

Using brain network features in motor imagery-based BCI for stroke rehabilitation

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ABSTRACT: Motor imagery brain-computer interfaces are promising tools for post-stroke rehabilitation, but most systems rely on spectral power features and are often tested in highly selected patient populations. Because stroke affects large-scale brain networks, connectivity-based markers may provide complementary information for decoding and monitoring rehabilitation. This pilot study evaluated the feasibility of an intensive 6-week MI-BCI protocol combined with functional electrical stimulation in five chronic stroke patients with heterogeneous and often severe motor impairment. Functional connectivity analyses revealed the emergence of motor imagery-related modulations over centro-frontal and centro-parietal regions. These findings support the feasibility of intensive MI-BCI rehabilitation in chronic stroke and suggest that functional connectivity may be a relevant biomarker for adaptive BCI strategies.

INTRODUCTION

Brain-computer interfaces (BCIs) have emerged as a promising approach to promote motor recovery after stroke by coupling motor imagery with contingent feedback, such as functional electrical stimulation, robotic assistance, or sensory feedback [1]. By directly linking brain activity to external effectors, BCIs aim to reinforce use-dependent plasticity and restore motor function through repeated activation of sensorimotor networks. This approach is particularly relevant in stroke rehabilitation, where impaired voluntary movement limits the delivery of conventional task-oriented therapies, especially in patients with severe motor deficits.

Despite encouraging results [2, 3], the transfer of BCI-based rehabilitation from controlled research settings to routine clinical practice remains limited. An important step is to evaluate BCI feasibility in patients reflecting the clinical complexity of stroke, including associated cognitive or language deficits, attentional fluctuations, fatigue, and comorbidities. These factors may contribute to al-

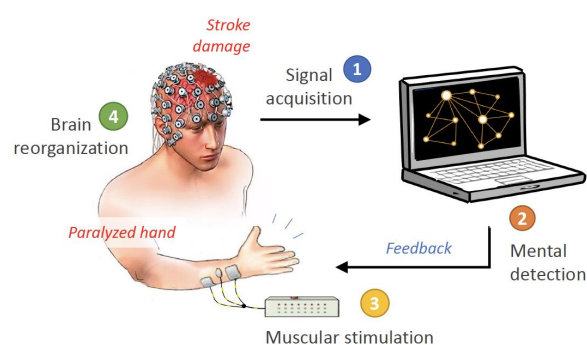


Figure 1: Schematic representation of the BCINET protocol. 1) EEG signals are acquired and transformed in functional brain networks via imaginary coherence. 2) Node-strengths are extracted from the resulting time-varying brain networks and considered as classification features. 3) A functional electrical stimulator (FES) commands the hand opening in case of correct detection. 4) This feedback is hypothesized to influence the brain network reorganization across sessions. More details ClinicalTrials.gov (NCT06951035)

tered sensorimotor rhythm modulation and increased BCI inefficiency [4]. They also highlight the need for decoding approaches that are robust to altered oscillatory activity and better adapted to heterogeneous stroke population.

In parallel, stroke is increasingly conceptualized as a network-level disorder rather than a purely focal lesion [5] Functional recovery depends on the reorganization of large-scale brain networks, including intra- and inter-hemispheric sensorimotor interactions [6]. In this framework, the activity of isolated cortical regions may provide only a partial description of the underlying neuroplastic processes. Connectivity-based decoding strategies may therefore be used in BCI protocols to integrate information across multiple cortical regions, thus reducing sensitivity to focal signal alterations [7]. Such network-level biomarkers could also facilitate adaptive and patient-specific training, which is essential for translating BCIs

Table 1: Patient characteristics

Patient	Age (years)	Stroke side	Time since stroke (months)	UE-FMA
P01	47	L	12	13
P02	62	R	63	49
P03	78	L	45	18
P04	51	R	17	19
P05	55	R	16	18

into clinical practice (Fig. 1). Among connectivity estimators, measures based on the imaginary part of coherency (ImCoh) have been recommended to reduce spurious zero-lag coupling and improve the physiological interpretability of EEG networks [8]. This choice is supported by previous network-based work showing that motor imagery after stroke involves altered functional brain network organization [9]. In MI-BCI settings, phase-synchronization measures, including ImCoh, have been shown to capture task-related sensorimotor modulations [10]. More recently, the FUCONE framework showed that functional connectivity estimators can provide complementary information for MI-BCI classification [11]. In this context, we designed an intensive and individualized rehabilitation protocol combining motor imagery-based BCI training with neuromodulation. The present pilot study aimed to evaluate the feasibility of this approach and to explore the neurophysiological changes associated with intensive, connectivity-based BCI rehabilitation.

MATERIALS AND METHODS

Study design and population: Five patients with chronic stroke were included in this pilot phase aimed at assessing the feasibility and tolerability of an intensive MI-BCI rehabilitation protocol (6 weeks, 3 sessions/week), prior to a subsequent phase investigating the additional effect of non-invasive brain stimulation. The study was registered on ClinicalTrials.gov (NCT06951035). Thus, consecutive chronic stroke patients with upper limb deficit were recruited (Table.1). The mean age was 58.6 years (range 47–78) and time since stroke ranged from 12 to 63 months. Three patients had right hemisphere lesions and two left hemisphere lesions. Four patients presented severe distal motor impairment (UE-FMA < 32), three of whom had no voluntary hand opening. Two patients presented aphasia but were able to understand the instructions and complete the protocol.

BCI protocol: Sessions were conducted in a quiet, shielded environment with patients seated in front of a screen table and the paretic arm supported on an arm-rest. EEG was recorded using a Brain products amplifier with active electrodes (impedance < 10 kΩ). FES was delivered using the Fesia Grasp system [12] placed on the paretic forearm.

The BCI paradigm consisted of a MI-baseline design [13] in which only the MI condition was presented and repeated 18 times per run. Each trial began with a 5-second

baseline resting period (hollowed circle). This was followed by a 4-second cue period during which a red circle appeared on the screen, instructing the patient to perform motor imagery. The cue period was followed by a 3-second feedback phase, during which FES was delivered when MI was correctly detected. Finally, an intertrial interval of 2 to 3 seconds (random jitter) was introduced to reduce temporal predictability and anticipation effects. Closed-loop BCI experiment was performed with Openvibe [14]. Each session consisted of one calibration run (only positive feedback) following 8 training run, corresponding to 144 MI trials in total. This number was selected to ensure a rehabilitation-oriented dosage exceeding 100 task repetitions per session [15].

EEG signal acquisition and processing: EEG signals were recorded with a 64-channel BrainAmp system (referenced to mastoids signals) with a 500 Hz frequency sampling. Left or right electromyogram signals were recorded on the affected arm to ensure that subjects were not moving their forearm while performing the tasks. Signal processing was computed with MNE python library. Online feature extraction and decoder training was performed with Happyfeat software [16].

Feature extraction: For the MI condition, features were computed from the last 3 seconds of the cue period to capture stable MI-related activity. For the Rest condition, the first 3 seconds of the baseline were used, ensuring sufficient distance from both the upcoming cue and the preceding MI and feedback periods. Each epoch was then divided into shorter time segments to enable reliable estimation of power spectral density and functional connectivity. A sliding-window approach was used, with windows of 0.5 seconds (250 samples) and a 36% overlap, corresponding to 90 shared samples between consecutive segments. As a result, each trial was decomposed into eight overlapping windows. PSD was estimated using an autoregressive Burg method. The model order was set to 25, and the spectral estimation was computed using 250 frequency points. A common average reference was applied. The imaginary coherence (ImCoh) was used to quantify phase coupling while removing zero-lag interactions:

$$\text{ImCoh}_{ij}(f) = \left| \frac{\text{Im}(S_{ij}(f))}{\sqrt{S_{ii}(f)S_{jj}(f)}} \right| \quad (1)$$

where $S_{ij}(f)$ is the cross-spectrum between signals i and j at frequency f , and $S_{ii}(f)$ and $S_{jj}(f)$ are the corresponding power spectral densities.

Node strength (NS) was computed for each electrode as the sum of its connectivity values with all other electrodes:

$$NS_i(f) = \sum_{j=1}^N \text{ImCoh}_{ij}(f) \quad (2)$$

where N is the total number of electrodes, and $\text{ImCoh}_{ij}(f)$ denotes the imaginary coherence between electrodes i and j at frequency f . This allows to reduce dimensionality and improving robustness for classification [7].

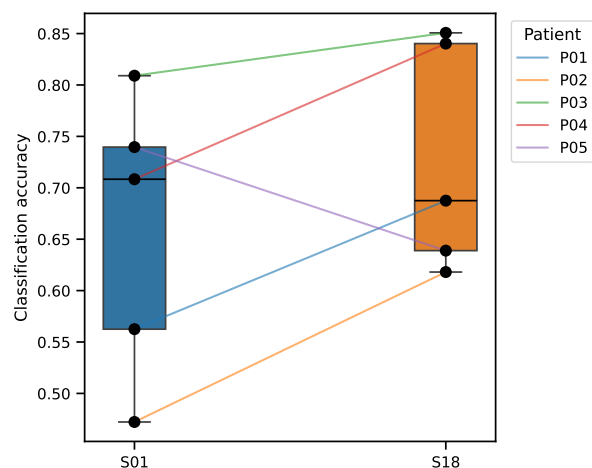


Figure 2: Evolution of classification accuracy between session 1 (S01) and session 18 (S18). Each line represents an individual patient.

Feature selection and decoder training: For each session, the linear discriminant analysis (LDA) decoder was updated at three predefined moments during the session in order to account for non-stationarities in EEG signals, including mental fatigue, strategy changes, and signal drifts. A first decoder was trained after an initial calibration run with a FES at each trial. The model was then retrained after two additional control runs, and a final update was performed after three further runs.

At each training step, candidate features were ranked using the r^2 metric computed between MI and Rest conditions [17]. The most discriminative electrode–frequency features within sensorimotor cortex (FC, C, and CP regions, including channels 1–6 and midline sites) and alpha/beta frequency band (8 to 30Hz) were then selected independently within each feature domain. Separate LDA classifiers were trained using different balanced combinations of PSD and functional connectivity features derived from ImCoh node strength. Specifically, models were computed using equal numbers of features across domains, including configurations with one to three electrode–frequency pairs per modality (i.e., 1 PSD and 1 FC, 2 PSD and 2 FC, and 3 PSD and 3 FC features). The best-performing classifier, based on classification accuracy within the current batch, was selected to control the subsequent runs.

Statistical analysis: To assess the evolution of electrophysiological features across rehabilitation, statistical comparisons between MI and baseline conditions were performed using a non-parametric cluster-based permutation test [18]. Analyses were conducted on calibration runs recorded at the beginning and at the end of the intervention. These runs used standardized MI-FES sequences with systematic feedback, but without online decoder-dependent control, allowing the assessment of MI-related electrophysiological activity under comparable calibration conditions. Test statistics were computed for each electrode–frequency pair and clustered across neighboring electrodes and adjacent frequency bins based

on spatial and spectral adjacency. Statistical significance was estimated by randomly permuting trial labels between conditions and comparing the observed cluster statistics to the null distribution of the maximum cluster statistic.

RESULTS

BCI performance: All patients successfully completed rehabilitation, with no dropouts. As shown in figure 2, mean classification accuracy over subjects increased from 0.66 at Session 1 (range: 0.47–0.81) to 0.73 at Session 18 (range: 0.62–0.85). Four out of five patients showed an improvement in BCI performance over the intervention period, with the largest gains observed in patients with initially lower accuracy. A wilcoxon signed-rank test did not confirm a significant difference due to a small number of patients.

Evolution of functional connectivity features: Figure 3 illustrates representative frequency profiles of PSD and NS-ImCoh during rest and motor imagery, highlighting that connectivity-derived features may provide information partially distinct from power-based markers. Figure 4 shows the evolution of ImCoh node strength modulations between Session 1 and Session 18, with topographic maps displaying r^2 values from calibration runs restricted to statistically significant clusters. At Session 1, no significant clusters were observed. At Session 18, clusters with higher r^2 values were identified over centro-frontal and centro-parietal sensorimotor regions within the alpha–beta range in four of the five patients.

DISCUSSION

This pilot study evaluated the feasibility of an intensive motor imagery BCI protocol integrating functional connectivity features in chronic stroke patients. Participants were recruited consecutively without selection based on BCI aptitude and included individuals with severe distal motor impairment and spasticity, profiles often excluded from BCI studies. Two patients initially failed to reach the conventional threshold for effective BCI control, but by the final sessions all participants achieved classification accuracies above 60% [19]. This progression may reflect preserved neural representations of motor imagery despite the absence of voluntary movement [20, 21].

All participants completed the intervention without dropout. Although the sample size was limited, these observations suggest that intensive BCI-based rehabilitation protocols may be feasible in a broader stroke population than typically included in experimental studies, an important issue for the clinical translation of BCI neurorehabilitation.

Electrophysiological analyses revealed the emergence of functional connectivity modulations after training. No significant clusters were detected during the initial calibration session, whereas significant NS ImCoh changes

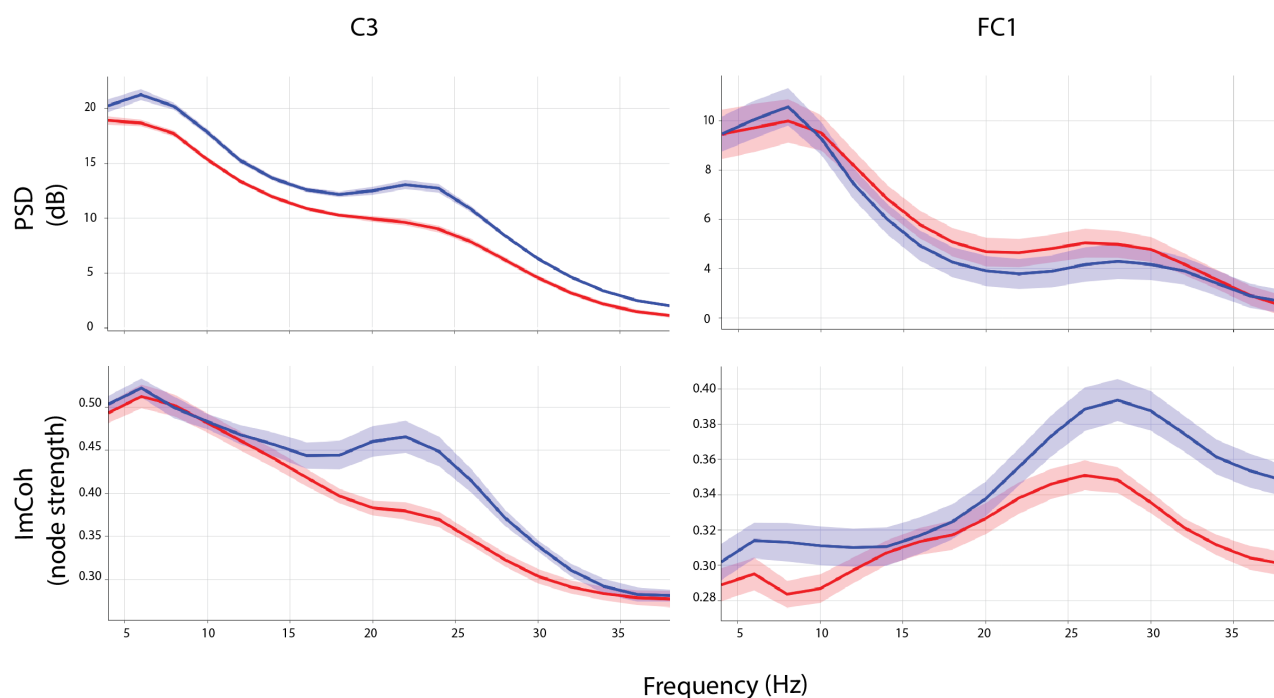


Figure 3: Two representative cases illustrate that PSD and NS-ImCoh can capture both redundant and complementary information. At C3, motor imagery (red) induced alpha/beta ERD in PSD (top row) together with beta-range decreases in NS-ImCoh (bottom row). At FC1, PSD showed mainly beta ERD, whereas NS-ImCoh revealed beta/gamma-range connectivity decreases. Shaded areas indicate standard error of the mean across trials.

were observed at the final session in four out of five patients. Although exploratory, these findings are consistent with previous studies reporting network-level plasticity following BCI-based rehabilitation [3, 22]. Stroke recovery is increasingly understood as a network reorganization process [5, 6], and the progressive emergence of connectivity-based discriminative features may reflect adaptations within distributed sensorimotor networks. These results also support the potential complementarity of connectivity metrics with traditional power-based features commonly used in motor imagery BCIs.

While the FUCONE framework [11] supports the offline relevance of functional connectivity estimators for MI-BCI classification, NS-ImCoh should be considered one possible network-based representation rather than a definitive choice. Other connectivity metrics, such as wPLI, may also reduce sensitivity to volume conduction, whereas source-space reconstruction could improve the anatomical interpretability of the inferred networks. Effective connectivity approaches could further address information flow within post-stroke sensorimotor networks [5]. Beyond pairwise connectivity, recent work on neuronal avalanches [23] also suggests that large-scale spatiotemporal brain dynamics may provide informative biomarkers for BCI training. These complementary approaches will be relevant for future analyses, while NS-ImCoh was selected here as a conservative, low-dimensional, and online-compatible first step.

Next, a second phase of the study will investigate whether combining BCI training with non-invasive brain stimula-

tion can produce synergistic effects on functional connectivity within sensorimotor networks.

CONCLUSION

These preliminary findings support the feasibility of intensive longitudinal network-based MI-BCI rehabilitation in chronic stroke patients with severe motor impairments. Connectivity features derived from imaginary coherence captured task-related sensorimotor network modulations and may represent promising biomarkers for improving BCI decoding and supporting adaptive rehabilitation strategies.

ACKNOWLEDGEMENTS

For this first preliminary work we would like to acknowledge the help of 1) Tristan Venot, Arthur Desbois, and Laurent Hugueville for the engineering support and 2) Marie Villain, Erin Soller, Sergio Talegon-de la Fuente, Celestine Allombert for the experiment assistance. This study was supported by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (Grant Agreement N° 864729) and by the Agence Nationale de la Recherche under the France 2030 program (Grant Agreement ANR-23-IACL-0008). The authors declare that they have no competing interests.

REFERENCES

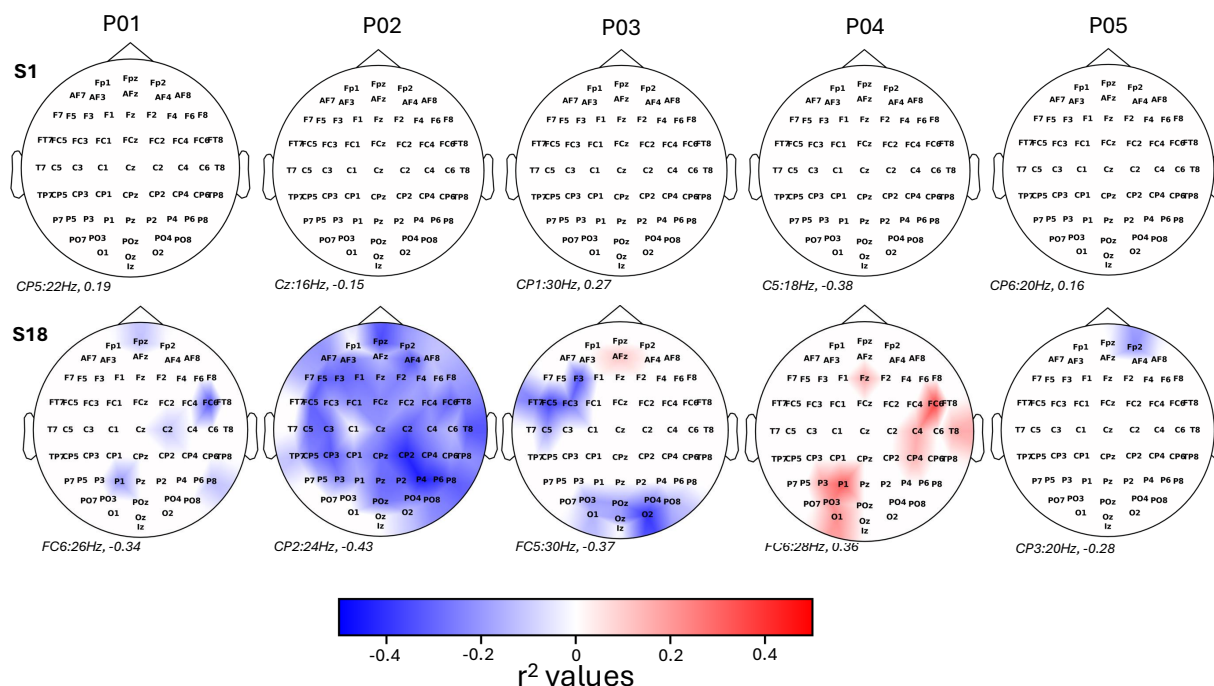


Figure 4: Evolution of the most discriminative brain network features (NS-ImCoh) as revealed by a cluster-based statistical analysis. Only significant clusters are displayed in the topographic maps. For Session 1 and Session 18, the electrode showing the strongest significant modulation was identified, and the corresponding frequency bin was selected. Topographic maps illustrate the spatial distribution of the signed r^2 values at the selected frequency. Warm colors indicate higher NS-ImCoh values during motor imagery relative to rest, whereas cool colors indicate lower NS-ImCoh values during motor imagery.

[1] Mane R, Chouhan T, Guan C. BCI for stroke rehabilitation: Motor and beyond. *Journal of Neural Engineering*. 2020;17(4):041001.

[2] Coscia M et al. Neurotechnology-aided interventions for upper limb motor rehabilitation in severe chronic stroke. *Brain*. 2019;142(8):2182–2197.

[3] Pichiorri F et al. Brain–computer interface boosts motor imagery practice during stroke recovery. *Annals of Neurology*. 2015;77(5):851–865.

[4] Kancheva I, Van Der Salm SMA, Ramsey NF, Vansteensel MJ. Association between lesion location and sensorimotor rhythms in stroke – a systematic review with narrative synthesis. *Neurological Sciences*. 2023;44(12):4263–4289.

[5] De Vico Fallani F, Richiardi J, Chavez M, Achard S. Graph analysis of functional brain networks: Practical issues in translational neuroscience. *Philosophical Transactions of the Royal Society B: Biological Sciences*. 2014;369(1653):20130521.

[6] Grefkes C, Fink GR. Reorganization of cerebral networks after stroke: New insights from neuroimaging with connectivity approaches. *Brain*. 2011;134(5):1264–1276.

[7] Gonzalez-Astudillo J, Cattai T, Bassignana G, Corsi MC, De Vico Fallani F. Network-based brain–computer interfaces: Principles and applications. *Journal of Neural Engineering*. 2021;18(1):011001.

[8] Nolte G, Bai O, Wheaton L, Mari Z, Vorbach S, Hallett M. Identifying true brain interaction from EEG data

using the imaginary part of coherency. *Clinical Neurophysiology*. 2004;115(10):2292–2307.

[9] De Vico Fallani F et al. Multiscale topological properties of functional brain networks during motor imagery after stroke. *NeuroImage*. 2013;83:438–449.

[10] Cattai T, Colonnese S, Corsi MC, Bassett DS, Scarano G, De Vico Fallani F. Phase/Amplitude Synchronization of Brain Signals During Motor Imagery BCI Tasks. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2021;29:1168–1177.

[11] Corsi MC, Chevallier S, Fallani FDV, Yger F. Functional Connectivity Ensemble Method to Enhance BCI Performance (FUCONE). *IEEE Transactions on Biomedical Engineering*. 2022;69(9):2826–2838.

[12] Santamaría-Vázquez M, Ortiz-Huerta JH, Martín-Odriozola A, Saiz-Vazquez O. Improvement of Motor Imagination and Manual Ability Through Virtual Reality and Selective and Nonselective Functional Electrical Stimulation: Protocol for a Randomized Controlled Trial. *JMIR Research Protocols*. 2024;13:e63329.

[13] Rimbart S, Trocellier D, Lotte F. 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: Sydney, Australia, Jul. 2023, 1–4.

[14] Renard Y et al. OpenViBE: An Open-Source Software Platform to Design, Test, and Use Brain–Computer

Interfaces in Real and Virtual Environments. *Presence: Teleoperators and Virtual Environments*. 2010;19(1):35–53.

[15] Lang CE et al. Dose response of task-specific upper limb training in people at least 6 months poststroke: A phase II, single-blind, randomized, controlled trial. *Annals of Neurology*. 2016;80(3):342–354.

[16] Desbois A, Venot T, De Vico Fallani F, Corsi MC. HappyFeat—An interactive and efficient BCI framework for clinical applications. *Software Impacts*. 2024;19:100610.

[17] Blankertz B, Dornhege G, Krauledat M, Müller KR, Curio G. The non-invasive Berlin Brain–Computer Interface: Fast acquisition of effective performance in untrained subjects. *NeuroImage*. 2007;37(2):539–550.

[18] Maris E, Oostenveld R. Nonparametric statistical testing of EEG- and MEG-data. *Journal of Neuroscience Methods*. 2007;164(1):177–190.

[19] Müller-Putz GR, Scherer R, Brunner C, Leeb R, Pfurtscheller G. Better than random? A closer look on BCI results. *International Journal of Bioelectromagnetism*. 2008.

[20] Di Rienzo F, Collet C, Hoyek N, Guillot A. Impact of Neurologic Deficits on Motor Imagery: A Systematic Review of Clinical Evaluations. *Neuropsychology Review*. 2014;24(2):116–147.

[21] Guillot A, Di Rienzo F, Collet C. The Neurofunctional Architecture of Motor Imagery. In: *Advanced Brain Neuroimaging Topics in Health and Disease - Methods and Applications*. InTech, May 2014.

[22] Biasucci A et al. Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke. *Nature Communications*. 2018;9(1):2421.

[23] Mannino C, Sorrentino P, Chavez M, Corsi MC. Neuronal avalanches as a predictive biomarker for guiding tailored BCI training programs. *Imaging Neuroscience*. 2026.