Investigating the Emotiv EPOC for cognitive control in limited training time

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by
Matt Lang

Supervised by Tanja Mitrovic

Department of Computer Science
University of Canterbury
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Abstract

Brain-computer interfaces (BCI) that utilise electroencephalography (EEG) have been studied for many years as a means of communication and control for physically disabled individuals. Through training, people can learn to use imagined motor movements as computer input or to control assistive technology. The Emotiv EPOC is an inexpensive, lightweight, wireless BCI headset, and provides systems for control and affective measurement. Some studies have successfully used this device for control, however most fail to indicate the time and effort required to achieve the reported results. As an initial step to provide a quantification of the training time required, we ran two studies investigating cognitive control. Using just their mind, participants in the first experiment moved a virtual cube left and right, and in the latter made three-choice selections. The first study employed a fixed training scheme approximating 11 minutes, and resulted in a 36% average success rate. The latter task allowed 15 minutes of self-directed training, increasing the average success to 46.8%. We detail our investigations with the EPOC, including analysis of detection filters for maximising cognitive control, and we review the Affectiv suite and how to analyse the user's emotional measurements it provides. Future applications should be aware that a more practical level of control requires a greater training time than one short session.

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Chapter I

Introduction

Normal computer input relies on physical interaction with control devices such as a keyboard or mouse. More recently, brain-computer interfaces (BCIs) have been under investigation as a new channel for communication and control [1]. Electroencephalography (EEG) provides a means of accessing and recording neural activity, allowing a computer to retrieve and analyse information from the brainwave patterns produced by thought. By removing the need for physical input, BCIs offer a range of assistive and rehabilitative applications for those with impaired or little physical control [2, 3].

While there are many beneficial BCI applications, such as for controlling wheelchairs, much of this technology has yet to leave the research lab. One large factor of this is due to the EEG devices. Most research and medical EEG devices are expensive, bulky, and require a number of skilled people to set up. Technology is continuously getting smaller and cheaper however, and recently some inexpensive consumer-grade devices have become available. An example of this is the Emotiv EPOC,[1] a compact, wireless headset that requires comparatively little effort to set up and allows much greater flexibility and mobility than traditional EEG.

The EPOC was aimed at the gaming market, and is not classified as a medical device, though a few researchers have since adopted it for a variety of applications. The EPOC comes with some processing tools that can detect facial movements, emotional states, and imagined motor movement. The last of these requires each individual to train both the system and themselves to be able to control. There have been some applications that successfully utilise this technology, such as for robot control [4–6]. However, many of them do not give a good indication of how much training is required or address other practicalities of using the EPOC. This report is an investigation of the EPOC and its EEG processing system for its practical use in further research.

1.1 Motivation

The ICTG research group is investigating systems to aid in the rehabilitation of cognitive functioning for people who have suffered from a stroke or traumatic

[1] http://emotiv.com

brain injury. Such patients have limited physical control and struggle to use traditional inputs, such as the keyboard and mouse. To interact with the ICTG systems it was proposed this group of patients could utilise a BCI, as they are the audience of much BCI research.

The Emotiv EPOC is an inexpensive BCI which allows much greater flexibility for the users than do traditional devices. However, Emotiv has not published any research validating the EPOC. While many of the studies utilising the EPOC claim success, very few of them give an indication of how long the users took to reach the reported level of control. In addition, many of them only test their application on a very small sample, such as one or a few people.

One part of the rehabilitation study requires patients to interact in a 3D virtual environment. We are therefore interested in whether participants could use the EPOC to navigate and interact with the environment simply by imagining movement-related actions. Another requirement of the rehabilitation study is that it will not take too long for the participants, as these patients tire very quickly. This means that participants must be able to control interactions with their thoughts within one short session. Although this research's audience comprises people who have suffered brain injuries, as this is an initial investigation we only involved healthy participants.

1.2 Goals

Our aim was to investigate the EPOC and its practical uses, evaluating whether it would be suitable for controlling a virtual environment after one session of training. The focus questions were as follows:

- What has been done and proven possible or not possible with the EPOC?
- How difficult is it to use the EPOC?
- Can users achieve a practical level of control in a short time period?
- What other useful measures does the system provide?
- Overall, would it be suitable for the ICTG rehabilitation research project?

1.3 Report Layout

In the next sections we explain our motivation behind this research and specify our goals. In chapter 2 we review the relevant literature and previous applications of the EPOC. Our first study, on controlling movement along one dimension, is then explained and the results discussed. This leads us to a second study using a three-way selection task, which is detailed and has its results discussed in chapter 4. Following this is a review and investigation of the emotional measurements provided by the Affectiv suite. We then discuss the implications of our investigations, and conclude with suggestions of further work.

Chapter II

Background and Related Work

2.1 *Electroencephalography (EEG)*

EEG has been most predominantly researched for medical applications, with a large history of use relating to epilepsy. It has been around since the early 1900s and has had much interest ever since [7]. Although more recent medical imaging methods, such as functional magnetic resonance imaging (fMRI), can provide a much finer spatial resolution, EEG has a much greater temporal resolution that allows millisecond-accuracy.

In the brain, neurons are constantly firing by a tiny change in their electric potential. Because this is happening everywhere across the head at very fast rates, it creates a constantly changing electric field on the scalp in the order of microvolts. Electroencephalographs use electrodes placed on the scalp to conduct these small electrical fluctuations. The electrodes are traditionally wired up to an amplifier to boost the strength of the detected signals, which are then recorded and processed.

After many years of EEG research, these brain wave rhythms are commonly categorised into bands of different frequencies, namely delta (0.1-3.5 Hz), theta (4-7.5 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (>30 Hz). Certain rhythms or bands have been found to reflect our brain's state as our environment and activities change. An example of this is the mu rhythm, (8-12 Hz), which can be measured over the sensorimotor region, known to relate to our physical movement, while in an idling state. Performing or imagining motor actions has been shown to create a detectable suppression of this rhythm [8], as described further in Section 2.2.1.

2.2 *Brain-Computer Interface (BCI)*

With advances in technology and research, it has become possible to process EEG data in real-time. By detecting features of the brain activity and creating a feedback loop, users can communicate to a computer without the need for any physical input [9]. A brain-computer interface is a hardware and software system that provides interaction to a computer directly from the user's brain. There are a number of ways of achieving this interaction, the more common of which are briefly explained here.

2.2.1 Types

P300

The P300 is a detectable peak in activity that appears approximately 300ms after some infrequent stimuli [10]. Most commonly users are presented a large number of choices, which are highlighted in a systematic manner, and the user counts every time the item of interest is highlighted, creating a P300 signal. The user typically has to be looking at the desired item, but other methods exist such as using auditory stimulus [11].

Steady-State Visual Evoked Potential

With steady-state visual evoked potentials (SSVEP) a number of choices are presented on screen in the form of stimuli flashing at unique rates [12]. When a user looks directly at one of these, brainwave modulations of that frequency are detectable in their visual cortex. This allows a large number of choices to be available, and can achieve relatively high information transfer rates (up to 60-100 bits/min) [9]. Systems using this method do not require training, but the user does need to be able to move their gaze to the item of interest.

Slow Cortical Potential

Slow cortical potentials are detectable changes in voltage that can take up to several seconds. Through much training with feedback users can learn to control increases and decreases in their levels of cortical activity, typically having only these two options (increase or decrease) at any time. The performance of this method can be sensitive to many factors however [13].

Sensorimotor Rhythms

When relaxing and not engaging in any motor movement, sensorimotor rhythms (SMR) can be detected in the brain. In particular are the rhythms in the mu (7-13Hz) and beta (13-30Hz) bands. These oscillations in the brain activity are naturally rhythmic, but are disrupted by engagement in motor movement, whether real or imagined [8]. Decreases and increases in these rhythms are known as event related desynchronisation (ERD) and event related synchronisation (ERS) respectively, which are detectable in the EEG, often across multiple channels. To detect the ERD or ERS the brain activity is compared to some reference or a base state of activity, which must be sampled from the user when they are relaxed and not imagining movement.

Manipulation of sensorimotor rhythms does not require actual physical movement, as motor imagery has similar effects [14]. The imagery must, however, be kinaesthetic and not simply visual representations [15]. Through constant visual or auditory feedback, users have to learn to control different actions [16]. This imagined motor movement can be very challenging though, and most SMR applications have no more than a few controllable actions, compared to the 36 options of the P300 Speller for example [17].

2.2.2 Applications

The audience for most BCI research is physically disabled people, especially those with very limited physical control who cannot make use of more common assistive technologies. Their disabilities can include anything from stroke to amyotrophic lateral sclerosis (ALS), though it has been shown that performance with a BCI declines with increased levels of impairment [18]. Important applications for these patients include communication, rehabilitation, and assistance in control. As communication is a critical human skill, BCIs have been developed to provide patients with a virtual keyboard [19] or a navigable hierarchy of grouped letters [13]. Among these is the well-known P300 Speller [17], which has had many further improvements over the years. There is potential for rehabilitation for stroke patients [20], but otherwise patients may be limited to using BCIs to restore or replace motor control through prosthetic devices [2]. BCIs have a number of possible uses as part of assistive technology [9]. As an example, BCI controlled wheelchairs would be greatly desired [21].

More recently there has been increased interest in BCI research for healthy users. While some are interested in using BCIs for control applications such as robots [22], a lot of work focusses on the subjective, time-aligned information that BCIs provide, such as user emotions [23] or cognitive load [24]. These measures can allow a system to infer how the user is feeling, and adapt so as to enhance the gaming experience [25], or to help a user of a tutoring system [26]. Similarly, these measures have been used for research into areas such as interface design [24], task classification [27], and even marketing [28].

2.2.3 Devices

EEG devices can have a range of electrodes, with standard medical EEG having 19, and some having many more. Most electrodes in use require an uncomfortable, conductive gel applied to the scalp. Each electrode of the cap would then be connected to an amplifier via an array of wires. These kits are typically designed for medical and research use, costing upwards of thousands of dollars, and are often large and cumbersome to move. Furthermore, the equipment can take considerable time and effort to set up.

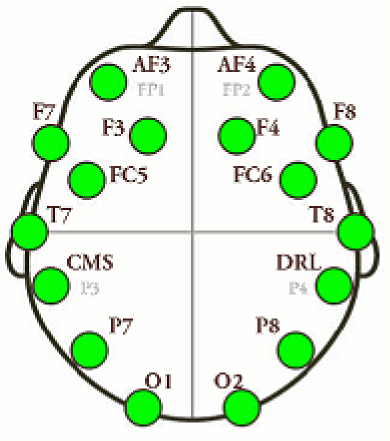

Figure 2.1: *The EPOC electrode positions on the head approximate the international 10-20 system.*

Much of the previous EEG research has targeted those with physical disabilities, but the technology ought to be much simpler before we would expect user adoption. More recently a range of inexpensive devices have become available, mostly aimed at the gaming market as a novelty peripheral input. One example is the NeuroSky[1] with just one sensor. The Emotiv EPOC is another such device with a 14 sensors, which is comparable to the traditional devices. This paper is an investigation of the EPOC neuroheadset and its accompanying software, both of which are described in more detail in the next section.

2.3 Emotiv EPOC

The EPOC was marketed as a gaming device for the Windows platform. It comes shipped with a 3D game, Spirit Mountain, in which the user must train cognitive skills, and use these skills to rebuild a virtual Stonehenge. The neuroheadset is inexpensive compared to most medical EEG, with a price tag of $299. It has 14 sensors arranged according to the international 10-20 System, as depicted in Figure 2.1. The device has an internal sampling rate of 2048Hz and, after filtering out artefacts, sends the data to the computer at approximately 128Hz. These signals are transferred from the headset to the computer through wireless technology. This offers much greater mobility, and it is relatively simple to slip the headset onto the head. Instead of requiring a special gel, the electrodes of the EPOC simply need to be dampened using a saline solution, which is both disinfectant and common.

[1] http://neurosky.com/

2.3.1 *Software*

The data collected by the headset is sent to the computer through an encrypted channel, and Emotiv supply an application called EmoEngine to decode and process the data. This provides a few built-in brainwave processing suites including Expressiv, which detects movement of facial features; Affectiv, giving a measure of five subjective emotions; and Cognitiv, where users can train the system to detect specific thoughts. These suites are discussed in more detail below. EmoEngine provides headset battery level, gyro readings, contact quality information, and researcher versions provide access to the raw EEG data too. There is a C++ API to allow custom applications using the supplied engine, and Emotiv supply examples of interfacing the engine using Java, .NET, and MatLab.

All of the above mentioned functionality can be used without a custom application through the supplied Control Panel. The panel has a tab for each suite with a simple interface for visualising and controlling each, along with a display of the contact quality of each sensor. Along with these tools comes EmoKey, for mapping thoughts and expressions to keyboard input; EmoCube, a standalone version of the demonstration virtual cube seen in the control panel, which allows custom applications to utilise the moving cube visualisation; and Testbench for researcher versions, which displays the electrode measurements and their fast Fourier transform, and allows recording of the data to disk.

Expressiv Suite

The Expressiv suite provides detection of a range of facial expression features. While all three software suites use the readings from the electrodes, the Expressiv suite is specifically concerned with the electromyography (EMG) present amongst the EEG. As EMG, such as from blinks, affects EEG, many applications treat this as noise and attempt to detect its presence to remove it from the data. The Emotiv system does this; however they classify the detected EMG into movement of facial muscle groups, allowing it to be another form of direct input. Similar to the EMG from muscle movements, electrooculography (EOG) is also present and classified into actions of looking left or right.

As most people have similar facial muscle structure the EMG from specific features are much the same between people, meaning the suite does not need to be trained by every individual. It can, however, be trained if the user desires greater accuracy, and the sensitivity can be tweaked.

Affectiv Suite

The Affectiv suite processes the EEG and gives a measure, between 0 and 1, of the current level for each of five subjective emotions. These include instantaneous excitement and long term excitement, described as an experience of awareness or positive physiological arousal; engagement, said to reflect alertness and conscious direction of attention towards task-relevant stimuli, with low values suggesting boredom; frustration; and meditation, which indicates a type of relaxed state.[2]

These detections cannot be explicitly trained, as they depend on seemingly universal characteristics of the EEG realisation of human emotions. Emotiv used relevant literature and experimentation with many users to find these characteristics and design their classification algorithms.[3] Unfortunately for the research community they did not publish any of their findings for proprietary reasons. While these constructs are said to be relatively similar amongst people, it is noted that the level of these measures can vary greatly between individuals. For example, one excitable person's lack of excitement may still produce a higher measure than another's maximum excitement. To handle this variation the Affectiv suite automatically scales new emotional readings for each user relative to that individual's previous readings.[2]

Cognitiv Suite

Unlike the previously mentioned suites, the Cognitiv suite will not automatically make detections without training. The Cognitiv system can be trained on specific thoughts, after which the engine will continually process the brainwaves and match them to the patterns of thought trained. This relies on event related desynchronisation (ERD) in the EEG, and is designed to be most effective for thoughts directly relating to imagined motor movement. There have been doubts about what it is actually measuring [29], and it is known that it will include EMG data too, however it is said that the system works best on pure thoughts detected in EEG anyway.[4]

To be able to detect thoughts the system must first sample the EEG while the user is in a relatively relaxed state and, most importantly, not thinking about any of the thoughts to be trained.[5] This is called neutral, or the base state of the user's brain, which the system can then compare to trained thoughts. After this the user can train the system to detect different actions depending on what the user is thinking. The Cognitiv suite supplies thirteen possible actions to train, but the engine limits how many it will detect to four at a time. These actions are named relative to physical actions to suggest

[2] http://emotiv.com/developer/SDK/UserManual.pdf

[3] http://emotiv.com/forum/messages/forum12/topic1926/message11109

[4] http://emotiv.com/forum/messages/forum15/topic1697/message9864

[5] http://emotiv.com/forum/messages/forum4/topic114/message392/?phrase_id=464885

Figure 2.2: *This virtual cube is used for training to control actions in the Emotiv Cognitiv suite. It floats about corresponding to detected actions and otherwise automatically returns to the middle of the screen.*

using kinaesthetic-related thoughts. The supplied demonstration application for training and using Cognitiv consists of a virtual cube that animates the actions applied to it, as shown in Figure 2.2. The trainable actions include push, pull, left, right, up, down, rotations of both directions about all 3 axes, and disappear.

Training any action (including neutral) is done in 8 second trials, during which the user must attempt to think a consistent thought. Generally the more training the system is given the more accurately it should be able to detect those thoughts. There are two main challenges for the user. One is to find thoughts that the system is able to detect, and that are considerably different from each other. Generally thoughts not relating to movement, such as those of visualisation or language, will not seem to be distinguishable by the system.[6] The other is to be able to think the thought consistently during all training trials for an action, and after training when wanting it to detect that action. It is important to note that both the system and the user are being trained in this process.

[6] http://emotiv.com/forum/messages/forum4/topic114/message392/?phrase_id=464885

2.3.2 Applications

A number of researchers have continued researching previous applications while adopting this new device, using its EEG recordings with their own processing. Different types of BCI can use this device, such as those utilising the P300 signal [30]. Others have investigated different EEG processing algorithms to achieve direct brain input such as classification of shapes being thought about [31], evaluation of cognitive workload [32], detection of unintentional interactions with an interface [33], or control of robot movement along one dimension [34]. Another application uses the EEG to detect hand movement intentions on the same side of the brain as the hand [35]. These detections then control an orthoses, allowing people who have lost control of a hand due to stroke or similar brain injury to control that hand with the same side of the brain. Further, this can take advantage of the brain's neural plasticity, meaning patients could rehabilitate their control.

Raw EEG from the EPOC has also been used in games, such as serious games for concentration training [36]. Through neurofeedback users can learn to control their concentration as detected in their EEG. Some games are simply for fun, like a tower-defence variant that is controlled by SSVEP [37], showing that detection of SSVEP with the EPOC is comparable to other devices.

Emotiv did not publish any research regarding the validity of the detections made by the EPOC and accompanying software. Regardless, some researchers have investigated uses of the in-built detection suites, such as using Cognitiv actions to control forward acceleration in a game of Mario Kart [38]. Others have used the Cognitiv suite to control various technologies, such moving robots [4, 5]. Szafir and Signorile send every tenth detection as a movement command to a robot [4]. They initially considered using the power of detections as an amount of movement, but decided it was difficult enough performing the action without considering the power. Thobbi, Kadam and Sheng also control a robot using Cognitiv [5]. They first did a small validation study and decided to filter out false detections by taking the integral of the power over time and comparing this to a threshold.

Another investigation of the EPOC's usability had 17 participants rotate cubes to aid in a cube comparison task [39]. Users in this study could rotate the cube through three trained Cognitiv actions, six facial movements detected in Expressiv, or using the 4 directions of the gyro in the headset. They found that participants chose to use all three input types about equally, and after one session of training achieved 59% success at making an action happen when intended. This approximate accuracy is crudely measured however.

Lievesley, Wozencroft and Ewins investigated the use of the EPOC to control a wheelchair [40]. Firstly they compared control using facial expressions to head switches which are currently available as a control alternative. They discovered that control using facial muscles, while achievable, is considerably less reliable and more tiring than head switches. They then investigate the Cognitiv suite, having 3 participants train two or three actions over five half-hour sessions. To test their control participants were instructed actions and given 8 seconds to perform each. Detections were filtered out if they did not persist long enough. They report final accuracies of around 94% for two actions (push and neutral), and 69% for 3 actions.

There are other applications utilising only the Expressiv suite. It is possible to control a robot arm by raising and lowering the eyebrows, and smirking to the left and right [41]. Facial expressions detected by the EPOC can even be used to steer a tractor [42], but Gomez-Gil and colleagues say that they could not achieve successful control when only using the Cognitiv suite.

Cernea and colleagues recognised the need to validate the facial and emotional detections of the EPOC first [43]. In one of their studies they instruct users to make facial movements to evaluate the accuracy of the Expressiv suite [44]. They find that detection varies around 70-100%, and after 20 minutes of training the Expressiv system this was increased by a further 12% on average. Another of their studies focusses on the Affectiv suite, comparing its detections to user's self-reported feelings during a range of tasks designed to evoke specific emotions. To compare these they transformed the recorded affect into the same Likert scale from 1 to 5, and found that the differences between the two are less than or close to 1 point on the scale, depending on the emotion.

The Affectiv suite has been used for a few different research applications [23]. For intelligent tutoring systems, the excitement and frustration recorded from the EPOC has been shown to reflect how users appraise feedback, potentially allowing the system to provide only the most effective feedback [45]. These two emotions have been proved by others to have a strong correlation with insight, which occurs in tasks that produce a sudden realisation, commonly known as the "Aha!" moment [46]. Another study found that with a computer-based training system users both experience and report more engagement when unclear or unexpected instructions are supplied [47]. It has even been proposed that this affective interface can create an emotion-driven economy [48]. Interestingly, other researchers have used the EPOC for emotion recognition without mentioning the Affectiv suite at all [49].

There have recently been a number of tools created to aid in using and recording the Affectiv information for research [50,51], and to combine it with other measures [52, 53]. Gonzalez-Sanchez and colleagues used their tool to detect frustration during gameplay [52], and there has since been a couple of studies utilising their tool [54,55]. Other than that, not many researchers have yet published work using these tools.

Chapter III

Movement Control

3.1 Research Design

Participants trained with the Cognitiv system to control the virtual cube supplied by Emotiv. We chose to use this as it is the demonstration application supplied specifically for training the Cognitiv suite, and is designed to suggest users think physical, movement-related thoughts. Much of the instructions given to the participants to aid in training and control were sourced from the Emotiv community forums.[1] The task for the user included moving the cube left or right, as these are relatively intuitive actions, and could be applied in a number of situations when controlling a virtual environment. Left and right hand imagined movement has also been previously shown to be discriminable [8].

Lievesley et al. suggested that a fixed training scheme could be investigated [40], so for more control in this experiment we had all participants complete the same training scheme of 8 trials for each action, in a set order. They were then tested on a set of 8 commands for each action, which was randomised for each person to reduce possible biases.

To test participant's control of the cube we instructed them to move the cube left or right or to keep it still. We could have classified a trial as being successful if the participant followed the instruction and the cube did not move in any uninstructed direction. However many of the previous research applications using the Cognitiv suite have found that the system often produces small, spurious detections that are unintended by the user. To avoid the possibility of these interfering with our experiment we did not classify trials successful or not during the experiment. Instead every trial lasted 8 seconds, during which participants could see any movement, but all of the detected states were simply recorded for off-line analysis.

[1] http://emotiv.com/forum

3.2 Method

3.2.1 Participants

10 people (3 female) participated in total. Eight were between the age of 19-30, and two were over 40. All were healthy and none had had any previous experience with EEG devices.

3.2.2 Apparatus

Participants were sat comfortably in front of a computer screen, and the experimenter sat to the side. The EPOC headset was fitted with dampened sensors, and connected up to the PC. The PC had a 2.33 GHz CPU, with 8gb RAM, running 64 bit Windows 7. Running all software required for the experiment appeared to consume well less than half of these system resources.

3.2.3 Software

The Emotiv control panel was used to initially ensure good contact quality of the sensors. During the experiment this was left open so that the contact quality could be monitored. The Expressiv tab was also closely monitored, and if it showed that users were making many facial movements they were reminded to keep their entire face relaxed. To control the experiment and log the data, a program was written in C++ that uses the EmoEngine through the proprietary API. After an action has been trained, the program can read states from the EmoEngine. These states consist of the current action being thought about and its power, which is the system's confidence that the user is thinking what they had trained (always 0 for neutral). Each state is both recorded and sent to a standalone application called EmoCube (as seen earlier in Figure 2.2) which renders a virtual 3D cube and its movement left and right.

3.2.4 Procedure

The headset sensors were dampened and device mounted on the participants head. Obtaining good contact quality could take some effort, especially if the participants had long hair. After setting up the experiment there were two phases. In the first the participants completed training trials and in the second they performed experimental trials. Once ready the system collected neutral data. During neutral training participants were informed to relax, read and listen to some instructions, and to look at the cube without intent to move it. Before training any movements this advice was given to participants: imagine rolling or pushing a ball sideways in front of you, movement-related thoughts are most important, the thoughts need to be consistent over the whole trial

NNNN $L_pL_pLL_p$ NN_pNN_p $R_pR_pRR_p$ LL_pLL_p RR_pRR_p

Figure 3.1: *Order of **L**eft, **R**ight, and **N**eutral training, and practice time ($_p$).*

and between trials, try not to move or tense any facial or neck muscles, and slight physical gestures with your hands is acceptable to help with visualization. Before training a new movement participants were given some time to ensure they had a concrete thought for that movement. Each training trial was 8 seconds, as depicted by the software. There were 8 trials for each direction and neutral, and between some trails the participants were given around 30 seconds to practice. The training and practice order is shown in Figure 3.1. The experiment consisted of 3 blocks of 8 trials, with a break between each block. There were 8 trials of each movement including neutral (making the cube stay still) in a randomised order for each participant. A trial would start with the participant being told which direction to move the cube and, after 8 seconds, ended with them being told to relax for 2 seconds before the next. After the experiment participants then filled out a short questionnaire (see Appendix A).

3.3 Results and Analysis

3.3.1 Detection Filtering

From this experiment we obtained an 8 second set of states for every experiment trial, and we can use these states to classify the trials as being successful or not. It is not very practical, however, to always look at the whole 8 seconds as most applications will not specify some arbitrary time window. Rather it is more useful to process input continually and act upon detections as they are recorded, perhaps first filtering out detections that do not meet a criteria or threshold. However to be able to achieve this some filtering method must first be chosen and applied. We discuss the results without any filters, and then compare some filtering methods documented in the literature.

No Filter

Without filtering we say a trial is successful if at least one state was in the required direction, and none were in the other directions. For example, a left trial would be successful if there were at least some left and no right; a neutral trial would fail if any left or right state was detected within the 8 seconds. Using this direct approach we obtain an average success rate of 36.25%. That is to say, given one of three commands to move in one of three ways, participants were successful only a little over one third of the time. By chance this happened

	Left	Neutral	Right	Average
	75	37.5	0	37.5
	25	25	87.5	45.83
	37.5	37.5	50	41.67
	50	25	37.5	37.5
	0	25	25	16.67
	0	50	25	25
	37.5	12.5	25	25
	25	100	62.5	62.5
	37.5	25	37.5	33.33
	75	25	12.5	37.5
Average	36.25	36.25	36.25	36.25

Table 3.1: *Movement control results showing each participant's percentage success rate for left, neutral, and right trials.*

to be true for all three commands, meaning the average success rate for left trials was the same for right and neutral, all 36.25%. As can be seen in Table 3.1 the success rates for participant varied greatly, but there was no significant difference between the results for the three actions (F_{27}=0, p=1).

Time Filter

Lievesley et al. looked at the amount of time the action was being detected [40]. It is unclear, though, whether this was summed over the whole 8 seconds or as a new sum for each block of consecutive detections. Summing over 8 seconds could make a trial that consisted of frequent but very brief action states add up all the time to a reasonable sum, without ever being confident about the detection. Again this is relying on the arbitrary 8 seconds too, which is less practical for online control. The other case, a block of consecutive detections, may consist of a couple of seconds of states for one action. We often see a couple of these blocks in one trial, with neutral states in between. An experimental trial would then be successful if there was at least one large enough amount of time the cube was moving in the correct direction, and none for the incorrect (and neither for neutral). A threshold amount of time would then have to be defined before being able to classify trial success. Lievesley et al. found these thresholds retrospectively, after each day, using the values from the last session in each later session. It is not stated how the threshold is found, presumably by taking the value that maximizes the successful trials for that session. Not only are they found retrospectively but the thresholds are found individually for

Threshold	Avg Left	Avg Neutral	Avg Right	Total Avg
Time (s)				
1.6	12.5	88.75	16.25	39.17
1	17.5	72.5	21.25	37.08
Individual	30	70	32.5	44.17
Time × Power				
44	18.75	85	16.25	40
Individual	31.25	71.25	32.5	45
Power (%)				
31	33.75	47.5	37.5	39.58
20	36.25	38.75	37.5	37.5
Individual	36.25	61.25	36.25	44.58

Table 3.2: *Average percentage successful trials using different filters and thresholds*

each user. This confounds comparing the accuracies achieved, as each person's results were found with different thresholds for classifying success.

We re-analysed the states with the above filter on time and found the optimal threshold given our data set, meaning the threshold that gave the greatest total number of successful trials. The results are summed in the first row of Table 3.2. As can be seen the threshold of 1.6 seconds has just resulted in a large amount of successful neutral trials and few other actions. This is because the states during trials were so varied that a larger total success can be found by making a large threshold so that most neutral trials will pass, even though not many other actions do. Another way of looking at this is that it is easier to relax for longer than it is to sustain an action. We therefore tried a smaller threshold of 1.0 seconds, shown in the second row of Table 3.2 which had a similar effect. The third line shows the results if the filter is used with different thresholds, each threshold being optimal for each individual. This gives another increase in the overall result, but is still largely maximising neutral trials.

Time-Power Filter

A similar method was adopted by Thobbi et al., where they take into account the power supplied by each state update [5]. Again by looking at blocks of one consecutive action, they instead integrate over power for each point in time (each state in that block). This method results in an action being taken if the action is detected long enough and strongly enough, but still requires one threshold. Thobbi et al. report that the threshold is set heuristically, but do not state any thresholds, when or if it is changed, or whether or not the same value is used for each person.

The second section of Table 3.2 shows the results of filtering by power and time. Using a universal optimal threshold of 44 (power-seconds) or the optimal threshold for each individual both resulted in a better accuracy than with no filter. However again these were simply large enough to classify many neutral trials as successful.

Power Filter

EmoKey is an application that comes with the Emotiv system that allows mapping Cognitiv and Expressiv action detections to mouse and keyboard input. The filter used by EmoKey is simply a threshold of the power. When setting up a key mapping, a condition must be chosen (e.g. greater than) and the power (between 0 and 1) that will be compared to the power of each updated state. The default threshold power is 0.2 (or 20%).

We tried filtering using a threshold for the power, as seen in the third section of Table 3.2. The optimal threshold power for our data was 31%, resulting in a similar total as previous filters. This filter gave a better spread across all actions, and not just neutral. Using the default power threshold of the proprietary EmoKey application (20%) we get a slight increase from that of no filter, and again a better balance of successes between the actions. The individual power threshold filter gives the highest result of 45% average successes, but like previous filters this is mostly due to neutral trials.

Other Filters

Other different approaches to filtering have been taken for specific contexts. One is by Szafir et al. [4], who only use every tenth state update to move a robot. And another by Gomez-Gil et al. [42], who check for new states every 100ms. Each action state then turns a tractor's steering wheel left or right by a slight increment. Using the first of these approaches decreases the average accuracy across all participants to 35%.

3.3.2 Questionnaire

We were curious whether those that play computer or console games more often would be better at controlling the virtual cube. Comparing participant's rating of how often they game to their total accuracy showed instead that those who play more games did worse. However, this was not significant (Spearman's rho correlation r_s=-0.49, p=0.07).

Participant's gender was recoded to compare male and female results. Unfortunately we only had 3 female participants. While the average was better for females, the effect of gender on the ability to control the virtual cube was not significant ($F_{1,8}$=4.37, p=0.07).

3.4 Discussion

Participants used the Emotiv EPOC to control left and right movements of a virtual cube. After training for less than 15 minutes, participants achieved an average success rate of approximately 36%. In other words, as a form of computer input, the system as a whole was only successful 36% of the time. This can seem quite a while just to train to use a device, especially for people with certain disabilities. It seems that this is not long enough, however, to attain good control with the EPOC. Many other factors may influence this poorness in performance.

These results can be compared to those of Lievesley et al. [40]. Their participants had about 150 minutes of training over a week, to train neutral and one or two other actions. The two participants who trained 3 actions (including neutral) had a final success rate of 50 and 56 per cent, or both 69 per cent when using their time filter. This is considerably better than that reported here, but took around five times longer in training to achieve.

The participants of Lievesley et al. trained by doing trials of whatever they felt needed training, but they report that it may be better to have a fixed time and format. In this study we used a fixed format and time for every participant. Unfortunately it is difficult to compare the two approaches in these studies though, as the total amount of time is considerably different. From this study we feel that a more dynamic approach would be appropriate, as each person differs considerably in how well they can keep their thoughts consistent. Alternatively, a more effective training order could be beneficial.

When using the device for control, it is usually desired that the system's detections are filtered to remove small unintentional actions. Applying filters to our data did not make much of a difference however. This could be due to the amount of neutral training compared to other training, as training more neutral gives the system more clarity of what brainwave patterns are not other actions. The choice of filter to use will depend on the context of control the device is being used for. For example, consider that the correct action is strongly detected, maybe even a number of times, but a different action is also weakly detected. This could be classified as a failure, but in many realistic contexts, like left-right control in a game, it would probably be fine to have a small amount right amongst mostly left.

Unfortunately we did not have enough participants to see any significant interactions between participant's results and their gender, or how often they play games. The participants scored the task as quite mentally demanding. Their overall opinions on using the device were rather mixed, most claiming that it was intriguing but frustrating. Further, a couple of people noted that the device became quite uncomfortable after a while, which would limit both gamer's and disabled user's willingness to adopt it.

Chapter IV

Three-way Selection

4.1 Research Design

While the movement control study was a good initial investigation, some improvable aspects were noted. It was decided that a second study would be conducted, keeping the same actions and similar training time, but this time using a general selection task. This allows more control over the instructions given to participants, and can be used more naturally to interact with options in any environment. The participant's comments during the first study indicated that they had a feel for how well they could control the system while training with it, so we decided to let them train the actions as they felt was required. To allow for more analysis, if time permitted, we also recorded the other measures supplied by the Emotiv system, including the Affectiv, Expressiv, and raw EEG data.

4.2 Method

4.2.1 Participants

This study had 21 healthy participants (4 female), 16 were between the ages 19-30 and 5 were over 30. Nine of them had used the device in our previous study, while the remaining twelve had not had any previous experience with EEG devices. Participation was rewarded with a $20 caf voucher.

4.2.2 Apparatus

The physical experimental set up was identical to that of the first experiment, described in Section 3.2.2.

4.2.3 Software

The Emotiv control panel was used to initially ensure good contact quality of the sensors and was monitored during the experiment. The Expressiv tab was also closely monitored, and if it showed that users were making many facial movements they were reminded to keep their entire face relaxed. We wrote a

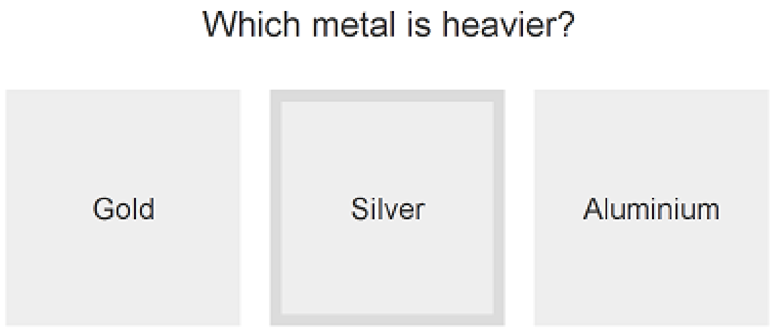

Figure 4.1: *Three-way selection graphical interface. The buttons go red when their corresponding action is detected.*

program in Java that interfaces with the EmoEngine to control the experiment and log all of the data. After an action has been trained, the program can read states from the EmoEngine. These states consist of the current action being thought about and its percentage power (between 0 and 1), which is the system's confidence that the user is thinking what they had trained. When no trained action is being detected, the system presents neutral states (which have power 0). The graphical interface consisted of instruction labels and three horizontal buttons, as shown in Figure 4.1. When the system detects an action it provides feedback by changing the colour of the buttons that the user sees. The colour is relative to the power of the action, scaling from grey at no action to bright red for full power. As neutral never has any power, the middle button only goes red after 8 seconds of no other detection. Detected actions were considered as a selection if their power exceeded a threshold, and a solid border would appear on the selected button. This study used a threshold of 0.31, as this was the optimal power threshold found from the analysis in the previous study. All interaction with the interface was initiated by the experimenter to avoid requiring the user to physically move their hands, potentially interfering with the task.

4.2.4 Procedure

Set up

The headset sensors were dampened and device mounted on the participants head. Good contact quality was ensured. Once ready, participants were asked to read some instructions. Two initial trials of neutral training data were collected during this, as neutral must be trained before other actions.

Training

Before training any movements participants were advised on how to make the selections. They were told the following: imagine pressing down on a large button with your hand, the selection (left or right) is determined by which hand is used, the thoughts must be directly related to imagining the movement, the thoughts need to be consistent over the whole trial and between trials, try not to move or tense any facial or neck muscles, and try to minimise any actual physical movement, only imagine it.

Before training a new action, participants were advised to ensure they had a concrete thought for that movement. Each training trial lasts 8 seconds, as enforced by the software. All participants initially trained neutral twice, however the number and order of training after this was up to them. Participants trained by saying which they wanted to train. There was a 3 second preparation time before the trial starts, and two distinct beep noises marking the start and end. They were given 15 minutes in which they could train actions. This is a similar timeframe to that of the first phase, where the training scheme had a fixed number and order of trials, totalling approximately 11 minutes. In comparison, this study is investigating a more flexible training scheme with a slightly longer training time.

Participants were advised to test their ability to make selections after each training trial, as it is important for them to recognise which thoughts the system is detecting. This way they could get a feel for which actions need training, and if spurious detections are being made they could supply the system with more neutral data. The number of training trials for each action was recorded. We ensured that participants did not under-train any action, and suggested that they train whichever was lacking if needed. Directly after a training trial the participant could accept or reject that trial. They were told to reject it if they got distracted during the 8 seconds, but that they should avoid rejecting trials as this wastes valuable time.

Experiment

The experiment consisted of 24 trials split into 4 blocks, with 30 second breaks between blocks to minimise fatigue. Each participant performed approximately 8 trials of each selection (left, right and middle) in a randomized order. To make this task more realistic, participants were asked a question to which they select the button that contains the answer. Each trial began by showing the question along with three horizontally aligned buttons, each with one of the possible answers, in a randomized order. Participants had 6 seconds to read and decide on an answer, and a further 2 seconds in which they were required to relax. The trial would not start until no actions were detected for 1 second, to reduce the possibility of an answer being selected immediately. A selection of the left or right option is then possible, or the middle button is chosen if no selection is detected after 8 seconds. Participants were told to make a decision quickly, and to guess if they were not sure of the answer. As soon as a button was selected a beep denoted the end of the selection phase. Immediately following this, participants were required to say which answer they were trying to select. This allows us to be sure which answer they were meaning to select, while still making the selection task a choice. It also means that participants would not necessarily do exactly 8 of each selection, as they may have been trying to select the wrong answer. They are reminded to be absolutely honest which they were trying to select. After mentioning which they were attempting for, participants were given a further 2 seconds to relax before the next trial begun.

There were 24 questions, so each participant answered the same set of questions in a random order. The questions were designed to be fairly simple common knowledge items that the target audience would be likely to know, as we were not interested in their performance at answering them. These can be seen in Appendix B. Preceding the experimental trials was one practice trial to help the participants understand the task, the results of which were not included in analysis. Following the experiment participants were asked to fill out a short questionnaire (see Appendix C).

4.3 Results

Participants were given 15 minutes for training, during which they completed an average of 24.1 training trials. Across the actions people trained an average of 9 left trials, 6.6 neutral, and 8.4 right. The minimum training for any action was 4, and there was no greater than 5 training trials difference between an individual's trained actions.

All participants completed 24 experimental trials approximating, though not necessarily, 8 of each action. The minimum number of experimental trials for an action was 5, and maximum 11. On average they were tested with 7.8 left and right trials, and 8.4 neutral. As seen in Table 4.1 the average success rate was 11.24, or 46.83% (SD 3.11, or 12.97%).

Nine of the participants had also done the first study. Their average success rate in the first study was 36.6%, which was significantly improved in the second to 48.6% (paired T-Test, T8=-2.27, p=0.027). Comparing their scores to the 12 people who did not do the first study (who got an average of 45.4%) we see that they were not significantly advantaged by their previous experience (unequal T-Test, T18=0.58, p=0.29).

The questionnaire provided some information about participants and how they found the experiment. We did not have enough range in the age of participants to be able to comment on any interaction. It has generally been found

	Left	Neutral	Right	Total Success	Success Rate
	5/8	6/9	0/7	11/24	45.8%
	3/7	6/9	2/8	11/24	45.8%
	2/9	2/9	5/6	9/24	37.5%
	2/7	6/8	4/9	12/24	50.0%
	2/7	5/9	1/8	8/24	33.3%
	3/7	4/8	6/9	13/24	54.2%
	3/8	8/8	5/8	16/24	66.7%
	7/9	7/9	2/6	16/24	66.7%
	5/9	1/7	2/8	8/24	33.3%
	3/7	0/9	7/8	10/24	41.7%
	5/5	2/10	3/9	10/24	41.7%
	3/9	2/7	4/8	9/24	37.5%
	7/8	4/9	7/7	18/24	75.0%
	4/8	5/7	2/9	11/24	45.8%
	1/6	1/11	4/7	6/24	25.0%
	2/8	7/8	4/8	13/24	54.2%
	3/9	2/7	3/8	8/24	33.3%
	7/8	1/8	5/8	13/24	54.2%
	6/6	2/8	7/10	15/24	62.5%
	5/8	0/8	5/8	10/24	41.7%
	5/10	3/9	1/5	9/24	37.5%
Average	3.6/7.8	3.5/8.4	3.8/7.8	11.24/24	46.83%

Table 4.1: *Three-way selection results showing each participant's success and number of attempts for left, neutral, and right trials. Every participant attempted 24 trials across the three actions.*

that BCI control does not vary considerably with age, but can be greater for younger people [56, 57]. Further, with only 2 left handed participants, and 4 females, these demographics cannot be reliably compared to success rates ($F_{1,19}$=0.70, p=0.41) and ($F_{1,19}$=0.12, p=0.74) respectively. Participants rated an average of 3.4 out of 5 for how mentally demanding this task was, with 1 being very easy and 5 very hard. Plotting these ratings of perceived difficulty against each participant's success rate did not show any obvious trend. When asked to rate how participants found using the device, from unpleasant (1) to pleasant (5), they rated an average of 3.6, with all ratings equal to 2 or greater.

During this study every participant's affect, as reported from the Affectiv suite, was recorded over the whole study. However, for two participants some the values read from the EmoEngine were not numbers, presumably due to an issue reading the affect at that time, such as noise or processing problems. These values cannot be used for analysis, reducing the number of participant's affect recordings to 19. Analysis of this data is discussed in chapter 5.

4.4 Discussion

This study used a threshold on power at 0.31 for all participants, which was found to be relatively effective in the first study. Using individually optimal threshold in the first study increased the success rate to 44.6%, which is similar to the success rate of this study with the universal threshold. It therefore seems likely that without the use of this filter there would be even less difference in the results of the two studies. Unfortunately we cannot investigate the use of different filters on the data of the second study, as the experiment trials ended as soon as a selection was made. That is to say there has already been a detection filter applied to make the decision of when to end the trial.

Despite the greater success rate, the two experiments had about the same number of training trials on average. There are three main differences that the increase in performance could be attributed to. Firstly, participants had a slightly longer practice time. Secondly, they were able to train whichever action they felt needed training during this time. Thirdly, the task was different and the task instructions were more explicit about what to think.

The order of training varied between participants. Some trained one of each action then tested their control; some quickly tested their control after every trial. While it is hard to compare the types of training methods of our two studies, some participants complained about the fixed scheme of the first experiment, saying that they could not control one action when told to start training the next. No one complained about the flexible training scheme however.

The training of the system is probably less vital than the training of the user. The critical requirement is that the user can think detectable thoughts consistently. In the simple evaluation of Cognitiv by Thobbi et al., all 4 participants completed 10 training trials. When tested, however, the two people that had used the system for 2 weeks prior did significantly better than the others who had not. Supporting this, in our second study there was no correlation between the number of training trials and success rate, meaning those who did more training trials did not necessarily do better or worse than those who trained less.

Participants who completed both studies did not achieve significantly better than those who did not do the first. While the tasks were different, simply using the Cognitiv system twice is likely to produce a learning effect. However, as the studies were over 2 months apart we are not surprised that no significant effect is evident.

Comparing techniques that the participants said they used showed that those who focused on movement, such as of the hand or arm, tended to have greater success than those who visualised pressing buttons or squeezing their hands. For example, the highest scoring participant, who achieved 75%, wrote "[I] imagined I was stretching my L/R arm." This is as expected with sensorimotor rhythms [15], and perhaps with more training the latter group could learn to produce more kinaesthetic thoughts than visual ones.

Chapter V

Analysis of Affect

As part of our investigation of the EPOC participant's affect was recorded during the second experiment. Here we review the Affectiv suite of the Emotiv system and the continuous measures of the user's subjective emotions it provides. As described in Section 2.3.1, these emotions are labelled short-term excitement, long-term excitement, engagement/boredom, frustration, and meditation. We were curious if there were any characteristic changes in affect after participants failed or succeeded experimental trials. We hypothesised that participants might experience an increase in the level of frustration after failing a trial, as a number of participants mentioned that it annoys them when it does not work. Similarly, we hypothesised that their excitement might increase following successful trials. The affective information produced by the system consists of values between 0 and 1 for each of the 5 emotions, which are read from the system several times per second. It is not clear, however, how this information can be effectively analysed.

We found that taking the average of an Affectiv measure over any reasonable time period was typically not useful, as they all tend to similar values (about 0.5). This could be related to the fact that the Affectiv suite automatically updates how much it scales the measures based on previous readings.[1] As a different approach we tried simply seeing which emotion levels were most often highest. By counting the number of times an emotion is the maximum of the 5 emotions after each trial we found some interesting differences. For example, frustration is more often the maximum of the emotions after failed trials than it is after successful trials. This is not significant however (Paired T-test T_{18}=-1.03, p=0.16).

The Emotiv control panel provides a graph of the affect updating in real time. The graph shows relative levels of emotions at any time, and the increase or decrease in emotion during any period. Cernea and colleagues based their approach off of this graph, to transform these measures into an integer scale from 1 to 5, which they then compared with Likert scale ratings [43]. Their scale consists of a combination of criteria for an emotion over a certain period. As they were interested in the increase in emotion, decreases are completely ignored. The score for a period of no increase is 1, and 1 point is added for each

[1] http://emotiv.com/developer/SDK/UserManual.pdf

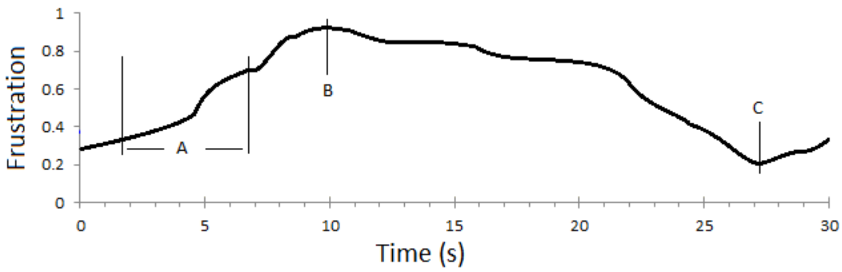

Figure 5.1: *Graph of frustration from the Affectiv suite for a 30 second period. The maximum and minimum are shown by **B** (0.91) and **C** (0.2). **A** is one possible 5 second window, the slope of which is given by 0.7-0.35. If **A** were the maximum slope, this period would have a score of 4 out of 5.*

of the following: if the difference between the minimum and maximum value during the entire period is greater than 0.3, if this difference is greater than 0.6, if the slope at any time is greater than 0.3, and if the slope at any time is greater than 0.6. As a simple approach to quantify the slope, they define it as the difference between the final and initial value of a small sliding window. This window was smaller than the entire period, typically 5 or 10 seconds, and produced a slope value for each increment in time within the period. The slope for the whole period is then the maximum of these slopes. This is illustrated in Figure 5.1.

We analysed the affect for the 8 second period following successful and failed trials using the method described above. To find a good window size we tried all integer windows from 1 to 8 seconds and compared the results. It was found that for all window sizes there is a significant increase in user's frustration after failed trials than successful trials. The 5 second window gave the largest average difference, and was most significant (Paired T-test T_{18}=-3.09, p¡0.05). None of the other 4 emotions showed significant differences. The thresholds used by Cernea et al., 0.3 and 0.6, were found through inspection of the graphed data. We used these values as it was proven that they provided reliable results. However, we note that they may not be optimal for all applications.

Another approach was taken by Salvador, Legaspi, and Suarez, in order to gain insight into how students appraise feedback supplied by an intelligent tutoring system. They recorded the levels of frustration and excitement provided by the EPOC. For each emotion these two values were used: the average of the readings for the three seconds prior to feedback, and the reading when the emotions stop varying greatly after feedback is given. They say emotions stop varying greatly when there is a change of only 0.08, though they do not specify if this is between readings, per second, or some other meaning. Their threshold value of 0.08 was found experimentally through inspection of the affective output. Again, this value may not be appropriate for different applications.

This method could be applied to our recorded data, for example, to see if the value for frustration is higher after failed trials than successful ones. Furthermore, this method would not require an arbitrarily chosen period such as the 8 seconds in the earlier method, and could take decreases in emotion into account too. It would require, however, finding the exact definition of when an emotion stops changing greatly, and experimentation with the threshold values. Unfortunately due to time constraints this has not been pursued.

Chapter VI

Conclusions

6.1 Discussion

While some studies have shown that control with the EPOC and Cognitiv suite is possible, such as for games [38] or robot movement [4], they do not quantify the time required or any measure of success. We can say that control is possible after only 15 minutes of training; however a success rate of 46.8% is probably not practical for most applications.

A few other studies have supplied some comparable results. In a cube comparison task participants could use the combination of Cognitiv, Expressiv, and the gyro to rotate cubes [39]. They used one more action than in our study, but managed to achieve an approximate (crudely-measured) success rate of 59% after one training session of an unspecified length. Although this is clearly a greater level of success, it includes control with Expressiv and the gyro, which are probably easier than Cognitiv. In another successful robot control study an initial validation had 10 training trials of the same number of actions as our study [5]. The two participants with no prior experience achieved about 66% success. These greater success rates could be due to differences in instructions, which may have come from more experienced users in their cases.

Lievesley and colleagues had people train neutral and only one other action for 30 minutes a day, achieving an average of 64.6% success after the first day. With more time training and one less action this higher rate than that of our results is expected. After 5 days Lievesley's participants achieved much greater success rates; however the 2 people that trained neutral and 2 actions in this time did not do as well, achieving only 50% and 56% success (or both 69% with their filter). Both the Emotiv community[1] and previous research on SMRs mention that controlling more actions becomes increasingly difficult [9].

Another suggestion by the Emotiv community is that it is best to master one action before attempting to train other actions.[1] We only trained four trials of left before starting right in the first experiment, and the participants decided when to train each in the second. Further, it appeared that early in training many participants were able to control the cube reasonably well,

[1] http://emotiv.com/forum/messages/forum4/topic114/message392/?phrase_id=464885

and that this would decline in later training. Over the trials as the person is training to think a consistent thought it is likely that they include a range of inconsistent thoughts. Therefore once they have had some practice it may possibly be of more use to wipe the trained data and start the training again. The system does give an option to reject a training trial immediately after training. However there is no way of knowing how consistent the thought was until it is accepted and updates the system, after which there is then no way of removing it again (without clearing all data for that action).

Many things can possibly affect the use of this technology, including even the time of day or other person specific attributes, such as sleep or diet [56]. EEG can also be disrupted by environmental noise, such as mains power, which is filtered out by the EPOC. Noise induced by the user through muscle movement or talking can greatly disrupt the EEG, meaning users must remain still during recording [9, 45]. Our participants were instructed to sit still but this was not enforced. Some people changed their posture or how they were holding their hands occasionally, potentially affecting their performance. Another issue found by many studies is that some fraction of people simply perform considerably worse with certain types of BCI, referred to as BCI illiteracy [58]. As far as other EPOC specific issues we note that the sensors need careful cleaning occasionally. Further, being a wireless device, it needs regular charging, though the battery lasts up to approximately 10 hours. All of these issues ought to be considered when adopting BCI technology.

Most participants were interested by the novelty of the EPOC and applications, some finding it fun. However, many participants, including some that found it interesting to use, found it frustrating as well. Both tasks were considerably harder than the participants expected, and as they were only given a short time in which to train before being tested, a number of people felt as though they had performed particularly worse than they were expected to.

A number of participants in both studies reported experiencing some discomfort after about half an hour of wearing the EPOC. This is most likely due to the sideways pressure that holds the headset in place. Previous studies have also mentioned this issue [40, 43, 50]. Any application of the EPOC would need to consider this restriction and not require the user to wear the headset for long periods of time. As the focus of our research was to investigate the EPOC's use in a limited time frame this discomfort is not such an issue. We have, however, discovered that users do not acquire reliable accuracies in one small training session, meaning they would require a number of these sessions to achieve a more practical success rate. Because of this discomfort, and other issues such as mental fatigue, these sessions would necessarily need to have breaks between them.

Setting up the EPOC can be delicate. It can often take a while to get good connection for all of the sensors, sometimes requiring removal of the headset to re-wet the sensors. We found this issue particularly prominent for users with long or thick hair. It is possible to equip the EPOC by one's self after some practice. However, those who have lost physical control of almost any of their upper body, or that struggle with delicate hand coordination, would require another person to set up the headset.

Although the analysis of the Affectiv data in this study does not validate the measurements, we did find some expected characteristics within the data, supporting both the device measurements and the methods used to analyse it. The Affectiv suite will be affected by many of the previously mentioned issues, such as person induced noise. The period we focussed our analysis on was directly after a selection was made, but during this time participants were not necessarily remaining still. In fact, during this time they were asked to say which answer they were trying to select, and indeed many people would react to the trial through movement such as laughing or moving their head. Had we initially intended to analyse the Affectiv information the study would have been designed to minimise movement.

6.2 Conclusions & Future Work

The Emotiv EPOC has advantages over traditional EEG devices, and comes with a number of useful tools, including the Cognitiv suite for detecting sensorimotor rhythms. While investigating the EPOC our main focus has been whether this Cognitiv system can be used within one session, after only a small amount of training. In the two studies detailed here, participants trained with the Cognitiv suite for up to 15 minutes before being tested for their level of control. While the success rates ranged from 16% to 75%, the averages for the first and second study were only 36.25% and 46.83% respectively. This, taken with previous studies on controlling sensorimotor rhythms, shows that more training time would be required to achieve more practical levels of control.

Given the constraints of the ICTG research project, it would not be suitable to expect participants to control the EPOC with imagined motor movement within the required time frame. For their project other types of BCI could be investigated with the EPOC, such as the P300 or SSVEP. As another future possibility, if the users have control of facial movements then the Expressiv suite might be able to offer them control without much training. However, it would have to be investigated whether the required facial movements are not too tiring. Furthermore, wearing the EPOC for a sustained time has been found to produce discomfort, meaning its use should be split into small sessions with breaks.

We also reviewed the Affectiv suite and some practical means of processing the information it provides. From the affect in second study we found that participants have greater increases in frustration after failed trials than successful ones, but not greater increases excitement after successful trials. Applications that could take advantage of this affect information include user evaluations of interfaces and games during research and design to replace questionnaire interruptions, adaptive games that scale difficulty or other immersive features through subjective feedback, and affect aware intelligent tutoring systems that personally scaffold content and can identify what feedback is most effective for the student. The processing methods covered here are appropriate for some applications, though in the future more effective techniques could be investigated.

As the sensors only need dampening, we found that the EPOC headset is relatively simple to use and offers mobility due to its wireless technology. In the future many BCI applications could benefit from adopting the EPOC to aid their progression out of the lab and into the real world. The time and effort required to use the technology needs to be considered for each application however. If the Cognitiv suite is to be used as a control modality, users can be expected to require many training sessions before they achieve a reliable accuracy. For most people this could take considerable time, and training can be quite demanding which is especially tiring for disabled users.

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Appendix A

Movement Control Questionnaire

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

Questionnaire:

1. What age range are you in? *(Please circle)*

< 21   21-30   31-40   41-50   51-60   61-70

2. You are… *(Please circle)*   Left handed   Right handed

3. You are… *(Please circle)*   Male   Female

4. Have you had any previous experience with an EEG device? *(Please circle)*

Yes   No

If yes, please explain

____

____

5. How often do you play computer or console games? *(Please circle)*

(Never)   1   2   3   4   5   (Very Often)

6. How mentally demanding was the task? *(Please circle)*

(Very easy)   1   2   3   4   5   (Very hard)

PTO

8. How did you find using the device? *(Please circle)*

(Unpleasant) 1 2 3 4 5 (Pleasant)

Comments:

____

____

9. Any other comments or questions about the experiment?

____

____

Thank you!

Appendix B

Selection Task Questions and Answers

Which metal is heavier? - Gold, Silver, Aluminium
How many legs do spiders have? - 8, 6, 10
How many vowels in the English alphabet? - 5, 6, 21
1000 milligrams = ? - 1g, 10 Ounces, 1Kg
What is the biggest planet in our solar system? - Jupiter, Earth, Venus
Another name for a tidal wave is a? - Tsunami, Earthquake, Tornado
The highest mountain on earth is? - Mt Everest, Mt Cook, Mt Fuji
How many zeros in 1 million? - 6, 9, 4
New Zealand's prime minister is? - John Key, John Travolta, Tim Shadbolt
Which element has the chemical symbol He? - Helium, Iron, Carbon
Capital of New Zealand? - Wellington, Christchurch, Sydney
6^2=? - 36, 32, 64
Which series is not animated? - MASH, The Simpsons, Pokmon
Which is a string instrument? - Cello, Trumpet, Flute
Mori name for New Zealand? - Aotearoa, tautahi, Aoraki
Electrical current is measured in? - Amps, Imps, Joules
Lead is a type of? - Metal, Wood, Zepplin
The city Rome is in what country? - Italy, Greece, Germany
Your mother's sister is your? - Aunt, Uncle, Cousin
What is the Roman Numeral for 5? - V, X, I
Who wrote "The Cat in the Hat"? - Dr. Suess, Dr. Dre, J. K. Rowling
Christmas day is December..? - 25th, 24th, 1st
The sun rises in the? - East, West, South
How many years in a millenium? - a thousand, a hundred, a million
Which is a primary colour? - Red, Pink, Orange

Appendix C

Three-way Selection Questionnaire

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

Questionnaire:

1. What age range are you in? *(Please circle)*

< 21 21-30 31-40 41-50 51-60 61-70

2. You are… *(Please circle)* Left handed Right handed

3. You are… *(Please circle)* Male Female

4. Have you had any previous experience with an EEG device? *(Please circle)*

Yes No

If yes, please explain

___

___

6. How mentally demanding was the task? *(Please circle)*

(Very easy) 1 2 3 4 5 (Very hard)

7. Please explain the thoughts/techniques you used to make selections

___

___

___

PTO

8. How did you find using the device? *(Please circle)*

(Unpleasant) 1 2 3 4 5 (Pleasant)

9. Any comments about the device or the experiment?

____

____

Appendix D

Ethics Application

UNIVERSITY OF CANTERBURY

LOW RISK APPLICATION FORM

(For research proposals which are not considered in full by the University Human Ethics Committee)

FOR STUDENT RESEARCH UP TO AND INCLUDING MASTERS LEVEL

ETHICAL APPROVAL OF LOW RISK RESEARCH INVOLVING HUMAN PARTICIPANTS REVIEWED BY DEPARTMENTS

PLEASE read the important notes appended to this form before completing the sections below

1 **RESEARCHER'S NAME:** Matthew Lang

2 **NAME OF DEPARTMENT OR SCHOOL:** Department of Computer Science and Software Engineering

3 **EMAIL ADDRESS:** mjl149@uclive.ac.nz

4 **TITLE OF PROJECT:** Study of a selection task with the Emotiv EPOC in limited training time

5 **PROJECTED START DATE OF PROJECT:** 04/07/2012

6 **STAFF MEMBER/SUPERVISOR RESPONSIBLE FOR PROJECT:** Prof. Tanja Mitrovic

7 **NAMES OF OTHER PARTICIPATING STAFF AND STUDENTS:** Moffat Mathews

8 **STATUS OF RESEARCH**: (e.g. class project, thesis) Honours Research Project

9 **BRIEF DESCRIPTION OF THE PROJECT:**
Please give a brief summary (approx. 300 words) of the nature of the proposal in lay language, including the aims/objectives/hypotheses of the project, rationale, participant description, and procedures/methods of the project:-

The objective of this project is to investigate the use of the Emotiv EPOC and the software that comes with it as general purpose input for a three-way selection task. The EPOC is a small, wireless, consumer-grade "brain-computer interface" device that rests on the head. It is designed for use in gaming and allows users to control a computer with their mind after training the system which thoughts to detect. Our aim is to investigate how well people can achieve using this device for a realistic selection task, when only given a limited amount of training. Volunteers will receive a $20 café voucher reward for participation. The study will be done in the Department of Computer Science and Software Engineering. The study is open to anyone who is willing to take part in this research, having no age limiting factors. Participants will typically be computer science post-graduates and their friends. We aim to have approximately 20 participants. A short introduction to the research will be given at the start of the experiment, and participants will receive a project description and a consent form which they will read and sign, should they wish to participate in the study. Participants will be told that they can elect to opt out at any point during the experiment. The participants will then be equipped with the device; this is simply a non-invasive headset with 14 sensors that sits on the head. There are two phases to this study, the first being training and the second being the experimental trials. The task is to select between three buttons on the screen by only using their thoughts to imagine the selection. For each training trial, participants are asked to complete one of three tasks consistently for 8 seconds. This includes imagining making a selection with the left or right hand (for the left and right buttons), or just relaxing (to select the middle button). There will be 24 of these trials, with breaks in between allowing the user to attempt selections and receive visual feedback of the buttons being selected. After this, the experimental trials will consist of the same three tasks, except they will not be told which task to perform (which button to select). Instead the system will show them an easy question and they will select whichever button has the correct answer, directly after which they will also be asked to say which answer they were attempting to select. In this case, the correctness of the answer does not matter; we are looking to see if they could select what they intended to select, given the short amount of training on the system. Left and right trials end as soon as the selection has been made, otherwise the default selection will be made after 8 seconds. There will be also 24 of these experiment trials. The total experiment should take no longer than 50 minutes. After the experiment, a short questionnaire will be administered to find out their perceptions of the system.

10 **WHY IS THIS A LOW RISK APPLICATION?**
Description should include issues raised in the Low Risk Checklist

Please give details of any ethical issues which were identified during the consideration of the proposal and the way in which these issues were dealt with or resolved. :-

This is a low risk application because it does not raise any issue of deception, threat, invasion of privacy, mental, physical or cultural risk or stress, and does not involve keeping personal information of sensitive nature about individuals. All participants will be given an information sheet describing the research project and will give consent for their results to be used for analysis. The participants will be fully aware that they can withdraw themselves or their results from the research at any stage. All the data will be kept in a secure environment and only those listed above allowed access to it.

Please ensure that Section A, B and C below are all completed

APPLICANT'S SIGNATURE: .... **Date** ....

A SUPERVISOR DECLARATION:

1 I have made the applicant fully aware of the need for and the requirement of seeking HEC approval for research involving human participants.
2 I have ensured the applicant is conversant with the procedures involved in making such an application.
3 In addition to this form the applicant has individually filled in the full application form which has been reviewed by me.

SIGNED (Supervisor): .... **Date** ....

B SUPPORTED BY THE DEPARTMENTAL/SCHOOL RESEARCH COMMITTEE:

Name .... **Signature:** .... **Date** ....

C APPROVED BY HEAD OF DEPARTMENT/SCHOOL:

Name .... **Signature:** .... **Date** ....

ACTION TAKEN BY HUMAN ETHICS COMMITTEE:

☐ Added to Low Risk Reporting Database ☐ Referred to University of Canterbury HEC

☐ Referred to another Ethics Committee - Please specify:

....

REVIEWED BY:.. **Date** ....

Please attach copies of any Information Sheet and/or Consent Form

Forward two copies to:

The Secretary
Human Ethics Committee
Level 6, Registry Building

All queries will be forwarded to the applicant within 7 days
Please include a copy of this form as an appendix in your thesis or course work

NOTES CONCERNING LOW RISK REPORTING SHEETS

1. This form should **only be used** for proposals which are **Low Risk** as defined in the University of Canterbury Human Ethics Committee Principles and Guidelines policy document, and which may therefore be properly considered and approved at departmental level under Section 5 of that document;

2. Low Risk applications are:

   a Masters theses where the projects do not raise any issue of deception, threat, invasion of privacy, mental, physical or cultural risk or stress, and do not involve gathering personal information of a sensitive nature about or from individuals.

   b Masters level supervised projects undertaken as part of specific course requirements where the projects do not raise any issue of deception, threat, invasion of privacy, mental, physical or cultural risk or stress, and do not involve gathering personal information of sensitive nature about or from individuals.

   c Undergraduate and Honours class research projects which do not raise any issue of deception, threat, invasion of privacy, mental, physical or cultural risk or stress, and do not involve gathering personal information of sensitive nature about or from individuals, but do not have blanket approval as specified in Section 4 of the Principles and Guidelines.

3. No research can be counted as low risk if it involves:

   (i) invasive physical procedures or potential for physical harm
   (ii) procedures which might cause mental/emotional stress or distress, moral or cultural offence
   (iii) personal or sensitive issues
   (iv) vulnerable groups
   (v) Tangata Whenua
   (vi) cross cultural research
   (vii) investigation of illegal behaviour(s)
   (viii) invasion of privacy
   (ix) collection of information that might be disadvantageous to the participant
   (x) use of information already collected that is not in the public arena which might be disadvantageous to the participant
   (xi) use of information already collected which was collected under agreement of confidentiality
   (xii) participants who are unable to give informed consent
   (xiii) conflict of interest e.g. the researcher is also the lecturer, teacher, treatment-provider, colleague or employer of the research participants, or there is any other power relationship between the researcher and the research participants.
   (xiv) deception
   (xv) audio or visual recording without consent
   (xvi) withholding benefits from “control” groups
   (xvii) inducements
   (xviii) risks to the researcher

   This list is not definitive but is intended to sensitise the researcher to the types of issues to be considered. Low risk research would involve the same risk as might be encountered in normal daily life.

4. **Responsibility**

   Supervisors are responsible for:

   (i) Theses where the projects do not raise any issues listed below.
   (ii) Masters level supervised projects undertaken as part of specific course requirements where the projects do not raise any issue.
   (iii) Undergraduate and Honours class research projects which do not raise any issue listed but do not have blanket approval as specified in the Principles and Guidelines.

   HODs are responsible for:

   (i) Giving final approval for the low risk application.
   (ii) Ensuring a copy of all applications are kept on file in the Department/School.

4. A separate low risk form should be completed for each teaching or research proposal which involves human participants and for which ethical approval has been considered or given at Departmental level.

5. The completed form, **together with two copies of any Information Sheet or Consent Form**, should be returned to the Secretary, Human Ethics Committee, Level 6 Registry, **as soon as the proposal has been considered at departmental level**.

6. The Information Sheet and Consent Form should NOT include the statement "This proposal has been reviewed and approved by the University of Canterbury Human Ethics Committee" as this is inappropriate for low risk proposals. A statement such as "This proposal has been reviewed and approved by the Department of ....., University of Canterbury" must however be used.

7. Please ensure the Consent Form and the Information Sheet has been carefully proofread; the institution as a whole is likely to be judged by them.

8. A Low Risk proposal may commence within 7 days of lodging the low risk application. No correspondence will be received back from the University of Canterbury Human Ethics Committee (UC HEC) concerning this Reporting Sheet **unless the Committee has concerns or would like clarification of any aspect of the proposal.**

9. The research must be consistent with the UC HEC Principles and Guidelines. Refer to the appendices of the UC HEC Principles and Guidelines for guidance on information sheets and consent forms.

10. Please note that if the nature, procedures, location or personnel of the research project changes after departmental approval has been given in such a way that the research no longer meets the conditions laid out in Section 5 of the Principles and Guidelines, a full application to the HEC must be submitted.

11. This form is available electronically at the following web address: http://www.canterbury.ac.nz/humanethics

CHECKLIST

Please check that your application / summary has discussed:

- procedures for voluntary, informed consent
- privacy & confidentiality
- risk to participants
- obligations under the Treaty of Waitangi
- needs of dependent persons
- conflict of interest
- permission for access to participants from other individuals or bodies
- inducements

In some circumstances research which appears to meet low risk criteria may need to be reviewed by the UC HEC. This might be because of requirements of:

- The publisher of the research
- An organisation which is providing funding resources, existing data, access to participants etc.

Research which meets the criteria for review by a Health and Disability Ethics Committee
See HRC web site

The Human Ethics Committee is happy to give advice on the appropriateness of research for low risk review.

Appendix E

Ethics Approval

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

HUMAN ETHICS COMMITTEE

Secretary, Lynda Griffioen
Email: human-ethics@canterbury.ac.nz

Ref: HEC 2012/49/LR

1 August 2012

Matthew Lang
Department of Computer Science & Software Engineering
UNIVERSITY OF CANTERBURY

Dear Matthew

Thank you for forwarding your Human Ethics Committee Low Risk application for your research proposal "Study of a selection task with the Motiv EPOC in limited training time".

I am pleased to advise that this application has been reviewed and I confirm support of the Department's approval for this project.

Please note that this approval is subject to the incorporation of the amendments you have provided in your email of 27 July 2012.

With best wishes for your project.

Yours sincerely

Michael Grimshaw
Chair
University of Canterbury Human Ethics Committee