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Profiling BCI users based on contralateral activity
to improve kinesthetic motor imagery detection

Sébastien Rimbert\textsuperscript{1,2,3}, Cecilia Lindig-León\textsuperscript{1,2,3} and Laurent Bougrain\textsuperscript{2,1,3}

Abstract—Kinesthetic motor imagery (KMI) tasks induce
brain oscillations over specific regions of the primary motor
cortex within the contralateral hemisphere of the body part
involved in the process. This activity can be measured through
the analysis of electroencephalographic (EEG) recordings and
is particularly interesting for Brain-Computer Interface (BCI)
applications. The most common approach for classification
consists of analyzing the signal during the course of the motor
task within a frequency range including the alpha band, which
attempts to detect the Event-Related Desynchronization (ERD)
characteristics of the physiological phenomenon. However, to
discriminate right-hand KMI and left-hand KMI, this scheme
can lead to poor results on subjects for which the lateralization
is not significant enough. To solve this problem, we propose
that the signal be analyzed at the end of the motor imagery
within a higher frequency range, which contains the Event-
Related Synchronization (ERS). This study found that 6 out
of 15 subjects have a higher classification rate after the KMI
than during the KMI, due to a higher lateralization during this
period. Thus, for this population we can obtain a significant
improvement of 13% in classification taking into account the
users laterization profile.

I. INTRODUCTION

Brain-Computer interfaces (BCI) allow users to interact
with a system using brain activity modulation mainly in
electroencephalographic (EEG) signals [1]. One major in-
teraction mode is based on the detection of modulations of
sensorimotor rhythms during a kinesthetic motor imagery
(KMI), i.e., the ability to imagine performing a movement
without executing it [2], [3]. More precisely, alpha (7-13
Hz) and beta rhythms (15-25 Hz) modulations can be ob-
served measuring Event-Related Desynchronization (ERD)
or Synchronization (ERS). In particular, before and during
an imagined movement, there is a gradual decrease of power,
mainly in the alpha band. Furthermore, after the end of the
motor imagery, in the beta band, there is an increase of power
called ERS or post-movement beta rebound [4].

A KMI generates an activity over specific regions of the
primary motor cortex within the contralateral hemisphere of
the body part used in the process [5]. Some BCIs are based
on this contralateral activation to differentiate the cerebral
activity generated by a right-hand KMI from a left-hand
KMI [6]. Usually, the modulation corresponding to a user
interaction is scanned in specific frequency bands such as
Alpha, Beta or Alpha+Beta (8-30 Hz). This activity is mainly
observed, during the KMI in the 8-30 Hz band, which merge
alpha and beta bands, or after the KMI in the beta band [7].

Detection rates for these two KMI tasks vary with subjects
and could be improved. Indeed, between 15% and 30% of
the users are considered as BCI-illiterate and cannot control a
BCI [8]. In this article, we suggest that some of the so-called
BCI-illiterate subjects have poor performance due to poor
lateralization during the KMI task. Several studies showed
activity only in the contralateral area [9] for a KMI, but other
studies showed that ERD and ERS are also in the ipsilateral
area [10] and could be a problem for BCI classification.

According to our knowledge, no studies compare the
classifier accuracy based on signals observed during the
KMI versus after the KMI. In this article, we hypothesize the
possibility to define specific profile of BCI users based
on the contralateral activity of the ERD and the ERS. We
define three BCI profiles based on accuracy: users with good
accuracy i) during the KMI in the Alpha band, ii) during
the KMI in the Alpha+Beta bands and iii) after the KMI in the Beta band. We also show that the accuracy is linked to
the absence or presence of a contralateral activity during the
observed periods.

II. MATERIAL AND METHODS

A. Participants

Fifteen right-handed healthy volunteer subjects took part
in this experiment (11 men and 4 women, 19 to 43 years old).
They had no medical history which could have influenced
the task. All experiments were carried out with the consent
agreement (approved by the ethical committee of INRIA) of
each participant and following the statements of the WMA
declaration of Helsinki on ethical principles for medical

B. Electrophysiological data

EEG signals were recorded by the OpenViBE [12] plat-
form from fifteen right-handed healthy subjects at 256 Hz
using a commercial REFA amplifier developed by TMS
International\textsuperscript{TM}. The EEG cap was fitted with 26 passive
electrodes, namely Fp1; Fp2; Fp2; Fz; FC5; FC3; FC1; FC2;
FC2; FC4; FC6; C5; C3; C1; C2; C4; C6; CP5; CP3; CP1;
CP3; CP2; CP4; CP6 and Pz, re-referenced with respect to
the common average reference across all channels and placed by
using the international 10-20 system positions to cover the
primary sensorimotor cortex.

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C. Protocol

Subjects were asked to perform two different kinesthetic motor imageries to imagine the feeling of the movement (left hand and right hand). They were seated in a comfortable chair with the arms at their sides in front of a computer screen showing the cue indicated the task to perform. The whole session consisted of 4 runs containing 10 trials per task for a total of 40 trials per class.

Two panels were simultaneously displayed on the screen, which were associated from left to right, to the left hand and right hand. Each trial was randomly presented and lasted for 12 seconds, starting at second 0 with a cross at the center of each panel and an overlaid arrow indicating for the next 6 seconds the task to be performed.

Fig. 1. Time scheme for the 2-class setup: left-hand KMI and right-hand KMI. Each trial was randomly presented and lasted for 12 seconds, starting at second 0 with a cross at the center of each panel and an overlaid arrow indicating for the next 6 seconds the task to be performed.

D. Common Spatial Pattern

We used the algorithm called Common Spatial Pattern (CSP) to extract motor imagery features from EEG signals; this generated a series of spatial filters that were applied to decompose multi-dimensional data into a set of uncorrelated components [13]. These filters aim to extract elements that simultaneously maximize the variance of one class, while minimizing the variance of the other one. This algorithm has been used for all conditions: the three frequency bands (Alpha, Beta and Alpha+Beta) during the ERD (0-6s) and ERS (6-12s) time windows (Figure 2).

Fig. 2. Accuracy results obtained by a Linear Discriminant Analysis (LDA) and using the CSP algorithm as feature extraction on the 2 classes (left-hand KMI and right-hand KMI) for 15 subjects. The classification method was applied on three frequency band (Alpha, Beta and Alpha+Beta) during the ERD (0-6s) and ERS (6-12s) time windows (Figure 2).

E. ERD/ERS patterns

To evaluate more precisely the modulation which appeared during the two different time windows, we computed the ERD/ERS% using the “band power method” [4] with a Matlab code. First, the EEG signal was filtered considering
one of the three different frequency bands (7-13 Hz, Alpha band; 15-25 Hz, Beta band; Alpha+Beta 8-30 Hz) for all subjects using a 4th-order Butterworth band-pass filter. Then, the signal was squared for each trial and averaged over trials. Then it is smoothed using a 250-ms sliding window with a 100 ms shifting step. The averaged power computed for each window was subtracted and then divided by the averaged power of a baseline corresponding to a 2s window before each trial. Finally, the averaged power computed for each window was subtracted and then divided by the averaged power of a baseline corresponding 2s before each trial. This transformation was multiplied by 100 to obtain percentages. This process can be summarized by the following equation:

$$ERD/ERS\% = \frac{x^2 - BL^2}{BL^2} \times 100,$$

where $x^2$ is the average of the squared signal over all trials and samples of the studied window, $BL^2$ is the mean of a baseline segment taken at the beginning of the corresponding trial, and ERD/ERS% is the percentage of the oscillatory power estimated for each step of the sliding window. It is done for all channels separately.

ERD and ERS are difficult to observe from the EEG signal. Indeed, an EEG signal expresses the combination of activities from several neuronal sources. One of the most effective and accurate techniques used to extract events is the average technique [14]. We decided to use this technique to represent the modulation of power of the Alpha, Beta and Alpha+Beta rhythms for two KMI tasks.

III. RESULTS

A. Three BCI user profiles

Table 2 shows the best accuracy obtained for each subject on a discriminative task of left-hand and right-hand KMI according to the three profiles defined in Section I. Thus, 6 subjects have a higher accuracy looking at the Beta band after the KMI, 3 subjects have a higher accuracy looking at the Alpha band during the KMI and 6 subjects have a higher accuracy looking at the Alpha+Beta band during the KMI. The best averaged accuracy over subjects were obtained considering modulations during KMI (in alpha or in alpha+beta bands). However, looking at the individual performances, we can see that 6 subjects were better considering the beta band after the KMI. For this population we can obtain a significant improvement of 13% in classification considering the activity after the KMI versus during the KMI. Using the best profile for each subject improves the averaged accuracy of 6%.

B. Classification rate and contralateral ERD/ERS activity

Subjects with a higher accuracy in the Beta band after the KMI (Profile 2) have a strong ERS in contralateral during this period and a bilateral desynchronization during the KMI in the Alpha and Alpha+Beta bands (see subject 2, Fig. 4). This result is confirmed by the grand average map (Fig. 3) which shows also an ipsilateral ERD after the KMI. Finally, bilaterally ERD during the KMI, contralateral ERS and ipsilateral ERD after the KMI could explain the high accuracy for these subjects. To validate our hypothesis, we show that the contralateral activity of subject 2 is higher for KMI tasks on the post-KMI period in the Beta band (Fig. 5).

Conversely, subjects with a higher accuracy in the Alpha and Alpha+Beta bands during the KMI (Profiles 1 and 3) have a strong contralateral ERD during the task (Fig. 3 and Fig. 4). After the KMI, in the three frequency bands, they have no contralateral ERS or no Beta rebound on the motor cortex (see subject 10, Fig. 4). Figure 6 shows that the contralateral activity of subject 10 is higher for KMI tasks during the KMI period in the Alpha band.

![Fig. 4. Topographic map of ERD/ERS% in three frequency bands (Alpha:7-13 Hz; Beta:15-25 Hz; Alpha+Beta:8-30 Hz) for two KMI tasks (left hand and right hand). Subject 10 is representative of Profile 1. Subject 2 is representative of Profile 2. Subject 11 is representative of Profile 3. The red color corresponds to a strong ERS and a blue one to a strong ERD.](image_url)

![Fig. 5. Box plots of the power spectrum for Subject 2 (Profile 2) within the Alpha band and the Beta band over electrodes C3 and C4 for right hand and left hand KMI tasks. It can be noticed that there is a higher difference between the contralateral activity during the post-KMI period in the Beta band.](image_url)
IV. DISCUSSION

Subjects carried out left-hand KMIIs and right-hand KMIIs. Results show that 6 out of 15 subjects had a higher classification accuracy based on the post-KMI period in the beta band. This specific accuracy is due to a higher lateralization of ERD and ERS during this period. Our study shows results which could allow to design an adaptive BCI based on contralateral activity on the motor cortex. The importance of BCI users profiles, especially for patients with severe motor impairments has already been established by other studies [15]. Moreover, it appears that there can be important changes of the contralateral activity under the choice of the frequency band [16], [17]. This is why, if we expect designing an adaptive BCI based on the specific contralateral activity of the motor cortex, it is necessary to merge these two methods.

More subjects are necessary to precise this BCI user profile. However, we investigated other KMIIs (not detailed in this article), especially combined KMI (i.e. right-hand and left-hand KMI together versus right-hand KMI) and it appears that some subjects have the same BCI profile.

V. CONCLUSIONS

In this article, we analyzed classification accuracies to discriminate right-hand and left-hand kinesthetic motor imageries. More specifically, we distinguished two periods (i.e., during the KMI and after the KMI) for three frequency bands (Alpha, Beta and Alpha+Beta). We defined three BCI profiles based on the accuracy of 15 subjects: users with a good accuracy i) during the KMI in the alpha band, ii) during the KMI in the Alpha+Beta band and iii) after the KMI in the Beta band. This work showed that 6 out of 15 subjects had a higher classification accuracy after the KMI in the beta band, due to a contralateral ERS activity on the motor cortex. Finally, taking into account the user’s lateralization profile, we obtained a significant improvement of 13% in classification for these subjects. This study show that users with a low accuracy analyzing the EEG signals during the KMI cannot be considered as BCI-illiterate. Thus, in future work, an automatic method to profile BCI users will be done allowing to design an adaptive BCI based on the best period to observe a contralateral activity on the motor cortex.

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