The importance of individual features for motor-imagery based BCI

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Abstract

The aim of the present study is to investigate the influence of various experimental parameters and features for future use in motor-imagery based BCI. Three types of movement are investigated: index tapping, sustained clenching and repetitive clenching. Real and imaginary movement executions are also compared. Finally, interindividual variability is addressed by comparing features common to all subjects with individually optimized ones. Results show that individual features, namely in the spatial and frequency domain, yield on average significantly enhanced differences between experimental conditions that could be exploited to optimize a future motor-imagery based BCI.

1 Introduction

Motor imagery is one of the most investigated process to implement an efficient and direct brain-computer interface (BCI) (see [1, 2] for a review). These BCI are generally based on mu rythm (8-12 Hz) desynchronization as observable with EEG over motor areas during motor imagery, in a similar way as in movement preparation or execution. Although a lot of studies have focused on signal processing techniques to reduce classification error in motor-based BCI, very few studies have provided insights on the role of movement types.

In the present study, we compare mu power desynchronization during the realization or imagination of three different movements: index tapping (IT), sustained clenching (SC) and repetitive clenching (RC). Movements are performed either with the right or the left hand. Our main goal is to identify crucial guidelines for optimizing a future motor-imagery based BCI. Therefore and since BCIs are meant to be optimized for individual usage, we investigate signal feature space, namely in the spatial and frequency domain. Hence we focus on subject differences in terms of scalp region of interest (ROI) for data acquisition and mu frequency range. In a multi-subject statistical analysis, we compare those individual features with some literature-based definitions of classical motor related ROIs and mu rhythms.

In this paper, we focus on the quantitative comparison between different possible features to discriminate between movement types. It tackles the preliminary question: do the considered movements exhibit significant differences at the single trial level, on average? We address this question with a classical factorial design and analysis of variance. We hoped the answer would be positive so that we can contemplate building a BCI paradigm based on the identified features. Evaluation of such a BCI will be the focus of future work that will then tackle the following question: how well can we classify single trial responses based on those features? This is typically addressed using cross validation.

2 Methods

2.1 Subjects

Six healthy right-handed female subjects (range age: 21-29 years, mean age: 22,7) participated in the experiment. They were all free of neurological diseases and had no previous experience with motor-imagery paradigms. All subjects signed an informed consent approved by the local Ethical Committee and received monetary compensation for their participation. Because she failed in performing the imaginary movement task, one subject was excluded from the analysis.

2.2 Experimental paradigm

During the recording, subjects were sitting in a comfortable armchair in an electrically shielded room. Task execution was monitored with the PsyScope software [3], using an Apple Macintosh G4 computer for visual display of instructions and cues within the acquisition room. Each subject started the experiment with a short training session to ensure they correctly understood the task. Then, the actual experiment was divided into 12 blocks whose order was randomized. Each block was made of 16 trials of 20 seconds each and was dedicated to one of the three movement types only. Each trial consisted in 2 seconds of rest (R), followed by 5 seconds of actual movement (M), 5 seconds of rest (R), 5 seconds of motor imagery (I) and 3 seconds of rest (R) (Figure 1). Within trial, imagery was always performed after the exact same real movement in order to ease the imaginary task. The hand to be used was randomly chosen and equally balanced within block. It remained the same within trial and was indicated by a right or left arrow during the whole task periods (M and I). The subject was also asked to fixate a cross at the middle of the screen to minimize eye movements. In total each participant underwent 192 trials, hence about one hour of experiment.

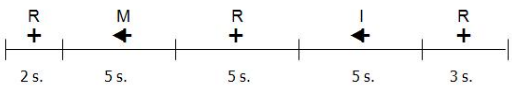


Figure 1: Timing of a trial.

2.3 Data acquisition and preprocessing

EEG activity was recorded from 32 scalp active electrodes (actiCAP, BrainProduct GmBH, Munich, Germany) placed at standard locations of an extended 10-10 international system (Figure 2). All electrodes were referenced to the nose and grounded to the forehead. Horizontal and vertical electrooculograms (EOG) were recorded from the right eye. Ag/AgCl bipolar electrodes were used on both arms and located in order to get EMG signals for each movement type. Electrode impedances were kept below 10 kΩ. EEG was amplified (BrainProduct GmBH, Munich), filtered (0.1-150 Hz), and digitized online with a sampling frequency of 1000 Hz.

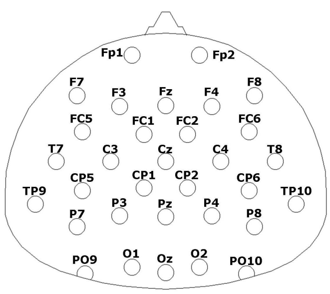


Figure 2: Electrode montage.

After epoching, all trial data with large muscular activity were rejected from further analyses. The eye blink component was automatically removed using ICA ([4]). This preprocessing step left at least 26 clean trials for each participant, each hand and each movement type.

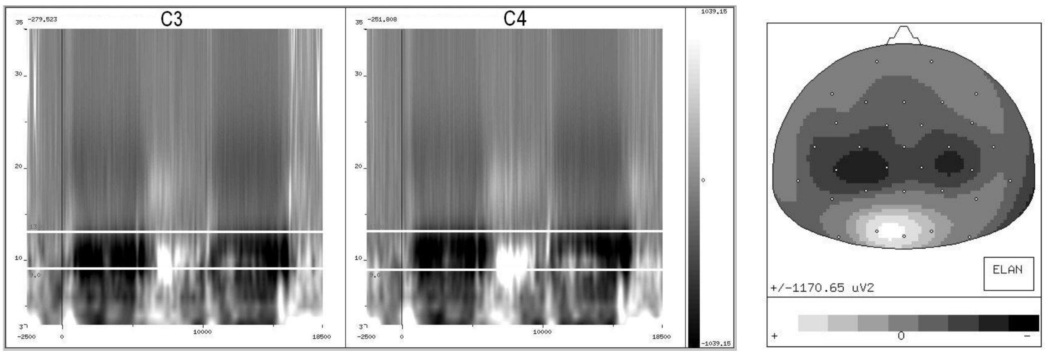
2.4 Data analysis

Data analysis focused on mu power during movement (desynchronization) relatively to mu power during rest. For each condition, the averaged time-frequency transform across single trials ([5]) was computed for both real and imaginary movements, using a three-second-length time window (from 1 to 4 seconds after movement cue onset). Data from the same trial were baseline corrected using the same initial resting period (from 1500 to 500 ms before the real movement cue onset). Two different spectral analysis were performed from the time-frequency representations: a common-feature based analysis and an individual-feature based one. In the first one, mu power was computed in the 8-12 Hz frequency band from electrodes C3 and C4 ([6]). In the subject specific procedure, individual features (specific mu range and ROIs) were identified from the averaged time-frequency plots over all conditions (see Table 1). Individual mu range was first determined from individual time-frequency plots over centro-parietal electrodes (Figure 3-a) and then individual ROIs were selected from the ensuing mu power topographies (Figure 3-b).

Using R software ([7]), linear mixed effect modeling [8, 9] was applied to both data sets, with Movement Type (real vs. imaginary movement), Movement (IT, RC and SC), Hand (left vs. right) and ROI (left vs. right) as fixed effects and Subject as random effect to account for between subject variability. An analysis of variance was then computed separately on both estimated fixed effects.

Subject	Mu band (Hz)	Left ROI	Right ROI
1	9-12	CP1, P3	C4, CP2, P4, CP6
2	8-10	CP1, P3, CP5	C4, CP2, P4
3	9-13	C3, CP1, CP5	C4, CP2, CP6
4	7-9	C3, CP1	C4, CP2
5	12-14	C3, CP5	C4

Table 1: Individual features.



(a) (b)

Figure 3: (a) Grand mean time-frequency plots over C3 and C4 for subject 3. The most important mu desynchronization can be observed between 9 Hz and 13 Hz. (b) Topographical distributions of the averaged mu power during actual movement. Mu desynchronization can be observed over the C3, CP1 and CP5 electrodes (left ROI) and over the C4, CP2, CP6 electrodes (right ROI).

3 Results

3.1 Towards a routine-based BCI

From spatial and frequency features common to all subjects, results showed a main effect of Hand ($p<0.001$), with lower mu power during left hand compared to right hand movement. The interaction between Hand and ROI factors proved also significant ($p<0.05$; Figure 4), showing a larger decrease in mu power on C4 than on C3 for left hand movements. Surprisingly, a similar pattern was observed for right hand. No other significant main effects or interactions were found, suggesting no significant differences in mu power due to movement type or between real and imaginary movements.

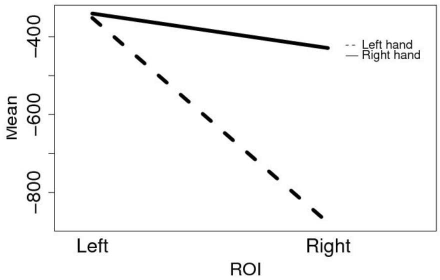
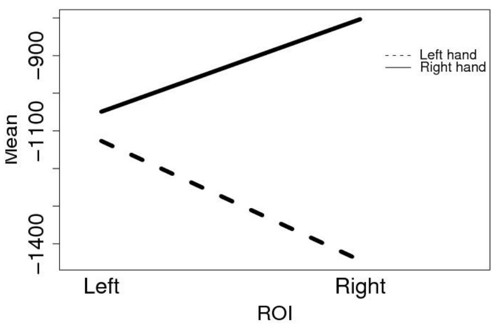


Figure 4: Two-way interaction (Hand × ROI) when considering the common mu-range definition.

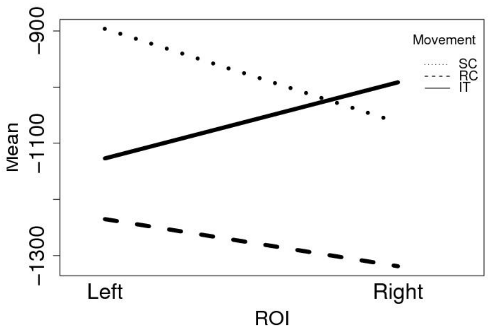
3.2 Towards a subject-specific BCI

Here considering individual features in terms of both mu frequency range and ROIs, a significant mu desynchonization was again observed for left hand movements ($p<0.0001$). Furthermore, significant interactions were observed: Hand × ROI ($p<0.01$) and ROI × Movement ($p<0.05$). Contrary to what was evidenced from the use of common features, a clear controlateralization for each hand is revealed (see Figure 5-a). This suggests that common features may fail to extract informative signals that can be revealed by subject specific features.

Moreover and contrary to the previous analysis, the ROI × Movement interaction proved significant here (see Figure 5-b). Indeed, while RC and SC movements reveal a similar pattern of relative mu power from left to right ROI, this pattern is inverted for IT movements. This may be due to the difference in either the movement effectors (index vs. full hand movement) or the kind of movement (tapping vs. clenching).



(a)



(b)

Figure 5: Plot of the two-way interactions (a) Hand × ROI and (b) ROI × Movement in the mu band for individual features.

On the other hand and as revealed by a significant main effect of Movement ($p<0.01$), a global mu power was found greater for SC compare to both IT and RC, and for IT compare to RC. This may be explained by the difference in performing a sustained versus repeated movement.

Finally, a significant main effect of Movement Type was found with individual features ($p<0.01$), due to lower mu power values for real compare to imaginary movements. Note however that mu power values are all negative (compare to resting periods), suggesting that the motor-imagery task was well performed.

4 Discussion and Conclusion

Although more subjects would need to be tested in order to confirm our findings, the present study provides clear evidence in favor of the use of individual features to optimize a motor-imagery based BCI.

Indeed, our comparison of common and individual features in the spatial and frequency domains revealed the following statistical differences. The difference between controlateral and ipsilateral mu desynchronization was only significant when considering individual features, as observed with both the left and right hand movements. This is probably due to the optimization of the ROI since C3 did not appear to be informative for both subjects 1 and 2 (see Table 1). This finding holds true for either real or imaginary movements. Note also, that in all cases, left movements induced a larger mu desynchronization than right movement, maybe reflecting the right-handedness of the subjects.

This study suggests, whatever the strategy (see e.g. [10] for a binary-command BCI based on the contrast between bilateral imagery and rest) that subtle and carefully indentified individual features or preferences (e.g. in the type of movements) could optimize motor-imagery based BCI in a significant way ([6, 11]). According to our results, lateralization of imaginary movements as well as movement type (e.g. clenching vs. tapping) are relevant parameters to be looked at individually.

To further assess the differences between conditions, we contemplate to analyze the dynamics of mu desynchronization during movements. It might be that the full period between 1 and 4 seconds after movement cue onset is not specific enough or subject dependent and could be also individually optimized. Indeed, the visual comparison of time-frequency plots during real and imaginary movements indicate a less stable mu desynchronization during motor imagery. This may be due to the fact that all the subjects were untrained and naïve regarding motor imagery.

Although it was designed in the perspective of optimizing a BCI application, the current experiment was performed offline and involved a classical factorial design with several-second-long trials. In BCI practice, decision would need to be taken more rapidly, on a few hundred of milliseconds basis. Therefore, studying and exploiting the temporal structure of the identified features will be crucial. One possible direction we are currently investigating is temporal integration in probabilistic decisions using dynamical classification models (see [12]).

Finally, we focussed the current analysis on mu rythm and motor related electrode sites. Further improvement could be obtained from including other locations and frequencies, such as beta (around 16-24 Hz) desynchronization, or faster rythms as proposed in [13].

5 Acknowledgements

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