

From Thought to Movement: Developing a Multimodal EEG/EMG/IMU Framework for Cue-Evoked Sensorimotor Rhythm Decoding Towards a Closed-Loop BCI for Parkinson's Disease

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Abstract

Parkinson's disease is a progressive neurodegenerative disorder affecting over 10 million people. It is caused by the loss of dopaminergic neurons in the substantia nigra pars compacta, disrupting the chemical balance in the basal ganglia and motor system, resulting in tremor, bradykinesia and rigidity. Brain-computer interfaces combine machine learning with EEG signals from a subject to control an actuator. This paper presents a multimodal BCI framework integrating 32-channel dry EEG, custom 3-axis IMU sensors and EMG onset detection of post-cue evoked sensorimotor rhythms for one healthy subject. The study systematically evaluated linear classifier models (LDA, SVM, Riemannian LDA), incorporated filter sweeps and multi-parameter Pareto optimisation for spatial-spectral feature selection. Under one artefact-rejected cue-locked execution condition, a Support Vector Machine with a RBF-kernel achieved a peak cross-validated accuracy of 72.1% ($p = 0.0038$) with $\sigma = \pm 13.6\%$ in post-cue time windows driven by sensorimotor rhythms desynchronisation (μ -ERD). The results provide preliminary evidence that post-cue EEG features contain discriminative information about motor execution. Finally, the study compared professional (CGX Quick-32r) and low-cost (OpenBCI 8-channel) dry-electrode hardware setups.

Keywords: Brain-Computer Interface, Parkinson's disease, Machine learning, Electroencephalography (EEG), Neuroscience, Motor execution, Motor imagery, Multimodal, Sensorimotor Rhythms

1. INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder caused by the gradual loss of dopaminergic neurons in the substantia nigra pars compacta. This disrupts the chemical balance of the direct and indirect pathways in the basal ganglia, leading to motor impairments such as tremor, rigidity and bradykinesia. Volitional motor intentions generate desynchronised neuronal activity, which is measured via Electroencephalography (EEG) on the scalp. In cue-driven paradigms, motor preparation and execution are characterised by sensorimotor rhythms (SMR), specifically event-related desynchronisation (ERD) and event-related synchronisation (ERS) in the μ -band (8–13 Hz) over the sensorimotor cortex (C3/C4). Unlike self-initiated movements that give rise to slow Bereitschaftspotentials

(BP) prior to movement, cued paradigms evoke post-cue SMR modulations immediately following the visual instruction.

Brain-computer interfaces (BCIs) take these neural signals and utilise machine learning to translate motor intentions into actuation. While BCIs offer a promising path toward motor restoration for patients with PD, developing robust models remains challenging due to low signal-to-noise (SNR) ratios, inter-session variability and muscle artefacts.

This study was conducted on a single healthy participant. Consequently, the reported results demonstrate within-subject rather than generalisability across multiple subjects. In this work, a multimodal BCI framework was developed and systematically evaluated for post-cue SMR decoding during both Motor Execution (ME) and Motor Imagery (MI)

paradigms. Using a homebuilt laboratory setup, 32-channel CGX dry-electrode system and a low-cost 8-channel OpenBCI dry-electrode system with synchronised electromyography (EMG) and 3-axis Inertial Measurement Unit (IMU) sensors to pinpoint the movement-onset time were integrated. EEG was used for the post movement SMR decoding. The following models were evaluated: classical spatial-spectral linear classifiers (LDA, Riemannian LDA, CSP-SVM) incorporating parameter sweeps and Pareto optimisation for feature extraction.

2. LITERATURE REVIEW

Raw EEG signals are inherently noisy, requiring dedicated signal processing and spatial feature extraction to achieve high classification accuracy in machine learning pipelines. For instance, cue-based MI paradigms utilising an Adaptive Support Vector Machine (A-SVM) achieved an accuracy of 91% on movement intention features [1]. Similarly, integrating Common Spatial Patterns (CSP) with a Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) yielded 84–92% accuracy when decoding upper-limb motor intentions in healthy subjects [2].

The electrical activity during contraction of a muscle, EMG, is an idiosyncratic signal [3] that can mark movement onset in a muscle group[4]. A BCI system combining pre-movement EEG and EMG achieved 91.2% accuracy for single-channel BP detection using the Teager–Kaiser Energy Operator (TKEO) [3], while studies show that ML models perform best when using subject wise and gender-separated training [5]. A study showed BP single channel left hand MI can yield 91.2% accuracy with a onset detection latency of -384.9 ± 296.5 ms [6]. Dopamine production is reduced in patients with PD due to dysfunction of the substantia nigra pars compacta, resulting in a changed functional brain connectivity. Patients with severe FOG had reduced β desynchronisation and increased θ activity above the Cz electrode before movement[7]. High δ - and low α -activity correlated with worsen FOG, while high θ - and low β -activity related to a worsen UPDRS-III-score. The results suggest EEG-slowness to be a biomarker for

motoric deterioration in PD[8]. Worsening FOG and mild cognitive impairment (MCI) correlate with high δ - and low α -activity and decreased connectivity in both bands. PD patients had randomised network topology with lower segregation and increased integration. The decreased integration in the β band correlated with worse executive function and working memory in MCI-patients[9]. De Novo patients with PD had reduced connectivity in α - and β -bands, while connectivity increased in the γ -band, which could be due to compensatory effects during the early stages of PD[10]. EEG signals from patients with PD can be distinguished from those of healthy subjects by using classification models such as Random Forest and Extra Trees, achieving 97.5% accuracy[11]. K-Nearest-Neighbour (KNN) could detect resting tremor in EEG by using IMU data, yielding 81.3% accuracy[12]. Classification of correlations between EMG measurements from the wrist in patients with PD and EEG signals above the frontal and temporal lobes using an artificial neural network (ANN) yielded 98.8% accuracy. Multimodal data achieved the best results [13]. The capability of different ML-models (MLP, LSTM) to predict EMG signals and improve the efficient in functional electric stimulation (FES) in patients with PD were compared. ML-models could precisely stimulate and predict EMG patterns in PD patients, which can enable more targeted and adaptive FES-treatment [14].

These reported accuracies are not directly comparable because the studies differ substantially in participant number, task design, signal preprocessing, validation strategy and whether prediction was performed within or across sessions. Overall, various ML models and classification methods for BCIs have been investigated while the EEG signals and functional brain connectivity of patients with PD are changed compared to healthy subjects, but they are still measurable and contain the physiological EEG signals behind motor intentions. Therefore it is reasonable for a medical BCI to be developed for patients with PD.

3. METHODOLOGY

EEG, EMG and IMU data during and before different motor paradigms, were collected simultaneously. EEG were acquired following the international 10-20 system from the scalp of the subject.

The hardware consists of a CGX Quick-32r dry-electrode EEG headset (32 channels with a sampling frequency of 500 Hz), a custom EMG Dev 1.0.1 sensor and 3 MPU6050 IMUs logged data at 20 Hz via an ESP32 microcontroller with a DHT11 humidity/temperature sensor (to ensure that the sessions were recorded under approximately same humidity and temperature, because a significant temperature difference can contaminate the data) and a custom LabStreamingLayer (LSL) bridge. All streams are synchronised into a single xdf file via LabRecorder. An 8-channel OpenBCI helmet with dry electrodes was used to compare the CGX helmet with a cheaper alternative.

3.1. Materials and Hardware

EEG data were obtained using a CGX Quick-32r, with a sampling frequency of 500 Hz according to the international 10-20 system. Each EEG signal was recorded from the 29 EEG electrodes at: Fpz, Fp1, Fp2, AF7, AF8, Fz, F3, F4, F7, F8, FC5, FC6, Cz, C3, C4, T7, T8, CP5, CP6, Pz, P3, P4, P7, P8, PO7, PO8, Oz, O1 and O2. The right mastoid (A2) was used as a reference and was connected using an ear-clip electrode.



Figure 1. CGX Quick-32r EEG helmet placement on the head of the subject.

EMG data were obtained using an EMG Sensor v1.0.1 and 3 disposable Ag/AgCl electrode pads.

- **RED** The active signal electrode was placed (coloured red) on forearm flexor muscle belly

(medial side).

- **BLUE** The differential reference electrode was placed 2 cm distal to the RED electrode.
- **BLACK** The ground reference electrode was placed on the lateral epicondyle (elbow bone)

IMU data were obtained using three MPU6050 IMU boards and TCA9548A I²C Multiplexer (MUX). IMU1 was mounted on the biceps and connected to a breadboard wired to the MUX and further to the ESP32 microcontroller, where EMG and IMU data were collected before digitally forwarded via LSL online to an .xdf file. IMU2 was mounted on the wrist and IMU3 was mounted on the dorsal surface of the hand.

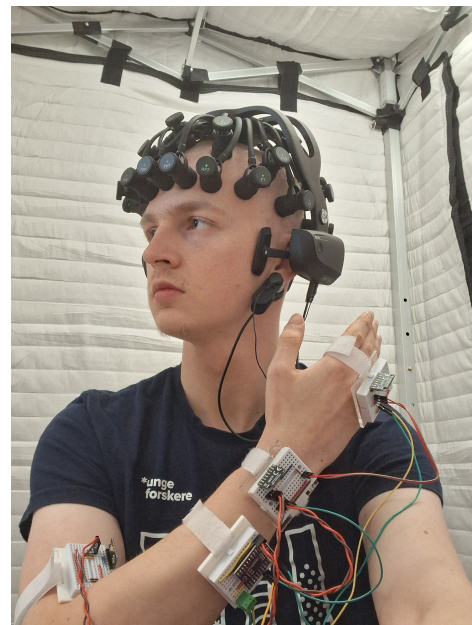


Figure 2. Three IMUs mounted on right arm to obtain precise gyroscope and accelerometer measurements to map the movement of the arm

3.2. Data Acquisitions

Data were recorded across ME and motor imagery MI conditions using ipsilateral and contralateral protocols:

- **Non-Cue Ipsilateral Motor Execution (NIME):** Un-cued, self-arm voluntary flexion and extension of the right wrist. Movement onset was determined post-hoc using synchronised EMG and IMU data and manual labelling.
- **Cue-Based Ipsilateral Motor Execution (IME) & Imagery (IMI):** Cued execution

or mental imagery of right arm flexion and extension

- **Cue-Based Contralateral Motor Execution (CME) & Imagery (CMI):** Cued execution or mental imagery involving alternating left- and right-hand closing.

For all cue-based paradigms (IME, IMI, CME, CMI), trials followed a structured timing protocol presented on a display positioned directly in front of the subject:

1. **Fixation (2.0 s):** A central fixation cross was displayed to prepare the participant and minimise ocular movement.
2. **Cue Presentation (2.5 s):** A directional visual cue (flexion, extension, left hand, or right hand) instructed the subject to execute or imagine the specific movement.
3. **Hold Phase (1.5 s):** The subject maintained the actuated or imagined motor state for the duration of the cue.
4. **Inter-Trial Interval (2.0 s + Jitter):** A baseline pause of 2.0 s was introduced between trials, supplemented with a random temporal jitter of up to 0.5 s to prevent anticipation.

To reduce electromagnetic interference (EMI), electrode cabling was systematically routed away from the acquisition hardware.

3.3. Sensorimotor Rhythm Signal Processing

Epochs were extracted relative to cue onset, either through EMG/IMU or the cue-pipeline. Because data were analysed in post-cue windows, feature extraction focused on SMR μ -ERD rather than pre-movement potentials such as the BP, which are absent in cue-triggered paradigms.

The raw EEG signal was processed to extract movement-related SMR (μ -ERD). Mains noise was suppressed using a 50-Hz IIR notch filter and the signal was high-pass (HP) filtered at 0.5 Hz. Automatic channel rejection excluded channels with standard deviations exceeding $5000 \mu\text{V}$ or falling below $0.5 \mu\text{V}$, after which Common Average Reference (CAR) was computed across

the remaining valid channels. FastICA was fitted on a 1-Hz HP filtered copy of the data and applied to the 0.5-Hz filtered signal to preserve slow potential shifts while removing ocular artefacts (detected via a frontal proxy channel, Fp1 or the next available channel among Fp2/Fpz/AF7/AF8, at a 2.5 SD threshold) and muscle-related artefacts.

Trial onset was determined differently depending on session type. For cue-based sessions, onset was taken directly from the LSL MI_Cue_Markers stream, using the marker timestamp at which the flexion/extension (or left/right) cue was presented. For sessions without cue markers (i.e. NIME), the subject was asked to perform altering flexion and extension movements, with the onset estimated from the EMG channel and IMU data: the raw signal was rectified, low-pass (LP) filtered at 5 Hz and z-scored relative to a 5-second baseline. The detection threshold was set at 35% of the inter-percentile range (10th-90th percentile, minimum 0.3) and a burst was accepted once the signal exceeded threshold for a minimum duration of 0.3 s.

Epochs were extracted uniformly from -1 s to $+3$ s relative to onset (baseline correction: -1 s to 0 s), with a default $500 \mu\text{V}$ peak-to-peak rejection threshold (raised to at least $500 \mu\text{V}$ for EMG onset sessions). Furthermore, an eye-inspection pipeline for manual labelling of onset was implemented to confirm the EMG/IMU findings of onsets.

Classification pipelines evaluated combinations of spatial filtering (CAR vs. Small Laplacian over C3/C4/Cz and their closest channel neighbours following the international 10-20 system), feature extraction (CSP, 2 or 4 components per band in the systematic comparison; 6 as the single-run default), frequency band(s) (μ : 8–13 Hz alone, or $\mu+\beta$: 8–13 Hz and 13–30 Hz combined) and classifiers (LDA with automatic shrinkage, SVM-RBF). To systematically capture the post-cue analysis window without temporal leakage, a nested cross-validation scheme (`run_nested_cv_time_windows`) was additionally implemented (5 outer folds, 3 inner folds by default). For each outer training fold, the inner loop evaluated five candidate post-cue

windows: $[0.0, 1.0]$ s, $[0.25, 1.25]$ s, $[0.5, 1.5]$ s, $[0.5, 2.0]$ s and $[1.0, 2.0]$ s using training data alone and the window with the highest mean inner-fold accuracy was selected for that outer fold. All spatial filtering, bandpass filtering and CSP projections were re-fitted strictly within each training fold (inner and outer) to prevent data leakage; SVM hyper-parameter optimisation (C, γ via `GridSearchCV`) was performed on the final outer-fold training set, while the inner window-selection loop used fixed default hyper-parameters.

Statistical significance of classification performance was assessed using an exact one-sided binomial test against chance level (50%). For a given configuration, the total number of correctly classified trials pooled across all outer test folds was compared to the number expected under the null hypothesis of chance-level performance, yielding a p -value $p = P(X \geq k \mid n, 0.5)$, where k is the number of correct predictions and n the total number of test trials; results were considered significant at $p < 0.05$.

3.4. Filter-sweeping for optimal LP-filter

In addition to the dedicated μ -band analysis, a systematic LP parameter sweep was performed to investigate the effect of spectral preprocessing on motor-related EEG features and classification. Fourteen LP cut-off frequencies were evaluated `filter_sweep_bp_optimized.py`: $LP \in [0.5, 1, 2, 3, 4, 5, 6, 7, 8, 10, 13, 20, 30, 40]$ Hz. LDA, Riemann LDA and ML models were trained on the μ -oscillations (8–13 Hz) post-cue. The dedicated SMR analysis was subsequently restricted to the μ -band (8 – 13Hz), where ERD/ERS and C3-C4 lateralisation were evaluated.

For each filter setting, four metrics were evaluated:

1. Peak C3-C4 lateralisation (the difference in μ -activity between C3 and C4, to measure which side is most active during movement)
2. Statistical significance of the C3-C4 lateralisation, quantified by the corresponding p -value, where lower p -values

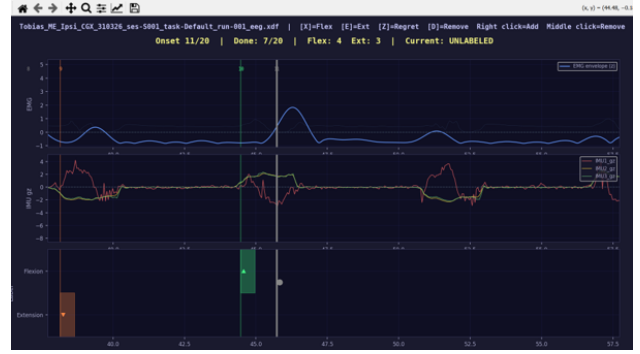


Figure 3. Manual eye-inspection labelling of onset in IMU and EMG data

indicate stronger statistical evidence for a lateralised response.

3. Central motor activity via bilateral Cz mean waveform amplitude.
4. μ -band (8–13 Hz) log power spectral density via Welch PSD.

This sweep allowed for the objective identification of the spectral transition between slow warning potentials (CNV, < 6 Hz) and oscillatory motor desynchronisation (μ -ERD, 8–13 Hz), while searching for the frequency range in EEG with most motor related information.

3.5. μ -Oscillation Feature Extraction and Pareto Optimisation

Post-onset ME and MI features were characterised in the μ -band using Morlet wavelet time-frequency representations (7 cycles, `mne.time_frequency.tfr_morlet`). To identify the optimal preprocessing configurations, a 54-combination grid search (`parameter_sweep_windows_final.py`) evaluated permutations across:

- **Baseline windows:** $[-2.5, -2.0]$ s, $[-1.5, -1.0]$ s, $[-0.5, 0.0]$ s
- **Frequency bands:** Full μ (8–13 Hz), Upper μ (10–13 Hz) and β (13–24 Hz).
- **Movement windows:** $[0.5, 1.0]$ s (classic), $[0.5, 1.5]$ s (extended), $[1.0, 2.0]$ s (late).
- **Spatial filtering:** Surface Laplacian vs. CAR.

Each configuration was evaluated using two

complementary objectives: C3-C4 lateralisation significance and CSP-based class separability. The statistical component was represented by the p -value associated with the C3-C4 lateralisation measure, where lower values indicate stronger statistical evidence for lateralisation. The second objective was the CSP eigenvalue, where higher values indicate greater spatial separability between the evaluated conditions.

The 54 preprocessing configurations therefore produced corresponding lateralisation p -values and CSP eigenvalues, which were evaluated jointly using a multi-objective Pareto analysis. A configuration was considered Pareto-optimal when no other configuration yielded both a lower lateralisation p -value and an equal or higher CSP eigenvalue.

Because the parameter sweep evaluates multiple preprocessing configurations, the lateralisation p -values were used as a comparative optimisation metric rather than interpreted individually as independent confirmatory hypothesis tests. In particular, selecting the configuration with the lowest p -value from the parameter sweep does not by itself give corrected statistical evidence for the presence of a lateralised motor response.

The resulting Pareto front therefore represents the trade-off between statistical evidence for C3-C4 lateralisation and spatial class separability, allowing configurations to be compared without reducing criterion to either the lowest p -value or the highest CSP eigenvalue alone.

3.6. Machine Learning Models

The literature review suggested the following models to evaluate: Transformer, LSTM-RNN, CNN, EEGNet and SVM. These models were trained using substantially more data from more patients compared to this work. Therefore, the following simpler linear classifier models were evaluated: Linear Discriminant Analysis (LDA), Riemannian LDA and CSP-LDA.

CSP + LDA: Spatial filters were extracted by maximising the variance difference between the two classes, followed by LDA classification.

CSP + SVM: Spatial filters were estimated using CSP to maximise variance differences between

the two movement classes, followed by SVM classification.

Riemannian LDA: Covariance matrices were mapped to the tangent space of the Riemannian manifold and subsequently classified using LDA.

4. RESULTS

4.1. Machine Learning Pipeline & Classification Performance

Across different paradigms (NIME, IME, IMI) and predefined filter settings, classification pipelines were evaluated on both single-session datasets and pooled multi-session datasets.

Table 1. Experimental results and dataset specifications across models and paradigms.

Paradigm	Model	Epochs (n)	Epoch Window	Accuracy	p -value
IME	SVM	37	[0.25s, 1.25s]	$72.1\% \pm 13.6\%$	$p = 0.0038$
IMI	SVM	73	[1.00s, 2.00s]	$54.9\% \pm 19.4\%$	$p = 0.2414$
CME	SVM	132	[0.50s, 2.00s]	$62.2\% \pm 5.0\%$	$p = 0.0034$
CMI	SVM	32	[0.00s, 1.00s]	$50.5\% \pm 19.5\%$	$p = 0.5700$
NIME	SVM	430	[0.00s, 1.50s]	$48.1\% \pm 4.1\%$	$p = 0.7938$
IME	LDA	37	[0.25s, 1.25s]	$61.4\% \pm 17.2\%$	$p = 0.0939$
IMI	LDA	116	[0.50s, 2.00s]	$52.6\% \pm 6.8\%$	$p = 0.3213$
CME	LDA	132	[0.50s, 2.00s]	$61.5\% \pm 5.4\%$	$p = 0.0057$
CMI	LDA	32	[0.00s, 1.00s]	$62.9\% \pm 11.5\%$	$p = 0.1077$
NIME	LDA	430	[0.25s, 1.25s]	$47.0\% \pm 2.3\%$	$p = 0.9036$

The best result achieved across the different experiment conditions was achieved by the IME-SVM paradigm which reached $72.1\% \pm 13.6\%$ accuracy ($p = 0.0038$) using a RBF-kernel on strictly cleaned post-cue epochs (37 clean epochs, $500 \mu V$ threshold). NIME-LDA performed the worst with $47.0\% \pm 2.3\%$ and $p = 0.9036$, while having the highest amount of epochs $n = 430$, signalling the data quality might be poor or the EMG/IMU movement-onset pipeline might've had some errors.

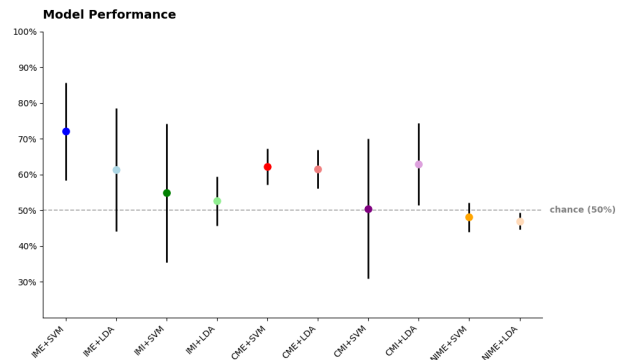


Figure 4. Cross-validated classification accuracy across the evaluated EEG decoding pipelines. Points indicate mean accuracy and error bars indicate ± 1 standard deviation. The dashed horizontal line denotes chance-level performance (50%)

4.2. Feature Optimisation

Optimal LP cut-offs, maximum C–C4 lateralisation and associated statistical significance metrics across tested paradigms, including multi-objective Pareto selection criteria, are detailed in Table 2.

The spatial distribution of μ -band modulation differed across the motor paradigms (Figure 5). CME and IMI showed relatively bilateral patterns, whereas IME showed a more spatially localised lateralisation as qualitatively interpreted from the topography

Evaluation of C3-C4 lateralisation of different movement paradigms (CME, CMI, IME, IMI, NIME) and hardware setups (CGX 32-ch vs. OpenBCI 8-ch) at optimal LP-filter cut-offs was performed.

Table 2. Optimal LP filter cut-offs, peak lateralisation amplitudes and statistical significance across motor paradigms. ‘C’ and ‘OB’ denote CGX and OpenBCI systems, respectively.

Paradigm	LP (Best Later.) (Hz)	Max Later. (μ V)	LP (Best p) (Hz)	p -value
CMI (C)	8.0	39.18	8.0	0.0960
CME (C)	30.0	7.91	20.0	0.230
IMI (C)	40.0	28.33	6.0	0.170
IME (C)	40.0	16.98	5.0	0.097
NIME (C)	13.0	11.94	0.5	0.114
CMI (OB)	40.0	8.99	0.5	0.287
CME (OB)	40.0	13.34	2.0	0.581
IMI (OB)	20.0	19.99	7.0	0.429
IME (OB)	40.0	8.23	30.0	0.302

Comparative analysis between λ -values of CSP and Δ dB can be seen in Table 3.

Table 3. Pareto-optimised μ -band (10–13 Hz) feature extraction metrics, CSP separability and C3-C4 log-power contrast.

Paradigm	Pareto Goal	CSP λ_1 (Max Ratio)	C3–C4 Later. (Δ dB)	p -value (Lat.)	Sig. Channels ($p < 0.05$)
CMI (C)	Pareto #1 (Min p)	2.14	+1.94 dB	0.1765	27 / 29
	Pareto #2 (Max λ)	2.56	+0.74 dB	0.5695	28 / 29
CME (C)	Pareto #1 (Min p)	1.65	+1.30 dB	0.1806	28 / 29
	Pareto #2 (Max λ)	1.65	+1.30 dB	0.1806	28 / 29
IMI (C)	Pareto #1 (Min p)	1.22	–2.07 dB	0.0237	24 / 29
	Pareto #2 (Max λ)	1.61	–1.13 dB	0.2635	29 / 29
IME (C)	Pareto #1 (Min p)	3.62	–1.72 dB	0.0415	26 / 29
	Pareto #2 (Max λ)	3.69	–0.00 dB	0.9977	26 / 29

5. DISCUSSION & FUTURE WORK

5.1. Machine Learning

The results provide preliminary evidence that post-cue SMR of EEG signals contain discriminative information about the upcoming

movement in the investigated subject and experimental condition using simple linear spatial-spectral models, as evidenced by the IME-SVM where a peak cross-validated accuracy of 72.1% ($p = 0.0038$) with $\sigma = \pm 13.6\%$ was obtained in a small, artefact-cleaned, cue-locked execution dataset using post-cue time windows. However, overall cross-session and multi-paradigm classification accuracy remained close to chance level.

A primary limitation of the current study stems from high inter-session variability and dry-electrode impedance degradation. Dry electrodes, while advantageous for rapid setup, exhibit higher contact impedance and sensitivity to motion artefacts compared to wet systems. Furthermore, the performance drop observed in NIME highlights the challenge of temporal label jitter introduced by automated EMG/IMU onset detection and presumably bad data quality.

5.2. The Effect of Motor Paradigms

The analysis across motor paradigms reveals the neurophysiological and signal processing differences between ME and IME as well as non-cue-based experiments.

IME vs IMI: The multi-objective Pareto sweeps show that IME yielded substantially higher spatial separability compared to IMI. Under Pareto #2 (Max λ), IME achieved a peak CSP eigenvalue ratio of $\lambda_1 = 3.69$, while IMI peaked at $\lambda_1 = 1.61$. This showcases the stronger synchronous cortical neural activity for actual movement compared with MI only. However, IMI demonstrated nominally significant cortical modulation under Pareto #1 (Min p), achieving a statistically nominally significant lateralisation contrast of -2.07 dB ($p = 0.0237$), validating that IMI produces detectable hemispheric power desynchronisation.

CMI vs IMI: CMI produced high raw lateralisation amplitudes in LP filtering (39.18μ V at 8.0 Hz), yet failed to reach statistical significance ($p = 0.0960$). In contrast, IMI exhibited tighter spectral distribution across significant channels (24/29 channels with $p < 0.05$), indicating that targeted single-limb imagery provides a more spatially stable feature set for BCI decoding than alternating bilateral

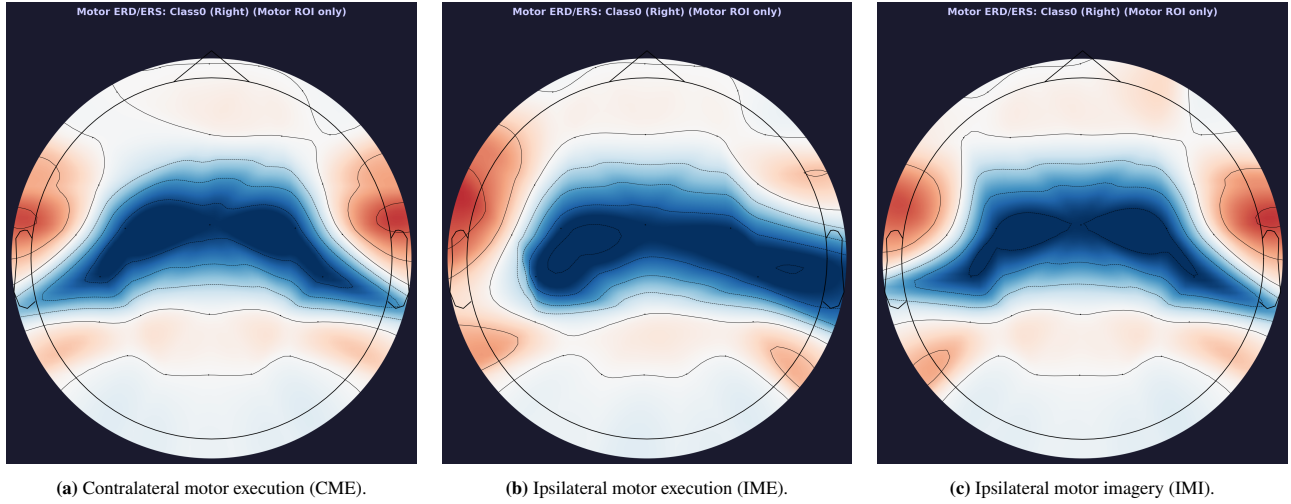


Figure 5. Topographic distribution of motor-related μ -band ERD/ERS across CME, IME and IMI. Maps show the change in μ -band power relative to baseline over the motor-region of interest. The same colour scale and spatial interpolation were used across all conditions to enable direct comparison.

tasks.

IME vs NIME: The performance difference between IME-SVM (72.1% accuracy, $p = 0.0038$) and NIME-SVM (48.1% accuracy, pooled) highlights the importance of temporal alignment. While NIME represents a ground-truth spontaneous movement paradigm, relying on automated EMG/IMU onset detection actually introduces millisecond-level timing jitter. This jitter smears the slow-wave negative shift of the BP filter sweeps. Cue-locked IME bypasses this jitter, preserving phase-locked post-cue dynamics required for LDA classification.

Overall, the results show that cue-based ME produces higher lateralisation and CSP eigenvalues, alongside better statistical significance compared to MI and non-cue based motor activity.

5.3. Perspective

Future work will focus on improving signal quality, expanding the dataset and transitioning toward self-initiated paradigms to enhance decoding accuracy and system stability. To mitigate single-subject constraints, public cross-subject datasets [15], [16], [17], [18], [19], [20] will be combined with additional single-subject recordings to evaluate transfer-learning approaches. SNR will be improved by adopting low-impedance wet EEG caps, reducing EMI, and refining physical helmet

fit to minimise muscle and tension artefacts. Advanced artefact rejection algorithms and non-parametric permutation tests will further refine preprocessing and statistical validation. Crucially, transitioning from cue-evoked SMR to self-initiated paradigms (targeting the BP) will require higher temporal precision and improved EMG/IMU onset detection to eliminate label jitter. Long-term goals include collaborating with PD laboratories and volunteers to evaluate system performance on pathological neurophysiology, advancing toward an assistive BCI framework for individuals with PD.

6. CONCLUSION

In this study, a multimodal BCI framework integrating 32-channel dry EEG, custom 3-axis IMUs and EMG onset detection was evaluated across motor execution and imagery paradigms in a healthy subject to decode post-cue sensorimotor rhythms for Parkinson’s disease applications.

The classification results showed that cue-locked ipsilateral motor execution achieved the peak performance using an RBF-kernel SVM (**IME-SVM**), reaching $72.1\% \pm 13.6\%$ accuracy ($p = 0.0038$) in the $[0.25\text{ s}, 1.25\text{ s}]$ window. Contralateral motor execution (**CME**) also yielded significant decoding ($62.2\% \pm 5.0\%$, $p = 0.0034$), whereas motor imagery paradigms (**IMI**, **CMI**) performed near chance level (50.5% – 54.9%). Crucially, uncued voluntary ipsilateral execution (**NIME**) failed to decode

above chance (48.1%, $p = 0.7938$) despite a large dataset ($n = 430$), demonstrating that post-hoc threshold-based EMG/IMU onset detection introduces temporal label jitter that disrupts post-cue SMR (μ -ERD).

Systematic LP filter sweeps and Pareto optimisation successfully isolated optimal spectral boundaries, while hardware comparisons highlighted suggest that higher-density EEG may be advantageous over lower-density alternatives for localised C3-C4 lateralisation.

Overall, these findings provide proof-of-concept evidence that cue-evoked SMR can be decoded when rigorous temporal synchronisation is maintained. Reducing label jitter in self-initiated movements remains essential to translating this work into an adaptive, closed-loop BCI for motor restoration in patients with Parkinson's disease.

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8. AUTHOR CONTRIBUTION:

T.B.N. designed the study, performed the experiments, built the laboratory, implemented the algorithms, wrote this paper and solely conducted the research.

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