Tampereen yliopisto

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VIRTUAL OBJECT MANIPULATION WITH A BRAIN-COMPUTER INTERFACE:

Comparing vertical and lateral command results using the Emotiv EPOC

Faculty of Information Technology and Communication Sciences
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ABSTRACT

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As brain-computer interfaces (BCI) have become more common in the last two decades, the change has raised questions about the usability and best practices for this relatively new modality of human-computer interaction. When giving simple two-directional commands with a BCI device, lateral axis commands using a BCI offer a potentially more intuitive and reliable way of interacting compared to vertical axis commands. However, there are only a few BCI studies that offer less insight into specific and practical interaction commands and focus more on evaluating the device itself.

The aim of my thesis is to explore the use of a commercial BCI device to compare two basic-level command axes for virtual object manipulation. This was done to determine whether one would perform significantly better than the other. For this purpose, an experimental test was conducted: the test included two rounds consisting of a calibration stage and a mental command success test for both the lateral and vertical axis, followed by a questionnaire, in which participants answered questions about their experiences with the test and the BCI device.

The results were collected using Emotiv EPOC, a commercial BCI headset, and analyzed with a paired samples t-test using the calculated means of the amounts of all participant's successful commands. Results showed that the horizontal axis commands were significantly more successful compared to vertical ones (paired samples t-test ($t(22) = 2.446$; $p = 0.023$; Two-sided)). Problems related to the use of the BCI device led some users to struggle with moving the virtual object or not being able to achieve a successful command. Removing device problems and gaining insight into best practices for BCI are vital for future research and application development. Questionnaire results showed that participants perceived the test as neutral or slightly mentally demanding (mean = 3.47; standard deviation = 0.874) and that the subjects perceived using the device as neutral to slightly pleasant (mean = 3,41; standard deviation = 1,278), both on a scale of 1-5.

Keywords: brain-computer interface, BCI, usability, user experience, human-technology interaction, Emotiv EPOC.

The originality of this thesis has been checked using the Turnitin OriginalityCheck service.

Dedicated to Jorma Keskinen and Iisakki Mäki-Ventelä,
my grandmothers, my mom, my dad and my brother.

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1 Introduction

“The human brain is claimed to be the most complicated human organ, which could be compared to a very powerful and complex computer, where, until today, no one was able to recreate and simulate successfully its entire structure” (Kawala-Sterniuk et al. 2021). After decades of scientific and multidisciplinary research into cognition and the brain, we are now living in a time where brainwave measurement and interpretation are becoming more available. This opens up new possibilities for average-income people to gain access to more common potential use cases of a brain-computer interface (BCI): these can range anywhere from a neurofeedback training tool (Birbaumer, 2006) to alertness monitor for improving users’ cognitive performance (Hramov et al., 2019). In addition to medical applications, there are now BCI systems in use in healthcare and military industries internationally. Still, most of the consumer market has barely seen any real, usable BCI products.

The advancement of brain imaging technology, signal processing, and smaller sensor devices together have made modern BCIs a technical possibility in the last 20 years. Before said changes, the devices were big, and complicated and needed enough power to prohibit mobile use in any meaningful form. In practice, the only way to use the devices or conduct studies with them was to have the user sitting or lying down with sensors physically attached to their head. This has limited the recording and study possibilities of brain signals and brain functions in various cases.

There is a significant difference in the BCI methods used today. The focus in this thesis, and most consumer BCI applications, has been non-invasive in nature: using non-medical grade hardware means that the user does not require surgery and the application of sensors inside the body. Non-invasive BCI has expanded in terms of consumer devices:

companies like Emotiv, InteraXon, and Muse have developed products that compete mostly in consumer and “prosumer” markets but some have been used and referenced in the research literature as well. It is worth mentioning that there is also an open-source BCI headset called OpenBCI, meaning there is a dedicated community also developing solutions in which price has less meaning. Making the devices mobile has opened up the field as they can now be further utilized for example in studies, health technology, and gaming, ultimately leading to discovering new ways for the devices to be used. Furthermore, the integration of BCI with virtual reality, where users already use headsets, has also been explored to some lesser commercial extent (Li et al., 2017).

The BCI as a system offers a new challenge for user interface and user experience designers. The novel way of measuring and triggering focus is more complex than traditional computer input. On the other hand, the number of combinations and variations far exceeds the traditional input as well. The challenge is to find those normalized and generalized mental triggers or mental commands that allow to keep the interactions voluntary, yet ubiquitous to the user. This also needs to work without a singular context for the use case, e.g., environment, lighting conditions, etc. As of right now, there is very little work done on finding and designing universal interaction sets for BCI devices for consumer purposes.

The main goal of the thesis was to test a commercial BCI to determine whether interaction with mental commands on lateral or vertical command axis would prove better in terms of making directional choices and thus successfully moving a virtual object in the test. In the experimental test, users attempted to move a virtual object, a 3D cube model in this case, on a monitor to left and right, and up and down. The test was followed by a questionnaire that measured how the participants perceived using the device and how they had created their mental commands during the experimental test. In addition to the experimental test, I did a literature review on BCIs that shortly explores some of the history of the field. The third and fourth chapters will showcase the experimental test and practicalities further. In the fifth chapter, I introduce the results of the experimental tests and questionnaire, and end with a discussion regarding the research results, in addition to recent and possible future research and development directions in the field.

2 Brain-computer interfaces

2.1 Overview

Brain-computer interface (BCI) technology has been an active area of research for several decades, and it holds the promise of revolutionizing human-computer interaction. In recent years, the field has grown rapidly, with numerous studies exploring different aspects of BCI technology. This literature review aims to provide a comprehensive overview of the state of BCI technology, focusing on research and studies published in the last 20 years in the field of human-technology interaction. This overview will cover the main types of BCI technology, applications, and challenges, and end with future visions in the field.

The research done by Jacques Vidal is the first to describe what a brain-computer interface is and how it works. Vidal's initial BCI system was fittingly called a "binary spelling system"; it was used to allow users to select on-screen letters using letter-specific brain patterns (Vidal, 1973). The system utilized 16 electrodes to record EEG from the user's scalp with placement according to the international 10-20 system for electrode placement (8 electrodes on both sides of the scalp). His further pioneering work details the core of modern BCIs: evoked responses and event-related potentials measured in epochs or specified time segments of data, were at the beginning of the quantization of brainwave data that would be used to create commands (Vidal, 1977). Vidal's work can be considered a significant leap forward in the development of BCIs and the field itself.

Before discussing the different types of BCI systems, it is important to understand what constitutes a BCI system. The most recognized definition of a BCI system is a "communicative system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles" (Wolpaw et al., 2002). One example of this could be a paraplegic user sending movement commands with the help of BCI to paralyzed body parts or functional prosthetics. While this definition is good, modern BCI definitions are more closely linked to the human-computer interaction field of study: "An interface is the set of hardware and software means by which the user communicates with the interactive system" (Si-Mohammed et al., 2019). To explain how a BCI works further, we need to examine where the system input originates, the brain. BCI systems use electroencephalograms (EEG) as input: EEG measures the neural oscillations or the electrical changes inside the brain, commonly referred to as brainwaves. From this measurement, the BCI can produce an output that can be translated into or used as computer input using a BCI system. Most common BCI systems use intricate signal processing to filter out signal noise and, in most instances, individual calibration and training data to determine patterns in the brainwave corresponding to the user.

There are three types of BCI technology based on how and where the brainwaves are being captured: invasive, semi-invasive, and non-invasive. Invasive BCI technology refers to the most invasive technology by implanting sensors directly inside the brain: this method is known as stereoelectroencephalography (sEEG). Semi-invasive (also sometimes referred to as invasive) BCI technology involves electrocorticography (ECoG) or intracranial electroencephalography (iEEG): both methods require a craniotomy to implant electrodes or an electrode grid directly into the cortex or the surface of the brain in order to capture the brainwaves without the added noise from capturing the signal through the scalp (Liu & Xue, 2022). While the electrodes are not implanted inside the brain in these methods, requiring craniotomy makes these applications less consumer-friendly and they are therefore mostly used for medical applications and research, notably epilepsy research (Song et al., 2021).

Non-invasive BCI technology uses external sensors to measure brain activity from the surface of the scalp instead of directly from the cortex. Methods used in capturing brain waves this way include EEG, magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and near-infrared spectroscopy (NIRS) (Pfurtscheller et al., 2010). Of these, EEG is the most prominently used due to its good temporal resolution, and portability and price (Baek et al., 2019). Due to the non-invasive nature of these designs, they are the preferred technology for non-medical BCI use and research.

There are three non-invasive hardware designs used for the sensors: EEG caps with electrodes sewn into the fabric, wearable electrodes in (usually) a plastic frame, and individual electrodes connected directly to the scalp with adhesive tape. These sensors have traditionally been wet electrodes that require either a gel or a saline solution to allow better signal conductivity through the scalp. This however makes the application of the electrodes difficult especially by oneself and for people with longer hair, requiring the user to apply and reapply the saline solution at each time of use, making it less desirable for consumer-level users. Due to the limitations of wet electrodes, multiple different types of dry electrodes have been created. These dry electrode approaches are divided into spiky, capacitive, non-contact, or other heterogeneous approaches. These designs utilize arrays of spikes, needles, and tubes of different materials in the millimeter to nanometer scales, some in direct contact with the scalp, others piercing the outer skin (or stratum corneum) of the scalp. Examples of these designs include silicon microneedles, multi-walled carbon nanotube arrays, 3D printed dry millielectrodes, polymer silver-coated bristles, and electrically conductive polymer foam covered by a conductive fabric (Lopez-Gordo et al., 2014). The amount and placement are also important in attaining high-quality brainwave recordings. While EEG setup with 32 channels has historically been regarded as best, this assumption has been challenged, showing potential for achieving better accuracy using fewer channels in specific scenarios (Soler et al. 2020).

The potential uses and use cases of brain-computer interfaces span from communication, rehabilitation of injured body parts, and alertness detection to controlling video games to attention training through biofeedback. Despite this, on its most basic level, BCI as a signal and signal processing medium can be utilized with any computer. BCI as a device may also contain a computer itself. Communication applications involve using BCIs to allow people with communication impairments (such as those with locked-in syndrome or amyotrophic lateral sclerosis, ALS) to communicate with others (Kübler et al., 2005) in a way similar to using gaze tracking with a virtual keyboard to allow text input, for example. Prosthetic device control involves using a BCI to allow people with amputations or paralysis to control prosthetic devices by activating their motor cortex (McFarland & Wolpaw, 2008). Neurorehabilitation applications involve using BCI technology to aid in the recovery of motor function in people with neurological injuries, such as stroke (Cervera et al., 2018).

Despite the potential of BCI technology, several challenges need to be addressed. These challenges include the development of more accurate and reliable sensors, the reduction of noise and artifacts in the EEGs, and the development of better algorithms for decoding brain signals into computer commands. Also, the development of out-of-lab use passive BCI (pBCI) would open up the possibilities of everyday use in multiple ways (Aricò et al., 2018). Additionally, there are ethical concerns that need to be addressed: physical factors (user safety), psychological factors (humanity and autonomy), and social factors have been identified as categories of ethical issues regarding BCI technologies.

One ethically complicated scenario could be the use of a Brain-to-Brain Interface (BBI, a suggested type of BCI) without an individual's consent or knowledge (Coin et al., 2020).

The future of BCI technology looks promising, with ongoing research aimed at addressing both hardware and software challenges and developing new applications for the technology. One direction is the further development of hybrid BCI systems that combine different types of sensors and algorithms to improve accuracy and reliability (Amiri et al., 2013). Another research direction is the further development of closed-loop BCI systems that provide feedback to the user and adapt to changes in brain activity (Chiang et al., 2021). Finally, there is ongoing research into the consumer use of BCI technology for gaming, entertainment, and education. With continued progress, BCI technology has the potential to transform the way we interact with technology and with each other.

2.2 BCI and neuroscience

BCIs utilize the underlying neuroscientific principles to obtain system input used in human-computer interaction. Therefore, understanding the basis of how the raw input is generated is important to further understand how BCIs work, and the signal processing they use. The bases of all neural signals are neural oscillations or brain waves which are generated inside the brain: the genesis of neural oscillations inside the brain are based on stimuli or underlying neural activity. Brain waves are recorded using an electroencephalogram (EEG), a method of recording the electrogram (EGM) or changes in the electric charges inside the brain, stemming from brain activity. EEG utilizes electrodes that are placed on the scalp to allow these charges to be measured, transformed from analog to digital format, amplified, and recorded with a separate device connected to the electrodes (Schomer & Fernando, 2017). The electric signals interfacing between the scalp and the electrodes encounter resistance known as impedance, which can affect the recordings negatively. To minimize impedance and signal noise in the EEG, the connection between the electrodes and the scalp has to be good and all hindrances should be removed or minimized as low impedances are essential for an EEG recording (Light et al., 2010). The electrodes pick up the weak signals from the brain and the BCI device amplifies this signal. The most relevant component for BCI use is event-related potential (ERP). ERPs are extremely small voltages that are generated inside the brain. They consist of positive and negative changes in voltage and can be considered a type of detectable trigger in the EEG signal that is generated in response to specific sensory, auditory, cognitive, or motor events in the brain. Coincidentally, there are also specific ERPs associated with the aforementioned senses. ERPs are commonly used in neuroscience research to study the underlying neural processes of various cognitive functions. ERPs are time-locked to specific events, such as the presentation of a visual or auditory stimulus, and can be measured with the use of electrodes that are placed on the scalp. The EEG signal is then recorded and analyzed to identify the ERP components, which are characterized by their timing, amplitude, and distribution over the brain. Human ERPs are divided into early wave and later wave components: early wave components peak approximately before the first 100-millisecond mark post-stimulus and later wave components are usually associated with the evaluation of the stimulus, thus called information processing or “cognitive” components (Sur & Sinha, 2009).

One of the most well-known ERP components is the P300, which is a positive wave that occurs approximately 300 milliseconds from the stimulus onset presented. The P300 is involved in attention, memory, and decision-making processes. This is the most prominently used ERP component in BCI at present.

While P300 is the most prevalent ERP used in BCIs, other ERPs can be used. They include the N100, N200, N2a, N2b, N2c, N300, N400, P3a, P3b, P50, SSVEP and MRCP. For example, N100 is a negative wave that occurs approximately 100 milliseconds from stimulus onset and is associated with sensory processing, and the N400, which is a negative wave that occurs approximately 400 milliseconds after a stimulus is presented and is associated with semantic processing.

ERPs are useful in clinical settings because they can provide information about cognitive function that is not apparent through behavioral testing alone. For example, ERPs can be used to study cognitive dysfunction in neurological disorders such as Alzheimer's disease (Rad et al., 2021) or to assess the degree of impairment in cognitive function (Jeżowska-Jurczyk et al., 2023). Overall, ERPs provide valuable insights into the neural mechanisms underlying cognitive function and have significant implications for both basic and applied research in neuroscience and clinical practice.

2.3 Consumer BCI devices

Reliable medical EEG data extraction typically requires an electromagnetically shielded environment (e.g., a Faraday cage) and an EEG cap covering the whole head with saline or gel used in the sensors to better conduct the electric signal. Most brain-computer interface devices have been designed for medical uses with little or no consideration for mobility and ease of use as they have not been significant factors in designing these systems. Despite the aforementioned limitations, medical BCI devices and systems are usually more reliable due to not using wireless technology such as Bluetooth and using an EEG cap that helps with the positioning of the electrodes on the user’s scalp. They also offer both better temporal and spatial resolution and are better in terms of signal quality. Medical BCIs are also developed specifically for clinical and research applications and, thus, are priced higher accordingly. While commercial BCIs are typically only non-invasive, they have worse temporal and spatial resolution and signal quality, they excel in ease of use, user mobility, affordability, and broader accessibility, with intended typical use cases ranging from basic control applications and entertainment to wellness.

A typical consumer BCI device consists of the following parts: a headset with electrodes for picking up EEG signals, a processor to clean and amplify the EEG signal and convert it into desired signals, and an output device. There is also a corresponding software and license that comes with most consumer devices: the individual software or software suites often include user interfaces with functionalities for raw EEG data access, visualization and recording, cognitive state tracking, device connection and electrode signal status, and mental command detection, calibration, and use. Mental command functions, which were used in the experimental test, use an interaction user interface for choosing, calibrating (or training), testing, and using of mental commands. Depending on the device, these commands can be detected using pre-built detection algorithms or by other means. Known consumer-level BCI devices are NeuroSky MindSet (a single-electrode device released in 2009), Emotiv EPOC (a 14-electrode device, released in 2010), InteraXon Muse (a 4-electrode device, released in 2014), OpenBCI Ultracortex Mark IV (a 16-electrode device, released in 2017), and NextMind (an 8-electrode device, released in 2020). The BCI used in this experimental test, Emotiv EPOC, was chosen due to existing studies that concluded that the device can measure research quality ERPs (Badcock et al., 2013), and while it does not compare to medical BCI devices (Duvinage et al., 2013), existing literature suggested that the ERPs captured by the device are highly similar to ones captured by a medical-grade BCI system (Barham et al., 2017).

2.4 Evaluation of BCI usability

In general human-technology interaction, usability refers to the ease and pleasantness of use of an interface. Nielsen’s usability heuristics have been an essential part of the study field since their introduction in 1994 (Nielsen, 1994). While a great basis for user interface and user experience evaluations, Nielsen’s usability heuristics do not offer much in terms of evaluating the tangible interaction interfaces themselves as the usual hardware is uniform for most users.

In terms of BCIs, usability becomes harder to assess. Interactions with BCI are (at least currently) based on calibration or training data, meaning they are normalized individually based on each user's calibration or training data instead of only using raw EEG data. Because of this, the act of making mental commands via the BCI system is intrinsically individually different between different users and their mental commands. It becomes increasingly hard to determine how usability should be evaluated as we are dealing with each user's individual EEG input complemented by the normalizing factor from the user's command calibrations: raw EEG as user input varies between users but mental commands can be made detectable from it by comparing it to the calibration or training data submitted by the user to the detection software algorithm.

The ISO 9241-11 usability model has been used in a 2018 BCI usability study to evaluate effectiveness, efficiency, and user satisfaction with the NeuroSky MindWave BCI headset (Noor et al., 2018), giving a good reference to other BCI usability study designs. However, this was not available at the time of creating the experimental test design for this thesis. Instead of using an existing design plan, I developed and reiterated ideas familiar from other interaction modality studies. The end result was an experimental test for a computer peripheral (in this case the BCI device) with task recordings (mental command power recordings) where a total of 4 tasks were given to the participants in two segments. In the test, participants tried to use mental commands to move a virtual 3D cube on the screen after having done calibration recordings for each of the tasks. This allowed me to use task success rate to compare the task groups and to determine differences in the test results without using the raw mental command power per axis. The objective of this research was to determine whether mental commands were more successful when using them to move a virtual 3D cube horizontally or vertically. In my original hypothesis, I assumed that due to evolution having developed human eyes side-by-side instead of one below the other, horizontal virtual object manipulation performance would exceed the vertical virtual object manipulation performance when tested. Additionally, the objective of the questionnaire was to gain further insight into how the participants' background might affect their test results, how they perceived the interaction, how they tried to create the mental commands, and to give more context to the participants' test results, especially for results deviating most from the average. In the end, the goal of the experimental test was to measure BCI use in an average setting, with limited base-level interaction commands, all this done with a commercial BCI device. The intention was to fill the gap of absent entry-level BCI usability research with commercial use and users in mind every step of the way for the possible results to be applicable specifically to this context.

3 Methodology

This chapter will introduce the overall research setup implementation and software and hardware that was used.

3.1 Participants

23 people participated in the main experimental test, with 7 female and 16 male participants. Participant's weighted average age was 26 years and the age group mode was 21-30 with 18 out of 23 participants, meaning the average age of participants falls in this age group. In addition, there were also participants in age groups 31-40 and 51-60.

3.2 Hardware

The Emotiv headset was used in the tests to capture brainwaves as EEG through its 14 channels (Image 1). The Emotiv headset was connected to a Windows laptop computer with the Bluetooth dongle that came with the headset (Image 2).

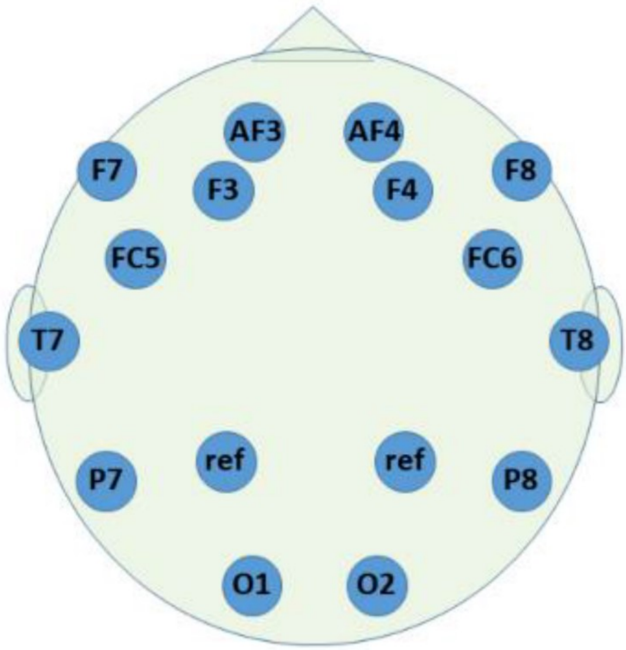

Image 1: The Emotiv EPOC headset devices electrode setup, showing placement of 14 channels and two reference points on a user's scalp (points marked as "ref" in the picture).

Image 2: The experimental test hardware setup: Lenovo Z500 laptop computer, and the Emotiv EPOC BCI headset.

The headset is placed on the user’s scalp with saline-doused electrode pads to allow the signals to pass through the scalp better. When starting to use the Emotiv headset, the user must first record calibrations onto the Emotiv Cognitive Suite software for a neutral or resting state of the user’s brain activity and then the desired command states of the user’s brain activity. The command states are recordings of the brain activity during the user’s intended mental commands (in whatever way the user might try to achieve them) that are compared to their resting brain activity state which is used as a baseline. These calibrations allow the system to distinguish a calibrated command from the live EEG of the user later on. The mental commands themselves can be whatever each user chooses to think or do during the mental command calibration recordings. As long as the user can repeat the same mental command afterward, they should be detected by the software algorithm, resulting in a successful command indicated by the command power indicator in the Emotiv Cognitive Suite software. After successful calibration of mental commands in the software, the commands can be connected to any traditional computer input, for example, movements of a mouse, individual character input of a keyboard, etc. The calibration recordings take 30 seconds to two minutes to do and can be done multiple times to increase command accuracy and detection. The Emotiv software shows the user their approximated calibration performance in percentages per command.

An external monitor was used as the monitor for the participants to use for the tests and the laptop monitor was used for setting up and starting result logging. The monitor showed the calibration view of the Emotiv Cognitive Suite during the calibration phase and the same view again in the test phase where they could move the virtual 3D cube on the screen using their mental commands. The purpose of the separate monitor was to allow the participants to focus only on their interaction with the virtual 3D cube inside the user interface and to minimize any distractions during the test. Software and user interfaces used for data streaming and logging were visible on the laptop screen which was only seen by the test moderator. During the test, the participants were tasked with moving the virtual 3D cube inside the user interface in four different directions using mental commands that correspond with said directions. This meant that whatever the participants thought of or did during the mental command calibrations, they could only achieve successful commands by reproducing the same mental command. A successful mental command was determined by the Emotiv Cognitive Suite and shown as a command power bar inside the user interface: a successful command was indicated by the initially empty bar reaching full power and any unsuccessful commands as the bar not reaching full power. This command power data was streamed and logged continuously during the test as values between 0.000 and 1.000 per every millisecond, and saved into a text file for later analysis. The interpretation and detection of commands and logging of command data was done with a single Windows laptop computer with the following components: Intel Core i7-2521QM CPU @ 3.2GHz, 8GB RAM, and NVIDIA GeForce GT 645M 2GB.

3.3 Software

The software used in the experimental test includes the Emotiv Suite SDK version 2.0.0.20 and more specifically the Cognitiv Suite functionality of the product (Image 3). The Cognitiv Suite functions as the brainwave and ERP detection algorithm engine and was provided with the Emotiv headset and license. It uses the Emotiv headset EEG data to recognize a maximum of 14 different calibrated commands.

In addition to the Emotiv Suite, Max 7, a visual programming language and software was used for creating a logging process for the command output (Image 3), and Mind Your OSCs, an open-source data streaming software (Image 4) that uses OSC or OpenSoundControl, an open-source streaming protocol. This was done to connect to both Cognitive Suite and Max 7 and to stream the individual directional command power data produced by the algorithm in Emotiv Cognitive Suite through the OSC protocol to Max 7 for logging purposes.

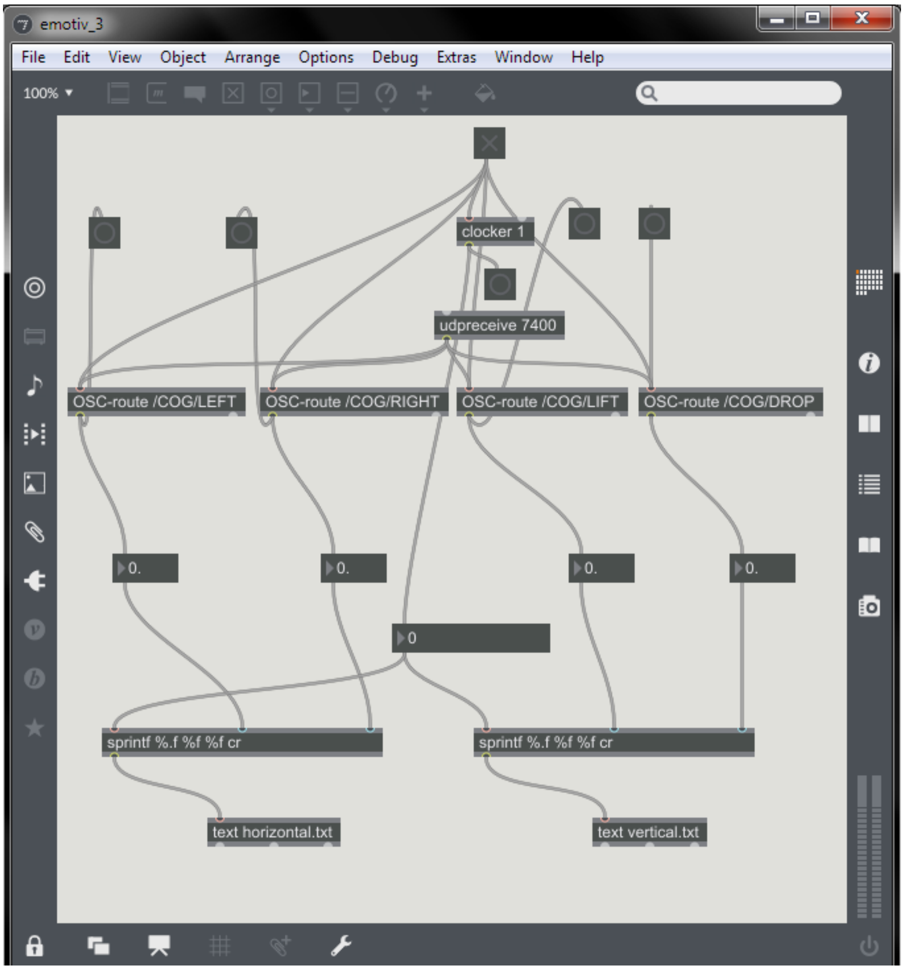

Image 3: The user interface of Max 7, a visual programming software, with the command power logging scheme for all 4 triggers, created for the test setup in Max 7 and used in the experimental test.

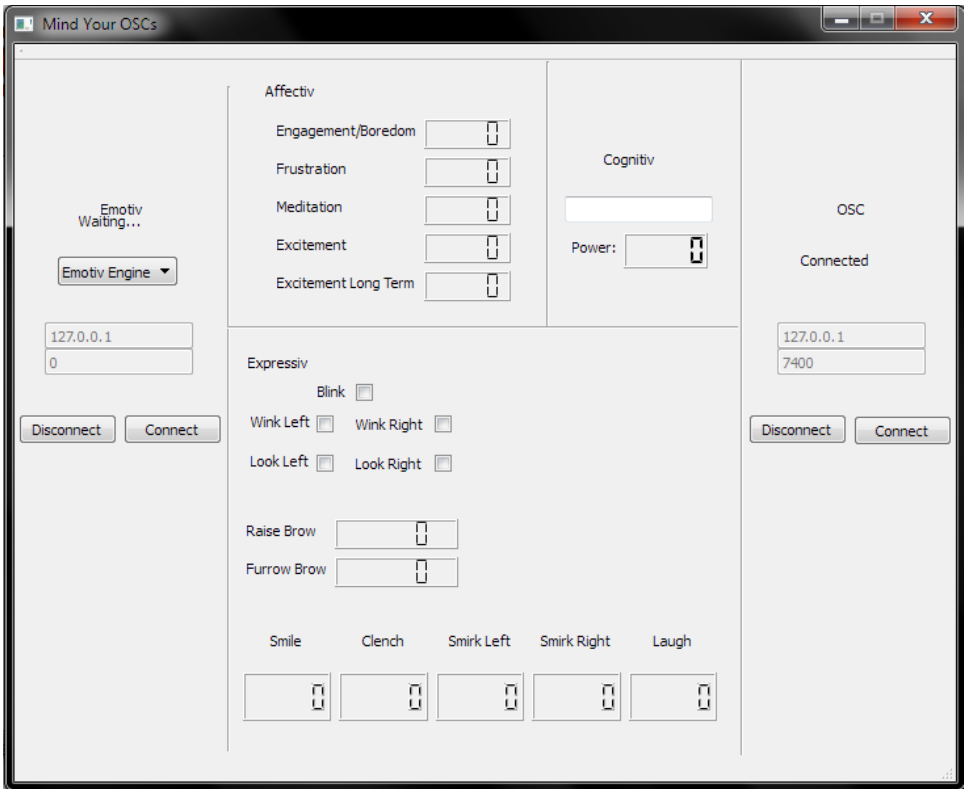

Image 4: The user interface of "Mind Your OSCs", an application used for data streaming in order to pass command power data from Emotiv Cognitive Suite to logging in Max 7.

The text files created with the logging process in Max 7 were converted into graphs using Python, a general-purpose programming language. A Python script was created to read all 96 log files in a folder and to generate individual mental command power graphs with both commands of the same axis visible with a command threshold line indicating the individual successful commands.

3.4 Pilot testing

Pilot testing was conducted before final experimental tests to determine the possible success rate and reliability of the hardware and other possible flaws in the test plan. The pilot tests took place in the University of Tampere usability laboratory with two participants, both Master's degree students at the time. The goal in the pilot was for the participants to move the 3D cube on the screen once to all sides of the panel (left, right, up, and down in this order). The results were written down during the test and based on visually analyzing the Emotiv Cognitive Suites command power: when the 3D cube moved to the edge of the screen in the right direction, a successful movement was marked. No logging was done during the pilot test, and no statistical analysis was created from the results.

Before beginning the 3D cube movement tasks, all four mental command directions were calibrated once using the Emotiv Cognitive Suite. After this the participants began trying to move the on-screen 3D cube, starting with moving the object to the left. The results showed one participant succeeding in moving the cube, while the other participant could not successfully move the 3D cube in all 4 directions, only in the first two directions (left, right). The second participant also experienced unintentional mental command power spiking which was visible in the Emotiv Cognitive Suite. While the first participant performed the tasks successfully, they experienced an unintentional break in achieving successful mental commands after completing the left-right –commands. The second participant failed to give successful mental commands at the same stage of the test.

The conclusion from this was that the calibrations and mental command tests should be broken apart to allow for easier object manipulation during each recording session: instead of testing for all 4 directions in the same recording session, testing with 2 directions at a time could make giving the mental commands easier and more reliable during a single recording session. This was implemented in the final experimental test: left-right commands were calibrated and tested successively before moving on to calibrating and testing for up-down commands. In addition, the number of calibrations was increased from one calibration to two calibrations per command direction to allow for a better success rate for all participants: more calibrations were expected to translate to a better chance of participants successfully giving mental commands. With this approach, even if one of the calibrations did not give a reliable baseline to compare the commands to, there would still be a chance that the second calibration could be successful. In addition to problems related to the calibration and command order and execution, the pilot test indicated other problems in the initial setup: the sensitive Bluetooth connection between the computer and the device which would sometimes disconnect altogether, and the non-practicality of using the electronically shielded room. The test sections also did not account for unintentional command power spiking nor did they include the use of consecutive commands on the axis as a basis for a successful command.

3.5 Procedure

The experimental test was conducted using a computer peripheral called a BCI device. Participants were given four tasks to move a virtual 3D cube on the screen using their thoughts. Before the test, calibration recordings were done for each task. The success rates of the task groups were compared to see if there were any significant differences in the results. Instead of using the raw data measured every millisecond, I found it easier and more practical to visually analyze the graphs and identify successful tasks. Additionally, a questionnaire was done to gather feedback from participants about the test and the device. The questionnaire included background information, two quantitative questions using a 5-point scale, and two qualitative questions. The 5-point scale was chosen for its simplicity and ability to provide balanced responses with a neutral midpoint, allowing for statistical analysis.

First, all participants were introduced to the general test procedure, and they were informed of the purpose and goals of the test and how the test would proceed. After this, participants began the test following the test routine. The experimental tests were conducted in a University of Tampere HTI usability laboratory on the University of Tampere campus. The participants were asked to take part in the test one by one. The tests were conducted between 20.6.2016 and 4.5.2017.

Participants were monitored during the test inside the usability laboratory visually in order to make notes on their test performance, to write down the participant's calibration data between calibration rounds, and to be able to quickly intervene and fix possible device issues during the experimental test. The participants were seated in a chair approximately half a meter away from the computer monitor that displayed the Emotiv Cognitive Suite with the movable virtual object. The default cube form was used for this test (Image 5).

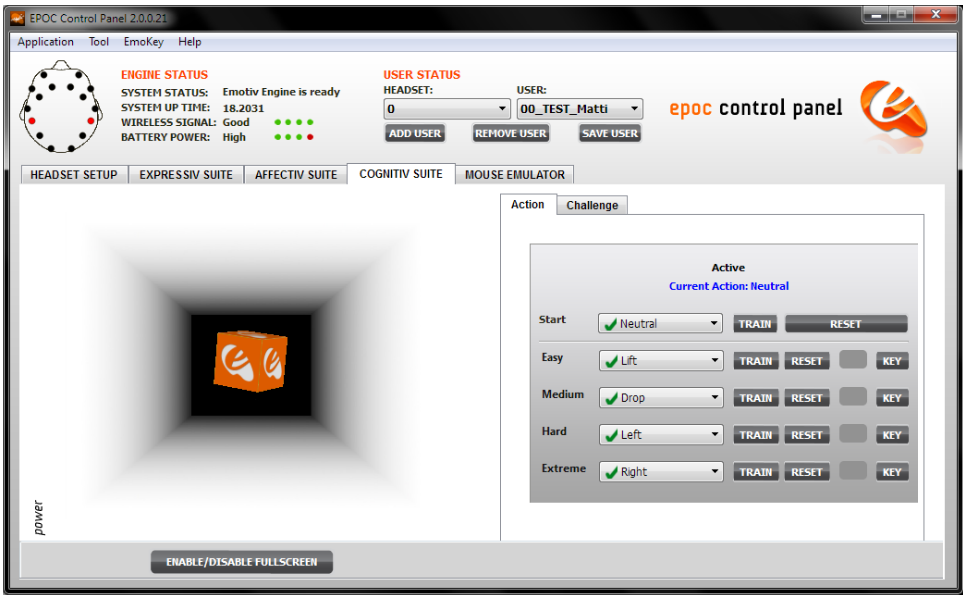

Image 5: The user interface of the Emotiv Cognitive Suite, shown inside the EPOC Control Panel software.

The experimental test design consisted of two parts: two test rounds, both consisting of mental command calibrations (used for establishing a baseline for users' mental commands) and actual mental commands during the test (the recording evaluated by the software against the baseline mental commands). Calibration recordings refer to both the neutral “baseline” EEG recordings where the test subject was asked to not focus on anything specific, and command-specific calibration recordings such as a separate calibration recording for the commands “up” and “down” so they can be identified separately and interpreted as commands. The participants were instructed that they were free to use whatever way of thinking or doing while sitting down to define and create the mental commands before beginning the calibrations. Participants were intentionally not given any hints or examples about what the supposed “preferred ways” to create the commands are. Participants were told that the individual calibrations would take 30 seconds each, resulting in a successful calibration. These calibration recordings were used by the Emotiv BCI system to differentiate other calibrated commands from an individual's baseline. Test recordings refer to the actual test part of this user test where participants were asked to repeat the same style of thinking or doing that they used in the mental command calibrations. Unlike in the calibration phase, the 3D cube inside the Emotiv Cognitive Suite user interface would move when the software detected user input corresponding to the calibration of the same mental command. Success was indicated with the Emotiv Cognitive Suites power bar indicator (command power), and the 3D cube being moved to the edge of the user interface panel, in the participants desired direction. This part is also referred to as the virtual object manipulation test: the test where the participant tries to move the 3D cube on the screen by giving mental commands that correspond to the calibrations that were made prior. The results of these attempts were saved into log files. After the tests were done, the participants were asked to answer a questionnaire, in which they were asked about their experiences and some personal information.

In the first part, the participant gave four neutral calibration recordings (each lasting 1 minute) and went on to give two calibration recordings for both left and right commands. This was followed by the two horizontal/lateral virtual object manipulation tests where the goal was to achieve successful left-right mental commands 5 times consecutively. This was followed by two calibrations for both up and down directions (or lift and fall, as categorized by the Emotiv Cognitive Suite), followed by two vertical object manipulation tests where the goal was to achieve up-down triggers 5 times consecutively. After this, part two began with another four neutral calibration recordings, followed by two consecutive left-right calibrations and two consecutive left-right test recordings. Following this, two up-down calibrations each were performed consecutively, followed by two consecutive up-down test recordings. Only consecutive left-right or down-up command pairs were considered a successful repetition in the virtual object manipulation tests. This was to make sure that accidental command spiking would not be automatically considered successful commands, something that happened repeatedly in the pilot test stage.

After the user test was over, participants were given a questionnaire to fill out. The questionnaire consisted of personal information questions (name, age group, dominant hand, and gender), and a yes or no question of whether they had prior experience using a BCI device (and if yes, asked to explain further). These personal information questions were used in order to gain context for possible differences in the experimental test results. The technique was evaluated with two semantic differential questions ("How mentally demanding were the tasks? 1 Very easy – 5 Very hard", and "How did you find using the device? 1 Unpleasant – 5 Pleasant"), and two free-form questions ("Please explain the thoughts/techniques you used to make selections" and "Any comments about the device or the experiment?"). The purpose of the semantic differential questions was to determine how the participants would subjectively perceive using the device and what they would think about the mental demand when performing the command tasks. The semantic differential was chosen to provide a structured and standardized way to measure the participant's perception of the device and the experiment. In addition, the purpose of the free-form questions was to gain insight into the more difficult-to-define aspects of using a BCI device that would have been more complicated to determine with a 5-point semantic differential scale. Free-form questions also allow for any user insight, not just predetermined points of interest. This is especially useful for collecting information about the varying types of mental commands the users reported performing for the virtual object manipulation commands.

3.6 Experimental test evaluation methods

The chosen commands were evaluated by measuring the Emotiv Cognitive Suites command performance during the tests, in addition to taking notes on each test subject's performance and calibration percentages and doing the subsequent questionnaire.

Success was based on two opposite object movements, for example, first moving the object left and then right. This was then repeated five times or as many times as possible. The recorded data shows an individual recording with a minimum score of 0.0 and a maximum score of 1.0 for command power. This corresponds to the Emotiv Cognitive Suites command power indicator (0-100%) and in the recordings as changes in the given mental commands power (Image 5) (Image 6).

A command success table was created based on the individual recordings (Image 6) that were visually analyzed for successive successful command pairs. In evaluating the experimental test results, only the mental command power derived from the Emotiv Cognitive Suite was used as an indicator of a successful pair of commands for both axes.

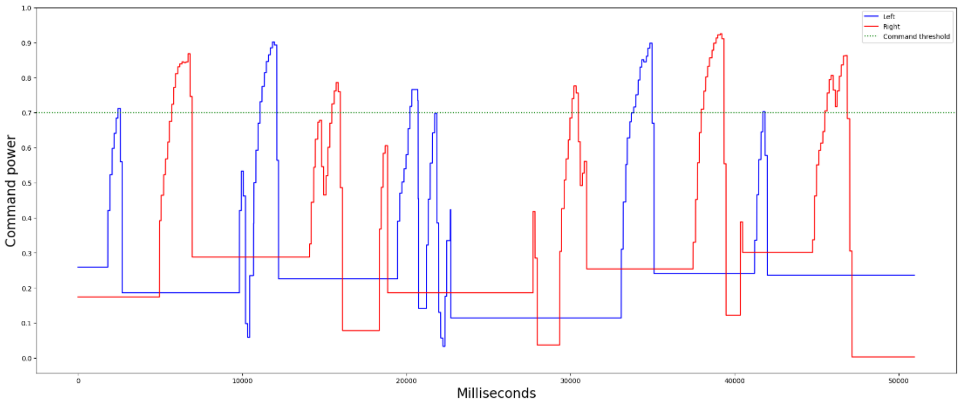

Image 7: Example of an individual participant's lateral command power graph, first test round. The graph indicates the command power level on a scale of 0.0 to 1.0 which is derived from and equivalent to the 0-100% indicator in the Emotiv Cognitive Suite user interface.

The command power table (Image 7) in turn was used to calculate the means of both lateral and vertical commands and compare them using a paired samples t-test. The table contains the number of individual participants' successful mental commands per axis and per test round, where 0 successful commands indicated a complete failure to move the 3D cube and 5 successful mental commands indicated 5 out of 5 successful mental commands or a perfect score. Means for both horizontal and vertical 3D cube manipulation were calculated from the aforementioned user-specific mental command scores (columns H1, V1, H2, and V2), The individual calculated combined axis means were added into the table and are found in columns Hmean (horizontal scores mean) and Vmean (vertical scores mean).

Subject	H1	V1	H2	V2	Kalibraatio1 vasen	Kalibraatio1 oikea	Kalibraatio1 ylös	Kalibraatio1 alas	Kalibraatio2 vasen	Kalibraatio2 oikea	Kalibraatio2 ylös	Kalibraatio2 alas	Hmean	Vmean
01	5	3	5	2	.0	22%	0%	0%	13%	35%	35%	3%	5.00	2.50
02	2	0	1	0	.0	0%	0%	0%	6%	25%	6%	5%	1.50	.00
03	5	0	5	0	.0	3%	0%	2%	5%	10%	11%	24%	5.00	.00
04	5	2	5	0	.0	0%	10%	0%	8%	4%	8%	1%	5.00	1.00
05	5	5	5	5	.0	0%	0%	9%	18%	16%	11%	14%	5.00	5.00
06	5	4	5	3	7.0	0%	4%	0%	60%	54%	35%	64%	5.00	3.50
07	3	1	5	0	.0	2%	0%	2%	7%	44%	1%	13%	4.00	.50
08	4	3	0	2	19.0	0%	25%	0%	10%	1%	13%	25%	2.00	2.50
09	1	0	0	0	.0	0%	0%	11%	27%	13%	46%	23%	.50	.00
10	1	1	3	5	7.0	0%	0%	0%	14%	22%	0%	6%	2.00	3.00
11	3	0	5	5	.0	1%	0%	6%	20%	44%	16%	77%	4.00	2.50
12	3	5	5	5	.0	0%	0%	0%	3%	16%	16%	9%	4.00	5.00
13	5	0	1	5	2.0	0%	0%	6%	34%	22%	10%	63%	3.00	2.50
14	5	0	5	1	.0	1%	3%	0%	54%	24%	3%	55%	5.00	.50
15	2	4	1	5	.0	0%	0%	0%	19%	3%	13%	12%	1.50	4.50
16	5	1	5	2	.0	2%	2%	0%	3%	3%	6%	9%	5.00	1.50
17	5	3	1	5	.0	0%	0%	6%	20%	1%	16%	11%	3.00	4.00
18	5	5	5	5	.0	12%	0%	0%	60%	74%	72%	37%	5.00	5.00
19	5	1	5	1	12.0	0%	0%	3%	7%	3%	4%	9%	5.00	1.00
20	5	3	5	5	.0	6%	32%	0%	76%	24%	53%	40%	5.00	4.00
21	3	5	0	2	.0	0%	0%	0%	6%	71%	7%	31%	1.50	3.50
22	5	1	0	0	.0	22%	0%	0%	19%	7%	13%	6%	2.50	.50
23	3	5	5	5	1.0	0%	0%	16%	32%	45%	34%	52%	4.00	5.00

Image 7: Command success and calibration data sheet with the calculated means for the successful lateral and vertical power commands.

4 Results

4.1 Object manipulation results

The experimental test measured the successfully performed consecutive object manipulation commands made by the participants from zero to five (0-5), 0 meaning the virtual object could not be successfully moved at all, and 5 meaning a total of five successful virtual object movements. The horizontal virtual object manipulation commands proved to be more successful (mean = 3.6304; standard deviation = 1.50919) than the vertical virtual object manipulation commands (mean = 2.50000; standard deviation = 1.80907). The performance difference proved to be significant in a paired samples t-test ($t(22) = 2.446$; $p = 0.023$; Two-sided) (Image 9). In the image we also see the upper half of the vertical command success mean reaching the horizontal command success median, showing that the mean command success performance of most of the participants was better with horizontal object manipulation than with vertical one. This is partly explained by the three recordings where vertical manipulation resulted in 0 successful vertical virtual object manipulations (Image 10).

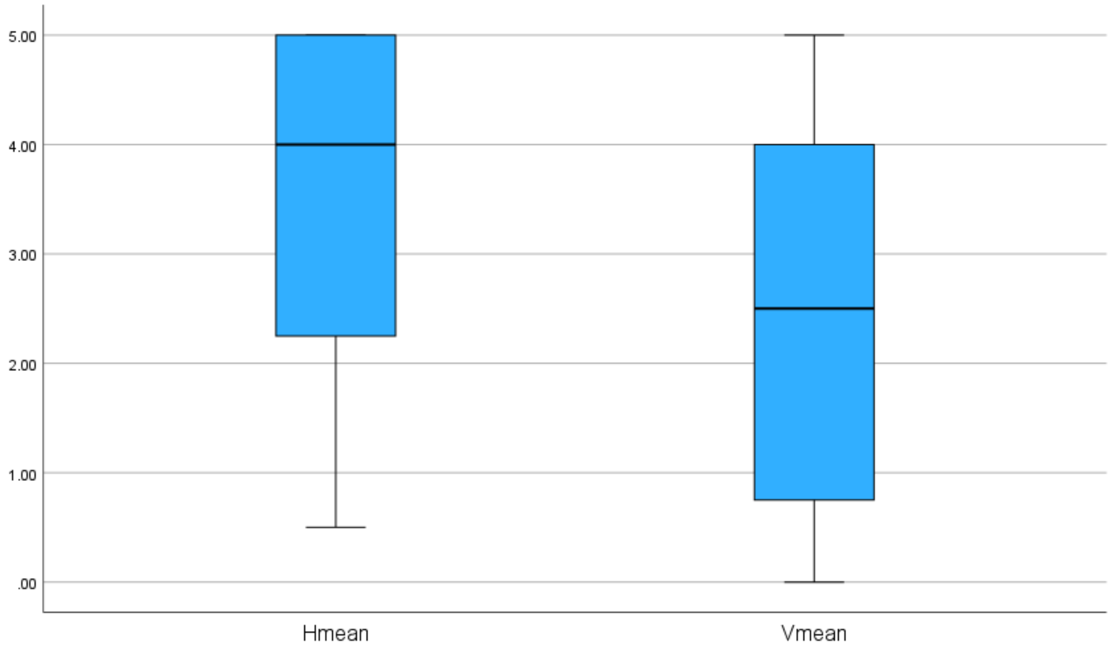

Image 9: Virtual object manipulation success means per axis, measured as zero to five successful commands. Hmean indicates the horizontal object manipulation success means and Vmean indicates the vertical object manipulation success means.

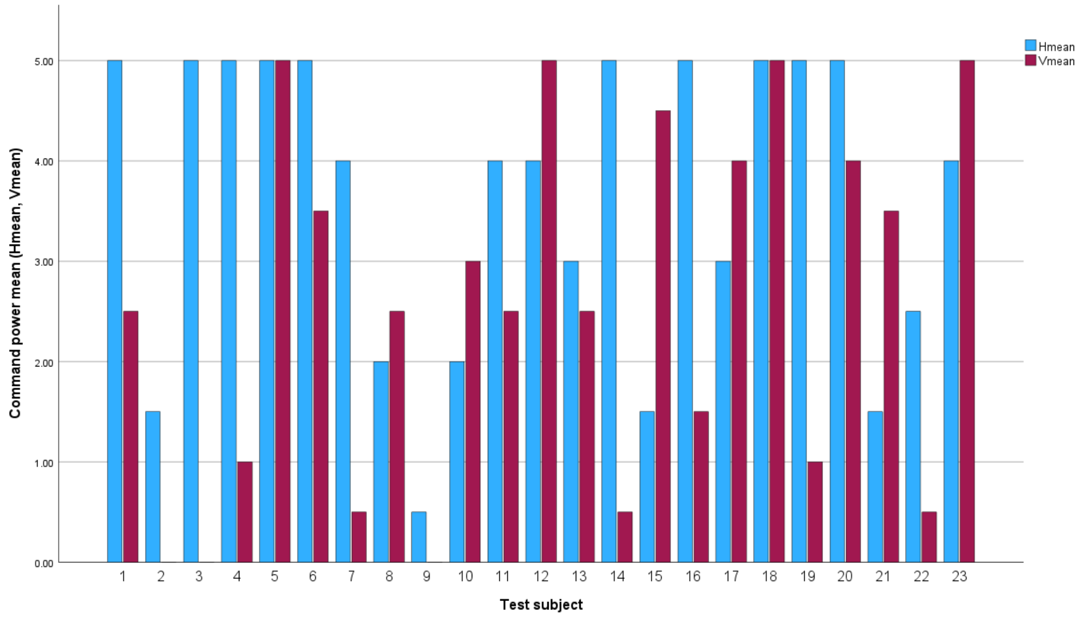

Image 10: Each participant's object manipulation performance per axis, demonstrating the differences between participant's object manipulation performance means for both horizontal and vertical axes.

When comparing the first test rounds' command success mean to the second round, the first round is found to be more uniform in command success (mean = 1.652; standard deviation = 2.308) than the second round (mean = 0.609; standard deviation = 2.872). The difference proved to be significant in a paired samples t-test (Round 1: $t(22) = 3.433$; $p = 0.002$; Two-sided)(Round 2: $t(22) = 1.016$; $p = 0.32$; Two-sided).

4.2 Questionnaire results

The questionnaire was conducted on 17 out of 23 experimental test participants. This was due to an error and continuous development of the research question.

The mean of the 5-point semantic differential scale answers was calculated for both questions. The results mean for the question "How mentally demanding were the tasks? (1 Very easy – 5 Very hard)" was 3.47 (standard deviation = 0.874) while the mean for the question "How did using the device feel? (1 Unpleasant – 5 Pleasant)" was 3.41 (standard deviation = 1.278). According to the calculated means from the semantic differential scale question results, the participants perceived the tests as neutral or slightly mentally demanding, and that the participants perceived using the device as neutral to slightly pleasant.

The answers to the freeform qualitative question "Please explain the thoughts/techniques you used to make selections" offers insight into how participants approached creating the mental commands. Most answers indicate some type of physical aspect to creating the commands. These methods include moving their eyes and hands to make the object move, some reported tensing up their body, smiling, using their teeth, mental images, word repetition, and moving their whole body in the desired direction. This question was answered by all 17 participants who filled out the questionnaire. The last question "Any comments about the device or the experiment?" was answered only by 12 of 17 participants, possibly because it was the last question, and because they might not have additional comments regarding the device or experiment, or they had already given their answer in the previous question. Multiple participants indicated an interest in the technology and/or experimental test, multiple also indicated frustration over the device and test due to not being able to move the virtual object at all or not well enough to succeed in achieving five consecutive command pairs. Additionally, two participants mentioned symptoms of headaches from using the device.

5 Discussion

This thesis explored the uses and usability of a commercial-grade brain-computer interface device, the Emotiv EPOC, and the differences in using the device for virtual object manipulation along lateral and vertical axes.

On average, participants were able to manipulate the virtual object in both lateral and vertical axes. These simple mental command directions were intended to be as basic interaction as possible, better allowing the imagining and reimagining of the user's commands: choosing different mental commands or a more complex command routine could have led to difficulties in forming and giving mental commands for the participants. The research compared the successful command results between axes, in addition to the variability of first and second-round command results.

The experimental test results indicated a significantly better mental command performance for horizontal commands compared to vertical ones. In addition, the results indicated a larger command success variability for both mental command axes during the first round of calibrations and tests than with the second round of calibrations and tests. In turn, this suggests the command success results in the second test round were more uniform, likely benefiting from the already performed first calibration and test. This can be interpreted to confirm that more calibration and testing equals increased command power success. The tests showed that problems with the device, Emotiv EPOC, impact both the system's functionality and usability negatively. At times the system was non-functional (no Bluetooth signal or signal detected by the device electrodes) and at times, unreliable in use (command power spiking, breaking Nielsen's "Consistency and standards" heuristic). While the spiking specifically made the individual command charts seem erratic, the test goal of 5 consecutive successful opposite commands was designed to distinguish successful and controlled tasks from simple device errors. This was done to avoid passing command power spiking as successful commands and to be able to distinguish between controlled consecutive mental commands on an axis and uncontrolled mental commands in only one direction. During the pilot, mental command power would spike uncontrollably at times but mostly in the same direction. All tests were conducted with the subject sitting down to normalize the results by limiting excessive physical movements that could affect the EEG. Ambient noise could also have contributed to the mental command reliability negatively: the intention was initially to conduct the tests in an electrically shielded space (i.e., a Faraday cage) to ensure the recordings would contain as little amount of ambient noise as possible. However, this proved to be difficult in practice due to the large sample group size and the total amount of time needed to reserve in the electrically shielded space. In addition, the research space was being used in Ph.D. research, both making reserving the space difficult for a sufficiently long time. In the end, the experimental test was conducted in the usability laboratory of the University of Tampere, in a room with no electrical shielding, possibly resulting in signal noise.

While not comprehensive in nature, the questionnaire attempted to gain insight into how the participants felt about the experiment and the device used. The chosen questions were meant to offer some insight into what an average future BCI user might think of both the simplified tasks and the device itself, indicating some direction for the device and interface development. The qualitative answers in turn go on to elaborate on the different ways participants tried to make the commands happen. While the more typical answers included moving their eyes and hands to make the object move, some reported tensing up their body, smiling, using their teeth, mental images, word repetition, and moving their whole body in the desired direction. Comments regarding the device and/or experiment as a whole suggested that multiple subjects found the device/experiment to be interesting. Another recurring comment was that the device/experiment felt frustrating due to the user not being able to move the object successfully despite trying. Two subjects reported that the device caused their head to hurt, likely due to the extended period of wearing the BCI headset and looking at a computer monitor.

Brain-computer interfaces offer a new frontier in human-technology interaction with many new challenges. Application of the technology to users as individuals raise the problem of designing a signal processing algorithm that would work without calibration with significant portions of the user base. There is also a very limited amount of usability guidelines and heuristics, specifically regarding best practices for creating reliable and easily repeatable commands. Despite the non-invasive BCI systems not needing a craniotomy to be used, they still cause headaches and nausea when used for extended periods. This needs to be solved for the devices to become ubiquitous to use, meaning a significantly smaller form and weight factor for the device and sensors.

6 Conclusions

The significance of the experimental test results may be compromised by measurement errors caused by practical issues during the test setup, such as device disconnection and zero EEG signals for certain commands. Additionally, the limited insights into the signal processing of the Emotiv Cognitive Suite and practical factors like electrode placement and saline solution application can impair the EEG signals. Although the sample size of 23 participants is decent for a Master's thesis, larger sample sizes would enhance the reliability and significance of the findings, which could be explored in a doctoral thesis. BCI systems need to address practical problems and improve recording resolution for wider adoption, considering the projected growth of the international BCI market. Achieving mass adoption would require advancements in BCI technology, leading to the development of applications and more research on usability and best practices. Various BCI devices exist, offering possibilities for immersion and biofeedback for user training. The technology's implications span diverse areas, including rehabilitation, augmentation for visually or audibly impaired individuals, and communication via BCI or potential brain-to-brain interfaces. However, ethical concerns arise, encompassing topics such as autonomy, research ethics, privacy, and societal implications, necessitating careful consideration as the technology advances.

7 References

Amiri, S., Fazel-Rezai, R., & Asadpour, V. (2013). A review of hybrid brain-computer interface systems. Advances in Human-Computer Interaction, 2013, 1-1.

Aricò, P., Borghini, G., Flumeri, G. Di, Sciaraffa, N., and Babiloni, F. 2018. "Passive BCI Beyond the Lab: Current Trends and Future Directions." Physiological measurement 39, no. 8 (2018): 08TR02–08TR02.

Badcock, N. A., Mousikou, P., Mahajan, Y., de Lissa, P., Thie, J., & McArthur, G. (2013). Validation of the Emotiv EPOC(®) EEG gaming system for measuring research quality auditory ERPs. *PeerJ (San Francisco, CA)*, *1*, e38–e38.

Barham, M. P., Clark, G. M., Hayden, M. J., Enticott, P. G., Conduit, R., & Lum, J. A. G. (2017). Acquiring research-grade ERPs on a shoestring budget: A comparison of a modified Emotiv and commercial SynAmps EEG system. Psychophysiology, 54(9), 1393–1404.

Hramov, A., Maksimenko, V., Zhuravlev, M., and Pisarchik, A., "Immediate effect of neurofeedback in passive BCI for alertness control," 2019 7th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea (South), 2019, pp. 1-5.

Birbaumer, Niels. "Breaking the silence: Brain–computer interfaces (BCI) for communication and motor control", 2006. Psychophysiology, 43 (2006), 517–532. Blackwell Publishing Inc.

Cervera, María A., Surjo R. Soekadar, Junichi Ushiba, José del R. Millán, Meigen Liu, Niels Birbaumer, and Gangadhar Garipelli. 2018. "Brain-computer Interfaces for Post-stroke Motor Rehabilitation: a Meta-analysis." Annals of clinical and translational neurology 5, no. 5 (2018): 651–663.

Chiang, Kuan-Jung, Dimitra Emmanouilidou, Hannes Gamper, David Johnston, Mihai Jalobeanu, Edward Cutrell, Andrew Wilson, Winko W. An, and Ivan Tashev. 2021. "A Closed-Loop Adaptive Brain-Computer Interface Framework: Improving the Classifier with the Use of Error-Related Potentials." In International IEEE/EMBS Conference on Neural Engineering, NER, 2021-:487–490, 2021.

Coin, Allen, Megan Mulder, and Veljko Dubljević. 2020. "Ethical Aspects of BCI Technology: What Is the State of the Art?" Philosophies (Basel) 5, no. 4 (2020): 31–0.

Duvinage, M., Castermans, T., Petieau, M. *et al.* Performance of the Emotiv Epoc headset for P300-based applications. *BioMed Eng OnLine* **12**, 56 (2013).

Fong, D. H. C., Cohen, A., Boughton, P., Raftos, P., Herrera, J. E., Simon, N. G., & Putrino, D. (2020). Steady-State Visual-Evoked Potentials as a Biomarker for Concussion: A Pilot Study. Frontiers in Neuroscience, 14, 171–171.

Hyun Jae Baek, Min Hye Chang, Jeong Heo and Kwang Suk Park, "Enhancing the Usability of Brain-Computer Interface Systems". Computational Intelligence and Neuroscience, Volume 2019, Article ID 5427154, 12 pages.

Jeżowska-Jurczyk K, Jurczyk P, Budrewicz S, Pokryszko-Dragan A. Evaluation of Event-Related Potentials in Assessing Cognitive Functions of Adult Patients with Epilepsy of Unknown Etiology. Journal of Clinical Medicine. 2023; 12(7):2500.

Li, S., Leider, A., Qiu, M., Gai, K, and Liu, M. "Brain-Based Computer Interfaces in Virtual Reality," 2017 IEEE 4th International Conference on Cyber Security and Cloud Computing (CSCloud), New York, NY, USA, 2017, pp. 300-305.

Light, G.A., Williams, L.E., Minow, F., Sprock, J., Rissling, A., Sharp, R., Swerdlow, N.R., Braff, D.L.. Electroencephalography (EEG) and event-related potentials (ERPs) with human participants. Curr Protoc Neurosci. 2010 Jul;Chapter 6:Unit 6.25.1-24.

Liu, Jing & Xue, Gui. "What is the contribution of iEEG as compared to other methods to cognitive neuroscience?", 2022.

Lopez-Gordo, M.A., Sanchez-Morillo, D., and Pelayo Valle, F. “Dry EEG electrodes”, 2014.

Kübler, A., Nijboer, F., Mellinger, J., Vaughan, T., Pawelzik, H., Schalk, G., ... & Wolpaw, J. (2005). Patients with ALS can learn to operate a sensorimotor-rhythm based brain computer interface (BCI). Neurology, 64, 1775-1777.

McFarland, D.J., and J.R. Wolpaw. 2008. “Brain-Computer Interface Operation of Robotic and Prosthetic Devices.” Computer (Long Beach, Calif.) 41, no. 10 (2008): 52–56.

Nielsen, J. (1994, April). Usability inspection methods. In Conference companion on Human factors in computing systems (pp. 413-414).

Noor, A., Umer, A., Umar, A. I., Ahmad, Z., & Khan, M. (2018). Usability evaluation of brain-computer interaction (BCI), based game for normal users. Int. J. Comput. Sci. Netw. Secur, 18(6), 168-175.

Pfurtscheller G, Allison BZ, Brunner C, Bauernfeind G, Solis-Escalante T, Scherer R, Zander TO, Mueller-Putz G, Neuper C, Birbaumer N. “The hybrid BCI”. Front Neurosci. 2010 Apr 21;4:30.

Schomer, Donald L., and Fernando H. Lopes da Silva (eds), Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields, 7 edn (New York, 2017; online edn, Oxford Academic, 1 Nov. 2017)

Si-Mohammed, H., Casiez, G., Sanz, F. A., Roussel, N., & Lécuyer, A. (2019, September). Defining Brain-Computer Interfaces: A Human-Computer Interaction Perspective. In GBCIC 2019-8th Graz Brain-Computer Interface Conference (pp. 1-4).

Soler, A., Muñoz-Gutiérrez, P.A., Bueno-López, M., Giraldo, E., and Molinas, M. “Low-Density EEG for Neural Activity Reconstruction Using Multivariate Empirical Mode Decomposition”, 2020. Frontiers in neuroscience, 14, 175.

Song, Z., et al., "Evaluation and Diagnosis of Brain Diseases based on Non-invasive BCI", 2021 9th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea (South), 2021, pp. 1-6

Sur, S., & Sinha, V. K. (2009). Event-related potential: An overview. Industrial psychiatry journal, 18(1), 70.

Vidal, J. J. (1973). Toward direct brain-computer communication. Annual review of Biophysics and Bioengineering, 2(1), 157-180.

Vidal, J. J. "Real-time detection of brain events in EEG," in Proceedings of the IEEE, vol. 65, no. 5, pp. 633-641, May 1977

Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., and Vaughan, T. M., "Braincomputer interfaces for communication and control.," Clin. Neurophysiol., vol. 113, no. 6, pp. 767–91, 2002.