Brain-Computer Interface using imagined time-locked hand tapping

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Imagining movement is a commonly used mental task in current Brain-Computer Interface (BCI) research. Most BCI systems based on imagined movement need much calibration and training. Much may be won by defining a movement more clearly and adding rhythmicity, thus introducing a tighter time-lock. In this way, the time-dimension can also be exploited. This study aims to develop a BCI system that uses imagined movement while requiring little or no training for subjects to use it. This has been done by doing a BCI experiment that aims to introduce this time-lock to the mental task of imagining movement, and the EEG pattern that arises when rest and movement are alternated. This was done by inducing a tapping tempo that was guided by an auditory stimulus. The goal was to distinguish between imagined left and right hand tapping. Three classification methods were used. The first method, based on Root Mean Square Error (RMSE), had a classification rate between 57% ($p < 0.01$) and 58% ($p < 0.01$) for actual movement, for imagery the results were non-significant. The second classification method was based on a normal distribution and did not give significant classification results in general. The third method was based on Sparse Logistic Regression and had a classification rate between 62% ($p < 0.001$) and 68% ($p < 0.001$) for actual and between 54% ($p < 0.05$) and 65% ($p < 0.001$) for imagined movements. Although classification rates are still modest, the short latencies and absence of a training period show this paradigm to deserve further investigation.

Introduction

Research into Brain Computer Interfaces (BCI), sometimes also called Brain Machine Interfaces (BMI), tries to develop methods and applications that allow people to communicate with electronic devices using only brain activity. Examples are controlling a computer or a wheelchair by performing certain mental tasks. The job of the BCI is to translate measured mental activity to commands that can be understood by an electronic device.

The holy grail of BCI research is to develop an application to help people suffering from Amyotrophic Lateral Sclerosis (ALS) communicate with their surroundings. Patients with ALS suffer from a degeneration of efferent nerves from the motor cortex to the muscles. In the final stadia of the disease, patients are completely paralyzed, but still aware of their surroundings. This is also referred to as the ‘locked in’ state. If these patients could use a BCI to communicate with people and devices around them, this would greatly increase their quality of life.

For a BCI to work, brain activity resulting from a mental task needs to be recorded. There are various recording methods that can be used to register brain activity. These include invasive methods, such as Electrocorticogram (ECoG) and implanted electrodes, and non-invasive methods such as Electroencephalography (EEG), Magnetoen-
ccephalography (MEG, function Magnetic Resonance Imaging (fMRI), and Near Infrared Spectroscopy (NIRS). These methods have all been applied in BCI research (e.g. Hochberg et al. (2006); Kim, Wilson, and Williams (2007); Pfurtscheller et al. (2006); Lal et al. (2005); Yoo et al. (2004); Tsubone, Muroga, and Wada (2007)), although EEG is predominantly used.

There is a wide range of mental activities that can be used to drive the BCI system. A number of mental tasks related to sensory stimulation and interpretation use steady state responses of the brain as a measurement: Steady State Visual Evoked Potential (SSVEP) (Solis-Escalante & Yáñez-Suárez, 2006), Steady State Somato-Sensory Evoked Potential (SSSEP) (Müller-Putz, Scherer, Neuper, & Tsubone, Muroga, and Wada (2007)), although EOG is predominantly used.

For an imagined movement paradigm, there are different kinds of imagined movement that can be used. Imagined movement can be subdivided into a visual-motor mode of imagery and a kinesthetic mode of imagery (Neuper, Scherer, Reiner, & Pfurtscheller, 2005). In visual-motor mode, subjects visualize the imagined movement. This can be done either from first person perspective, where subjects visualize their own hands moving, or from a third person perspective, where they visualize someone else’s hands moving. In the kinesthetic mode of imagery, subjects imagine what it would feel like to actually perform the movement.

Although the imagined movement paradigm is used often in BCI applications, it requires many hours of training for subjects to be able to use such a system effectively (McFarland, Sarnacki, Vaughan, & Wolpaw, 2004; Pfurtscheller et al., 2006).

The main question in the current research is whether it is possible to create a BCI system based on an imagined movement paradigm, that can be used without intensive training. In order to test this, an offline experiment was set up that tries to exploit the pattern that arises when rest and movement are alternated rhythmically. In order to capitalize on this mechanism and introduce a higher time-lock, an experiment is described here in which a time-locked hand-tap has been used. The time period analyzed in this case consists of a period of rest followed by a period of (one-single) movement. It is expected that ERD and ERS are alternated in this data segment, i.e., an ERS is expected in the rest period and an ERD is expected in the movement period.

The subjects were instructed to imagine how it would feel to make the hand tap, and try not to visually imagine it. In other words, participants were urged to use the kinesthetic mode of motor imagery instead of the visual-motor mode. The main reason for this is that the visual-motor mode does not have a clear spatial pattern as opposed to the kinesthetic mode, where the focus of activity was found in the sensorimotor hand area (Neuper et al., 2005). A method of realizing this is to hide the subject’s hands from sight.

To classify the motor imagery, three classification methods were used. Two of these utilized all features and the third first selected a number of features to use in classification. The first method was based on the Root Mean Square Error of the trial to be classified with the average of all trials in a certain class. The second method used the probability that the trial to be classified belonged to a normally distributed set of features. The last and
most complex method is based on Sparse Logistic Regression and performs the feature extraction and classification in one.

Methods and materials

Subjects

Three subjects participated in this study. Two subjects were male, one female, aged 30 to 51 years. They were all free of medication and without central nervous system abnormalities. They participated voluntarily and were not paid for their contribution.

Stimuli

A continuous auditory stimulus was used in the procedure. It consisted of a base frequency of 300 Hz. This base frequency was used during the rest period, where both hands are resting on the table. This resting period is 750 ms long. During the movement period, the frequency of the sound rises gradually to 400 Hz over a period of 500 ms, corresponding to the rising of the hand. Then, it quickly falls back to the base frequency of 300 Hz in 250 ms, corresponding to the falling of the hand. When the hand is to land there was an increase in the amplitude of the sound, resulting in a kind of tick. This means that the whole movement section is 1.5 seconds long, where the hands are in rest for 750 ms and in movement for 750 ms. This sound is repeated throughout the trial. A visual representation of the sound is shown in Figure 1.

A video of tapping hands was used in the observed movement task. This video was recorded in such a way that it looks like the participant is observing the hand of someone on the other side of the table move. An example frame of the video can be seen in Figure 2.

Equipment

The stimuli were presented using Logic Express 7.2, on an iMac PowerPC G5 with 2.0 GHz processor and 2.0 Gb of memory, running Apple Mac OS X version 10.4.10. The stimuli were displayed on a 17" TFT screen. EEG was recorded using 256 sintered AG/AgCl active electrodes. The EEG signals were amplified using a Biosemi ActiveTwo AD-box and sampled at 2048 Hz. This data was recorded on a Sony VAIO, with a 2.0 GHz processor and 1.0 Gb of memory, running Windows XP Professional SP2, using the Biosemi Actiview software version 6.04. Subject’s EEG
signal was recorded in an electrically shielded cabin to minimize contamination of environmental noise. A foot pedal was used for participants to indicate when to start the next trial.

Procedure

The experiment was partitioned into six blocks. Each block consisted of 12 trials. The trials were subdivided into four tasks: rest (used as baseline), observed movement, actual movement, and imagined movement.

A trial starts with a baseline measurement, where the subjects were asked to relax and look at a fixation cross in the middle of the screen. After a cue (the text "kijken"), came the observed movement task. Here, the subject watched a video of someone tapping one of his hands, timed by a sound (see Stimuli). This sound, with pitch height reflecting hand position, starts at the beginning of the trial and continues through to the end of the trial (45s in total). The observed movement task was also used as an instruction of the type of trial (left hand versus right hand trial): when the participant saw the hand on the left side of the screen move, it indicated a left hand trial and vice versa. Subjects saw five of these subsequent movements in this observation task. After another task change cue, there was an actual movement task. Here, the participants were asked to mimic the movement they had observed in the previous task. They had to perform five actual movements in this task. As mentioned earlier, the sound continued throughout this task to time their actions. After yet another task change cue, the imagined movement task started, this was also the last task of the trial. The subjects were asked to imagine making the movement they had observed and performed earlier, again paced by the auditory stimulus, and do this 10 times. A graphical representation of this paradigm can be seen in Figure 3. During the experiment, the hands of the subject were obscured to keep the visual stimulus identical during the actual movement and imagined movement periods.

The subject’s hands were hidden from sight during the experiment to keep the visual stimuli during the different tasks as similar as possible. As the subjects were not able to see their own hands move during the actual movement task, it also becomes less likely that they will use a visual-motor strategy of imagined movement.

Subjects were able to press a foot pedal to control when the next trial would start. This allowed participants to move or blink in between trials. The trials consisted of left hand trials and right hand trials, which would appear in random balanced order, i.e., six left hand and six right hand trials per block.

Data analysis

As the possibility of using this paradigm for BCI is the topic of the current research, the data analysis will focus only on classification results. Therefore no statistics are performed on the differences between conditions, only on the classification of this data.

Preprocessing. Preprocessing of the data was done using EEGLab (Delorme & Makeig, 2004), and consisted of a number of steps. First, to make the data-sets more manageable, the data was down-sampled from 2048 Hz to 256 Hz. After down-sampling, bad channels were removed by visual inspection. Next, the data was re-referenced using an average reference over the remaining channels. To improve the signal to noise ratio and to keep processing time during feature extraction and classification to a minimum, the data was spatially down-sampled to a standard 64 channel layout, using spherical splines interpolation (Perin, Pernier, Bertrand, & Echallier, 1989). See Figure 4 for an overview of the 64-channel layout (10/20). To remove eye-blinks from the data without removing trials, Independent Component Analysis (ICA) was used (Delorme & Makeig, 2004). The ICA component that contained the eye-blinks was removed from the data and the remixed data was used for feature extraction and classification. Lastly, the data was highpass filtered with a threshold of 2 Hz and movement artifacts were removed using visual inspection.

Feature extraction. Feature extraction was done using Matlab and the Fieldtrip open source Matlab toolbox (http://www.ru.nl/fcdonders/fieldtrip/) that was developed at the F.C. Donders Centre for Cognitive Neuroimaging. The ERD/ERS, as described by Pfurtscheller and Da Silva (1999) was calculated. The method they describe for calculating the ERD/ERS is theoretically the same as the one used here in extracting the features. To obtain power in certain frequency bands (from 5 Hz to 40 Hz).
Figure 3. An overview of the experimental design. It shows the four tasks in each trial. It starts with a baseline period of 6 seconds, followed by a cue and the observed movement task. After another cue, the actual movement task starts. The trials ends with another cue and the imagined movement task. The time indicated is the time the screen indicated with the screenshot before it is displayed to the subject.

Figure 4. Standard, 64 channel 10/20 layout used in the experiment.

Hz, with bandwidth of 1 Hz), we used the Fourier Transform. To be able to analyse low frequencies from 5 Hz and upward, the data was partitioned into segments of 3.5 seconds, with the trial (1.5 seconds of rest and movement) in the middle. This means there is one second overlap with the previous trial and 1 second overlap with the next trial. A time frequency representation (TFR), in this case a power spectrum, of this data segment was made using Fieldtrip. This was done using a frequency dependent Hanning window of four cycles (Challis & Kitney, 1991). This resulted in a power value for each time point x frequency x channel combination for the data segment. Each feature that was used consisted of the mean of a time range for each frequency x channel combination. Only the data of the trial (the 1.5 seconds in the middle) was used, the 2 second of overlapping data were only used as padding. The time points in the movement period of the trial (750 ms – 1500 ms) were averaged, resulting in a time bin of 750 ms, with each 36 frequency bins (5 - 40 Hz), times 64 channels. This resulted in a total amount of 2,304 features per trial.

Feature selection. For feature selection, an algorithm based on Sparse Logistic Regression, developed by Gerven, Hesse, Jensen, and Heskes (2007) is used. To increase the generalizability of the classification, the algorithm is able to do both the feature extraction and the classification. Sparse Logistic Regression prevents over-fitting of the data by selecting a small number of informa-
tive features. As input, it uses a two-dimensional matrix of trials x features and a vector with the class of each trial. Thus, if there are 200 trials, say 100 left hand trials and 100 right hand trials, the features matrix is 200 x 2,304 and the class vector has a length of 200.

Ten-fold cross-validation is used in the algorithm. This means that the data is split into ten (semi-) equal parts. Ten-fold cross validation implies that the classification and feature extraction is trained on 90% of the data and tested on the remaining 10% of the data for all ten permutations of the data sets. This results in a weight matrix \( W \) of size Classes x Features per fold, i.e., ten in total. These weight matrices can be used to classify the features of the data sets. This results in a weight matrix of size Classes x Features per fold, i.e., ten in total.

The probability that a feature \( j \) belongs to a normal distribution is given by (5).

\[
\sigma_j(X^m) \equiv \sqrt{\frac{1}{N} \sum_{i=1}^{N} (X_{ij} - \mu_j(X^m))^2}
\]  

The second classification method is an expansion of the first, where the variance was also taken into account. Here, the classification was based on the probability that the features of the trial to be classified belonged to a normal distribution of each feature, based on the trials in \( X^{m,c1} \) or \( X^{m,c2} \).

The mean of feature \( j \) is defined as described in (1). The standard deviation of feature \( j \) given matrix \( X^m \) is defined in (4), where \( N \) is the total number of trials.

\[
\sigma_j(X^m) = \frac{1}{\sqrt{2\pi\sigma_j(X^m)}} e^{-\frac{(x^m - \mu_j(X^m))^2}{2\sigma_j(X^m)^2}}
\]  

A final measure of class membership is calculated by averaging the probabilities for each feature in \( a \), as can be seen in (6).

\[
S(d^m, X^m) = \frac{1}{M} \sum_{j=1}^{M} f_j(d^m, X^m)
\]  

Finally, the classification itself is described in (7).

\[
C(d^m | X^{m,c1}, X^{m,c2}) = \begin{cases} 
    c_1 & S(d^m, X^{m,c1}) > S(d^m, X^{m,c2}) \\
    c_2 & \text{otherwise}
\end{cases}
\]  

The third classification algorithm does not utilize all features, but only a selection. This selection has been described in Feature selection. This classification algorithm is based on Sparse Logistic Regression and was developed by van Gerven et al. (2007). The equation used for classification is given in (8). It calculates the probability a certain trial belongs to one of the classes, where \( k \)
is the current class, $\vec{x}$ is the feature vector of the current trial, and $W$ is the weight matrix of class $k$. This probability is obtained by taking the exponential of a multiplication of the sparse weight matrix and the feature matrix, divided by a normalisation term. This normalisation term is calculated summing the multiplications of the weight matrix of each class with the feature matrix.

$$P(k|\vec{x}, W) = \frac{e^{W_k \vec{x}}}{\sum_j e^{W_j \vec{x}}}$$

(8)

The classification itself is also done in ten parts (i.e., like the feature selection). Therefore, the output of the algorithm consists of ten matrices $W$, one for each part, of size number of trials by number of classes. These matrices contain the probabilities that each trial belongs to a certain class. To which class a trial is actually attributed is determined by taking the maximum of all class probabilities. The final classification rate is an average of the classification rate of each of the ten parts.

**Results**

**Results from Time Frequency Representation (TFR) Analysis**

To give an impression of the activity patterns that were found in the data, the TFRs of only one subject (Subject 2) are reported here. This subject was chosen because he shows the clearest patterns. Two different kinds of figures are used. In the overview figures (Figures 5 and 8), multiple channels are shown in one figure to give an overview of the distributional pattern over channels. The single plot figures (Figures 6, 7, 9, and 10) zoom in on one single channel and shows the temporal pattern. The single plots were selected for the channels where either the temporal pattern occurs where it is expected from previous research, or where the power fluctuations in the patterns are very strong. For both of these plots, a baseline subtraction was done to make the power perturbations visible. In this baseline subtraction, a mean of the signal for each channel over a time period from 0 – 1500 ms was subtracted from the signal.

**Actual movement.** The overview plots in Figure 5 show the spatial distribution of activity. For a clearer overview of the channel locations, see Figure 4. One can clearly see that there is more power in the right hemisphere for left hand movement and more power in the left hemisphere for right hand movement. One can also see that there is a high power in channels ‘C3’ and ‘C4’. This expected, because these channels are approximately above the hand area of the motor cortex. There is also a high amount of power in channels ‘FC3’ and ‘FC4’, these channels are approximately above the premotor cortex. Figure 6 zooms in on channels ‘C3’ and ‘C4’ and shows their temporal patterns for both left and right hand movement. The contralateral pattern mentioned before is also clearly visible in these single plots. Their is also a very distinct temporal distribution pattern: there is more power during the rest period of each movement section (0 – 0.75s) and a decrease in power in the movement period (0.75 – 1.5s). Figure 7 zooms in on channels ‘FC3’ and ‘FC4’. These channels show the same temporal pattern as the previous pair of channels, albeit somewhat less strong. The lateralization that can be observed in channels ‘C3’ and ‘C4’ is absent in these channels.

**Imagined movement.** The spatial distribution of activity for imagined movement can be seen in Figure 8. The lateralization that was clearly visible in the spatial distribution of the actual movement is absent here. One can also see that the focus of the activity is more frontal (above the medial frontal gyrus) in imagined movement than in actual movement. This frontal activity can also be seen in actual movement, but there the activity above primary motor cortex is stronger. Also note that the power fluctuations are lower in imaged movement than in actual movement, because the power limits in the plot are -1 and +1 dB. Figure 9 zooms in on channels ‘C3’ and ‘C4’. Although there still is a temporal pattern where the rest period (0 – 0.75s) has a higher power in the beta range than the movement period (0.75 – 1.5s), the pattern is not as clearly defined as in actual movement. The clear lateralization that was visible in actual movement is not visible in that of imagined movement. The temporal pattern of channels ‘F3’ and ‘F4’, which are approximately above the medial frontal gyrus, is shown in Figure 10. Here also, the lateralization is not clearly visible and the pattern is less clear than in actual movement.

**Classification results**

The results for the classification method based on Root Mean Square Error for Subject 1 were 52% (n.s.) for actual movement and 50% (n.s.) for imagined movement. For Subject 2, these values were 57% ($p < 0.01$) for actual movement and
Figure 5. An overview of the time frequency representations for each single channel. On the top side the TFRs for actual left hand movement, and on the bottom the TFRs for actual right hand movement.
Figure 6. A number of time frequency representations for selected channels: C3 and C4 (approximately above the primary motor cortex). Top-left: TFR of channel C3 (left hemisphere) for actual left hand movement. Top-right: TFR of channel C3 for actual right hand movement. Bottom-left: TFR of channel C4 (right hemisphere) for actual left hand movement. Bottom-right: TFR of channel C4 for actual right hand movement. At the bottom of each plot is an average trace of the EMG measured during this period. The upper plot represents the left hand EMG and the lower plot the right hand EMG.

52% (n.s.) for imagined movement. Subject 3 had a classification rate of 58% ($p < 0.01$) and 53% (n.s.) for actual and imagined movement respectively. An overview of these values can be found in Table 1.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Actual movement C.R.</th>
<th>Imagined movement C.R.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td>52% (n.s.)</td>
<td></td>
</tr>
<tr>
<td>Subject 2</td>
<td>57% ($p &lt; 0.01$)</td>
<td>52% (n.s.)</td>
</tr>
<tr>
<td>Subject 3</td>
<td>58% ($p &lt; 0.01$)</td>
<td>53% (n.s.)</td>
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The results for the classification method using variance for Subject 1 were 49% (n.s.) for actual and 48% (n.s.) for imagined movement. Subject 2 showed classification rates of 58% ($p < 0.01$) and 50% (n.s.) for actual and imagined movement respectively. For Subject 3, the classifier had 51% (n.s.) correct for actual movement and 51% (n.s.) correct for imagined movement. For an overview
of the classification rates and the exact p-values, see Table 2.

The classification algorithm based on Sparse Logistic Regression performed at 62.25% (p < 0.001) for actual movement and 65.21% (p < 0.001) for imagined movement with Subject 1. For Subject 2, the classification rate was 67.50% (p < 0.001) for actual and 59.44% (p < 0.001) for imagined movement. The classification rate for actual movement for Subject 3 was 61.67% (p < 0.001) and 54.03% (p < 0.05) for imagined movement. An overview of these results can be found in Table 3.

Table 2

<table>
<thead>
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<th></th>
<th>Actual movement</th>
<th></th>
<th>Imagined movement</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>C.R.</td>
<td></td>
<td>C.R.</td>
</tr>
<tr>
<td>Subject 1</td>
<td>49%</td>
<td>n.s.</td>
<td>48%</td>
</tr>
<tr>
<td>Subject 2</td>
<td>58%</td>
<td>&lt; 0.01</td>
<td>50%</td>
</tr>
<tr>
<td>Subject 3</td>
<td>51%</td>
<td>n.s.</td>
<td>51%</td>
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Figure 7. A number of time frequency representations for selected channels: FC3 and FC4 (approximately above the premotor cortex). Top-left: TFR of channel FC3 (left hemisphere) for actual left hand movement. Top-right: TFR of channel FC3 for actual right hand movement. Bottom-left: TFR of channel FC4 (right hemisphere) for actual left hand movement. Bottom-right: TFR of channel FC4 for actual right hand movement. At the bottom of each plot is an average trace of the EMG measured during this period. The upper plot represents the left hand EMG and the lower plot the right hand EMG.
Figure 8. An overview of the time frequency representations for each single channel. On the top the TFRs for imagined left hand movement, and on the bottom the TFRs for imagined right hand movement.
Figure 9. A number of time frequency representations for selected channels: C3 and C4 (approximately above the primary motor cortex). Top-left: TFR of channel C3 (left hemisphere) for imagined left hand movement. Top-right: TFR of channel C3 for imagined right hand movement. Bottom-left: TFR of channel C4 (right hemisphere) for imagined left hand movement. Bottom-right: TFR of channel C4 for imagined right hand movement. At the bottom of each plot is an average trace of the EMG measured during this period. The upper plot represents the left hand EMG and the lower plot the right hand EMG.

Table 3

<table>
<thead>
<tr>
<th></th>
<th>C.R.</th>
<th>p</th>
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<tbody>
<tr>
<td>Actual movement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subject 1</td>
<td>62%</td>
<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>Subject 2</td>
<td>68%</td>
<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>Subject 3</td>
<td>62%</td>
<td>(&lt;0.0001)</td>
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<tr>
<td>Imagined movement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subject 1</td>
<td>65%</td>
<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>Subject 2</td>
<td>59%</td>
<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>Subject 3</td>
<td>54%</td>
<td>(&lt;0.05)</td>
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Discussion

The data in this experiment shows the clear ERD/ERS pattern in actual movement that have been shown by other experiments (Pfurtscheller & Neuper, 1994; Pfurtscheller & Da Silva, 1999). This pattern is also visible in the imagined movement data, be it to a lesser extent.

The main focus of the signal was found in the channels approximately above the motor and pre-motor cortex for actual movement. For imagined movement this focus was located more frontally in the channels above the medial frontal gyrus. This
Figure 10. A number of time frequency representations for selected channels: F3 and F4 (approximately above the medial frontal gyrus). Top-left: TFR of channel F3 (left hemisphere) for imagined left hand movement. Top-right: TFR of channel F3 for imagined right hand movement. Bottom-left: TFR of channel F4 (right hemisphere) for imagined left hand movement. Bottom-right: TFR of channel F4 for imagined right hand movement. At the bottom of each plot is an average trace of the EMG measured during this period. The upper plot represents the left hand EMG and the lower plot the right hand EMG.

Frontal activity is also visible during actual movement, but the activity in the primary motor cortex is stronger. When this activity is not present, because the subject is not moving anymore, this frontal activity becomes the most prominent activity.

We also found that there is a much stronger signal for actual movements than in imagined movements. The power in actual movements has been found to be in the range of -2.5 dB. – +2.5 dB., while the power in imagined movement is in the range of -1 dB. – +1 dB.

The data also shows that there is a clear lateralization of activity in actual movement, while this lateralization is absent in imagined movement. This was also found by Pfurtscheller, Neuper, Flotzinger, and Pregenzer (1997).

It has been shown here that classification methods that utilize all features perform rather poorly. One method has been used that selects informative features to use in classification and this method performs significantly better than the methods that utilize all features. This indicates that the information needed to classify correctly between left and right hand imagined movement is contained in a subset of the total number of fea-
tures. By weighing all features equally in the classification process, the information actually important for the classification is suppressed, leading to a lower classification rate.

The classification rate of the Sparse Logistic Regression method, although good for data from untrained subjects, is not very high. This could be improved by adding more time bands, for instance including the rest period of the movement. Currently, only the movement period is used in the classification. By adding the information in the rest period, the classifier may be better able to distinguish left hand from right hand imagined movement.

The current classification rate of maximally 65% is not enough to build a reliable BCI system, but by including multiple trials in the classification, the classification rate could be improved to an acceptable rate. For instance, if the classification is based on five trials instead of one single trial, the classification rate could be increased. If a subject imagines for instance five left hand movements in a row and the final classification is based on a majority, i.e., the class that has been assigned to 3 or more of these five trials. Then with a classification rate of 65% for each single trial, the classification rate for five trials will increase to 77%. An overview of the increase in classification rate by including multiple trials can be seen in Figure 11. A disadvantage of using more than one movement in classification is that it takes more time before the system is able to make a decision.

\[ R = \log_2N + P \cdot \log_2P + (1 - P) \cdot \log_2 \frac{1 - P}{N - 1} \] (9)

Overall, the classification performs well, considering the subjects have had no training whatsoever and the time span of data used in the classification is rather short (750 ms).

Future work includes researching the effect of varying the movement tempo or using a different type of movement. Next, it could be determined if the classifier still performs well when the data has not been cleaned manually as has been done in the offline experiment. Another addition to this research could be to use more time bands, i.e., more information, in the classification, to improve the overall classification rate. If the classification rate is acceptable, this offline experiment could be changed into an online BCI system.

Acknowledgements

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\(^2\) The actual classification is done on 750 ms of data, but the length of the movement task, including the rest period is 1.5 seconds.
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