Brains on Fire

Bachelor Thesis

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Abstract

To use a Brain Computer Interface (BCI) for a game that is dependent on timing, a useful brain signal needs to be produced quickly by the user. The purpose of this study was to see if a Lateralized Readiness Potential (LRP) can occur in imagined movement, that could be used to control games that rely on precise timing. This signature brain signal is known to be present in actual movement tasks just before the onset of the movement, but it is unclear if it is present in imagined movement tasks.

A modified version of Frets on Fire, a Guitar Hero clone game, was used, called Brains on Fire. It uses actual drumming and imagined drumming to investigate the occurrence of LRPs. The results of this study indicated that LRPs do not occur in imagined movement tasks. However, the results do show that a BCI game with actual movement, like air drumming, could be used with a high performance accuracy.

Contents

Chapter 1

Introduction

It can be very frustrating and dull to get used to working with a Brain-Computer Interface (BCI). With the use of a game this process can be more fun and less dull. In this thesis, I will describe how I created a simple drum game, based on the Guitar Hero series that will use a BCI as input device with actual movement and imagined movement. The goal of this research is to make a simple functional version of this game and to investigate if it is possible to make a BCI that is dependent on strict timing. Moreover, we want to research if there occurs a Lateralized Readiness Potential (LRP) during imagined movement. This game can be used as a training application for other BCI purposes, which makes the training phase fun and exciting. After this training phase the user is also able to use other applications, like selecting between options or moving a cursor.
The area of brain-computer interfacing has grown rapidly the last decade. This is a result of new technologies and ideas. Brain-computer interfacing is a more specific way to communicate with machines, i.e., human-computer interaction (HCI). Much of the current research within this subject aims at improving the lives of patients with severe neuromuscular disorders, for example amyotrophic lateral sclerosis (ALS). These patients gradually lose control of their bodies and even of simple functions, such as eye-gazing. Because these patients cannot communicate with the external world, they live in social isolation and this might cause frustration. However, these patients are still able to use their higher cognitive functions, which could allow them to operate a BCI (Hinterberger, Birbaumer, & Flor, 2005). The goal of the majority of studies within this field is to provide these patients with a possibility to independently operate machines (e.g., a lightswitch, switching channels on a TV, mechanical prosthetic devices) or to communicate with other people (e.g., spell words). This means that there is no muscle contribution at all to execute these actions. The possibilities to operate machines and to communicate can improve the quality of life extremely for these patients.

However the techniques that are developed can also be used for healthy users. They could use BCI technology for entertainment, such as playing games driven by their brainwaves. BCI systems can also be used for attention monitoring and adaptation. An air traffic controller that loses his visual attention after a long period of being focused on a radar, can be suggested to take a break by a BCI system that detects that he lost is focus (Nijholt, Erp, & Heylen, 2009).

1.1 Non-invasive BCI

There are two different approaches within brain-computer interfacing: invasive and non-invasive. This experiment is based on a non-invasive BCI, which means that electroencephalography (EEG) will be used to measure brainwaves. The brain produces small electric potentials between neurons when you think, act or feel something. To measure these electric potentials, several electrodes are attached to the outside of the scalp of the subject. The signal that the electrodes measure is very weak and therefore, it needs to be amplified. There are also small electric potentials inside the brain that EEG cannot pick up, simply because these potentials are too small to arrive at the electrode (Mason, Bashashati, Fatourechi, Navarro, & Birch, 2007). To analyse the signal that the EEG measured, software is needed. The software has to filter out the noise and analyse the waves using complex algorithms. The goal of the software is to classify the brainwaves, dependent on the task, for example classifying when someone attends to his left hand or to his right hand.
Unfortunately, at the moment, non invasive BCI systems suffer from a performance that is too low to be usable in daily life. Performance is increased by smart classification algorithms and training sessions, but to be usable in daily life it should have an accuracy of nearly 100% (Santhanam, Ryu, Yu, Afshar, & Shenoy, 2006). Other problems with non-invasive BCI systems are inter-subject and inter-session variability (Krauledat, Tangermann, Blankertz, & Muller, 2008). Inter-subject variability means that a device could work properly for one user, while someone else gets a very low performance with the same device. Inter-subject variability can be improved and this is being researched by the Berlin BCI group since 2000 (Blankertz et al., 2008). Because brain patterns are non-stationary over time, a device can work well for a user at one time, but may be unusable at another time for the same user. This is called inter-session variability and this problem has not been solved so far (Roijendijk, 2009).

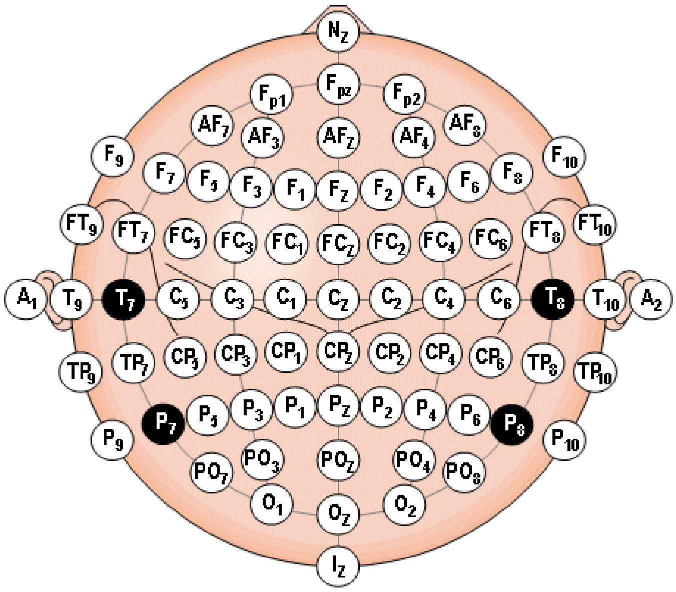

Figure 1.1: International 10-20 system (Klem et al., 1999) illustrating the standard placement of EEG electrodes on the head (Malmivuo & Plonsey, 1995). The letters and numbers correspond to different areas of the brain.

1.1.1 Brain Architecture

Small electric potentials between neurons produced by the brain can be measured and analysed with the use of several electrodes attached to the outside of the scalp (Mason et al., 2007). As stated before, this measuring technique is called EEG. However, what regions are interesting to us, how do we place these electrodes and what can we expect to see?
BCI systems use an EEG cap with fixed places for electrodes, which are named correspondingly to the brain areas. There are different EEG cap layouts, these layouts can contain up to 256 electrodes (Vausanen, 2008). It is important that a cap fits with the head of the user and that the electrodes are of a good quality. A typical EEG cap architecture can look like figure 2.1. The areas that are interesting for this research are the sensorimotor areas, because these areas are known to be responsible for hand movements and they could generate typical signatures that can be used for classification (Wang, Hong, Gao, & Gao, 2007). Especially the electrode channels C3 and C4 cover this important area for hand movements.

1.1.2 EEG Signature

Before, during and after an actual or imagined movement, brain patterns emerge that can be used as signatures to detect if a subject makes a move-

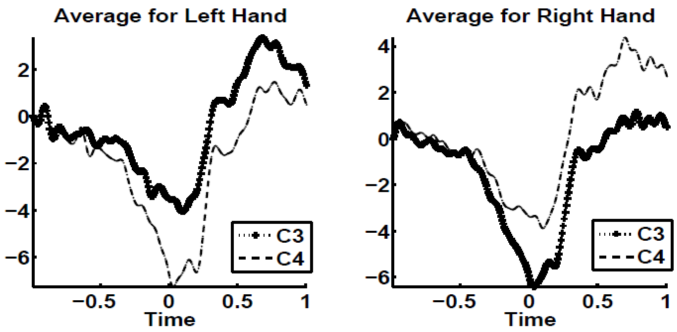

Figure 1.2: The two plots show an example of EEG signals averaged over all trials in a BCI study (Shenoy & Rao, 2005) in the motor-related electrode channels that are called C3 and C4. These figures show a decrease in power around 0 seconds, the onset of the movement.

ment. There are three distinct signatures for these time points. In preparation of hand movements a Lateralized Readiness Potential (LRP) occurs, this is a negative event-related brain potential (Krauledat, 2008). This can be recorded, caused by the way the brain is split up in areas that are dependent on different tasks, the corresponding areas for the left hand movement and right hand movement generate LRPs (Verhagen Metman, Bellevich, Jones, Barber, & Streletz, 1992). During the movement an Event Related Desynchronization (ERD) occurs, followed by an Event Related Synchronization (ERS). The ERD decreases the power in the sensorimotor frequency bands, while the ERS increases the power in the same frequency bands (Pfurtscheller & Silva, 1999).
The signature of the LRP starts around 500 milliseconds before the onset of the event (see figure 2.2), the moment when the actual movement starts. In the ERD/ERS the signature can be seen at 1500/2000 milliseconds after the onset of the event. Moreover, the LRP is measured from the time domain signal, while ERDs are first filtered before the signature can be seen (Sergeant, Geuze, & Winsum, 2007). However, the ERD signals are known to be present in imagined movement tasks (Pfurtscheller & Silva, 1999). It is yet unclear wheter this is also the case for LRPs, studies have not lead to a decisive answer.

1.2 Training

To use a BCI and overcome the problems of a non-invasive BCI, like inter-subject variability, training is needed. Training can increase the performance of the system significantly (Pradeep, Krauledat, Blankertz, Rao, & Muller, 2006). Many samples need to be collected and analysed since there is a lot of noise in non-invasive BCI systems, this needs to be filtered out. There can also be bad samples, by eye blinking, head movement or other or by noise

from the surroundings. By averaging all the good samples, patterns can be found in these average plots, referred to as signatures (Blankertz, Dornhege, Krauledat, Muller, & Curio, 2007). These training sessions typically are repetative and dull, and they can take a lot of time. To produce enough data the user needs to do a simple task over and over again. The produced data is analysed with different techniques, like spatial filtering (Gao, Gao, & Hong, 2008).
With the use of a game, training can be more exciting and fun, and less dull. This can increase the usability of BCIs in general. In this study a game is described and tested, which can make the training phase more fun, but still effective. This can make BCI more accessible for healthy users and it is a step forward in the commercialisation of BCIs.

1.3 Actual Movement or Imagined Movement

A lot of research within BCI is focused on controlling a BCI device with imagined movement, also referred to as motor imagery. Imagined movement is used, because the main goal is to develop products for handicapped people who are not able to use actual movement (Prasad, Herman, Coyle, McDonough, & Crosbie, 2009). Imagined movement can be hard to learn, because it is more unknown to people than doing an actual movement. A BCI can also be controlled with actual movement signals, this can be useful in gaming, for example. The BCI adds a new dimension to the game that can be entertaining. Actual movement is a more reliable (McFarland, Miner, Vaughan, & Wolpaw, 2000) source in comparison to imagined movement in the motor cortex and for healthy users actual movement is a more natural way to communicate.

1.4 Frets on Fire

For this experiment we will use an existing game called Frets on Fire (Kyostila, 2006). This game is based on the popular Guitar Hero games (Kay, 2005), but it is open source software and written in Python (Van Rossum, 1989). It can be run on almost every operating system and is very flexible. Frets on Fire can be played with a keyboard, an external joystick or even a Guitar Hero controller. There is also a very useful song editor tool, to create songs or edit existing ones. Frets on Fire has the possibility to import Guitar Hero songs or random songs stored in OGG format. A midi track can be created manually for the notes and can be edited with the song editor tool. This game can be used for a BCI, it is easy to modify and it is fun to play!

1.5 Our Study

As our previous sections show, there are a couple of things to think about before setting up an experiment. Our goal is to create a game that is playable with a BCI. As stated before, it is important that it can handle quick responses from a subject and gives feedback in a short amount of time, preferably without a lag. Additionally, preferably, training sessions have to be fun. Using actual movement to initially control the game is important to detect the LRP signatures, they can be very clear and typical. We are interested if this also occurs with imagined movement. Literature is vague about this, some say it is in the signal of imagined movement (Kranczioch, Mathews, Dean, & Sterr, 2009) and some say it is not present in the signal (Nazarpour, Praamstra, Miall, & Sanei, 2009). This is a interesting question and our experiment appropriate for this question. The game will effect an LRP in the actual movement task, after training the subject, imagined movement is used and compared with the actual movement data. We investigated the following question:

- Do LRPs occur in imagined movement?

To produce an answer to this question, we created a rhythm game with a BCI as an input device. Actual movement and imagined movement were measured and analysed. In the next chapter the experiment design is clarified.

Chapter 2

Methods

2.1 Experiment Goal

The goal of this experiment was to ivestigate if LRPs occur in imagined movement tasks. Do subjects produce them? And if so, are they suitable to use as a signature to classify between left and right hand movement?
The experiment consisted of a training block, an imagined movement block and a control block. We compared the training block EEG data with the imagined movement block EEG data. We checked for LRP signals, which most probably will be present in the training block, but the question is if they were also present in the imagined movement block. The control block was used to ivestigate the signal-to-noise ratio in our data, and what kind of brain signals a subject is producing just by looking to the game while not playing it.

2.2 Equipment

To record the brainsignals, 64 AG/AgCl active electrodes were used according to the international 10 - 20 system (Klem et al., 1999). The offsets of these electrodes was kept under 25 mV. A Biosemi box amplifier (Honsbeek, Kuiper, & Rijn, 1999) was used to record and amplify the brainsignal. The signals were sampled at 2048 Hz. Electro-oculographic activity (EOG) was measured for detection of eye movements and eye blinks, this was filtered from the data in a later stage. Two electrodes placed directly above and below the left eye, measured the vertical EOG. The horizontal EOG was measured by two electrodes placed on the outer sides of both eyes. Furthermore, arm movements were measured by electromyographic (EMG) activity. Surface EMG was recorded from muscles just beneath the elbow on the right

and left arm. These signals were used to remove movement artefacts out of trials that did not require movement. It was also used during the training phase, to compare the timing of the movement with the signal.
The experiments were run in BrainStream (Severens, 2009) in combination with Brains on Fire, our modified version of Frets on Fire (Kyostila, 2006). In the training block two midi drum-blocks are used. The subject will play the game in this training block with the use of drumsticks. The midi drum-blocks correspond to the left button and the right button. By hitting one of the midi-drum blocks, the button is triggered. With the use of the midi drum-blocks we know the exact points in time where the subject wants to send his signal, this can be used in the training phase to detect the delay in the BCI processing and to train a classifier to distinguish between left and right hand hits.

2.2.1 Brains on Fire

For this experiment we used an existing game called Frets on Fire (Kyostila, 2006). This game is based on the popular Guitar Hero games (Kay, 2005), but it is open source software, written in Python (Van Rossum, 1989). Frets on Fire simulates guitar playing, while our experiment is more suitable for simulating drumming. Guitar playing needs two hands for playing one note, a strum, or rhythm hand and a fret, or melody hand. Moreover, notes can be played long or short, so there is a lot of variability. To simulate this successfully with our BCI equipment is rather time consuming and has a high potential for failure, therefore, making a simulation of drumming is the more effective way to go. To make it suitable for brain-computer interfacing there are a lot of modifications applied. The modifications that are being made are:

1. Disable the rhythm button.
2. Decrease the number of buttons from five to two.
3. Make a larger time span to hit the notes.
4. Create new songs for training and testing.
5. Create a new input device

The rhythm button needs to be disabled, because only one button at a time will be used. The number of buttons is decreased from five to two, because of the simplicity. One button is operated by the left hand, the other button is operated by the right hand. This makes clear what needs to be classified. If it works well, it can be elaborated. Timing and BCI is a important factor in this experiment. The game is dependent on timing, if the user hits a note too late he missed the note, but also if the BCI software takes too long to classify and send the results, the note can be missed. This can be very frustrating, therefore the time span in which a note can be hit, is enlarged with 50 milliseconds. There were no songs with only two buttons, therefore the creation of new songs was needed. A song with different rhythms and isolated beats is used for training and some famous songs with simple drum patterns, e.g., Blur's Song2 and Cocaine by Eric Clapton, are used for later training stages and for the testing phase. The last and most important modification is creating a new input device. The game needs to communicate with the BCI, and vice versa. The BCI software can communicate with the game using a network socket and JSON messages (Bates, Nelson, & Wilmes, 2009). JSON messaging is a simple protocol, and in our case, used to encode the actions that are send from the BCI to the game.

Figure 2.1: An in-game picture of Frets on Fire, the two buttons that we use are red and green. The notes scroll from the upper part of the screen to the bottom of the screen. When the notes pass the button line, the correct button needs to be pushed, in this case the red button needed to be pressed. When a button is pushed it will lit.

2.3 Participants

Six students (Five men and one woman, 20-26 years old) participated in this study. Four of them had participated in a BCI experiment before, including an imagined movement experiment. All participants were right-handed and were free of neurologic disorders.

2.4 Experiment time-line

2.4.1 Preparation phase

To prepare the subject for this experiment, the EEG-cap needs to be attached. The participant is asked to sit down in a comfortable position. When the EEG-cap is attached the midi drum-blocks are adjusted to the preferences of the subject, for example, the height and how the blocks are tilted. A short instruction is given to the subject about EEG in general. Also, a short introduction of the game is given and the subject can already get familiar with the drumsticks. Every subject will hit the drum-blocks differently, especially the force that the subjects use, will differ. A common issue with midi drum-blocks is that users hit the blocks too softly. To measure a baseline the subject is asked to hit the left drum block 10 times. After this calibration, the subject is asked to do the same thing for the right drum-block. Now a threshold can be set for this subject.
This preparation phase, including attachment of the EEG-cap, should take about 45 minutes.

2.4.2 Training phase

Training block

Before the training phase begins, the game will be started. The first block uses the midi drum-blocks, the sensor registers when and which button is pressed or, preferably, hit by the subject. The electrodes attached to the EEG-cap of the subject will register the brain signals that the subject produces in the sequences. The subject needs to hit the target that is shown in the game. The target can be the left midi drum-block or the right midi drum-block. The left midi drum-block is operated by the drumstick in the subject's left hand. The right midi drum-block is operated by the drumstick in the right-hand.
Finally the software needs to distinguish between two classes, left midi drum-block hit or right midi drum-block hit. In this training phase there is

direct feedback from the game, because the subject operates it with the midi drum-blocks and not with brain signals. Initially there will be six sequences. Every sequence consists of one training song with a length of around two minutes. This song consists of simple beat patterns, first a beat pattern is played by the computer, and after this, it needs to be played by the subject. The song will have 70 evenly distributed notes that need to be played by the subject. This will add up to 420 samples of left and right hand hits.

Imagined movement block

For the imagined block, the user gets specific instructions on how to imagine movement. The subject needs to imagine it vividly and not in third person (Prasad et al., 2009). Think about the feeling of hitting the drum-block. After the instruction the block is started. There will be three sequences, for every sequence one training song is used, again without feedback.

Control/Nothing block

To detect what happens in the brain while the subject is simply just watching and listening to the game, we do a so-called nothing block. The subject gets instructed to just look at the screen during the game and without imagining movement. This way we have a control condition to compare to the other data; for example, in the visual brain areas class dependent information could occur, caused by the stimuli on the screen. Moreover, it is useful to know how the brain signal of a subject looks when there are no actions involved. If that signal is known, it is possible to differentiate between actual or imagined movement and non-movement.

2.4.3 Global time-line

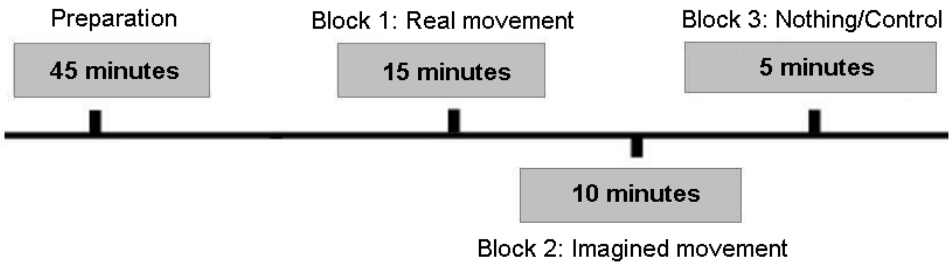

Figure 2.2: Global experiment time-line

- Preparation phase (45 minutes)
  - Attach EEG-cap
  - User Instructions
  - Threshold Detection
- Training phase 40 minutes
  - Block 1: Real movement block (with drumsticks)
    * 6 training songs
  - Block 2: Imagined movement block
    * 3 training songs
  - Block 3: Control/Nothing block
    * 1 training songs

2.5 Data analysis

The methods that were used to analyse the data will be explained in this part. In our experiment, the data analysis took place after the experiment, this was possible since it was an offline experiment. All analyses were done by Matlab (Moler, 1984).

2.5.1 Preprocessing

Recorded raw EEG data includes a lot of environmental noise. This noise can mask the brain signal that is of interest to the experiment. To reduce the amount of environmental noise, preprocessing was used. Our data is gathered by an offline experiment. To analyse this data different techniques were used. First the raw data was down sampled from 2048 Hz to 32 Hz. Next the data was sliced into epochs of 1 second. To remove slow drifts, linear detrending was applied to the sliced data. With an average reference over all channels, the data was re-referenced to improve the signal-to-noise ratio (Vanrumste et al., 2002). After these first steps of preprocessing, bad epochs were rejected. The rejections are based on variances between epochs. The variance of every individual epoch was calculated, also the standard deviation of all epoch variances was calculated. An epoch was removed when the power of an individual epoch deviated more than 3 standard deviation from the mean of all epoch power. Not only bad epochs needed to be removed, the data could also contain bad channels. The rejection of bad channels works in a similar way as the rejection of epochs. When a channel was rejected, the data needed to be re-referenced again. There cannot be a bad channel in the reference, because the accuracy will be decreased by the noise the bad channel generates (Delorme et al., 2010).

2.5.2 Feature selection and classification

After the preprocessing the data will be filtered using a bandpass filter. This step is needed to remove noise and frequencies that are uninteresting to us. We applied a bandpass filter, with a cutoff frequency of 3dB, between 0.75 and 11 Hz. All the frequencies above 12 and beneath 0.25 Hz are completely removed, because they will mainly consist out of noise (Luck, 2005).

An important step is training the classifier. A common approach in BCI research is linear logistic regression (Tomioka, Aihara, & Muller, 2007). This is also what we used, with L2 regularization (Farquhar, 2009), to prevent overfitting. Overfitting means that the training will be too specific on one kind of dataset and will not be able to classify not-seen data decently. After this ten-fold cross validation is used to find the optimal regularization strength.

The data is sliced into ten subsets, subsequently a classifier is trained on nine of the ten subsets. The last, untrained, subset is used for testing the classifier and to get a performance accuracy. The test subset is changed ten times, the ten performances are averaged. This mean will be a representative performance accuracy for the trained classifier.

Chapter 3

Results

3.1 Real movement plots

In this section we show that LRPs occur when playing the game during the real movement training block. When using real movement an LRP can be seen in a event-related potentials plot (ERP). In ERP plots the EEG data of all the trials is averaged, this will suppress all the other brain activity that can be found in the data (Pfurtscheller & Silva, 1999), but are not dependent on the action that the subject needs to carry out.

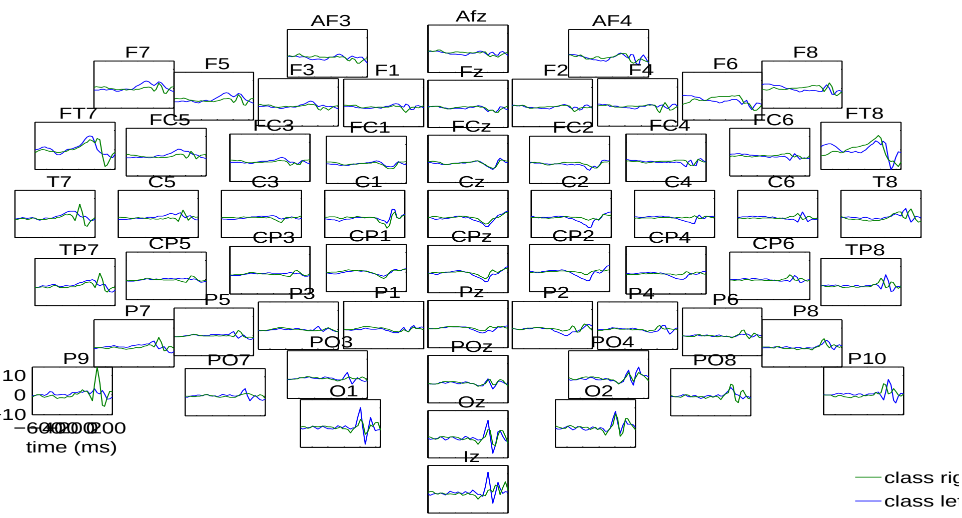

Figure 3.1: An ERP plot of one subject while doing a real movement training block. A typical LRP can be seen in the C2 and C4 region.

In figure 3.1 the ERP plot of one subject is shown, while doing the real movement training block. This is an average of around 700 trials. When we zoom in to the areas of interest (see figure 3.2), an LRP can be seen very clearly in C2 and C4. This subject is representative for the other subjects that participated in this experiments, except for some small deviations.

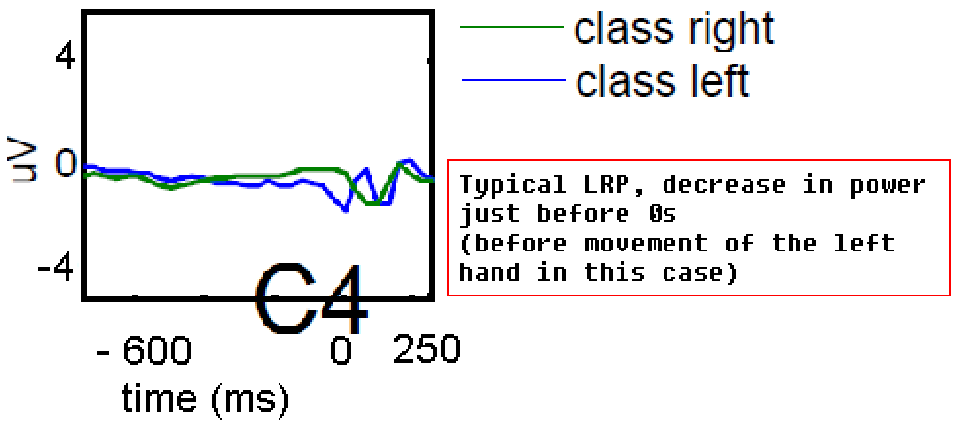

Figure 3.2: Zoomed in picture of the C4 area, where a typical LRP occurs.

The complete ERP plot also shows that there is a lot happening in the visual cortex, respectively in electrode area P9, P10, O1 and Iz. This could be a visual response that is caused by the flashing buttons, but it could also be caused by movement artefacts. Therefore, in addition, data is recorded while the subject only watches the screen. If the visual response is also present in this additional data, it is caused by the visual input that the game gives to the subject, because the subject will not move in this block.

Corresponding to this ERP plot, there is a receicer operating characteristics curve plot, which is shown below. This plot is called an AUC plot (Bamber, 1975). This plot shows a mapping of the electrodes on the scalp. The AUC plot also shows at what time and for which channels the two classes, in our case left versus right, differentiate the most. In this plot we can see which channels are the most responsible for the classification.

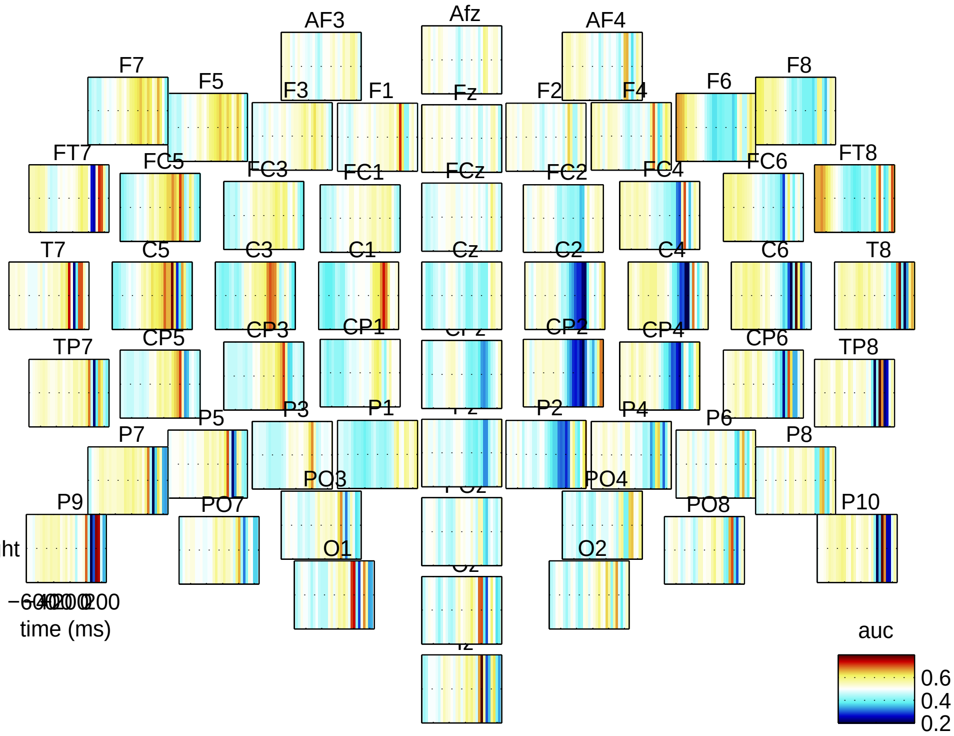

Figure 3.3: An AUC plot of one subject while doing a real movement. Strong colours (e.g., values 0.2 and 0.8) correspond to strong class information, while white colours correspond to weak or no class information (e.g., value 0.5).

Figure 3.3 shows that there are different areas responsible for the classification. Our areas of interest also contribute to this classification: C2, C4, CP2 and CP4 can classify for left hand movement; C1, C3 and C5 can classify for right hand movement. There are also electrodes that tend to leak information, like the electrodes more to the side of the head: T7, T8 and TP8. This can be caused by slight movements of the neck or other muscles around the head. However, it could also be a protracted or inverted signal of the motor cortex. There is some class information in the virtual cortex too, respectively in electrode area P9, P10, O1 and Iz. It could be real class information based on visual information, or it could be caused by movement.

3.2 Imagined movement plots

The question is, are these LRP signatures also visible when imagining the task? To get an answer to this question we take a look at the same plots of a subject, but this time motor imagery is used.

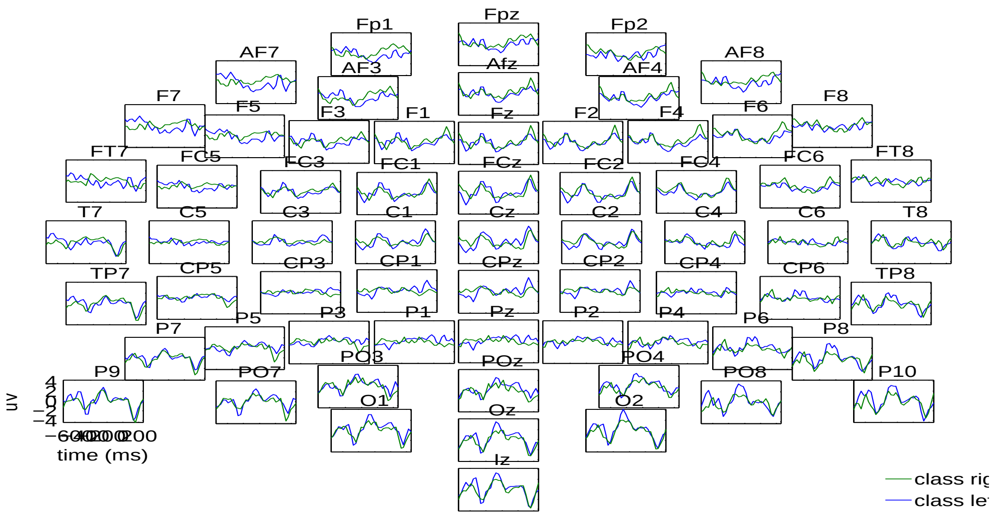

Figure 3.4: An ERP plot of one subject while doing an imagined movement block. There are no LRPs and almost no class dependent information in the areas that are responsible for (imagined) movement.

In figure 3.4 the ERP plot of one subject is shown, after doing the imagined block. On average, this consists of 200 trials. When we zoom in to some areas of interest (see figure 3.5), there is neither LRP nor class information present in the interesting brain areas and time-points.

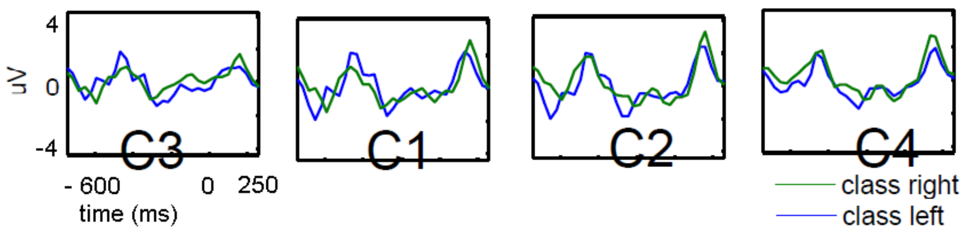

Figure 3.5: Zoomed in picture of the C1, C2, C3 and C4 area, where no LRP occurs.

For this task we can also have a look at the AUC plot, and see where the class information could be located in the brain.

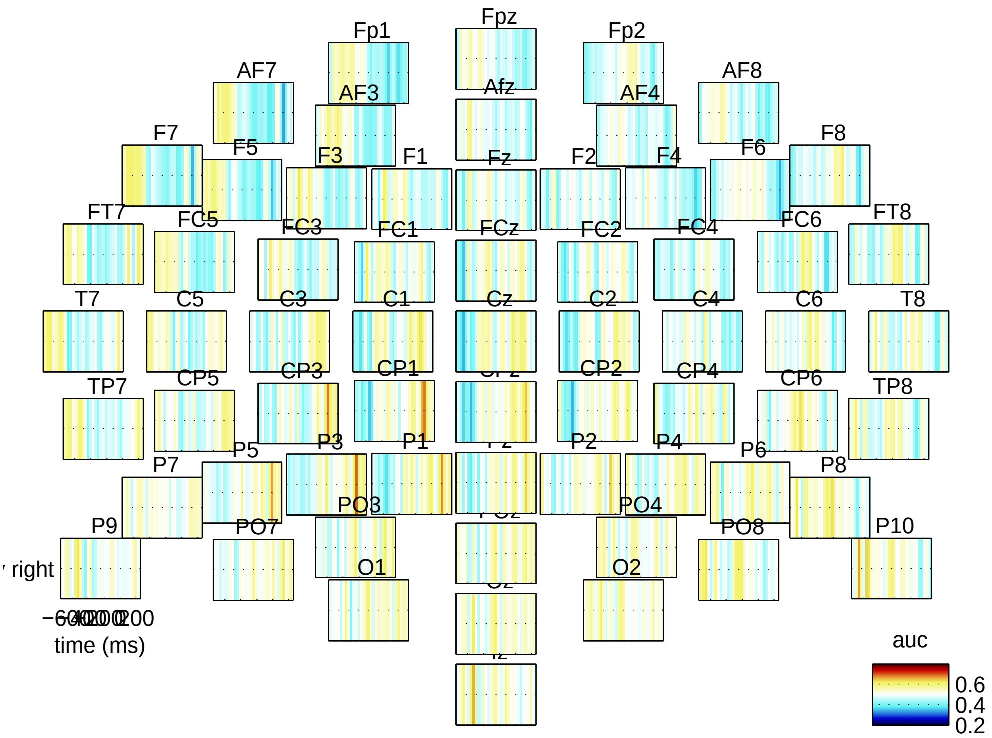

Figure 3.6: An AUC plot of one subject while doing imagined movement. Strong colours (e.g., values 0.2 and 0.8) correspond with strong class information, while white colours correspond to weak or no class information (e.g., value 0.5).

The figure above shows that there is almost no class information around time 0. Using LRP as classification signature and imagined movement to control the game, seems unlikely. In this time window there is no usable class information, the same is true for regions other than the motor cortex.

3.3 Control plots

These previous plots can be compared to an additional condition, the control condition, where the subject is just looking at the screen.

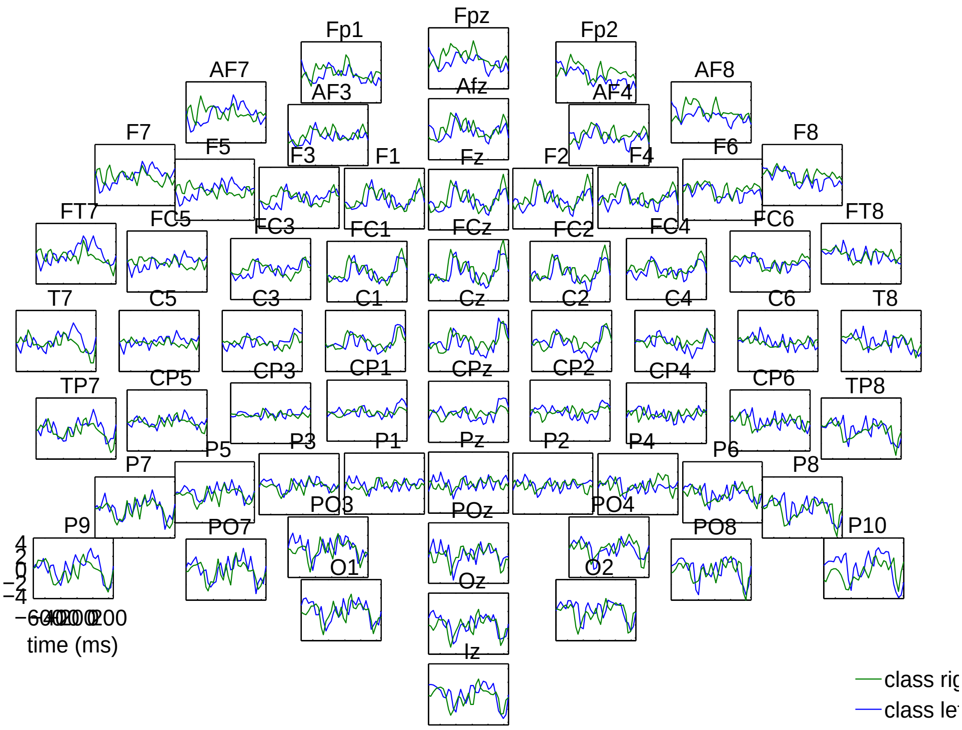

Figure 3.7: An ERP plot of one subject while doing no actual movement, nor imagined movement, but just observing the screen.

A similar pattern as with the imagined movement can be seen above, the regular spikes that occur in the imagined ERP plot (see figure 3.7) around -500 ms in the motor cortex, are also present in this control condition. This could be caused by the visual metronome line that is present in the game.

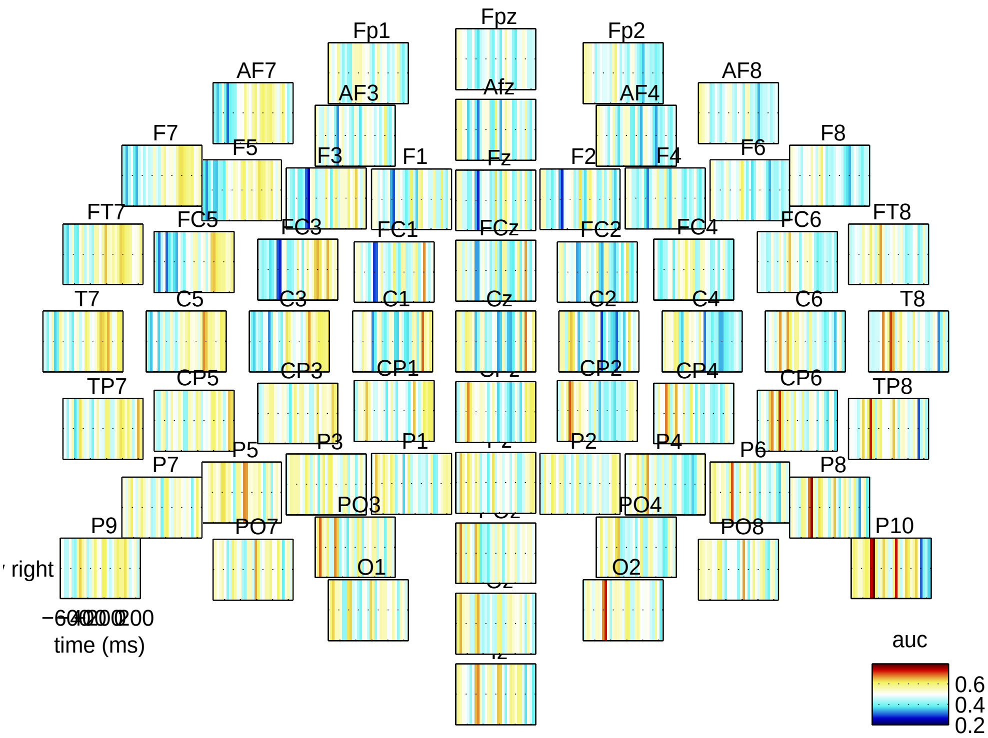

Figure 3.8: An AUC plot of one subject while doing no actual movement, nor imagined movement, but just observing the screen. Strong colours (e.g., values 0.2 and 0.8) correspond with strong class information, while white colours correspond to weak or no class information (e.g., value 0.5).

By looking at the AUC plot (see figure 3.8), it is clear that there is almost no class information present by just looking at the screen around time 0. It is comparable to the AUC plot of the imagined movement.

3.4 Classification performance

In this section, we compare classification performances between the different conditions. We are interested in the difference in performance between real movement and imagined movement.

Table 3.1 shows the cross validated estimated classification performance of all conditions that are tested, using the data analysus method described in section 2.5.

Subjects	Training	Imagined	Control/Nothing
S1	86 (+/-1%)	x	x
S2	92 (+/-1%)	x	x
S3	82 (+/-2%)	50 (+/-3%)	55 (+/-5%)
S4	81 (+/-3%)	*	56 (+/-5%)
S5	64 (+/-3%)*	62 (+/-3%)	55 (+/-6%)
S6	77 (+/-1%)	53 (+/-5%)	x
Average	80	55	55

Table 3.1: Cross validated estimated classification accuracy and standard error rates (in %) for each subject and available conditions. (* indicates that there is probably something wrong with this dataset, some broken markers or a part of the data missing, caused by software problems)

Unfortunately some datasets were broken, because the software did not save the midi time points correctly and therefore the data is impossible to analyse. Looking at the performance difference between the training block and imagined block, we see a big difference of 80% versus 55%. Moreover, the nothing block and imagined block do not show a significant difference, both 55%.

Chapter 4

Discussion

In the reported experiment, we explored the possibility of the occurrence of LRPs in imagined movement. The results of the training block, which uses real movement, are good overall and are as we expected. With an average classification accuracy of 80%, with only one subject with a performance lower than 77%, we can state that in this short time frame around the onset of the action, a good performance can be reached. The standard errors are low, all around 1%.
The results of the imagined movement task are not very high, the average classification accuracy resulted in 55%, which is near chance-level. The standard errors of the imagined movement task are around 5%.
Classification accuracy between the real movement task and the imagined movement task differed a lot. The high classification accuracy from the real movement task indicates that LRPs are present in the brainsignal during this task. Also the standard errors of the imagined movement task are higher than in the real movement task, which indicates that the software is just guessing what the subject did.
The low performance accuracy for the imagined movement task is in line with previous research about LRPs in imagined movement (Nazarpour et al., 2009). We have not found any form of an LRP in our imagined movement task results, neither were there attenuated signals, as stated by certain literature (Kranczioch et al., 2009). The imagined movement task had the same performance as the nothing task, both around chance-level. This also indicates that LRPs do not occur in imagined movement tasks.
The low performance in imagined movement can have several explanations: the task, making big hitting movements, could be difficult for participants, especially for people who never participated in imagined movement experiments before. Participants may have used a wrong kind of imagery, or their timing was not correct. None of the subjects had a high standard error in imagined movement, not even when they had already participated in motor

imagery experiments.
Subject 5 has some remarkable results, the performance of the training block is the lowest of all the subjects, but the imagined movement block is almost as high, both having the same standard error. The low performance in the training data could be caused by the amount of epochs and channels that were rejected out of the data, or by the fact that a part of the data was corrupted by saving problems. Reasons could also be of technical nature, e.g, the type of feature extraction and classification, the corresponding classification window, the equipment. For generalization purposes, more data needs to be be acquired.
Despite the fact that imagined movement cannot be used for this game, actual movement can be used for enabling people to control this game by air drumming. Additionally we ran two experiments without using drumsticks, or the midi drum-pads. The performance accuracy was relatively high, 92% and 75%. Only simple data analysis tools were used, so performance could be higher when using more complex algorithms to analyse the data.
To play a game like this, it is important that the BCI software can analyse data quickly and correctly. The data indicates that the BCI can be accurate enough to play a game with an accuracy of around 80%, only using the EEG data, simple analysis and drumming motions. This indicates that playing games that are dependent on timing and are operated using actual movement, are possible.

Chapter 5

Conclusions and future work

This experiment indicates that there are no LRPs in imagined movement. To prove this, more data needs to be acquired. Furthermore, the data needs to be analysed more thoroughly. Maybe other signatures can be used to control a game that is dependent on precise timing. Unfortunately, known signatures in Brain-Computer Interfacing cannot be used to operate a game that is dependent on precise timing (Pfurtscheller & Silva, 1999).
The results of the actual movement task indicate that it is possible to control this game by air drumming. The game itself needs to be tested online with this actual movement. If this works correctly, new buttons can be added, e.g., a foot pedal. This can be seen as a new feature for games, allowing people to operate games with air drumming.
The results indicate that playing games that are dependent on timing could be operated using actual movement. We only used fixed time points and two classes, left or right. This could be elaborated to an asynchronous BCI, which means it can classify movement in time without fixed time points. Asynchronous BCIs can classify whether there is movement or not for every point in time, if there is movement the same classification can be used for left and right hand movement that we used in our experiment. This asynchronous BCI could be applied to comparable games.
To make it more suitable for healthy users and gamers, a wireless headset could be incorporated in the game (Shende, 2008). The headset would make it easier for people to play the game and it would be more inviting. Also a multiplayer mode could be created and air guitar might actually be introduced. Playing as a whole band with Brains on Fire, the possibilities are endless!

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