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Reliable predictor of BCI motor imagery performance using median nerve stimulation

Valérie Marissens Cueva^{1,2,*}, Laurent Bougrain², Fabien Lotte¹, Sébastien Rimbart^{1,*}

¹ Inria Center at the University of Bordeaux / LaBRI, Talence, France

² Université de Lorraine, CNRS, LORIA, F-54000 Nancy, France

E-mail: sebastien.rimbart@inria.fr, valerie.marissens@loria.fr

Abstract. *Objective* Predicting performance in Brain-Computer Interfaces (BCI) is crucial for enhancing user experience, optimizing training and identifying the most efficient BCI approach for each individual. *Approach.* This study explores the use of Median Nerve Stimulation (MNS) as a predictor of Motor Imagery (MI)-BCI performance. MNS induces Event Related (De)Synchronization (ERD/ERS) patterns in the brain that are similar to those generated during MI tasks, providing a non-invasive, user-independent, and easy-to-setup method for performance prediction. *Main results.* Our proposed predictor, based on the minimum value of the ERD induced by the MNS, not only exhibits a robust correlation with the MI-BCI performance accuracy ($\rho = -0.71$, $p < 0.001$), but also effectively predicts this performance with a significant correlation ($\rho = 0.61$, mean absolute error = 9.0, $p < 0.01$). These results demonstrate its validity as a reliable predictor of MI-BCI performance. *Significance.* By systematically analyzing patterns induced by MNS and correlating them with subsequent MI-BCI task performance, we aim to establish a robust predictive method of motor activity to each individual only based on MNS, making it possible, among other things, to passively predict BCI deficiency or proficiency, and to potentially adapt BCI parameters for an efficient BCI experience or BCI-based recovery.

1. Introduction

Motor Imagery (MI) is the ability to imagine performing a movement without executing it. It is a major paradigm in Brain-Computer Interfaces (BCI) [1], which have successfully been used in a wide range of applications for rehabilitation, control, communication, artistic creation, and more [2]. These interfaces allow users to control external devices by imagining specific motor movements, thereby generating distinct brain activity patterns that can be interpreted by the BCI system. Despite these successes, significant challenges remain for widespread adoption. Even in controlled laboratory settings, BCI detection accuracy is suboptimal. Studies show that around 30% of users cannot effectively use a MI-BCI, a phenomenon known as BCI illiteracy or deficiency [3, 4, 5, 6]. This term underscores the variability in user ability to generate consistent brain patterns suitable for MI-BCI control. Indeed, the practical performance remains insufficient, typically below 75-80% accuracy, on average, for distinguishing between two different types of motor imageries [7, 8, 3, 6, 9]. This limitation is coupled with a high variability of performance, both within and between individuals [10]. Factors contributing to this variability include internal factors such as differences in brain anatomy and neurophysiology [11, 12, 13], motor imagery ability [14], psychological states (e.g., motivation and fatigue) [15] and external factors like signal acquisition quality [8], electrode placement [16] or signal noise [17]. Addressing these challenges requires not only technological advancements but also a deeper understanding of the underlying neurophysiological mechanisms during MI.

Given these challenges, accurately predicting a user's ability to use a MI-BCI is crucial for several reasons. First, it might be essential to significantly enhance the effectiveness and user experience of BCI applications. Indeed, developing tools that allow experimenters to assess a subject's likely performance in advance could provide valuable predictive insights. These insights would allow researchers to proactively adjust BCI parameters, ensuring subjects maintain high levels of motivation and engagement throughout the session [18]. By customizing difficulty levels and feedback mechanisms according to daily individual capabilities, such tools have the potential to improve both user experience and performance outcomes. Second, another interesting application could be the introduction of a subject selection step prior to an experiment [19]. This step could be particularly valuable for research studies, allowing investigators to harmonize the study population in terms of BCI performance. By selecting subjects with similar BCI capabilities, researchers can reduce variability

and obtain more reliable and interpretable results comparing various conditions. For example, identifying a reliable predictor of MI-BCI performance could provide a better understanding of why some users are inherently better at using these systems. Uncovering these underlying factors could lead to significant advancements in the field, enabling more personalized and effective BCI systems in the future. Third, and more importantly, in the specific case of BCI-based rehabilitation, the prediction of MI-BCI performance could support the development of tailored therapeutic MI-BCI protocols to help post-stroke patients regain limb control [14, 20]. In this particular scenario, the sensitivity and specificity of the BCI performance predictor are critical. A high sensitivity is essential to avoid false negatives, which would deny patients the opportunity to benefit from potentially life-changing MI-BCI-based care. On the other hand, high specificity would prevent false positives, ensuring that resources are allocated effectively and only to those who can truly benefit. Consequently, identifying whether a subject will perform well or not can save valuable time and resources for researchers, clinicians and patients, and increase the likelihood of a positive outcome for BCI patients and end-users.

Predicting a MI-BCI user's future performance is an active research question that is still open [21]. Researchers have explored various approaches to identify reliable predictors, but consistent results remain elusive. Subjective and psychometric questionnaires, such as the Motor Imagery Questionnaire (MIQ; [20]), the Kinesthetic and Visual Imagery Questionnaire (KVIQ; [22]), the Sixteen Personality Factor (16PF5; [23]), and the mental rotation test [24] have been proposed to predict performance with a MI-BCI [25, 26]. Unfortunately, the results from these questionnaires are not consistent, indicating the complexity and individual variability in MI-BCI performance. Indeed, a first study suggested that the Kinesthetic MI (KMI) scores obtained from the KVIQ can predict MI-BCI performance of healthy subjects [27]. This study suggested that individuals with higher kinesthetic imagery abilities might have a better capacity to engage with MI-BCI systems. A second study found that the representation of subjective behavior calculated with the MIQ-RS and BCI control performance seem strongly related [28], highlighting a potential link between how users perceive their imagery abilities and their actual BCI performance. In contrast, a third study showed that the MIQ-RS questionnaire cannot be used as a predictor of MI-BCI performance based on the distinction between a resting state and a right-hand MI task [19]. Altogether, these findings underscore the variability in results and the challenge of finding a one-size-fits-all predictor. A recent study showed for the first time

an association between Event-Related Desynchronization (ERD), BCI performance, and self-control item from the 16PF5 questionnaire, but correlations remain low [29]. Unfortunately, the low correlations indicate that while there may be a relationship, it is not strong enough to serve as a reliable predictor on its own.

Predicting a user’s performance in motor imagery tasks can also be achieved by analyzing neurophysiological signals that reflect the ability to activate the motor cortex. For instance, [4] demonstrated that mu peak power (with respect to the noise floor) during a two-minute baseline with eyes open correlated with SensoriMotor Rhythms (SMR)-BCI performance ($r = 0.53$). Similarly, another study found that the Performance Potential Factor (PPfactor), which combines power from the low alpha and theta ratio during a non-task-related state, also correlated with BCI performance ($r = 0.48$) [5]. Spectral entropy measured with eyes closed appears to be a more robust predictor of BCI performance ($r = 0.65$), though its reliability decreases when applied to other datasets ($r = 0.23$) [30]. Recently, [31] introduced the meanSP predictor, which uses an eyes-open baseline and performs comparably well ($r = 0.53$), but has the advantage of requiring fewer electrodes. The meanSP predictor is derived using the Nonlinear Interaction Decomposition (NID) method [32]. This technique identifies pairs of brain activity sources that are synchronized such that one source oscillates at a frequency that is exactly twice the frequency of the other, resulting in a 1:2 phase relationship between mu and beta frequencies. Another promising approach by Kwon et al. combines both eyes-open and eyes-closed baselines to enhance prediction accuracy, yielding a strong correlation ($r=0.5$; if outliers are not removed of the dataset), though this needs validation with additional datasets [33]. Alternative approaches for predicting BCI performance include using sensorimotor connectivity [34], long-range temporal correlations measured with Hurst exponents during calibration sessions [35], the variability of the mu peak and the slope of the $1/f$ EEG spectrum in motor areas [36, 37], and Bayesian Spatio-Spectral Filter Optimization [38]. However, the correlations between these methods and BCI performance are too moderate to serve as robust predictors. Interestingly, the residual SMR power induced by Neuromuscular Electrical Stimulation —quantified as the maximal difference between the maximum peak and the noise at a specific frequency bin— has been found to correlate with arm vs. feet MI-BCI performance when the same limb is simultaneously stimulated during MI ($\rho = 0.71$) [39]. Despite these efforts, the search for a reliable and robust predictor remains ongoing.

Currently, such MI-BCIs exploit the modulation of SMR over the motor cortex [40], which are respectively

known as Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS). These rhythms cover the mu (7-13 Hz) and beta (15-30 Hz) frequency bands [41]. Typically, MI-BCIs use the ERD that occurs during MI in the motor cortex contralateral to the imagined hand (e.g., in C3 for a right hand imagined movement) to detect left or right hand MI [42]. Interestingly, electrical stimulation of the median nerve also induces changes in the sensorimotor cortical activity, which are visible in the EEG signal and similar in shape but faster than for an intention of movement [43, 44, 45]. This rapid cortical response is due to the direct activation of the somatosensory pathways, which subsequently influence the motor cortex. The efficiency of this pathway highlights the potential for Median Nerve Stimulation (MNS) to serve as a robust tool in BCI applications. Indeed, several studies suggested that using MNS can improve MI detection accuracy (up to +15%) [43, 46] and opened up the possibility of designing a high-performance and asynchronous BCI with enhanced usability, as shown in the context of general anesthesia monitoring [47, 48].

While MNS primarily activates the primary somatosensory cortex, several studies have shown that it can also produce secondary activation in the primary motor cortex [49, 50]. This dual activation is relevant in the context of BCI, as it suggests that motor-related EEG features can still emerge from somatosensory stimulation. In this article, our hypothesis is that such MNS-induced EEG patterns could be also predictors of motor cortex activation underlying performance of the MI task. Since MNS causes ERD/ERS modulations over the motor cortex, in a similar way to what occurs during a MI [44, 43], it is reasonable to ask whether this can be used to predict the performance of MI-based BCI. Indeed, the information relating to the ERD generated by MNS (amplitude, frequency, onset time-window) could be directly related to that generated during MI, since in both cases the motor cortex is activated. In fact, in a preliminary study using a single dataset, we have already shown that the ERD following MNS is similar to that observed during MI and is strongly correlated with BCI performance in the mu frequency band [51]. By evaluating MNS-induced EEG patterns, we aim to assess the user’s potential for engaging in MI tasks, thereby providing a non-invasive, user-independent predictor of MI-BCI performance. We show that this tool can be used to estimate future MI-BCI performance with only a couple of minutes of stimulation, thus saving the need for running a full MI-BCI session (which typically lasts half an hour or more) for users who are likely not be able to control such an MI-BCI.

Thus, median nerve stimulation would appear to have all the qualities required to predict MI-BCI

performance: (i) by producing ERD/ERS patterns similar to those generally obtained during MI, these patterns could serve as a proxy for assessing the brain’s readiness and capability to engage in motor imagery tasks that could be detected in EEG. Additionally, (ii) by being passive for the user and therefore independent of how the subject understands and performs the MI task, MNS offers a standardized measure that is not influenced by the user’s cognitive or emotional state, thus ensuring consistency and reliability in the predictions. Finally, (iii) by being easy to set up (i.e., in terms of time) before a BCI session, MNS can be seamlessly integrated into existing BCI protocols with minimal additional preparation.

The purpose of this study is to assess the potential of Median Nerve Stimulation (MNS) as a MI-BCI performance predictive tool, rather than as a direct method for controlling devices, thus supporting user performance estimation even before active MI-BCI use. Our first objective is to investigate the ERD/ERS patterns induced by median nerve stimulation and correlate them with subsequent MI-BCI performance. In addition to simply correlating our MNS-based predictor and BCI performances, our second objective is to actually predict the future BCI performance of the users from their MNS-induced ERD patterns, using a Least absolute shrinkage and selection operator (LASSO). Thirdly, we evaluated the number of stimulations needed to maintain a significant correlation between the MNS-related characteristic and MI-BCI performances, in order to determine the signal acquisition time required for these stimulations. By establishing this predictive method, we aim to tailor BCI settings to individual users, thereby enhancing overall system efficiency and user experience.

2. Material and Methods

2.1. Data description

Two datasets, including a total of 31 right-handed healthy subjects (8 females; aged 27.38 years old; $STD = 11.48$) were utilized for this study. The subjects had no medical history that could have influenced the task (i.e., diabetes, antidepressant treatment, or neurological disorders). The experiment follows the statements of the WMA declaration of Helsinki on ethical principles for medical research involving human subjects [52] and the participants signed an informed consent approved by the local ethical committee of Inria (COERLE, approval number: 2016-011/01). Initially, these two datasets contained 41 subjects, but ten were excluded due to technical issues, in particular 3 had responses to MNS exceeding 10 dB, 4 had some very noisy electrodes and 3 had overall highly artifacted signals.

2.1.1. Motor tasks: For both datasets, two conditions were performed: a right hand kinesthetic motor imagination and a passive median nerve stimulation. In the first dataset, the first 15 subjects performed 51 trials per condition, and the next 5 performed 64 trials per condition. In the second dataset, 52 trials were conducted per condition (2 merged runs with 26 trials each). Because these experiments were originally designed to investigate the impact of general anesthetic conditions on the EEG (see [46, 47] for more details), the subjects were male to avoid blood pregnancy tests, but no gender difference in brain activity have been proved with motor imagery [53]. In this paper, we only utilized data from subjects who were not administered a general anesthetic. Moreover, subjects were lying on a comfortable bed with their eyes closed, and their right forearm was put on a cushion to prevent any movement. The order of the two conditions were randomized between subjects.

For the MI condition, subjects had to imagine a clamp between the thumb and index finger, i.e., they had to try to imagine a maximum of sensations that would be caused by a real movement, but without any movement. A low frequency beep indicated when the subject had to start the motor imagery, the grasping MI was maintained during 2 seconds, then a second beep indicated the end of the imagined task. Prior to the study, the subject learned to perform the MI task progressively (for more details, see [54]).

The MNS only condition consisted of a series of passive stimulations of the median nerve during resting state. We placed the two electrodes of stimulation on the wrist according to the standards [55, 56], so that stimulation generates a slight movement between the thumb and index. The stimulation intensity was previously adapted for each subject and varied between 8 and 15 mA.

2.1.2. Electrophysiological recordings: EEG signals were recorded through the OpenViBE software platform with a Biosemi Active Two EEG system. In accordance with the ABC layout, the EEG was recorded from 128 sites, sampled at 2048 Hz. An external electromyogram (EMG) electrode was used for all conditions in order to check that there was no movement during the MI task. Impedance was kept below 10 k Ω for all electrodes to ensure that the background noise in the acquired signal was low.

2.2. MNS predictor

2.2.1. MNS features:

Time-Frequency Analysis: To analyze the differences between both conditions (MI and MNS) and select

the optimal time window for the post-MNS ERD, we performed an event-related spectral perturbation (ERSP), following a Common Average Reference (CAR) across all 128 channels. CAR is particularly advantageous for analyzing motor modulations, as it enhances the detection of localized patterns [40]. We computed the ERSPs using the gain model approach [57] which is equivalent to the *band power method* [40]. We used a 256 point sliding fast Fourier transform (FFT) window with a padratio of 4, and computed the mean ERSP 1 second before the start beep to 5 seconds after it. These time-frequency and topographic analyses were performed using the EEGLAB toolbox [58] and MATLAB R2023a (The MathWorks Inc).

MNS induced ERD/ERS modulations: In order to predict BCI performance from MNS-induced motor patterns, we quantified the ERD and ERS resulting from MNS as features. In particular, we computed the ERD/ERS% using the *band power method* [40] with a MATLAB script. First, the EEG signal was filtered in the mu band (7-13 Hz), mu and beta (8-30 Hz) or in the beta band (15-30 Hz) for all subjects using a 4th-order Butterworth band-pass filter. Then, the signal was squared for each trial and averaged over trials. Next, it was smoothed using a 1-second sliding window with a 100 ms shifting step. We chose a sliding window because the nature of the motor imagery task, as well as the components ERD or ERS that underline them, required a short window. Finally, we subtracted the average power from the baseline to the average power computed for each window, and then divided the result by the same baseline power. This baseline corresponded to the window [-3; -0.5] s, where $t = 0$ s is the beginning of each trial, i.e., the first beep. The resulting value was multiplied by 100 to obtain percentages. This process can be summarized by the following equation:

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

where $\overline{x^2}$ is the average of the squared signal over the sliding window of interest, $\overline{BL^2}$ is the mean of a baseline segment taken at the beginning of the corresponding trial, and ERD/ERS% is the percentage of ERD/ERS estimated for each step of the sliding window. This procedure was applied to each channel individually, in particular C3 with and without a small Laplacian filter, as the motor imagery and median nerve stimulation conditions involved the subjects' right hand.

2.2.2. Offline MI-BCI performances: We computed offline BCI performances by classifying EEG signals of a resting state versus EEG signals of right-hand

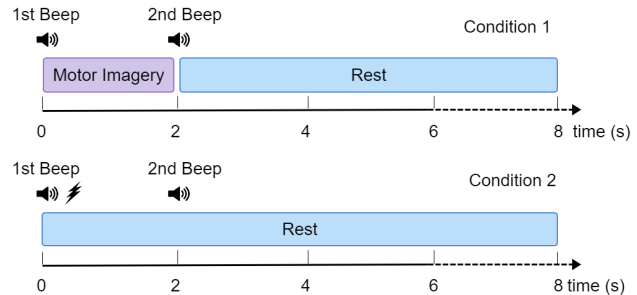


Figure 1: Timing schemes of a trial for Condition 1 (Motor Imagery task) and Condition 2 (Median Nerve Stimulation). A first beep at $t = 0$ indicated the start of the motor imagery task, a second beep the end. The MNS was a discrete stimulation lasting 100 ms. After the second beep, the participant remains at rest for 6 to 8 seconds (random duration changed at each trial).

KMI. Classifications were performed using the MNE [59], Scikit-learn [60] and pyriemann [61] packages in Python 3.10. These performance metrics were estimated offline by first downsampling EEG signals to 128 Hz, band-pass filtering in 7-13, 8-30 or 15-30 Hz, and then extracting 2.5 seconds long MI and rest epochs from each trial. The rest and MI periods correspond respectively to [-3; -0.5] s and [0.5; 3] s. A baseline correction was applied, with a baseline in [-1.5; -0.5] s, to each epoch and each channel individually, where the mean signal of this baseline was subtracted from each epoch. Only 40 electrodes were used for the classification, specifically those positioned over motor areas: Cz, C1, C3, C5, C2, C4, C6, FC4, FC2, FCz, FC1, FC5, FC3, FC6, CPz, CP2, CP6, CP4, CP1, CP5, CP3, FC3h, FC1h, FC6h, FC4h, FC5h, C3h, C5h, C1h, C4h, C6h, CP5h, CP6h, CP4h, CCP3h, CPP2, FCC2h, FCC2, FFC4h and FCC1h.

We used a Riemannian classifier, the current state-of-the-art EEG classifiers for BCI [62]. More precisely, we first estimated the EEG covariance matrices of each trial, which are projected in the tangent space centered at the global Riemannian mean of the training data. A Tangent Space Logistic Regression (TSLR) classifier was subsequently trained to separate the covariance matrices of MI and rest trials. This TSLR classifier was trained with the first 70% trials (between 35 and 44 trials per class, depending on subjects) and tested on the remainder (between 15 and 19 trials per class).

2.2.3. Prediction of MI-BCI performances using MNS:

One of our primary objectives is to investigate the correlation between the strength of the ERD induced by MNS and MI-BCI performances. To achieve this, we assessed the minimum ERD value, i.e., the strongest desynchronization, within the time window from 200 to 800 ms after the go signal in one of

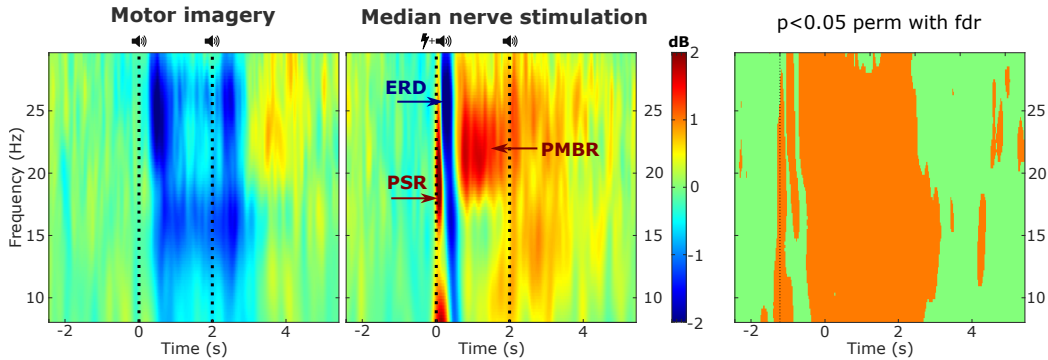


Figure 2: Event-related spectrum perturbation (ERSP) analysis of Motor Imagery (MI) and Median Nerve Stimulation (MNS) for electrode C3, among 31 subjects. $t = 0$ corresponds to the go signal to start the MI or the MNS. Statistical differences between MI and MNS following a permutation test at a significance level of 0.05 are shown on the right figure. For the MNS condition, a post-stimulation rebound (PSR) appears, then an ERD, followed by a post-movement beta rebound (PMBR).

three frequency bands: mu (7-13 Hz), mu+beta (8-30 Hz), or beta (15-30 Hz). The [200; 800] ms time window was selected using the time-frequency analysis, where the ERD for the MNS condition is stronger. Spearman’s correlation between this MNS-related feature, calculated at electrode C3 (with or without a small Laplacian filter, LapC3), and users’ offline MI-BCI performance in the same or another frequency band were calculated. Due to the large number of tests performed ($n=18$), the significance level α was adjusted for multiple comparisons using Benjamini-Hochberg’s procedure [63].

As a second key objective, we aimed to determine whether these MNS-related characteristics could predict MI-BCI performance. To this end, we used a Least Absolute Shrinkage and Selection Operator (LASSO) Regression [64], which promotes sparse solutions and enhances interpretability. This method selects the most relevant features to predict MI-BCI performance using the smallest subset, ensuring that only one among correlated features is chosen. LASSO regression minimizes prediction error through feature selection by imposing an L1 norm penalty on the regression coefficients, driving some coefficients to zero and thereby eliminating irrelevant features. The LASSO equation can be formulated as follows:

$$\beta_{lasso} = \arg \min_{\beta \in \mathbb{R}^p} \|\mathbf{Y} - \mathbf{X}\beta\|_2^2 + \lambda \|\beta\|_1 \quad (2)$$

where n is the number of subjects, $\|\mathbf{u}\|_2^2 = \sum_{i=1}^n \mathbf{u}^2$ for $\mathbf{u} \in \mathbb{R}^n$, $\|\beta\|_1 = \sum_{i=1}^p |\beta_i|$, $\mathbf{Y} \in \mathbb{R}^n$ the n MI-BCI performances, $\mathbf{X} \in \mathbb{R}^{n \times p}$ the p MNS-related features, $\beta \in \mathbb{R}^p$ the regression coefficients and $\lambda \in \mathbb{R}$ the regularization parameter.

To evaluate the model, we performed a leave-one-subject-out cross validation. Specifically, the regression model was trained on data from all subjects

except one, and tested on that remaining subject. This process was repeated for each subject as the test set, and the final prediction performance was obtained averaging all results (one result per subject). Additionally, an inner cross-validation process, i.e., a cross validation on the $n - 1$ training subjects, was performed to determine the optimal value of λ among $\{0.0001, 0.001, 0.01, 0.1, 1.0\}$ using 5 folds. The best λ was selected according to the smallest mean absolute error (MAE) of this inner cross validation. In order to assess the quality and statistical significance of these models’ prediction performances, we estimated the empirical chance level, i.e., the MAE for random regression models, using a permutation test, following

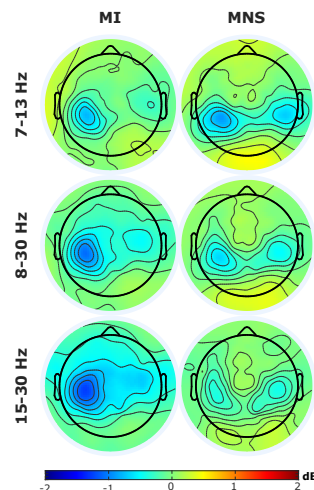


Figure 3: Grand-average ($n=31$) scalp topographies of EEG power in mu, mu+beta and beta frequency bands for right hand Motor Imagery (MI) and Median Nerve Stimulation (MNS) conditions in the time window [200-800] ms after the go signal.

the same procedure as [36]. For that, we created a random model by permuting randomly the labels of the training data, before training the regression model and using it to predict \mathbf{Y} . Hence, we obtained a list of 1000 MAEs, which was sorted, so that the 95th and 99th percentiles would correspond to the empirical chance level MAEs for $p = 0.05$ and $p = 0.01$ respectively. The model was provided three features: the minimum ERD value after an MNS within the [200; 800] ms window, calculated in the Laplacian of channel C3, across three different frequencies (mu, mu+beta and beta). In summary, an inner cross-validation allows us to determine the best lambda value. Then, across the external cross-validation (leave-one-subject-out), we counted the number of times each feature was used to compare its relevance in the prediction.

Our third objective is to evaluate how many stimulations are required for the correlation between the MNS-related characteristic, calculated in the C3 Laplacian, and MI-BCI performances to remain significant. We applied Spearman’s correlation and the Benjamini-Hochberg procedure to compute the correlations across a range of stimulations, from 1 to all stimulations (51 trials for 14 subjects, 64 trials for 3 subjects and 52 trials for the remaining 14 subjects, see Section 2.1). This enables us to assess the number of stimulations necessary to obtain a reliable predictor, ideally one that can be estimated in a short time with a minimal number of stimulations.

3. Results

3.1. Cortical motor activity of motor imagery and median nerve stimulation

The analysis of ERD/ERS modulations provides us with a better understanding of the activation of the motor cortex during motor imagery and median nerve stimulation (Figure 2 and Figure 3). For the MI condition, we observed an ERD in both mu (7-13 Hz) and beta (15-30 Hz) frequency bands followed by an ERS, primarily in the beta frequency band, approximately 1 second after the end of the 2s-MI

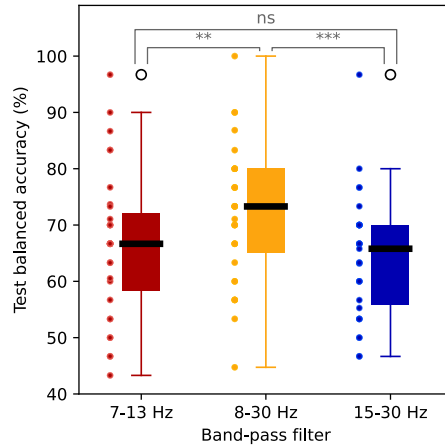


Figure 4: Boxplots of the average accuracies ($n = 30$ subjects) for MI vs. rest classification, where the EEG signals were filtered in a particular frequency band: mu (7-13 Hz), mu+beta (8-30 Hz) and beta (15-30 Hz).

task (Figure 2). For the MNS condition, three distinct phases can be identified, as previously described in the literature (see [43, 51]): an initial ERS phase, known as Post-Stimulation Rebound (PSR), primarily due to the electrical stimulation of the median nerve; an ERD phase occurring from 200-800 ms, present in both the mu and beta frequency bands; and a post-stimulation ERS phase occurring after 800 ms, mainly in the beta frequency band. It should be noted that the second rebound for the MNS condition is very broad, affecting both frequency bands.

Topographic analysis shows that the ERD during the MI period (200-800 ms) is predominantly contralateral, around the C3 electrode, with no strong ipsilateral activity around the C4 electrode, regardless of the frequency band analyzed (mu, beta, or 8-30 Hz; Figure 3). Median nerve stimulation generates ERD at both C3 and C4 electrodes. The analysis of ERD/ERS modulations for both conditions reveals that the ERD observed during median nerve stimulation is slightly less pronounced and more bilateral compared to the ERD phase generated by motor imagery, though the

| | | C3 ERD-MNS | | | LapC3 ERD-MNS | | |
|--------------------|---------|-----------------|-----------------|---------------|---------------|-----------------|----------------|
| | | mu | mu+beta | beta | mu | mu+beta | beta |
| MI-BCI performance | mu | -0.63*** | -0.64*** | -0.36 | -0.41* | -0.60** | -0.35 |
| | mu+beta | -0.56** | -0.52** | -0.39* | -0.48* | -0.71*** | -0.49* |
| | beta | -0.09 | -0.12 | -0.33 | -0.16 | -0.41* | -0.54** |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: Spearman’s correlation coefficient between (i) minimum value of ERD of the MNS condition calculated in C3 or in Laplacian C3 (LapC3) channels, in the time window [200; 800] ms, and (ii) users’ offline BCI performance in a MI vs. rest task obtained by the TSLR classifier, where the EEG signals were filtered in a particular frequency band.

two patterns remain highly similar.

3.2. MI-BCI performances

In terms of classification performance, Figure 4 indicates that the average accuracy for classifying MI vs. rest within the 8-30 Hz frequency band is 72%. Classifications using only the mu (7-13 Hz) or beta (15-30 Hz) frequency bands resulted in lower average accuracies of 66% and 64%, respectively. These findings suggest that the broader 8-30 Hz frequency band yields the highest accuracy, aligning with established BCI literature. The classifier performance, remaining below 75%, can be attributed to the motor imagery task involving only the thumb and index finger rather than the entire hand, as evidenced in the time-frequency maps. Additionally, the limited number of training trials (≤ 44 , see section 2.2.2) also contributes to this performance level.

3.3. Correlations between ERDs of the MNS and MI-BCI accuracies

The ERD generated by median nerve stimulation (MNS) is present in both mu (7-13 Hz) and beta (15-30 Hz) frequency bands (Figure 2). Consequently, we observed, across the three frequency bands (mu, beta, and mu+beta), the Spearman’s correlation coefficients (see Table 1) between the minimum value of ERD and the user’s offline BCI performance. The choice of the time window for the appearance of ERD after MNS (200-800 ms) was based on the time-frequency analysis and topographic maps (see Figures 2 and 3). We present the results with and without a small Laplacian filter in C3, as MNS activates both the primary motor cortex and the somatosensory cortex.

Table 1 presents the Spearman’s correlation coefficients between the minimum value of ERD within the 200-800 ms time window during the MNS condition, calculated at the C3 electrode and its small Laplacian, and the users’ offline BCI accuracy in an MI vs. rest task, using the TSLR classifier with EEG signals filtered in specific frequency band. Our

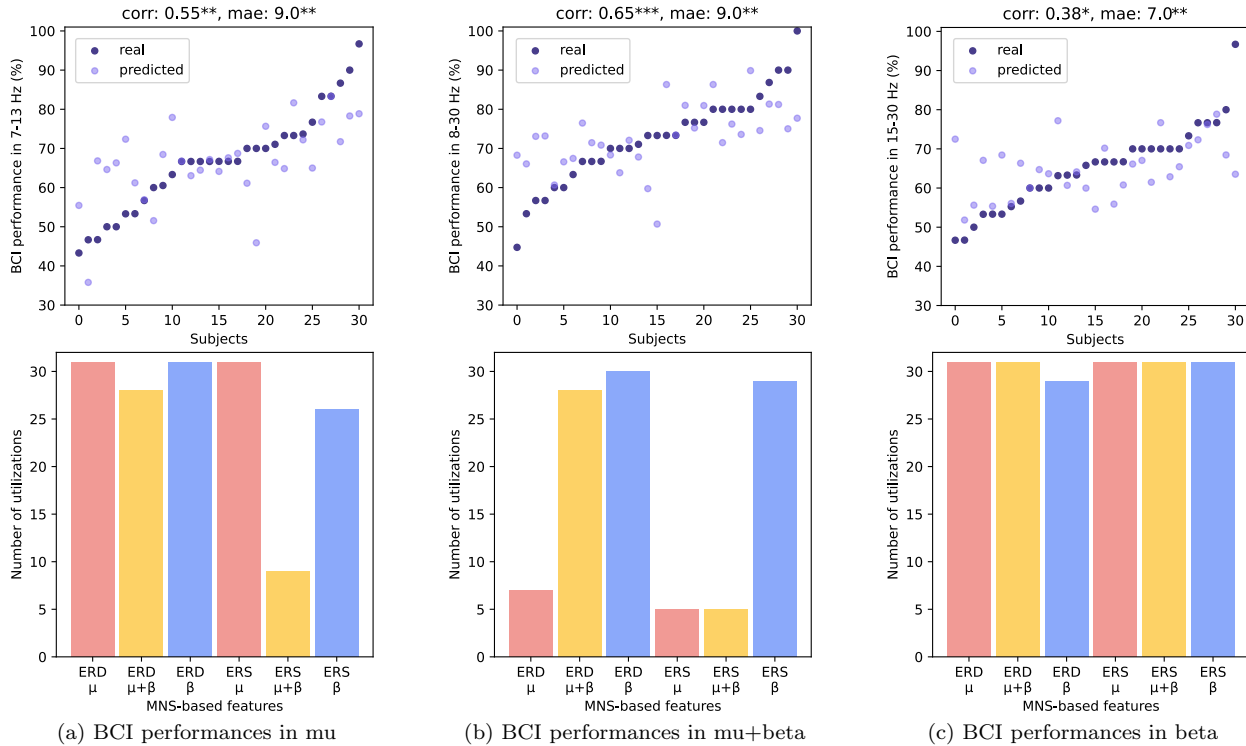


Figure 5: Top figures present real and model predicted BCI performances for each of the 31 subjects for three specific frequency bands. Spearman’s correlation and average mean absolute error between real and predicted performances using the leave-one-subject-out models (a specific model for each subject) are also reported on top of the figures. Bottom figures present the number of times each feature was selected to learn the corresponding models. The predictors used here are: the minimum ERD value induced by MNS, measured at channel C3 with a small Laplacian filter, within the time window [200; 800] ms, and the maximum ERS in the time window [800; 1500] ms at the same channel, both calculated at particular frequency bands. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

results reveal significant negative correlations between the ERD-MNS values and BCI performance across different frequency bands. It is quite logical that the correlations are negative, as this indicates that a stronger ERD is associated with a better MI-BCI performance.

Specifically, BCI performance based on the mu band shows a stronger correlation with the minimum post-MNS ERD value computed in the mu band and even most pronounced ($\rho = -0.64$, $p < 0.001$) in the mu+beta band (at C3 when the Laplacian filter is not applied). The more significant correlations are achieved when both BCI performances and the minimum ERD value induced by MNS are calculated in the mu+beta frequency band, with the Laplacian filter applied ($\rho = -0.71$, $p < 0.001$). Additionally, BCI performance obtained using the beta band is correlated with the MNS-based minimum ERD only when the Laplacian filter is applied and calculated in the beta band ($\rho = -0.54$, $p < 0.01$). These findings suggest that the ERD-MNS, particularly in the mu and mu+beta frequency bands, is a strong predictor of BCI performance, with a Laplacian of C3 providing further insights into the relationship between sensorimotor cortex activation and BCI accuracy.

3.4. Using MNS to predict MI-BCI performances

To evaluate whether a user’s MNS-related characteristic can be used to predict future MI-BCI performances, we selected the minimum ERD value induced by MNS, recorded at channel C3 using a Laplacian filter, during the [200; 800] ms time interval. The maximum post-MNS ERS value was also calculated at channel C3 using a Laplacian filter, but during the [800;1500] ms time interval. The upper part of Figure 5 shows that BCI

performance is most accurately predicted when signals are filtered within the mu+beta band, as evidenced by the significant correlation between real and model predicted BCI accuracies ($\rho = 0.65$, $p < 0.01$). Hence, the model was able to successfully account for 42% of the variability in MI-BCI performances obtained within the mu+beta frequency band. It is important to note that BCI performances in the mu band were also correctly predicted, although with lower significance ($\rho = 0.55$, $p < 0.01$). The lower part of Figure 5 shows that when predicting BCI performances in the mu frequency band, all information was used, with the exception of ERS in the mu+beta band, as it was deemed redundant. All used characteristics are complementary, as the model selected these features for nearly all 31 subjects. For BCI performances in the mu+beta band, the MNS-related characteristic calculated within the same band is the most informative, as well as ERD and ERS in the beta band. The model was also able to predict BCI performances computed with signals filtered at the beta frequency band ($\rho = 0.38$, $p < 0.05$). Here, all post-MNS ERD and ERS features were utilized for all subjects. For each frequency band, the 31 models obtained an average MAE significantly better than the empirical chance level, given our data, at $p = 0.01$. However, the model was not able to predict BCI performances computed with signals filtered at the beta frequency band, as the correlation was not significant.

3.5. Number of stimulations

Figure 6 shows the improvement in the correlation coefficient (and its reliability) as a function of the number of stimuli used to estimate the MNS-induced ERD, i.e., to estimate our MNS-based predictor. To

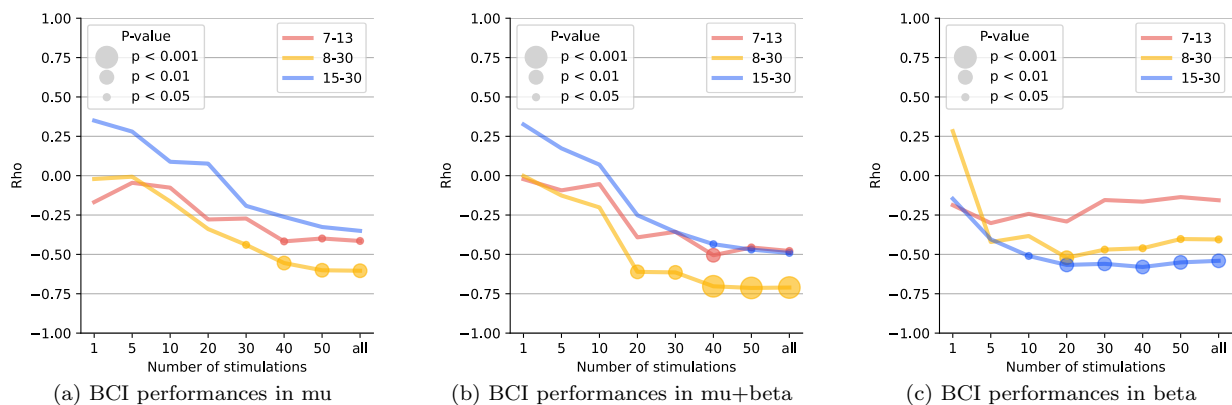


Figure 6: Evolution of Spearman’s correlation between user’s BCI performance and the MNS-based predictor with a varying number of stimulations. Offline BCI performances in a MI vs. rest task are obtained by the TSLR classifier, where the signals were filtered in a particular frequency band. The MNS-based predictor is the minimum value of post-MNS ERD calculated in Laplacian C3 channel in the time window [200; 800] ms.

interpret these results, it is important to consider that the interval between each stimulation is approximately 5 seconds, meaning that performing 10 median nerve stimulations would take less than one minute of signal acquisition.

Our results show that increasing the number of stimulations improves the correlation with BCI performances and its significance, although a plateau is observed beyond 50 stimulations, where additional stimulations do not necessarily lead to increased significance or improved correlation. For correlating BCI performance in the mu band, a minimum of 30 median nerve stimulations is required to achieve significant results ($\rho = -0.44$, $p < 0.05$), with the MNS characteristic needing to be filtered in the mu+beta band. Concerning BCI performances in the mu+beta band, the MNS-characteristic should also be filtered in the mu+beta band and computed using 20 stimulations collected in less than 2 minutes ($\rho = -0.61$, $p < 0.01$). The most significant results within the shortest time are achieved using the mu+beta band, attained with 40 stimulations, which corresponds to less than 4 minutes of signal acquisition ($\rho = -0.70$, $p < 0.001$). A significance of 0.05 can be reached with only 10 median nerve stimulations, which requires less than a minute of data collection, provided that both the MNS-characteristic and BCI performances were obtained with data filtered in the beta band ($\rho = -0.51$, $p < 0.05$).

3.6. Importance of the temporal window used to estimate the predictor

In addition, the impact of the temporal window in which the MNS-based predictor is estimated was assessed, to understand how robust this predictor is to various parameters. Figure 7 presents the results of Spearman’s correlation between BCI performances and the MNS-based predictor, estimated in different time windows, varying the windows’ length and starting time. To this end, two extended time windows (100 to 1000 ms, 300 to 1300 ms post-MNS) and two brief windows (100 to 600 ms, 300 to 800 ms post-MNS) were also assessed. In instances where brief windows are employed or starting at 300 ms, it appears that these windows fail to capture the true minimum ERD value in certain subjects. This is evidenced by a diminished correlation value, despite the outcomes maintaining a comparable level of statistical significance. When the time window begins directly from 100 ms post-MNS and is extended, the outcomes are enhanced compared to the 200-800 ms window in mu ($\rho = -0.60$, $p < 0.01$) and beta ($\rho = -0.53$, $p < 0.01$), yet equivalent in the mu+beta band ($\rho = -0.71$, $p < 0.001$). Consequently, it is recommended to employ the 100 to 1000 ms window for better outcomes.

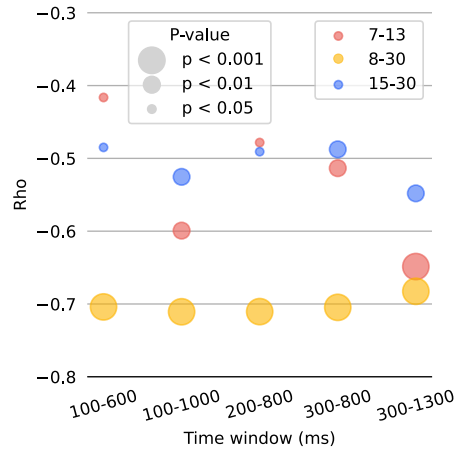


Figure 7: Spearman’s correlation between user’s BCI performance and the MNS-based predictor calculated in various time windows.

4. Discussion

For a MI-BCI performance predictor to be widely adopted by the community, it must meet several critical criteria. Firstly, it should exhibit a strong correlation with MI-BCI performance and, critically, it must also be predictive, a feature often underreported in the literature. Additionally, the predictor needs to be reliable and applicable across different experimental conditions, while being adaptable to various users. Finally, for practical use, it should be quick to set up for the experimenter, ideally before the experimentation begins, requiring only a few electrodes and minimal EEG signal acquisition time.

In light of these criteria, we propose a predictor based on median nerve stimulation (MNS) that meets these key requirements for effective MI-BCI performance prediction. Specifically, our method utilizes the minimum ERD value induced by MNS, measured at channel C3 with a small Laplacian filter within the time window [200; 800] ms. This approach not only correlates strongly with MI-BCI performance but also proves to be predictive and adaptable to various users. Additionally, it requires minimal setup, involving only a few electrodes and a brief EEG recording period, making it practical for pre-experimentation use. However, it is important to note that the results presented in this study were obtained with both conditions (MI-BCI and MNS) in which users had their eyes closed. It is still necessary to validate these findings through a database in which MI and MNS are performed with eyes open, since MI-BCI is typically used with eyes open.

4.1. Differences with current predictors

Our predictor demonstrates superior correlation with MI-BCI performance ($\rho = -0.71$, $p < 0.001$) compared to the current state of the art, including the SMR predictor ($r = 0.53$) [4], meanSP ($r = 0.53$) [31], PPfactor ($r = 0.48$) [5] and spectral entropy ($r = 0.65$) [30]. On top of that, we have shown that our predictor not only exhibits a strong correlation with MI-BCI performance but also reliably predicts performance, even in unseen subjects, which was not assessed in most of the papers introducing these previous predictors.

However, our results differ in certain aspects. Firstly, we computed Spearman’s correlation coefficients, whereas other studies used Pearson’s correlation [4, 5, 31]. The latter is based upon the assumption that variables are normally distributed. However, a Shapiro-Wilk test on our BCI performances was not significant, thus preventing us from calculating Pearson’s correlation and comparing our correlations values with those obtained in other studies, with the same correlation metric.

Besides, in both of our datasets, subjects were instructed to lie down with their eyes closed during both the MI and MNS conditions, as these experiments were originally designed to investigate the impact of general anesthetic conditions on the EEG [46, 47]. This contrasts with the conditions used in other studies [4, 5, 31]. It would be interesting to assess whether our predictor maintains its efficacy when subjects have their eyes open, particularly during MI-BCI tasks. Notably, other predictors were trained and tested with eyes open. The predictor by Blankertz et al. [4] was trained with eyes closed and tested with eyes open, resulting in a lower correlation ($r = 0.27$), likely due to the increased power in the alpha band in the occipital and parietal regions when the eyes are closed. Unfortunately, our datasets do not include a continuous two minutes baseline of rest with eyes open, which prevents us from recalculating the predictors proposed in other studies and based on such a baseline using the same data.

Additionally, in other studies [4, 31, 33, 34], BCI performances were evaluated during online sessions where participants received feedback on their MI tasks. In contrast, our MI-BCI performance evaluations were conducted offline, which is more appropriate for developing a robust predictor, as users are not influenced by feedback. However, it is feasible to use MI sessions without feedback to adjust the duration of data collection in an online setting—specifically, determining how many stimulations to administer for each user in each session.

Another distinction is that our predictor focuses on MI vs. rest performance, whereas most other predictors are designed to contrast two MI classes

without considering MI vs. rest [4, 31, 33]. The classification between different classes of motor imagery used in these other studies is different than the MI vs. rest distinction. Thus, in future work, it would also be interesting to assess whether our predictor can be used to predict performance with BCI involving multiple MI classes (and not just one as here). In fact, in the protocols used by other studies, BCI performance was based on the binary distinction between two of the following three motor imagery tasks: left-hand, right-hand or feet motor imagery. In this case, the classifier primarily relies on the contralateralization of the motor imageries. In contrast, our BCI performance is based on the distinction between right-hand motor imagery and rest, where the classifier relies on overall power differences in motor areas.

4.2. Advantages of using an MNS-based predictor

The sensorimotor rhythms induced by a median nerve stimulation are visible both in the mu and beta frequency bands, as the ones occurring during motor imagery. Therefore, our predictor based on MNS can be used to predict BCI performances in the combined mu+beta frequency band, which is the most commonly used band for classification [65], but also in the separate mu and beta bands. For instance, BCI performances can be assessed using EEG signals filtered in the mu band to measure mu rhythm suppression as in [66] or for neurofeedback training [67]. In this particular case, the MNS-related predictor should be calculated at the C3 channel without a Laplacian filter, for maximal correlation ($\rho = -0.64$, $p < 0.001$). Similarly, in certain cases EEG signals are filtered in the beta band, e.g., to provide feedback related to the cortico-muscular communication for motor rehabilitation after a stroke [68]. Here, the MNS-related predictor must be computed at channel C3 applying a small Laplacian filter ($\rho = -0.54$, $p < 0.01$). The observation that mu rhythms are more prominent without the Laplacian filter, while beta rhythms become more visible with the filter, can be attributed to the fact that a Laplacian filter reduces the frequencies present in the neighboring electrodes of C3 and amplifies those at C3. Since one of the dominant frequencies in these neighboring electrodes is the alpha frequency—especially given that the subjects have their eyes closed—and because higher frequency signals propagate less easily [69], the beta frequency remains primarily localized at C3. Consequently, the Laplacian filter diminishes the influence of the mu rhythm while enhancing the beta rhythms.

Additionally, as illustrated by the grand-average topographic analyses (Figure 3), MNS induces both contralaterally and ipsilaterally ERD, as shown in

other studies [43, 44]. However, it would be interesting to determine whether, in certain subjects, the effect is predominantly ipsilateral, contralateral, or bilateral. In such cases, we could analyze whether the MNS-related feature might provide a better prediction of MI-BCI performances if calculated in C4 rather than in C3, for example.

As a complement to the study of whether post-MNS ERD serves as a predictor of MI-BCI performance, an attempt was also made to use post-MNS ERS. To this end, the maximum value of the post-MNS ERS in the beta band between 800 and 1500 ms was calculated, and the correlation of this additional MNS-based predictor with MI-BCI performances was computed. However, the results were not significant: $p > 0.9$ for BCI performances in μ , $p > 0.7$ in μ +beta and $p > 0.2$ in beta. Therefore, used alone, the maximum post-MNS ERS lacks predictive capacity. However, it is noteworthy that this feature was employed in a LASSO model to predict BCI performance, indicating that it is not redundant and can indeed enhance prediction accuracy. The LASSO model, when trained exclusively with the minimum post-MNS ERD in the three frequency bands (μ , μ +beta, and beta), exhibited an enhancement in its prediction when the maximum post-MNS ERS was incorporated. Specifically, when predicting the BCI performances in μ , the LASSO model exhibits an enhancement in the correlation between real and predicted accuracies, shifting from $\rho = 0.61$, $p < 0.001$ to $\rho = 0.65$, $p < 0.001$. For BCI performances in μ +beta, it increases from $\rho = 0.43$, $p < 0.05$ to $\rho = 0.55$, $p < 0.01$; and for BCI performances in beta, the correlation progresses from $\rho = 0.2$, $p > 0.13$ to $\rho = 0.38$, $p < 0.05$. This finding confirms that the post-MNS beta rebound power may offer complementary insights into individual performance in the MI vs. rest task. This assertion is supported by the evidence from neuromagnetic recordings, which demonstrate that motor imagery engages the same cortical circuitry that generates post-MNS beta rebound [70].

While MNS-induced ERD/ERS patterns are reactive, they nonetheless provide valuable insights into the sensorimotor cortex’s readiness to engage in MI tasks. This readiness assessment, even if passive, serves as an effective predictor for MI-BCI proficiency without substituting MI’s active control role in BCI applications.

4.3. Practical procedure

In summary, to predict MI-BCI performance in a motor imagery versus rest task, a pre-calibration period in which the user’s median nerve is stimulated can be included. Less than two minutes of slow stimulation

is sufficient to estimate a robust MNS-based predictor ($\rho = -0.61$, $p < 0.01$). When the MI-BCI features are based on the power in the 8-30 Hz band, the most robust predictor is the minimum ERD value at 8-30 Hz, measured at electrode C3 with a small Laplacian filter. Since the latency of this minimum ERD varies across subjects, to maximize the probability of including it in the time window used to estimate the predictor, it is best to use a wide window, for instance 100 to 1000 ms post-MNS.

4.4. Reflection of the signal-to-noise ratio

To calculate the offline performance in MI-BCI, we used a simple (and not regularized) covariance matrix estimator. We also explored the impact of regularization by applying the Ledoit-Wolf shrinkage estimator [71], yet found that the correlations with our MNS-based predictor were less significant with this approach. One possible explanation is that the correlations between the predictor and the MI-BCI performances are influenced by the signal-to-noise ratio, as the signal-to-noise ratio improves (thanks to regularization), the correlation decreases. This hypothesis was further supported by our analysis using a Common Average Reference (CAR) of 128 electrode signals to compute the MI-BCI performances, which are only based on 40 motor and somatosensory electrodes, and the MNS-based predictor. CAR reduces widespread noise and artifacts across the scalp, and improves the signal-to-noise ratio in sensorimotor activities [72]. Consequently, while CAR reduced common noise, it also led to a degradation in the correlations between MI-BCI performance and our MNS-based predictor. Besides, since the predictor would not rely on 128 electrodes but on just 1 or 5 electrodes (such as C3 or a small Laplacian in C3), it is not reasonable in practical applications to record 128 electrodes only to apply a CAR.

4.5. Future investigation

Towards user profile personalization As future improvements to our study, we could isolate the lowest BCI performances in our dataset—specifically those corresponding to BCI illiteracy—to assess whether our MNS-based characteristic can reliably identify when a BCI system fails to correctly detect the mental state of a user, i.e., BCI illiterates [4]. Additionally, we might reevaluate our prediction of certain users using LASSO regression by training on a dataset where some outliers are removed, for instance by excluding accuracies with a Mahalanobis distance from the data center greater than 10%, as in [4].

Moreover, it may be beneficial to develop a predictor that integrates multiple neurophysiological

features, such as spectral entropy and the mu peak in the resting state with eyes open, to further enhance MI-BCI prediction performance, especially for users with lower performance. It is indeed possible that each predictor holds a piece of the puzzle in predicting a user’s BCI performance. By combining the best predictors into a single model, we could achieve highly promising results that adapt to different users.

Finally, we aim to personalize the MNS-based predictor for each subject. The literature shows that it is more effective to adapt the classification algorithm to each individual user [73, 74]. This adaptation involves selecting the most relevant frequency bands and the most discriminative electrodes for that specific user. Specifically, it could be beneficial to select, for each individual, the frequency band, time window, and electrode where the post-stimulation ERD is strongest, thereby tailoring the predictor to maximize its effectiveness for each user. By doing so, we hope that the MNS-based predictor will become even more accurate in predicting BCI performance.

Current MI-BCI predictor limited to right-handed participants It is important to note that all participants in our study are right-handed. Differences in sensorimotor activation between left- and right-handed individuals are well documented [75], which is particularly relevant to our study, as only the dominant hand’s median nerve was stimulated in right-handed participants. We are currently conducting a follow-up study to assess the generalizability of our findings with left-handed participants stimulated on their left hand.

5. Conclusion

Accurately predicting a user’s ability to utilize an MI-BCI is crucial for i) selecting subjects who are most likely to benefit, ii) harmonizing groups prior to an experiment to minimize bias, and iii) proactively adjusting BCI parameters—such as maintaining high levels of motivation and commitment, or ensuring that each patient receives an appropriate therapeutic solution.

To underscore the potential of our MNS-based characteristic as a predictor, we highlight its strong correlation with MI-BCI accuracies, particularly when both are computed in the mu+beta frequency band ($\rho = -0.71$, $p < 0.001$, with 4 minutes of median nerve stimulation). Notably, even with less than two minutes of stimulation, a significant correlation is achieved ($\rho = -0.61$, $p < 0.01$). Furthermore, using a LASSO regression model, we were able to predict the accuracies of unseen subjects with a significant correlation and a low prediction error ($\rho = 0.61$, $MAE = 9.0$, $p < 0.01$).

Median nerve stimulation (MNS) is valuable for

predicting MI-BCI performance for three main reasons: (i) it produces ERD/ERS patterns similar to those observed during motor imagery (MI), indicating brain readiness; (ii) as a passive method, it provides a consistent measure that is not influenced by the user’s cognitive or emotional state, or their familiarity with the MI task, ensuring reliable predictions; and (iii) it is easy to set up and integrates smoothly into existing BCI protocols with minimal preparation. Overall, our study introduces a robust new predictor for MI-BCI performance, offering BCI designers a useful tool to enhance, personalize, and better understand MI-BCI systems and their effectiveness.

In conclusion, our findings indicate that MNS can serve as an effective predictor of future MI-BCI performance by providing a non-invasive, objective and fast measure of a user’s motor readiness, while maintaining MI as the principal control mechanism within BCI systems. This predictive approach has the potential to optimize user performance estimation protocols and thus enhance MI-BCI applicability across diverse fields, quickly identifying people likely to be able to control MI-BCI, contributing to more personalized and efficient BCI experiences.

6. Acknowledgments

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7. Ethical statement

This research was conducted following the principles embodied in the WMA Declaration of Helsinki on ethical principles for medical research involving human subjects and all participants signed an informed consent approved by the local ethical committee of Inria (COERLE, approval number: 2016-011/01).

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