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LOOKING FOR CORTICAL PATTERNS OF SUCCESSFUL MOTOR IMAGERY-BASED BCI LEARNING

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ABSTRACT:

Non-invasive Brain-Computer Interfaces (BCIs) based on motor imagery (MI) tasks represent a valuable tool both from a societal and a clinical perspective. Nevertheless, performances vary inconsistently across subjects and the mechanisms underlying a successful skill acquisition is poorly understood. In this longitudinal study performed with the electroencephalography (EEG), we show that BCI training can be characterized by patterns that rely on the neurophysiology. We observed that the desynchronization effect increases significantly over the sessions within the α and β sub-bands for subjects who showed a significant improvement of their BCI scores. Notably, we observed that they also presented a decrease of the functional connectivity in regions beyond those targeted during the BCI experiments, whereas the subjects who did not improve their performances did not show any significant change over sessions. Taken together, these results give additional insights about the skill acquisition process during MI-based BCI trainings.

INTRODUCTION

Non-invasive BCIs are largely used to produce thought-provoked action, by exploiting the ability of subjects to voluntary modulate their brain activity through mental imagery. Despite its societal and clinical applications [1], [2], voluntarily modulating brain activity to control a BCI appears to be a learned skill [3], [4], based on the feedback presented to the user, and, in general, several weeks or even months may be needed to reach relatively high-performance (> 90 %) in BCI control [1],[15]. Furthermore, between 15 and 30 % of the users [6] face difficulties in controlling a BCI even after several training sessions, eliciting a high inter-subject variability. This point shows the difficulty to understand the key-aspects, or subject-related patterns, of an efficient learning process in MI-based BCI more specifically.

In previous studies, two main types of predictors of MI-based BCI success have been elicited [7]. The first category corresponds to the behavioral or psychological predictors. Among them, kinesthetic imagination score, mental rotation ability, self-reliance, visuo-motor coordination and concentration have shown significant correlations with BCI scores [8]–[11]. The second category corresponds to the neurophysiological predictors. Most of them relied on resting state or pre-stimulus recordings and are associated with power spectra. More specifically, these activations involve mainly sensorimotor areas (μ, low α and high θ power [12], [13]) and the fronto-parietal axis (within the γ band [14], [15]).

However, while there is a large number of inter-subject comparisons, less longitudinal studies have been conducted and little is known about how the communication between brain areas may differ during the learning process and between subjects.

In this work, we propose an original approach that aims at eliciting patterns that come from functional connectivity (FC) of successful learning process based on a longitudinal study performed with EEG. We hypothesize that the FC changes over the training, involving areas beyond those targeted during the BCI experiment, and that the associated properties present a specific pattern of learning efficiency.

MATERIALS AND METHODS

BCI protocol and participants

Twenty healthy subjects (aged 27.45 ± 4.01 years, 12 men), right-handed and BCI-naïve, participated in the study. It consisted of a longitudinal EEG-based BCI training composed by four sessions (i.e. twice in a week for two weeks). None presented medical or psychological disorders. A written informed consent was obtained from subjects after explanation of the study, approved by the ethical committee CPP-IDF-VI of Paris. All participants received financial compensation at the end of their participation. The BCI task consisted of a standard 1D, two-target box task [16] in which, to control the vertical position of a cursor moving from the left to the right side of the screen, the subjects modulated their brain activity. To hit the target-up, the subjects imagined a sustained movement of the right hand (MI condition) and they remained at rest to hit the target-down (Rest condition). Thus, the BCI scores are defined here as the proportion of hit targets. Each session was composed by 6 runs of 32 trials. Each trial lasted 7 s and consisted of a 1 s of inter-stimulus, followed by 2 s of target presentation, 3 s of feedback and 1 s of result presentation (Fig 1). At the beginning of each session, BCI features (EEG channels and frequency) were selected in a calibration phase in which the subjects were instructed to perform the BCI tasks without any visual feedback. We selected the features within the α-β band and localized within the motor area contralateral to the movement. The online classification was performed with a Linear Discriminant Analysis, suited for a two-class paradigm [17].

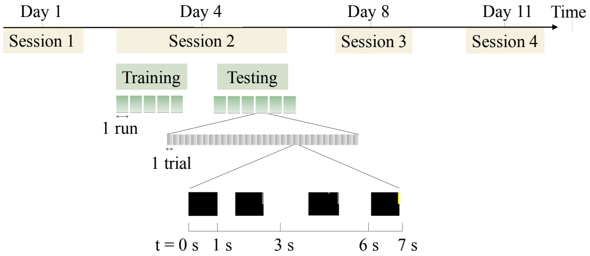

Fig 1 Experimental design. The different timescales (session, run, trial) are presented.

Following the last inclusion, we selected two groups of five subjects each to elicit the most extreme profiles in terms of learning process. The selection was based on the difference in terms of BCI scores between the first and the last session. The five subjects who showed the best improvement in terms of BCI scores (aged 27.40 ± 2.07 years, 4 men) were gathered within the Group 1 (G1). The five subjects who improved the less (aged 27.60 ± 3.36 years, 1 men) were gathered within the Group 2 (G2).

Materials

EEG signals were collected with a 74-channel BrainAmp system (referenced to mastoids signals). Left and right electromyogram (EMG) signals were recorded to ensure that subjects were not moving their forearm while performing the tasks. Recordings were performed with a 1 kHz frequency sampling and an offline filter applied between 0.1 and 300 Hz. BCI sessions were performed from EEG signals transmitted via the Fieldtrip buffer [18] to the BCI2000 toolbox [19].

After the fourth session, individual T1 scans were obtained by using a 3T Siemens Magnetom PRISMA. The experiment consists in a 15 minute-resting-state task to obtain an accurate head model for the source reconstruction.

EEG processing

After having downsampled the signals to 250 Hz, we performed an Independent Components Analysis with the Infomax approach [20] using the Fieldtrip toolbox [18] to remove potential ocular and/or cardiac artifacts.

Once the signals epoched and average referenced, we performed source reconstruction by computing the individual head model with the Boundary Element Method (BEM) [21], [22]. BEM surfaces resulted from three layers associated with the subject's MRI (scalp, inner skull, outer skull) with 1922 vertices each. The weighted Minimum Norm Estimate [23] method was used to estimate the sources via the Brainstorm toolbox [24]. Here, the identity matrix was defined as the noise covariance matrix. The minimum norm estimate corresponds in our case to the current density map. The regions of interest (ROIs) relied on the use of the Destrieux atlas [25].

To compute the power spectrum density of the signals at the source level, we used the Welch method with a window length of 1 s and a window overlap ratio of 50 % applied during the feedback period that ranges (from t = 3 s to t = 6 s) within the individual anatomical space.

Functional connectivity analysis

Functional connectivity has already been shown to be a valuable tool in the BCI domain [26]–[28]. Here, we were particularly interested in eliciting patterns of successful learning that rely on FC. Thus, we used the imaginary coherence, weakly affected by volume conduction and spatial leakage [29], [30], between each pair of ROIs. In this study, we used a concise metric that could elicit highly connected hubs: the node strength, defined as the sum of the connectivity weights of the edges linked to each node i.

Metrics and statistical analysis:

To take into account the subjects' specificity, we defined our frequency bands according to the Individual Alpha Frequency (IAF) [31]. We restricted our study within the α-β frequency bands for two reasons. First, because it corresponds to the frequency bands targeted during the BCI experiments (i.e. modulated during motor imagery task). Secondly, because both α and β bands have been shown to be involved in learning processes [32], [33]. Here, the IAF corresponds to the first peak comprised between 6 and 12 Hz. The α_1 band ranges from IAF – 2 Hz to IAF, the α_2 band from IAF to IAF + 2 Hz, $\boldsymbol{\beta_1}$ from IAF + 2 Hz to IAF + 11 Hz and β_2 from IAF + 11 Hz to IAF + 20 Hz.

We computed statistical differences among activations (i.e. power spectra) recorded in the MI and the rest conditions at the subject level via a paired t-test. Statistics were corrected for multiple comparisons using the cluster approach [24], [34], with a statistical threshold to 0.05, a minimum number of neighbors of 2 and a number of randomization of 500. Cluster-level statistics are obtained by using the sum of the t-values within every cluster. Besides the correction for multiple comparisons, this method avoids any spatial a priori about areas that show a significant desynchronization effect.

To obtain a single value that takes into account the desynchronization effect, we worked with the relative power, ΔP, defined as follows:

$$\Delta P = 100 \times \frac{P_{MI} - P_{Rest}}{P_{Rest}}$$

where P_{MI} and P_{Rest} correspond, respectively to the averaged power calculated across the cluster from MI and Rest trials. Similarly, we computed the relative node strength ΔN as the relative difference in terms of node strength between the conditions.

RESULTS

Behavioral performances

G1 showed a significant improvement of the BCI scores (one-way ANOVA, $F_{3,12} = 15.1$, $p_{FDR} = 2.36\text{x}10^{-4}$) whereas the scores obtained by G2 did not show a session effect ($F_{3,12} = 0.14$, $p_{FDR} = 1$) (Fig. 2A). These results enabled us to check that we did have two groups that strongly differed. Notably, this difference became prominent from session 3 (Fig. 2A).

Brain activation

From the activation perspective, we observed a strong decrease of the relative power from session 3 for G1 (Fig. 2B). Nevertheless, a significant session effect was observed only within the α_2 band (one-way ANOVA, $F_{3,12} = 5.16$, $p_{FDR} = 0.02$). ΔP did not present a session effect for G2 both in α_2 and β_1 frequency bands. Notably, this trend is similar to the one previously observed with behavioral performances (Fig. 2A). As expected, with the practice, the desynchronization effect will increase only within G1. This result is in line with [6] where subjects with poor performances show fewer significant features than the other subjects.

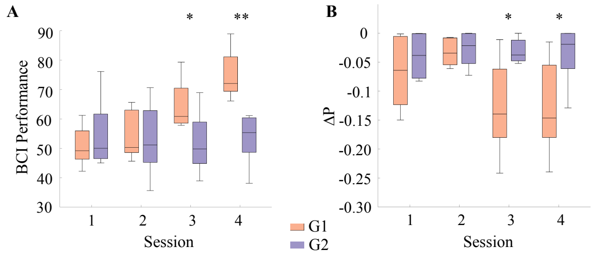

Fig. 2 Trends over sessions obtained for G1 and G2. (A) BCI performances. (B) Evolution of the relative power (ΔP) within the α_2 band. *$p < 0.05$; **$p < 0.05$ (Mann-Whitney test).

Brain connectivity

A way to assess potential differences in terms of connectivity is to compare the relative node strength values, obtained during the fourth session when the behavioral results are the most discriminative between the two groups of subjects. First, as shown in Fig. 3 in absolute values, the ΔN values were larger within G1 than within G2, meaning that there was a larger discrimination between conditions within G1 than within G2 from the FC perspective. Secondly, within G1, the strongest negative values of ΔN involved the pre-frontal, parietal and occipital areas (bilateral) whereas the strongest positive ones were located in pre-and postcentral gyri (bilateral) in α_1 and α_2. Thus, at the

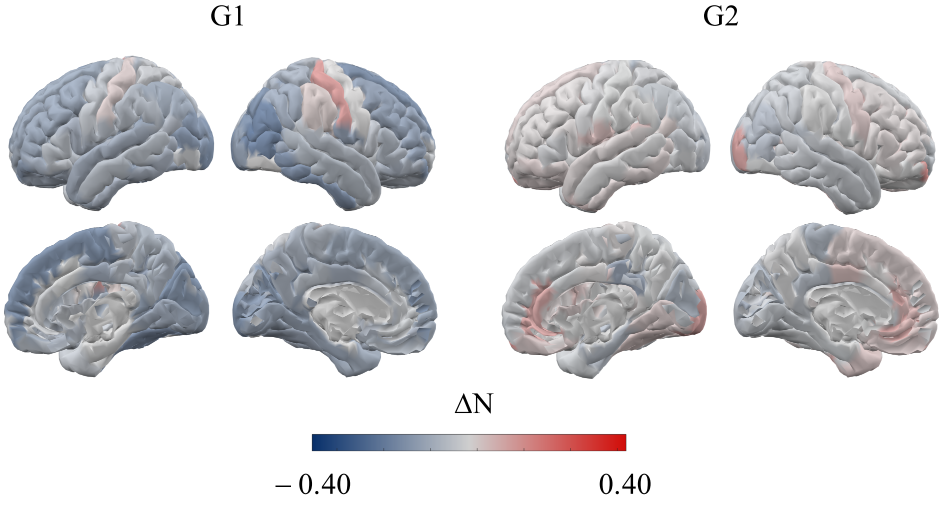

Fig. 3 Averaged relative node strength, obtained during the fourth session, across the subjects from respectively G1 and G2 within the α_2 band.

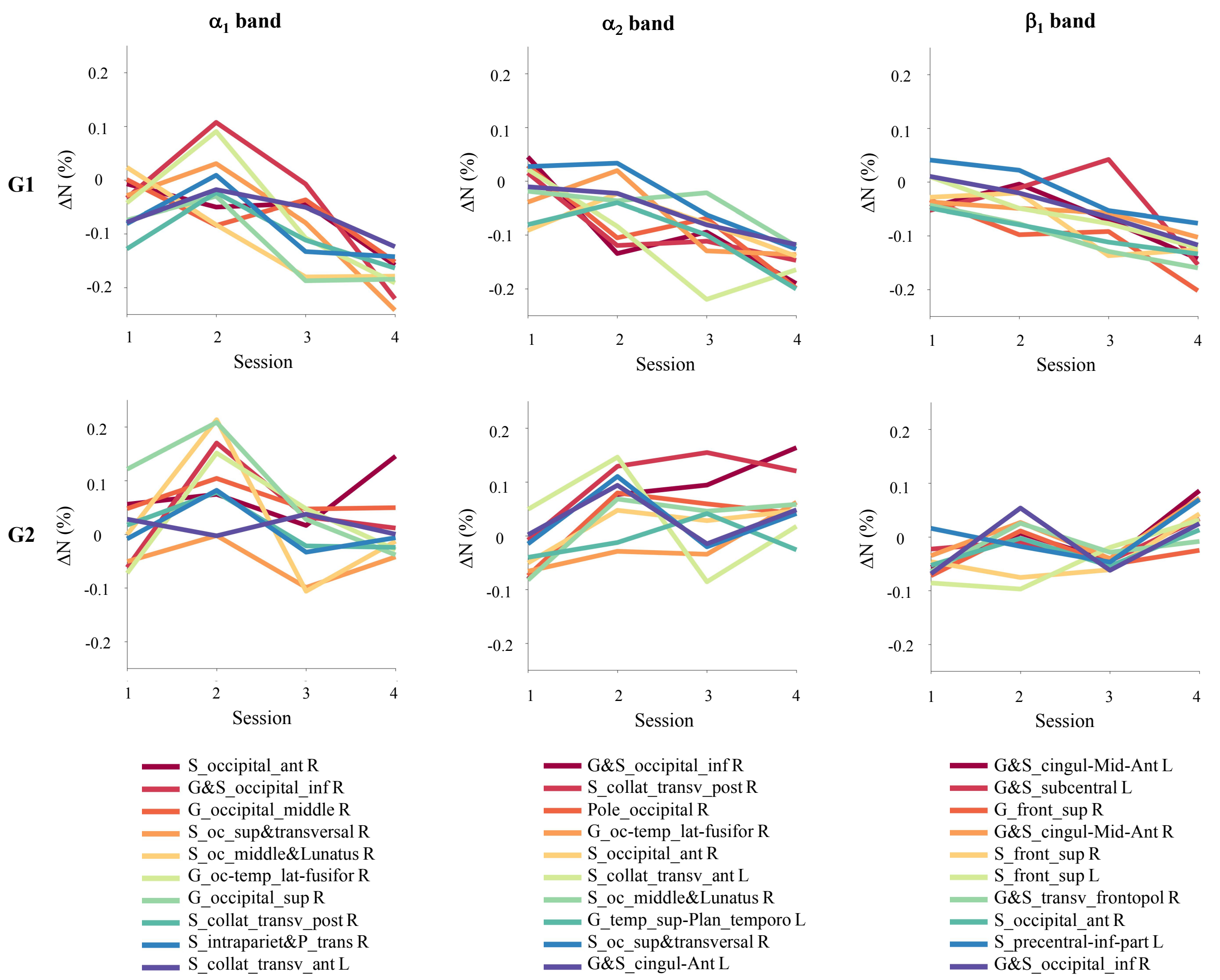

Fig. 4 Evolution of the relative node strength, averaged across subjects from respectively G1 and G2, over the sessions. For each frequency band (i.e. column), we selected the 10 ROIs that discriminate the best the two groups during the last session. The only ROI that shows a significant session effect is the subcentral gyrus (central operculum) and sulci left within G1 and the β_1 band (one-way ANOVA, $F_{3,12} = 4.30$, $p = 0.03$).

end of a successful training, performing a MI task tends to engender a lower connectivity, with respect to the Rest task, within frontal, parietal and occipital areas and engenders higher connectivity in primary somatosensory cortex and primary motor cortex.

To take into account the training effect, we studied the evolution of the node strength over the sessions by focusing our work on the ROIs that showed the highest difference between the groups (Fig. 4). Within the α_1 and the α_2 bands, most of the selected ROIs were located in areas involved in visual perception; in the retinotopic representation of the peripheral visual field (posterior transverse collateral sulcus), the visual attention (intraparietal sulcus and transverse parietal sulci), the peripheral vision (anterior transverse collateral sulcus) and preparation of the movement (inferior occipital gyrus and sulcus). Within G1, the ΔN values tended to decrease with the training whereas they were stable (or increased in the case of the α_2 band) within G2. The trends tended to be similar to those obtained with ΔP.

Notably within the β_1 band, the selected ROIs are known to be involved in the preparation of the movement (inferior occipital gyrus and sulcus), and in working memory (superior frontal gyrus, superior frontal sulcus). Among the selected ROIs some of them belong to the salience network (middle-anterior part of the cingulate gyrus and sulcus), or to the sensorimotor network (subcentral gyrus and sulci, inferior part of the precentral sulcus). Once again, within G1, the FC tended to decrease over the sessions whereas they are stable within G2.

DISCUSSION & CONCLUSION

Understanding the variations of BCI performances between subjects is crucial to improve the reliability of BCI systems. To reduce the inter-subject variations in terms of BCI performances, different approaches have been described, going from the improvement of feature extraction [35] and of the classification algorithm [36] to the adaptation to the user's profile [8]. Another element could be the combination of different modalities to take advantage of their complementarity in terms of sensitivity towards noise for instance. The present study relies on EEG signals only. Nevertheless, it has been previously shown that combining for instance EEG and magnetoencephalography could strongly improve the classification accuracy [37].

From the subject-based perspective, one approach consists of identifying factors that can influence BCI scores to adapt the training to the subject's profile [7]. If psychological and power-based predictors have been elicited [7], functional connectivity has been less considered so far whereas it has been proved to provide reliable monitoring of cognitive function such as working memory for instance [38] and to be used as alternative features [35]. In a previous study, we demonstrated that neurophysiological and FC information could be used as predictors of BCI performances [39]. Here, we focused our study on the changes at the neurophysiological level associated with a successful learning process. For that purpose, we used simple metrics to elicit FC behavior from longitudinal study. Our results suggest that an efficient training is accompanied by a decrease of the FC. Notably, as expected, this phenomenon affects areas involved in the sensorimotor network but also areas involved in the movement preparation and the working memory, especially within the β_1 band. In the case of subjects who showed the weakest improvement, the relative node strength tends to remain stable or to increase within these areas. Nevertheless, we acknowledge that increasing the number of sessions and the number of subjects would enable to get a more reliable idea of the neural mechanisms underlying the learning process, in terms of potential re-organization of the brain network but also in terms of learning speed.

Previous studies reported a lack of learning metric in sensorimotor rhythm-based BCI [3] and therefore, a lack of evidence of learning. Here, common trends between BCI scores, relative power and FC can be elicited. Indeed, in the case of G1, after the session 2, BCI scores start to increase significantly, accompanied by an increase of the desynchronization effect and a decrease of the node strength within the α_1, the α_2, and the β_1 bands. In the case of G2, none of the tested metric showed a session effect. Thus, combining power-based and FC markers, which rely on separability of brain features, to identify learning metrics based on neurophysiological information and not only on the BCI accuracy could be a tool to better assess individual learning.

In this study, by using metrics based on FC we could elicit specific patterns that involve regions beyond the sensorimotor areas, mainly characterized by a decrease of the node strength over a successful training. Further experiments and analysis relying on more sophisticated methods, based notably on graph theory, will certainly help to consolidate this result, and to understand the mechanisms underlying the learning process.

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