Decoding 3d hand movement from EEG: A replication of the work by Bradberry et al.

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Abstract

Bradberry et al. [1] has shown that the assumption that brain signals obtained through electroencephalography(EEG) do not contain enough information to decode complex movements such as 3d hand movements is invalid. He showed this by running an experiment where participants had to make self-initiated center-out reaches. He estimated these movements by decoding the EEG signal and showed comparable results to more invasive recording methods. For my thesis I replicated this experiment and showed comparable results to that of Bradberry et al.. However, there were some complications which makes our results not truly comparable.

Keywords: 3d, Bradberry, EEG, movement

Contents

1 Introduction

Brain-computer interfaces (BCIs) use brain signals to deduce the user's intent [10], which allows people with severe motor disabilities to use them, since they do not rely on peripheral nerves and muscles. Therefore, these people could operate a speller or a robotic arm using a BCI. BCIs are however far from perfect and still have trouble making rapid and accurate classifications for more complex problems. One of the complex problems researchers have been trying to resolve is the decoding of multidimensional hand movement trajectories [1, 5, 7, 8]. Being able to rapidly and accurately decode such trajectories could mean giving people who have lost the use of their arm(s) through periperal nerve or muscle damage control over a prosthetic arm. Bradberry et al. did an experiment in which they decoded 3d hand movement trajectories using signals acquired by an electroencephalogram (EEG) [1]. The novel thing about this is that EEG signals have a much lower accuracy when decoding movement compared to signals obtained via electrocorticography (ECoG), magnetoencephalography (MEG) and cortically implanted electrodes.[3]. Because of this lower accuracy there has been a lack of attention on using EEG signals to decode more complex hand kinematics such as 3d movement. However, Bradberry et al. showed that it is possible to obtain comparable accuracies and that the lack of attention was unjustified. For my thesis I intented to replicate the results of Bradberry et al. , and extend upon it by incorporating imagined movement. Just as Bradberry et al. I used EEG signals to decode the users' real movements. With the decoder trained on the real movements, I intended to apply that decoder to imagined movement, where the user imagined executing the movement instead of actually doing it. Due to lack of time however, I did not incorporate this. I will first discuss the background of BCIs and hand movement trajectory decoding in greater detail. Secondly, I will describe the experiment I conducted to replicate the results obtained by Bradberry et al. I will then show that I obtained results comparable to that of Bradberry et al., but that there are some complications with the validity of those results. I will end with the conclusion that the decoding technique of Bradberry et al. is a simple yet effective way of decoding 3d hand movement trajectories.

2 Background

In this section I will begin with an in-depth discussion of the different ways of recording brain-signals and conclude with why it is important to investigate the capabilities of EEG. Secondly, I will show where on the brain I expect to find the relevant brain signals for movement decoding. Thirdly, I will discuss the previous research done on the subject of hand movement trajectory decoding. Finally, I will discuss the experiment of Bradberry et al. in further detail.

2.1 Recording techniques

In this section I will discuss some of the methods used to record the activity in the brain. The activity of the brain is defined by the activity of all the neurons which are in it. When a neuron becomes active, the number of "action potentials" it fires increases. Action potentials are short increases in potential across the axon. The more "active" a neuron becomes, the more action potentials it fires. When an action potential reaches the end of the axon, which is called the synapse, neurotransmitters get released, which causes sodium/potassium pumps to become active on the receiving neuron. This then causes an increase in potential in that neuron, which is called the postsynaptic potential. In figure 1 is a schematic representation of two neurons. The methods I will describe here all incorporate different ways of recording the activity of the neurons in our brain. Gerven et al. [11] also made a small summary of the several recording techniques, and have made a schematic overview of the temporal and spatial resolution of several recording techniques.

2.1.1 Electroencephalography

Electroencephalography(EEG) records electric activity of the neurons via electrodes placed on the scalp. Because this activity has to pass through the skull, which does not conduct electricty very well, the signal-to-noise ratio is very low. The only electric activity from the neurons it is able to detect is the postsynaptic potential, because the electric activity of a single neuron is far too weak to be detected. However, the combined potential of numerous postsynaptic potentials can be detected. Action potentials do not sum up, and thus can not be detected using EEG.

2.1.2 Electrocorticography

Whiile electrocorticography follows the same principle as EEG, the electrodes are not placed on the scalp, but instead directly on the cortex. They both record the electric activity of the brain, but the brain signal does

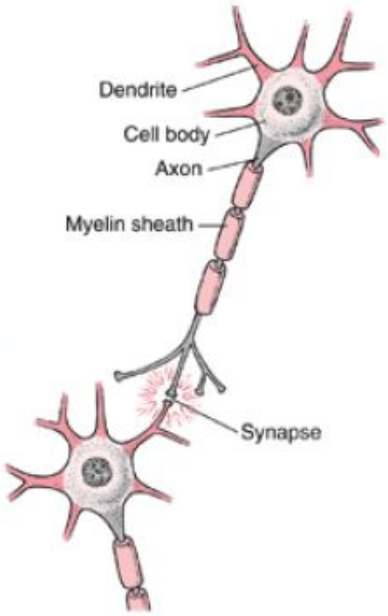

Figure 1: A schematic representation of two neurons. At the synapse is where the neurons connect and where the neurotransmitters get released which causes an increase in action potential frequency.

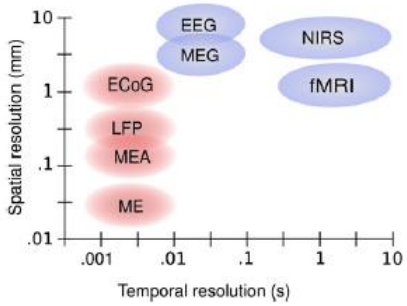

Figure 2: Schematic overview of the scale of spatial and temporal resolution of measurement methods for BCI. Measurement methods are electroencephalography(EEG), magnetoencephalography(MEG), near-infrared spectroscopy(NIRS), functional magnetic resonance imaging(fMRI), electrocorticography(ECOG), local field potential (LFP) recordings, micro-electrode array(MEA) recording and microelectrode(ME) recordings. Non-invasive methods are shown in blue and invasive methods are shown in red.

not have to pass through the skull, which means the signal-to-noise ratio is much better. Furthermore, the spatial accuracy is significantly better. The drawback of this method is that the electrodes must be placed through surgery.

2.1.3 Magnetoencephalography

Magentoencephalography records brain activity via magnetic fields. All electric currents, including the currents in our neurons, cause magnetic fields, which an MEG machine can detect. The advantages over EEG is that the magnetic fields are not disrupted by the skull, which means they have a relatively high signal-to-noise ratio. It also has a far greater spatial resolution. However, the signal is very small compared to EEG. The major drawbacks are that MEG machines are significantly more expensive and not very practical. The signal is disrupted by other magnetic fields, so a MEG has to be recorded inside a chamber which blocks out magnetic fields. As you can see in figure 3, the machine is quite large. Moreover, it requires complete stillness from the user. For these reasons MEG is far from ideal if you want to use it for a real-life practical application such as control of arm prosthetics.

2.1.4 Local Field Potentials Recordings

Local field potentials are recorded by a up to hundreds microelectrodes inserted into the cortex. These acquire the most spatially and temporally accurate signal of the methods discussed here. However, the invasiness of the surgery is even larger than that of ECoG, it causes damage to the brain when inserted and there are some longterm compatibility problems. Polikov et al. [6] investigated the damage it can cause and the brain's response. The insertion of the electrodes can cut through neuron and glial cells. Glial cells support neuron cells by granting structure, protection and nutrients and make up around 75% percent of the brain. Each electrode insertion has 60% chance to cause hemorrhage and 25% chance to cause edema, this may seem a lot but only 3-5% percent of the affected area was actually covered with hemorrhage or edema. They do suggest however that this may have been underestimated due to the analytical methods employed. An electrode can also cause a high-pressure region in the area around it. One of the major responses of the brain is the forming of a "glial scar" after about 6 weeks around the electrodes. A glial scar is an isolation of an electrode by a barrier formed by glial cells. The purpose of this glial scar is unclear, but it reduces the effectiveness of the electrode signifcantly. Reports show that between 40-60% of the electrodes can lose their functionality. However, there are many researchers investigating several ways to solve this problem. Polikov et al. suggest that if these longterm problems can be resolved, implanted

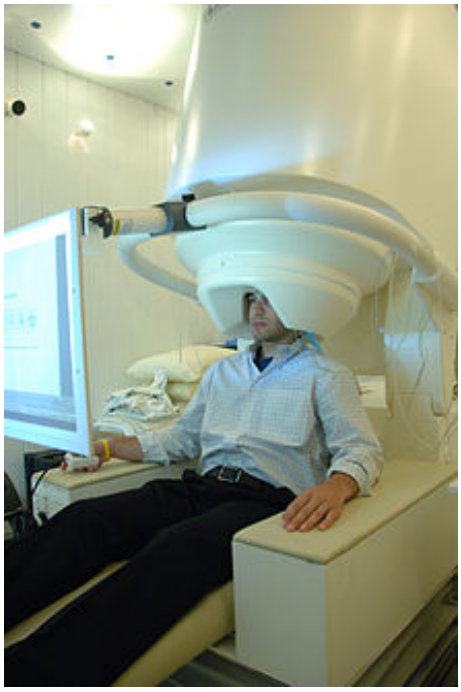

Figure 3: An MEG machine, note how the size of this machine would severely reduce the practicality if it were to be used in a real-life application. MEG recording also requires complete stillness, which reduces the practicality even further.

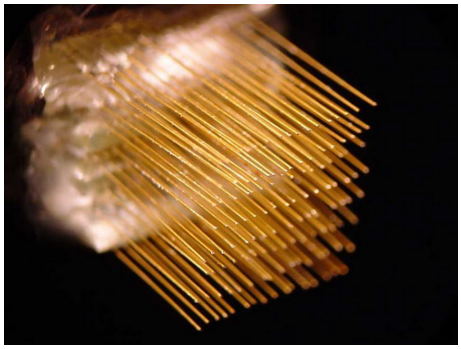

Figure 4: These electrodes can be inserted into the cortex, where they can very accurately obtain readings of brain activity. However, the insertion of these electrodes can cause brain damage which can be risky.

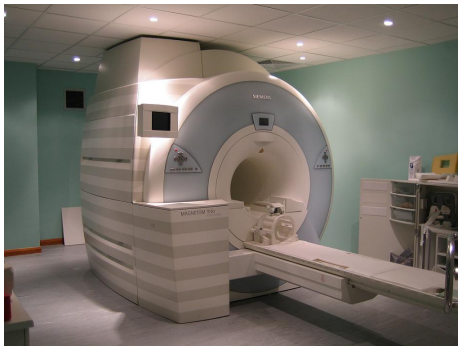

Figure 5: An fMRI machine, this method has the same drawbacks as MEG.

microelectrodes have significant potential for providing control for BCIs such as neuroprosthetic devices.

2.1.5 Functional Magnetic Resonance Imaging

Functional Magnetic Resonance Imaging measures the oxygenation level of the blood. The underlying assumption is that when neurons become active, they require more oxygen. A decrease in oxygenation of the blood causes a change in the magnetic properties of hemoglobine, which an fMRI machine is able to detect. Thus, an fMRI machine can detect where in the brain neurons are becoming active. This technique is very accurate at determing the spatial properties of the activity in the brain. However, because it detects blood oxygenation, the lag between the activity of the neurons and the decrease in oxygenation causes fMRI to be very bad at determining when exactly the neurons started becoming active. It is however impractical for the same reasons as MEG and is relatively expensive: it also requires the subject to be completely still and it requires a large, immobile machine.

2.1.6 Why EEG?

Whilst signals acquired by EEG have a much lower spatial accuracy and signal-to-noise ratio than many other recording techniques, it is a lot cheaper and more practical to use for BCI's than MEG and fMRI and a lot less risky and invasive than ECoG and implanted electrodes. That is why it is important to find out what I can do with EEG, even though it provides us with sub-par recordings. The decoding limits of EEG for 3d hand kinematics and finger kinematics have been investigated by Jose L. Contreras-Vidal et al .(2010) [2]. They tested the accuracy of decoding 3d hand movement and finger and whole hand gestures from EEG.

They tested 3d hand movement using the 'center-out-and-back' task in which participants self-initiated and self-selected one of the eight possible spatial targets to reach for and touch in a given trial. The study showed that the correlation between measured and reconstructed movements compared reasonably well to the correlation reported by studies which used MEG or invasive methods(ECoG).

They tested decoding finger movement by reconstructing finger joint angles during a finger tapping task in which participants were asked to tap their right index finger three times in quick succession in a self-paced manner. It showed that these finger joint trajectories can be reconstructed reasonably well when using EEG. Their results were comparable to studies using invasive methods. Finally, it was suggested that EEG signals provide enough information to reconstruct detailed movement kinematics. They show promising results supporting the idea of decoding 3d movements using EEG signals.

2.2 Where do I expect to find relevant brain signals?

Although I am not specifically guiding the decoder to certain brain areas, it's important to know beforehand at what location I should find the relevant brain signals. Further inspection is needed if, for instance, I find out the decoder is looking at completely the wrong areas but it still has reasonable results, or the other way around. The left precentral and postcentral gyri are the parts of the brain presumed to be responsible for motor execution in the right part of the body, as seen in figure 6. Porro et al. [4] used fMRI to investigate the intensity and spatial distribution of functional activation of these areas during actual movement and imagined movement of self-paced finger-to-thumb opposition movement of the dominant hand(which was the right hand for all subjects, thus corresponding to the area of interest, the left precentral and postcentral gyri). They were specifically trying to determine whether imagined movement has increased activation in the same brain areas as actual movement. They showed that imagined movement has increased activation in the same areas as actual movement, but the

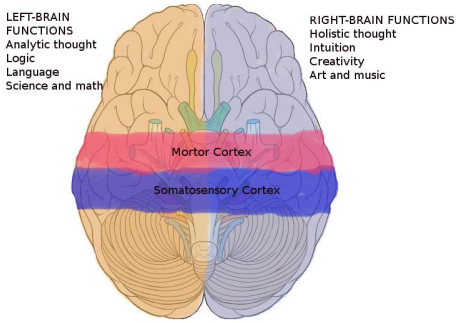

Figure 6: Top view on a brain, the red and blue area(the precentral and postcentral gyri) are parts of the brain presumed responsible for motor execution. I expect to see the most relevant brain signals to originate from the left part of the brain from these two areas, this is simply because in our experiment participants only use their right hand.

increase is about 2-3 times smaller. These are promising results, because they mean I can train a decoder on actual movement and then use it to decode imagined movement. It also has a negative aspect, since the signal strength of imagined movement seems very small. Another important aspect of imagined movement is that the participants should imagine their movements from a first-person perspective (motor imagery, MI), as if they were doing it themselves, and not as if someone else were doing it (visual imagery, VI). Neupera et al.[17] investigated the difference between MI and VI in classification accuracy in a single-trial EEG study. Good recognition rates were only achieved when the participant used the first-person perspective, whereas the recognition was almost impossible when the participant used the third-person perspective. They also support the notion that there is overlap of brain activity between real and imagined movement. However, they do show that thus far there is no consensus whether the primary motor cortex is involved in imagined movement, while it is certainly involved in actual movement.

2.3 Research on hand movement trajectory decoding

In this section I will discuss some of the research that has been done on movement trajectory decoding.

2.3.1 3d robot arm control using implanted electrodes in monkeys

Schwartz [7] investigated 3d robot arm control in monkeys using electrodes implanted into the cortex . In this experiment, monkeys had to complete a reaching task with a robotic arm with 7 degrees of freedom. The monkeys completed the task rapidly and accurately. This research showed that BCIs can obtain very high amounts of control.

2.3.2 Braingate, implanted electrodes in humans

Hochberg et al. [19] investigated the amount of control their braingate system had when used by a 25-year old male tetraplegia patient (MN). The braingate system is an array of microelectrodes, similar to that which Schwartz used [7]. The array was implanted into the motor cortex hand area, known as the "knob", the area of the brain which controls hand movements. Hochberg et al. investigated the amount of control via several tasks in which MN had to use imagined limb movements to control the BCI. One of the tasks MN had to do was following a 2d cursor with his own cursor. The results showed a significant correlation between neural cursor and followed cursor(x: 0.56, y: 0.45), which is equal or better than the results obtained via the decoding of real movement with intracortical electrodes in monkeys. A few of the other tasks were opening a simulated e-mail or drawing a circle in a paint program. MN could also adjust the volume, change the channel, turn a television on/off and was able to play a game of neural pong. MN also achieved control over two prosthetic limbs, which allowed him to manipulate the environment around him. After a few trials, MN was already able to control the opening/closing of a robotic hand. Lastly, MN used a simple multi-jointed robotic arm to transport an object from one place to another. These tasks illustrate control of several devices without requiring computer cursor feedback, however the task dit . This could allow tetraplegic patients to have some ability to manipulate their environment, which could enable, for instance, self-paced eating. Each of these tasks was achieved rapidly and could be completed while conversing, suggesting the amount of disruption when using braingate to control prosthetic devices is comparable to that of able-bodied humans using their own limbs. In other recording devices, for instance EEG, brain signals get can get disrupted by even small movements such as eye-blinks and conversing can make it nearly impossible to obtain a brain signal at all.

2.3.3 2d movement decoding using ECoG

Schalk et al. [5] investigated the effectiveness of ECoG in decoding 2d movement. By showing that ECoG can obtain comparable accuracy they disproved the widespread assumption that the necessary kinematic parameters can only be derived accurately from signals recorded via cortically implanted electrodes. They also discovered a new brain signal, which they called the "local motor potential" (LMP), which contains substantial amounts of information about movement direction as seen in figure 7. It has also later been shown that this LMP can also be detected via EEG. This was a significant step into investigating less invasive ways for decoding movement trajectories.

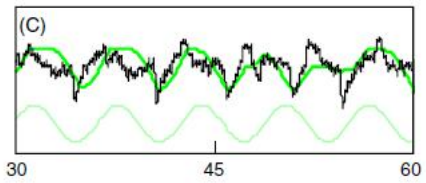

Figure 7: A plot of non-preprocessed brain signal(black) and the actual recorded movement. The slow wave which is highly correlated with the actual movement is called the "local motor potential". This has been taken from a channel situated near the motor cortex.

2.3.4 2d cursor control with EEG by Wolpaw and McFarland

One of the first steps into multi-dimensional movement control with non-invasive techniques (EEG) were done by Wolpaw and McFarland [8]. They focussed on two rhythms in the brainsignal, the mu(8-12 Hz) and beta(18-26Hz) rhythms. After a large amount of training, subjects were able to gain greater control over the amplitudes of these rhythms. Wolpaw and McFarland used an adaptive algorithm which encouraged the users to increase their control in these rhythms. The algorithm was able to adapt in such a way that it would choose to decode from the rhythm the user has most control over. Each user developed two independent control signals which did not interfere with each other: one for vertical movemement and one for horizontal movement. This allowed for 2d cursor control comparable to that of invasive studies.

2.4 The experiment of T.Bradberry et al.

In the previous section I discussed several ways to obtain control of cursors or robot arm. All the methods described were either invasive, impractical or required weeks to months of extensive training. Bradberry et al. went a step further: with a minimal amount of training and setup they were able to online decode 3d hand movement trajectories with EEG signals with comparable accuracies to other methods. In this section I will discuss the setup, preprocessing and decoding of the experiment of Bradberry et al. in detail.

2.4.1 Experiment setup

There were five healthy, right-handed participants, sitting upright in a chair, executing self-initiated, center-out reaches to self-selected push buttons near eye level. These buttons were about 22 cm away from the central target. The subjects were instructed to attempt to make a uniformly distributed selection of eight targets without counting. For each subject, the experiment was concluded when each target was acquired at least 10 times. To minimize

the effects of blinking or eye-movements, subjects were asked only to blink when their hand was resting in the center target and to fixate on the LED on the central target. A researcher was also monitoring eye movements during data collection.

2.4.2 Signal preprocessing

The EEG data were decimated from 1 kHz to 100 Hz by applying a low-pass, anti-aliasing filter with a cutoff frequency of 40 Hz and then downsampling by a factor of 10. A zerophase, fourth-order, low-pass Butterworth filter with a cutoff frequency of 1 Hz was then applied to the kinematic and EEG data. This was done because it was shown by Birbaumer et al. [20] that only slow waves contain information about hand movements. Next, the temporal difference of the EEG data was computed. To examine relative sensor contributions in the scalp map analysis described in the section below, data from each EEG sensor were standardized according to Equation 1, as follows:

$$S_n[t] = \frac{V_n[t] - \mu}{\sigma} \tag{1}$$

For all n from 1 to N, where Sn[t] and Vn[t] are, respectively, the standardized and differenced voltage at sensor n at time t, μ and σ are, respectively, the mean and SD of Vn, and N is the number of sensors.

2.4.3 Decoding method

To continuously decode hand velocity from EEG signals, the following linear decoding model was used:

$$x[t] - x[t-1] = a_x + \sum_{n-1}^{N} \sum_{k=0}^{L} b_{nkx} S_n[t-k] \tag{2}$$

$$y[t] - y[t-1] = a_y + \sum_{n-1}^{N} \sum_{k=0}^{L} b_{nky} S_n[t-k] \tag{3}$$

$$z[t] - z[t-1] = a_z + \sum_{n-1}^{N} \sum_{k=0}^{L} b_{nkz} S_n[t-k] \tag{4}$$

$x[t]-x[t-1]$, $y[t]-y[t-1]$, $z[t]-z[t-1]$ are, respectively, horizontal, vertical and depth velocities of the hand at time sample t. N is the number of EEG sensors, L(=10) is the number of time lags, $S_n[t-k]$ is the standardized difference in voltage measured at time lag k for sensor n, and the a_x, a_y, a_z, b_{nkx}, b_{nky} and b_{nkz} variables are weights obtained through multiple linear regression.

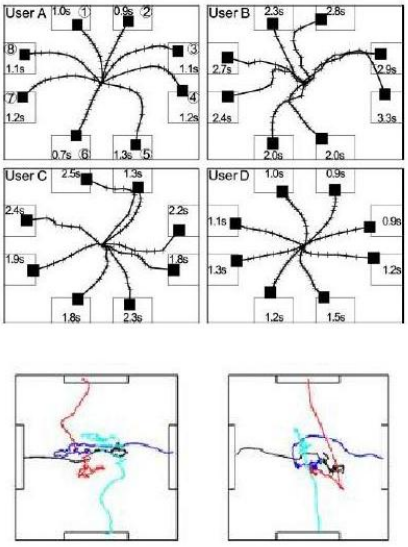

Figure 8: Task of Wolpaw et al.(top) and Bradberry et al.(bottom), note how the task of Wolpaw has twice as many targets as Bradberry et al.: this makes the results of Bradberry et al. not truly comparable to the results of Wolpaw et al.

2.4.4 Later Research

Bradberry et al. later investigated 2d cursor control with imagined movement, using the same decoding technique as in their original experiment [18]. They obtained accuracies comparable to those of other invasive or non-invasive methods. They calibrated their decoder using motor imagery during observation of cursor movement which took about 20 minutes and had a practice session for the participant which also took about 20 minutes before the participant could use it. This is a significant decrease in preparation times compared to those of Wolpaw and McFarland [8], which took weeks or months of training to obtain the level of control needed. It is however important to note that the task of Bradberry et al. was easier than that of Wolpaw et al., as Wolpaw et al. had twice as many targets, as seen in figures 8. This makes the results of Bradberry et al. not truly comparable to the results of Wolpaw et al..

3 Experiment

This section describes how I ran the experiment to replicate the results found by T.Bradberry et al. and how I incorporated imagined movement. With it, I intended to obtain the data to investigate whether it is possible to predict 3d hand movement by continuously decoding the EEG signal, and if so, whether the EEG-signal of the imagined movement can be decoded to predict the average movement of the hand.

3.1 Participants

A total of six healthy, right-handed male volunteers were tested in this experiment. Five of them were between the ages of 20-24 and a very handsome man of only the age 37.

3.2 Software

For this experiment I used the matlab [13] environment. I did this because there are several useful toolboxes available for running BCI experiments. Two of these toolboxes I used were brainstream [12] and psychtoolbox [14]. Brainstream handles all the electrode recording and saving of the data. It also allows other software, such as the software which was used to run the experiment, to place markers directly into the data, which makes it very easy to slice the data into the different trials during the analysis phase. Psychtoolbox has several functions which are useful when writing code for a psychology experiments. Two of the major functionalities psychtoolbox provided for the experiment was the view for giving instructions to the subject and functions which have increased accuracy when determining timestamps of the button-presses.

3.3 Apparatus

A monitor was used to display instructions and the clock which was used for the imagined movement trials. A normal computer mouse was used to allow the participant to indicate clock times. A rigging with four targets and a central button was also constructed from a disassembled computer mouse, buttons and piping used for plumbing, which can be seen in figure 9. I soldered the buttons to some wiring which I soldered to the mouse, so that each button in the rigging was coded as a mouse press.

3.4 Recording

A total of 64 electrodes were used to record the brain activity. Electrodes were placed using the International 10-20 system [15]. The brain signals were

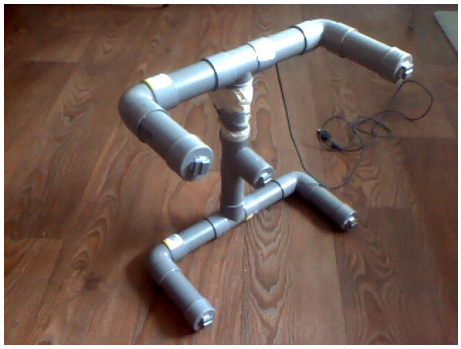

Figure 9: Picture of the rigging. It has 4 targets and a central button and is made from a disassembled computer mouse, buttons and piping used for plumbing.

amplified and recorded at a rate of 2 kHz using a biosemi box. Although T. Bradberry et al. used electrodes strapped to the forearm to record muscle movement, I did not do so. An accelerometer of analog devices [16] was strapped to the middle and index finger of the subject to record the actual movements at a rate of 50 Hz. Our recording systems are quite different from that of Bradberry et al.: I use all the electrodes, our EEG recording device does not already incorporate some preprocessing and Bradberry et al. recorded hand movements via a motion sensing system and a LED on the finger of the subject.

3.5 Procedure

The participants were placed in an experiment booth with the rigging with buttons in front of them on a table, and the fully visible monitor behind that. A normal mouse was on the table. The EEG cap and accelerometer were placed while the participants were reading the instructions. The experiment consisted of two trials: the real and the imaginary trial. Both trials were center-out reaches, self-initiated to self-selected buttons near eye level. The participants were instructed to make uniformly distributed selections of the four targets without counting, for both real and imaginary trials. They were also asked to make their movements, also across real and imaginary, as consistent as possible. Lastly, they were instructed to relax their face and not blink during the trials. The experiment was finished when all four targets were selected at least 10 times for both the imaginary and the real trial, which means there was a minimum of 80 trials.

Before the experiment started, a couple of practice trials were run to ensure the participant understood what he should do at what point. The real experiment started with 10 real trials and then alternated between real and imaginary. Here I will explain what each trial entailed.

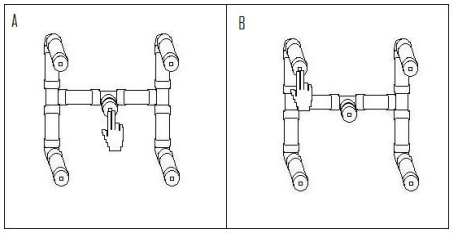

Figure 10: Schematic representation of the real trial. In A the participant presses the center button, at which point a marker is sent to branstream. In B the participant presses a target, where another marker is sent to brainstream and the identity of the target is saved. The data was sliced two seconds before the center press and two seconds after the target press.

3.5.1 Real trial

The real trial was very straight-forward.The screen simply stated that the real trial should begin. The participant had to press the center button and then press one of the four targets with his right-hand using the fingers the acceloremeter was strapped to.

3.5.2 Imagined trial

The imaginary trial was not as straightforward, and had several steps.

(A) The screen stated the imagined trial should start and the participant pressed the center button, indicating he was ready to start.

(B) A clock was presented on the screen, with some text saying "Get ready...", for a period of two seconds. During this time, the participant should relax his arms and make himself ready for the upcoming imagined movement.

(C) The clock started running for five seconds. During this time, the participant should perfrom the imagined movement, while keeping in mind at what time on the clock he started and finished his movement.

(D) The participant indicated the time he started his imagined movement, using the normal mouse to place the pointer.

(E) The participant does the same, but now indicates when he finished his imagined movement.

(F) Lastly, he had to indicate to which target in the rigging he imagined moving to by pressing it.

3.6 Analysis

The results of my preprocessing was similiar to those of Bradberry et al. I also applied a low-pass, anti-aliasing filter with a cut-off frequency of 40 Hz,

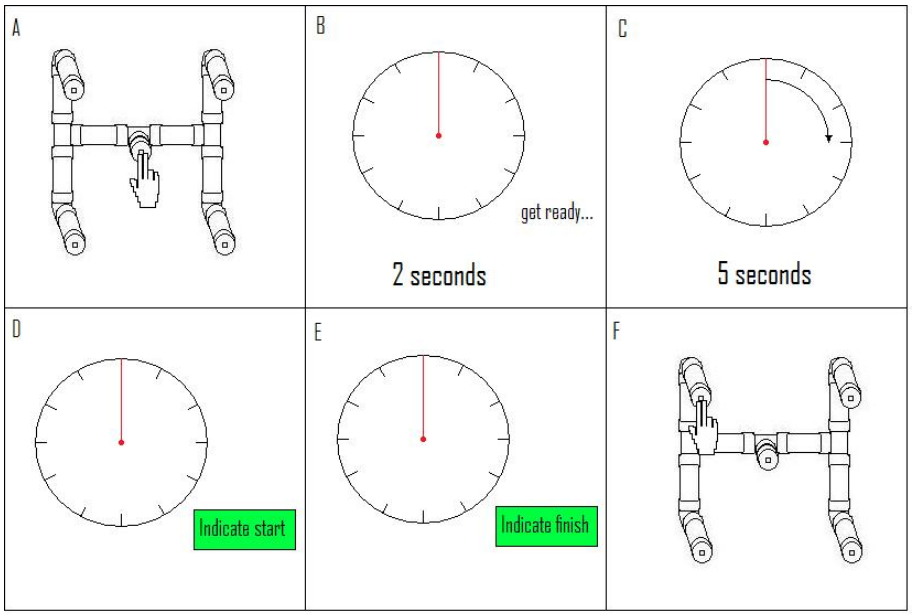

Figure 11: Schematic represenation of the imagined trial. In A the participant pressesd the center button, indicating he was ready to start. In B the clock appears, at which point the participant should relax his arms and prepare for the imagined movement. In C the clock starts running, during this time the imagined movement should be performend. In D and E the participant indicates when he performed the imagined movement, D for when he started it and E for when he finished it. In F the participant indicates to which target he imagined moving to.

but I downsampled by a factor of 20 instead of 10. This is simply because our recording device has a sample rate of 2 kHz instead of 1 kHz, and thus needed twice as much downsampling to obtain a frequency of 100 Hz. I then applied a bandpass filter from 0.5 Hz to 1 Hz. The result of this is similiar to the preprocessing of Bradberry et al., their recording device already applied a filter between 0.5 and 100 Hz, and later applied a low-pass filter of 1 Hz. I also removed bad trials and channels. For the real trials I sliced the data by taking the data 2 seconds before the participant pressed the center button, and 2 after the participant pressed one of the targets. The decoding method was identical to that of Bradberry et al.: I also performed multiple linear regression analysis to obtain weights for the decoding and used exactly the same formulas.

4 Results

My results were comparable to the results of Bradberry et al., argueably they were better. I computed the mean correlation between the measured and computed acceleration across cross-validation folds. The mean decoding accuracy across subjects were 0.45, 0.35 and 0.39 respectively for the X,Y and Z directions as seen in figure 12. Peak performance was a correlation of 0.65, as seen in figure 12. Bradberry et al. obtained average accuracies of 0.19, 0.38 and 0.32 for the X,Y and Z directions respectively.

To check how accurate the accelerometer was, I computed the position of the hand recorded by the accelerometer by taking the cumulative sum of the accelerometer data and then taking the cumulative sum of the result of that; the first one to turn acceleration into velocity, and the second one to turn velocity into position. It is important to note that because the accelerometer was strapped to the participants' fingers and I was not able to place it at the angle needed to make sure that the X direction decoded by the accelerometer corresponds to "left/right", the Y direction corresponds to "up/down", or the Z direction corresponds to "forward/backward". I also computed the variance of the end positions of the movements to each target separately and together to see whether the high accuracies could be due to a low variability of the movement. In figure **??** you can see the variance of all the movements and in figure 14 you can see the average of the variance of the separate targets. There does not seem to be a correlation between the variance and the accuracy which implies that our results are not dependant on the variability of the actual movement. If there were a high correlation

In figures 15 and 16 you can see the results for two subjects, where each different plot represents a different target, which demonstrates how much the recordings could differ from each other. The recordings of subject 4 branch out to several directions, while the recordings of the different targets of subject 6 stay relatively close together.

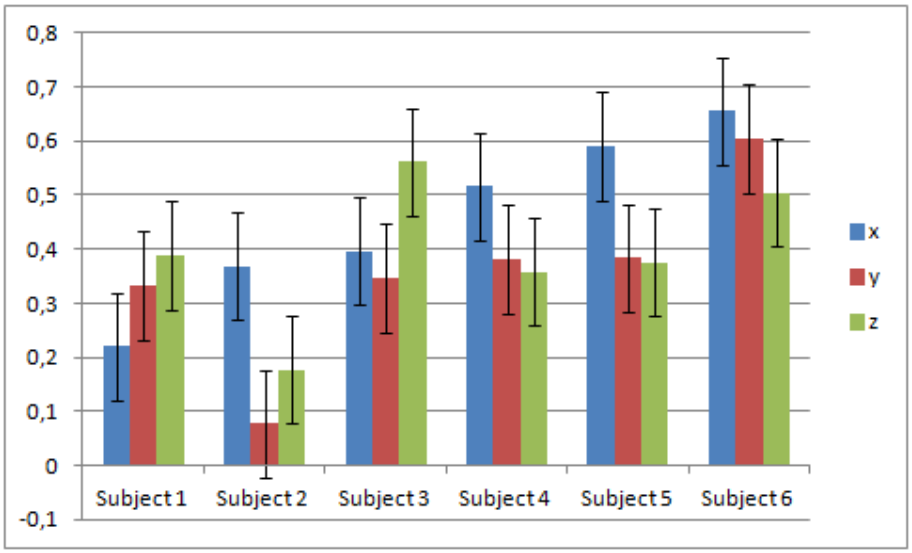

Figure 12: The correlations for the different directions. The mean accuracy across subjects were 0.45, 0.35, and 0.39 respectively for the X,Y and Z directions, these results are slightly better to those of Bradberry et al. who obtained accuracies of 0.19, 0.38 and 0.32 for X,Y and Z respectively. However, I will show that the validity of these results are affected by the lack of accuracy in our accelerometer.

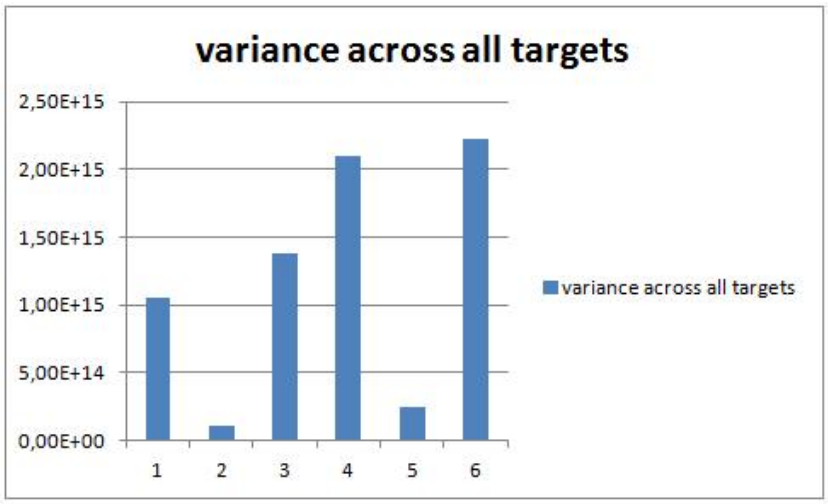

Figure 13: Variance of the end points of the accelerometer recordings across all targets. There does not seem to be a correlation with the results. Subject 5 and 6 have comparable performance but subject 5 has much lower variance.

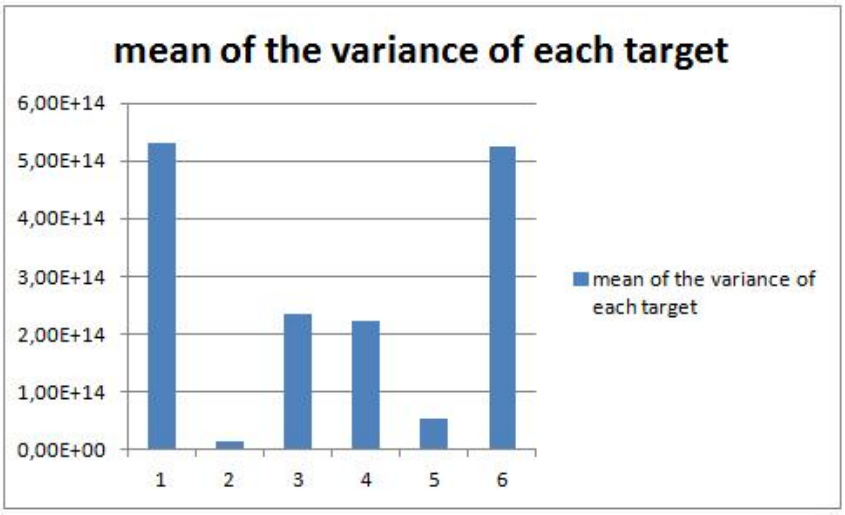

Figure 14: The mean of the variance of the movements towards a single target. Again, there does not seem to be a correlation with the results.

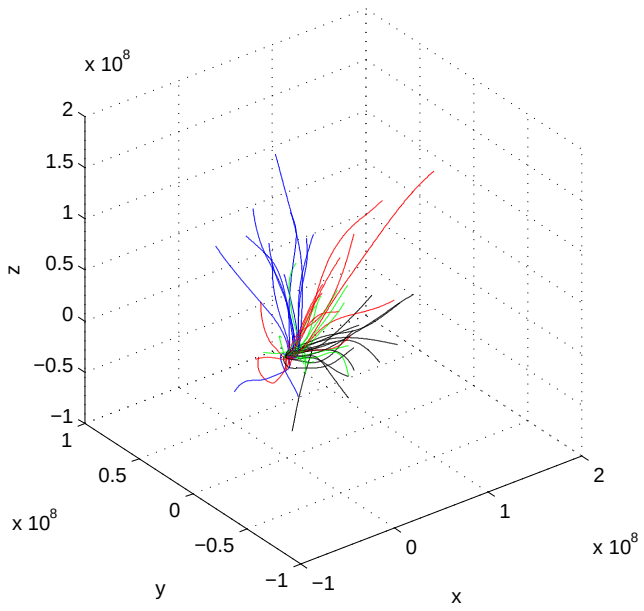

Figure 15: Accelerometer recordings of subject 4. Each different color represents the recordings of the movements towards a single target. Note how they branch out towards the different targets.

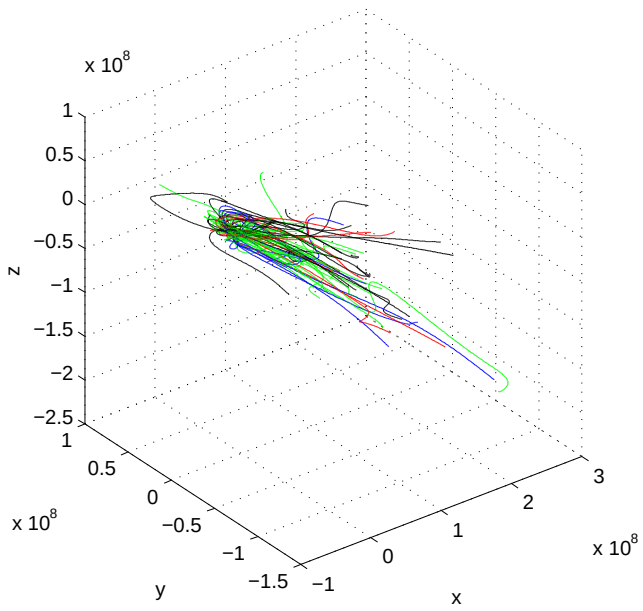

Figure 16: Accelerometer recordings of subject 6, here you can see that the recordings of the different targets are very much alike. Note how they do not branch out nearly as much as subject 4. This could explain why subject 6 has such high performance.

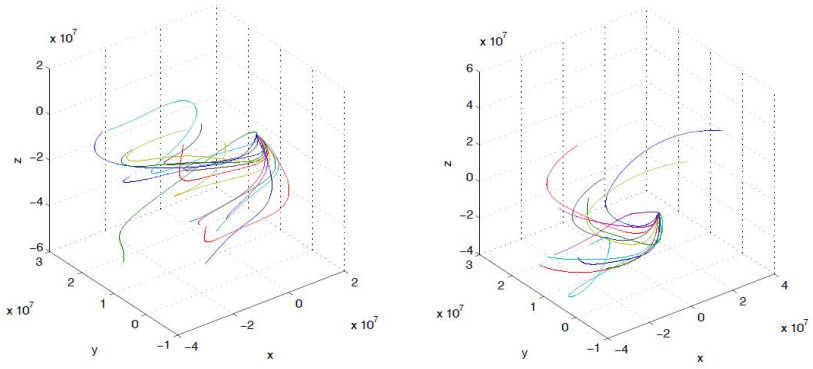

Figure 17: Accelerometer recordings of the trajectories towards a single target, note that the recordings do not converge back into a specific position as would be expected.

In figure 17, you can see two plots of recorded trajectories towards a single target. Note how the recordings do not converge back to a single position as would be expected of an accurate accelerometer. Although these plots represent the most erratic recordings, they do imply that our accelerometer could not have recorded the actual movements accurately, which implies our decoder was not only trained to decode actual movements, but also artifacts created by the accelerometer.

I calculated the sum of the weights b_x, b_y and b_z, as seen in equation 2-4, across all time lags across all trials for each electrode to determine the importance of that electrode for the decoder. I plotted this as can be seen in figures 18 and 19. Although some weight maps showed unexpected areas with great importance, such as in figure 18, some weight maps showed a clear centering around the motor cortex as seen in figure 19. The weight maps showed expected results, because the subject with the least centering around the motor cortex has the worst performance, while the subject with a very clear centering has the greatest performance. This shows that I are decoding from the area of the brain presumed to contain the most information about the actual movement.

These results show that I was able to obtain high accuracies, but that there were some complications with the accuracy of the accelerometer which could have affected the validity of the results. The calculations of the validity have shown that the similarity of the movements is not the reason the subject 6 has such a high performance, as I previously suspected. The weight maps show that our results have validity as I are decoding from the area of the brain presumed to contain most of the most information about the actual movement.

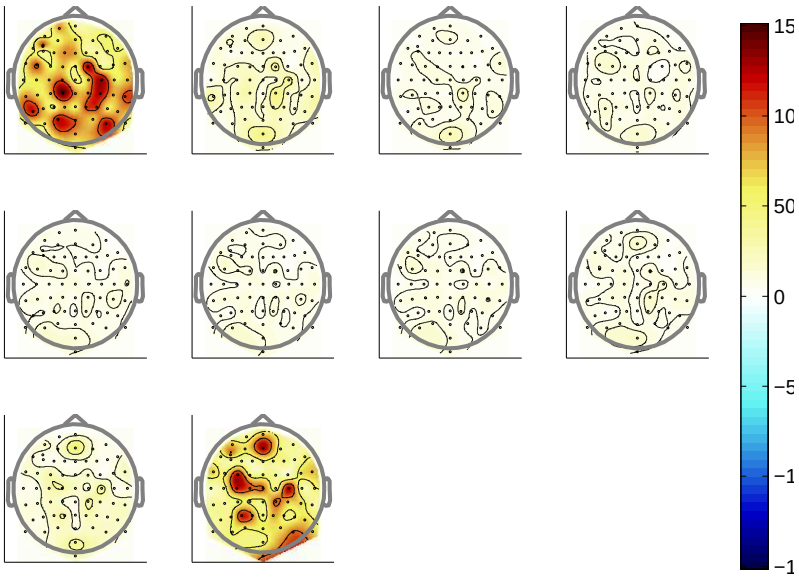

Figure 18: Absolute weight map of subject 2. There are many unexpected areas which are have a large importance for this subject. This subject has the worst performance.

5 Discussion

In this section I will discuss the several differences between my replication and the actual experiment of Bradberry et al. and the implications of those differences, after that I will discuss the implications of the experiment of Bradberry et al. and my replication on research on BCIs. There are several differences between the replication and the actual experiment which I will discuss here. The difference with the most impact was the actual position detector. Bradberry et al. used a motion sensing system and I used an accelerometer. The lack of accuracy of the accelerometer means I cannot truly say I are decoding the real 3d hand trajectory. This means I am not able to conclude definitely that I was able to replicate the results obtained by Bradberry et al. Another difference is that in my experiment there were only 4 targets, and in the experiment of Bradberry et al. there were 8 targets. Bradberry et al. investigated the effect of movement variability on the decoding accuracy and concluded there was a negative correlation, meaning that the more variable the movement, the lower the accuracy. Because my experiment only had 4 targets there were only 4 kinds of movements instead of 8, which implies a lower movement variability, which implies I should have obtained a higher accuracy. Although I did obtain a higher accuracy, I cannot determine how well my participants would have done if

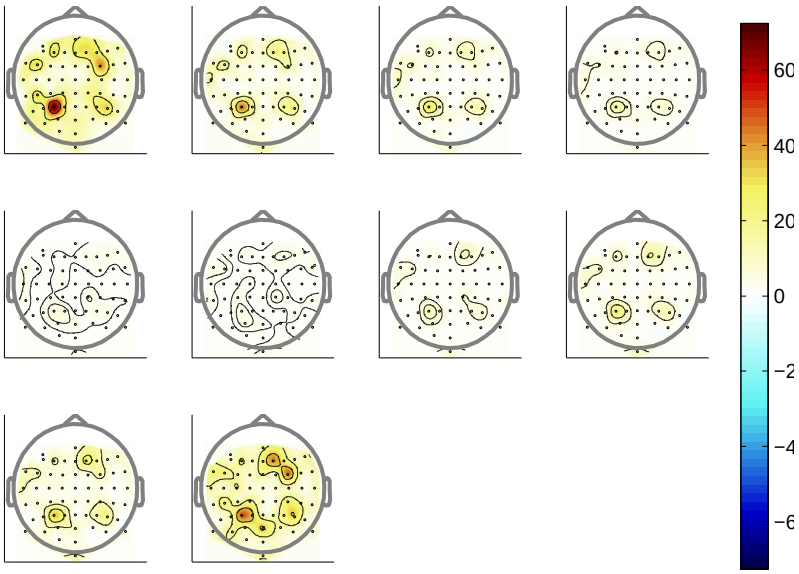

Figure 19: Absolute weight map of subject 6. Although it seems as if the centering is around the parietal cortex, the EEG cap was placed a row of electrodes too much forward, which means this is actually a very clean and centering around the motor cortex. This subject has the best performance. The most important time-lags seem to be the first and the last time-lag. The reason for this could be that I am decoding accuracy and thus determining the difference between these two time points is how the decoder is determining the estimate.

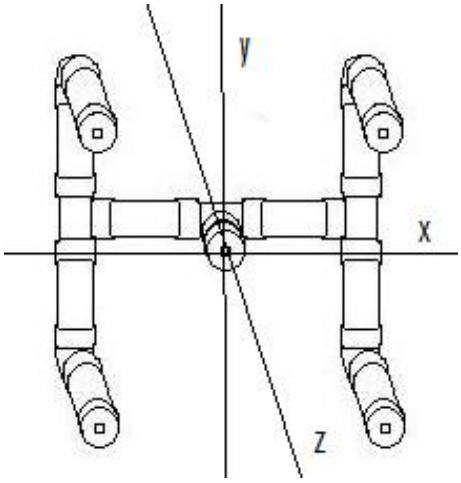

Figure 20: Split the space into 8 areas

there would have been 8 targets. This also makes the results I obtained not truly comparable to the results of Bradberry et al. The final difference between the two experiments is that my decoder was decoding the acceleration and Bradberry et al. was decoding velocity of the movements. This is should not have a significant difference on the results, simply because you are still decoding movement and the only difference is the representation of that movement.

I originally intended to incorporate imagined movement, with the decoder trained on the real movement and tested on the imagined movement. However, due to lack of time I did not incorporate this. To test the accuracy of imagined movement I intended to determine whether I could accurately predict the general direction of the imagined movement. I intended to split the 3d space up into 8 areas, one for each combination of X,Y and Z direction, as seen in figure 20, and test whether the decoder would decode the imagined movement towards the right area. However, the areas are not split up as seen in figure 20. The reason for this is that the X,Y and Z directions as recorded by our accelerometer are not in the same direction for each subject. The angle of the accelerometer for each subject was slightly different, which means the recorded directions are also slightly different. In order to determine the general direction I would have to calculate the general direction by taking the mean of all the movements towards the targets and fit the 8 areas around them.

6 Conclusion

Although there were some complications with the validity of our results due to poor accuracy of the accelerometer and the fact that my experiment has fewer targets, I were able to conclude through the weight maps that the results have some validity. This allows us to conclude that I were able to replicate the results of Bradberry et al. to a certain extent, and that the decoding method of Bradberry et al. provides rapid and effective way of decoding 3d hand movement trajectories and that it is possible to accurately decode 3d movements from EEG signals. In the last decade there has not been many research into decoding multidimensional movement from EEG signals. Although it still has to be shown whether this can be used in real-life applications such as robotic arm control, researchers who have used less-invasive recording techniques have continued to show comparable accuracies to their more invasive counterparts.

7 Future Research

There are several things which can be done to adapt the experiment for future research, and the imagined movement data could still be analysed as described in the results section. This experiment could be repeated, but with a more accurate movement recorder, such as a motion sensing system used by Bradberry et al., which records the actual postion of the finger. The low accuracy of our accelerometer impacted the validity of our results, and resolving this issue would increase that validity significantly.

8 Acknowledgements

I would like to acknowledge several people who helped me complete this thesis. I will start with my main supervisor: Jason Farquhar, he guided me through the whole process and helped solve several problems. I would also like to say thanks to Gerard van Oijen and Ceci Verbaarschoot for the help with setting up the experiment. Finally I would like to say thanks to Renske Janssen for triple checking my thesis.

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