Abstract

The Brain-Computer Interface (BCI) is a non-traditional method of machine control that has the potential to revolutionise the gaming industry. However, we have little fundamental understanding of the speed and accuracy with which users can control virtual objects using only the excitement levels of their brain. This research conducts a series of studies to investigate the use of BCI techniques in the context of gaming.

- We first investigated the accuracy with which users could select multiple visual states. Five states were found to be the most comfortable and users were able to move quickly in both directions (relaxation/excitement).
- In a second study, we found that users take a linearly increasing amount of time to increase and decrease their level of excitement.
- Finally, we investigated the practicalities of simultaneously controlling an avatar with traditional input and fighting a daemon with a BCI. Experienced users were more accurate in this parallel input task than novices.
- Based on these experimental results we discuss several game design principles.

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Introduction n

The availability of off-the-shelf Electroencephalography (EEG) kits (such as the Emotiv Epoc Neuroheadset and OCZ Neural Impulse Actuator - NIA) has made it possible to explore novel Brain-Computer Interfaces (BCI) for applications ranging from gaming [46] to cursor control [32]. EEG senses the underlying states of brain activity by interpreting the cortical potentials [33]. Researchers have demonstrated the capability of EEG based computer controllers through different point-designs and in a number of applications [33-19]. Examples range from using an EEG signal for classifying user tasks [1] to controlling a wheelchair [17].

A common feature with most of these applications is their use of a sensed brain signal to manipulate a spatial parameter, such as moving a virtual cursor [32] or even a physical ball in different directions [46]. However, there exist only limited generic design principles to guide application developers in mapping a sensed parameter, such as the amount of excitement, to virtual control. For example, we do not know how many discrete levels of emotional arousal/excitement can be comfortably controlled.

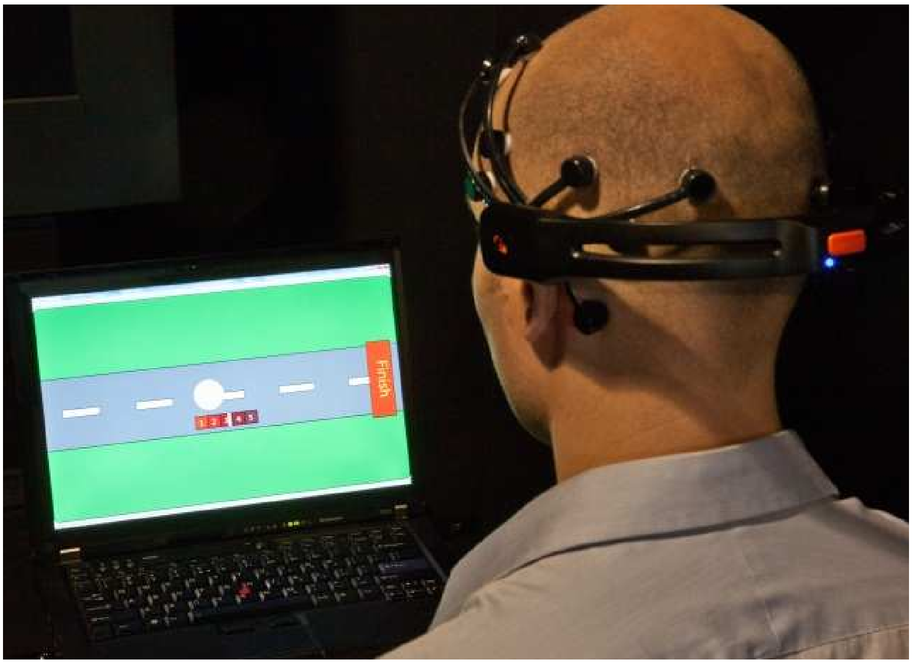

Figure 1: A user wearing the Emotive EEG headset in the study setup

Different sensed parameters have been explored in the literature ranging from engagement [34] to relaxation [46]. In this research we focus primarily on deriving design principles based on emotional excitement as captured by the EEG signals. We conducted a systematic investigation into the parameters that can affect user control of an on-screen object. We implemented three experiments—two exploring the parameters related to one dimensional selection and one gaming scenario that require both traditional input and the use of a BCI.

From these experiments we observed that (a) users can comfortably control five discrete levels of cursor movement with brain excitement; (b) the time taken to move to a particular level of excitement is proportional to the distance of the target; and (c) that the direction of control is uniform (it is as easy for users to relax than to get excited). In a final experiment we immersed the users in a multi-tasking scenario, analogous to one found in video games. In this environment, users were asked to use a wireless remote and BCI input to move an avatar and destroy a demon. Most users were capable of multitasking but experienced users were more accurate at completing this task, confirming further the guidelines we derived from our results.

The main contributions of this research are:

1. A systematic exploration of various parameters that influence mappings of EEG signals to virtual cursor control.
2. Quantifying the number of discrete levels that can be controlled via excitement 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.

Chapter 1: Background and related works

Human brain is made of approximately 100 billion nerve cells called neurons [1]. These neurons communicate with each other using electrical and chemical messages. Advances in cognitive neuroscience and brain imaging techniques have shown that by measuring these electrical signals (5-100µV) [1] it is possible to translate human thoughts and intentions to controlling signals.

> *A Brain Computer Interface (BCI) is a system which by sensing vital activities of brain such as electrical signals tries to understand underlying state of the brain (without relying on the normal output pathway of nervous system) [1].*

The result of implementing such systems is rewarding in different areas like:

- People with severe motor disabilities [7].
- Supporting biofeedback[1] training for people suffering from epilepsy, stroke or AHDH[2] [7].
- New input control for computer games enthusiasts [7].
- Valuable information for Human Computer Interaction (HCI) experts [1, 25].

[1] Allow user to see otherwise invisible psychological process in his/her body [23].
[2] Attentional deficit hyperactivity disorder

As a matter of fact, much of the BCI real applications to date have been developed to help people with limited movement skills [4], however, several efforts were made to make BCI an applicable approach for normal people. Unfortunately most of these efforts have failed due to lack of insight or ignoring technological boundaries.

Up to the present time, BCI falls short of being a valuable approach for normal people, mostly because of its limitations, like low bandwidth of input compared with other type of inputs (e.g. keyboard) [3], low accuracy, expensive hardware, unfamiliar shapes, and usually long preparation time. Nevertheless, there are situations where uses of BCI systems seem applicable and promising. Some of these situations are listed below [8]:

- **Induced Disability**: Situations where hand or voice communication is not possible. (Surgeons, soldiers, etc.)
- **Confidentiality**: The nature of BCI is such that makes it the most private communication channel ever.
- **Otherwise Unavailable Information**: As an example, real-time error recognition could be done by understanding the user's brain state.
- **Novelty**: Of course using this technology is exciting and it can attract some users to use it.

Despite all the above interesting possible usages, it should be pointed out that there are some issues which hinder the everyday use of BCI systems.

One reason for the limited usages of BCI systems is the lack of knowledge about abilities, capabilities, and preferences of human brain in controlling its outputs. In fact, even it is not identified that to what extent human brain is able to control its outputs. One area of research which could help to make BCI systems ready to use in everyday lives is to identify these characteristics of human brain in order to discover ways that the brain is able or prefers to control itself.

From a speculative point of view, traditional input controls are based on movements of human body, the skills learnt from the very beginning of life, whereas controlling brain is something into which the scientists have started to research recently. Hence, there is not that much idea about the possible ways of mapping intensions to actions. However, it is hoped to discover good mapping methods regarding users' experience of movement which is a reflection of their intensions.

Introduction to BCI Systems

Brain Computer Interface (BCI) is a new emerging field which tries to make a direct interface between human brain and computers. BCI is a multi-disciplinary domain formed by cooperation of scientists in Electrical Engineering, Computer Science, Medical Engineering, Neuroscience, Bioengineering, and even Art. Therefore, for understanding its abilities and capabilities a perspective of this field with its variety of domains should be depicted.

A BCI system usually consists of 3 major parts [7], signal acquisition, feature extraction, and feedback mechanism. There are several methods and techniques tailored for answering responsibilities of each part. Regarding to combination of methods used for each part, the characteristics of the BCI system will be changed. Hence, a decent level of knowledge about each part is necessary.

Methods used in signal acquisition part are divided into two categories of invasive and non-invasive methods. In the former, an array of electrodes is placed in the cortex layer of the subject's brain to record neural firing of neurons (Figure 2).

Since there is a need for brain surgery in invasive approaches, the trend amongst researchers for acquisition of brain signals have not been for using these methods. However, very interesting works have been done using invasive methods like controlling a wheelchair by a completely locked-in user [17], or controlling a robotic arm by rats and monkeys [16]. Nevertheless, in some recent research it has been proven that it is possible to reach the same level of accuracy and performance of invasive methods by implementing a non-invasive approach [9].

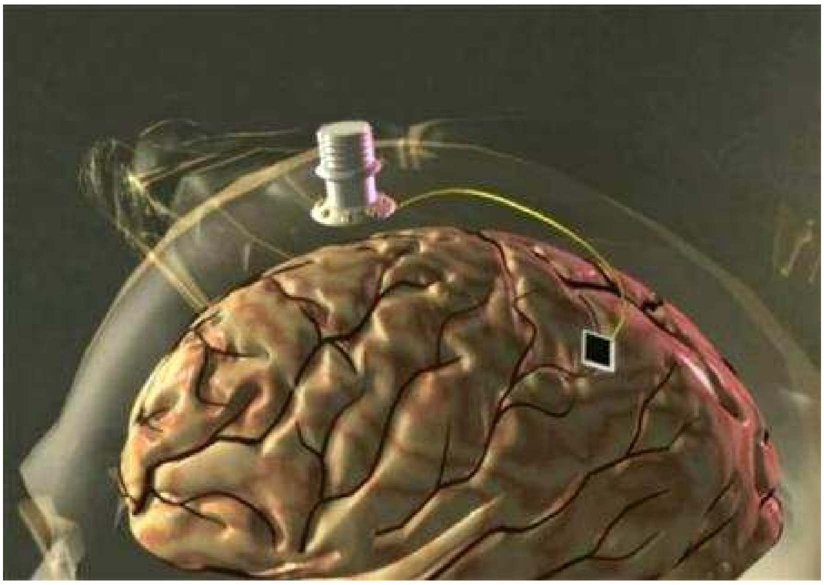

Figure 2: A matrix of electrodes installed in the cortex layer[3].

None-invasive approach is based on the fact that a variety of vital signs can be sensed from outside of the scalp. However, there are different kinds of sensors for collecting these vital signs. Functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), and Electroencephalograph (EEG) are three well-known methods of collecting signals from outside of the scalp.

fMRI senses the magnetic field around the scalp, while fNIRS measures the concentration of blood oxygen using infrared light [31]. fMRI is an effective technique for brain function imaging in medical science. However, it is vulnerable to the existence of metal objects and head movements [31], both of which are common

[3] Taken from http://forum.prisonplanet.com/index.php?topic=149466.0

when using a computer. For this reason, it is not favoured by BCI researchers. fNIRS has low temporal resolution making it challenging to detect fast responses after an event happened [35]. This precludes real-time interaction for controlling GUI-based systems.

Figure 3: Installation of non-invasive electrodes on scalp[4].

Electroencephalograph (EEG) is the most practical method of non-invasive signal acquisition used extensively in the labs [10]. The reason for using EEG as the signal acquisition method is not that strong. In fact, because of the impracticality of other approaches, EEG is considered as the most reasonable solution.

EEG is based on measuring sensible electrical potential caused by brain activities [25]. In order to measure these voltages a number of electrodes must be sited on the fixed places on the scalp (Figure 4). The electrode placed exactly in the middle of the scalp (C_z in Figure 4) is usually selected as the reference point of voltage; hence there are 64 possible independent channels for measuring EEG signals.

[4] Taken from http://realitypod.com/category/science_tech/robotics-science_tech/page/2/

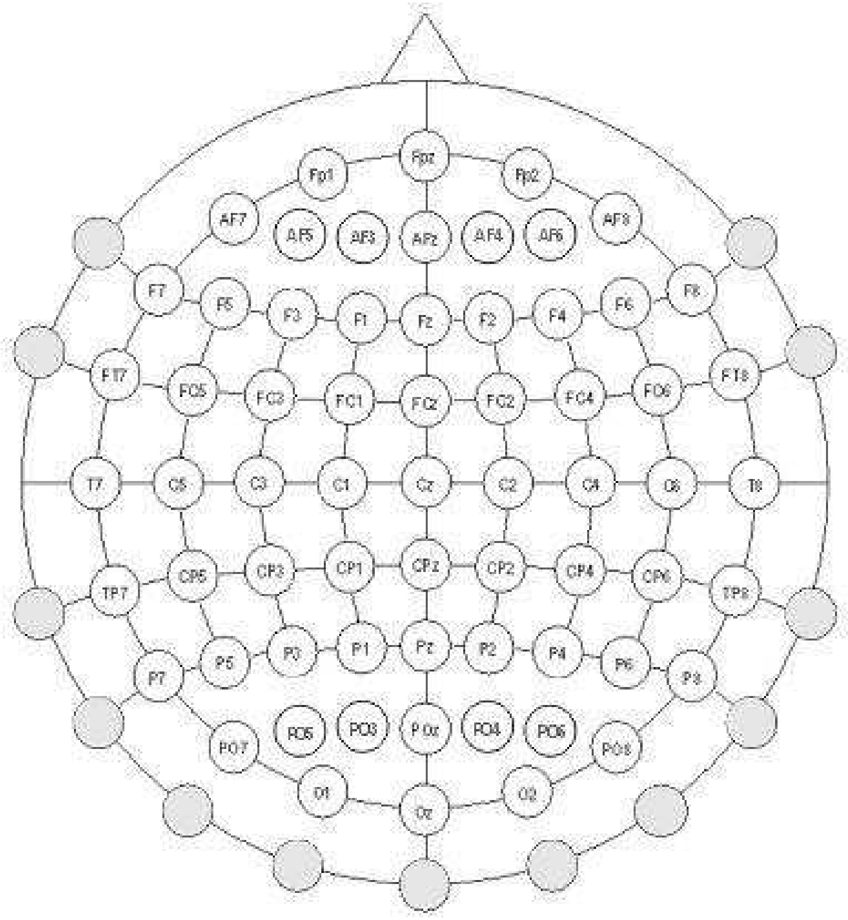

Figure 4: Standard placements of electrodes[5].

As it is clear from Figure 3 and 4, connecting 65 electrodes to users scalp could not be a practical solution. In the recent studies researchers have tried to reduce the number of electrodes compulsory for performing a task. Fortunately, using sophisticated techniques, they have shown that it is possible to reach adequate level of accuracy using only a small fraction of these electrodes (e.g. 3 [1], 9 [25], 16 [30] electrodes). It is not surprising that most of these ingenious techniques are based on machine learning algorithms used in the feature extraction part of the BCI systems.

However, there is a very big obstacle which hinders the way in which the EEG signals are used. It is the noise problem. In addition to lack of easy procedure for EEG measurements [3], the electrical potentials caused by brain interactions are really tiny. Hence, the EEG sensors must be really sensitive to be able to sense EEG signals (gain of amplifier which is used for EEG system is around 20,000 [1]) and as a result various things can affect the output signal of signal acquisition component.

- Some of these noises are caused by the nature of non-invasive signal acquisition. Separation of the electrodes from the source of electrical activity because of blood, bones, skin, and hairs [1, 25] is unavoidable.

[5] Taken from http://www.gtec.at/products/g.Accessories/gEEGcap_ge.htm

- Body movements are another source for noises. Body movements of person who is the subject of an experiment may cause very small vibration in electrodes, or change blood pressure, or even change the effect of gravity on the brain cells and these small changes may cause an undesirable noise on the signals [27].
- EEG signals cannot be separated from the Electromyography (EMG) signals. EMG signals are signals that are produced by electrical activity of skeletal muscles. Facial expressions, blinking, and eye movements are the most usual EMG related noises that appear on EEG signals [26].
- In case of using wires to connect EEG sensors to computer, electric potentials of wires can affect each other. Also movements of wires could cause noise in the output.
- In case of using wireless solutions for making the connection between device and its base, wireless radiations is another source of noise on EEG signals.
- EEG based BCI systems, as a practical solution, can work in a normal environment (e.g. an office). There are different sources of noise in a normal environment that can affect the EEG signals. Some examples are: computer hum, indoor power lines, florescent lights, electrical charges, mobile devices signals, Wi-Fi signals etc.
- Different mental states could also be considered as noise. For example if the goal of BCI system is to detect whether user is frustrated or not, other emotions such as drowsiness or happiness could have an effect on the signals.

Therefore, noise is a big factor in EEG based BCI systems and removing it from the EEG signal is extremely difficult**.**

Despite these obstacles, the results of research have been good and unexpected. There are many methods which can be used to minimise the effect of noise. Some of these methods try to purify the signals and some of them try to ignore the noises and keep working with noisy data. However, both of these methods rely on signal processing techniques.

Therefore, signal processing and machine learning algorithms play key roles in the practicality of BCI systems. The two major ways of processing EEG signals are monitoring Self-Regulatory Activities and Event Related Potentials (ERP) [10]. In self-regulatory activity approach slow cortical potentials or changes in cortical rhythms is the subject of the feature extraction, while the focus of the second technique is on the detection of the effect of a stimulus on user's brain waves.

The advantage of ERP approach is that it does not need any training data for feeding into its classifier; in fact it just relies on natural responses of human brain [10]. There are also some other techniques which are derived from ERP, for example visual Evoked Potential (VEP) and Steady State VEP (SSVEP) [11] are two well-known techniques which work similarly to ERP.

As a matter of fact the study of signal processing of BCI systems is not within the scope of this project. However, in a case study of practical BCI systems some of the relatively successful signal processing methods will be discussed in brief.

Feedback mechanism and selecting a mental strategy is the last building block of a BCI system. Mental strategy is the way that BCI system tries to stimulate something in the user's brain and feedback mechanism looks for the effect inside his/her brain waves. Similar to previous parts there are several methods for doing this job, two most prominent are Operant Conditioning and Pattern Recognition.

The difference between these two techniques from user's point of view is that the Operant Conditioning forces him/her to learn how to control his/her brain waves, while Pattern Recognition put the burden of learning on the BCI system itself [1].

Operant Conditioning requires that the user first train the system and then operates the application by repeating the same thoughts whereas Pattern Recognition uses signal processing and machine learning techniques to reveal the mental states or activities of untrained users.

Pattern recognition became more interesting when researchers found that imaginary body movements produce the same brain signals as the real ones [7]. As a result, it is possible to create a BCI based game which by imaginary foot and hand movements an agent walks [32] and punches.

In Pattern recognition, when the BCI system wants to know about mental state of the user, it picks some small amount of brain waves and tries to find out to which mental state this new signal belongs. It is obvious that because of the noise and many other technical issues signals cannot be exactly like each other, hence the output of the classifier is a number which represents the similarity of that signal to a category. But how much similarity to a category means that the mental state of the user belongs to that category?

In order to answer this question, scientists usually use statistical methods. For instance they calculate the mean and standard deviation of similarity parameter for training data, then by using these two statistical parameters calculate a threshold which helps to indicate to which category a signal belongs [21]. One possible way of calculating threshold can be seen in the following equation:

$$\text{Threshold} = \mu + k.\sigma$$

Where μ is the mean, σ is the standard deviation of similarity for training data and k is a constant factor.

Finally, with regards to BCI systems, it should be borne in mind that the presence of feedback is an essential element in them. Therefore, a BCI system should be placed in a closed-loop (Figure 5) [1]. A closed loop causes that when a BCI system makes a change in the environment that user is interacting with, some detectable effects trigger in the brain of user, which the BCI system will be able to make new changes in the environment according to the responses received from brain waves and so on.

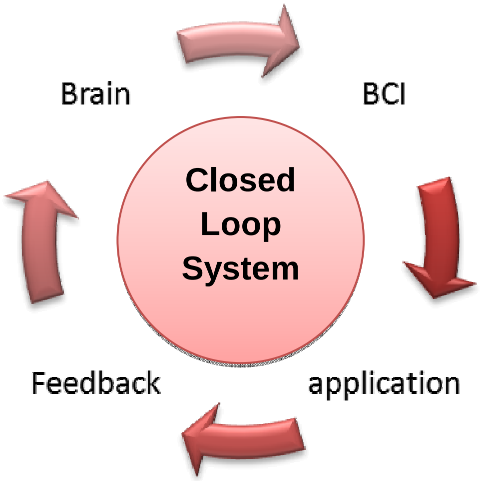

Figure 5: BCI system is a closed loop.

Related works

Electroencephalography (EEG)—the recording of electrical activity along the scalp caused by the firing of neurons—was invented a century ago [1]. Neuroscientists have shown that it is possible to understand the underlying states of the brain by sensing the vital activities of the brain through electrical signals that were caused by firing neurons in the cortex layer.

A logical progression of this understanding has been to use this output to control computing machinery leading to the creation of the Brain-Computer Interface (BCI) research field which has a number of interesting applications. These include, new input methods for people with severe motor disabilities [15], extracting emotional and cognitive user states from users whilst interacting with computing machinery [5], facilitating real-time interface adaptation based on the user's cognitive states [28], and augmenting traditional input controls with an additional emotional state, such as for computer games[6].

However one fact had been ignored about nature of this input controller in the first stages. Basically the amount of data that can be transferred from computer's normal terminals to human brain is significantly larger than the highest possible bandwidth that can be imagined from brain to computer [6]. In addition, technological limitations such as noise, high cost of sensitive sensors, and impracticality of having isolated environment [1, 4] forced researchers to look for new applications for EEG based BCI systems.

As regards this point the trend has recently shifted towards using systems which use EEG signals along other inputs [5] or systems which use EEG signals for understanding the state of the user (not for directly controlling something by the

[6] http://hothardware.com/Reviews/OCZ-NIA-BrainComputer-Interface/?page=5 (visited 14/09/2010)

user). Effectively, the later approach called passive usage of BCI systems is more interesting for Human Computer Interaction (HCI) designers [2, 4].

As it was mentioned already, applications of BCI technology which can be categorised as passive method are mostly interesting for HCI researchers. Using cognitive state of users for understanding their interaction with an interface [5], classifying the task which is being done by users according to their brain waves [1], and designing Attentive User Interface (AUI) which tries to maximise the focus of the user with regard to attentive resources of the system and the user [2] are three successful examples of using passive BCIs.

The fact that makes passive method interesting for HCI researchers is that BCI is able to supply some information which either was not accurate enough such as measurement of workload caused by interacting with an interface, or was not accessible before such as real-time recognition of emotions. This potential makes HCI researchers eager to find new ways that measure different factors such as memory workload, task engagement, satisfaction, and frustration using passive BCIs [1].

Traditional metrics for user interface designers such as task completion time or error rate are worthy parameters for measuring quality of an interface. However, none of these parameters give any information about more complex factors such as cognitive workload of user.

For example, user interface designers always try to minimise the workload of the user while working with an interface. In other word, the goal that HCI experts pursue is to make the user interface as transparent as possible for its users [26]. However, measuring transparency of a user interface is somehow impossible. This is due to the fact that there is no traditional way to measure the workload that user interface has caused apart from the workload of the task itself. However, by using BCI methods this measurement could be done [26].

To date, most of the techniques that can supply some information about state of the user are based on observation of user actions. This technique works because there is a relation between mind and body. However, it is essential not to ignore the fact that this relation is not direct, hence the comprehension gained by these observations will be indirect as well [25]. Therefore, finding ways that convey some information about state of the user from a direct medium have become very important for HCI experts [1].

For example, one device which is used in HCI experiments extensively is eye tracking devices which can give some information about the interface or the device which is being used by the user. However, unfortunately, it cannot distinguish whether the user is really engaged with that device or interface, or simply he/she is just looking at them [2]. The advantage of using BCI techniques in HCI is that they are searching for the state of the user source of intelligent and awareness rather than guessing it from its signs [1].

In addition to these typical usages, BCI systems might help us to understand the way that the human brain interacts with a user interface and might make it possible to improve user interfaces in a way that they are more compatible with the natural pathway of our thinking [22].

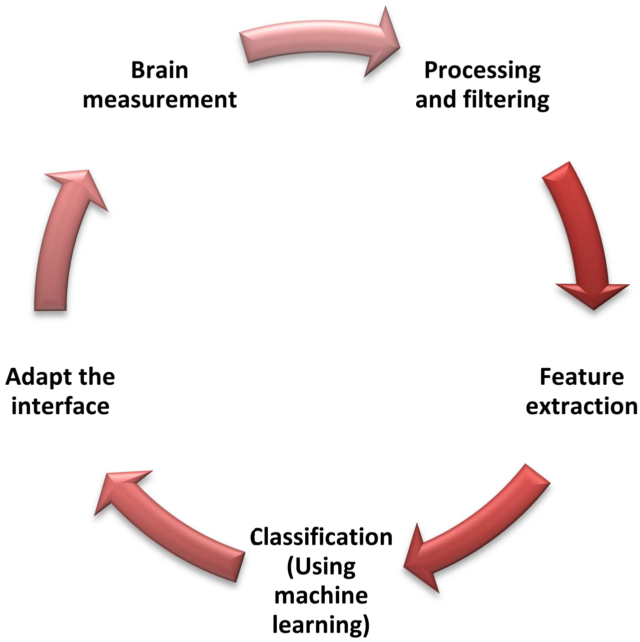

Figure 6: Process of making an adaptive user interface (Taken from reference [28]).

In addition to this helpful information, there are other benefits in using BCI systems. For instance it has not been possible to have a user interface able to adapt itself to the preferences of its users. The most important reason is that the process of measurement and consequently the process of evaluation of output measurement were not automatic before. BCI suggests solutions for writing software that can measure suitability of its own interface and then change it dynamically with regards to the preferences of its users (Figure 6).

To show capability of BCI systems for making adaptive user interfaces, it is possible to take a look at the applications developed with this idea in mind. The first example is applications which are able to understand frustration of users in doing a task and try to show some guidance on the underlying task [23]. And the second instance of using this paradigm is an application which is able to understand level of concentration of user and not to disturb him/her by sending unimportant interruptions [2].

Another domain which is really suitable for BCI system is game development. Computer games have progressed from keyboard and joystick input to rich physical movements (such as the Nintendo Wii and Microsoft Kinect). The expectation is that future games would take advantage of BCI input to increase the user's involvement.

The incorporation of BCI input technology into games can be categorized into three different groups: traditional games with BCI input, non-traditional games with BCI input, and games with BCI assisted input.

Traditional games with BCI input. These games were designed for more traditional forms of input (like keyboard or mouse) but have been adapted to utilize BCI as the only input control for the game. By controlling different cognitive states, gamers can walk through and play the game without the assistance of their hands. Examples of these games include the walking game [20], or playing Ping-Pong using a BCI controller[7].

Non-traditional games with BCI input. The BCI input for 'non-traditional' games affords 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 in order to win the game [19].

BCI-input assisted games. The third group augments BCI input with traditional input control 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 [23]. Another example is Mindflex (mindflexgames.com) a game that requires users to navigate 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.

Also, in addition to attempts to enrich games by BCI technology some companies have tried to produce commercial input controllers using this exciting technology. These products can be considered as two major groups. The first group consist of controllers which are produced to have same abilities as traditional input controls, and the second one consist of devices which are more like a novel game console. In the following section an example of both groups are given.

BCI in Practise

In this part, methods of collecting, analysing and mapping of data in practical BCI systems are discussed. Selecting the case studies, their relations to the objectives of this project and coverage of the contents of previous parts have also been carefully considered.

P300, A Well-known Selection technique

P300 response is one neurological phenomenon that can be measured using EEG signals and pattern recognition. P300 can be considered as a composite index of both attention and memory [1]. It is based on detecting a specific type of EEG signal which peaks at around 300ms (but could be up to 900ms) after presenting a stimulus. The amplitude of a P300 signal is changed with the target's higher

[7] http://www.emotiv.com/apps/applications/117/685 (visited 14/09/2010)

probability and lower discriminability and P300 latency decreases when targets are easier to distinguish [36].

In order to use this method selectable items start to flash over a period of time on screen and users are asked to count the number of times an object of interest flashes to help them focus on the object and improve the P300 signal [13]. In result, the amount of time taken to select an option depends on the number of items in the list can be relatively high [12] (e.g. consider a speller with letters, numbers, and important keys like backspace, space, and enter as options).

In order to improve the performance of this method, there is a method known as “N-chromatic technique” [13] which is based on decision trees. This technique suggests putting options in a 2 dimensional matrix (Figure 7). In this technique rows and columns start to flash instead of selectable items. Using a simple decision tree, it is possible to identify which item is selected in a more reasonable time.

P300 has been widely used in various areas such as to improve the life of patients who cannot move or communicate but are still aware and awake [4]. Further examples include playing a virtual piano [16] or selecting different objects on a multi-touch screen [15]. However, due to its low performance and accuracy, P300 control remains an inconvenient input choice for the normal user [37].

The data collecting method and analysing the signals in P300 are based on ERP method [11]. One characteristic of P300 technique which helps to ignore noise and other stimulus is that if it is considered as a graph of finite states, the transition between states is possible only in specific times [13] (300ms to 900ms after a stimulus).

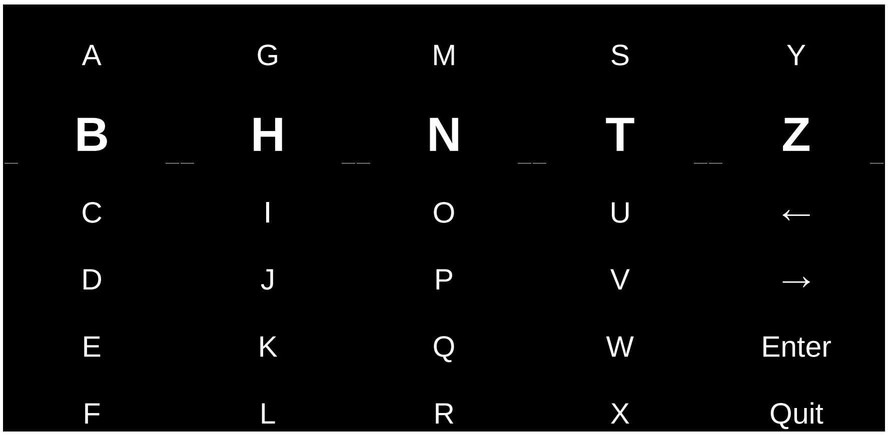

Figure 7: P300 table while the second row is flashing.

As it was mentioned before, in order to select an item, user should focus on a character of his own choice. Then as a consequence the rows and columns of the matrix start to flash (Figure 7). If one considers a flash of row or column in Figure 7 as an event, there are 11 events in the system (5 columns + 6 rows). However, when user’s attention is focused on just a one cell, only 2 (1 column + 1 row) events out of 11 possible events have an effect on the brain waves [11].

By recognising related events, P300 signal processing unit would try to narrow down the state space of the options and finally select one as the selected option. In order to process signals for extracting their features, usually signals are broken down into some windows which contain the important part of the signal. In P300 the important part of the signals usually starts from 220ms after stimuli and ends in 500ms [11].

Four different features are used for signal processing and finding the effect of stimuli on brain waves in a simple P300 system [11]:

1. **Stepwise Linear Discriminant Analysis (SWDA):** Before the start of process, it calculates the mean of a group of trial windows. While the selecting process is running it collects sample windows from EEG signals and measures the distance of each epoch of them. Using these parameters, it assigns a score to each window.
2. **Peak Picking:** The difference between the lowest negative and the highest positive points in a window is another feature that is used for signal classification.
3. **Area**: The area under the signal can be seen as another feature that can be extracted from each window for classification.
4. **Covariance**: A template of an ideal signal which depicts the effect of stimuli is derived from a set of training data. Covariance of this template and the real-time signal can be used as another feature for classification.

Using a combination of above algorithms, a score is assigned to each cell of the matrix. After repeating the above procedure a number of times, the cell that has the highest score should be the selected cell by the user.

The reason that four different features have been used for classification is quite ingenious. Actually this set of four features covers each other's disadvantages and make it possible to recognise P300 signals with more accuracy.

Covariance and SWDA are somehow the same. Both of them compute the similarity of signal to a template; however SWDA is more effective than covariance because it gives more weight to effective points in the signal. The disadvantage is that both of these features are sensitive to the latency of the effect of stimuli. It means that if an effect of a stimulation delayed in the signal, both of the features will assign low scores to it [11].

On the other hand Pick Peaking is not sensitive to latency but it ignores a great deal of other useful information in the signal. Finally Area feature considers all the points but ignores shape of the signal which helps to ignore noises [11]. By giving a good weight to score of each feature it is possible to achieve satisfactory results.

NIA[8], an EEG Based Input Controller for Gaming

One commercial EEG based input controller which is available for game players and researchers is NIA by OCZ Technologies[9]. NIA is based on a non-commercial device known as Cyberlink-Brainfingers by Brain Actuated Technologies[10].

NIA, because of its fancy look (Figure 8) and robust functionalities has gained some attentions from game players. By a quick search on the web one can find several reviews and videos about this device in different communities. The point which is emphasised in nearly all of the reviews is that using this device is like something that one has never experienced before.

Figure 8: NIA controller by OCZ Technologies (Taken from OCZ website)

NIA is a relatively inexpensive (i.e. about 140$) BCI system which can be used by game players. Beside reasonable price, there are other factors that make this device an important example of commercial BCI systems. Most important features of NIA that make it one step ahead of its competitors are:

- Sensible looking which does not make player like an alien.
- It needs nearly no preparation time
- The injection of conductive gels on its sensors is not needed.
- It delivers an amazing experience by only 2 channels (One sensor is reference).

Of course, in addition to these benefits it has some disadvantages as well. The most important one is flexibility of its usage. NIA is designed in a way that it can sense

[8] Neural Impulse Actuator
[9] http://www.ocztechnology.com
[10] http://www.brainfingers.com

facial expression related signals better than other signals. Moreover, users reported facial expressions have to be really exaggerated for being detected by NIA, making it a bit hard to use for a long time [14].

Emotiv[11] Epoc Neuroheadset, an EEG Based Gaming Console

Epoc Neuroheadset is another EEG based input controller which due to its online application store can be considered as a game console. Moreover, Epoc Neuroheadset has much functionality which makes it an ultimate device to be used for research purposes. Because of these reasons this headset had been used for the purpose of this project. Hence this device is described in more depth.

As Figure 9 shows the Epoc Neuroheadset is relatively more complicated than NIA. Not only does it cover all the functionalities of NIA but it is also able to deliver a number of more interesting functionalities. Specification of the device in the user manual is as follows [30]:

- 16 saline sensors (14 channels, two of which are reference sensors).
- A gyroscope is embedded in the device for detecting head movements.
- Wireless communication gives users the opportunity of free movement. It also can be helpful for reducing noises.
- Sampling rate is around 128Hz.

The device is relatively expensive (300$ for the headset, research suite costs 750$) but still affordable. It should not be forgotten that if one wants to play with a device at the cutting edge of technology, for example a jetpack, one has to consider selling one’s house or robbing a bank to be able to pay for that [30].

Figure 9: Emotiv Epoc Neuroheadset. (Taken from Emotiv website)

[11] http://www.emotiv.com/

The process of setting up -when you take the device out of the box for the first time- is not that difficult, however it is time consuming. It takes nearly 10 minutes to setup the device for the first use. After wearing the headset it should be checked that sensors are sited in their places. Fortunately there is a control panel which shows whether each electrode is sited in correct position or not (Figure 10). However it still takes around 5 minutes to place all the electrodes in their correct position to get a good signal quality.

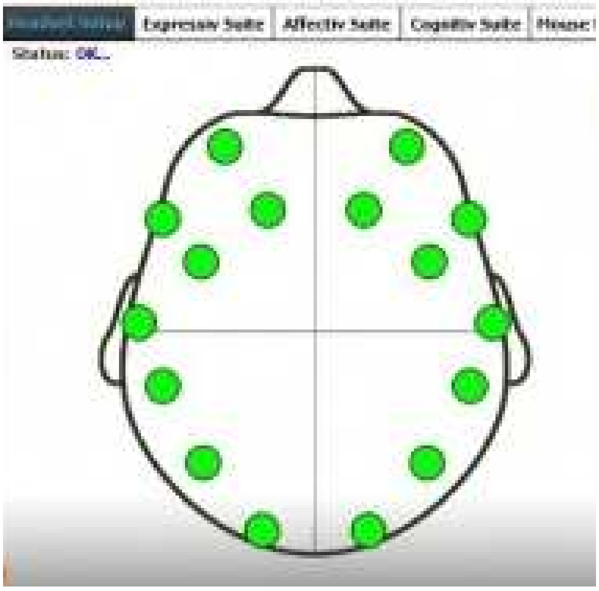

Figure 10: Electrodes positions on scalp. Green colour is the indicator of well-placed electrode.

Epoc can detect and respond to three kinds of actions; in fact Epoc has three different suites for playing around its abilities, Cognitiv suite, Expressiv suite, and Affectiv suite (Emotiv drops the letter ‘e’ at the end of the words. No orthographic errors here) [29].

Cognitiv Suite

Actually the most interesting feature of this controller for game players is in Cognitiv Suite. Cognitiv suite is able to recognise13 distinct actions, 6 directional movements (push, pull, left, right, up, down), 6 rotational movements (clockwise, counter-clockwise, left, right, forward, backward) and one imaginary movement (disappear). For understanding each action, it needs 10 second training data related to each action.

In order to use this suite, user should teach the classifier by a sample brain wave which is associated with a specific movement. Then in order to trigger the action detection algorithm, user should be able to produce the same brain wave again.

By trying and exercising to produce the same brain waves for an action, user will be able to improve his/her ability to control. However, this ability of Emotiv Neuroheadset is not that suitable for most of users, most of users do not want to spend hours to learn to control their brain waves.

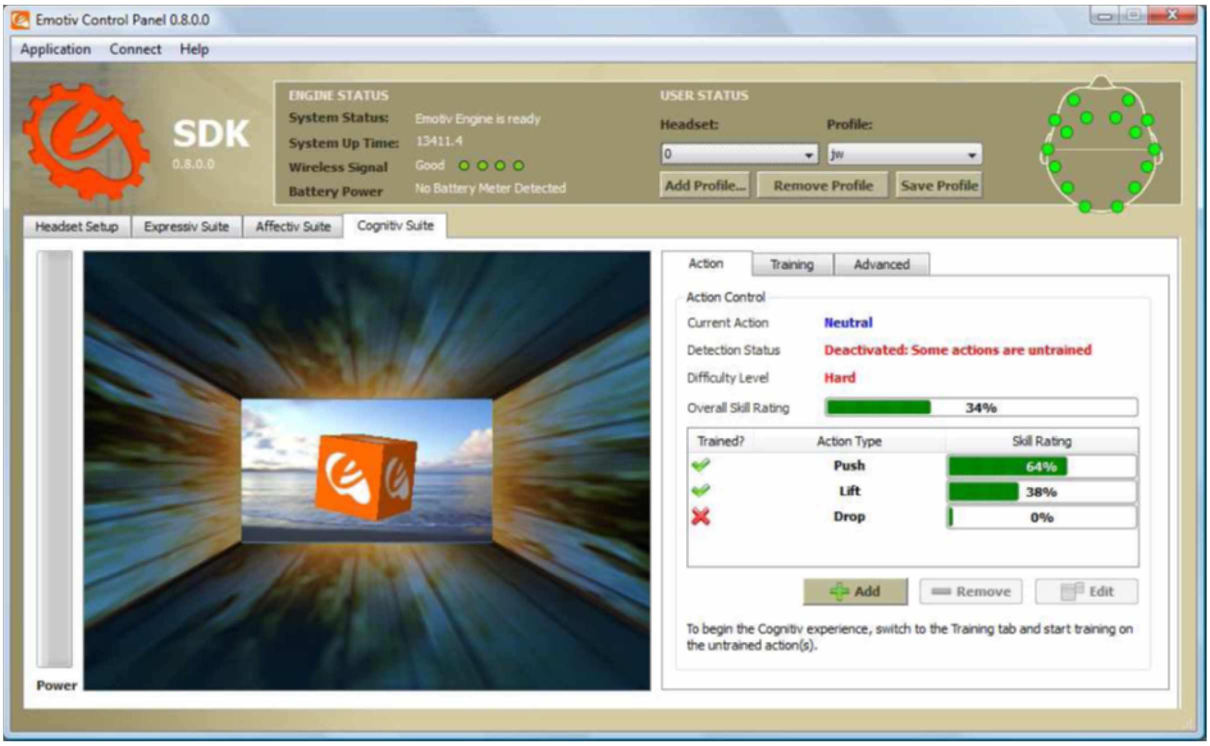

Figure 11: A snapshot from Cognitiv Suite control panel.

The irony about Cognitiv Suite is that the mental strategy and feedback mechanism that it uses is Pattern recognition, the goal of which is to put the burden of learning on the BCI system. However, in order to use Cognitiv Suite, users must spend considerable amount of time to be able to control their brain waves.

On the other hand it should be mentioned that this failure is not only because of bad implementation of Cognitiv Suite. In fact, the task of focusing on the desired mental state is nearly impossible for a beginner and if a user cannot produce same brain waves, it is not possible to recognise that by any mean.

Expressiv Suite

Expressiv Suite can detect facial expressions like wink, laugh, blink, raise brow, smile, etc. This suite does not need any training data to detect users' facial expression. However there is a sensitivity panel that enables users to customise the threshold being used for recognising the signal patterns (right panel in Figure 12).

The quality of functionalities that Expressiv Suite delivers is much better than the Cognitiv Suite. Of course there is some random facial expressions detection; however a fair critic would not say that it is a random response. Also all of the possible facial expressions which are recognised by Expressiv Suite are working together and it does not need to limit the usage to some of them.

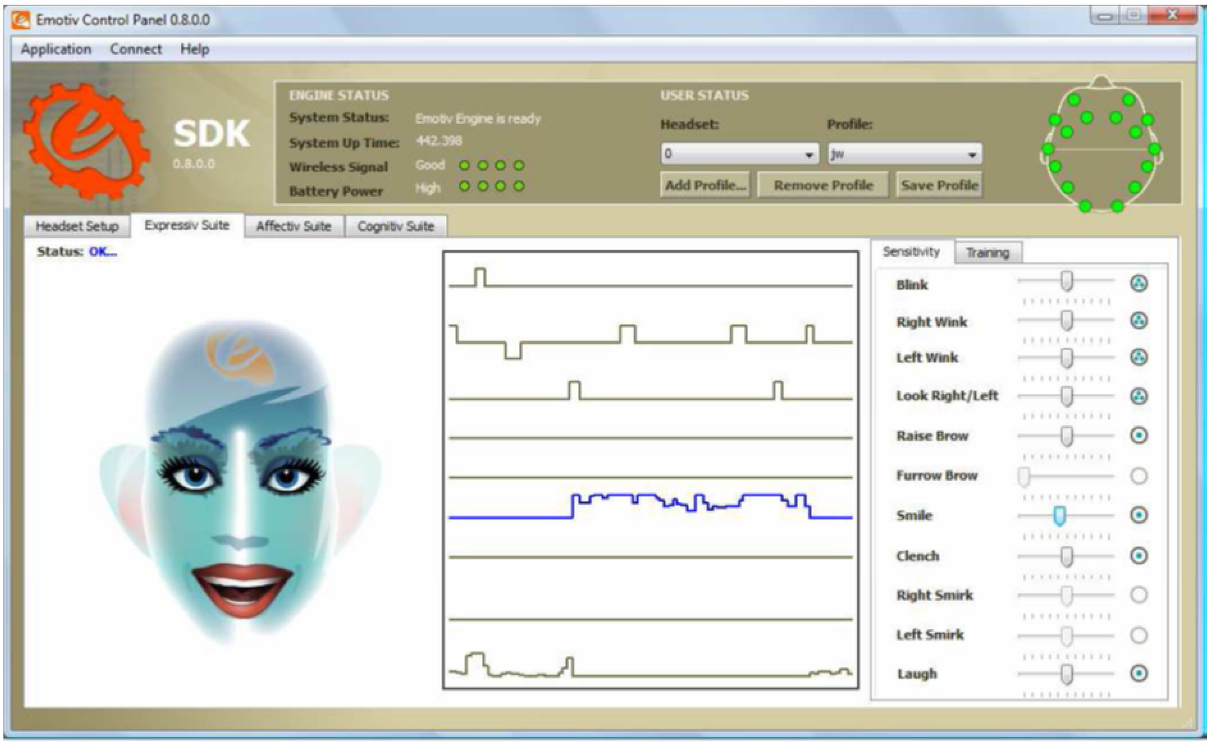

Figure 12: A snapshot from Expressiv Suite control panel.

This Suite is not very precise in detecting facial expressions due to minor differences of EEG signals on different persons. In order to solve this problem, Expressiv Suite enables users to tweak the sensitivity of each facial expression to make it more precise. However, it causes a longer preparation time which is not suitable in some cases.

Affectiv Suite

Affectiv Suite makes it possible to trace the emotions of user such as engagement/boredom, instantaneous excitement, long term excitement, frustration and meditation. The ability of recognising emotions in Affectiv Suite is completely satisfactory and without any prior adjustment or training is able to understand emotions of a new user. Moreover, the precision of its detections improves while user is working with it for a period of time.

Figure 13: A snapshot from Affectiv Suite.

In our pilot studies and tests we found that controlling meditation is usually very hard which was somehow predictable. Also, long term excitement is just a regression on instantaneous excitement on a specific period of time which makes it slow to response. Engagement/Boredom as another emotion that can be detected by Emotiv kit is hard to control for some users, and for all users it was nearly impossible to reach to the both ends of emotion range. Also, values corresponding to each Suite are floating-point numbers between 0 and 1 that shows the percentage of similarity of one's state to a specific emotion or action.

Mind Balance, a Game with EEG Based Input Controller

Mind Balance is a relatively simple 2-dimensional BCI game which utilises EEG signals as traditional input controllers. The objective of this game is to help a virtual agent to walk on a tightrope without falling down. The tightrope walking character walks towards the player on a rope and each 1.5 to 5 seconds bends on one side which is chosen randomly. The task of player is to change the balance of agent in order to help him to remain on the tightrope [10].

Figure 14: A snapshot from "Mind Balance" (Taken from reference [18]).

The method of controlling the agent is fairly simple and it does not need long training time. There are two checkerboards (Figure 14) on each side of the character; player can change the balance of tightrope walking character by looking at those checkerboards.

The method of signal processing is similar to P300 approach. It is based on causing two separate stimulations and searching brain waves to find the effect of one of them. The difference from P300 is that the stimuli in this game is steady, in fact those checkerboards are two steady signals which are phase reversed. Hence, when the user attention is focused on one of them, it is possible for the BCI system to understand which checkerboard is being looked at by the player [18].

Brainball, an EEG Based Game for Improving Mental Awareness

Brainball is a game designed by "The Interactive Institute"[12]. The importance of Brainball is that it created a new paradigm of game playing using capabilities of EEG technologies. Due to its fascinating parameters, Brainball is the most successful BCI game to date [19]. The factor which makes Brainball bold among other BCI games is that it works with the level of relaxation of its users.

[12] http://www.tii.se/

Figure 15: Brainball Game; Players compete in relaxation (Taken from reference [19]).

In this game two players wearing an EEG equipped headband and sit at two ends of a table with the Brainball on top of it (Figure 15). When the game is started the Brainball will roll away from the person who is more relaxed to the other end of the table. When the Brainball reaches to one end of the table the game is over and the person who is next to the ball has lost the game.

The controversial fact about Brainball is that it is a competition as well as being relaxing. Researchers have shown that Brainball does help people to decrease their stress level by playing it [24]. Also people who were subject of this research were asked about their enthusiasm for playing this game one more time, and not surprisingly more than 90% of them were eager to play it again [24].

In order to understand the underlying method used in feature extraction of this game, an abstract level of knowledge about neuroscience is useful. Human brain emits some waves which are related to its long term emotions. Researchers have found that by measuring these waves it is possible to understand the emotional state of the subject. These waves are categorised into four different groups by their range of frequency. Also some emotional states have been associated with each frequency band [19]:

- **Alpha waves**: These waves are in the range of 8 to 13 Hz. In the relaxing state, alpha waves are very strong.
- **Beta waves**: These waves are usually in the range of 14 to 30 Hz. Beta waves are associated with the alert state of brain. In the moments of pressure and intense mental activity they can even reach to 50 Hz.

- **Theta waves**: These waves are in the range of 4 to 7 Hz. and can be seen during the time of drowsiness.
- **Delta waves**: These waves are below the 3.5 Hz and can be seen during deep sleep.

By measuring EEG signals and extracting above waves from brain waves it is possible for a BCI system to access some novel parameters such as a measure for relaxation.

Measurement of Suitability

In order to compare different methods of utilising BCI technologies, some suitability measures should be defined. Therefore, selecting measures and finding ways for extracting them from the data collected during experiments is another part of this research.

One good measure which can be used in comparison of two BCI systems is performance. However performance has a broad meaning, for instance performance can be translated either as speed of doing a task or accuracy of doing a task [15]. Hence the definition of performance will be defined by the aim of the experiment.

Nevertheless, it is good to keep the fact in mind that performance is not everything [21]. Undoubtedly there are some situations where people do not like or want to do a task with highest possible performance; sometimes user does a task in a different way because he/she simply prefers to do it in that way.

Research has shown that people like to do their task in a way that they prefer as long as it is not 20% slower than the efficient way of doing that task [21]. Thus preference is another measure which should be studied alongside with the performance. Hence, designing questionnaires to find out the preferences of the users of BCI systems is one of the measures that have to be considered.

Emotions and Decision Making

Emotion is an individual's state of mind about a complex psychological experience based on sensory stimulation [38]. Emotion is externally expressed in terms of "affect", such as joy, sadness, anger, fear, surprise and disgust. These were referred to as the Big Six emotions [39] and do not include affects such as elevation [40], pride [41] or confusion [42], which were reported in the literature. An important aspect of emotion is arousal (or sometimes referred to as excitement) which is the state of responsiveness to sensory stimulation[13]. Arousal can be viewed as a call to action while affect provides the direction of experience [43]. As emotions can affect our actions in the physical world, there is a rich set of possibilities in harnessing these emotions in the virtual realm. However, from the review of the literature we cannot find generic design principles to guide application developers in mapping a sensed parameter.

[13]Dorland's Medical Dictionary for Health Consumers

To gain this understanding we focus primarily on deriving design principles based on emotional excitement as captured by the EEG signals; we focus on excitement as this refers to the state of responsiveness to sensory stimulation.

Final word

Despite the fact that this field is relatively young, outstanding results have been achieved until now. In some cases BCI has opened completely new research areas, and in some other cases it enriched the existing fields.

Nevertheless, nearly no one has considered the capabilities of human in control of his own mind, thus further improvements in this field bind to understanding these capabilities. As it will be discussed in the next chapter, the contribution of this project to the BCI domain is to investigate parameters that can make control of an interface using brain waves more suitable.

Chapter 2: Project Design

Factors influencing designs of BCI systems

There are several factors that need to be considered when designing an EEG based system. Here we identify four factors that can guide the design of BCI-based systems: EEG emotion, mapping method, selection technique, and visual feedback.

EEG Emotion

There are a number of parameters of emotion that can be identified by measuring the EEG signals. Typical emotions include Joy, Sadness, Anger, Surprise, Fear, and Disgust [39] which can be mapped using machine learning techniques.

Typically, the centre of a brain's emotions is activated when people make a decision [43]. As a result, emotions can affect our decisions in ways unaware to us: thinking about the future can raise feelings that consequently affect our actions [44]; we make quick choices based on emotional instincts (such as in flight-or-fight situations) [47]; decisions based on our emotional states are influenced by gender [48]; and realistic decisions are made under the influence of emotions of sadness or desperation [48].

Designers must choose an appropriate emotion to map onto their required task. Some emotions, such as surprise, may be harder for users to replicate than others or be inappropriate for the task at hand (e.g. asking a user to be sad when they are winning the game).

Discretization of Movement Space

BCI input devices provide a continuous stream of constantly changing brain activity along a scale. In the case of the Emotiv Epoc Neuroheadset this scale ranges from zero to one. Continuous input control makes immediate use of this input value of parameter control. For example it is possible to use continuous input control to enhance-first person shooter games in this way such that if a player is excited, small movements which make targeting harder are executed more often.

However, brain signals often spike and change quickly, making on-screen parameter control difficult. To provide more smooth 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 of users to select a specific value along a parameter range. Game designers need to balance the number of discrete states with the error tolerance desired – large number of states can lead to a finer the level of user control but with lower tolerance to fluctuations. To the best of our knowledge there is no reported results our how to suitably discretize this space, we investigate this issue in our later studies.

Mapping Method

The aim of a discrete mapping is to translate a level of human emotion 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 emotion state. This can be done either linearly or non-linearly. In the former, all of the emotion states are given the same weight whereas in the later different states afford different weights. In a linear mapping the position of the cursor is a direct one-to-one function of the current value of an emotion. Commercial games like MindBall (www.mindball.se) and Mindflex (mindflexgames.com) use absolute mapping to map the excitement level to the distance of a physical ball which the user needs to control as part of a game.

Relative Mapping

In this mapping method, the position of the cursor is based on the difference between the current and the previous emotional states of the user. This can be performed in different ways. One approach is to calculate the distance of two consequent emotional states and with a function (linear or non-linear) calculate the displacement that should be applied to 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 emotional 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: one is within band, i.e. using BCI capabilities and the other is out-of-band, i.e. using a traditional input controller. Examples of techniques that only use BCI capabilities include dwelling, hovering upon one state for a number of times, and using another emotion for triggering selection. Examples of the second approach include double-clicking on the mouse, a keyboard, or voice recognition.

Visual Feedback

Feedback is one of the main building blocks of control systems. It is possible to visualize the feedback of a system in different ways according to needs and specification of the system. Because feedback is a part of closed control loop, the effect of it on the performance of user could be significant.

Visual feedback is a key component of P300 based systems. Thus different visual representations could have different outcomes. For instance, Ramos et. al. [44] showed in their study that users performed better with full visual feedback compared with spatial feedback. Many BCI-based outputs have been used as control input. However, there is little research which investigates how well a user can control these input states in different conditions and different forms of representations. We conducted some experiments to study these questions.

Detail of the experimental design

In order to find which of the above factors can affect suitability of BCI systems for users, an iterative process was designed. This process contained design, implementation, and pilot test phases. The goal of each step was to improve achievements and remove problems of previous phases and iterations. Iterations continued until the final version of software got ready for the real experiment. During iterations some of our misunderstandings about abilities of users' brain discovered which caused to change some of the objectives of the research.

In the beginning, suitability of different mapping methods was an interesting topic to investigate. The aim of a mapping method is to translate level of human emotion into an action. Emotiv kit maps each detectable emotion to a range from 0 to 1; the outcome of a mapping method is to map location of a cursor on the screen using this value.

There are two ways for mapping emotions to actions. One is absolute mapping and the other one is relative mapping. In order to identify fitness of each mapping method one example from each of them developed for comparing performance of users in controlling them.

In order to implement an absolute mapping, a linear absolute mapping method was implemented, essentially because the level of accuracy of emotions by users was unknown. In that situation using more complex type of mappings (e.g. Non-linear absolute mapping) just made analysis of the results more complex than a simple one to one mapping. The formula below designed and used for this mapping:

$$\mathrm{Cursor} = \mathrm{BS(t).\,d}$$

Where BS is Brain State, t is current time, and d is a factor that change dimension of brain state to dimension used by cursor (pixels).

In order to implement a relative mapping, an average state which is average of user's brain state during a period of time was defined. Using average state and current value of user's emotion, a formula designed for changing position of cursor.

$$\mathrm{AS} = \left(\sum_{0}^{n} \mathrm{BS}(\mathrm{t}-\mathrm{n})\right)/n$$

$$\Delta = \mathrm{Cursor} - (\mathrm{BS}(\mathrm{t}).\mathrm{d})$$

$$Displacement = \Delta/\mathrm{c}$$

$$Cursor = Cursor + Displacement$$

Where AS is average state, t is current time, n is period of time for calculating average state, BS is Brain State, d is a factor that change dimension of brain state to dimension used by cursor (pixels), and c is a constant to make the jumps smaller.

In the next iterations we found that our knowledge about control of users on their emotion is very limited. Because implementation of a good relative mapping function needs decent knowledge about inputs of the function, it was decided to just focus on absolute mapping method.

We also designed and developed two selection methods, selection by click and selection by dwelling on chosen state. In pilot experiments we found that both of them are controllable by user. However in the design of the real experiment we found that for collecting enough data points to be able to do statistical analysis we need a large number of trials from each user. Because in our opinion selection technique had the least importance between other factors, we omitted investigation about this factor to reduce the time of experiment to around 1 hour.

As it discussed before, since comparing accuracy of user on controlling different emotions was not a topic of interest for us, we focused on excitement as this refers to the state of responsiveness to sensory stimulation.

In order to control excitement we should define what excitement is precisely first, however definition of excitement cannot be found clearly. In everyday use of word excitement, it is always coupled with other emotions like excited/angry, excited/happy, excited/curious, and more. Moreover, the algorithm which Emotiv used for measuring excitement is unknown and proprietary. Hence it was hard to discover which form of excitement is detectable by Emotiv.

In Emotiv documentation it is mentioned that they record brain wave of 2,000 people from all around the world to make a universal signature for understanding user's emotion and actions. Collection of universal signature for each emotion suggests that they stimulated users to bring them to an emotional state and record their brain waves.

The problem in this situation is that reactions of people to a specific stimulus could be different. For example imagine that for stimulating people to get excited they showed them a card trick. Probably most of people get excited when they see a card trick, however type of these excitements are not the same. For example, some people may get curious and excited while some other get happy and excited.

In result, because of vague definition of excitement and also uncertainty about the emotional state that Emotiv kit discovers as excitement, we tried different ways to understand which emotions can trigger excitement detection algorithm. We suggested these ways before experiment sessions to all the participants and let them to try and find a way which they are more relaxed with it.

These ways include thinking about complex things and reasoning about them (doing mathematical operation doesn't help), thinking about a joyful memory or event, thinking about a joke or a funny scene, thinking about favourite music, and thinking about shocking or surprising situations.

Also it is mentionable that four participants were not able to control the cursor using their excitement at all. In total 30 different participants participated in our experiments. In one case we were not able to install the headset properly due to small size of skull. However for three other participants we do not have any particular scientific reason that why they were not able to control the device.

Meanwhile a framework which is capable of doing different experiment was designed. This framework was developed in C# because (a) Emotive SDK is only available in C++ and C#; (b) C# has more convenient features for user interface design. Also, because of relatively better performance of Windows Presentation Foundation (WPF) than Graphical Device Interface (GDI) in redrawing 2D objects on the screen, graphical parts had been developed using this technology.

Because of importance of logging, responsiveness of application had been considered as one of the important issues in the design phase. Hence, along trying to improve performance of code, different threads had been mounted for handling different tasks.

Model-View-Controller (MVC) pattern had been used for the design of the framework. As it can be seen in Figure 18 EEGPresentation package is the View, EEGcontroller package is the Controller, and EEGSignalReader, Emotiv and Log packages are parts of Model.

In the rest of this section class diagram and sequence diagram of the main components of the system can be found. These two diagrams cannot be mapped on the code entirely, because lots of unimportant data is omitted from them to make it more readable. However they are useful for understanding data flow and low level design of the program.

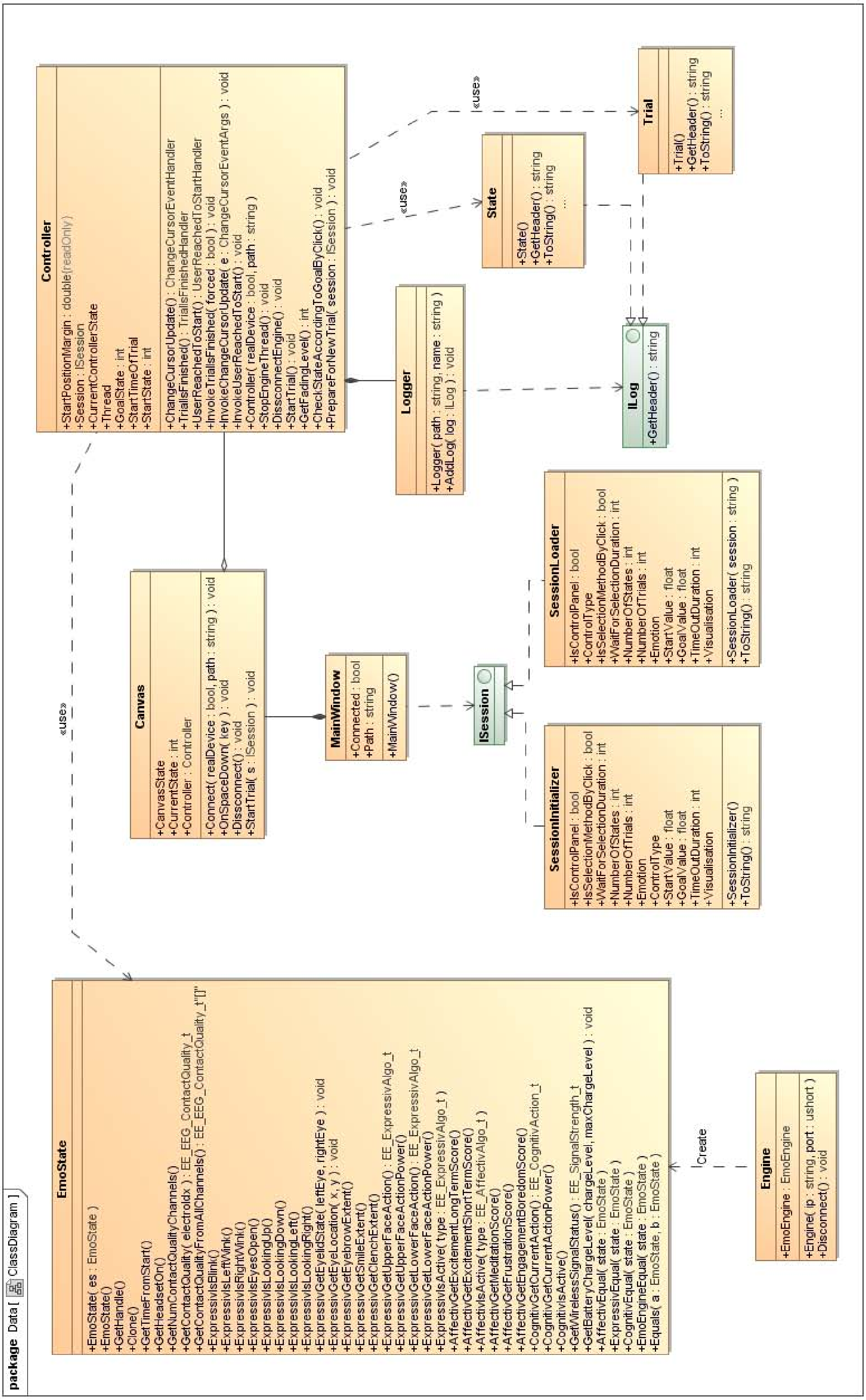

Figure 16: Class Diagram.

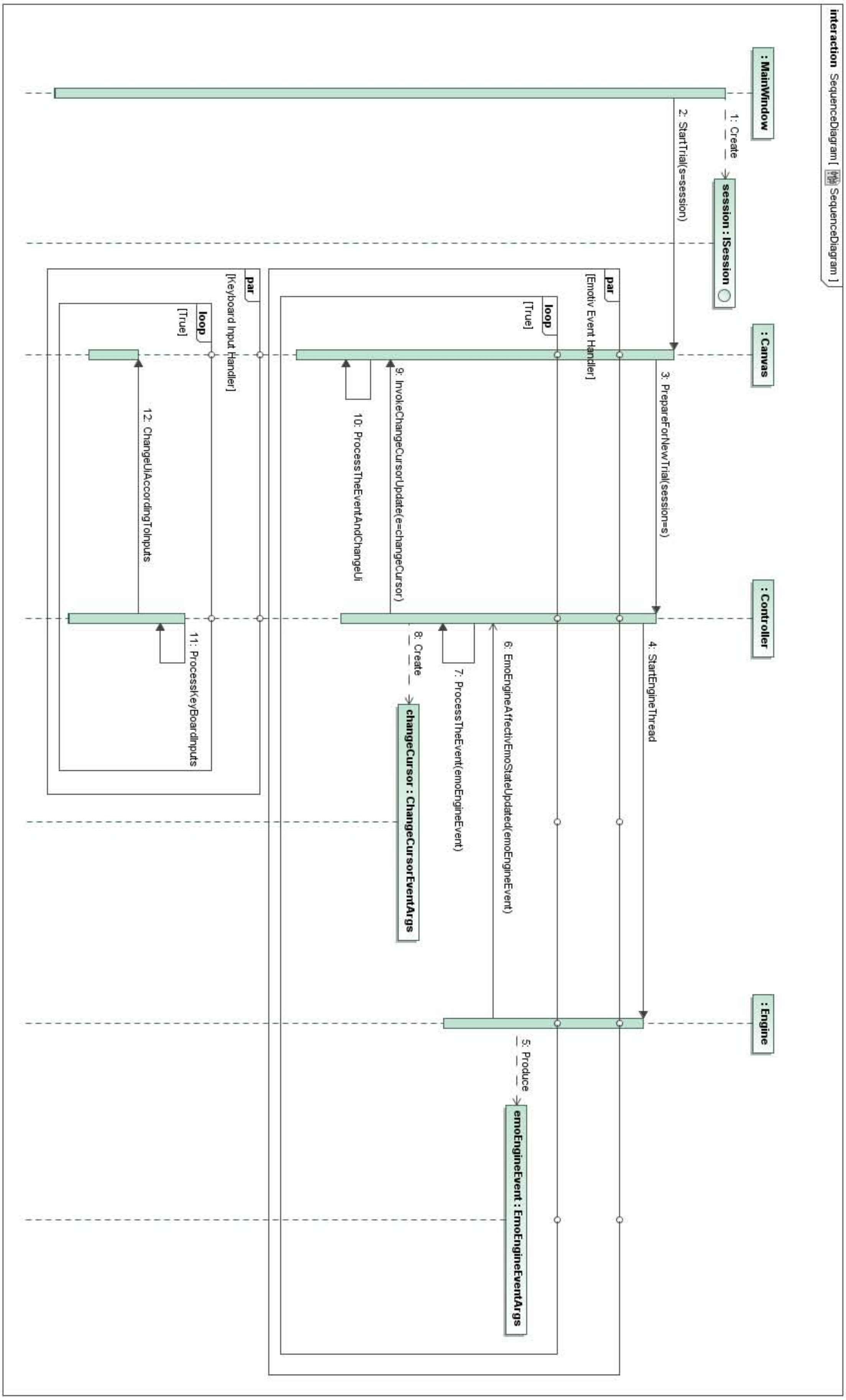

Figure 17: Sequence Diagram.

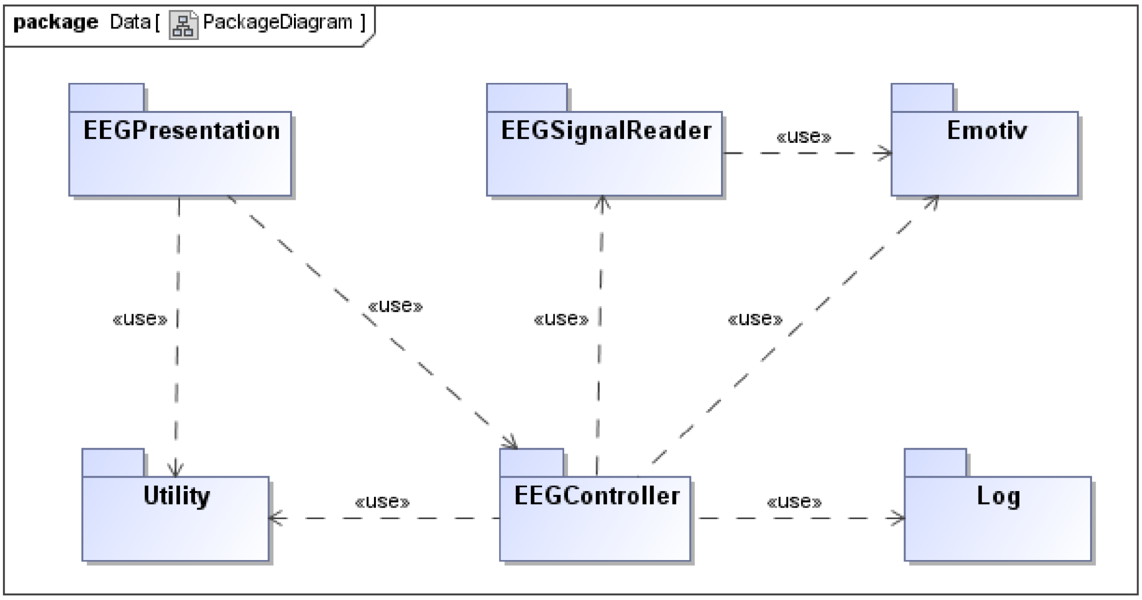

Figure 18: Package diagram.

In the following sections specification of experiments are described, and then the collected data from the experiments are analysed and discussed.

Experiment 1: Identifying levels of control

The primary goal of this experiment is to establish the accuracy with which a user can manipulate their excitement levels to control an object. A secondary goal was to examine the suitability of different types of visual feedback.

Participants wore the *Emotiv Epoc Neuroheadset* headset to measure their levels of excitement. They were then asked to move a cursor from a starting position to an end position by becoming more excited or more relaxed. Since excitement is a measure of brain activity, participants were informed that mentally solving complex problems or thinking of past memories would stimulate brain activity.

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 Interface and Task

The experimental interface (Figure & 20) had a size of 1280×800 pixels and was displayed on a 14 inch widescreen monitor (resolution 1400×900 pixels). Participants sat 70cm from the screen (Figure 21). At the beginning of a trial, the start position is shaded orange and end state is shaded green. To ready the participant, a three-second countdown begins (Figure 19). During this time, the end state fades from fully shaded to only an outline. Once the countdown completes, the user can move the cursor by changing their excitement.

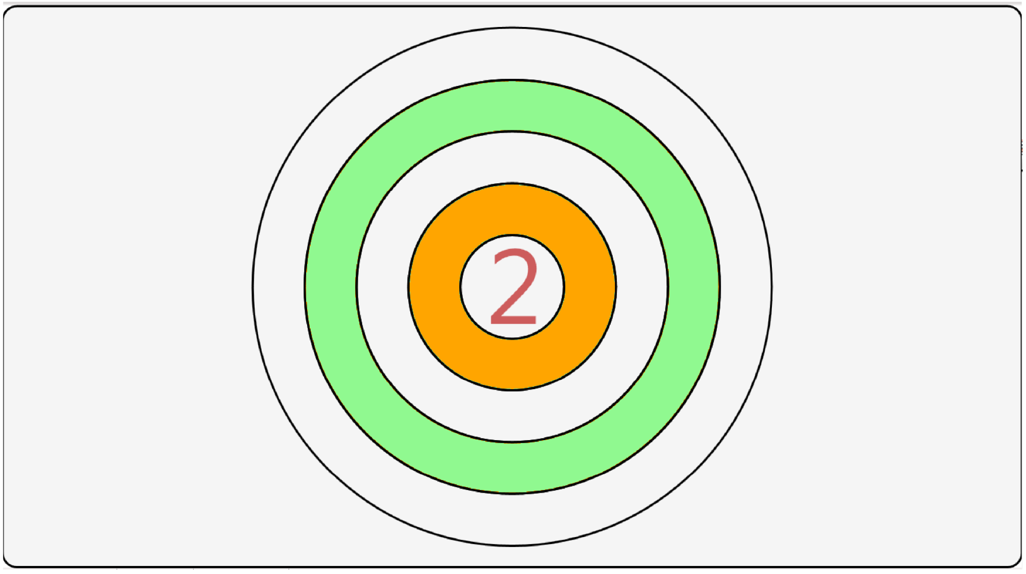

Figure 19: Bull's eye visualizations. After count down, trial will be started. Orange circle shows the start state, green circle shows the end state.

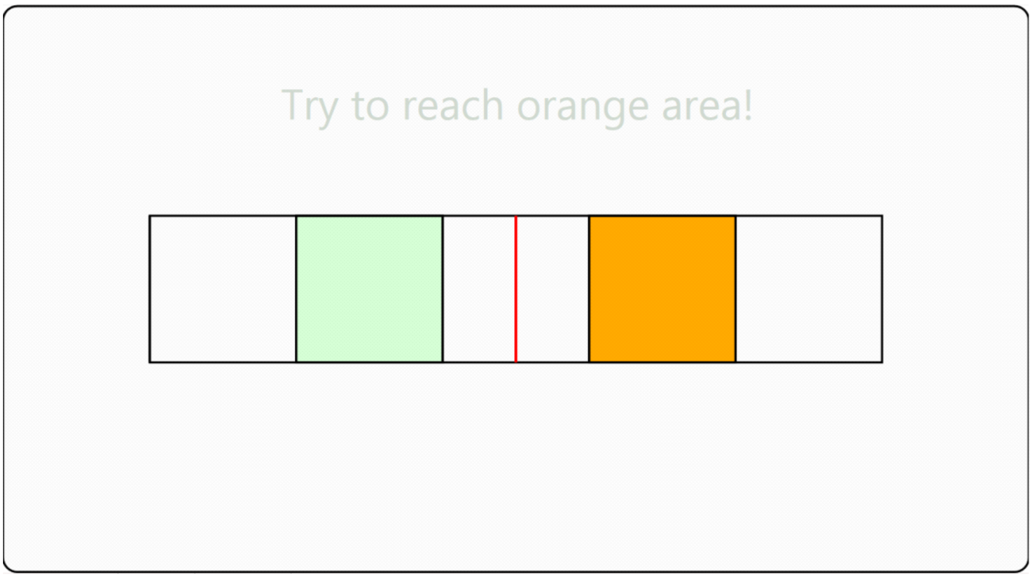

Figure 20: Linear visualizations. User should bring cursor to orange square first. Orange square shows the start state, green square shows the end state, and red line shows cursor.

The participants' initial excitement level must match the start state before a trial begins. To achieve this, the participant must modify their excitement level to move the cursor into the start state, and keep it at a constant excitement for at least 200ms, at which point the trial begins (Figure 20). The user then adjusts their excitement level to reach the target. Once over the target, the user presses a key on a wireless remote (Figure 21) 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 excitement level cursor position.

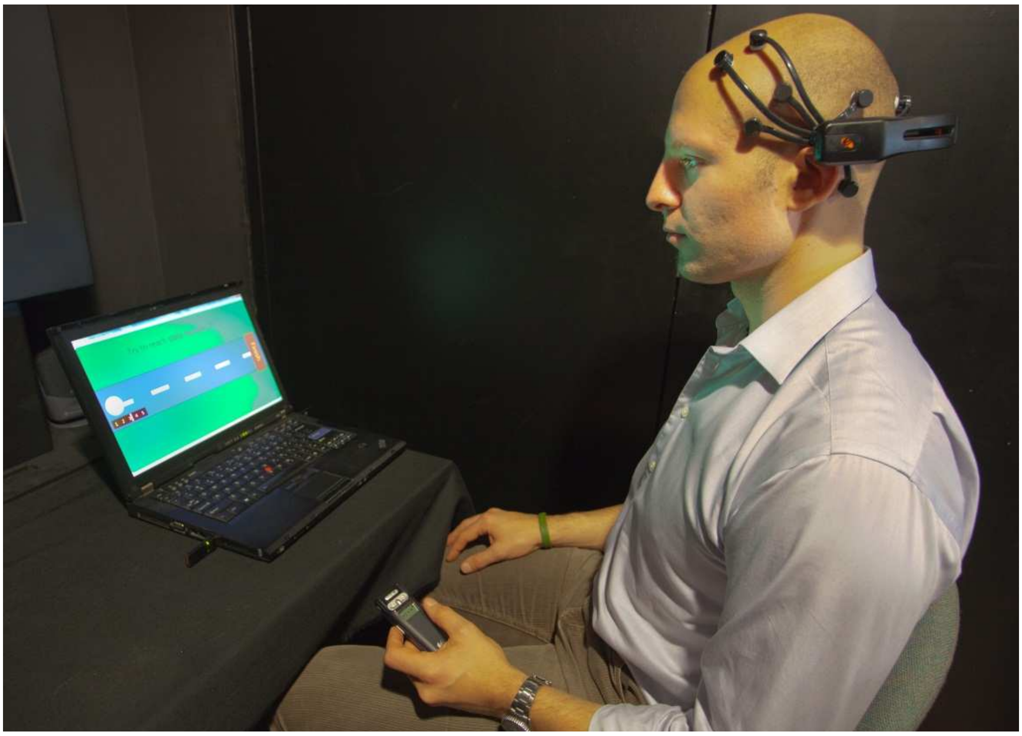

Figure 21: Experiment environment. Headset and remote controller can be seen.

To reduce cursor jitter, we set a threshold for showing cursor movement. If the change of excitement was less than that threshold (set at 0.03 in our experiments), the cursor became thicker (and faded in colour) (Figure 22). This indicated small scale 'bouncing' movement to the user. The cursor returned to its normal thin line visualization when the user's excitement settled or if a large scale excitement was detected.

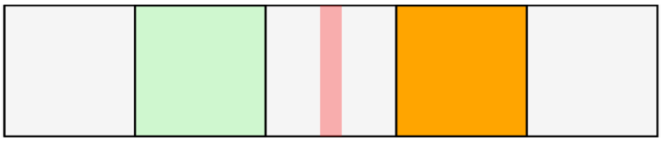

Figure 22: the cursor became thicker and faded in colour.

Procedure

After completing appropriate consent forms, the Emotive headset was placed on the user and their comfort confirmed. Each participant was provided with an explanation of the control mechanism—by relaxing they would move the cursor towards the left (or centre, depending on the visualization, see below) and by becoming more excited they would move the cursor up or outwards.

Participants were then given ample time to practice the control mechanism with both of the visualizations used. Each experiment consisted of 4 blocks of 16 trials. Between each block of trials the participant were given the opportunity to rest for three minutes. 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. By increasing the number of states, users should be able to more accurately select items from those available.
- **Emotional Distance:** +0.29, +0.59, -0.59. Excitement is measured on a linear scale from 0 to 1. Emotional distance is a measurement along this scale—positive distance indicates movement from relaxed to excited, negative movement from excited to relaxed.
- **Visualization:** Linear, Bull's-eye. A one-dimensional matrix layout or a bull's-eye-like set of concentric circles (see Figure s 19 & 20).

The factors visualization and number of states were counterbalanced between participants. The experiment consisted of four blocks of 16 trials with the presentation of distances modified between blocks.

Participants

Seven participants (6 male and 1 female) between the ages of 24 and 31 volunteered for the study. All were from a local university and they had all heard of an EEG headset but none of them had used one before.

Results

The total number of trials that were successfully completed was 424 out of 448. The average trial completion time for successful trials was 12.45 sec (s.e. = 0.54 sec). We carried out statistical tests using a univariate ANOVA with Tamhane post-hoc pair-wise comparisons (not equal variance assumed) to compare the effect of *number of states* and *visualization*.

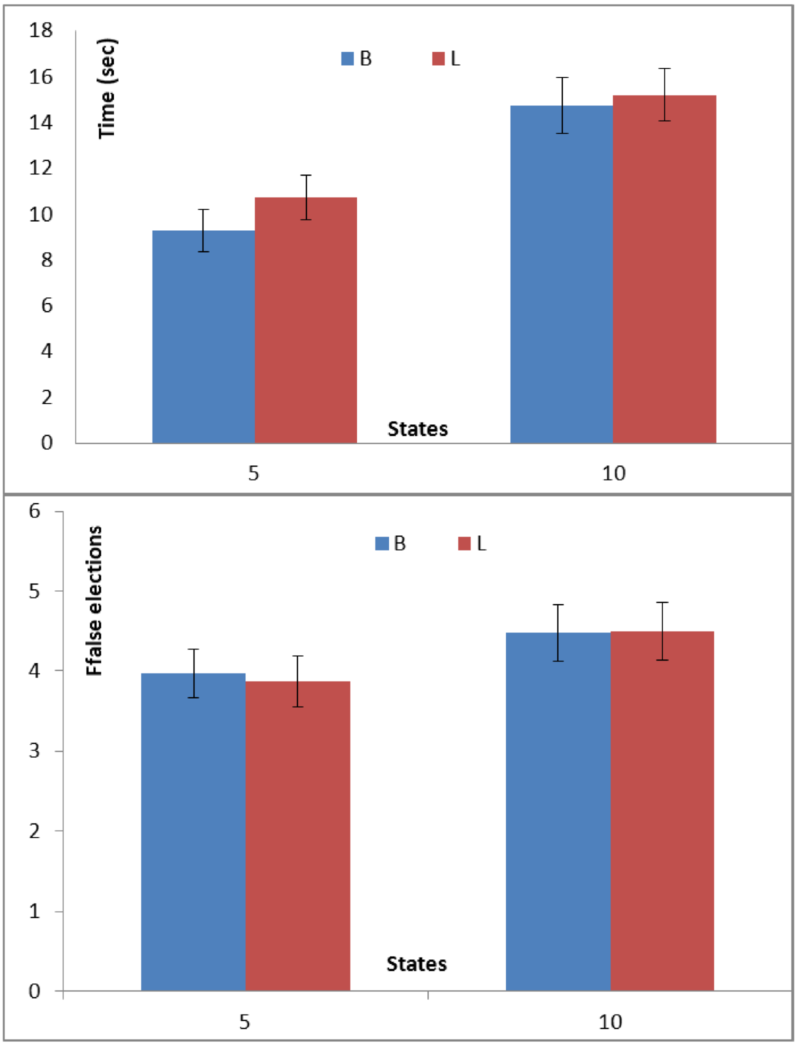

Figure 23: Task completion time in sec (up) and false targets selected (down) over number of states and visualizations (B = Bull's-eye visualization, L = Linear Visualization) for Study 1A.

There was a significant effect of number of states on trial completion time ($F_{1,6}$ = 39.7, $p < 0.01$), with five states significantly faster (10.02 sec) than ten states (14.97 sec). We found no significant effect of number of states on false target selection ($F_{1,6}$ = 3.76, $p = 0.07$)—five states had an average of 3.9 false selections, ten states 4.5**.** Figure shows the mean task completion time per state for each visualization.

We found no significant effect of visualization on trial completion time ($F_{1,6}$ = 0.259, $p > 0.1$, linear = 7.75sec, bull's-eye = 7.64s) or number of false targets selected ($F_{1,6}$ = 0.013, $p > 0.1$, linear = 0.239, bull's-eye = 0.233). An exit survey showed no differences in user perception of frustration or effort between these two visualizations.

There is a significant effect of distance on trial completion time ($F_{2,18}$ = 3.66, $p = 0.032$) and number of false targets selected ($F_{2,18}$ = 46.748, $p = 0.001$). As can be seen from Figure 24, post-hoc pair-wise comparisons showed users were significantly faster ($p < 0.05$) at relaxing (-0.59) than getting excited (0.59). They also had significantly fewer false targets selected when going to 0.29 than 0.59. None of the other pairs showed significance.

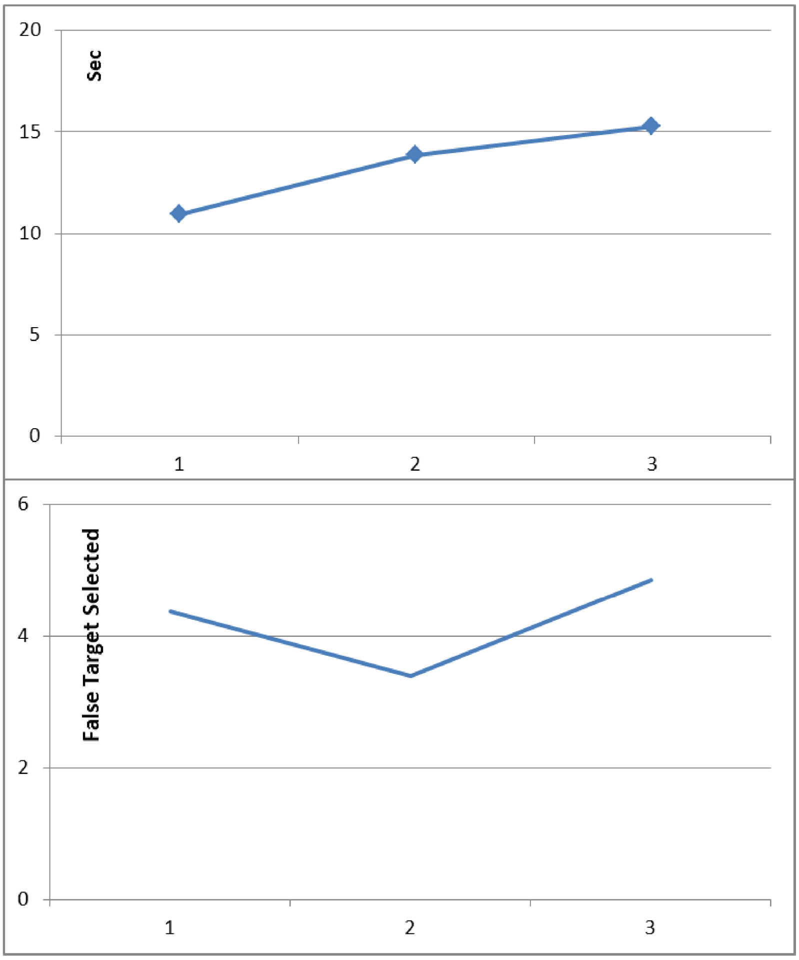

Figure 24: Task completion time in sec (up) and false targets selected (down) over distances for Study 1A (1 = -0.59, 2 = 0.29, 3 = 0.59).

Study 1B

In Study 1A we saw 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. We ran Study 1B to test 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

To validate or refute our hypothesis, we modified the levels of the *number of states* factor to three and five.

An additional seven participants (2 male and 5 female) between the ages of 25 and 30 were recruited for study 1B. As per experiment 1A, all had heard of an EEG headset but none of them had used one before.

Results

The total number of trials that were successfully completed was 420 out of 448. The average trial completion time for successful trials was 12.6 sec (s.e. = 0.56 sec). We carried out similar statistical tests to study 1A.

We found no significant effect of number of states on trial completion time ($F_{1,83}$ = 0.152, $p > 0.05$) or number of false targets selected ($F_{1,83}$ = 2.86, $p > 0.05$). Interestingly, users were marginally faster and selected fewer false targets when performing with *five* states (mean 12.5 sec, 1.84 errors) than with *three* (mean 12.7 sec, 2.12 errors) as can be seen from Figure 25.

As with Study 1A, we found no significant effect of visualization on trial completion time ($F_{1,83}$ = 2.205, $p > 0.05$). However, we did find a significant effect of visualization on number of false targets selected ($F_{1,83}$ = 5.64, $p = 0.02$). Users were more accurate with the linear visualization (mean 1.85 false selections) than with the bull's-eye visualization (2.12).

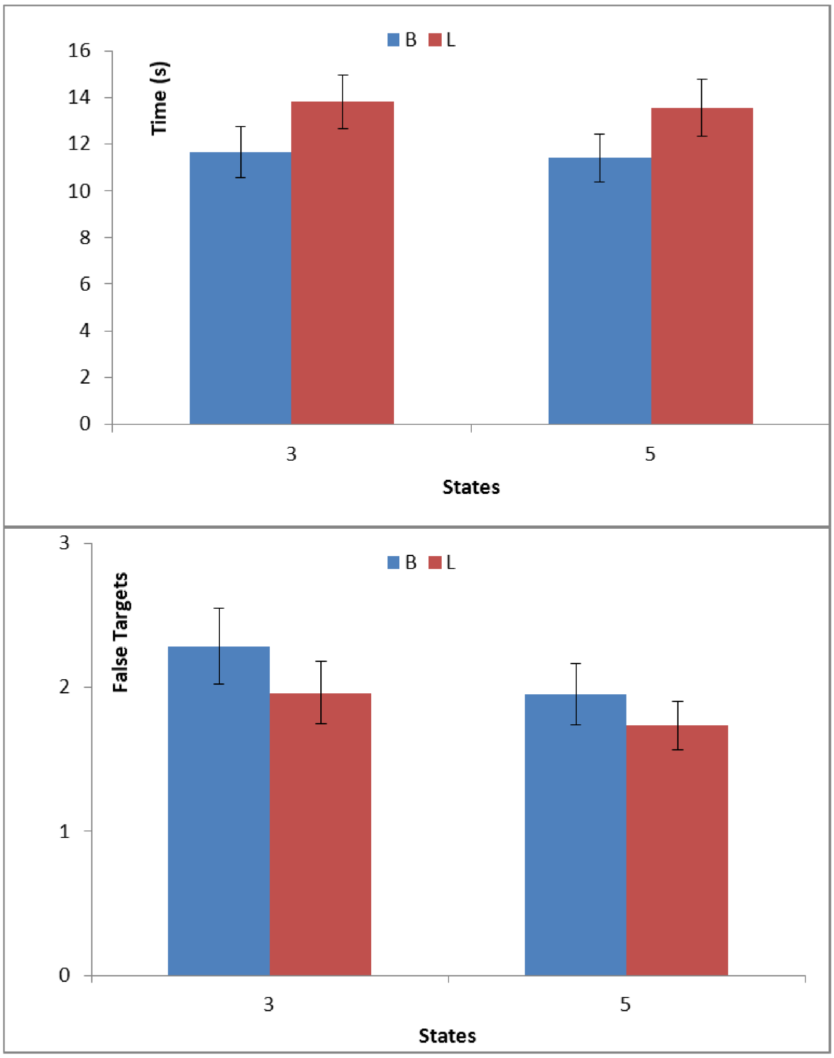

Figure 25: Task completion time in sec (Up) and false targets selected (Down) over number of states and visualizations (B = Bull's-eye visualization, L = Linear Visualization) for Study 1B.

Discussion: Study 1A and 1B

From studies 1A and 1B we learned that the number of states is an important factor in the control of an on-screen cursor using BCI input. Our studies showed that five states is preferable over ten states, however, we did not show that three states were significantly faster than five. We therefore choose five states as a comfortable range in which users can move a cursor. We use this value for our remaining studies.

Experiment 2: Excitement-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. In this experiment, we sought to investigate the effect of excitement 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 one factor, the selection distance.

Number of states: From the previous two studies we saw that five states was optimal for this type of cursor movement and selection task. For this experiment, the number of states remained constant at five.

Visualisation: The first experiment showed that there was no significant difference between the selection times for the two visualizations, with study 1B finding the linear visualization was more accurate for selection. For this reason, we choose to only use 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 (increasing excitement) and four backward (decreasing excitement) distances: +0.2, +0.4, +0.6 +0.8 and -0.2, -0.4, -0.6, -0.8 (see Figure 26). 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.

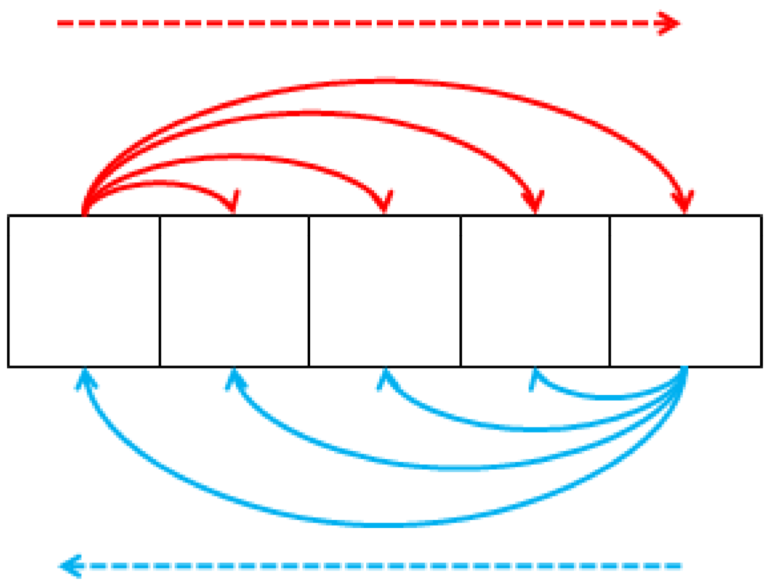

Figure 26: Eight different direction and distances used in experiment 2

Participants

Seven participants (5 male and 2 female) between the ages of 24 and 27 were recruited from a local university to participate in the experiment. All participants had heard of an EEG headset but none of them had used one before.

Results and Discussion

The total number of trials that were successfully completed was 414 out of 448. The average trial completion time for successful trials was 16.22 sec (s.e. = 0.68 sec).

As one would expect, an ANOVA showed that there was a significant effect of distance over trial completion time ($F_{7,42} = 9.64$, $p < 0.01$). Tamhane post-hoc pair-wise comparison revealed the following pairs of distances were significant (-4, -3), (-4, -2), (-4, -1), (-4, 1), (-3, -1), (-1, 2), (-1, 3), (-1, 4), (1, 4).

Our results show that users are equally proficient in both directions (relaxing to excited or excited to relaxing state) as post-hoc comparisons did not reveal significant difference between pairs (-4,4), (-3,3), (-2,2) and (-1,1).

Figure 27 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 0.93 and 0.96. There are two important observations from this plot. First, the similar trend slopes on the graph 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.

While we observed in Study 1 that participants found relaxing easier to achieve than becoming excited we could not find a similar affect in Study 2. In Experiments 1A, 1B and Experiment 2 the mean trial completion times at 5 states are similar for -0.6 and 0.6. Note that Figure 24 (down) includes mean time for both 5 and 10 states so cannot be directly compared to Figure 27 but 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 5 states than higher states.

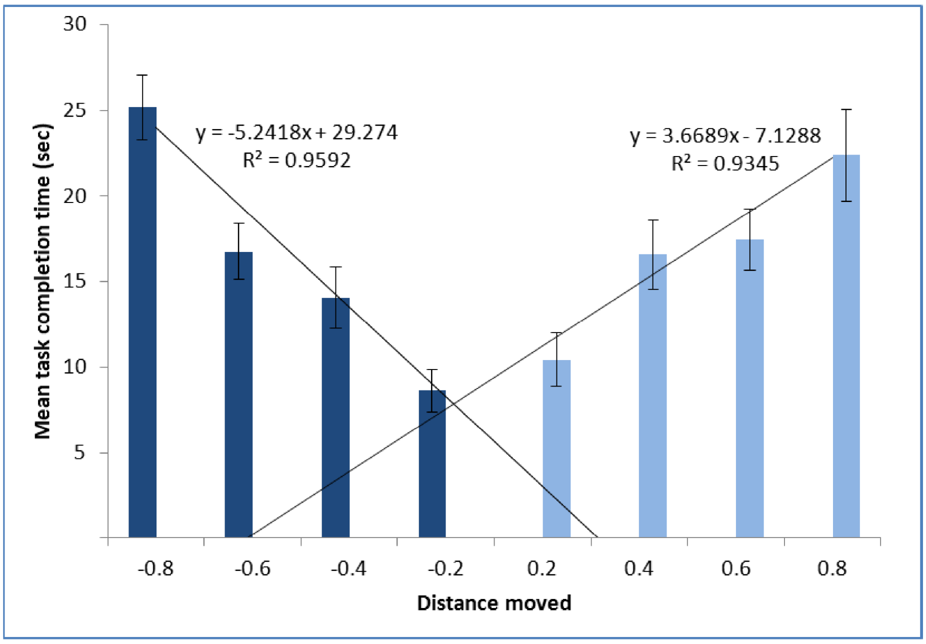

Figure 27: Mean task completion time with a trend line showing linear correlation between time and distance.

Finally, we found no significant effect of distance on number of false targets selected ($F_{7,42} = 0.642$, $p > 0.1$). Figure 28 shows the mean false targets selected for each distance.

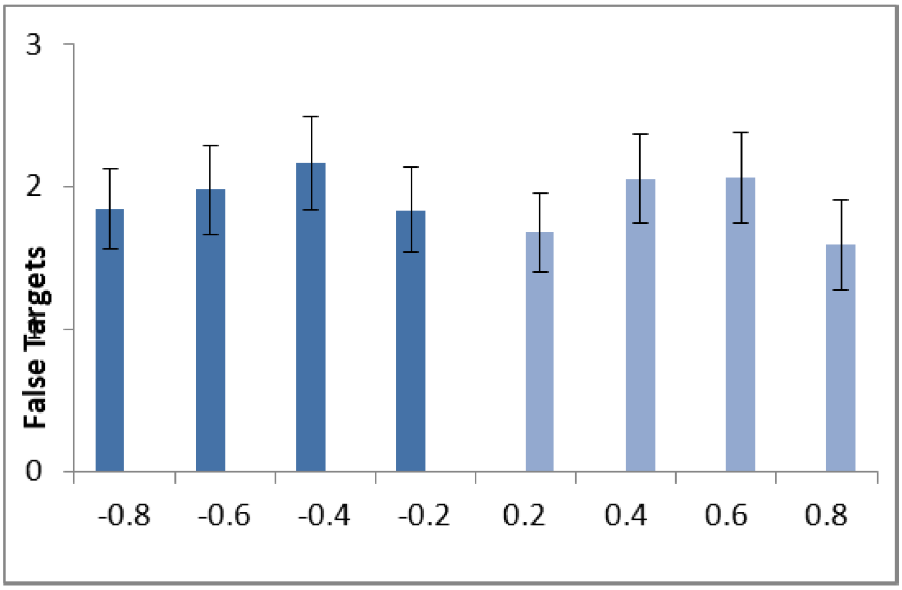

Figure 28: Mean false targets selected for each distance with standard error bars for experiment two.

Experiment 3: Distractions and Multi-tasking in a Game setting.

With a better understanding of the low-level performance of BCI input from experiments 1 and 2, we were then interested in employing our guidelines to a gaming environment. The goal of this experiment was to examine users' performance in their ability to control their emotions in a situation that required multi-tasking.

Design

We designed a simple 2D game that required players to complete two tasks simultaneously—one required the use of a traditional input (wireless remote button), the other BCI-measured excitement. The user is required to move an on-screen avatar from the starting position on the left, to the end position on the right. During this task, a demon sends a fireball towards the avatar, which the player must destroy by modifying their excitement to the required level. If the player fails to destroy the fireball and/or fails to reach the end point within 30 seconds then the avatar is killed (Figure 29).

Experimental Interface and Task

The experimental game interface (Figure 1) was displayed on a 14 inch widescreen monitor (resolution 1400×900 pixels). Participants sat around 70 cm from the screen.

Each trial begins when the user reaches a specified level of excitement, as visually indicated on the screen. This ensures all participants begin with the same excitement level. The participant presses a key on a wireless remote to move the character toward the finish line. A fireball appears as the user starts to move. A linear visualization with five states of excitement is attached to the character. Each state has a number inside and it is coloured in a different shade of red. The fireball has a shade of red and a number inside that matches one of the states on the visualization.

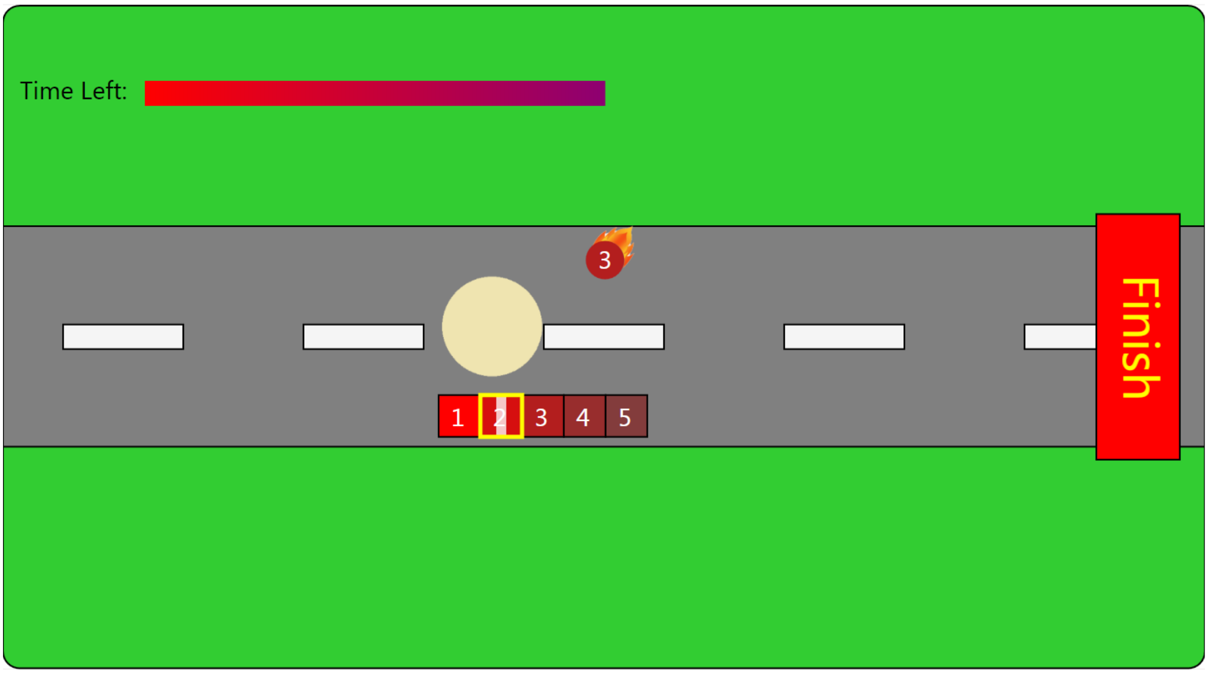

Figure 29: the khaki circle is the avatar, red circle with a number inside is the fireball, and the grid is linear visualisation of player emotion. Player should destroy the fireball and reach to finish line before timeout.

In order to destroy the fireball the user adjusts their level of excitement to match the number that is on the fireball. Once at that state, the user presses a second key to destroy the fireball. The matching of emotional state with the fireball's 'kill' state is indicated visually by the avatar changing in appearance.

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 three 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 (participants were informed of this), leaving only 10 seconds which is less than the average time needed for completing the task, if they needed to pause to complete the excitement portion of the task (participants were informed of this). 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 25 and 31. Another five participants (4 male and 1 female) between the ages of 22 and 27 who had heard of an EEG headset but none of them had used it before were recruited from a local university to participate in the experiment.

Results & Discussion

With 10 participants, the system recorded a total of 480 trials. Of the 240 trials that corresponded to experienced users, 202 resulted in successful completion of the task. In the remaining 38 trials the user either failed to reach the finish-line in time (in 28 of the 38 trials) and/or failed to kill the demon before reaching the end (in 30 of the 38 trials).

Novice users failed to complete the trial on 68 occasions; in 41 of the trials, the finish line was not reached and in 65 the daemon was not killed.

Univariate ANOVA did not show any significant effect of experience ($F_{1,63} = 0.786$, $p > 0.05$) or distance on trial ($F_{7,63} = 1.35$, $p > 0.05$) completion time. The average trial completion time was about 22.5sec across all users. This is expected as the task was time-bound and participants were encouraged to complete the task in the time allocated.

Univariate ANOVA on number of false targets selected showed a significant effect of experience ($F_{1,63} = 4.67$, $p < 0.05$), no effect of distance ($F_{7,63} = 0.252$, $p > 0.05$) and no interaction between the two. Experienced users selected significantly fewer false targets than novice users (experienced mean = 1.57, s.e. = 0.33; novice mean = 2.62, s.e. = 0.34).

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 excitement task. Univariate ANOVA did not show any significant effect of experience or distance on either of these measures. Figure 30 shows the mean frequency and number of false targets selected for experienced and novice users.

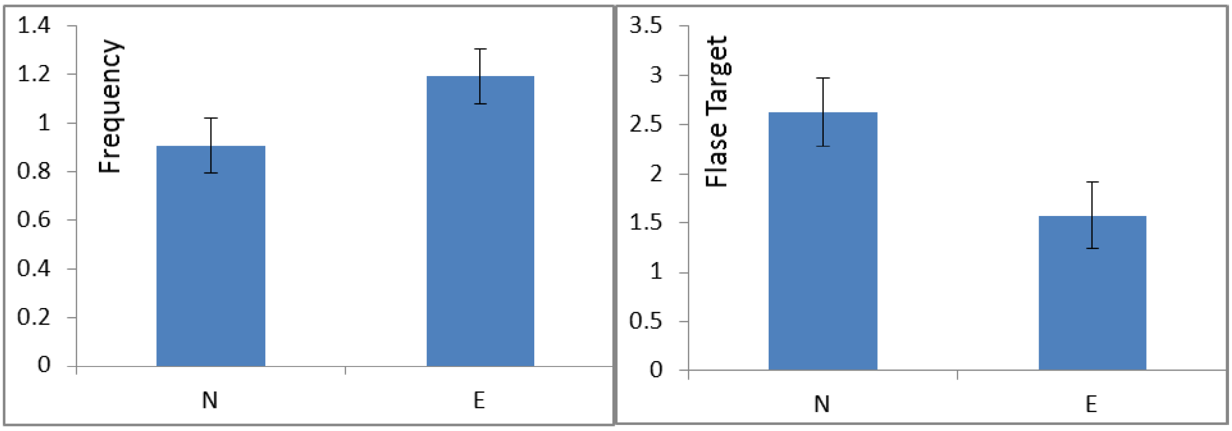

Figure 30: Mean frequency and number of false targets for Experienced (E) and Novice (N) users.

Overall Experiment 3 indicates that novice users are able to control excitement in a game like setting with similar finesse than experienced users. The biggest disadvantage is that novice users tend to select far more false targets than experienced users.

Discussion, implications, and Applications in Game Design

BCI-based input has the potential to revolutionize the game-playing experience. The results from the studies in this research can provide guidance on how best to begin designing such experiences.

Continuous vs. Discrete Input Control

The studies in this research 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 excitement range, game developers can modify the difficulty of parameter manipulation—increasing the number of levels requires more accuracy and a greater practice and skill level. The studies also showed that one direction of selection is not favoured over the other and that a linear mapping of excitement to cursor is appropriate for this type of task.

The assignment of the emotional channel to a control should also characterize the selection of continuous or discrete input. For example, the selection of a weapon 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 relaxed or excited brain states could adjust the balance between armour 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 different characters which work better in a specific level of emotion. For example, in a game like Warcraft Dota Allstars (www.playdota.com/) where characters have intelligence, strength and agility characteristics, low excitement could increase intelligence; medium excitement could increase strength and high excitement could increase the agility of the character.

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 excitement. 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 excitement.

Game input needs to provide error tolerance to cope with this additional and possibly erratic input stream. Triggering actions such as firing a gun or casting a spell should not be purely based on the user's excitement level, as this could likely lead to unintentional actions. In this work, small scale fluctuations were smoothened by the cursor becoming thicker combined with users indicating via a button when their excitement 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, it is not like a mouse or a keyboard where it is clear when an input starts and ends. EEG input is 'always on', so designers must consider when a game is to utilize this input stream. For BCI-assisted games, there are two options: serial or parallel interaction.

Serial interaction allows gamers time to concentrate on producing the excitement level required to complete the task—they do not need to perform mouse or keyboard input at the same time. Once their excitement level is measured they will 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 flow of a game. For example, in a game like Delta Force a sniper's target aim can be proportional to their level of excitement. If a player needs to aim at a small or far target he would need to bring down his level of excitement to the lowest level before firing the gun.

Conversely, parallel interaction requires the user to continue input using traditional controllers, while appropriately adjusting their excitement 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 emotion. 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 excitement level and if the character is too close to the monster then a strong spell can also kill the player. This would encourage players to be careful in selecting the spell level (encouraging greater control of excitement) but would also support error resilience by allowing players to kill a monster through multiple lower-level spells.

Generalizability of Results

Our experiments looked at users' ability to control excitement. We used the Affectiv suite of Emotiv to carry out our experimental study. It is possible that if users perform the experiment with different hardware the results of the study may be different. We believe this will not be the case as arousal is a well understood concept within the computational neuroscience community with several pattern recognition approaches to compute it. Recent research has also have validated it against other physiological measure [45].

Arousal can be viewed as a call to action while affect provides the direction of experience. It is therefore possible that users might have different levels of control for excitement depending on their affective state. This can be viewed as a limitation of our study but we believe that it is important to see in the first instance if arousal can be controlled and what design guidelines can be generated for it. Future research can look at carefully managing users' affective state while examining their ability to control excitement.

Lessons for Designers

We provide the following guidelines to designers:

- To the greatest extent possible, discretize the raw BCI signal into five discrete states;

- Visual feedback showing the cursor, current state, and goal states should be abundantly clear to the user;
- Novice users require training, thus short games suited as 'training wheels' could prove beneficial to transfer learners into expert mode;
- Combined input with a typical controller is possible for both walk-up and expert users.

Future works

During the experiments some situation happened that did not have any known scientific reason. Basically they happened because complex structure of brain and complex relation of various emotions human have.

Effect of Operant conditioning

One observation which is quite interesting was effect of operant conditioning on participants. During design and development phases the experiment was ran several times on different people to find that the program is completely ready for the real experiment situation.

In one session participant *A* took part in a pilot experiment. *A* was completely able to control his emotions to control the cursor on the screen (Figure 31 & 33). From the results we got from this experiment, it was decided to change flow of trials to quantify some more data about users' control. However this change made trials a bit harder than before.

Figure 31: Example of situation when user has control on her/his emotion to be relaxed.

In order to compare the new experiment with previous one, *A* was asked to take part in the new version of experiment. However before the experiment session, the examiner told him that this experiment is harder to complete than before. Strangely, A was not able to control cursor at all (Figure 32). The first idea was that maybe there is a failure in development of new experiment. Hence, we tried to run previous experiment to make sure that there is a bug inside the new program. Oddly *A* was not able to control previous program as well.

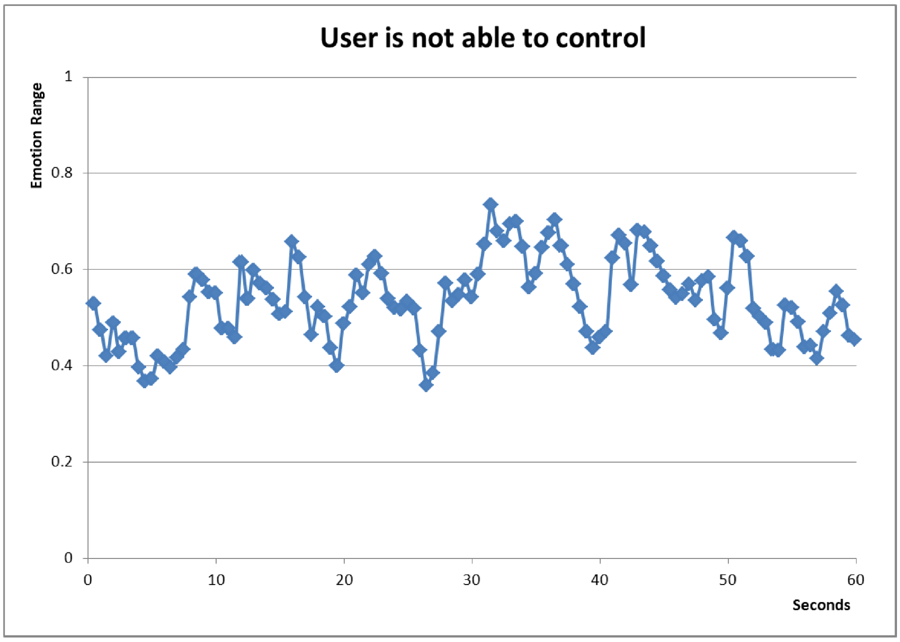

Figure 32: Example of situation when user is not able to control her/his emotions

We ran the new experiment without any change on other participants without any precaution about hardness of the experiment. All of the participants were able to control the cursor successfully in new experiment. We asked *A* to participate in new experiment again, but this time we told him that the problems we had in previous session are solved and other people are able to control it. Amazingly, he controlled cursor successfully in that experiment session.

Also, this condition happened in 3 other cases during pilot studies that a participant who was aware from some of the problems or did not believe on her/his ability to control emotions was failed to control cursor.

These observations suggest studying effect of operant conditioning on ability of emotion control on users.

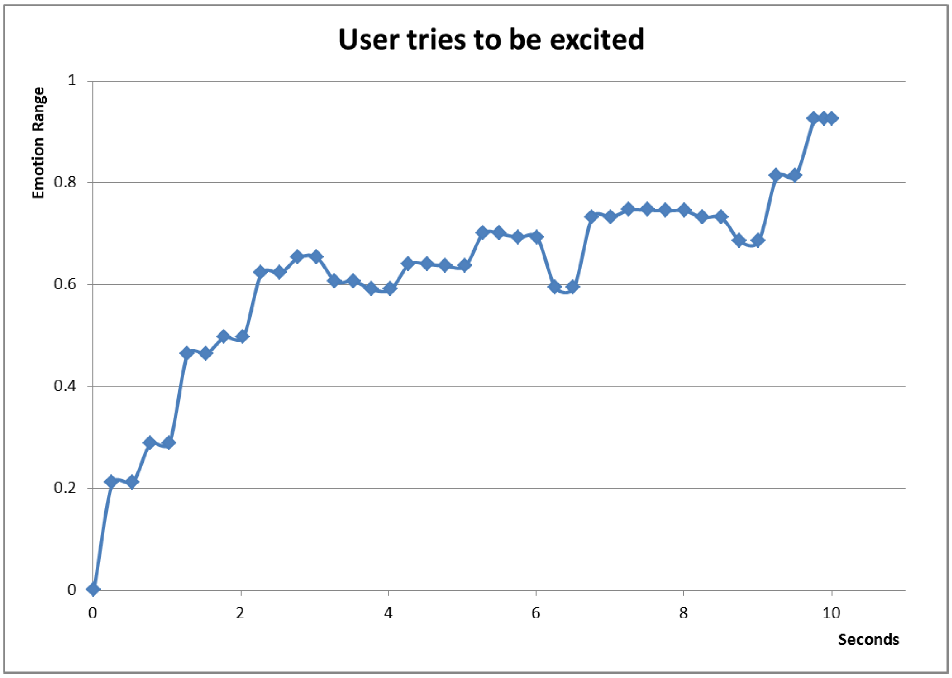

Figure 33: Example of situation when user has control on her/his emotion to be excited.

Measuring users' awareness about their emotion control ability

In order to understand requirements of users and designing next experiment, advantages and disadvantages of this kind of input control were discussed with participants. Most of the participants believed that the cursor is truly moving according to their excitement level. However, there were few participants who doubted that the cursor is moving according to their emotions. These statements suggest testing awareness of users about their control ability.

In order to measure user's awareness, one way is to design a random emotion generator engine. This engine should be able to produce same output as real engine in a way that users can finish trials with same statistical results.

In the experiment user should be asked to complete a task using one of the engines without knowing which one is used. Then user should identify which engine was used in the trial. Using this experiment, it is possible to understand that how much perception of users about their awareness is close to reality.

Effect of discouragement on user performance

Another interesting observation we had was about effect of discouragement on users. In experiment 2 which was ran by 5 states, for the most of participants reaching to state 5 was very difficult, and in case it was the end state the probability of failure in completion of the trial was higher (Figure 34). In comparison reaching to state 4 was not that difficult for users (Figure 34). However most of the time that user was asked to go to state 5; they were usually even failed to reach state 4 (Figure 35).

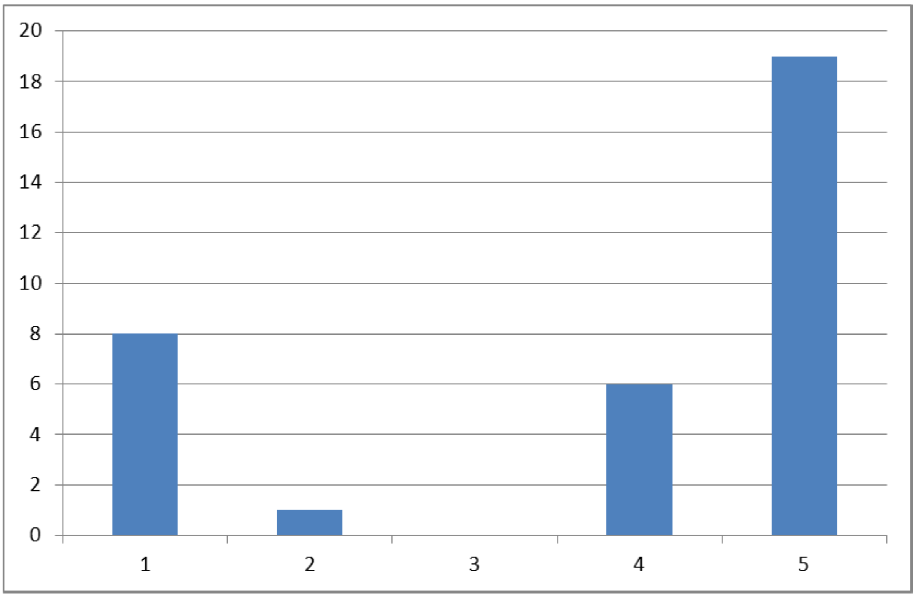

Figure 34: Number of times users failed to reach different states as end state. (Taken from experiment 2)

This strange response of participants could be caused by discouragement of them in reaching to number 5. In fact, observations suggest that when user is not confident that it is possible to finish a task, her/his performance decreases radically.

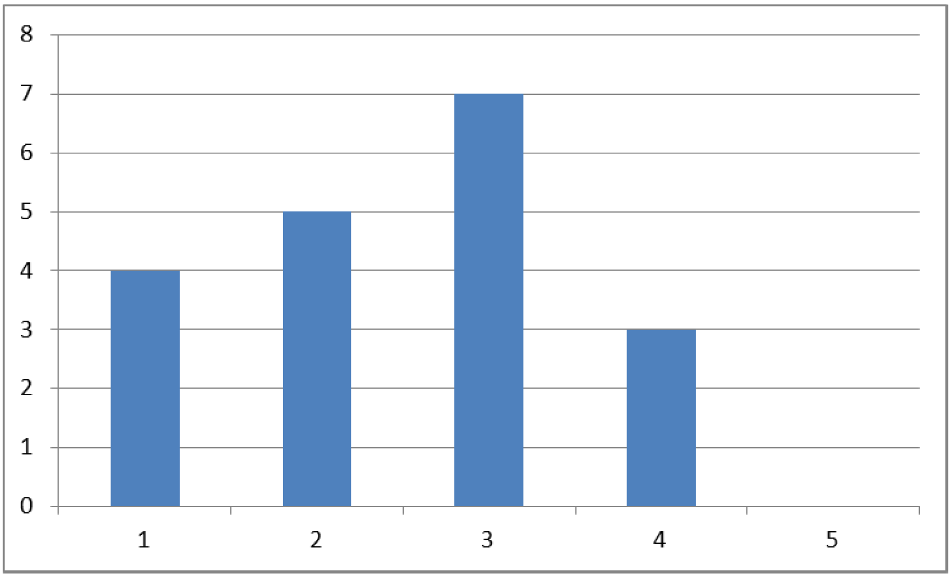

Figure 35: States that user ended up when they asked to go to state 5 and they failed.

One way to examine effect of discouragement is to design another experiment which uses a new kind of trial along normal trials secretly. These new trials show the same interface to users (5 states); however they map excitement level of users into four first states. By comparing results of situations that users are asked to reach to state 4 in new trials and when they are asked to reach to fifth state in normal trials (the level of excitement needed to reach both of them is the same), it is possible to identify effect of discouragement on users.

Moreover it is mentionable that this situation may be caused by effect of other emotion than discouragement. For example, frustration of user on doing a task may decrease the excitement level.

Conclusion

The experiments described in this research offer valuable guidelines for designers. We show that when discretizing raw excitement values five levels provide a good balance of speed and accuracy, users have good bi-directional control of excitement and are able to effectively control excitement in game-like multi-tasking scenarios. Our results also show that novice users are able to control excitement 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 research are a systematic exploration of various parameters that influence mappings of excitement 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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Appendix A: Game scenario ideas

Game development could be considered as a potential field for usage of BCI technology. By a quick look at the evolution of computer games, one can find that making players more involved in the game has been one of the key factors that game developer focused on.

In the beginning, games consisted of simple graphical interfaces .Usually players used their imagination to believe that they are actually controlling a real object like a spaceship, tank or a human.

Trend to make people more involved in the games started from early stages. Primitive games let players to select the name or colour of the character that they are controlling. By the advent of technology, game players had the chance to select the character they want to control among a set of characters with different abilities and styles. By improvement of graphical devices and engines, games let players to feel themselves in the shoes of character they are controlling.

New competition between game consoles today is also could be considered as an improvement in players' involvement. Nintendo Wii, Microsoft Xbox 360 Kinect and Sony PS3 Move are all example of game consoles that want to make players physically involved in the games.

Emotional involvement could be considered as a new way to make players more involved in the games. The results of this research could be used in various ways. In this section, some game scenarios respect to result of this research discussed.

Boxing

Boxing is a game that has been available on most of the gaming consoles, even on primitive gaming consoles like Atari (Figure 36). However new consoles such as Nintendo Wii transformed the way players playing this kind of games. In fact, instead of using a joystick, players can cause aggressive and defensive actions of boxer by their body movements (Figure 37).

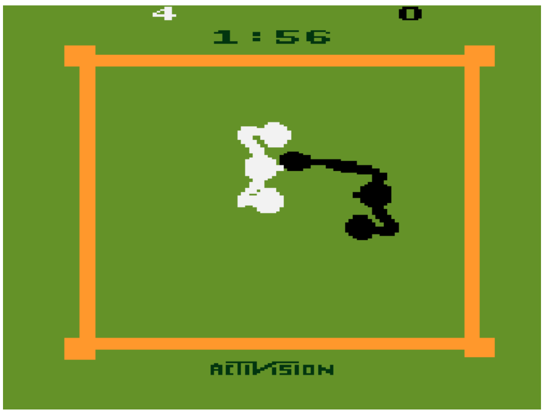

Figure 36: Boxing game on Atari[14].

[14] http://rohitbandaru.wordpress.com/2009/12/03/nostalgia-lane-old-games-like-really-old-games/

In such situation player has to simulate real movements of a boxer in order to control the game. However player is able to move her/his arms aimlessly and the boxer will punch or defend. In fact player does not need to feel that s/he is on the ring. Using BCI systems it is possible to drive user in a way that s/he put her/himself in the game situation. Results of this research are useful in designing such a game.

Figure 37: Player controlling a boxer in Nintendo Wii[15].

Designers should always remember that design of such games should be error resilience. In another word, player should be able to play the game even s/he is not able or want to be emotionally involved.

For example if user is very excited he can deliver a bit more damage than the situation that user is not excited. In this situation user is still able to play the game without excitement, however design of the game encourage player to be excited to be more powerful.

Another possible design is to consider various advantages on different part of the emotion range. For example user could increase defensive skills by being not excited and increase aggressive skills by being excited. With this strategy player has some benefits in all situations, however s/he is driven to control her/his emotions to have better performance in the game.

Also, the research suggests that reaching to higher level of excitement is a bit harder for players. According to this fact, the bonuses that player gets in higher states could be slightly better than lower states.

Sniper games

Sniper games are another category of games that could utilise results of this research. In these category player should destroy a subject from far distances using a sniper rifle (Figure 38). In order to making the game more realistic, usually aim is constantly moving. Using EEG based BCI it is possible to relate range of instability of

[15]http://www.zimbio.com/pictures/LjJ1gnb-k_R/Next+Generation+Video+Games+Unveiled

aim to excitement of player. In fact, player can reduce fluctuation of aim by being less excited and focused.

Figure 38: Screen shot of a sniper game (Sniper Art of Victory).

Like previous example, design of the game should be error resilience. However because being not excited is a state which is a bit easier to reach for players, it is sensible to increase fluctuations of the aim more rapidly in case of excitement.

Next thing that should be considered is number of states. Designers should consider that 5 states are more suitable for user to control. Hence using more than 5 states or using a continuous control could make it difficult to control for user.

Defence of the Ancient (DotA) – Warcraft

DotA is a costume map for the real-time strategy game Warcraft from Blizzard (Figure 39). The goal of this game is to fight with enemies and destroy their forth using the agents that are controlled either by players or artificial intelligence.

Figure 39: Screen shot of DotA – Warcraft Frozen Throne (From Blizzard).

Each player should select a hero in the beginning of the game from a set of available heroes. Each hero has 3 basic characteristics; agility (speed and pace of hero), intelligence (power of spells) and strength (hit point). These characteristics improve when player raise their levels by fighting with enemies. Also it is possible to improve them by buying some items. For each hero one characteristic is more important, improving that characteristic will cause better overall improvement of the hero's ability. Hence, heroes can be categorized by their main characteristic.

Players usually prefer to play with heroes inside one group, because playing with heroes from different groups needs different game strategies. Usually heroes who are very weak in the beginning, by selecting a good strategy can be very strong, while heroes who are strong in the beginning cannot be very strong near the end of the game.

According to this fact, intelligent heroes usually better for novice players, strong heroes are usually selected by average players, and experts usually prefer to select agile heroes.

The point which makes this game different from the previous ones is that players usually select the heroes according to their skills. It suggests that it is possible to add EEG based BCI to this game in a way that people who are able to control their brain better have the chance to select weaker heroes who can be stronger user brain waves, while novice user can select stronger heroes who do not need users brain control constantly but they cannot get more strong.

Appendix B: Submitted Paper

Thinking about Control: Quantifying Properties of BCI for Gaming Applications

ABSTRACT

The Brain-Computer Interface (BCI) is a non-traditional method of machine control that has the potential to revolutionise the gaming industry. However, we have little fundamental understanding of the speed and accuracy with which users can control virtual objects using only the excitement levels of their brain. This paper conducts a series of studies to investigate the use of BCI techniques in the context of gaming. We first investigated the accuracy with which users could select multiple visual states. Five states were found to be the most comfortable and users were able to move quickly in both directions (relaxation/excitement). In a second study, we found that users take a linearly increasing amount of time to increase and decrease their level of excitement. Finally, we investigated the practicalities of simultaneously controlling an avatar with traditional input and fighting a daemon with a BCI. Experienced users were more accurate in this parallel input task than novices. Based on these experimental results we discuss several game design principles.

Author Keywords

Brain-Computer Interface, gaming, input devices, non-traditional input

ACM Classification Keywords

H5.2. Information interfaces and presentation (e.g., HCI): Input devices and strategies.

INTRODUCTION

The availability of off-the-shelf Electroencephalography (EEG) kits (such as the Emotive Epoc Neuroheadset and OCZ Neural Impulse Actuator - NIA) has made it possible to explore novel Brain-Computer Interfaces (BCI) for applications ranging from gaming [1] to cursor control [2]. EEG senses the underlying states of brain activity by interpreting the cortical potentials [3]. Researchers have demonstrated the capability of EEG based computer controllers through different point-designs and in a number of applications [3-4]. Examples range from using an EEG signal for classifying user tasks [5] to controlling a wheelchair [6].

A common feature with most of these applications is their use of a sensed brain signal to manipulate a spatial parameter, such as moving a virtual cursor [2] or even a physical ball in different directions [1]. However, there exist only limited generic design principles to guide application developers in mapping a sensed parameter, such as the amount of excitement, to virtual control. For example, we do not know how many discrete levels of emotional arousal/excitement can be comfortably controlled.

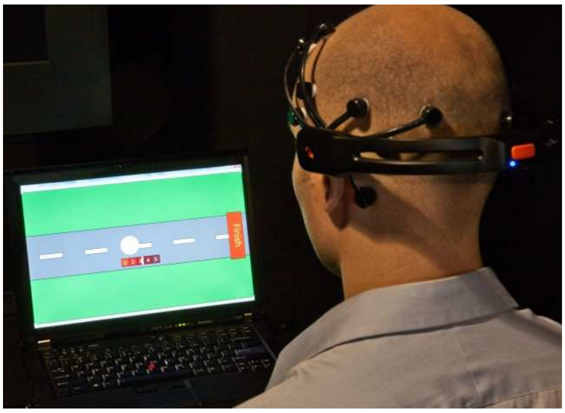

Figure 4: A user wearing the Emotive EEG headset in the study setup

Different sensed parameters have been explored in the literature ranging from engagement [7] to relaxation [1]. In this paper we focus primarily on deriving design principles based on emotional excitement as captured by the EEG signals. We conducted a systematic investigation into the parameters that can affect user control of an on-screen object. We implemented three experiments—two exploring the parameters related to one dimensional selection and one gaming scenario that requires both traditional input and the use of a BCI.

From these experiments we observed that (a) users can comfortably control five discrete levels of cursor movement with brain excitement; (b) the time taken to move to a particular level of excitement is proportional to the distance of the target; and (c) that the direction of control is uniform (it is as easy for users to relax than to get excited). In a final experiment we immersed the users in a multi-tasking scenario, analogous to one found in video games. In this environment, users were asked to use a wireless remote and BCI input to move an avatar and destroy a demon. Most users were capable of multitasking but experienced users were more accurate at completing this task, confirming further the guidelines we derived from our results.

The main contributions of this paper are: 1) a systematic exploration of various parameters that influence mappings of EEG signals to virtual cursor control; 2) quantifying the number of discrete levels that can be controlled via excitement states from EEG input; 4) a series of guidelines for designers; 5) a demonstration of the practical value of our mappings in a gaming application.

RELATED WORK

Electroencephalography (EEG)—the recording of electrical activity along the scalp caused by the firing of neurons—was invented a century ago [5]. Neuroscientists have shown that it is possible to understand the underlying states of the brain by sensing the vital activities of the brain through electrical signals that were caused by firing neurons in the cortex layer.

A logical progression of this understanding has been to use this output to control computing machinery leading to the creation of the Brain-Computer Interface (BCI) research field which has a number of interesting applications. These include, new input methods for people with severe motor disabilities [8], extracting emotional and cognitive user states from users whilst interacting with computing machinery [9], facilitating real-time interface adaptation based on the user's cognitive states [10], and augmenting traditional input controls with an additional emotional state, such as for computer games[16].

The remainder of this section examines methods of brain-sensing technology other than EEG, techniques for measuring and processing EEG signals, use of EEG in games, and emotions and decision making.

Alternative Brain Sensing Technology

Functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS) are two additional methods of sensing the vital activities of the brain. fMRI senses the magnetic field around the scalp, while fNIRS measures the concentration of blood oxygen using infrared light [11].

fMRI is an effective technique for brain function imaging in medical science. However, it is vulnerable to the existence of metal objects and head movements [11], both of which are common when using a computer. For this reason, it is not favored by BCI researchers. fNIRS has lower temporal resolution compared to EEG making it challenging to detect fast responses after an event happened [12]. This precludes real-time interaction for controlling GUI-based systems. Despite the strength of this technique, EEG remains the choice sensing method for BCI research.

Measuring and Processing EEG Signals

There are two approaches to measuring EEG signals: invasive (implanting an array of electrodes in the cortex layer of brain) and non-invasive (attaching a number of electrodes to the scalp). Non-invasive approaches can now reach the same level of accuracy and performance as invasive approaches [13]. Recent research has enabled a reduction in the number of required electrodes to collect EEG signals from outside of the scalp (e.g. 3, 9, and 16 electrodes [5, 14]).

Raw EEG signals can be mapped to application control using *Operant Conditioning* and *Pattern Recognition* [5]. Operant Conditioning requires that the user first train the system and then operates the application by repeating the same thoughts whereas Pattern Recognition uses signal processing and machine learning techniques to reveal the mental states or activities of *untrained* users.

P300 response is one neurological phenomena that can be measured using EEG signals and pattern recognition. P300 can be considered as a composite index of both attention and memory [5]. It is based on detecting a specific type of EEG signal which peaks at around 300ms (but could be up to 900ms) after presenting a stimulus. The amplitude of a P300 signal is changed with the target's higher probability and lower discriminability and P300 latency decreases when targets are easier to distinguish [15].

P300 has been widely used in various areas such as to improve the life of patients who cannot move or communicate but are still aware and awake [16]. Further examples include playing a virtual piano [17] or selecting different objects on a multi-touch screen [8]. However, due to its low performance and accuracy, P300 control remains an inconvenient input choice for the normal user [18].

Use of EEG in Games

Computer games have progressed from keyboard and joystick input to rich physical movements (such as the Nintendo Wii and Microsoft Kinect). The expectation is that future games would take advantage of BCI input to increase the user's involvement. One discovery that has made BCI more interesting for gaming has been to use imaginary movements to produce the same brain signals as real movements [19]; it is then possible to create a BCI based agent which replicates the user's imagination [6].

The incorporation of BCI input technology into games can be categorized into three different groups: traditional games with BCI input, non-traditional games with BCI input, and games with BCI assisted input.

Traditional games with BCI input. These games were designed for more traditional forms of input (like keyboard or mouse) but have been adapted to utilize BCI as the only input control for the game. By controlling different cognitive states, gamers can walk through and play the game without the assistance of their hands.

[16] http://hothardware.com/Reviews/OCZ-NIA-BrainComputer-Interface/?page=5 (visited 14/09/2010)

Examples of these games include the walking game [20], or playing Ping-Pong using a BCI controller[17].

Non-traditional games with BCI input. The BCI input for 'non-traditional' games affords 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 in order to win the game [21].

BCI-input assisted games. The third group augments BCI input with traditional input control 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 [22]. Another example is Mindflex (mindflexgames.com) a game that requires users to navigate 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.

Emotions and Decision Making

Emotion is an individual's state of mind about a complex psychological experience based on sensory stimulation [23]. Emotion is externally expressed in terms of "affect", such as joy, sadness, anger, fear, surprise and disgust. These were referred to as the Big Six emotions [24] and do not include affects such as elevation [25], pride [26] or confusion [27], which were recently reported in the literature. An important aspect of emotion is arousal (or sometimes referred to as excitement) which is the state of responsiveness to sensory stimulation[18]. Arousal can be viewed as a call to action while affect provides the direction of experience [28]. As emotions can affect our actions in the physical world, there is a rich set of possibilities in harnessing these emotions in the virtual realm. However, from the review of the literature we cannot find generic design principles to guide application developers in mapping a sensed parameter.

To gain this understanding we focus primarily on deriving design principles based on emotional excitement as captured by the EEG signals; we focus on excitement as this refers to the state of responsiveness to sensory stimulation.

FACTORS INFLUENCING DESIGNS OF BCI SYSTEMS

There are several factors that need to be considered when designing an EEG based system. Here we identify four factors that can guide the design of BCI-based systems: EEG emotion, mapping method, selection technique, and visual feedback.

EEG Emotion

There are a number of parameters of emotion that can be identified by measuring the EEG signals. Typical emotions include Joy, Sadness, Anger, Surprise, Fear, and Disgust [27] which can be mapped using machine learning techniques.

Typically, the center of a brain's emotions is activated when people make a decision [28]. As a result, emotions can affect our decisions in ways unaware to us: thinking about the future can raise feelings that consequently affect our actions [29]; we make quick choices based on emotional instincts (such as in flight-or-fight situations) [30]; decisions based on our emotional states are influenced by gender [31]; and realistic decisions are made under the influence of emotions of sadness or desperation [32].

Designers must choose an appropriate emotion to map onto their required task. Some emotions, such as surprise, may be harder for users to replicate than others or be inappropriate for the task at hand (e.g. asking a user to be sad when they are winning the game).

Discretization of Movement Space

BCI input devices provide a continuous stream of constantly changing brain activity along a scale. In the case of the Emotiv Epoc Neuroheadset this scale ranges from zero to one. Continuous input control makes immediate use of this input value of parameter control. For example it is possible to use continuous input control to enhance-first person shooter games in this way such that if a player is excited, small movements which make targeting harder are executed more often.

However, brain signals often spike and change quickly, making on-screen parameter control difficult. To provide more smooth 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 of users to select a specific value along a parameter range. Game designers need to balance the number of discrete states with the error tolerance desired – large number of states can lead to a finer the level of user control but with lower tolerance to fluctuations. To the best of our knowledge there is no reported results our how to suitably discretize this space, we investigate this issue in our later studies.

Mapping Method

The aim of a discrete mapping is to translate a level of human emotion 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 emotion state. This can be done either linearly or non-linearly. In the former, all of the emotion states are given the same weight whereas in the later different states afford different weights. In a linear mapping the position of the cursor is a direct one-to-one function of the current value of an emotion. Commercial games like MindBall (www.mindball.se) and Mindflex (mindflexgames.com) use absolute mapping to map the excitement level to the distance of a physical ball which the user needs to control as part of a game.

Relative Mapping

In this mapping method, the position of the cursor is based on the difference between the current and the previous emotional states of the user. This can be performed in different ways. One approach is to calculate

[17] http://www.emotiv.com/apps/applications/117/685 (visited 14/09/2010)

[18] Dorland's Medical Dictionary for Health Consumers

the distance of two consequent emotional states and with a function (linear or non-linear) calculate the displacement that should be applied to 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 emotional 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: one is within band, i.e. using BCI capabilities and the other is out-of-band, i.e. using a traditional input controller. Examples of techniques that only use BCI capabilities include dwelling, hovering upon one state for a number of times, and using another emotion for triggering selection. Examples of the second approach include double-clicking on the mouse, a keyboard, or voice recognition.

Visual Feedback

Feedback is one of the main building blocks of control systems. It is possible to visualize the feedback of a system in different ways according to needs and specification of the system. Because feedback is a part of closed control loop, the effect of it on the performance of user could be significant.

Visual feedback 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 an object of interest flashes to help them focus on the object and improve the P300 signal [30]. Thus different visual representations could have different outcomes. For instance, Ramos et. al. [29] showed in their study that users performed better with full visual feedback compared with spatial feedback. Many BCI-based outputs have been used as control input. However, there is little research which investigates how well a user can control these input states in different conditions and different forms of representations. We conducted three experiments to study these questions.

EXPERIMENT 1: IDENTIFYING LEVELS OF CONTROL

The primary goal of this experiment is to establish the accuracy with which a user can manipulate their excitement levels to control an object. A secondary goal was to examine the suitability of different types of visual feedback.

Participants wore the *Emotiv Epoc Neuroheadset* headset to measure their levels of excitement (hardware details of the headset are in the Appendix-1). They were then asked to move a cursor from a starting position to an end position by becoming more excited or more relaxed. Since excitement is a measure of brain activity, participants were informed that mentally solving complex problems or thinking of past memories would stimulate brain activity.

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 Interface and Task

The experimental interface (Figure) had a size of 1280×800 pixels and was displayed on a 14 inch widescreen monitor (resolution 1400×900 px). Participants sat 70cm from the screen. At the beginning of a trial, the start position is shaded orange and end state is shaded green. To ready the participant, a three-second countdown begins. During this time, the end state fades from fully shaded to only an outline. Once the countdown completes, the user can move the cursor by changing their excitement.

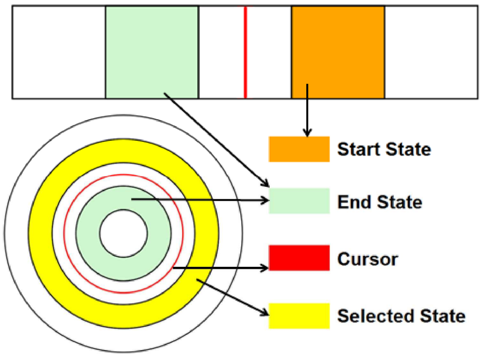

Figure 5: Linear and Bull's eye visualizations. Yellow circle shows the state of the user, orange square shows the start state, green circle/square shows the end state, and red line/circle shows cursor.

The participants' initial excitement level must match the start state before a trial begins. To achieve this, the participant must modify their excitement level to move the cursor into the start state, and keep it at a constant excitement for at least 200ms, at which point the trial begins. The user then adjusts their excitement 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 excitement level cursor position.

To reduce cursor jitter, we set a threshold for showing cursor movement. If the change of excitement was less than that threshold (set at 0.03 in our experiments), the cursor became thicker (and faded in colour). This indicated small scale 'bouncing' movement to the user. The cursor returned to its normal thin line visualization when the user's excitement settled or if a large scale excitement was detected.

Procedure

After completing appropriate consent forms, the Emotive headset was placed on the user and their comfort confirmed. Each participant was provided with an explanation of the control mechanism—by relaxing they would move the cursor towards the left (or center, depending on the visualization, see below) and by becoming more excited they would move the cursor up or outwards.

Participants were then given ample time to practice the control mechanism with both of the visualizations used. Each experiment consisted of 4 blocks of 16 trials. Between each block of trials the participant were given the opportunity to rest for three minutes. 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. By increasing the number of states, users should be able to more accurately select items from those available.
- *Emotional Distance*: +0.29, +0.59, -0.59. Excitement is measured on a linear scale from 0 to 1. Emotional distance is a measurement along this scale—positive distance indicates movement from relaxed to excited, negative movement from excited to relaxed.
- *Visualization*: Linear, Bullseye. A one-dimensional matrix layout or a bullseye-like set of concentric circles (see Figure).

The factors visualization and number of states were counterbalanced between participants. The experiment consisted of four blocks of 16 trials with the presentation of distances modified between blocks.

Participants

Seven participants (6 male and 1 female) between the ages of 24 and 31 volunteered for the study. All were from a local university and they had all heard of an EEG headset but none of them had used one before.

Results

The total number of trials that were successfully completed was 424 out of 448. The average trial completion time for successful trials was 12.45 sec (s.e. = 0.54 sec). We carried out statistical tests using a univariate ANOVA with Tamhane post-hoc pair-wise comparisons (not equal variance assumed) to compare the effect of *number of states* and *visualization*.

There was a significant effect of number of states on trial completion time ($F_{1,6}$ = 39.7, $p < 0.01$), with five states significantly faster (10.02 sec) than ten states (14.97 sec). We found no significant effect of number of states on false target selection ($F_{1,6}$ = 3.76, p = 0.07)—five states had an average of 3.9 false selections, ten states 4.5**.** Figure shows the mean task completion time per state for each visualization.

We found no significant effect of visualization on trial completion time ($F_{1,6}$ = 0.259, $p > 0.1$, linear = 7.75sec, bullseye = 7.64s) or number of false targets selected ($F_{1,6}$ = 0.013, $p > 0.1$, linear = 0.239, bullseye = 0.233). An exit survey showed no differences in user perception of frustration or effort between these two visualizations.

There is a significant effect of distance on trial completion time ($F_{2,18}$ = 3.66, p = 0.032) and number of false targets selected ($F_{2,18}$ = 46.748, p = 0.001). As can be seen from Figure 4, post-hoc pair-wise comparisons showed users were significantly faster ($p < 0.05$) at relaxing (-0.59) than getting excited (0.59). They also had significantly fewer false targets selected when going to 0.29 than 0.59. None of the other pairs showed significance.

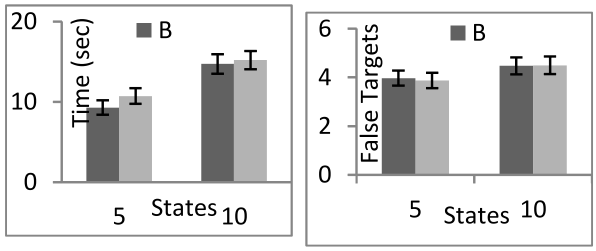

Figure 6: Task completion time in sec (Left) and false targets selected (right) over number of states and visualizations (B = Bullseye visualization, L = Linear Visualization) for Study 1A.

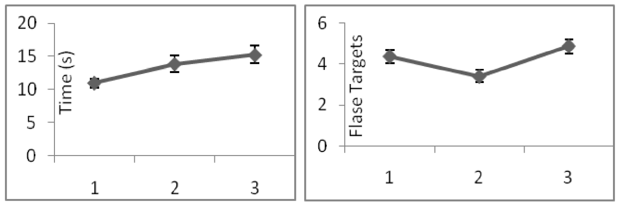

Figure 4: Task completion time in sec (Left) and false targets selected (right) over distances for Study 1A (1 = -0.59, 2 = 0.29, 3 = 0.59).

Study 1B

In Study 1A we saw 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. We ran Study 1B to test 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

To validate or refute our hypothesis, we modified the levels of the *number of states* factor to three and five.

An additional seven participants (2 male and 5 female) between the ages of 25 and 30 were recruited for study 1B. As per experiment 1A, all had heard of an EEG headset but none of them had used one before.

Results

The total number of trials that were successfully completed was 420 out of 448. The average trial completion time for successful trials was 12.6 sec (s.e. = 0.56 sec). We carried out similar statistical tests to study 1A.

We found no significant effect of number of states on trial completion time ($F_{1,83}$ = 0.152, $p > 0.05$) or number of false targets selected ($F_{1,83}$ = 2.86, $p > 0.05$). Interestingly, users were marginally faster and selected fewer false targets when performing with *five* states (mean 12.5 sec, 1.84 errors) than with *three* (mean 12.7 sec, 2.12 errors) as can be seen from Figure 5.

As with Study 1A, we found no significant effect of visualization on trial completion time ($F_{1,83}$ = 2.205, $p > 0.05$). However, we did find a significant effect of visualization on number of false targets selected ($F_{1,83}$ = 5.64, p = 0.02). Users were more accurate with the linear visualization (mean 1.85 false selections) than with the bulls-eye visualization (2.12).

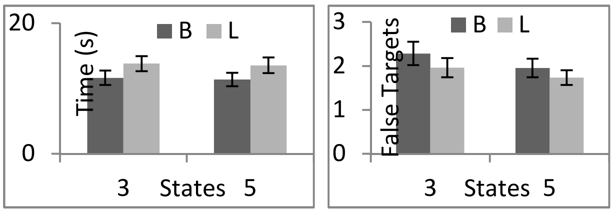

Figure 5: Task completion time in sec (Left) and false targets selected (right) over number of states and visualizations (B = Bullseye visualization, L = Linear Visualization) for Study 1B.

Discussion: Study 1A and 1B

From studies 1A and 1B we learned that the number of states is an important factor in the control of an on-screen cursor using BCI input. Our studies showed that five states is preferable over ten states, however, we did not show that three states were significantly faster than five. We therefore choose five states as a comfortable range in which users can move a cursor. We use this value for our remaining studies.

EXPERIMENT 2: EXCITEMENT-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. In this experiment, we sought to investigate the effect of excitement 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 one factor, the selection distance.

Number of states: From the previous two studies we saw that five states was optimal for this type of cursor movement and selection task. For this experiment, the number of states remained constant at five.

Visualisation: 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 choose to only use 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 (increasing excitement) and four backward (decreasing excitement) 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

Seven participants (5 male and 2 female) between the ages of 24 and 27 were recruited from a local university to participate in the experiment. All participants had heard of an EEG headset but none of them had used one before.

Results and Discussion

The total number of trials that were successfully completed was 414 out of 448. The average trial completion time for successful trials was 16.22 sec (s.e. = 0.68 sec).

As one would expect, an ANOVA showed that there was a significant effect of distance over trial completion time ($F_{7,42}$ = 9.64, $p < 0.01$). Tamhane post-hoc pair-wise comparison revealed the following pairs of distances were significant (-4, -3), (-4, -2), (-4, -1), (-4, 1), (-3, -1), (-1, 2), (-1, 3), (-1, 4), (1, 4).

Our results show that users are equally proficient in both directions (relaxing to excited or excited to relaxing state) as post-hoc comparisons did not reveal significant difference between pairs (-4,4), (-3,3), (-2,2) and (-1,1).

Figure 6 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 0.93 and 0.96. There are two important observations from this plot. First, the similar trend slopes on the graph 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.

While we observed in Study 1 that participants found relaxing easier to achieve than becoming excited we could not find a similar affect in Study 2. In Experiments 1A, 1B and Experiment 2 the mean trial completion times at 5 states are similar for -0.6 and 0.6. Note that Figure 4 (right) includes mean time for both 5 and 10 states so cannot be directly compared to Figure 6 but 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 5 states than higher states.

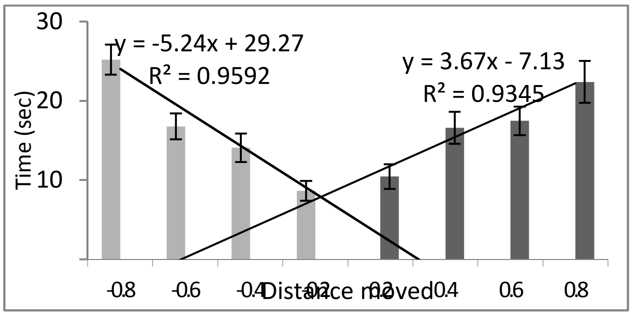

Figure 6: Mean task completion time with a trendline showing linear correlation between time and distance.

Finally, we found no significant effect of distance on number of false targets selected ($F_{7,42}$ = 0.642, $p > 0.1$). Figure 7 shows the mean false targets selected for each distance.

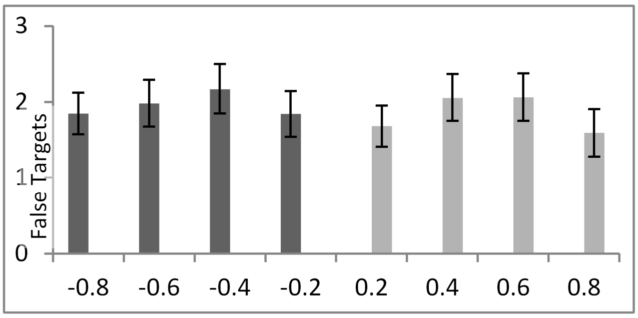

Figure 7: Mean false targets selected for each distance with standard error bars for experiment two.

EXPERIMENT 3: DISTRATIONS AND MULTI-TASKING IN A GAME SETTING.

With a better understanding of the low-level performance of BCI input from experiments 1 and 2, we were then interested in employing our guidelines to a gaming environment. The goal of this experiment was to examine users' performance in their ability to control their emotions in a situation that required multi-tasking.

Design

We designed a simple 2D game that required players to complete two tasks simultaneously—one required the use of a traditional input (wireless remote button), the other BCI-measured excitement. The user is required to move an on-screen avatar from the starting position on the left, to the end position on the right. During this task, a demon sends a fireball towards the avatar, which the player must destroy by modifying their excitement to the required level. If the player fails to destroy the fireball and/or fails to reach the end point within 30 seconds then the avatar is killed.

Experimental Interface and Task

The experimental game interface (Figure 1) was displayed on a 14 inch widescreen monitor (resolution 1400×900 px). Participants sat around 70 cm from the screen.

Each trial begins when the user reaches a specified level of excitement, as visually indicated on the screen. This ensures all participants begin with the same excitement level. The participant presses a key on a wireless remote to move the character toward the finish line. A fireball appears as the user starts to move. A linear visualization with five states of excitement is attached to the character. Each state has a number inside and it is colored in a different shade of red. The fireball has a shade of red and a number inside that matches one of the states on the visualization.

In order to destroy the fireball the user adjusts their level of excitement to match the number that is on the fireball. Once at that state, the user presses a second key to destroy the fireball. The matching of emotional state with the fireball's 'kill' state is indicated visually by the avatar changing in appearance.

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 three 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 (participants were informed of this), leaving only 10 seconds which is less than the average time needed for completing the task, if they needed to pause to complete the excitement portion of the task (participants were informed of this). 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 25 and 31. Another five participants (4 male and 1 female) between the ages of 22 and 27 who had heard of an EEG headset but none of them had used it before were recruited from a local university to participate in the experiment.

Results & Discussion

With 10 participants, the system recorded a total of 480 trials. Of the 240 trials that corresponded to experienced users, 202 resulted in successful completion of the task. In the remaining 38 trials the user either failed to reach the finish-line in time (in 28 of the 38 trials) and/or failed to kill the demon before reaching the end (in 30 of the 38 trials).

Novice users failed to complete the trial on 68 occasions; in 41 of the trials, the finish line was not reached and in 65 the daemon was not killed.

Univariate ANOVA did not show any significant effect of experience ($F_{1,63} = 0.786$, $p > 0.05$) or distance on trial ($F_{7,63} = 1.35$, $p > 0.05$) completion time. The average trial completion time was about 22.5sec across all users. This is expected as the task was time-bound and participants were encouraged to complete the task in the time allocated.

Univariate ANOVA on number of false targets selected showed a significant effect of experience ($F_{1,63} = 4.67$, $p < 0.05$), no effect of distance ($F_{7,63} = 0.252$, $p > 0.05$) and no interaction between the two. Experienced users selected significantly fewer false targets than novice users (experienced mean = 1.57, s.e. = 0.33; novice mean = 2.62, s.e. = 0.34).

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 excitement task. Univariate ANOVA did not show any significant effect of experience or distance on either of these measures. Figure 8 shows the mean frequency and number of false targets selected for experienced and novice users.

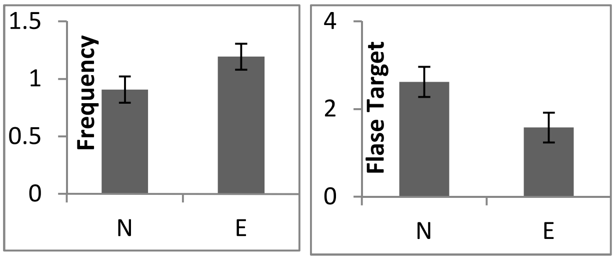

Figure 8: Mean frequency and number of false targets for Experienced (E) and Novice (N) users.

Overall Experiment 3 indicates that novice users are able to control excitement in a game like setting with similar finesse than experienced users. The biggest disadvantage is that novice users tend to select far more false targets than experienced users.

DISCUSSION, IMPLICATIONS, AND APPLICATIONS IN GAME DESIGN

BCI-based input has the potential to revolutionize the game-playing experience. The results from the studies in this paper can provide guidance on how best to begin designing such experiences.

Continuous vs. Discrete Input Control

The studies in this paper 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 excitement range, game developers can modify the difficulty of parameter manipulation—increasing the number of levels requires more accuracy and a greater practice and skill level. The studies also showed that one direction of selection is not favoured over the other and that a linear mapping of excitement to cursor is appropriate for this type of task.

The assignment of the emotional channel to a control should also characterize the selection of continuous or discrete input. For example, the selection of a weapon 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 relaxed or excited 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 different characters which work better in a specific level of emotion. For example, in a game like Warcraft Dota Allstars (www.playdota.com/) where characters have intelligence, strength and agility characteristics, low excitement could increase intelligence; medium excitement could increase strength and high excitement could increase the agility of the character.

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 excitement. 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 excitement.

Game input needs to provide error tolerance to cope with this additional and possibly erratic input stream. Triggering actions such as firing a gun or casting a spell should not be purely based on the user's excitement level, as this could likely lead to unintentional actions. In this work, small scale fluctuations were smoothened by the cursor becoming thicker, combined with users indicating via a button when their excitement 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, it is not like a mouse or a keyboard where it is clear when an input starts and ends. EEG input is 'always on', so designers must consider when a game is to utilize this input stream. For BCI-assisted games, there are two options: serial or parallel interaction.

Serial interaction allows gamers time to concentrate on producing the excitement level required to complete the task—they do not need to perform mouse or keyboard input at the same time. Once their excitement level is measured they will 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 flow of a game. For example, in a game like Delta Force a sniper's target aim can be proportional to their level of excitement. If a player needs to aim at a small or far target he would need to bring down his level of excitement to the lowest level before firing the gun.

Conversely, parallel interaction requires the user to continue input using traditional controllers, while appropriately adjusting their excitement 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 emotion. 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 excitement level and if the character is too close to the monster then a strong spell can also kill the player. This would encourage players to be careful in selecting the spell level (encouraging greater control of excitement) but would also support error resilience by allowing players to kill a monster through multiple lower-level spells.

Generalisability of Results

Our experiments looked at users' ability to control excitement. We used the Affectiv suite of Emotiv to carry out our experimental study. It is possible that if users perform the experiment with different hardware the results of the study may be different. We believe this will not be the case as arousal is a well understood concept within the computational neuroscience community with several pattern recognition approaches to compute it. Recent research has also have validated it against other physiological measure [31].

Arousal can be viewed as a call to action while affect provides the direction of experience. It is therefore possible that users might have different levels of control for excitement depending on their affective state. This can be viewed as a limitation of our study but we believe that it is important to see in the first instance if arousal can be controlled and what design guidelines can be generated for it. Future research can look at carefully managing users affective state while examining their ability to control excitement.

Lessons for Designers

We provide the following guidelines to designers:

- To the greatest extent possible, discretize the raw BCI signal into five discrete states;
- Visual feedback showing the cursor, current state, and goal states should be abundantly clear to the user;
- Novice users require training, thus short games suited as 'training wheels' could prove beneficial to transfer learners into expert mode;
- Combined input with a typical controller is possible for both walk-up and expert users.

CONCLUSION

The experiments described in this paper offer valuable guidelines for designers. We show that when discretizing raw excitement values five levels provide a good balance of speed and accuracy, users have good bi-directional control of excitement and are able to effectively control excitement in game-like multi-tasking scenarios. Our results also show that novice users are able to control excitement 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 excitement 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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APPENDIX 1 - BCI HARDWARE

There are several commercial EEG based BCI devices available such as the Emotiv Epoc Neuroheadset, OCZ Neural Impulse Actuator (NIA) and PLC devices XWave. In this work we use the Epoc Neuroheadset.

The Emotiv Epoc Neuroheadset is a readily available and relatively cheap EEG based controller ($750 for a research kit). It is currently being used by many game developers (both board games and digital games) to augment the users' gaming experience. The Emotiv headset is a dry cap set which does not require wet gel and instead uses 16 saline sensors. A gyroscope is embedded in the device for detecting the head's orientation and wireless communication allows free head movement. The set has an internal sampling rate of 1280Hz which is used to produce an output rate of 128Hz. It can detect and respond to three kinds (or Suites) of EEG signals:

- Expressiv Suite: Facial expression detection, for example winks, laughing, blinking, raising brows and smiling.
- Affectiv Suite: This suite can detect the emotions of users, for example excitement, engagement/boredom, meditation and frustration.
- Cognitiv Suite: This suite is able to recognize mental states of user. It can recognize 13 distinct actions: six directional movements (push, pull, left, right, up, down), six rotational movements (clockwise, counter-clockwise, left, right, forward, backward) and one imaginary movement (disappear).

Values corresponding to each Suite are floating-point numbers between 0 and 1 that shows the percentage of similarity of one's state to a specific emotion or action.