Assessment of Task Engagement using Brain Computer Interface Technology

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Abstract. The electrical activity of the brain can be quantified by measuring the electroencephalogram (EEG), a technology that underpins emerging commercial Brain Computer Interface (BCI) devices. The EEG can be used to directly assess measures of brain function: sensory, motor and cognitive processes. In this paper we assess the readiness of this technology for application to teaching and learning. We propose a hybrid BCI methodology that can be used to gather EEG metrics during an immersive control task. The changes in EEG provide objective measures regarding user engagement with the task. When used in conjunction with eye tracking technology, a hybrid BCI offers the potential of exploring learning at a more granular level.

Keywords. Immersion, Task, Engagement, Brain Computer Interface, Eye gaze

1. Introduction

The Brain Computer Interface (BCI) is no longer considered as purely an assistive technology. With the advancements in electronics, wearable sensors, algorithms and software development kits there has been a shift towards exploring other applications that use ‘thought processes’ to interact with computing systems. BCI has gained interest within gaming [1], assessing creativity [2] and as a non-invasive physiological observation mechanism [3].

In terms of mental state, certain characteristics within the ongoing electrical activity of the brain, known as the electroencephalogram (EEG), can be derived which provide insight into the ongoing sensory, motor and cognitive processes. Features that determine levels of engagement may be measured and quantified. These are based on derived EEG components, such as theta and alpha waves which are diffusely distributed across the scalp. In the future with appropriate technology it may be possible to investigate more subtle location specific cognitive processes, whilst a user is actively learning. Of course researchers in the field of neuropsychology have been active in this pursuit for many decades. However, over the last few years, devices have become widely available that record this activity away from the dedicated neurophysiology laboratory, allowing for a more pervasive solution. In addition software applications can provide feedback in real-time, allowing the effects of sensory stimulation to be assessed in an interactive manner, and facilitating the user to become more actively involved in the paradigm.

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In this paper we assess the possibility of using a commercial BCI to provide an objective measure of task engagement. The research is at an early stage. If engagement can be measured, then this could be an initial step towards assessing whether a person is actively involved with a learning paradigm. Indeed it can potentially allow known conditions such as dyslexia to be quantified and alternative learning strategies to be investigated. The remainder of the paper is structured as follows. Section 2 reviews this emerging technology to support an immersive environment. It proposes that engagement can be enhanced by combining an EEG headset with eye tracking technology. Thus we can assess 'where' the person is looking and if this is having an effect on the EEG. Section 3 defines the concept of engagement and evaluates previous work on EEG components that could objectively measure engagement. Section 4 details a preliminary experiment, which shows that EEG can be used to differentially classify 4 navigation tasks, which the user must actively engage with. Section 5 concludes with a discussion of the possibility of using this technology in an education scenario.

2. Advances in BCI and Eye Tracking Technology

Commercial BCI is increasingly targeting health and wellbeing applications, such as brain training, cognitive state monitors and digital entertainment controllers [4]. Vendors such as Emotiv (EPOC), Neurosky, Advanced Brain Monitoring (B-Alert X10), Interaxon (Muse) and Melon provide "lifestyle" BCI systems that employ headsets and headbands designed for ease-of-use and comfort. Dry and water based electrodes have been introduced to promote user acceptance. The technology has been designed with portability in mind, using wireless communication protocols, linked to laptops, tablets and smart phones. Additional sensor technologies such as accelerometer and gyroscope can provide contextual information on movement and orientation. Other channels such as electrocardiogram (ECG), electromyogram (EMG), electro-occulogram (EOG) and eye gaze may also be recorded, providing the possibility of a 'hybrid' BCI. On the downside, this emerging technology is restricted in the number of recording positions (4-14 electrodes) by comparison with laboratory systems (typically 16-32 electrode positions). Vendors have also provided psychophysiological assessment using proprietary signal analysis, yielding ab array of user behaviour metrics such as 'focus', 'engagement', 'interest', 'excitement', 'stress', 'confusion' and 'fatigue'. For example, the Melon headband measures brainwave activity at the front of the scalp, and claims to facilitate the detection and analysis of mental states including 'focus' and 'meditative states'.

Eye tracking is useful technology to assess task engagement. Until recently it has been expensive and restricted to dedicated laboratories. However this is changing; vendors such as Eyetribe have introduced a low cost, portable device with an Application Programming Interface (API) that facilitates integration with BCI to provide a hybrid BCI system where eye tracker and BCI can be used in a collaborative fashion.

3. User Engagement in an Immersive Environment

In order to address the effectiveness of any immersive environment, it is desirable to measure the level of engagement that a subject has with computer-generated content being played. Conventional objective measurement approaches involving visual (e.g. eye tracking) or aural sensing (e.g. speech analysis) do not necessarily indicate fully objective engagement with the user's thought and reasoning processes. Self-report data in the form of a questionnaire may be used but these data are subjective.

Engagement comprises the "perception-cognition-action-experience"; it refers to sustained involvement with an activity. Peters et al. [5] state that many overlapping user states are termed as engagement: interest, sustained attention, immersion and involvement. They suggest that a key factor in promoting engagement is the design and implementation of intelligent interfaces that can adapt to both the user and context. They further partition engagement as attentional and emotional involvement, leading to affective involvement.

States of extreme engagement, as in gaming for example, have been described: bored, apathetic, in-flow or anxious. Transitions between states occur as the balance between task demand and the user's skills change (this is why games need different levels of challenge). Task engagement can be defined with respect to cognitive activity (mental effort), motivational orientation (approach versus avoidance) and affective changes (positive versus negative valence) [6]. The engagement cycle, as defined by O'Brien and Tom [7], consists of four phases: point of engagement, sustained engagement, disengagement, and re-engagement. They propose the following definition: *"Engagement is a category of user experience characterized by attributes of challenge, positive affect, endurability, aesthetic and sensory appeal, attention, feedback, variety/novelty, inter- activity, and perceived user control"*.

Hence an effective computer mediated task must comprise feedback, user control, attention, motivation and the ability to challenge individuals at levels appropriate to their knowledge and skills. Engagement has also been described as the first in three levels of immersion. A mechanism that has been previously considered as a measure for engagement is 'where' the user is looking on the screen in correlation with certain times. Additional useful information may be derived from user attributes such as head direction, blinking, body movement and gestures. EEG can provide a direct channel to the brain's sensory and cognitive processing, providing a direct channel to measure engagement. This provides a further area of investigation, particularly with the deployment of appropriate low cost technology.

3.1. EEG for Measuring Engagement

In terms of measuring engagement as a cognitive process, EEG and other physiological signals may offer insight. According to Fairclough et al [6]: *"Physiological computing describes a category of technological systems that capture psychophysiological changes in the user in order to enable and inform real-time software adaptation."*

To evaluate suitable mechanisms for extracting such useful information, it is important to understand how physiological signals, such as EEG, can be used to determine a measure of engagement. The role of EEG in determining levels of alertness, attention and cognitive tasks, suggests that measuring brain activity can form a valuable input to such a system [8]. Using EEG, alone or combined with other sensor inputs, it is possible to evaluate the degree of engagement or immersion that a user has with different types of digital content. The content can potentially be updated in reaction to the user's response. Table 1 gives an overview of the 'classic' frequency bands within the EEG, i.e. the rhythms, which can signify certain characteristics.

Gevins et al. [9], [10], used theta activity from central frontal sites combined with suppression of alpha activity from occipital areas to indicate an increase in mental workload with an emphasis on remembering information. Davidson et al. [11] investigated frontal asymmetry as a potential metric, on the basis that positive emotions relate to high levels of left frontal activity and negative emotions are associated with higher activity in the right frontal location. Fairclough et al. [6] investigated frontal asymmetry combined this with frontal theta activity and cardiovascular response, namely, systolic blood pressure.

Table 1. Frequency Bands of the EEG

Rhythm	Freq (Hz)	Amp (μV)	Description
Delta	1-5	20-200	Present during deep sleep but may also increase during mental activities requiring concentration.
Theta	4-8	10	Present during sleep but may also occur at times when subject is frustrated, daydreaming or performing automatic tasks. In general, the occurrence and amplitudes of delta and theta rhythms are highly variable within and between individuals.
Alpha	8-13	20-200	Prominent wave pattern of an adult who is awake but relaxed typically with eyes closed although some subjects can use relaxation techniques to maintain the signal amplitude while eyes open. Greatest amplitude from the occipital areas but also from the parietal and frontal regions of the cerebral cortex.
Beta	13-32	5-10	Present when subjects are alert with attention to external stimuli, or engaged in a mental task. Recorded from the parietal and frontal lobes. Lower in amplitude than alpha waves
Gamma	32-100	5-10	Observed as neural synchrony from visual cues (both conscious and subliminal). The waves are link to consciousness and may relate to perception. They may be enhanced by meditation. The waves are prominent at 40Hz and may be linked to sensory processing in the visual cortex.

3.2. Examples of the use of BCI systems and EEG for self-quantification

Aspinall et al. [3] used a consumer-grade BCI headset, specifically the Emotiv EPOC, to monitor the effect of the surrounding environment on the mental states of their subjects. They asked subjects to walk through different areas of Edinburgh, which had been categorized as urban shopping streets, a green space, and a busy commercial district. From their recordings they looked for periods of excitement, frustration, engagement and meditation.

Crowley et al. [12] evaluated the use of Neurosky's Mindset headset to measure the attention and meditation levels of a subject. They found that the device provided information about the user's change in emotions. Szafir et al. [8] presented a system with an adaptive agent; and with the goal of monitoring and improving engagement. They also used the Mindset headset, gathering recordings from 4 electrodes. Reinecke et al. [13] analysed the EEG in the alpha, beta, theta, and gamma bands. Their results reinforced the capability of EEG as a suitable measure of user engagement and mental state, applied to sports science.

Zander et al. used of passive BCI; in [14] they suggest that passive BCI could be used to enable a greater understanding of important contextual information during mental tasks. Similarly, it has been proposed that electrophysiological patterns associated with specific cognitive processes, such as concentration, may be identified and explored using

BCI technologies [15]. Rebolledo-Mendez [16] used the Mindset to investigate alpha wave activity for meditative states; they compared these with self-reported attention levels.

A series of experiments demonstrated that augmentation of theta activity (4–7 Hz) from central frontal sites and suppression of alpha activity from occipital areas were both associated with increased mental effort in response to working memory load (i.e. number of items to be retained in memory) [9] [10]. In addition, Andujar et al. [17] [18] focused on improving subjects' experience during a reading task using the EPOC. They established a baseline for engagement and when the signal values dropped beneath this level they improved engagement by showing snippets of videos. They use a simple ratio devised by Pope [19] to give a measure of enagement from alpha, beta and theta bands:

$$Engagement\ =\ beta/(alpha + theta) \qquad (1)$$

Goldberg [20] devised an Intelligent Tutoring Systems using outputs from Emotiv's Affectiv Suite; short-term excitement, long-term excitement, and engagement. Overall, this study supported the use of the Emotiv as a low-cost solution to model cognitive state for desktop training applications. Roe at al. [21] also employ Emotiv's Affective Suite, using excitement, frustration, engagement, long-term excitement, and meditation measures to evaluate a subject's response to natural versus urban settings.

4. Experimental Methodology and Results of a Pilot Study

How useful could the information obtained from these devices be for measuring engagement? A pilot study was conducted, which evaluated a consumer-grade BCI device, the Emotiv EPOC, in order to engage subjects in an immersive task.

4.1. Methodology

Eight healthy participants (age range 23-56, 7 male and 1 female, all with prior BCI experience) took part in a short recording session that lasted approximately 30 minutes inclusive of setup and data acquisition. The Emotiv EPOC was cleaned with a 50% diluted solution of white vinegar and a soft cloth. The rear of each sensor was gently agitated with this solution to remove any corrosion. Before each trial, all electrodes and felt pads were placed in a hydrator pack and a saline solution applied. After this, each electrode was secured to the device and positioned appropriately on the head of the participant.

At the beginning of the session, the participant was required to undergo a training procedure facilitated by the Cognitiv Suite, which employs various approaches such as EEG and electrooculography (EOG). It records and interprets a user's conscious EEG and intent so as to enable the user to manipulate virtual objects. The Cognitiv Suite was used to train a 'neutral' state plus four navigation commands; left, right, lift, and drop. When training the neutral state the participants were required to relax and clear their thoughts. To train the left and right commands, the participants were asked to focus their gaze on markers to the left and right of the screen. To train the lift command, the participants were required to clench their teeth, and to train the drop command the participants were asked to tap their left foot.

Each trial commenced only after the individual participant had trained each command to an accuracy of greater than 60% (as advised by the Emotiv software). For all participants, each command had 3-15 training periods, with each training period lasting eight seconds. Once the session began, the participant was issued with twenty requests (e.g. move a virtual object in one of four directions) and allowed ten seconds to complete each request. A five second rest period was given between each request in which the participant was asked to relax in order to simulate the neutral state. For each request the participant had to concentrate on moving an object to one of four locations on the screen; top, bottom, left, or right.

4.2. Results

Including the training phase, each session took no longer than 30 minutes to complete. The easy to use interface with real-time feedback on the status of the electrodes also improves usability. The EEG time activity for each channel and spectral bands may also be viewed in real-time. Within this study, it was established that the use of a consumer-grade BCI headset (and accompanying software) for manipulating a virtual object based on gaze direction and actual movement is possible. These results suggest that the quality of EEG recorded using the EPOC is of an acceptable level for such tasks.

Over the initial training phase all four participants acquired a reported skill level greater than 60% for each command, as shown in Table 2, which also defines the skill rating of each individual command for all participants. From Table 3 it can be observed that each participant exceeded the 20% accuracy expected by chance. The mean accuracy for all participants equates to 78%, with participants B, C and G performing greater than 85%. Each of the four commands was issued five times per participant in a random order. All participants were able to correctly complete the lift command 97.5%, the right command 70%, the drop command 60%, and the left command 52.5% of the time. In addition, Table 3 represents the actual accuracy and defines the number of each request that was completed correctly.

Table 2. Training skill rating as reported by the Cognitiv suite

Subject	Gender	Overall Skill Rating	Left	Right	Lift	Drop
A	M	83%	86%	94%	76%	76%
B	M	79%	77%	71%	91%	78%
C	M	81%	74%	83%	87%	80%
D	F	81%	80%	95%	71%	78%
E	M	73%	70%	70%	81%	70%
F	M	76%	79%	75%	81%	70%
G	M	68%	60%	60%	72%	78%
H	M	86%	86%	99%	78%	81%
Mean		**78%**	**77%**	**81%**	**80%**	**76%**

Table 3. Subject accuracy achieved for each subject for each request

Subject	Gender	Actual Accuracy	Left	Right	Lift	Drop
A	M	35%	1	1	5	0
B	M	85%	4	3	5	5
C	M	90%	5	3	5	5
D	F	45%	0	4	5	0
E	M	75%	0	5	5	5
F	M	80%	5	5	5	1
G	M	90%	3	5	5	5
H	M	60%	3	2	4	3
Total		**70%**	**21**	**28**	**39**	**24**

Within this study, it is evident that reasonable control can be achieved with little training. Nevertheless, there are number of previous studies that suggest that the performance of the EPOC is lower than that of a research-grade BCI [22]. All participants had experience of research-grade devices and stated that the EPOC was much more comfortable and less difficult to setup. Furthermore, all participants agreed that, as with any BCI device, prolonged use causes fatigue. However, this study demonstrates that specific users are able to gain reasonable control with little effort, though suggests that this will not be the case for all users.

5. Discussion

The data presented in this paper shows that it is possible to interact with an immersive environment using a BCI headset alone. Albeit, we must be cautious due to the small sample size (N=8). However, this is not sufficient to study the active learning process. A further challenge is to analyze the EEG activity for robust measures of engagement using metrics such as suggested in Equation 1. To date, we have utilized purposely created classification algorithms, and these show some promise. Whilst engaged in a learning task, the EEG activity will include artifact due to eye movement and muscle activity. For a BCI to have merit in an education environment ‘cognitive features’ must be able to compensate for this or we may well be recording reading (ocular movement) without comprehension, for example.

An important educational ‘use case’ could be the automated assessment of engagement for children with special educational needs, such as sensory impairments, dyslexia, autism, etc. Part of this could be the assessment of comprehension and assimilation of information provided to the subject. Assuming that a robust measure can be derived from this engagement task, it may be possible to further address specific tasks such as reading. This could be valuable for understanding learning and the lack of educational progress associated with these conditions. Andujar and Gilbert [17] have used a BCI approach to investigate ‘physiological reading’; in this innovative reading approach the reader’s learning experience is enhanced by displaying engaging videos related to the reading when the engagement metric drops under an EEG determined baseline. In further work we have combined commercial devices (EPOC and Eye Tribe Eye Tracker) to achieve better control and interactivity with a virtual environment. This hybrid BCI has the potential to provide a finer grained environment for investigating engagement as we will be able to determine the link between where the person is looking and EEG measures of engagement.

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