



HAL
open science

Quantifying Inter-and Intra-Subject Variability of Sensorimotor Desynchronization Induced by Median Nerve Stimulation and Motor Imagery for BCI

Valérie Marissens Cueva, Fabien Lotte, Laurent Bougrain, Sébastien Rimbart

► To cite this version:

Valérie Marissens Cueva, Fabien Lotte, Laurent Bougrain, Sébastien Rimbart. Quantifying Inter-and Intra-Subject Variability of Sensorimotor Desynchronization Induced by Median Nerve Stimulation and Motor Imagery for BCI. EMBS 2025 - 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Jul 2025, Copenhagen, Denmark. <hal-05195827>

HAL Id: hal-05195827

<https://hal.science/hal-05195827v1>

Submitted on 1 Aug 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY 4.0 - Attribution - International License

Quantifying Inter- and Intra-Subject Variability of Sensorimotor Desynchronization Induced by Median Nerve Stimulation and Motor Imagery for BCI

Valérie Marissens Cueva^{1,2}, Fabien Lotte¹, Laurent Bougrain^{2,3} and Sébastien Rimbart¹

Abstract—Motor Imagery-based Brain-Computer Interfaces (MI-BCIs) enable users to control external devices by interpreting sensorimotor activity recorded via electroencephalography (EEG). Median Nerve Stimulation (MNS) has recently emerged as a promising alternative motor task for BCI applications. However, intra- and inter-subject EEG variability remains a major challenge, affecting BCI system reliability. While variability is a well-known issue, its precise sources and impact on different EEG patterns remain unclear, with a lack of formal and quantitative studies of BCI variability. Thus, this study quantifies intra- and inter-subject variability in MNS-induced sensorimotor desynchronization (ERD) and compares it to MI. Results show that MI elicits stronger ERD with lower intra-subject variability, suggesting more consistent activation patterns, while inter-subject variability is similar between tasks. Additionally, the variability of classification accuracies based on Riemannian geometry exhibits a similar trend. These findings provide insights into EEG variability and its implications for BCI design. Identifying stable neural patterns could improve MI- and MNS-based BCIs, particularly for applications such as intraoperative awareness monitoring.

I. INTRODUCTION

Motor Imagery-based Brain-Computer Interfaces (MI-BCIs) enable users to control external devices or interact with computers by interpreting brain activity — typically measured by ElectroEncephaloGraphy (EEG) — associated with the mental simulation of movement, without its actual execution [1], [2]. These systems hold significant promises in various applications, including neurorehabilitation, assistive technologies, and communication [3].

Median Nerve Stimulation (MNS), a painless low-amplitude electrical stimulation applied to the wrist, has recently emerged as a promising motor task for BCI applications, as its sensorimotor patterns are similar to those observed during MI [4]. Several studies explore the use of MNS in BCI, either as a predictor of MI-BCI performance [5], [6] or as a strategy to enhance MI-BCI classification accuracy [4]. The latter is achieved by redefining the classification task from distinguishing MI from a resting state (MI vs. rest) to distinguishing MI+MNS vs. MNS, leading to a 15% improvement in MI detection accuracy [4]. Indeed, an MNS

leads to Event-Related Desynchronization and Synchronization (ERD/ERS) that are considerably attenuated when an MI is performed simultaneously, leading to increased differences (and thus improved classification) between MNS and MNS+MI. Building on this principle, MNS could be used to detect movement intention and imagination. We are currently exploring its potential application in detecting movement intention that might occur under general anesthesia, when patients accidentally regain awareness during a surgery [7], [8]. This could pave the way for an MNS-based BCI to monitor depth of anesthesia, potentially improving intraoperative awareness detection [9].

Despite their potential, BCIs face numerous challenges, among which a major one is their performance inconsistency, both within and between subjects. Indeed, BCI performance and EEG signals fluctuate significantly, over time, across users and contexts, which undermines reliability and stability of BCI systems, and thus ultimately, their usability [10], [11], [12]. This variability can be so pronounced that some individuals are unable to effectively use a BCI, a phenomenon referred to as BCI illiteracy/deficiency, affecting up to 30% of users [13]. Similarly, for a given user, the BCI performance can be good one day, but poor another day, with the same BCI [14]. Several factors contribute to this variability, including technical, physiological, and psychological factors. Technical factors include differences in EEG hardware, electrode positioning, and signal processing algorithms [15]. Physiological and psychological factors might be the users' age, personality, cognitive state, fatigue, neural plasticity, as well as the individual characteristics of neural patterns [16], [17], [18], [19], [20].

Such variability presents a critical obstacle for developing stable and robust MNS-based and/or MI-based BCIs, e.g., for anesthesia monitoring. For instance, for the latter, a key challenge is to minimize false positives in detecting intraoperative awareness, that are unfortunately likely to happen because of EEG variability, in order to prevent the unnecessary increase of anesthetic doses.

However, while variability is a known problem in BCI [11], especially concerning the ERDs and ERSs patterns [21], [22], difficulties remain in understanding the origin of such phenomenon [20]. Indeed, many sources of variabilities are still unknown, their impact on EEG and BCI performances is unclear, and the intrinsic variability of various EEG patterns and BCI paradigms is usually not formally studied nor quantified. This issue is even more pronounced for emerging

¹S. Rimbart, V. Marissens Cueva and F. Lotte are with the Inria Center at the University of Bordeaux / LaBRI (CNRS / Univ. Bordeaux / Bordeaux INP), 33405, Talence, France. ²L. Bougrain and V. Marissens Cueva are with the Université de Lorraine, CNRS, LORIA, F-54000 Nancy, France. ³L. Bougrain is with Sorbonne Université, Institut du Cerveau – Paris Brain Institute -ICM, CNRS, Inria, Inserm, AP-HP, Hôpital de la Pitié Salpêtrière, 75013 Paris, France. valerie.marissens@loria.fr

BCI paradigms, such as MNS-based BCIs. Therefore, to tackle this, our paper focuses on analyzing and quantifying intra-subject and inter-subject variability in MNS-induced sensorimotor patterns during BCI experiments. Specifically, we investigate the evolution and distribution over time and trials of the MNS-induced ERD patterns (estimated as the minimum EEG desynchronization values following MNS) across trials for each subject, and across subjects, assessing how stable or variable MNS-induced EEG patterns are. We also compare such variability measures of MNS patterns to those of the more commonly used MI patterns. We hope these new insights would prove useful to better understand variability in BCI, identify which BCI paradigms and EEG patterns are the more stable, and design better algorithms to handle this variability in the future.

II. MATERIAL & METHODS

A. Participants & experimental paradigm

Two datasets, consisting of 17 and 14 right-handed healthy subjects (8 females in total; aged 27.38 ± 11.48 years old) were used in this study. Each dataset involved two conditions: right-hand kinesthetic motor imagery (MI) and right-hand passive median nerve stimulation (MNS). Both experiments followed the ethical principles of the WMA Declaration of Helsinki on medical research involving human subjects [23]. Informed consent was obtained from all participants, with approval from the ethics committees of Inria (COERLE, approval number: 2016-011/01) and Nancy university hospital. From an initial pool of 41 subjects, ten were excluded due to technical issues, particularly MNS responses exceeding 10 dB or highly artifacted signals, resulting in a total of 31 usable subjects. Participants lay on a comfortable bed with their eyes closed, as the experiments were initially designed to investigate EEG activity under general anesthesia [7]. Each subject completed in a random order the two conditions: one run of 51 MI trials and one run of 51 MNS trials.

Prior to the study, subjects were taught how to perform the kinesthetic MI task [24] by imagining a discrete pinch movement between the thumb and index finger, aiming to evoke as many sensations as possible typical from a real movement, without executing it [7]. The MI task was initiated by an auditory cue, sustained for 2 seconds and terminated with a second beep.

The MNS condition involves a series of passive stimulations during a resting state, applied at a frequency of about 0.125 to 0.167 Hz. Two stimulation electrodes were placed on the wrist according to established standards [25], ensuring that the stimulation elicited a slight movement of the thumb. Stimulation intensity was adjusted for each subject, ranging between 8 and 15 mA.

EEG signals were recorded using the OpenViBE software [26] and a Biosemi Active Two with 128 channels, sampled at 2048 Hz. Electrodes were arranged according to the ABC layout. An external electromyogram electrode was used in all conditions to check the absence of movement during MI trials. Impedance was maintained below 10 k Ω .

B. Preprocessing & feature selection

To quantify motor patterns induced by MNS or MI, we computed ERD/ERS% using the band power method [27] implemented in a MATLAB script. EEG signals were filtered into the mu (7–13 Hz), mu-beta (8–30 Hz), or beta (15–30 Hz) frequency bands using a 4th-order Butterworth filter. The squared signals for each trial were smoothed using a 1-second sliding window with a 100 ms shift. Baseline power, calculated from -3 to -0.5 seconds relative to the task start, was subtracted from the average power of each window, then normalized by dividing by the baseline power and multiplied by 100 to obtain the ERD/ERS% measure. The minimum ERD/ERS% value (noted min-ERD) was computed within the 0 to 3 seconds window, capturing the peak desynchronization of both MI or MNS task [28]. Hence, for each subject, the min-ERD was computed for each of the 51 trials at electrode C3 and CP3 (over the right-hand motor and sensorimotor cortices respectively) using small Laplacian filters (LapC3 and LapCP3).

C. Quantifying variability

In this study, we analyzed both intra-subject and inter-subject variability of the min-ERD value. To quantify variability, we use a robust coefficient of variation based on the median — specifically, the ratio of the median absolute deviation (MAD) and the absolute value of the median [29]. This measure provides an estimation (in percent) of the min-ERD variability that is independent of the scale and robust to outliers. For simplicity, we will refer to this measure as CV throughout the paper:

$$CV(\mathbf{X}) = \frac{MAD(\mathbf{X})}{|median(\mathbf{X})|} \times 100 \quad (1)$$

Here, inter-subject variability relates to how ERD patterns, induced by either MI or MNS, differ across subjects. To analyze this variability, we need to first estimate the median value of min-ERD per subject (for MI and MNS) and then calculate the dispersion of this value between subjects. Thus, instead of considering all 51 trials per subject, we first computed the median of the minimum ERD across trials per subject, reducing each subject’s data to a single representative value. We then calculated the CV of this value across subjects, yielding one CV value for the MNS task and another for the MI task. To assess the statistical significance of these values, we performed a bootstrap resampling procedure in which we randomly sampled 31 values (one per subject) with replacement 1000 times, and recalculated the CV for each resampling. This resulted in two distributions of 1000 CV values: one for MI and one for MNS, using the same resampled subjects in both cases. We then compared these distributions by constructing the 95% confidence interval for the difference between MI-CV and MNS-CV. If the confidence interval includes a difference of zero, we conclude that there is no significant difference in inter-subject variability between MI and MNS.

Intra-subject variability relates to how MNS or MI-induced ERD differ across trials, for each subject. The procedure for

estimating this variability differs from that of inter-subject variability. Indeed, to analyze intra-subject variability, it is necessary to have several values for each subject. To achieve this, we computed the CV across the desynchronization values (min-ERD) obtained in each trial, quantifying how desynchronization varies over the 51 trials of a single subject. This results in a list of 31 CV values (one per subject), representing the variability of either the MNS or MI task within subjects. We compared these two distributions using a paired t-test.

In addition, we conducted complementary analyses to investigate the effect of repeated task execution on sensorimotor desynchronization. Indeed, the repeated activation of the motor cortex within a session ($n > 50$ trials) could impact ERD dynamics [30]. To test this hypothesis, first at the intra-subject level, we examined whether the minimum ERD (min-ERD) values varied trial after trial within a run for each subject. At the inter-subject level, we computed the median desynchronization value across subjects for each trial. This resulted in a sequence of 51 trials, where each min-ERD value represented the aggregated response across all participants. Then, we assessed the Spearman’s correlation between min-ERD values and trial number across all studied frequency bands at electrodes LapC3 and LapCP3, and applied a Benjamini-Hochberg correction for multiple comparisons.

D. Offline classification variability

In addition to statistics on desynchronization patterns, we also investigated variability in terms of EEG classification performance, both within and between subjects. To this end, offline classification accuracies were calculated for both conditions: right-hand MI vs. rest, and right-hand MNS vs. rest. EEG signals were downsampled to 128 Hz and band-pass filtered within mu, mu+beta or beta frequency bands, then epochs corresponding to rest (-3 to -0.5 s) and motor task (0.5 to 3 s) periods were extracted. Classification was restricted to data from 40 electrodes positioned over the motor and sensorimotor areas. A Tangent Space Logistic Regression (TSLR) classifier was used [31]. All classifications were performed using Python 3.10 with the Scikit-learn 1.2.2 [32], MNE 1.4.2 [33], and pyriemann 0.6 [34] libraries.

To assess inter-subject variability, we trained the classifier on 70% of the trials for each subject and tested it on the remaining 30%, yielding an accuracy value per subject. We then quantified variability across subjects by computing the CV of the accuracy values, obtaining one CV value for the MNS vs. rest classification and another for the MI vs. rest classification. To compare these two variability measures, we followed the same bootstrap procedure described in Section II-C: we performed 1000 resampling iterations with replacement, each time drawing 31 accuracy values. This resulted in 1000 bootstrapped CVs for MNS and 1000 for MI. In each iteration, we computed the difference between the CV of MNS and the CV of MI, constructing the distribution of variability differences. Next, we calculated the 95% confidence interval (CI) of this distribution. If 0

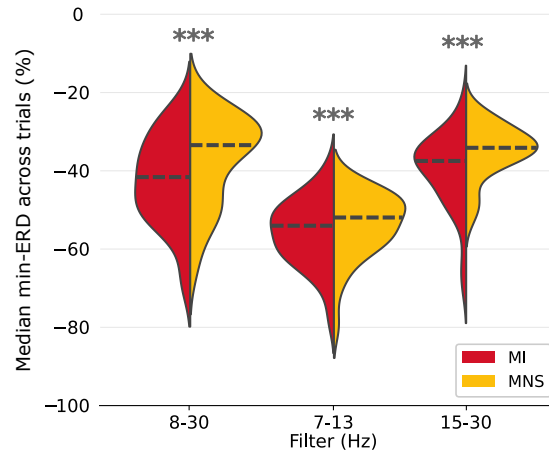


Fig. 1. Violin plots of ERD elicited during the MI or MNS task across 31 subjects, in electrode C3 with a small Laplacian filter. The dashed line corresponds to the median value across subjects. A Student’s t-test with repeated measures compares MI and MNS ($***p < 0.001$).

is included within the CI, this indicates that there is no significant difference between the variability associated with MNS vs. rest and MI vs. rest. In this case, we conclude that the variability measures are not significantly different.

To assess intra-subject variability, we performed 5-fold cross-validation across the 51 trials for each participant, using 40 trials for training and the remaining 11 for testing. This procedure allowed us to obtain multiple (5) classification accuracy values per subject, enabling us to quantify trial-to-trial variability by calculating the CV of accuracy across folds. This results in a list of 31 accuracy values corresponding to the variability within subjects in the MNS vs. rest task, or in the MI vs. rest task. These two distributions were then compared with a paired t-test.

III. RESULTS

We focus on two types of variability: the desynchronization variability and the EEG classification performance variability. The former is quantified as the variability of the minimum ERD value within the 0 to 3 seconds window relative to task onset (min-ERD) (see Section II-C), while the latter is assessed through the variability of test accuracy obtained from classifying motor tasks (MI or MNS) vs. resting period using a TSLR classifier (see Section II-D).

To better understand the variability induced by MNS — in desynchronization or performance — we first compare it to the variability observed during MI. This comparison provides a meaningful reference, as MI is already an established BCI task, and allows us to distinguish between absolute and relative variability, justifying the use of the coefficient of variation (CV) as a variability metric. Specifically, we first analyze the median desynchronizations elicited both during MI and after MNS to determine which motor task generates a stronger response. Then, we compare intra and inter-subject variability in both desynchronization and EEG classification performance. For clarity, we only present the results obtained at electrode C3 after applying a small Laplacian filter (LapC3) in the figures. Results from LapCP3 are also discussed but not explicitly shown in the figures.

A. Variability in desynchronization

a) *Comparison of MI-ERD and MNS-ERD:* To better understand the desynchronization elicited after MNS and how it differs from the one observed during MI, we first computed the min-ERD value for each trial in every subject. Then, for each subject, we computed the median min-ERD across trials, resulting in two lists: one containing 31 desynchronization values associated with MNS and another for MI. Figure 1 presents the distribution of min-ERD across the 31 subjects elicited by MI or MNS. A Student's t-test with repeated measures was performed to compare these two distributions, revealing that, in all three studied frequency bands — mu+beta, mu, and beta — the desynchronization was significantly more pronounced during MI compared to MNS ($***p < 0.001$). This effect was observed at LapC3 as presented in the figure, but also at LapCP3.

b) *Intra-subject min-ERD variability:* We also aimed to study how MNS-desynchronization varies within subjects. For each participant, the CV quantifies the dispersion of desynchronization across the trials relative to the (absolute) median desynchronization value. This results in two lists: one containing 31 CV values associated with MNS (one per participant) and another with 31 CV values for MI. Figure 2 presents a histogram displaying the median CV for each motor task, with an error bar representing the distribution across participants. A Student's t-test with repeated measures confirms that intra-subject dispersion across trials is significantly greater following MNS than during MI ($***p < 0.001$), consistently across the three frequency bands and at electrodes LapC3, as shown in the figure, and LapCP3.

c) *Inter-subject ERD variability:* Regarding inter-subject variability, we analyzed the desynchronization across participants. To do so, we first computed the median desynchronization value for each subject across their 51 trials, obtaining a single desynchronization value per subject. We then calculated the CV across the 31 subjects for both the MI and MNS conditions. To assess the significance of these

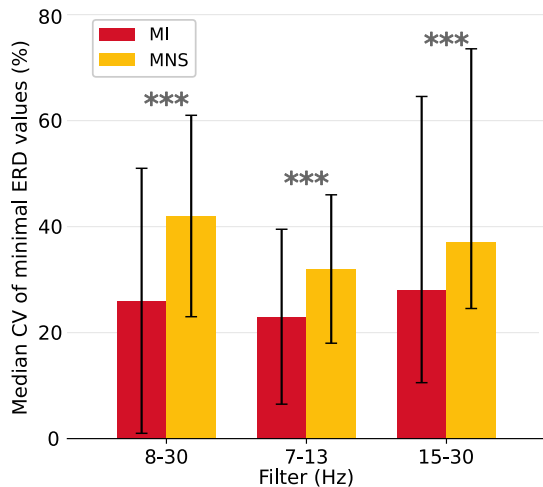


Fig. 2. Median value across subjects of the ERD variability across trials. The error bar presents minimum and maximum CVs obtained across subjects. A Student's t-test with repeated measures compares the intra-subject variability, during MI and MNS conditions ($***p < 0.001$).

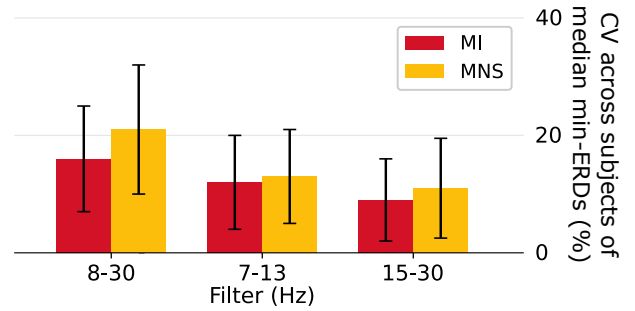


Fig. 3. Coefficient of variation (CV) of the median min-ERD value, across participants, for the MI or MNS task. A bootstrap approach with a 95% confidence interval confirms that the inter-subject variability of desynchronizations obtained by MI and MNS are not significantly different.

values, we performed a bootstrap procedure, as described in section II-C. For both LapC3 and LapCP3 electrodes, and across all studied frequency bands, the difference in inter-subject variability between MI and MNS desynchronizations was not statistically significant. Figure 3 presents a histogram with the CV value across subjects, with the error bars representing the range of CV values obtained from the 1000 bootstrap iterations.

Additionally, we repeated the same procedure using standard deviation (STD) instead of CV as a measure of variability. In this case, we found that MI and MNS exhibited similar inter-subject variability across all frequency bands except in the beta band. Specifically, in the beta band, MI was more variable than MNS, as indicated by the confidence intervals: $[-3.63, -0.72]$ in LapC3 and $[-4.53, -0.01]$ in LapCP3. These results indicate that the difference (STD of MNS - STD of MI) was negative, meaning that the standard deviation of MNS was lower than that of MI.

d) *Effect of task repetition:* We also examined whether motor task repetition influenced sensorimotor desynchronization across trials for both MNS and MI. At the group level, no significant correlation was found, suggesting that repeated execution of MI or MNS does not systematically alter desynchronization. However, at the individual level, a subset of 6 participants exhibited significant correlations, which became non-significant after multiple comparison corrections. Interestingly, in these subjects, MI trials displayed a negative correlation, indicating a progressive decrease in min-ERD, while MNS trials displayed a positive correlation, suggesting an increase in min-ERD over repetitions. For instance, in participant PM26, a negative correlation was observed during MI ($\rho = -0.412, p = 0.606$), whereas in participant PM7, MNS exhibited a positive correlation ($\rho = 0.413, p = 0.087$).

B. Variability in EEG classification performances

a) *Intra-subject performance variability:* The variability in EEG classification performance was assessed by classifying motor tasks (MI or MNS) vs. resting periods. For each participant, we performed a 5-folds cross-validation to obtain multiple classification accuracies per subject. To evaluate within-subject variability, a Student's t-test was conducted to compare the dispersion of classification performance in

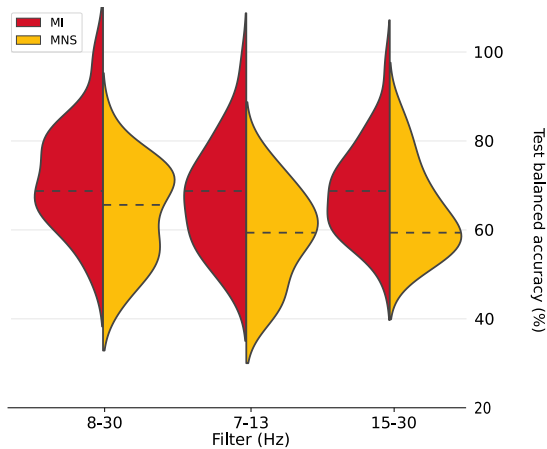


Fig. 4. BCI offline test balanced accuracies (distribution over 31 subjects) for MI vs. rest (in red) or MNS vs. rest (in yellow) classifications, obtained with a Tangent Space Logistic Regression (TSLR) classifier.

the the two tasks. Results reveal that in the mu+beta band, variability in MI and MNS performance was not significantly different. However, in the mu ($*p < 0.05$) and beta bands ($**p < 0.01$), intra-subject classification performance dispersion was significantly higher for MNS than for MI. This suggests that classification accuracies are more stable within subjects during MI vs. rest compared to MNS vs. rest.

b) Inter-subject performance variability: To assess inter-subject variability, we compared the test accuracies obtained by all subject. This process yielded a distribution of accuracies across participants (Fig. 4), from which we computed the coefficient of variation based on the median value (CV). We then applied the same procedure used to evaluate inter-subject variability in desynchronization (see Section II-C). The resulting confidence intervals (CIs) were: [-0.04, 0.09], [-0.06, 0.07] and [-0.05, 0.06] in mu+beta, mu and beta respectively. Since all CIs include a difference of zero, we conclude that there is no significant difference in inter-subject variability in BCI performance between the MI vs. rest task and the MNS vs. rest task.

IV. DISCUSSION

We quantified desynchronization variability during two motor tasks: median nerve stimulation (MNS) and motor imagery (MI). Our results indicate that, at the intra-subject level, MNS exhibits greater variability than MI. This finding holds true regardless of whether variability is measured using the coefficient of variation (CV) or standard deviation (STD), meaning that both relative (CV) and absolute (STD) dispersions across trials are higher for MNS compared to MI. Furthermore, this effect is consistent across both LapC3 and LapCP3 electrodes, suggesting that increased MNS variability is observed in both the primary motor cortex and the sensorimotor cortex. However, at the inter-subject level, desynchronization variability in MI and MNS appears to fluctuate similarly across subjects. Interestingly, when variability is quantified using STD instead of CV, we observe that in the beta frequency band, MI is more variable than MNS. This suggests that while MI and MNS exhibit similar

relative inter-subject variability around the median in the beta band, MI is characterized by a greater absolute variability than MNS in the beta band.

A. Variability sources in MI and MNS tasks

Interestingly, despite inter-subject differences in MNS intensity (ranging from 7 to 14 mA), potential variations in electrode positioning and anatomical differences in median nerve formation [35] or cortical structure [16], we did not observe higher inter-subject variability in ERD or classification performance for MNS compared to MI (see Fig. 3). This contrasts with the intuitive expectation that such differences would amplify variability across subjects [36]. One possible explanation is that, despite variations in stimulation parameters, MNS elicits a stereotyped cortical response via direct activation of somatosensory pathways, leading to relatively stable inter-subject ERD patterns. In contrast, MI, though an internally driven cognitive task, may also produce a reproducible neural response across individuals, potentially due to a shared engagement of sensorimotor networks after training. Indeed, in our study, participants were specifically trained to perform the KMI task (see [37], [30]), which may have contributed to the consistency of their ERD patterns across trials. Another factor that could explain the similar inter-subjects variability in MNS and MI might be that both tasks engage similar sensorimotor areas, leading to shared inter-individual neural patterns after training. This is reinforced as the results are the same in both LapC3 and LapCP3, so that MNS and MI seem to engage overlapping cortical areas, especially in the sensorimotor cortex.

Regarding intra-subject variability, our findings show that ERD variability is lower for MI than for MNS, which may seem counterintuitive given the active, voluntary nature of MI compared to the passive, externally driven nature of MNS. A possible hypothesis is that MI, despite being cognitively demanding, involves a learned motor imagery strategy that participants apply consistently across trials, leading to more stable ERD patterns. Interestingly, we found that MI has greater absolute inter-subject variability than MNS in the beta band, where in previous findings by Wriessnegger et al., inter-subject variability in the mu band was greater than in the beta band for MI [20]. However, their study used average-ERD (avg-ERD) rather than minimum-ERD (min-ERD) as a metric, which might explain the differences. Further investigations are needed to determine how different ERD quantification methods influence variability assessments in MI-based BCIs. These findings raise important questions about the factors that drive EEG variability in BCIs and suggest that task-related constraints, learning effects, and physiological adaptation mechanisms may play a key role. Further investigations should explore how different task demands, cognitive engagement, and neurophysiological responses shape intra- and inter-subject variability, ultimately contributing to more robust and adaptive BCI paradigms.

B. Effect of task repetition on ERD

Additionally, we investigated the effect of repeated task execution on sensorimotor desynchronization. We did not

find a global correlation between the number of trials and the min-ERD value. However, in certain subjects a trend seems to appear: with task repetition, MI led to a progressive decrease in min-ERD, whereas MNS resulted in an increasing min-ERD over trials. These trends may reflect individual differences in neuroplasticity or attentional modulation. For MI, stronger desynchronization over time could suggest a training effect, while for MNS, decreasing ERD may indicate habituation to passive stimulation. Yet, other studies have found that overall signal strength of evoked potentials in the brain does not vary significantly over repeated median nerve stimulation, suggesting that habituation effects are not significant [38]. Further studies are needed to clarify these mechanisms, with more trials and across sessions, and their implications for BCI applications.

C. Implications for an MNS-based BCI

Our objective is to utilize MNS to detect movement intentions, which are expected to exhibit greater variability than MI, as subjects are not trained to standardize their intention-related neural activity. The higher intra-subject variability in MNS could pose a challenge for BCI reliability, as detecting movement intentions may require more adaptive classification algorithms that account for fluctuations in neural responses. To address this, BCI adaptation mechanisms, such as subject-specific calibration or transfer learning, may be needed to compensate for the increased variability. However, further studies are required to determine whether the cross-session variability of MNS remains higher than that of MI, which is already known to be substantial [39]. Additionally, in some MNS-based BCI, MI is combined with MNS (simultaneous MI during MNS) [4]. Thus, it would be interesting to study, in the future, the variability of this combined scheme.

D. Baseline influence on ERD variability

The variability observed in ERD responses following both MI and MNS may be influenced by differences in baseline power. The selection of the baseline period is known to have a critical impact on ERD estimation, as the power level in this reference window directly affects the magnitude of the computed desynchronization [40]. In MI-BCI studies, if the baseline is too close to the previous trial, residual activity may lead to an overestimation of ERD, while a baseline taken too close to the upcoming trial may result in underestimation. This issue is particularly relevant when analyzing trial-to-trial variability, as fluctuations in baseline power could introduce additional variance in ERD measurements.

In our study, we did not explicitly examine the influence of baseline power on ERD variability. However, given the intra- and inter-subject differences observed in desynchronization (see section III), it is possible that variations in resting-state activity contributed to these effects. Subjects with higher baseline power may exhibit stronger ERD, while increased variability in baseline power across trials could lead to greater fluctuations in ERD magnitude. Future work should investigate these aspects by quantifying baseline power variability across trials and assessing its correlation with ERD

fluctuations. A better understanding of this influence could refine normalization strategies and improve the reliability of ERD-based BCI paradigms.

E. Multi-Dimensional Analysis of ERD Variability

Understanding ERD variability requires examining its modulation across temporal, spatial, and spectral dimensions. Analyzing these aspects post-task could reveal inter and intra-subject differences in motor cortex engagement. For MI, variability in ERD timing across trials may reflect differences in execution strategies. Some users may engage their motor cortex consistently, while others show fluctuating activation patterns, affecting BCI performance. For MNS, while ERD typically peaks 200–800 ms post-stimulation ([5], [28]), its trial-to-trial variability remains unexplored. Since MNS is passive, these fluctuations may reveal intrinsic motor cortex responsiveness. Spatial and spectral variations may further impact ERD reliability. Differences in topography and frequency engagement could contribute to BCI inefficiency. Future work should characterize these multi-dimensional variations to improve MI and MNS-based BCI paradigms, making them more robust and adaptive.

V. CONCLUSION

This study analyzed intra and inter-subject variability in sensorimotor desynchronization (ERD) induced by Median Nerve Stimulation (MNS) and Motor Imagery (MI) for BCI applications. Our results show that MI elicits stronger ERD with lower intra-subject variability than MNS, while inter-subject variability remains similar. Additionally, classification performance based on Riemannian geometry follows a comparable trend, reinforcing the impact of variability on BCI reliability. These findings highlight the need for a deeper understanding of EEG variability in BCI research. Future work should explore the factors influencing ERD variability across temporal, spatial, and spectral dimensions and investigate adaptive strategies to enhance BCI robustness. Ultimately, reducing EEG variability could improve the reliability of MI- and MNS-based BCIs, particularly for applications such as intraoperative awareness monitoring.

ACKNOWLEDGMENT

This work has been partially supported by the CHU-Brugmann hospital foundation and the ANR project BCI4IA ANR-22-CE19-0016.

REFERENCES

- [1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, no. 6, pp. 767–791, 2002.
- [2] R. Scherer and C. Vidaurre, "Chapter 8 - motor imagery based brain-computer interfaces," in *Smart Wheelchairs and Brain-Computer Interfaces*, P. Diez, Ed. Academic Press, 2018, pp. 171–195.
- [3] M. Clerc, L. Bougrain, and F. Lotte, *Brain-computer interfaces 2: technology and applications*. John Wiley & Sons, 2016.
- [4] S. Rimbart, 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.

- [5] S. Rimbart, V. Marissens Cueva, L. Bougrain, and F. Lotte, "Prediction of Motor-Imagery-BCI performance using Median Nerve Stimulation," in *12th International Winter Conference on Brain-Computer Interface, BCI 2015*, 01 2024.
- [6] V. Marissens Cueva, L. Bougrain, F. Lotte, and S. Rimbart, "From post-median nerve stimulation to mi-bci expertise prediction," in *13th International Winter Conference on Brain-Computer Interface*, 01 2025.
- [7] S. Rimbart, D. Schmartz, L. Bougrain, C. Meistelman, C. Baumann, and P. Guerci, "Motana: study protocol to investigate motor cerebral activity during a propofol sedation," *Trial*, vol. 20, no. 534, p. 9, Sep. 2019.
- [8] S. Rimbart, J. Lelarge, P. Guerci, S. J. Bidgoli, C. Meistelman, G. Cheron, A. M. C. Alvarez, and D. Schmartz, "Detection of motor cerebral activity after median nerve stimulation during general anesthesia (stim-motana): Protocol for a prospective interventional study," *JMIR Research Protocols*, vol. 12, 2022.
- [9] V. Marissens Cueva, S. Rimbart, A. M. C. Alvarez, M. Petieau, V. Vitkova, I. Hashemi, G. Cheron, C. Meistelman, P. Guerci, D. Schmartz *et al.*, "Towards riemannian eeg classifiers to detect awake and anesthetized states using median nerve stimulation," in *9th International Graz Brain-Computer Interface Conference*, 2024.
- [10] B. Allison and C. Neuper, *Brain-computer interfaces: applying our minds to human-computer interaction*. Elsevier, 2010, ch. Could anyone use a BCI?, pp. 35–54.
- [11] 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, 2020.
- [12] S. H. Fairclough and F. Lotte, "Grand challenges in neurotechnology and system neuroergonomics," p. 602504, 2020.
- [13] C. Vidaurre and B. Blankertz, "Towards a cure for bci illiteracy," *Brain topography*, vol. 23, pp. 194–8, 11 2009.
- [14] C. Benaroch, K. Sadatnejad, A. Roc, A. Appriou, T. Monseigne, S. Pramij, J. Mladenovic, L. Pillette, C. Jeunet, and F. Lotte, "Long-term bci training of a tetraplegic user: adaptive riemannian classifiers and user training," *Frontiers in Human Neuroscience*, vol. 15, p. 635653, 2021.
- [15] B. Oken and K. Chiappa, "Short-term variability in eeg frequency analysis," *Electroencephalography and Clinical Neurophysiology*, vol. 69, no. 3, pp. 191–198, 1988. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/0013469488901289>
- [16] M. Antonakakis, S. Schrader, Ümit Aydin, A. Khan, J. Gross, M. Zervakis, S. Rampp, and C. H. Wolters, "Inter-subject variability of skull conductivity and thickness in calibrated realistic head models," *NeuroImage*, vol. 223, p. 117353, 2020. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1053811920308399>
- [17] S. Rimbart and F. Lotte, "ERD modulations during motor imageries relate to users' traits and bci performances," in *Proc. IEEE EMBC 2022*, vol. 2022, 04 2022.
- [18] S. Rimbart, N. Gayraud, L. Bougrain, M. Clerc, and S. Fleck, "Can a subjective questionnaire be used as bci performance predictor?" *Frontiers in Human Neuroscience*, vol. 12, p. 529, 2019.
- [19] 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," in *Brain-Computer Interfaces: Lab Experiments to Real-World Applications*, ser. Progress in Brain Research, D. Coyle, Ed. Elsevier, 2016, vol. 228, pp. 3 – 35. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0079612316300061>
- [20] 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 in Human Neuroscience*, vol. 14, 2020. [Online]. Available: <https://www.frontiersin.org/journals/human-neuroscience/articles/10.3389/fnhum.2020.576241>
- [21] G. Pfurtscheller, C. Brunner, A. Schlögl, and F. L. da Silva, "Mu rhythm (de)synchronization and eeg single-trial classification of different motor imagery tasks," *NeuroImage*, vol. 31, no. 1, pp. 153 – 159, 2006.
- [22] 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," *International Journal of Industrial Ergonomics*, vol. 41, no. 5, pp. 428–436, 2011. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0169814111000540>
- [23] A. World Medical, "World medical association declaration of helsinki: ethical principles for medical research involving human subjects." *J Postgrad Med*, vol. 48, no. 3, pp. 206–208, Jul-Sep 2002, kIE: KIE Bib: human experimentation.
- [24] S. Rimbart, L. Bougrain, and S. Fleck, "Learning how to generate kinesthetic motor imagery using a bci-based learning environment: a comparative study based on guided or trial-and-error approaches," in *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2020, pp. 2483–2498.
- [25] A. Schnitzler, S. Salenius, R. Salmelin, V. Jousmaki, and R. Hari, "Involvement of primary motor cortex in motor imagery: a neuromagnetic study," *Neuroimage*, vol. 6, no. 3, pp. 201–208, Oct 1997.
- [26] Y. Renard, F. Lotte, G. Gibert, M. Congedo, E. Maby, V. Delannoy, O. Bertrand, and A. Lécuyer, "Openvibe: An open-source software platform to design, test and use brain-computer interfaces in real and virtual environments," *Presence : teleoperators and virtual environments*, vol. 10, no. 1, 2010.
- [27] 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.
- [28] V. Marissens Cueva, L. Bougrain, F. Lotte, and S. Rimbart, "Reliable predictor of bci motor imagery performance using median nerve stimulation," *Journal of Neural Engineering*, 2024, submitted.
- [29] C. N. Arachchige, L. A. Prendergast, and R. G. Staudte, "Robust analogs to the coefficient of variation," *Journal of Applied Statistics*, vol. 49, no. 2, pp. 268–290, 2022.
- [30] S. Rimbart and S. Fleck, "Long-term kmi practice with a bci: Impacts on user experience, motor cortex oscillations and bci performances," *Computers in Human Behavior*, vol. 146, p. 107789, 2023.
- [31] A. Barachant, S. Bonnet, M. Congedo, and C. Jutten, "Riemannian geometry applied to bci classification," in *International Conference on Latent Variable Analysis and Signal Separation*. Springer, 2010, pp. 629–636.
- [32] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
- [33] A. Gramfort, M. Luessi, E. Larson, D. Engemann, D. Strohmeier, C. Brodbeck, R. Goj, M. Jas, T. Brooks, L. Parkkonen, and M. Hämläinen, "Meg and eeg data analysis with mne-python," *Frontiers in Neuroscience*, vol. 7, p. 267, 2013.
- [34] A. Barachant, Q. Barthélemy, J.-R. King, A. Gramfort, S. Chevallier, P. L. C. Rodrigues, E. Olivetti, V. Goncharenko, G. W. vom Berg, G. Reguig, A. Lebeurier, E. Bjäreholt, M. S. Yamamoto, P. Clisson, and M.-C. Corsi, "pyriemann/pyriemann: v0.5," 2023.
- [35] M. Akhtar, S. Kumar, C. Chandan, B. Kumar, R. Sinha, M. Akhtar, and A. Kumar, "Variations in the formation of the median nerve and its clinical correlation," *Maedica*, vol. 17, pp. 878–884, 12 2022.
- [36] A. Akhtar, J. Sombeck, B. Boyce, and T. Bretl, "Controlling sensation intensity for electrocutaneous stimulation in human-machine interfaces," *Science Robotics*, vol. 3, no. 17, p. eaap9770, 2018. [Online]. Available: <https://www.science.org/doi/abs/10.1126/scirobotics.aap9770>
- [37] S. Rimbart, L. Bougrain, R. Orhand, J. Nex, S. Gaborit, and S. Fleck, "Grasp'it : ICO pour l'amélioration de l'apprentissage d'une tâche d'imagination motrice kinesthésique," in *29ème conférence franco-phonie sur l'IHM*, Poitiers, France, Aug. 2017, p. 2 p.
- [38] S. Thees, F. Blankenburg, B. Taskin, G. Curio, and A. Villringer, "Dipole source localization and fmri of simultaneously recorded data applied to somatosensory categorization," *NeuroImage*, vol. 18, no. 3, pp. 707–719, 2003. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S105381190200054X>
- [39] J. Ma, B. Yang, W. Qiu, Y. Li, S. Gao, and X. Xia, "A large eeg dataset for studying cross-session variability in motor imagery brain-computer interface," *Scientific Data*, vol. 9, 09 2022.
- [40] S. Rimbart, D. Trocellier, and F. Lotte, "Impact of the baseline temporal selection on the erd/ers analysis for motor imagery-based bci," in *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2023, pp. 1–4.