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ERD modulations during motor imageries relate to users' traits and BCI performances

Sébastien Rimbert[1] and Fabien Lotte[1]

Abstract— **Improving user performances is one of the major issues for Motor Imagery (MI) - based BCI control. MI-BCIs exploit the modulation of sensorimotor rhythms (SMR) over the motor and sensorimotor cortices to discriminate several mental states and enable user interaction. Such modulations are known as Event-Related Desynchronization (ERD) and Synchronization (ERS), coming from the mu (7-13 Hz) and beta (15-30 Hz) frequency bands. This kind of BCI opens up promising fields, particularly to control assistive technologies, for sport training or even for post-stroke motor rehabilitation. However, MI-BCIs remain barely used outside laboratories, notably due to their lack of robustness and usability (15 to 30% of users seem unable to gain control of an MI-BCI). One way to increase user performance would be to better understand the relationships between user traits and ERD/ERS modulations underlying BCI performance. Therefore, in this article we analyzed how cerebral motor patterns underlying MI tasks (i.e., ERDs and ERSs) are modulated depending (i) on nature of the task (i.e., right-hand MI and left-hand MI), (ii) the session during which the task was performed (i.e., calibration or user training) and (iii) on the characteristics of the user (e.g., age, gender, manual activity, personality traits) on a large MI-BCI data base of N=75 participants. One of the originality of this study is to combine the investigation of human factors related to the user's traits and the neurophysiological ERD modulations during the MI task. Our study revealed for the first time an association between ERD and self-control from the 16PF5 questionnaire.**

I. INTRODUCTION

One of the most prominent Brain-Computer Interface (BCI) paradigm is Motor Imagery (MI) BCI that users control by performing MI tasks, e.g., imagined hand or foot movements detected from electroencephalographic (EEG) signals. MI-BCIs exploit the modulation of sensorimotor rhythms (SMR) over the motor and sensorimotor cortices, known as Event-Related Desynchronization (ERD) and Synchronization (ERS), coming from the mu (7-13 Hz) and beta (15-30 Hz) frequency bands [1].

Many articles have described ERD/ERS modulations during motor tasks. As a reminder, MI 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 MI, an ERS, also called post-movement beta rebound, occurs mainly in the beta band while the ERD in the mu band slowly returns to baseline [2]. During MI, the ERD occurs bilaterally around the sensorimotor cortex and has a somatotopic cortical distribution of the engaged limb [3], but can also have a contralateral predominance, especially in the beta band [4]. In many cases, the ERD has a larger amplitude in the mu 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, type of movement performed [4]). The BCI domain mainly exploits ERD and ERS phenomena in the merged mu and beta band (8-30 Hz) to discriminate mental states from EEG. Such MI-BCIs usually rely on classical machine learning algorithms (e.g., Linear Discriminant Analysis) or on a Riemannian geometry framework, the current state-of-the-art EEG classifiers, to discriminate several mental states and enable user interaction [5].

While they are very promising for numerous applications, MI-BCIs remain barely used outside laboratories, notably due to their lack of robustness and usability. Indeed, the performance of MI-BCIs largely varies across users and experiments and 15 to 30% of users seem unable to gain control of an MI-BCI, a phenomenon sometimes called BCI illiteracy/deficiency [6]. Despite current research, the relationship between ERD/ERS modulations generated during different MI tasks and other factors such as user personality or experimental context are still not well understood. Indeed, numerous studies have previously reported substantial inter-subject and intra-subject variability in ERD/ERS patterns [7], but difficulties remain to understand the origin of such phenomenon [8]. Correlations were reported between the users' BCI classification performance and both psychology questionnaires measuring users' traits (e.g., MIQ-RS, KVIQ, 16PF5 [9]) and some users' skills (e.g., meditation [10], manual activity [11]). However, there is a lack of knowledge about the relationaships between user traits and ERD/ERS modulations underlying such BCI performance.

This lack of knowledge about variability of ERD/ERS during MI limits the possibilities of improving BCI performances, which remain quite poor on average [6], [12]. We believe that a better understanding of the intra-individual variability of ERD/ERS during BCI use is crucial for developing effective BCIs. Therefore, in this study we analyze how cerebral motor patterns underlying MI tasks (i.e., ERDs and ERSs) are modulated depending (i) on nature of the task (i.e., right-hand MI and left-hand MI), (ii) the session during which the task was performed (i.e., calibration or online user training) and (iii) on the characteristics of the user (e.g., age, gender, manual activity, personality traits) on a large MI-BCI data base of N=75 participants.

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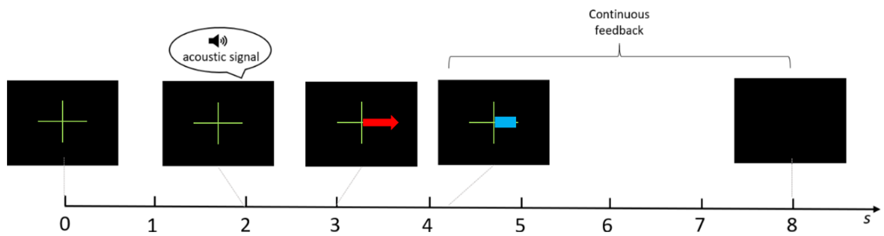

Fig. 1: The BCI session included 6 runs divided into two steps: (1) data acquisition to train the system (2 runs) and (2) user training (4 runs). After Run 2, the classifier is trained on the data acquired during the two first runs.

II. MATERIAL AND METHODS

A. Data base used for analysis

1) Participants: Our analyses were performed on a data base of 75 right-handed healthy subjects (37 women; 25.83 $\pm$ 9.52 y.o.), coming from two previous experiments [13], [14]. These experiments used the same MI-BCI protocol, which was approved by the ethical committee of Inria (COERLE, approval number: 2018-13). The subjects had no known medical history that could have influenced then MI task.

2) Experimental BCI protocol: Each participant completed one MI-BCI session. Participants were first asked to read and sign the consent form and complete several questionnaires (see Section II-A.3 -Questionnaires-). 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 and second, the training of the user. 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 user-specific frequency band (comprising 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 [13], [14] for details). The trained MI-BCI was used to provide online feedback during the four subsequent runs.

During the first two runs (calibration session), users were provided with a sham feedback, i.e., a blue bar randomly appearing and varying in length. During each run (see Figure 1), 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, namely left or right for left or right MI. 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 [15]. 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) User experience and questionnaires: In addition to their age, gender and education level, we asked all the subjects to rate their self-perception of manual ability on a five-point Likert scale, and to indicate the frequency of manual activities (e.g., sport practice or musical instrument in their everyday life). The 5th edition of the 16 Personality Factors (16PF5) questionnaire, i.e., a validated psychometric questionnaire to assess different aspects of people's personality and cognitive profile was also filled-in by participants [16]. This questionnaire identifies 16 primary factors of personality, and 5 global scores of personality. According to results previously reported in the BCI domain [13], [17], subsequent analysis used the 5 global scores.

4) 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 cortex (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).

B. Electrophysiological and correlation analyses

In this paper, we first investigated the average ERD/ERS modulations (n=75 subjects) for the two sessions (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 both users' traits and BCI performances. 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 were performed using the EEGLAB toolbox 14.1 [18] and MATLAB 2016a. The EEG data were divided in 11 seconds epochs corresponding to 3 seconds before and 8 seconds after the MI-cue for each run. Then, a baseline was defined 2.5 seconds before each cue.

2) Event-related spectral perturbation: To analyze the differences between each task (i.e., right-hand and left-hand MIs), and each session (calibration and user training), we performed an event-related spectral perturbation (ERSP) between 5-35 Hz. We compute the ERSPs using the gain model approach which is equivalent to the *band power method* [1]. In this model, the ERSP at each time-frequency point is divided by the average spectral power in a 2.5s pre-stimulus baseline period for each frequency band. Then, a log-transformed ERSP measure was used to highlight our results. We used a 256 point sliding Fast Fourier Transform (FFT) window. We computed the mean ERSP 3 seconds before the MI-cue to 8 seconds after (Figure 3).

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 ERSPs (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 2). A surrogate permutation test (3000 permutations) from EEGLAB toolbox was used to validate difference in term of time-frequency ERSPs and localization of this ERSPs with alpha level ($< 5\%$) (Figure 2). We also applied a false discovery rate (FDR) correction test for multiple comparisons.

4) Correlations of ERD modulations with users' traits and BCI performances: The originality of this study is to combine the investigation of human factors related to the user's traits and the neurophysiological ERD modulations during the MI task. Our primary hypothesis was that there is a correlation between the ERD modulations and the collected personal factors (age, gender of experimenter, gender of participant, education level, meditation practice, manual activity, mental rotation score, BCI performance and items from the 16PF5 questionnaire). Thus, we analyzed the average ERD modulations in [3-8s] 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 4 ERD-related variables were then correlated with users' traits related variables (see Table I). Due to the large number of correlation tests performed (n=52), the significance level α was adjusted at ($p < 0.01$ and $p < 0.05$) for multiple comparisons using the Benjamini-Hochberg procedure [19]. In this study, a positive correlation means that the modulation calculated over the time window of the ERD increases, i.e. the desynchronisation is less large, and therefore the motor cortex is less activated [1].

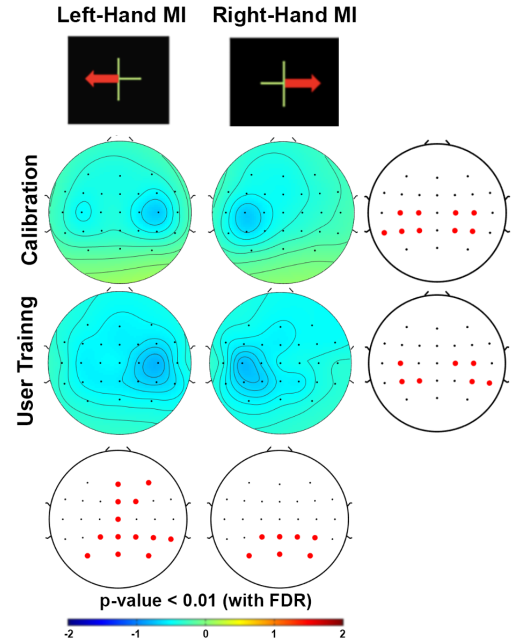

Fig. 2: Topographic map of ERD/ERS% (grand average, n=75) in the alpha/mu+beta band during the right-hand and left-hand MIs for both calibration and user training sessions. A blue colour corresponds to a strong ERD and a red one to a strong ERS. Red electrodes indicate a significant difference ($p<0.01$) with a FDR (False Discovery Rate) correction.

III. RESULTS

A. Right-hand vs Left-hand MI

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 2). Then, following the end of the task, when ERD decreases, a contralateral ERS is observed for several seconds (Figure 3). These results are in harmony with the literature: the ERD phase is mainly observed during the MI task and represents an activation of the motor cortex. After the end of the MI task, the motor cortex re-synchronizes significantly to allow a new movement. It should be noted that the ERD is predominantly contralateral in the mu and beta frequency band, but also occurs on the ipsilateral electrode. This effect was observed for both right-hand MI (see Figure 3) and left-hand MI.

B. Calibration vs User Training

Results in Figure 2 showed a significant difference between the calibration and the user training session for many electrodes during the MI tasks. This result is observed for both the right and left hand MI tasks ($p < 0.01$). This result will be discussed below (see section IV-A) and may be related to the specific instructions given to the participant for the user training session. The topographic map indicated the limited presence of ERD during the user training session in the 8-30 Hz band (Figure 2) but the time-frequency map

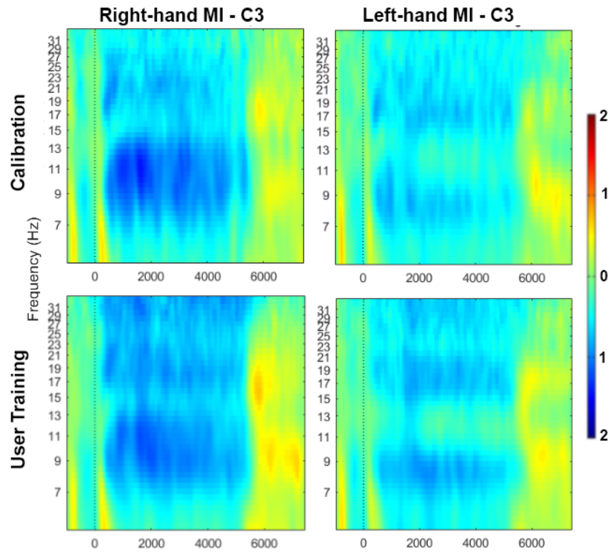

Fig. 3: Grand average time-frequency analysis (n=75) with event-related spectral perturbation (ERSP) for both Calibration and User Training sessions for electrode C_3. t=0 on this plot corresponds to t=3 on the trial showed in Figure 1

TABLE I: Correlation between ERD modulations and users' traits. rho denotes the Spearman's correlation coefficient. Significant results are indicated in orange. * indicates $p < 0.05$ after FDR correction.

	ERD modulations			
	Calibration		User Training	
	RH-C3	LH-C4	RH-C3	LH-C4
	rho	rho	rho	rho
User gender	0.03	0.012	0.09	0.02
Experimenter gender	-0.08	-0.05	-0.17	-0.21
Age	0.10	0.22	0.17	0.16
Level of study	0.07	-0.09	-0.12	-0.12
Meditation practice	0.16	0.08	**0.41***	0.20
Manual activity	0.10	0.12	0.04	0.17
Mental rotation	0.004	-0.07	-0.07	-0.02
BCI performance	**-0.29****	**-0.32****	**-0.25****	**-0.24****
Extraversion	-0.02	-0.10	-0.07	-0.06
Anxiety	0.19	0.13	0.05	0.13
Though-mindedness	0.15	0.25	0.22	0.13
Independence	-0.04	-0.13	-0.06	-0.007
Self-control	0.25	**0.30***	**0.35***	**0.37***

(Figure 3) showed that an ERD is specifically present in the beta band (15-30 Hz).

C. Associations of ERD modulations with user's traits and BCI performance

Our results revealed that meditation practice ($\rho = 0.41$; $p = 0.017$) was positively correlated with ERD modulation only for the right-hand MI during the user training session. Our results also indicate that BCI performance is negatively correlated with both right and left-hand MI ERD during the calibration phase, i.e. as the ERD modulation value decreases, BCI performance increases. The personnality trait Self-Control (or conscientiousness) was associated to lower ERD during calibration and user training sessions. Highly conscientiousness and self-controlled people also tend to be tough-minded and less open to emotions and new ideas [16]. No significant correlations were found with the ERD modulation for the variables gender, gender of experimenter, meditation practice, manual activity, mental rotation or others global scores from the 16PF5.

IV. DISCUSSION

A. Right-hand vs Left-hand MI discrimination

Our results highlight the phenomenon of lateralization during the activation of the motor cortex. In this way, the recognition of an MI is based on the location over the motor cortex of the ERD patterns associated with the body part that is engaged in the task [5] seems possible. Our results during the calibration session (Figure 2 and 3) confirm that contralateralized activation of the motor cortex enables right-hand vs. left-hand MIs discrimination.

B. Difference between calibration and user training sessions

Our results show a significant difference both in terms of ERD between the calibration and user training sessions (Figure 2 and 3). Indeed, during the user training session, the ERD modulations are comparable to those observed in the literature, but the amplitude tends to decrease or even disappear in certain frequency bands for the calibration session (in the beta band mainly; see Figure 3). Several hypotheses can explain this difference between the two sessions. Firstly, the instructions given to participants consisting of improving their strategy and adapting it to obtain better feedback may explain why the average ERD is stronger during this session.

C. Users' traits (un)correlated with ERD modulations

In our study, age is not correlated with ERD modulations or BCI performances, which is contrary to past findings which found reduced lateralized ERD with increasing age [20], [4]. Overall that may suggest that older users may not have reduced performance with MI-BCIs based on ERD, and thus facilitating the application of BCIs to older people. Results showing that Self-Control was associated to lower ERD, might indicate that highly conscientiousness and self-controlled users have more difficulties in achieving the MI task. One hypothesis could be that self-controlled people also tend to be tough-minded and less open to emotions and new ideas [16], and that this personality trait seems to be important for performing motor imageries with a BCI. Altogether (Figure 2, Table 1), our results could suggest that the nature of the feedback (sham or real) may result in a significant difference in participants' behaviour, thus modifying ERD amplitude generated. Finally, contrary to previous studies which showed significant correlations between BCI performances and mental rotation abilities, gender, manual activites or meditation experience, see, e.g., [11], [9], we did not observe correlations between these traits and ERD. This might suggest either 1) differences of such traits associations with either ERD or BCI performances, 2) differences due to within-users variabilities, which might be smoothened out only with enough BCI sessions [17] or 3) false positives in previous studies or false negatives here, due, e.g., to lack of participants.

V. CONCLUSIONS

In this paper, we studied how ERD/ERS during MI-BCI are modulated depending on the MI task performed (left vs right hand MI), the session (calibration vs online training) and the users' profile (traits and demographics), on a large MI-BCI data set (N=75 participants). Our results confirmed a stronger ERD contralateraly, while we still observed a bilateral ERD overall. We also observed stronger ERD during online training (with real-time feedback and instructions to explore promising MI strategies) comparing to calibration (with sham feedback). Finally, and more importantly, our study revealed for the first time, associations between ERD and self-control. This may suggest that this factor should be taken into account when designing MI-BCI based on ERD or when selecting an ERD-based BCI for a given user. As future work, we plan to extend such analyses across several data bases, to confirm or disprove such results with a larger number of participants and study how ERD/ERSs relate to users' states.

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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] 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.

[4] 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.

[5] 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.

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

[7] 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.

[8] 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.

[9] C. Jeunet, B. N'Kaoua, and F. Lotte, "Advances in user-training for mental-imagery-based BCI control: Psychological and cognitive factors and their neural correlates," *Progress in brain research*, 2016.

[10] L.-F. Tan, Z. Dienes, A. Jansari, and S.-Y. Goh, "Effect of mindfulness meditation on brain–computer interface performance," *Consciousness and Cognition*, vol. 23, pp. 12 – 21, 2014.

[11] S. Rimbert, N. Gayraud, L. Bougrain, M. Clerc, and S. Fleck, "Can a subjective questionnaire be used as brain-computer interface performance predictor?" *Frontiers Hum. Neurosc.*, 2019.

[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] 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.

[14] 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, in press.

[15] 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.

[16] R. Cattell and H. P. Cattell, "Personality structure and the new fifth edition of the 16pf," *Educ Psychol Meas*, vol. 55, no. 6, 1995.

[17] C. Benaroch, C. Jeunet, and F. Lotte, "Are users' traits informative enough to predict/explain their mental-imagery based BCI performances ?" in *8th Graz BCI Conf.*, 2019.

[18] 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.

[19] 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.

[20] C. Zich, S. Debener, M. De Vos, S. Frerichs, S. Maurer, and C. Kranczioch, "Lateralization patterns of covert but not overt movements change with age: An EEG neurofeedback study," *Neuroimage*, vol. 116, pp. 80–91, 2015.