Exploring the possibilities of the Emotiv Insight: discriminating between left- and right-handed responses

Bachelor's Project Thesis

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Abstract: A new low-cost EEG device has recently entered the market. The Emotiv Insight is a wireless 5 channel EEG headset which promises to provide meaningful EEG data during everyday use. The goal of this study was to determine whether its measurements can reliably be used in EEG research and whether the device can be used as a Brain Computer Interface.

The Emotiv Insight was used to measure brain activity during an experiment in which participants were consecutively asked to move or imagine movement of either their left or their right hand. Previous EEG research has found that this causes a larger activity in the contralateral brain hemisphere. The data were used to examine whether similar significant differences of brain activity could be found with the Emotiv Insight. The statistical machine-learning methods ridge regression and LASSO were used to analyze whether classification in left and right trials was possible.

No evident differences between conditions were found, only few significant short-lasting differences of activity regarding location between conditions were encountered. Furthermore, the differences that were encountered between conditions contradict previous well-grounded findings. No model fitted with ridge regression or LASSO was able to gain an accuracy higher than chance. The conclusions of this study are that measurements taken with the Emotiv Insight do not prove to be reliable for a classification task as simple as right versus left motor activity and that the device is not recommended as a Brain Computer Interface.

1 Introduction

With his research, Vidal (1973) was one of the first to explore the topic of Brain Computer Interfaces (BCI). He examined the possibility of "utilizing the brain signals in a man-computer dialogue" (Vidal, 1973, p. 157) through electroencephalography (EEG). However, one of his conclusions was that "direct brain-computer communication still lies somewhat in the future" (Vidal, 1973, p. 178), due to the at-the-time shortcomings in signal analysis techniques and computing power. More research on the topic has been done in the subsequent forty years. EEG technology as well as computational technology has advanced, causing BCI to be a an applied science at the present. Moreover, further advances in the field of BCI lead to an introduction of the technology in a new environment. Usage of BCIs has advanced to the world outside of the laboratory and has proven to be useful to healthy users too (Allison et al., 2014). This implies we have arrived at the future Vidal (1973) forecasted.

An obvious application was to use theory in combination with BCI to help those who are disabled to some degree. BCI has for example been used to give people with a locked-in syndrome a possibility to communicate (Birbaumer et al., 1999) and people who are paralyzed a possibility to control a wheelchair with their brain (Galán et al., 2007; Wang et al., 2014). The technology has also proven to be useful outside of the labarotory. An interesting state-of-the-art summary of games using BCI is given by Marshall et al. (2013). Besides applications in games, one could also think of applications in vehicle control, such as control of a car (Zhao et al., 2009). An often used, and in games the most used (Marshall et al., 2013, p. 88), BCI mechanism is that based on the theory about limb movement

Figure 1.1: The Emotiv Insight

Figure 1.2: The Emotiv Epoc

and the corresponding contralateral activity in the brain.

The relation between motor execution (ME) and associated brain regions has been studied extensively in the past. Pioneers in examining this topic in mammals were Fritsch and Hitzig (1870). Their study laid the foundation for the now widely accepted theory that execution of motor movement is caused by activity in the contralateral brain hemisphere, e.g. Kalat (2016). In addition to research on contralateral brain activation during action execution, the relation between motor control and motor imagery (MI) has been explored. Motor imagery is defined as the process in which execution of motor movement is imagined, but no actual movement takes place. Previous fMRI and EEG research has found that MI causes activity in the primary motor cortex as ME does and that both phenomena have anatomical similarities (Jeannerod, 1994, 1995; Porro et al., 2000; Caldara et al., 2004).

Numerous commercialized BCIs have entered the market in the past years (Georgescu et al., 2014). With the production of new devices, questions about performance and usability arise. This study focuses on the Emotiv Insight (Figure 1.1), a new low-cost 5 channel EEG device (Emotiv Inc.) of which production has been funded through a successful crowdfunding campaign. Another low-cost EEG device previously merchandised by Emotiv, the Emotiv EPOC (Figure 1.2), has already been on the market for several years. The device features 14 channels, in contrast to the Insight's 5 channels, and has proven to be reliable in measurements involving MI tasks (Martinez-Leon et al., 2016; Taylor and Schmidt, 2012). This implies that Emotiv does possess the technology and the knowledge to produce EEG devices capable of detecting differences in activity between hemispheres.

The goal of this study is to determine whether the Emotiv Insight's measurements can reliably be used in EEG research. Based on the knowledge about the relations between ME and brain hemispheres and the relations between ME and MI, the device will be tested using an experiment. During the experiment, subjects will be asked to execute or imagine movement of one of their hands, differing per trial. Based on previous research, increased activity in the contralateral brain hemisphere is expected to be found. Furthermore, the same activation patterns are expected to be found during MI.

2 Methods

2.1 Participants

Thirteen subjects participated in the experiment. Seven participants were male, six were female. All subjects were right-handed. All participants were students of the University of Groningen and were aged between 19 and 29, with a mean age of 23.1 and a standard deviation of 2.8. Not all students had English as their mother tongue, but all had an academic level in English. Participants received a monetary compensation in the form of €8 for their participation.

All subjects performed two sessions of the experiment. Subjects participated in another EEG study in between the two runs of the current experiment,

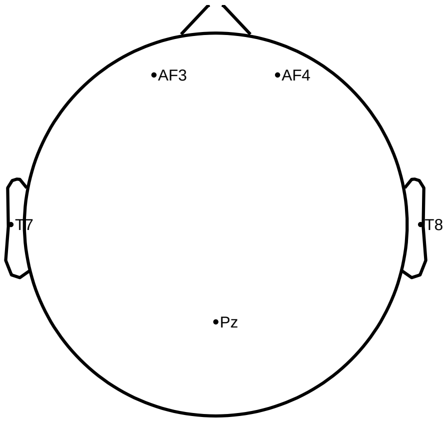


Figure 2.1: Locations of electrodes on the Emotiv Insight

which took 30 minutes. During that experiment, participants were asked to solve equations while their brain activity was measured with the Emotiv Insight. Thereafter, this experiment was conducted once more for a second run.

2.2 Apparatus

The EEG device that was used in the experiment was the Emotiv Insight (Emotiv Inc.). The Emotiv Insight features 7 electrodes, of which 2 are reference electrodes. The remaining electrodes have locations on the scalp according to the 10-20 system (Klem et al., 1999) and correspond to the locations AF3, AF4, T7, T8 and Pz as displayed in Figure 2.1. The connection between the Insight and an iMac, which ran the software, was established through a Bluetooth connection. The software that was used to record the EEG data was Emotiv TestBench (Emotiv Inc.). This software was provided by Emotiv and enables recordings of EEG data per channel, i.e. per electrode. The software that was used to run the experiment was OpenSesame (Mathôt et al., 2012). Markers between OpenSesame and TestBench were sent via virtual COM ports.

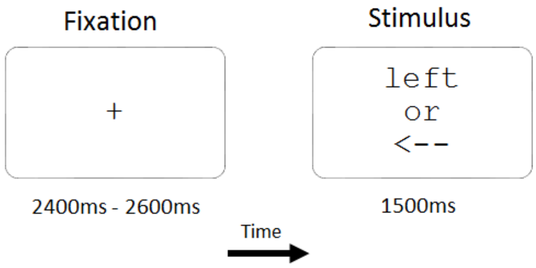


Figure 2.2: Timeline of a trial

2.3 Design

The question in this study is whether it is possible to distinguish between activity in different hemispheres in the brain, based on EEG recordings of participants who move or imagine movement of their fingers on either their left or right hand. The experiment therefore consisted of six blocks:

- Practice: execute movement
- Practice: imagine movement
- Test: execute movement
- Test: imagine movement
- Test: execute movement
- Test: imagine movement

Stimuli were an arrow or text indicating on which side to execute or imagine the movement. The two kinds of stimuli were used in an attempt to exclude systematic errors caused by subjects reading the stimuli or executing eye movement when following an arrow. Both stimuli were centered in the middle of the screen. An arrow was simply an arrow to the left or to the right, text was a string saying "left" or "right". A timeline of a trial is represented in Figure 2.2. Each block consisted of 12 trials, of which 3 trials had a text stimulus and indicated right, 3 trials had an arrow stimulus and indicated right, 3 trials had a text stimulus and indicated left and 3 trials had an arrow stimulus and indicated left. The independent variables therefore were the direction and the kind of stimulus, i.e. text or arrow, and the activity requested, i.e. ME or MI.

2.4 Procedure

Before the experiment, participants were asked to fill in an informed consent and were thereafter fitted with the Emotiv Insight. TestBench was used to make sure the contact quality of the electrodes to the scalp was sufficient. Markers indicated bad (red), medium (orange) or good (green) contact quality, the experiment was started when all markers indicated a good contact quality. Whenever it was not possible to accomplish a good contact quality with a dry electrode, some conducting gel was applied to the concerning electrode. The experiment was then started.

Three screens were first presented to the participants, consecutively asking for their age, gender and handedness. Thereafter, instructions were presented and subjects were instructed to sit as still as possible and rest their hands on the table. Depending on the block, they were asked to move their fingers or imagine movement of their fingers for the duration of presentation of the stimulus. By a click with the mouse, the first block was started. A screen indicating that the block would be a practice block was presented and the subject was asked to move the fingers during presentation of the stimuli. With a click, the loop of trials was started.

Every trial began with a fixation point in the center of the screen for a randomly assigned duration drawn from a uniform distribution between 2400 ms and 2600 ms. After the fixation point, the stimulus was presented for a duration of 1500 ms. The total length of a single trial was therefore between 3900 ms and 4100 ms. The order in which the trials were presented to the subject was randomized per block.

After the first block, new instructions were presented, indicating the type of the following block and the desired action. The same happened for the four test blocks. Each block started with instructions on what the desired action was, ME or MI. After the last block, a screen was presented thanking the subjects for their participation.

2.5 Data processing

The software that was used to process the raw EEG data was EEGLAB (Delorme and Makeig, 2004). The data was re-referenced according to the average over all electrodes, a common technique in EEG data pre-processing (Dien, 1998), and filtered by a low-pass filter of 1 Hz and a high-pass filter of 50 Hz. Furthermore, the data was epoched with epoch lengths of 1500 ms and a baseline of 200 ms. Mean baseline values were subtracted per epoch. With epoch lengths of 1700 ms and a sample rate of 128 Hz, this resulted in epochs with 218 measurements each. Outliers were marked automatically with a lower threshold limit of -75 μV and an upper threshold limit of 75 μV. Outliers were removed manually. Outliers due to eye movement, were not removed from the dataset.

2.6 Data analysis

Data analysis was performed in R (R Development Core Team, 2008) in combination with RStudio (RStudio Team, 2015).

2.6.1 Examining differences between conditions

To analyze differences in means between conditions, paired t-tests with significance levels of 0.05 were applied per electrode per time-step in a trial between the set of average values of all subjects in one condition and in another. The process was executed for each kind of block, i.e. imagination of movement and execution of movement, and for imagination and execution of movement taken together.

Mean voltage over the total amount of subjects per electrode per condition were plotted, including the standard error. The standard error was calculated using the plotrix package (Lemon, 2006).

2.6.2 Classification

The classification algorithms that were used were ridge regression and LASSO, both implemented in the package glmnet (Friedman et al., 2010). Both algorithms were applied in the same manner, hence only one explanation is provided hereafter.

From the original dataset, a random subset a of 12.5% of the set was extracted as a test set. Training was done with the remaining set b, 87.5% part of the dataset. Leave-one-out cross validation was applied to find an optimal tuning parameter λ with a minimal mean cross-validated error. The specified response variable was of the family binomial. The resulting tuning parameter λ was implemented in a model to predict the trials in subset a and calculate the accuracy of predictions.

3 Results

3.1 Examining differences between conditions

Differences between conditions per channel per block were examined. Plots for the ME blocks are presented in Figure 3.1, plots for the MI blocks are displayed in Figure 3.2 and plots for the ME and MI blocks together are presented in Figure 3.3, with arrangements based on the locations of electrodes on the scalp. Plots include the standard error per timestep and significant differences in means between conditions are highlighted in grey.

Effects that were expected to be observed based on the theory, were higher activity measured by the electrodes on the right hemisphere (AF4 and T8) during ME and MI of the left hand, and higher activity measured by the electrodes on the left hemisphere (AF3 and T7) during ME and MI of the right hand. The activity measured by electrode 3 with location Pz was expected to not show a difference between conditions, as the electrode is located at the center of the scalp in between the two hemispheres. Analogously, results were summarized per block in tables 3.1, 3.2 and 3.3, in periods of 500 ms. The summaries are based on trends that were identified in the plots, not only on the differences in means that were found by applying t-tests. Effects other than what was expected based on previous research, are represented by a minus sign. Effects according to what was expected, are represented by a plus sign. No difference between conditions where a difference was expected, is represented by an equality sign. Results from channel 3 with location Pz are excluded in the tables, as no differences between conditions were expected for this channel.

Table 3.1: Summary of differences between conditions for ME blocks based on the plots in Figure 3.1

Channel	0 ms - 500 ms	500 ms - 1000 ms	1000 ms - 1500 ms
AF3	+	=	=
T7	=	=	=
T8	-	=	=
AF4	-	=	=

Table 3.2: Summary of differences between conditions for MI blocks based on the plots in Figure 3.2

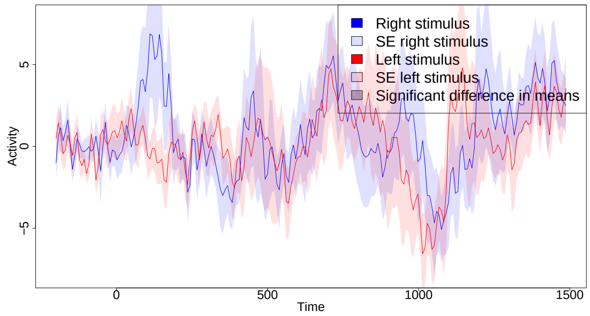
Channel	0 ms - 500 ms	500 ms - 1000 ms	1000 ms - 1500 ms
AF3	-	-	=
T7	+	=	=
T8	-	=	=
AF4	+	=	=

Table 3.3: Summary of differences between conditions for ME and MI blocks together based on the plots in Figure 3.3

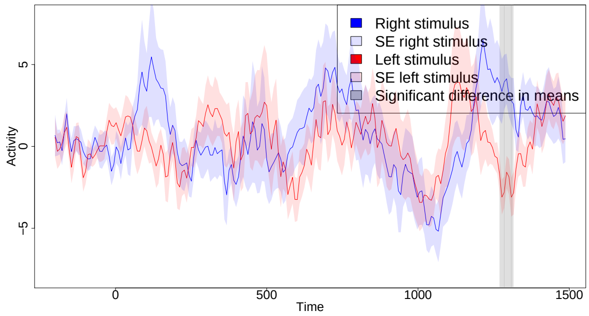
Channel	0 ms - 500 ms	500 ms - 1000 ms	1000 ms - 1500 ms
AF3	=	=	=
T7	=	=	=
T8	=	=	=
AF4	=	=	=

3.1.1 Channel AF3

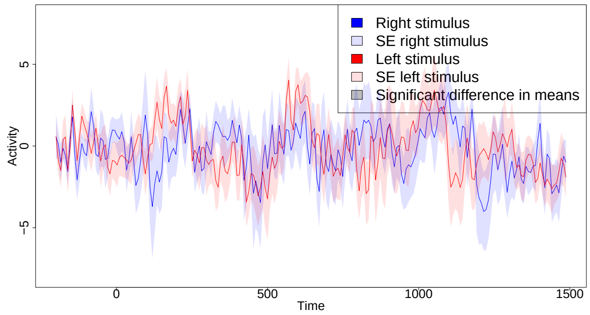
What can be seen in the results from channel 1 with location AF3, is that results vary excessively. Average activity measured during ME as displayed in Figure 3.1a, seems to show an obvious peak after 100 ms when movement of the right hand is desired. This is in line with what is expected based on previous research. However, t-tests do not report a statistically significant difference in means between results taken during right-trials and results taken during left-trials. There is a great standard error during the peak at 100 ms, due to the large variation in average activity among subjects. Furthermore, average activity during MI for the same channel in Figure 3.2a, implies results that do not correspond to what was expected based on previous research. Peaks for left-trials are observed after 100 ms and 550 ms. For the rest of the time-steps during the trials, the plots do not show differences between conditions in all three Figures 3.1a, 3.2a and 3.3a.



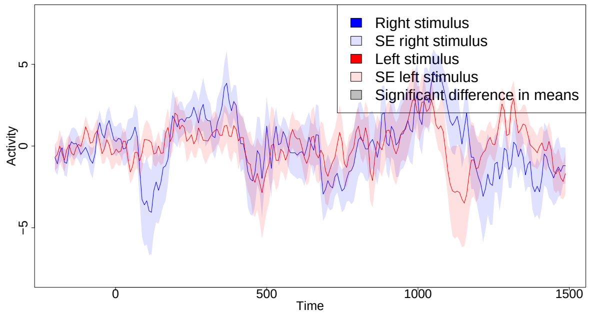
(a) Average activity measured during ME through channel 1: AF3



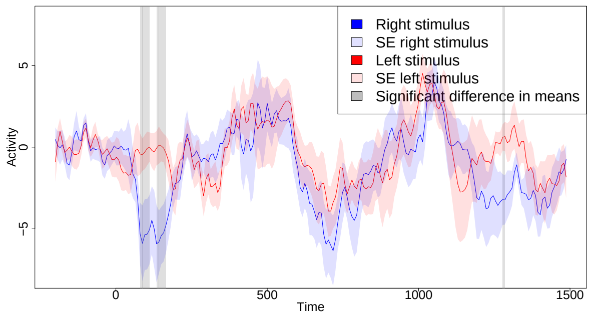
(b) Average activity measured during ME through channel 5: AF4



(c) Average activity measured during ME through channel 2: T7



(d) Average activity measured during ME through channel 4: T8

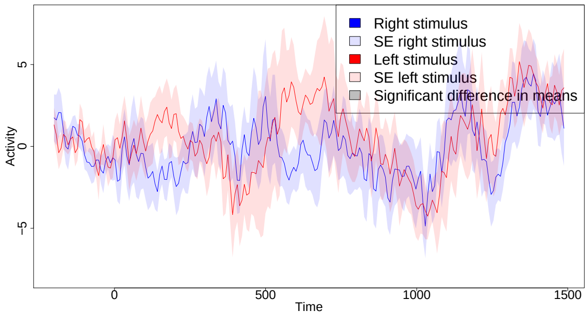


(e) Average activity measured during ME through channel 3: Pz

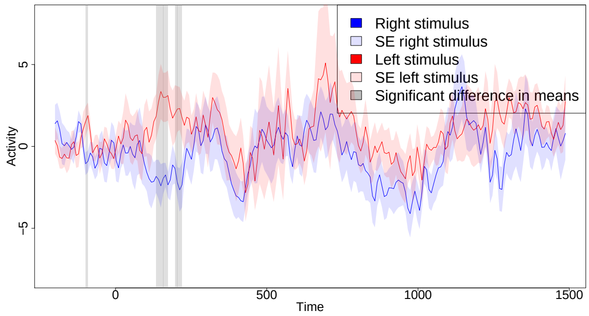
Figure 3.1: Average activity measured during ME per channel

3.1.2 Channel T7

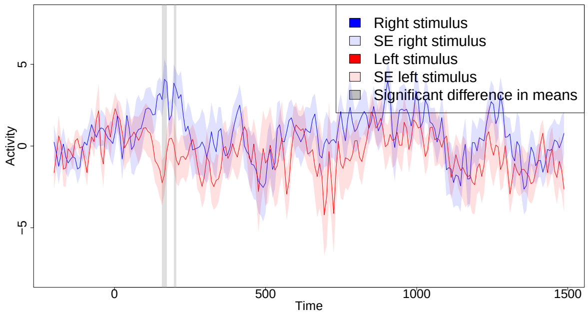
No significant differences in means are recognized in the results from the ME blocks and there seems to exist a high correlation between results from both conditions as seen in Figure 3.1c. Furthermore, results appear to suffer from a lot of noise. Abundant fluctuations are present in the signals and the data contain numerous outliers, resulting in considerable amounts of standard error. Nonetheless, differences between conditions are apparent in the results from the MI blocks, Figure 3.2c. A statistically significant difference in means that supports the hypothesis is present in the early stages of the average trials. Thereafter, as in the ME blocks, cor-



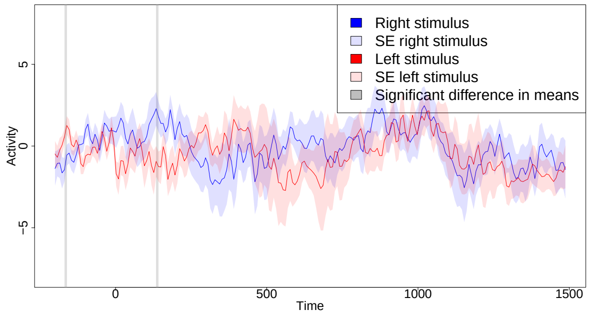
(a) Average activity measured during MI through channel 1: AF3



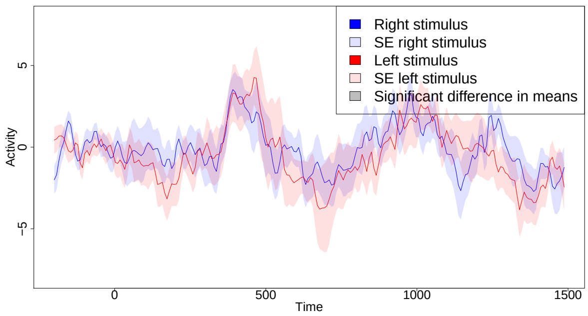
(b) Average activity measured during MI through channel 5: AF4



(c) Average activity measured during MI through channel 2: T7



(d) Average activity measured during MI through channel 4: T8



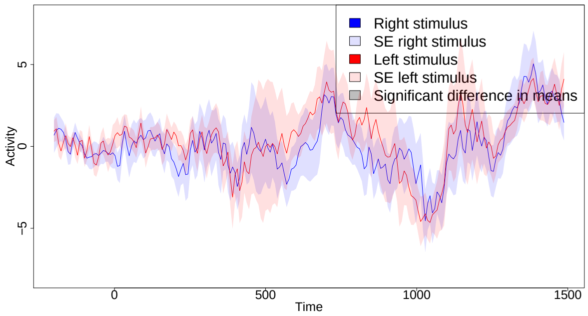
(e) Average activity measured during MI through channel 3: Pz

Figure 3.2: Average activity measured during MI per channel

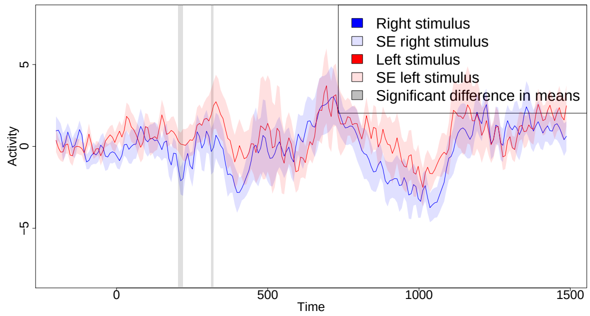
relation between conditions is present. The same correlation goes for the results from the ME and MI blocks together, as displayed in Figure 3.3c.

3.1.3 Channel Pz

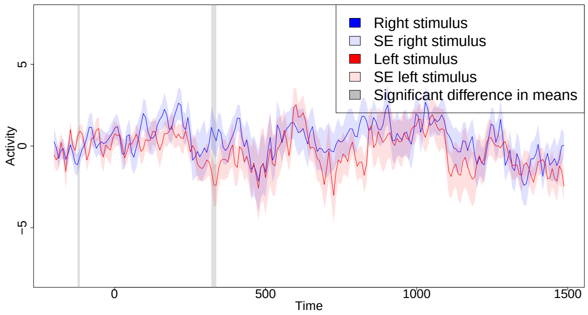
For this channel, no difference between conditions was expected. The location of the electrode is in the center of the scalp, therefore no statistically significant differences were predicted. The results from the MI blocks and especially from the ME and MI blocks together (Figures 3.2e and 3.3e) support the expectations. However, results from the ME blocks as seen in Figure 3.1e show a substantial statistically significant valley in the results from the right-



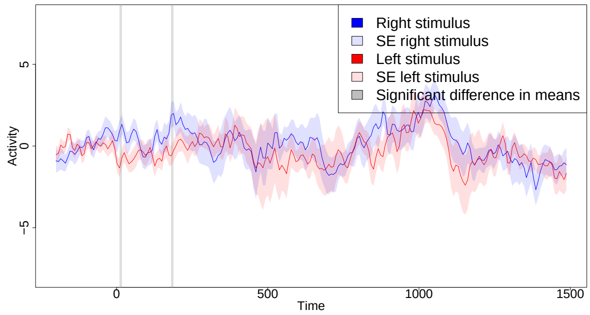
(a) **Average activity measured during ME & MI through channel 1: AF3**



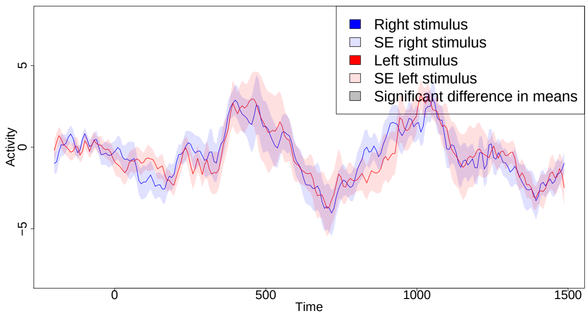
(b) **Average activity measured during ME & MI through channel 5: AF4**



(c) **Average activity measured during ME & MI through channel 2: T7**



(d) **Average activity measured during ME & MI through channel 4: T8**



(e) **Average activity measured during ME & MI through channel 3: Pz**

Figure 3.3: Average activity measured during ME & MI per channel

trials which strongly interferes with the supposition.

3.1.4 Channel T8

Correlation between the signals is present in the results from all blocks. A small valley seems to occur for activity during ME in right-trials (Figure 3.1d). However, this is not statistically significant and it is visually evident that no differences in means occur. In the early stages of results from the channel during MI (Figure 3.2d), t-tests report a statistically significant difference between conditions. Yet, this is short-lasting and it further opposes the hypothesis.

3.1.5 Channel AF4

Channel 5 with location AF4 seems to have quite strong positive differences between conditions in the first 500 ms of the results from the MI blocks, as seen in Figure 3.2b. Thereafter, there appears to be no difference again between results from both conditions. Results from the ME blocks interfere with the results from the MI blocks, as can be seen in Figure 3.1b. A strong peak in activity during right-trials is visible between 100 ms and 250 ms. However, there is no statistically significant difference in means due to the great amount of standard error.

3.2 Classification

Ridge regression and LASSO were performed for every block type. Average accuracy over six runs of the algorithms with different seeds including standard deviation is displayed in Table 3.4. Usage of different seeds resulted in different training and test sets per run.

Classification was examined for both conditions and for both conditions taken together. No classification method was able to produce an accuracy notably better than chance (50% in the case of a binomial problem).

Table 3.4: Average accuracy of classification with corresponding standard deviation in percentage points (p.p.)

	Ridge regression	LASSO
ME	49%, 6.1 p.p.	51%, 5.7 p.p.
MI	44%, 4.2 p.p.	46%, 4.0 p.p.
ME & MI	48%, 7.5 p.p	50%, 4.0 p.p.

4 Discussion

Results do not seem to give one evident answer to the question whether it is possible to measure differences in activity between hemispheres during ME and MI with the Emotiv Insight. Results of one electrode from one type of block, e.g. ME, support the hypothesis, although results of the same electrode from the other type of block, e.g. MI, oppose the hypothesis.

A possible explanation of the poor results during ME, is that movement of the hands significantly influenced the signals, resulting in abundant amounts of noise and poor measurements. Similar effects were observed when setting up the experiment, which is why subjects were asked to sit as still as possible. This assumption is supported by the great extent of standard error that has been observed.

Following the previous assumption, results should be more accurate during MI as no hand movement took place during those trials. This is the case for channel 3 with location Pz, which does not show a significant difference between results from both kinds of conditions. For channels 1 and 4 however, corresponding to locations AF3 and T8, the assumption does not hold. What can be seen though, is that for these negative results the differences between conditions are not undoubtedly significant.

Considering the hypothesis of the current study is based on extensive research (Fritsch and Hitzig, 1870; Jeannerod, 1994, 1995; Porro et al., 2000; Caldara et al., 2004) and consequently a well-grounded theory, similar effects, thus significant differences between conditions, should simply be evident. If not during MI, due to a possible lack of training time for subjects (Li and Zhang, 2012), effects should be visible during ME. Additional measures were taken which are not present during everyday BCI usage, the experiment took place in a quiet laboratory, subjects were instructed to sit as still as possible and conducting gel was applied occasionaly in order to ensure a good contact quality. Results from the Emotiv Insight altogether do not show clear distinctions between conditions during any circumstance, though this should be apparent.

The ability to distinguish between left and right motor execution or motor imagery is a basic competence of any BCI. Whether it is in the process of controlling a wheelchair, a car or any other vehicle or piece of assistive technology, it is key for a BCI to be able to distinguish at least between two kinds of signals with a considerable accuracy, in order to prevent false positives which result in frustration for the user (Georgescu et al., 2014). The current study concludes that the accuracy of the Emotiv Insight does not meet these requirements and usage of the device as BCI is therefore discouraged.

4.1 Further research

Classification using ridge regression and LASSO has not resulted in an accuracy higher than chance. One could argue that the classification methods that were used might not be suitable for classification of the current high-dimensional problem. Previous research has used other classifications methods, also during online classification, such as a neural network by Pfurtscheller et al. (1998). However, based on Borst et al. (2013), an accuracy at least higher than 50 % was expected, as the concerning study was based on only one region in contrast to the two hemispheres on which the current study is based. Further research could explore whether classification methods such as neural networks acquire a higher accuracy in combination with the Emotiv Insight.

Even though the data was filtered and outliers were removed, noise was abundantly present, as can clearly be seen for example in Figure 3.1c. In order to account for the amount of noise in the data, PCA could be introduced. However, with regard to usage of the Emotiv Insight as an online BCI, further transformation of the data using PCA would withstand in the notion of using online data as raw as possible.

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