

## Influence of Median Nerve Stimulation Intensity on ERD/ERS, BCI Performance and User Experience

Loïc Bechon<sup>1</sup>, Fabien Lotte<sup>1</sup>, Stéphanie Fleck<sup>2</sup>, Sébastien Rimbart<sup>1</sup>

<sup>1</sup> Inria Center at Univ. Bordeaux / LaBRI, Talence, France

<sup>2</sup> University of Lorraine, Perseus, Metz, France  
E-mail: loic.bechon@inria.fr

**ABSTRACT:** Median Nerve Stimulation (MNS) has recently emerged as a promising approach to enhance Motor Imagery (MI)-based Brain-Computer Interfaces (BCIs) by providing additional somatosensory input that modulates sensori-motor rhythms. While previous studies have shown that MNS interacts with MI-related activity and can improve BCI performance, the influence of stimulation intensity on the resulting cortical patterns remains largely unexplored. In this study, we investigate how different MNS intensities affect ERD/ERS patterns, offline classification performance, and user experience (UX) with these stimulations. Thirteen participants performed right-hand motor imagery while receiving three stimulation levels relative to their motor threshold: low (below threshold), medium (twitch-inducing), and high (above threshold). Results show similar ERD/ERS patterns across stimulation intensities and no significant differences in classification accuracy. Participants reported very low levels of discomfort associated with the MNS. These findings suggest that relatively low-intensity MNS is sufficient to elicit detectable sensorimotor responses while improving user comfort, supporting the design of more usable MNS-based BCI systems. This opens the possibility of using MNS at the lowest effective level, which is particularly beneficial from a user experience perspective for prolonged BCI interaction.

### INTRODUCTION

Brain-Computer Interfaces (BCIs) enable users to interact with external systems by translating brain activity into control signals [1]. Among the various BCI paradigms, Motor Imagery (MI)-based BCIs are one of the most widely studied approaches. In MI-BCIs, users imagine performing movements without executing them, typically involving limb movements. Such mental tasks modulate sensorimotor rhythms over the motor cortex, producing Event-Related Desynchronization and Synchronization (ERD/ERS) patterns in the mu and beta frequency bands of the electroencephalographic (EEG) [2]. In particular, contralateral ERD during MI, followed by a post-task beta rebound (ERS), can be detected in EEG signals and used as discriminative features to infer the user's intention. Despite significant progress, MI-based BCIs still face important limitations. Classification accuracy often remains below practical usability thresholds (around

70–75% for two-class MI tasks), and performance varies considerably across users and sessions [3].

One promising approach to improve MI detection consists in combining MI tasks with external somatosensory stimulation. Various forms of stimulation have been explored, including tactile stimulation, functional electrical stimulation (FES), neuromuscular electrical stimulation (NMES), and tendon vibration [4, 5]. Among them, Median Nerve Stimulation (MNS) has recently emerged as a promising candidate. Electrical stimulation of the median nerve produces reproducible cortical responses characterized by an ERD during stimulation followed by a beta-band ERS. When MNS occurs during MI, this post-stimulation ERS is strongly reduced or suppressed, suggesting an interaction between sensory input and motor cortex activation that can improve MI detection. Previous studies reported classification improvements exceeding 12% when integrating MNS within MI-based paradigms, as compared to MI alone [6].

However, several key parameters of MNS-based BCI paradigms remain poorly understood. Previous work has investigated temporal aspects of stimulation, showing, for instance, that closely spaced MNS pulses can alter sensorimotor dynamics and lead to dominant ERD patterns due to overlapping cortical responses [7, 8]. More generally, studies on somatosensory evoked potentials (SEPs) have demonstrated that stimulation intensity strongly modulates cortical responses, affecting the amplitude, latency, and spatial distribution of early somatosensory components [9]. These findings suggest that stimulation intensity may also influence sensorimotor oscillations such as ERD/ERS. In practice, MNS intensity is commonly adjusted around the motor threshold, defined as the level producing a small involuntary movement between the thumb and index finger [10–12]. Yet it remains unclear whether such micromovements are necessary to evoke useful cortical patterns for BCI purposes, or whether lower intensities could produce comparable neural signatures. Conversely, higher intensities might enhance ERD/ERS responses but could also increase discomfort and reduce task concentration. From a human-computer interaction perspective, stimulation should ideally remain imperceptible while still eliciting sufficiently strong and detectable cortical responses.

In this study, we therefore investigate how median nerve stimulation intensity influences (i) ERD/ERS patterns

over the sensorimotor cortex, (ii) offline classification performance for discriminating MNS alone from MNS combined with motor imagery, and (iii) participants' perception of the stimulation. Our goal is to better understand how to calibrate stimulation intensity to design effective and usable MNS-based BCI systems.

## MATERIALS AND METHODS

### *Participants:*

Fifteen right-handed healthy volunteers (6 females, 9 males; mean age  $23.56 \pm 3.94$  years) provided written informed consent and participated in this study, approved by Inria's ethical committee (the COERLE: approval number: 2025-67). Inclusion criteria required normal or corrected-to-normal vision and no neurological or psychiatric disorders. Participants sat in a chair with armrests for arm stabilization, facing a screen with experimental instructions. Prior to the session, they watched a short video explaining the motor imagery tasks. Two participants were excluded due to poor EEG signal quality, leaving thirteen in the final analysis.

### *Experimental Paradigm:*

Each participant completed a single experimental session. After informed consent, a short calibration procedure was performed to determine the individual stimulation intensity. EEG and stimulation electrodes were then installed before the experiment. The protocol consisted of three blocks, each containing four runs of 40 trials. Three stimulation intensities were tested relative to the motor threshold: low ( $T - 2$  mA), medium (*Threshold*), and high ( $T + 2$  mA). As the low condition was set below the motor threshold, no visible twitch occurred. Stimulation intensity was fixed within each block following a Latin square design (Fig. 1) to counterbalance the order of conditions across participants (Low–Medium–High, Medium–High–Low, High–Low–Medium). During each trial, participants performed either right-hand motor imagery for 5 s with MNS delivered at 0.75 s or waited to receive only MNS, depending on the visual instruction displayed on the screen. A visual cue was presented only during MI trials and remained visible throughout the trial. Trials were randomized within runs, yielding 80 per task and condition. Short breaks (1–3 min) were provided between runs, and participants completed short questionnaires between blocks.

### *EEG Acquisition and MNS:*

EEG signals were recorded using a 64-channel EEG system (ANT Neuro) with active wet electrodes positioned according to the international 10–20 system. Signals were acquired at 500 Hz and processed online using the OpenViBE platform (version 3.6.0). For subsequent analyses, the signals were downsampled to 128 Hz. MNS was delivered using a Micromed ENERGY LIGHT stimulator. Two stimulation electrodes (Ambu Neuroline 700) were placed at the wrist over the median nerve following standard positioning described in [6]. Electrical stimulation consisted of single pulses of 100  $\mu$ s duration. Before

the experiment, several test stimulations were delivered to determine the individual stimulation levels. Participants were asked to report their perceived sensation and confirm that the stimulation was neither painful nor uncomfortable. None of the participants reported excessive discomfort during this calibration procedure.

### *Time–Frequency and Topographic Analysis:*

Offline EEG preprocessing, time–frequency analyses, and topographic analyses were performed using the EEGLAB toolbox (version 2025.0.0)[13] in Matlab 2020 (The MathWorks Inc., Natick, MA, USA). From the 64 recorded electrodes, a subset of 36 electrodes covering the sensorimotor areas was selected for further analysis (see Fig. 1). A common average reference (CAR) was computed on this subset of electrodes.

For time-frequency analyses, EEG signals were segmented into 7 s epochs ranging from  $-2$  s to 5 s relative to task onset. Event-related spectral perturbations (ERSPs) were computed to visualize the time-frequency dynamics associated with the different stimulation conditions and to characterize ERD/ERS patterns during MNS alone and during MNS combined with motor imagery. Topographic analyses were performed in the 8–30 Hz frequency band and within the 750–2750 ms time window after task onset. In our paradigm, this window corresponds to the period encompassing the stimulation and the associated post-stimulation ERD/ERS activity. It was therefore selected to visualize the spatial distribution of task-related sensorimotor modulations across conditions.

### *Classification and Performance Evaluation:*

Offline classification was performed using MNE-Python (v1.11.0) and Scikit-Learn (v1.8) on preprocessed EEG data exported from EEGLAB. The task consisted of discriminating between two conditions: MNS alone and MNS combined with right-hand motor imagery. Features were extracted from the 8–30 Hz frequency band within the 750–2750 ms time window after task onset, corresponding to the stimulation period and the associated sensorimotor response. Four classifiers were evaluated on 80 trials per class per condition, per participant with 4-fold cross-validation: Common Spatial Patterns (decomposed in 4 component) combined with Linear Discriminant Analysis(CSP+LDA), Minimum Distance to Riemannian Mean (MDM), and Tangent Space classifiers with logistic regression using either a Ledoit–Wolf (LWF\_TS+LR) or Oracle Approximating (ORC\_TS+LR) covariance estimator. Performance was evaluated using classification accuracy (see Tab. 1). Differences between stimulation intensity conditions and group were assessed using one-way Anova for global comparison, then paired Wilcoxon signed-rank tests with Bonferroni correction for multiple comparisons (see Fig. 4).

### *User Experience Assessment:*

User experience and perception of the stimulation were assessed throughout the experiment. Right-handedness was verified using the Edinburgh Handedness Inventory (EHI) [14]. Participants' subjective state was evaluated before and after the session using the NExT question-

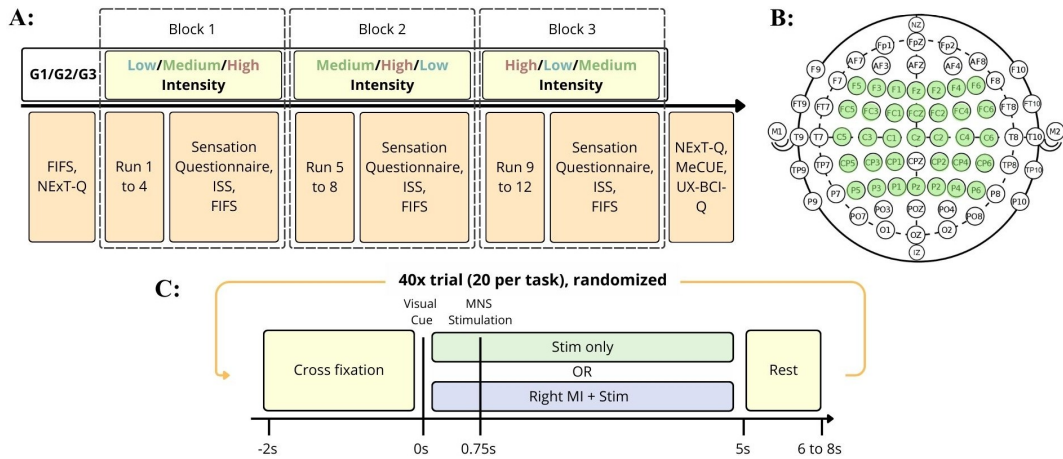


Figure 1: Experimental design. (A) Structure of the session with three stimulation intensity blocks (Low, Medium, High) counterbalanced across participants using a Latin square design. Each block contained four runs separated by questionnaires. (B) EEG electrode layout highlighting the 36 sensorimotor electrodes used for analysis. (C) Trial structure: fixation (−2 s), motor imagery cue at 0 s, and median nerve stimulation at 0.75 s. Each run contained 40 randomized trials.

naire, which measures mood, motivation, cognitive load, and agency [15]. Fatigue was monitored after each stimulation block using the Four-Item Fatigue Scale (FIFS) [16]. Perception of the stimulation was assessed using a short questionnaire including qualitative descriptions of the sensation, a Likert scale evaluating valence and urge to move, and a pain rating scale [17]. After the session, participants completed the emotional scale of the meCUE questionnaire [18], along with selected items from a custom UX-BCI questionnaire designed for this study to assess perceived task activity and sensations associated with kinesthetic motor imagery. Pre- and post-session scores were compared using paired Student’s t-tests or Wilcoxon signed-rank tests when assumptions were not met, with Bonferroni correction applied for multiple comparisons.

## RESULTS

**ERD/ERS Patterns Across Stimulation Intensities:** Figure 2 shows time-frequency dynamics observed at electrode C3 across stimulation intensities and task conditions. In the MNS-only condition, stimulation induces a typical sensorimotor pattern across all intensities, characterized by an initial ERS at stimulation onset followed by a short ERD in the mu band (7-13 Hz) and a post-stimulation beta rebound (15-30 Hz), consistent with previous reports of MNS-induced responses [6]. With MNS+MI, the initial ERS is reduced and replaced by a sustained ERD lasting for most of the task duration, and the beta rebound is largely suppressed, reflecting the dominance of MI-related desynchronization. These temporal dynamics are consistent with the spatial patterns shown in Fig. 3. In the MNS-only condition, a central ERS is mainly visible around the Cz region, whereas the MNS+MI condition produces a bilateral ERD over sensorimotor areas centered around C3 and C4. Importantly, both the temporal dynamics and the spatial distribution

of ERD/ERS patterns remain qualitatively similar across Low, Medium, and High stimulation intensities. Statistical comparisons (right column in Fig. 2 and bottom row in Fig. 3) confirm that with permutation-based one-way ANOVA test and False Discovery Rate correction, no significant differences are observed between intensity conditions.

Table 1: Mean classification accuracy obtained with the different classifiers.

| Classifier | Mean accuracy |
|------------|---------------|
| CSP+LDA    | 0.739         |
| MDM        | 0.697         |
| LWF_TS+LR  | 0.750         |
| ORC_TS+LR  | <b>0.754</b>  |

**Classification Results:** Classification performance obtained with the different classifiers is summarized in Tab. 1. Among the evaluated methods, the Tangent Space classifier with logistic regression using the Oracle Approximating Shrinkage covariance estimator (ORC\_TS+LR) achieved the highest average performance (mean accuracy = 0.754, SD = 0.090). Although this value is approximately 7% lower than that reported in previous MNS-based BCI studies [6], tangent space classifiers remained the most effective overall. Pairwise comparisons between classifiers using Wilcoxon signed-rank tests with Bonferroni correction showed that MDM performed significantly worse than CSP+LDA ( $p < 0.01$ ), LWF\_TS+LR ( $p < 0.01$ ), and ORC\_TS+LR ( $p < 0.01$ ), while no significant differences were observed among the other classifiers. Based on these results, subsequent analyses focused on the ORC\_TS+LR classifier. We further investigated whether classification performance was influenced by the order of stimulation conditions introduced by the Latin square design. A one-way ANOVA revealed no significant differences between groups corresponding to the three possible condition orders ( $p =$

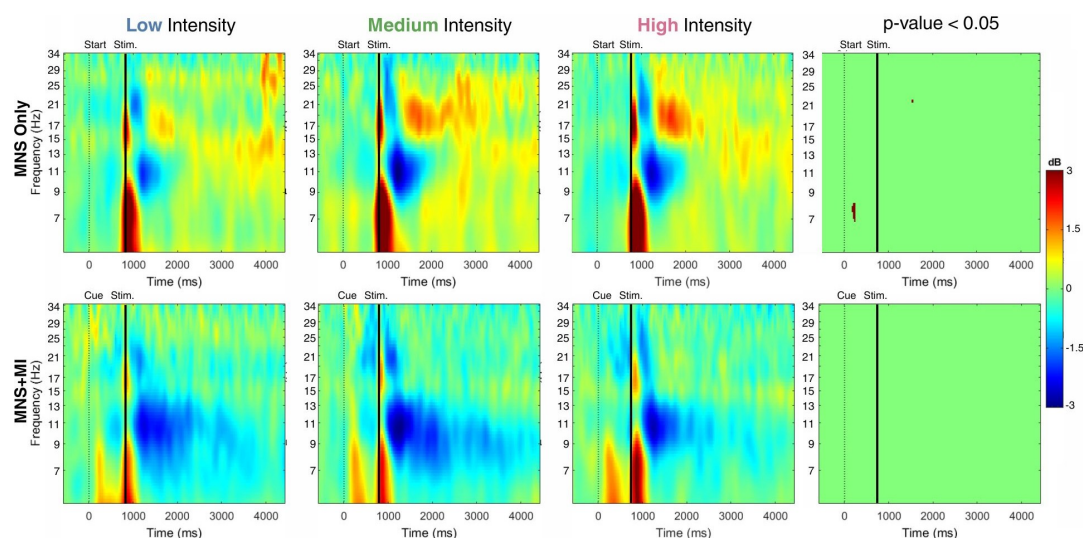


Figure 2: Time-frequency representations at C3 for three stimulation intensities (top: MNS-only; bottom: MNS+MI). Dashed line: cue onset; solid line: stimulation. MNS induces ERS, mu-band ERD (7–13 Hz), and beta rebound (15–30 Hz); during MNS+MI, the rebound is suppressed and replaced by sustained ERD. No significant differences across intensities (right column,  $p < 0.05$ ).

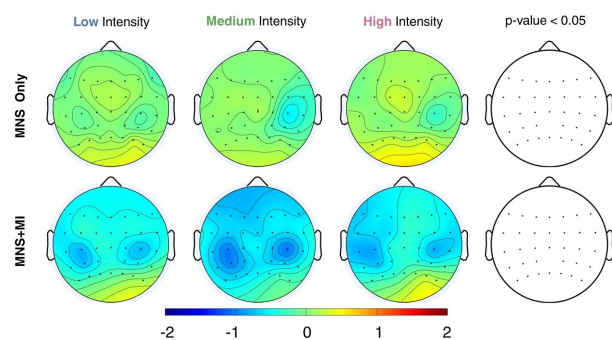


Figure 3: Topographic maps of ERD/ERS (%) in the mu+beta band (1–3 s after task onset) for each stimulation intensity and task. Red indicates ERS and blue ERD. Electrodes highlighted in red in the right panel denote significant differences between conditions ( $p < 0.05$ ).

0.392), nor between stimulation intensity conditions ( $p = 0.814$ ). These results indicate that classification accuracy was not affected by stimulation intensity or by the order in which the intensity conditions were presented.

Additional analyses were conducted using a broader 5–35 Hz frequency band, motivated by previous studies suggesting that including lower-frequency activity, particularly in the theta band, may improve MNS-based MI detection [19]. Figure 4 presents classification accuracy across stimulation intensities for the ORC\_TS+LR classifier in both frequency bands. In the conventional 8–30 Hz band, no significant differences were observed between stimulation intensities. In contrast, the 5–35 Hz analysis revealed a small but significant difference between the Low and Medium conditions, while all other comparisons remained non-significant. Although limited, this effect suggests that including lower-frequency components may reveal subtle intensity-related differences not captured by the standard sensorimotor band.

#### Subjective User Experience Assessment:

Participants reported low to moderate fatigue before the session (FIFS: mean = 4.15, SD = 1.99), which increased significantly by the end of the experiment (mean = 6.61, SD = 2.29;  $p = 0.002$ ; 10-item scale), likely due to the sustained attention and immobility required during the protocol. Emotional state remained globally stable: NEXT results showed a decrease in depression scores ( $p = 0.005$ ), while meCUE emotional scores indicated neither strong negative (mean = 3.38, SD = 0.89; 5-item scale) nor strong positive emotions (mean = 3.92, SD = 0.75). UX-BCI responses indicated moderate difficulty in performing the MI task (Activity: mean = 2.56, SD = 0.78; Kinesthetic MI: mean = 3.38, SD = 0.82), consistent with typical MI-based BCI studies [20]. Overall, MNS was well tolerated across intensity conditions. Participants reported a generally neutral perception of the stimulation (mean = 2.94, SD = 0.46; 5-item scale), commonly described as tingling or vibration-like sensations in the hand. Reported discomfort remained very low (mean = 0.35, SD = 0.46; 10-item scale), and no noticeable differences were observed between stimulation intensities. The urge to move occasionally reported during stimulation remained moderate (mean = 3.30, SD = 1.12) and did not lead to overt movements. These results indicate that the different stimulation intensities were similarly well tolerated and did not notably affect subjective perception.

## DISCUSSION

This study investigated the influence of median nerve stimulation (MNS) intensity on sensorimotor EEG responses and motor imagery (MI) detection performance. Similar ERD/ERS patterns were observed across the three stimulation intensities, with no significant differences in either ERSP analyses or classification accuracy. One possible explanation is that the tested intensity range

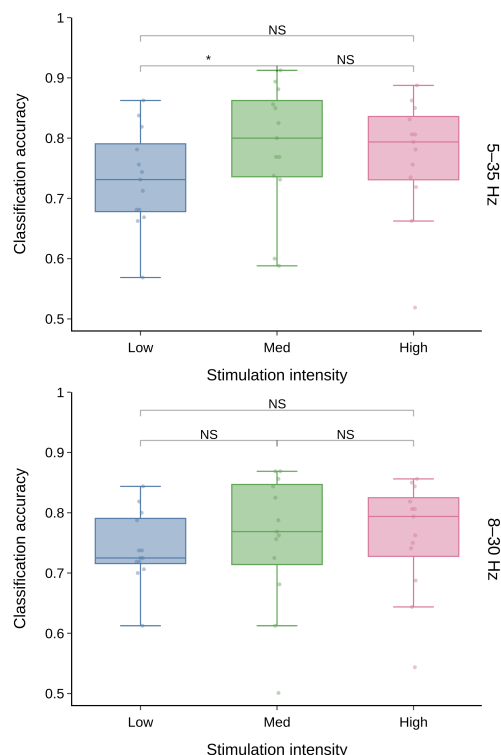


Figure 4: Offline classification accuracy for ORC\_TS+LR classifier across stimulation intensities (Low, Med, High) for the 5-35 Hz and 8-30 Hz bands. Points represent individual participants. A significant difference was observed between Low and Med in the 5-35 Hz band ( $*p < 0.05$ ), while other comparisons were not significant.

( $\pm 2$  mA around the motor threshold) was insufficient to induce measurable cortical differences. Once afferent pathways are sufficiently activated, increasing stimulation intensity may not substantially modify the resulting cortical oscillatory responses. In other words, stimulation levels near the motor threshold may already recruit the neural mechanisms underlying the observed sensorimotor activity, leading to comparable ERD/ERS patterns across the tested intensity range. Nevertheless, the stability of the observed patterns suggests that MI-related responses remain robust within this range, indicating that relatively low stimulation intensities may already be sufficient to elicit detectable sensorimotor activity. User questionnaires further indicated that the protocol was well tolerated and elicited subjective responses comparable to those of conventional MI-BCI paradigms, suggesting that repeated MNS remains acceptable for participants and compatible with practical BCI applications.

#### Comparison with Previous MNS-Based BCI Studies:

A previous work reported accuracy improvements of about +12% when combining MNS with MI compared to MI alone [6], and in some datasets, gains exceeding 18% have been observed with mean accuracies around 85% in MI vs Rest paradigms [21]. In contrast, the best performance in the present study reached approximately 80% accuracy (5–35 Hz band, medium intensity; Fig. 4). This

difference is somewhat surprising, as time–frequency and topographical analyses still show a clear gating effect when MNS is combined with MI: the post-stimulation beta rebound is strongly reduced during MI, likely due to dominant ERD activity [6, 8]. Methodological factors may explain this discrepancy. In the present study, participants performed the task with eyes open, whereas previous studies were conducted with eyes closed, a condition known to modulate sensorimotor rhythms [22]. Participants were also seated, while previous experiments often involved a lying position in clinical monitoring contexts [6]. In addition, the present protocol did not include a baseline MI vs Rest condition without stimulation, which would have allowed a direct estimation of the performance gain induced by MNS.

Interestingly, classification results suggest that the broader 5–35 Hz frequency band slightly improves performance compared to the classical sensorimotor band (8–30 Hz). This indicates that lower-frequency components, including the theta band, may contribute to MI detection in MNS-based paradigms, though the contribution of the 30–35 Hz range remains to be investigated. Topographical analyses suggest that a central and fronto-central rebound observed in the MNS-only condition becomes more prominent when theta frequencies are included, thereby increasing the contrast with the MNS+MI condition. This is consistent with previous findings reporting that MNS can modulate low-frequency oscillatory activity beyond classical mu and beta rhythms [19].

#### Exploratory Analysis of Stimulation Intensity:

A complementary analysis examined whether the absolute stimulation intensity influenced classification performance across participants. Spearman correlation revealed a weak but significant positive relationship between stimulation intensity and ORC\_TS+LR classifier accuracy in the 8–30 Hz band ( $p = 0.37$ ,  $p = 0.019$ ), while no significant correlation was observed in the broader 5–35 Hz band ( $p = 0.21$ ,  $p = 0.207$ ). Although this suggests that higher stimulation amplitudes may slightly enhance sensorimotor discriminability in the narrower band, this effect was not reflected in comparisons between the three discrete stimulation conditions. One possible explanation is that once afferent pathways are sufficiently activated, increasing stimulation intensity may not substantially modify the resulting cortical oscillatory responses.

#### Influence of Analysis Window:

Another possible explanation for the absence of clear differences between stimulation intensities lies in the use of a fixed analysis window for ERSP and classification analyses (8–30 Hz, 750–2750 ms). While this approach ensures consistent comparisons across participants, it may mask individual variability in the temporal or spectral characteristics of sensorimotor responses. Future analyses could therefore explore more individualized approaches, for example by extracting participant-specific ERD minima or optimizing subject-specific time–frequency features for classification, which may better capture inter-individual variability in sensori-

motor responses.

## CONCLUSION

This study investigated the influence of median nerve stimulation (MNS) intensity on sensorimotor EEG responses and motor imagery (MI) detection performance. Similar ERD/ERS patterns were observed across stimulation intensities below, at, and above the motor threshold, and classification accuracy was not significantly affected by stimulation intensity. These results indicate that stimulation levels around or below the motor threshold are sufficient to elicit robust sensorimotor responses for MNS-based MI detection. Importantly, participants reported very low discomfort, suggesting that such low-intensity stimulation remains well tolerated during prolonged sessions. Overall, these findings suggest that MNS-based BCI paradigms can operate effectively with minimal stimulation levels, opening the way to more lightweight, comfortable, and user-friendly systems. Future work should investigate subject-specific optimization of stimulation parameters and analysis windows to better capture inter-individual variability and further improve MI detection performance.

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