

Movement-Related Interhemispheric Connectivity Dynamics and their Link to Asynchronous EEG-BCI Performance

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ABSTRACT: Directed interactions between bilateral sensorimotor cortices are important for voluntary movement, yet their relevance for asynchronous brain-computer interface (BCI) control remains unclear. Using EEG, we quantified time-frequency directional connectivity between sensorimotor regions during cue-based and self-paced hand movements in 25 participants using time-varying multivariate autoregressive models. Connectivity from the contralateral to the ipsilateral cortex was consistently stronger and positively associated with movement detection performance. Connectivity increased in low-frequency bands around movement onset and in the beta band after movement execution. These findings suggest that interhemispheric EEG connectivity reflects motor network coordination and may serve as a neurophysiological marker of successful asynchronous BCI control.

INTRODUCTION

Restoring reliable communication for individuals with severe motor impairments is a key goal of brain-computer interface (BCI) research. Movement-related BCIs provide an intuitive approach by relying on endogenous cortical activity linked to voluntary motor preparation and execution. By translating motor intent into control commands, these systems enable self-paced, asynchronous operation without external stimulation, preserving user autonomy and interface flexibility.

Two complementary neurophysiological signatures underpin motor-based BCIs. Movement-related cortical potentials (MRCPs) are slow negative shifts appearing up to ~2 s before movement onset, reflecting premotor and supplementary motor area activation [1]. Event-related desynchronization/synchronization (ERD/ERS) [2] represents alpha and beta power modulations over sensorimotor cortex during movement preparation and execution. While MRCPs provide robust time-domain markers of impending movement, ERD/ERS reflects oscillatory dynamics of sensorimotor networks. Both have been widely used for movement-intent detection and asynchronous BCI control [3–12].

We recently developed a fully asynchronous MRCP-based EEG speller that enabled reliable online communication in healthy participants, detecting self-initiated hand movements without external cues [3,4]. Performance in a self-paced validation run strongly predicted online spelling performance ($r \approx 0.81$), and high-performing participants showed stronger MRCP

negativity and greater contralateral sensorimotor contributions. These results suggest that individual neurophysiological characteristics influence BCI controllability and motivate investigation of the neural determinants of successful control. Voluntary movement involves coordinated interactions between bilateral sensorimotor cortices, yet most BCI studies focus on local signal features such as MRCP amplitude or ERD magnitude. Although connectivity measures have been used as classifier features [13], particularly in motor imagery paradigms, they are rarely examined as neurophysiological variables explaining differences in asynchronous BCI control. For sensorimotor rhythm couplings, various connectivity measures have been proposed, including phase-based metrics (e.g., phase-locking value) [13,14], coherence-based approaches [13], and other synchronization indices. Among these, multivariate autoregressive (MVAR) modelling [15–19] is widely used to study directed interactions in EEG [20]. Frequency-domain measures such as directed coherence estimate directional information flow [21–24] and can reveal asymmetries between contralateral and ipsilateral motor areas. However, it remains unclear whether interhemispheric directional interactions during movement are consistent across individuals, whether they exhibit systematic time-varying patterns before, during, and after movement, or whether they relate to successful asynchronous BCI control.

This study addresses this gap by quantifying time-frequency directed connectivity between left and right sensorimotor regions using MVAR-based directed coherence (DC). We examine whether interhemispheric directionality is consistent across cue-based and self-paced conditions and whether it relates to local motor signatures (MRCP magnitude, ERD/ERS strength) and the BCI's ability to detect movements. Our goal is to determine whether connectivity provides a stable neurophysiological marker of successful motor-based asynchronous control.

MATERIALS AND METHODS

Experimental Paradigm: In our previous study [3,4] we evaluated a fully asynchronous MRCP-based EEG BCI for online spelling in 25 healthy participants (8 female, mean age 28.1 ± 7.5 years). Participants completed an eye-artifact recording block followed by calibration and online spelling sessions. Calibration included a cue-based movement round with visually

prompted right hand movements (i.e., fist with wrist extension, average inter-trial interval 3.3 s) and a self-paced round in which the same movements were executed without external cues (average inter-trial interval 4.13 s). The cue-based round contained 300 movements, whereas the number of self-paced movements varied across participants, ranging from 50 to 187. A detection model trained during calibration identified MRCPs associated with self-initiated movements during the online spelling task, where detected movements triggered character selections. EEG was recorded at 500 Hz from 60 electrodes (10–10 system) using a BrainAmp amplifier (BrainProducts, GmbH), with four electrooculography (EOG) channels for artifact correction and a motion capture system to determine movement onsets.

EEG Preprocessing: For the present analysis, only the calibration data were used. EEG signals were cleaned of 50 Hz line noise and band-pass filtered (0.5–60 Hz, 4th-order Butterworth), and ocular artifacts were removed using an EOG regression-based approach based on a dedicated eye block. The EEG was resampled to 100 Hz, and movement onset events from motion capture were downsampled accordingly to preserve temporal alignment. In addition, a binary movement trace indicating the presence or absence of movement at each time point was derived from the motion capture data.

Connectivity Analysis: To characterize cortical interactions around movement onset, connectivity was estimated using a time-varying multivariate autoregressive (MVAR) framework with overlapping windows. EEG epochs (channels $\times$ time $\times$ trials) were segmented around movement onset, and for each window a single MVAR model was fitted across all trials using the ARFIT algorithm (window length: 1 s, step: 0.125 s) [25]. Model order was selected using the Akaike Information Criterion, and the median optimal order across windows and participants was used for the final analysis to ensure consistent model complexity (7th order). The estimated MVAR model was transformed into the frequency domain to compute spectral directed coherence using the eMVAR toolbox from Faes et al. [26]. DC values from each window were assigned to all samples within that window; overlapping estimates were averaged to obtain smooth time–frequency connectivity maps across the epoch. Because the self-paced round contained a variable number of movements, the minimum number of valid trials (50) was used. For each participant, 50 self-paced movements were selected, while the 300 cue-based movements were split into six sets of 50 trials, yielding six cue-based and one self-paced connectivity estimate per participant. The cue-based estimates were then averaged, ensuring equal trial numbers across conditions for fair comparison.

The resulting DC estimates form time–frequency maps for all channel pairs, representing directional interactions between EEG channels. In this study, we focused on interhemispheric connectivity between the left and right sensorimotor channel groups (C_L and C_R), analyzing directional interactions from $C_L \rightarrow C_R$ and

$C_R \rightarrow C_L$. For frequency-specific analysis, DC values were averaged within canonical bands (δ : 1–3.5 Hz, θ : 4–7 Hz, α : 8–12 Hz, β : 13–30 Hz, γ : 30–50 Hz) to obtain band-limited time series. These were used to examine interhemispheric connectivity dynamics and compare cue-based and self-paced conditions. Subject-level DC values at each time point were entered into a linear mixed-effects (LME) model [27]:

$$Y \sim \text{Condition} + (1 \mid \text{Subject}) \quad (1)$$

where Y denotes the DC value, *Condition* indicates the experimental condition (cue-based or self-paced) and the term $(1 \mid \text{Subject})$ represents the subject-specific random intercept capturing between-subject variability. The resulting p-values indicated whether DC differed significantly between conditions and were corrected for multiple comparisons across time, frequency bands and connectivity direction using the Benjamini–Hochberg false discovery rate (FDR) procedure [28].

ERD/ERS and MRCP Analysis: In addition to connectivity measures, ERD/ERS maps and MRCP waveforms were estimated for each participant. ERD/ERS maps were computed based on [2], using a baseline interval of –4 to 0 s relative to movement onset. This enabled characterization of time–frequency power modulations associated with movement preparation and execution. MRCP waveforms were obtained by averaging the time-domain EEG signals across trials to capture slow cortical potentials around movement onset.

Linking Directional Connectivity to Self-Paced Decoding Performance: As described previously [3,4], movement detection performance based on MRCP features was quantified using the Matthews Correlation Coefficient (MCC) [29], computed from self-paced movement predictions alongside metrics such as true positive rate and false positives per minute. Here, we focused on MCC as a balanced measure of detection accuracy and false positives. To test whether performance was associated with directional connectivity, linear mixed-effects (LME) models were fitted at each time–frequency bin of the DC maps, separately for each connectivity direction:

$$Y \sim \text{MCC} + (\text{Condition} \mid \text{Subject}) \quad (2)$$

where Y denotes the DC value, *MCC* represents the subject-level classifier performance metric. The term $(\text{Condition} \mid \text{Subject})$ specifies a random intercept for each subject together with a random slope for condition (cue-based vs self-paced), allowing connectivity differences between conditions to vary across participants and accounting for the repeated-measures structure of the data. *Condition* was modeled as a random effect to control for within-subject variability between cue-based and self-paced connectivity estimates while assessing the association between connectivity and decoding performance. Statistical significance of the MCC effect was evaluated across all bins and FDR corrected for multiple comparisons.

Temporal Coupling Between Interhemispheric Connectivity and Sensorimotor Activity: To examine temporal relationships between connectivity and

sensorimotor activity, correlations were computed between DC, ERD/ERS, and MRCP time courses. Band-specific DC trajectories were analyzed separately for cue-based and self-paced conditions and for each connectivity direction. ERD/ERS time series were obtained from left and right sensorimotor channel groups by averaging ERD/ERS maps within the alpha and beta bands, while MRCP time series were derived from the corresponding averaged sensorimotor waveforms. All trajectories were computed from group-average signals to capture dominant temporal dynamics around movement. Pearson correlations between DC, ERD/ERS, and MRCP trajectories produced matrices describing connectivity–activation coupling. P-values were corrected for multiple comparisons, and non-significant correlations were set to zero for visualization. Cue-based and self-paced correlations were compared using Fisher’s r-to-z transformation [30].

RESULTS

Sensorimotor Oscillatory Dynamics: Figure 1a,b shows the grand-average EEG dynamics during cue-based and self-paced movements, including ERD/ERS maps, MRCP time courses, and time–frequency directional connectivity (DC) between the left (C_L) and right (C_R) sensorimotor regions. The average binary movement trace from motion capture is overlaid in all panels, indicating the probability and timing of movement across trials. ERD/ERS maps (Fig. 1a) showed clear sensorimotor rhythm modulations around movement onset in both hemispheres, with alpha and low-beta power (~8–20 Hz) decreasing before and during movement and a post-movement beta ERS 1–2 s afterward. MRCP waveforms (Fig. 1b) displayed the typical slow negative potential preceding movement onset and returning to baseline within 1–2 s. In the self-paced condition, ERD/ERS and MRCP patterns were more diffuse and temporally variable.

Directional Connectivity Dynamics: The directional connectivity maps (Fig. 1c) revealed structured time–frequency interactions between the two sensorimotor regions. In both directions and conditions, connectivity increased in low frequencies (<10 Hz) and especially in the delta band around movement onset. After movement execution, connectivity increased in the beta band, temporally coinciding with the beta rebound observed in the ERD/ERS maps. Connectivity from the left (i.e., contralateral) to the right (i.e., ipsilateral) hemisphere ($C_L \rightarrow C_R$) was generally stronger than in the opposite direction (Fig. 1c,d). To quantify this effect, a single average DC value was extracted from the connectivity maps for each participant and direction. In both cue-based and self-paced movements, $C_L \rightarrow C_R$ connectivity was significantly stronger than $C_R \rightarrow C_L$ connectivity ($p < 0.001$). This directional asymmetry was consistent across participants, as illustrated by the violin plots of Fig. 1d showing individual subject values. In contrast, connectivity in the $C_R \rightarrow C_L$ direction was weaker and less structured, with more diffuse low-frequency

fluctuations. Band-specific time courses (Fig. 1e) further showed that the most pronounced differences between cue-based and self-paced conditions occurred in the delta band around movement onset, with a smaller but significant beta-band difference after movement, aligned with the beta rebound. Overall, connectivity profiles across frequency bands were similar between conditions. The main difference arose from movement timing, as the longer and more irregular inter-trial intervals in the self-paced condition produced broader transitions and greater variability in the averaged movement trace.

Relationship Between Connectivity and Decoding Performance: The bottom row of Fig. 1f shows the t-statistics from the LME models relating the DC time–frequency maps to detection performance (MCC) for both connectivity directions. Higher t-statistics indicate stronger positive associations between connectivity and MCC. Overall, higher connectivity in the $C_L \rightarrow C_R$ direction appeared to be associated with higher MCC values, suggesting that stronger interhemispheric coupling from the left to the right sensorimotor cortex may support improved detection performance. Green contours mark clusters where the corresponding p-values remained significant after FDR correction. Significant clusters were observed only in the $C_L \rightarrow C_R$ direction, in the beta band (~20–25 Hz) both before (~2 s) and after movement onset, indicating that stronger connectivity in this direction was associated with higher detection performance. In contrast, no significant relationship between connectivity and MCC was observed for the $C_R \rightarrow C_L$ direction, although the strongest non-significant associations occurred mainly in the 10–20 Hz range.

Temporal Coupling Between Connectivity and Sensorimotor Activity: To investigate the temporal relationships between interhemispheric connectivity and sensorimotor activity, we correlated the time evolution of MRCP signals and ERD/ERS activity in the alpha and beta bands with the band-specific DC time series. The ERD/ERS trajectories were extracted from the ERD/ERS maps by averaging within the alpha and beta bands, while MRCP time courses were obtained from the averaged sensorimotor waveforms of the left (C_L) and right (C_R) regions. These physiological time series were then temporally correlated with DC trajectories computed for the canonical frequency bands and for both connectivity directions ($C_L \rightarrow C_R$ and $C_R \rightarrow C_L$). Figure 2 summarizes the correlations between band-specific DC time series and physiological signals (ERD/ERS and MRCP) for cue-based and self-paced movements. Overall, DC trajectories correlated more strongly with ERD/ERS than with MRCP signals in both conditions, particularly for beta-band ERD/ERS. In the cue-based condition, clear frequency-specific patterns emerged: beta-band ERD/ERS in both hemispheres showed strong positive correlations with alpha and beta DC, while delta connectivity showed negative correlations with ERD/ERS. In contrast, the self-paced condition showed reduced alpha- and beta-band ERD/ERS–connectivity correlations in the $C_R \rightarrow C_L$ direction. For $C_L \rightarrow C_R$, coupling shifted toward correlations with both alpha- and

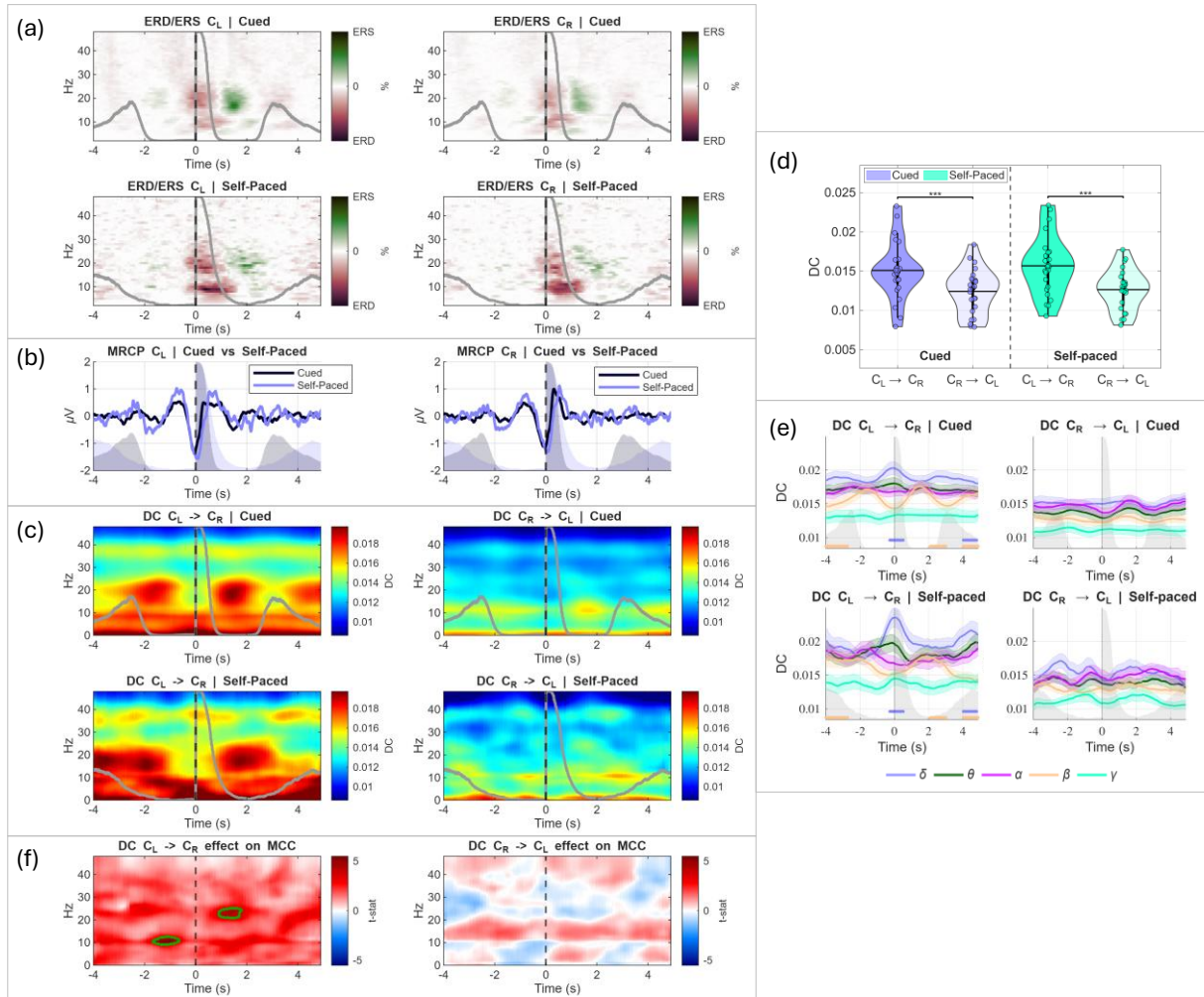


Figure 1. Grand-average (a) ERD/ERS maps and (b) MRCP patterns for the left (CL) and right (CR) sensorimotor regions during cue-based (top panel) and self-paced (bottom panel) movements. (c) Grand-average time–frequency DC maps for both directions (CL → CR left column and CR → CL right column) for cue-based (top row) and self-paced (bottom row) movements, estimated using a sliding-window MVAR framework. (d) Violin plots showing the distribution of average DC values across participants for both connectivity directions and conditions. (e) Band-specific (δ , θ , α , β , γ) DC time courses for the two connectivity directions during cue-based (top row) and self-paced (bottom row) movements. (f) Relationship between directional connectivity and decoding performance for both connectivity directions (left and right columns), expressed as t-statistics from LME models relating DC to the MCC obtained from the MRCP-based decoder in the self-paced round. Red indicates positive associations and blue negative associations between connectivity and decoding performance. Significant regions after FDR correction are outlined in green. The gray curve overlaid in panels (a, c) and the shaded areas in panels (c, e) represent the average binary movement trace derived from motion capture recordings, indicating the probability of movement across trials. Time 0 is the movement onset.

beta-band ERD/ERS, producing a more distributed connectivity–activation pattern across frequency bands.

DISCUSSION

Sensorimotor Oscillatory Dynamics During Movement Preparation: Consistent with previous studies, both cue-based and self-paced movements showed typical sensorimotor rhythm modulation, with alpha and low-beta desynchronization before movement and a post-movement beta rebound. MRCPs also exhibited the characteristic slow negative potential preceding movement onset. While patterns were similar across conditions, self-paced movements showed slightly greater variability, likely reflecting their more irregular timing and longer inter-trial intervals.

Interhemispheric Connectivity Dynamics: Directional connectivity revealed structured time–frequency interactions between the left and right sensorimotor cortices. In both directions, low-frequency connectivity, especially in the delta band, increased around movement onset, likely reflecting slow cortical potentials underlying MRCPs. In contrast, beta-band connectivity (particularly lower beta) increased after movement, coinciding with the beta rebound in ERD/ERS maps and consistent with stronger interhemispheric coupling during post-movement beta synchronization [31]. These results suggest that interhemispheric interactions follow the temporal structure of local oscillatory dynamics, linking connectivity changes to motor-related processes [2,32]. Prior studies comparing internally and externally paced finger movements reported strongest task-related

differences in interhemispheric coupling in the beta band (~20–22 Hz) [33], further supporting our results.

A key finding in our study was the directional asymmetry of interhemispheric connectivity, with connectivity from the left to the right sensorimotor cortex ($C_L \rightarrow C_R$) consistently stronger than in the opposite direction. Because participants performed right-hand movements, the left sensorimotor cortex represents the contralateral motor area responsible for movement generation. The stronger $C_L \rightarrow C_R$ connectivity likely reflects propagation of motor-related activity from the contralateral cortex to ipsilateral motor areas via interhemispheric pathways, consistent with ipsilateral involvement in unilateral movement through transcallosal interactions [34]. This directional asymmetry also argues against a purely power-driven explanation, where connectivity increases arise mainly from higher EEG signal power or signal-to-noise ratio rather than from genuine interactions between cortical regions. In that case, similar connectivity increases would be expected in both directions. Instead, the consistent dominance of $C_L \rightarrow C_R$ connectivity suggests structured interhemispheric communication. Band-specific analyses showed that the main condition differences occurred in the delta band around movement onset and, to a lesser extent, in the beta band after movement. Overall, connectivity profiles were similar between cue-based and self-paced movements, with differences mainly reflecting movement timing due to the longer and more variable inter-trial intervals in the self-paced condition.

Connectivity and Movement Detection Performance:

A key finding was the relationship between directional connectivity and BCI movement detection performance. Higher $C_L \rightarrow C_R$ connectivity was associated with improved MRCP-based detection accuracy (MCC). Significant clusters appeared in the beta band before and after movement onset, suggesting that directional connectivity reflects neural processes relevant for movement prediction. Beta-band activity is known to support sensorimotor network coordination and motor control, indicating that these interactions provide complementary information about movement-related neural activity. Notably, this effect was observed only for the $C_L \rightarrow C_R$ direction, highlighting the functional relevance of this asymmetric pathway.

Coupling Between Connectivity and Sensorimotor Activity:

To further examine how connectivity relates to local brain activity, we analyzed the temporal coupling between DC trajectories and physiological signals derived from ERD/ERS and MRCP measures. Across conditions, connectivity time courses correlated more strongly with ERD/ERS dynamics than with MRCP signals, particularly for beta-band ERD/ERS, suggesting that oscillatory power modulations are more closely linked to large-scale network interactions than slow cortical potentials. In the cue-based condition, beta-band ERD/ERS in both hemispheres showed positive correlations with alpha- and beta-band connectivity. In contrast, the self-paced condition showed reduced

ERD/ERS–connectivity correlations in the $C_R \rightarrow C_L$ direction and a shift toward broader coupling with alpha- and beta-band ERD/ERS in the $C_L \rightarrow C_R$ direction. These findings suggest that self-paced movements may rely on more flexible interhemispheric coordination than externally cued actions. In cue-based tasks, external timing cues impose a consistent temporal structure on motor preparation, which may promote tighter synchronization between hemispheres. In contrast, self-paced movements are internally generated and temporally more variable, likely engaging more distributed network interactions involving higher-order motor planning regions such as premotor and supplementary motor areas [33]. Such differences are consistent with previous findings showing that internally generated and externally triggered movements involve distinct patterns of cortical interaction [33].

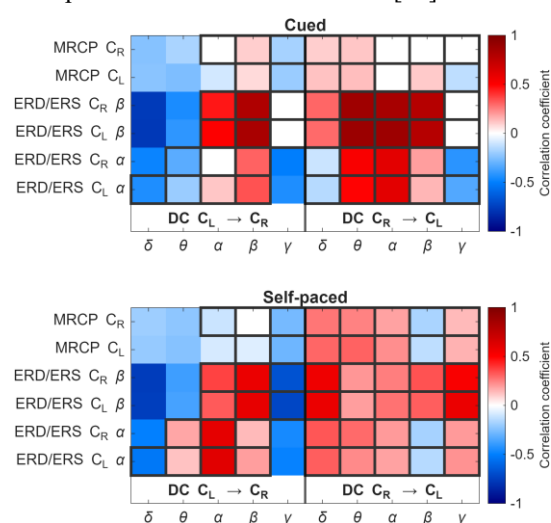


Figure 2. Correlation matrices between band-specific directional connectivity (DC) trajectories and physiological signals during cue-based (top) and self-paced (bottom) movements. DC was computed for canonical bands in both directions ($C_L \rightarrow C_R$, $C_R \rightarrow C_L$). Physiological signals include MRCP time courses from left (C_L) and right (C_R) sensorimotor regions and alpha/beta ERD/ERS trajectories. Each cell shows the Pearson correlation between a physiological signal and a DC trajectory. Red indicates positive and blue negative correlations. Non-significant correlations after multiple-comparison correction are set to zero. Black boxes mark correlations that differed significantly between conditions (Fisher r-to-z test, corrected).

Implications for BCI Systems: These findings highlight the role of interhemispheric connectivity in EEG-based BCI performance. Beta-band connectivity, particularly in the $C_L \rightarrow C_R$ direction, was associated with movement detection despite the classifier relying on MRCP features, suggesting that directional connectivity captures complementary information on motor network coordination. Incorporating connectivity features may improve BCI robustness and detection. Moreover, directional connectivity could serve as a network-level biomarker for predicting and monitoring user-specific BCI performance and explaining inter-individual variability, with relevance for clinical BCI applications where interhemispheric interactions are often altered by

neurological injury.

Limitations and Future Directions: Several limitations should be considered. First, connectivity was computed between aggregated sensorimotor channel groups, capturing large-scale interactions but potentially missing finer spatial patterns. Second, the smaller number of self-paced movements may have increased variability and reduced statistical power despite using equal trial sets. Finally, only unilateral hand movements were analyzed. Future work should integrate directional connectivity into BCI decoding pipelines and further investigate its relationship with MRCPs, ERD/ERS, and motor intention decoding.

CONCLUSION

These results provide a network-level perspective on movement-related brain dynamics and motivate further investigation of interregional interactions in motor control.

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