Is Event-Related Desynchronization variability correlated with BCI performance?

Sébastien Rimbert, David Trocellier, Fabien Lotte

Is Event-Related Desynchronization variability correlated with BCI performance?

1st Sébastien Rimbert
Inria Bordeaux Sud-Ouest
Talence, France
sebastien.rimbert@inria.fr

2nd David Trocellier
Inria Bordeaux Sud-Ouest
LaBRI / Univ. Bordeaux
Talence, France
david.trocellier@inria.fr

3nd Fabien Lotte
Inria Bordeaux Sud-Ouest
LaBRI
Talence, France
fabien.lotte@inria.fr

***Abstract*—Despite current research, the relationship between the variability of Event-Related Desynchronization (ERD) generated during Motor Imagery (MI) tasks and MI-BCI performances is still not well understood. Indeed, numerous studies have previously shown that there is a lot of inter-subject and intra-subject variability in ERD patterns, but difficulties remain to understand the origin of such variability. This lack of knowledge about variability of cerebral motor patterns limits the possibilities of improving the performance of BCIs, which remains quite poor on average. We believe that a better understanding of the variability of ERDs during BCI use is crucial for developing effective interfaces. Indeed, analysis of inter-trial ERDs and their variability throughout the experimental session during MI are largely neglected in most studies, which have mainly focused on identifying ERD patterns averaged across trial and possibly across participants. In this study, we propose to analyze large MI-BCI databases (n=75 subjects) and investigate how the inter/intra-individual variability of the cerebral motor patterns underlying the right-hand and left-hand MIs task (i.e., ERDs) is associated to BCI performance. Our study revealed that although ERD amplitude and baseline power are correlated with BCI performances, variability of ERD amplitude or baseline power are not.**

***Index Terms*—Motor Imagery; Brain-Computer Interface; Electroencephalography; Variability**

I. Introduction

One of the most prominent Brain-Computer Interface (BCI) types of interaction is Motor Imagery (MI)-based BCI. MI-BCI users control a system by performing MI tasks, e.g., imagining hand or foot movements detected from electroencephalographic (EEG) signals. Indeed, movements and imagination of movements activate similar neural networks [1], enabling the MI-based BCI to exploit the modulation of sensorimotor rhythms (SMR) over the motor cortex, respectively known as Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS), coming from the mu (7-13 Hz) and beta (15-30 Hz) frequency bands [2]. Then, such MI-based BCI relies on machine learning algorithms (e.g., Linear Discriminant Analysis, Support Vector Machine or Riemannian classifiers [3]), typically in the merged frequency band between mu and beta (8-30 Hz), to enable user interaction.

Many articles have described the modulations of ERD/ERS during the MI task (see Figure 1). As a reminder, motor imagery is typically preceded by an ERD in the mu and beta frequency bands. This gradual decrease in power starts in the preparatory phase of the motor task and reaches a maximum during its execution [2]. After the motor imagery, an ERS, also called post-movement beta rebound, occurs mainly in the beta frequency band while the ERD in the mu band slowly returns to the baseline. During the imagination of movements, the ERD occurs bilaterally around the sensorimotor cortex and has a somatotopic cortical distribution of the engaged limb [4], but can also have a contralateral predominance, especially in the beta frequency band [5]. In many cases, the ERD has a larger amplitude in the mu-band than in the beta-band, and seems to be modulated according to the experimental criteria (e.g., uncertainty of the direction of movement, attention to the task or type of movement performed [5]). Finally, in both the BCI and neuroscience domains, it is usual to present the ERD/ERS responses averaged together, either for all trials of a subject or for all subjects through a grand average.

Despite current research, the relationship between the variability of ERD/ERS patterns generated during MI tasks and MI-BCI performances is still not well understood. Indeed, numerous studies have previously shown that there is a lot of inter-subject and intra-subject variability [6], especially concerning the ERD and ERS modulations [7], [8], but difficulties remain to understand the origin of such phenomenon [9]. Some experimental conditions (i.e., nature of the movement [5], force or direction [5], eyes open or eyes closed [10]) seem to modulate the ERD/ERS but such variation is poorly investigated in a BCI-specific context. Furthermore, although some authors mention variability in data from one subject to another, this variability is rarely quantified nor measured with precision. This lack of knowledge about variability of cerebral motor patterns limits the possibilities of improving the performance of BCIs, which remain quite poor on average [11], [12]. Such variability may influence the accuracy of the BCI which could be problematic for various BCI applications.

We believe that a better understanding of the intra and inter-individual variability of ERD/ERS during BCI use is crucial for developing effective interfaces. Indeed, analysis of inter-trial ERD/ERS and their variability throughout the experimental session during MI are largely neglected in most studies, which have mainly focused on identifying patterns that are averaged across trials and possibly across all participants. We believe that it is important to analyze the existing variability in detail across the trials of a single run or block performed by a subject, but also across all the trials of a session. In this study, we propose to analyze large MI-BCI

databases (n=75 subjects) and investigate how the inter/intra-subject variability of the ERDs underlying the right-hand and left-hand MI task (i.e., ERDs and ERSs) is associated to the BCI performance of three different classification tasks: (i) right-hand MI vs left-hand MI, (ii) right-hand MI vs resting state and (iii) left-hand MI vs resting state.

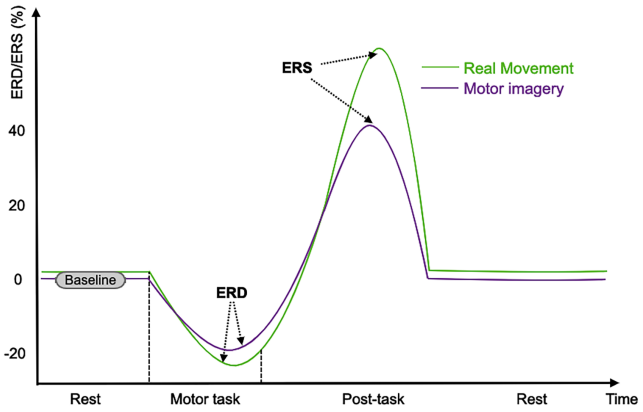

Fig. 1. Illustration of the timings and amplitudes of the desynchronization and the followed synchronization induced by a real movement or a motor imagery according to [13] in the mu and beta frequency bands

II. Material and method

This study investigates inter/intra-subject variability of the ERDs underlying the right-hand and left-hand MI task and BCI performances. To this end, we favored an exploratory study combining the study of neurological motor patterns (i.e., ERDs) recorded in two different phases of the experiment (Calibration and Online User Training), their evolution across trials, and the associated BCI performances.

A. Database used for analysis

1) Participants: Our analyses were performed on a data base of 75 right-handed healthy subjects (35 women; 25.83 $\pm$ 9.52 y.o.), coming from two previous experiments [14], [15]. These experiments used the same MI-BCI protocol, and followed the statements of the WMA declaration of Helsinki on ethical principles for medical research involving human subjects. In addition, all participants signed an informed consent, and the study was approved by the ethical committee of Inria (COERLE, approval number: 2018-13). The subjects had no known medical history that could have influenced the MI tasks.

2) Experimental BCI protocol: Each participant completed one MI-BCI session. Then, participants performed six 7-minutes runs during which they had to learn to perform left and right hand MI tasks with the BCI. The Graz training protocol was used and was divided into two steps: first, the training of the system (i.e., calibration phase, collecting data to train the EEG machine learning classifier) and second, the training of the user with online feedback (see Figure 2). The EEG data of the first two runs were used as calibration data for the MI-BCI machine learning algorithms. More precisely, EEG signals were first band-pass filtered in a data-driven user-specific frequency band (comprised within 5-35 Hz), then spatially filtered using Common Spatial Patterns (CSP) filters. Finally, the resulting features were classified using a Linear Discriminant Analysis (LDA) classifier (see [14], [15] for details). The trained MI-BCI was used to provide online feedback based on right-hand vs. left-hand MI discrimination during the four subsequent runs.

During the first two runs (calibration phase), users were provided with a sham feedback, i.e., a blue bar randomly appearing and varying in length. Such feedback (whether sham here, or real during the next phase) represents the BCI classifier decision (left or right hand MI when the bar goes left or right) and its associated confidence in such decision (the longer the bar the more confident). During each run (see Figure 2), users had to perform 40 trials (20 per MI-task, presented in a random order), each trial lasted 8s. At t = 0s, a cross was displayed on the screen. At t = 2s, an acoustic signal announced the appearance of a red arrow, which appeared one second later (at t = 3s) and remained displayed for 1.25s. The arrow pointed in the direction of the task to be performed. Participants were instructed to start performing the corresponding MI-task as soon as the arrow appeared, and to keep doing so until the cross disappeared. Finally, from t = 4.25s, a visual feedback was continuously provided in the shape of a blue bar, the length of which varied proportionally to the BCI classifier output, i.e., the distance to the LDA hyperplane (for run 3 to 6) or randomly (for the first two runs). Only positive feedback was displayed, i.e., the feedback was provided only when the recognized task matched the instructed task. The feedback was provided for 3.75s and was updated at 16Hz, using a 1s sliding window. After 8 seconds, the screen turned black again until the beginning of the next trial. The participant could then rest for a few seconds.

Following the recommendations from the literature, the participants were encouraged to perform a kinesthetic imagination and to choose their own mental imagery strategies, e.g., imagining waving at someone or playing the piano [16]. Participants were instructed to find a strategy for each MI task so that the system would display the longest possible feedback bar. Note that participants were instructed to use a single strategy (per MI task) during the calibration runs, but were encouraged to explore to find possibly better strategies during the feedback runs.

3) Electrophysiological recordings: EEG signals were recorded with two g.USBAmp (g.tec, Austria), sampled at 512 Hz, from 27 electrodes around the primary motor, the motor and the somatosensory cortices (F_z, F_4, FC_z, FC_1, FC_2, FC_3, FC_5, FC_4, FC_6, F_3, C_z, C_5, C_3, C_1, C_2, C_4, C_6, CP_5, CP_3, CP_1, CP_z, CP_2, CP_4, CP_6, P_z, P_3, P_4).

4) BCI performances: In addition to the online BCI performances (here classification accuracy) based on right-hand MI vs left-hand MI discrimination on runs 3 to 6, we also estimated, offline, BCI performances for classifying resting state EEG signals from a single hand MI task EEG (either left-hand or right-hand MI). That provided us with two additional BCI performance metrics: rest VS left hand MI and rest VS right hand MI classification accuracies. These performance metrics were estimated offline by first band-pass filtering EEG signals in 8-30Hz and then extracting 3 second long MI and rest epochs from each trial, starting respectively at t=3.5s (for MI) and t=8.5s (for rest) of each MI trial (see Figure 2.B). Such epoch length was chosen to ensure that

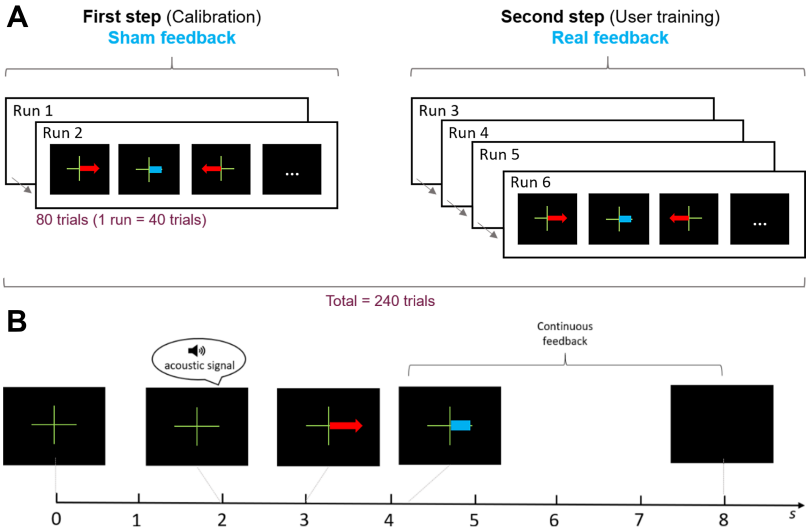

Fig. 2. (A) The BCI session included 6 runs divided into two steps: (1) data acquisition to train the system (2 runs, 80 trials in total with sham feedback) and (2) user training (4 runs, 160 trials in total). After Run 2, the classifier is trained on the data acquired during the two first runs and then begins the user training with real feedback. (B) Detailed steps of one MI trial with the corresponding visual feedback

the rest epochs did not contain the audio stimuli. From such epochs, a left hand MI vs rest and a right MI vs rest classifiers were built using CSP spatial filters and an LDA classifier, as done online for left-hand VS right-hand MI classification. Such classifiers were also trained on the first two calibration runs and tested on the four subsequent runs to obtain (offline) classification accuracies.

B. Electrophysiological and correlation analyses

In this paper, we first investigated the average ERD/ERS modulations (n=75 subjects) for the two phases (calibration and user training) and the two MI tasks (right-hand and left-hand). Then, we notably analyzed the possible associations that ERD modulations could have with our 3 BCI performance metrics: 1) left hand VS right MI (obtained online); 2) left hand MI VS rest (obtained offline) and 3) right hand MI VS rest (also obtained offline). We have chosen to focus on the ERD modulations because they occur during the MI task and because ERDs are the typical features most often used for classification in MI-BCI.

1) Pre-processing: All offline analyses of ERD/ERS modulations were performed using the EEGLAB toolbox 14.1 [17] and MATLAB 2016a. The EEG data were divided in 5 seconds epochs corresponding to 5 seconds after the MI-cue for each run. Then, a baseline was defined as the time window starting 2.5 seconds before each MI-cue and ending on that cue.

2) ERD/ERS modulations: We compute the ERD/ERS% (see Figure 3) using the "band power method" [1].

$$ERD/ERS\% = \frac{\overline{x^2} - \overline{BL^2}}{\overline{BL^2}} \times 100 \ , \qquad (1)$$

where $\overline{x^2}$ is the average of the squared signal smoothed using a 250-millisecond sliding window with a 100 ms shifting step, $\overline{BL^2}$ is the mean of a baseline segment (2.5 s) taken 3.5 s before the visual cue indicating the go signal, and ERD/ERS% is the percentage of the oscillatory power increase/decrease estimated for each step of the sliding window. A positive ERD/ERS% indicates a synchronization whereas a negative ERD/ERS% indicates a desynchronization. This percentage was computed separately for the C_3 and C_4 electrodes (i.e., C_3 for the right hand MI and C_4 for the left hand MI). The EEG signals were filtered in the merged mu+beta band (8-30 Hz) for all subjects using a 4th-order Butterworth band-pass filter.

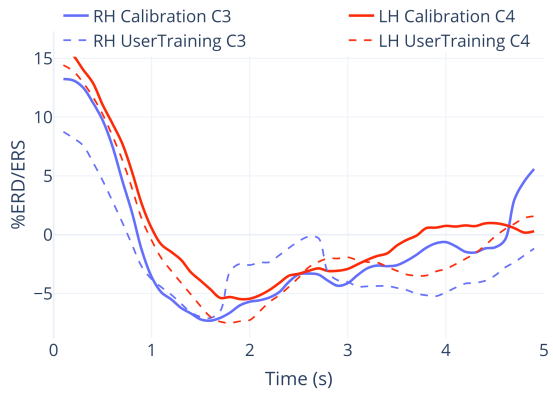

Fig. 3. Grand average (n=75) ERD/ERS% curves in the merged mu+beta band (8-30 Hz) for right-hand MI (in blue) and left-hand MI (in red) tasks during both Calibration (dotted blue line) and User Training (dotted red line) phases for electrode C_3 and C_4. The beginning of the MI task started at 0s on this Figure and last for 5 seconds.

3) Topographic ERD/ERS map: Brain topography allows us to display the possible changes over different electrodes on the scalp in order to localize which part of the brain was involved when the subject performed the requested task. In this article, we computed the topographic Event-related spectral perturbations (ERSP; which is equivalent to ERD and ERS) in the alpha/mu + beta (8-30 Hz) band during the left-hand and right-hand MIs task in the time window [3;8]s (Figure 4). A surrogate permutation test (3000 permutations) from EEGLAB was used to validate differences in term of time-frequency ERSPs and localization of this ERSPs with alpha level $< 5\%$ (Figure 4). We also applied a false

discovery rate (FDR) correction for multiple comparisons.

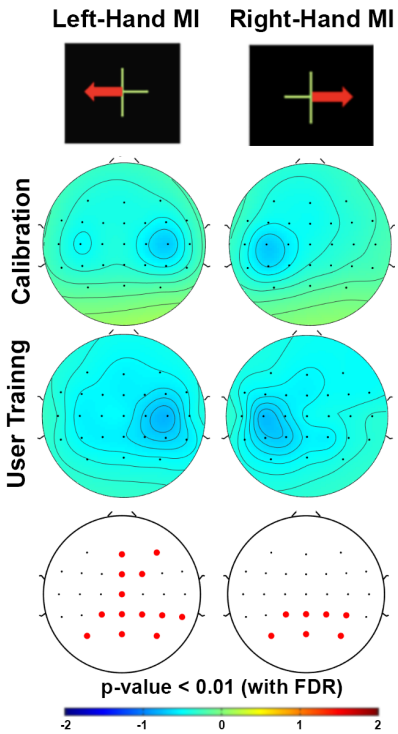

Fig. 4. Topographic map of ERD/ERS% (grand average, n=75) in the alpha/mu+beta band during the right-hand and left-hand MIs for both calibration and user training phases. The time window used for the topographic map corresponds to [3;8]s. A blue color corresponds to a strong ERD and a red one to a strong ERS. Red electrodes indicate a significant difference (p<0.01) with a FDR (False Discovery Rate) correction.

4) ERD variability metrics: In order to study the variability of ERD modulations during this BCI experiment, we considered several metrics:

- **The standard deviations of the ERD** for both classes (left hand - LH - and right hand - RH - MI) and phases (calibration - Calib - and user training - UserT -) (thus named STDERD.Calib-LH, STDERD.Calib-RH, STDERD.UserT-LH and STDERD.UserT-RH). We measured the standard deviation of the trial mean ERDs across all trials for each class and phase.
- **The means of the ERD** for both classes and phase: MeanERD.Calib-LH, MeanERD.Calib-RH, MeanERD.UserT-LH, MeanERD.UserT-RH. We measured the mean of the trial mean ERDs across all trials in the [3;8]s time window for each class and phase.
- **The standard deviations of the baseline** for both classes and phases: STDBAS.Calib-LH, STDBAS.Calib-RH, STDBAS.UserT-LH, STDBAS.UserT-RH. Since the baseline is directly related to the ERD produced during the task, we hypothesized that variability in the ERD could be correlated with BCI performance. We measured the standard deviation of the baseline power mean across all trials for both classes and phases. To do this, we filtered the signal between 8-30 Hz, squared it and finally calculated the standard deviation.
- **The means of the baseline** for both classes and phases: BAS.Calib-LH, BAS.Calib-RH, BAS.UserT-LH, BAS.UserT-RH. We measured the mean of each trial's baseline power mean across all trials in the [0; 2.5]s time window for both phases and classes.

5) Correlations of ERD modulations and baseline variabilities and BCI performances: The originality of this study is to investigate the potential link between neurophysiological ERD modulations variability during the MI task and BCI performances. Our primary hypothesis was that there is a correlation between the intra/inter subjects variability of the ERD and three different forms of BCI performance: (i) right-hand MI vs left-hand MI, (ii) right-hand MI vs resting state and (iii) left-hand MI vs resting state. To do this, we estimated the average mean ERD modulations and standard deviations associated in [0;5]s of all subjects on the contralateral electrodes in both tasks (i.e., C3 for the right hand MI and C4 for the left hand MI) for both calibration and user training sessions. These variables were then correlated with BCI performance in a correlogram (see Figure 5A). We also analyzed the average power of the baseline and standard deviations associated in [0;2.5]s of all subjects on the contralateral electrodes in both tasks (i.e., C3 for the right hand MI and C4 for the left hand MI) for both calibration and user training phases. These variables were then also correlated with BCI performances in a correlogram (see Figure 5B). Due to the large number of correlation tests performed (n=242), the significance level α was adjusted at ($p < 0.01$ and $p < 0.05$) for multiple comparisons using the Benjamini-Hochberg procedure [18]. In this study, a positive correlation with the Mean.ERD indicates that the modulation calculated over the time window of the ERD increases, i.e. the synchronization is less large, and therefore the motor cortex is less activated [1].

III. Results

A. Right-hand vs Left-hand MI ERDs

Our results showed an activation of the motor cortex with a controlateral ERD, i.e., covering either right and left-hand motor areas depending on the task, during the 5s when the MI task was performed (Figure 4). This result is in harmony with the literature: the ERD phase is mainly observed during the MI task and represents an activation of the motor cortex. Note that a slightly bilateral desynchronization was observed for the left-hand MI. Observing the modulations of the ERD over time (Figure 3) shows that the amplitude desynchronization is maximal two seconds after the beginning of the right-hand MI (in blue) and reaches approximately -7%. The ERD amplitude for the left-hand MI (in red) is slightly lower and reaches -5%. After the ERD has attained a maximum desynchronization amplitude, it gradually returns to a baseline in the following seconds.

B. Calibration vs User Training

Results in Figure 3 and 4 showed no significant difference between the calibration and the user training phase during the MI tasks, especially for contralateral electrodes (C_3 and C_4). However, considering the central and occipital electrodes, some significant differences could be noted (p<0.01; with FDR correction). This result is observed for both the right and left hand MI tasks. In addition, although not significant, we observed an increase in the ERD amplitude associated

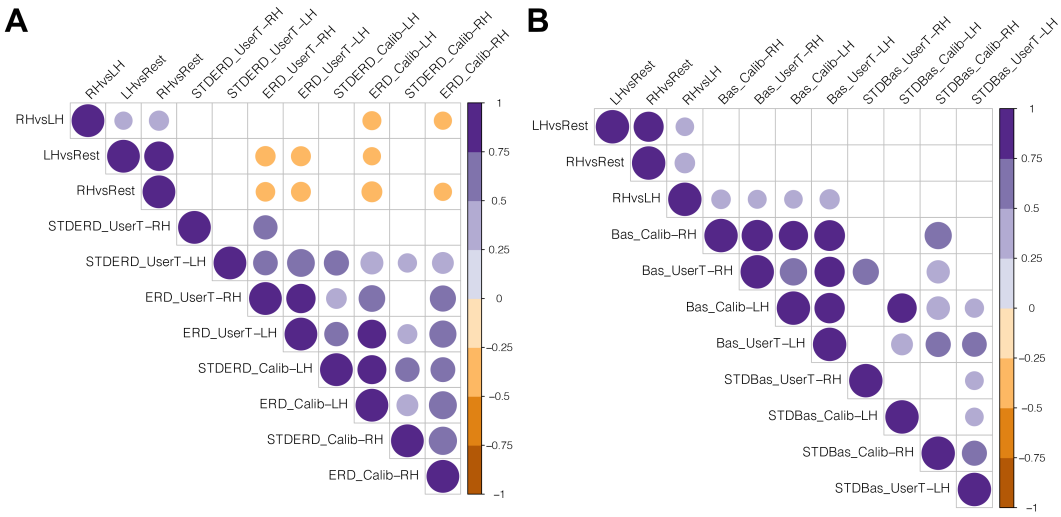

Fig. 5. Correlograms representing pearson correlations between BCI performances and (A) ERD modulations variability metrics, (B) baseline variability metrics. Correlations with a p-value > 0.05 are considered as not significant and are in blank. Positive correlations are displayed in blue and negative ones are in orange. The intensity of the color and the size of the circles are proportional to the correlation coefficients.

with a larger spatial area during the user training phase. The observation of ERD modulations over time (Figure 3) also showed little difference between the calibration and user training phases for electrodes C_3 and C_4.

C. ERD, baseline and associated variabilities behavior

Figure 6 shows the large variability existing across subjects regarding the amplitude of the ERD or the baseline power during the MI task for the calibration and user training phases. The value of the standard deviation of the ERD is very high compared to the average amplitude of the ERD during the task. In comparison, the baseline standard deviation is smaller than the ERD standard deviation, suggesting that the cerebral state of the subjects is more comparable in the resting state than during MI. Note that there is no significant difference between mean.ERD amplitudes, and baseline power values across phases and MI tasks. Similarly, the standard deviation values are not significantly different.

D. BCI performances

On average, the BCI accuracy for right-hand MI vs left-hand MI was 63.9% $\pm$ 16.5%. The offline accuracy based on right-hand MI vs resting state was 71.2% $\pm$ 16.0% and the offline accuracy based on left-hand MI vs resting state was 71.9 $\pm$ 14.6%. Interestingly, BCI performance is higher using the classification based on one of the MI tasks vs. resting state. A possible explanation for this phenomenon is a poor contralateralization or a bilateralization of the ERD. Indeed, in the case where the ERD during the left-hand or right-hand MI tasks is bilateral, then a classification based on the discrimination of the two tasks is more difficult.

E. Correlation between BCI performances, ERD and associated variability

The study of the correlogram of the ERD and BCI performances (Figure 5A) shows that there is no significant correlation between the variability of the ERD and BCI performances, whatever the phase studied (calibration or user

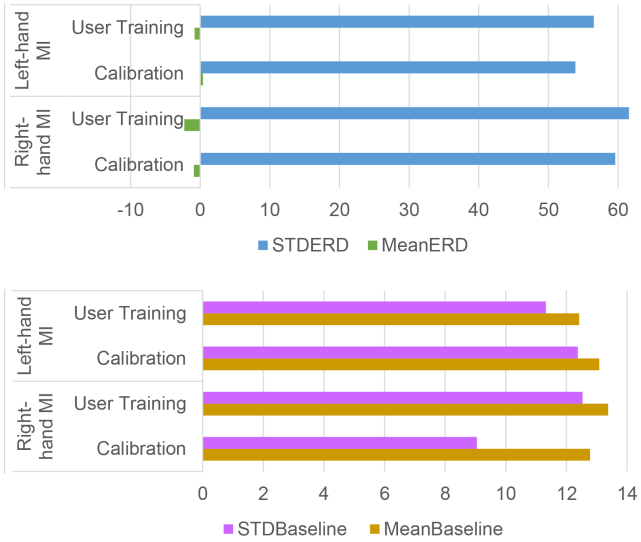

Fig. 6. Representative of the grand average (n=75 subjects) ERD amplitude (top), baseline (bottom) and associated variabilities for the right and left-hand MI tasks in both sessions (calibration and User training).

training) or the motor task performed (right-hand or left-hand MIs). A negative correlation is observed between the mean.ERD of the different phases and BCI performance, showing that the larger the desynchronization (i.e., the more negative its value), the more BCI performances increase. This result is quite logical since BCI performances are most often based on the desynchronization amplitude of the ERD.

More precisely, the amplitude of the ERD (for RH and LH MIs) in the calibration phase correlates both with the online performance based on RH vs LH, and also with the off-line performance based on RH vs Rest and LH vs Rest. This is not the case for the ERD amplitude during the user training phase, which is only correlated with the (offline) classification performance of LH vs Rest and RH vs Rest. While the standard deviation of the ERD does not correlate with BCI performance, the figure shows that ERD variability

seems associated to the ERD amplitude. For example, the ERD variability during the calibration phase (for RH and LH MIs) correlates strongly with the ERD amplitude for the same calibration phase. This implies that the higher the variability of the ERD, the weaker the desynchronization.

Overall, the BCI performances are positively correlated with each other. For example, the offline classification performances (LH vs Rest and RH vs Rest) are strongly positively correlated with each other. The correlation is lower between the online classification performances (RH vs LH) and the offline ones (LH vs Rest and RH vs Rest).

F. Correlation between BCI performances, baseline and associated variability

The second correlogram (Figure 5B) shows that there is no correlation between the variability of the baseline power and BCI performances. However, The power of the baseline is positively correlated with online classification performances based on LH vs RH, but not with LH vs rest nor RH vs rest (offline) BCI performances. This suggests that the more powerful the baseline, the better the online performance.

IV. Discussion

In this study, we observed that the variability of ERD amplitude was not correlated with any BCI performances. Similarly, variability in baseline power was not correlated with BCI performance. However, ERD amplitude or baseline power values were correlated with BCI classification accuracy (see section III-E; Figure 5), which is quite logical since the ERD amplitude depends directly on the value of the baseline [1], and the BCI mostly uses this value to discriminate between mental states. One possibility for the non-correlation between ERD variability and BCI performance is that the temporal and spatial variability of ERD is not taken into account in our analyses. Indeed, the amplitude of the ERD is strongly modulated over time (see Figure 3). Similarly, the topographic images indicate that between the calibration and user training phases, there is an amplification of the contralateral area where the ERD is generated. This temporal and spatial variability should be studied and taken into account in future analyses. Note that the BCI may also use other patterns than the ERD to discriminate MIs, which would explain why the intrinsic variability of the ERD or the baseline is not sufficient to explain the variability of BCI performance. The analysis of user traits (e.g., age, gender, motivation, personality) could also help to understand the variability of ERDs and BCI performances [19].

V. Conclusion

In this paper, we studied how the inter/intra-subject variability of the ERDs underlying the right-hand and left-hand MI task is associated to the BCI performance of three different classification tasks: (i) right-hand MI vs left-hand MI, (ii) right-hand MI vs resting state and (iii) left-hand MI vs resting state. Our results confirmed a stronger contralateraly observed ERD during calibration (with sham feedback) and during online training (with real-time feedback and instructions to explore promising MI strategies). Finally, and more importantly, our study revealed that although ERD amplitude and baseline power are correlated with BCI performances, variability of ERD amplitude or baseline power are not. As future work, we plan to extend such analyses including the temporal and spatial variability of the ERD, but also taking into account the ERS pattern.

VI. Acknowledgment

This work was supported by the ERC with project Brain-Conquest (grant ERC-2016-STG-714567). The authors thank Pauline Dreyer for helping with the experiments.

References

[1] G. Pfurtscheller and F. H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clin Neurophysiol*, vol. 110, no. 11, pp. 1842–57, Nov 1999.

[2] G. Pfurtscheller and T. Solis-Escalante, "Could the beta rebound in the EEG be suitable to realize a "brain switch"?" *Clin Neurophysiol*, vol. 120, no. 1, pp. 24–9, Jan 2009.

[3] F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, and F. Yger, "A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update," *Journal of neural engineering*, vol. 15, no. 3, p. 031005, 2018.

[4] D. Sochůrková, I. Rektor, P. Jurak, and A. Stancak, "Intracerebral recording of cortical activity related to self-paced voluntary movements: A bereitschaftspotential and event-related desynchronization/synchronization. seeg study," *Experimental brain research*, vol. 173, pp. 637–49, 10 2006.

[5] B. E. Kilavik, M. Zaepffel, A. Brovelli, W. A. MacKay, and A. Riehle, "The ups and downs of beta oscillations in sensorimotor cortex." *Exp Neurol*, vol. 245, pp. 15–26, Jul 2013.

[6] S. Saha and M. Baumert, "Intra- and inter-subject variability in eeg-based sensorimotor brain computer interface: A review," *Frontiers in Computational Neuroscience*, vol. 13, p. 87, 2020.

[7] G. Pfurtscheller, C. Brunner, A. Schlögl, and F. Lopes da Silva, "Mu rhythm (de)synchronization and eeg single-trial classification of different motor imagery tasks," *NeuroImage*, 2006.

[8] Y. Jeon, C. S. Nam, Y.-J. Kim, and M. C. Whang, "Event-related (de)synchronization (erd/ers) during motor imagery tasks: Implications for brain–computer interfaces," *Int. J. Indus. Erg.*, 2011.

[9] S. C. Wriessnegger, G. R. Müller-Putz, C. Brunner, and A. I. Sburlea, "Inter- and intra-individual variability in brain oscillations during sports motor imagery," *Frontiers Hum. Neuros.*, 2020.

[10] S. Rimbert, R. Al-Chwa, M. Zaepffel, and L. Bougrain, "Electroencephalographic modulations during an open- or closed-eyes motor task," *PeerJ*, p. e4492, 2018.

[11] B. Allison and C. Neuper, *Could anyone use a BCI?*, 01 2010, pp. 35–54.

[12] S. Hétu, M. Gregoire, A. Saimpont, M.-P. Coll, F. Eugène, P.-E. Michon, and P. Jackson, "The neural network of motor imagery: An ale meta-analysis," *Neuroscience and biobehavioral reviews*, 2013.

[13] S. Rimbert, P. Riff, N. Gayraud, D. Schmartz, and L. Bougrain, "Median nerve stimulation based bci: A new approach to detect intraoperative awareness during general anesthesia," *Frontiers in Neuroscience*, vol. 13, p. 622, 2019.

[14] L. Pillette, A. Roc, B. N'Kaoua, and F. Lotte, "Experimenters Influence on Mental-Imagery based Brain-Computer Interface User Training," *Int. J. Hum.-Comp. Stud.*, p. 102603, 2021.

[15] C. Benaroch, C. Jeunet, and F. Lotte, "When should MI-BCI feature optimization include prior knowledge, and which one?" *Brain-Computer Interfaces*, vol. 228, pp. 3–35, 2022.

[16] S. Kober, M. Witte, M. Ninaus, C. Neuper, and G. Wood, "Learning to modulate one's own brain activity: the effect of spontaneous mental strategies," *Frontiers in Human Neuroscience*, vol. 7, 2013.

[17] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis," *Journal of Neuroscience Methods*, vol. 134(1), 2004.

[18] Y. Benjamini and Y. Hochberg, "Controlling the false discovery rate: a practical and powerful approach to multiple testing," *Journal of the royal statistical society. Series B (Methodological)*, pp. 289–300, 1995.

[19] S. Rimbert and F. Lotte, "How ERD modulations during motor imageries relate to users' traits and BCI performances," in *44th International Engineering in Medicine and Biology Conference*, Glasgow, United Kingdom, Jul. 2022.