG signals, as demonstrated through the various possibilities for game design, for example. We specifically considered the sensed parameter of engagement. We used Emotiv's SDK to access EEG signals in real-time to carry out our experimental studies. Our studies were based around the raw EEG signals to provide the most flexible set of guidelines that can be then be applied to other EEG toolkits such as MindWave from Neurosky™, which also provide access to raw signals. One limitation is the need to calibrate the EEG signal to each user's engagement ability. While this may be somewhat mechanical for our studies, we can better integrate this through an initial game-play. This needs to be done only once and can be changed adaptively over time.

Lessons for Designers

We provide the following guidelines to designers: 1) For best performance discretize engagement into five or fewer discrete states; 2) Visual feedback showing the cursor, current state, and goal states should be clear to the user; 3) Engagement states tend to rapidly fluctuate and users should be allowed to achieve 'hard to reach' states in multiple steps; 4) Novice users require training, thus short games suited as 'training wheels' could prove beneficial to transfer learners into expert mode; 5) Combined input with a typical controller is possible for both walk-up and expert users.

Motivation of this work

There may be a question why engagement is chosen to investigate. Previously engagement was used to passively improve users' performance during various tasks when their engagement to the tasks changed. However we want to investigate whether users can manipulate their engagement actively. If so, how do we quantify engagement and can it be an additional input for interactive applications are valuable questions for application designers. Moreover, practicing the ability to control engagement can help users engage to the tasks better which improves productivity. Similar work has been investigated with the Brainball game [22] where it was proposed to be an interesting way of practicing control over brain activity and of learning how to relax.

CONCLUSION

The results of our experiments have led to a series of guidelines for designers of BCI-based games. We show that when discretizing raw engagement values five levels provide a good balance of speed and accuracy, users have good bi-directional control of engagement and are able to effectively control engagement in game-like multi-tasking scenarios. Our results also show that novice users are able to control engagement in a game like task and with a short training session they can noticeably improve their accuracy. Through detailed discussions and examples we show how our results could be used in game settings. The main contributions of this paper are a systematic exploration of various parameters that influence mappings of engagement to virtual cursor control; a series of guidelines for designers and a demonstration of the practical value of our mappings in a gaming application.

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