

Beyond Hemispheric Laterality: Riemannian Metrics as Markers of Motor Imagery Performance in BCI Training

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ABSTRACT: A major challenge in motor imagery based brain-computer interfaces (MI-BCIs) is BCI illiteracy, where many users fail to achieve reliable control despite training. Most MI-BCI decoding approaches rely heavily on hemispheric laterality of sensorimotor rhythms, overlooking a key aspect of BCI learning - the user's ability to generate distinct and stable neural representations during MI. Here, we aimed to identify a quantifiable neural marker of MI by examining whether neural dynamics captured by Riemannian geometry-based EEG metrics relate to users' self-reported MI performance across runs. Participants were categorized as Improved, Worsened, or Unchanged based on perceived BCI accuracy across multiple runs, and three covariance-based metrics - class stability, class distinctiveness, and rest distinctiveness were estimated. Our results show that these metrics are modulated differently across participant groups, suggesting that MI decoding reflects multidimensional neural dynamics beyond hemispheric laterality and that Riemannian metrics may help assess an individual's ability to generate effective MI signals for BCI control.

INTRODUCTION

Brain-computer interfaces (BCIs) enable direct communication between the brain and external devices by translating neural activity into control signals. These systems have shown promise for restoring motor function in individuals affected by neurological disorders such as stroke, spinal cord injury, and neurodegenerative diseases [1, 2]. Among BCI paradigms, motor imagery-based BCIs (MI-BCIs) are widely studied because they are noninvasive and can promote neuroplasticity through effective engagement of motor networks [3]. During motor imagery, users imagine movements without physical execution, producing characteristic modulations in sensorimotor rhythms (SMRs), particularly event-related desynchronization (ERD) in the mu (8–13 Hz) and beta (13–30 Hz) bands [4]. These neural patterns can be decoded to control external devices or provide neurofeedback. Despite advances in signal processing and machine learning tools, MI-BCI performance remains highly variable across individuals. Approximately 10–30% of users fail to achieve reliable control, a phenomenon often referred to as BCI

inefficiency or BCI illiteracy [5]. While many studies have focused on improving decoding algorithms, evidence suggests that variability in user performance often exceeds differences between classifiers [6]. Consequently, MI-BCI control is increasingly viewed as a learnable cognitive motor skill, requiring users to discover and consistently reproduce neural patterns that are both stable and discriminable. This learning process depends on both neurophysiological factors and cognitive aspects such as attention, strategy, and perceived agency [6].

Traditional approaches to evaluating MI-BCI performance rely primarily on classifier accuracy as the measure of neural control. Within this framework, successful BCI operation is interpreted as the classifier's ability to distinguish between neural patterns generated during left and right-hand motor imagery. Improvements in decoding accuracy are therefore typically attributed to stronger hemispheric lateralization, where contralateral sensorimotor regions exhibit greater modulation than ipsilateral regions during imagined movement [7]. Studies combining EEG and fMRI have shown that individuals capable of controlling MI-BCIs often exhibit clear contralateral activation patterns in sensorimotor areas, whereas users lacking such lateralization frequently struggle to achieve reliable control [8].

Classifier accuracy provides only an indirect measure of neural organization and primarily reflects the separability between task-related neural representations. In practical BCI operation, effective control not only requires neural representations of different tasks to be separable, but also these representations to diverge sufficiently from baseline neural activity. If task-related signals remain close to resting-state dynamics, decoding may remain unstable even when class representations are distinguishable. Consequently, understanding how neural representations evolve during training requires metrics that capture multiple dimensions of neural structure rather than relying solely on classifier accuracy.

To address this limitation, Lotte and Jeunet proposed classifier-independent neural performance metrics based on Riemannian geometry [9]. These metrics operate directly on the covariance structure of multichannel EEG signals and quantify key properties of neural representations, including class distinctiveness (separation between

imagery classes), class stability (consistency of neural patterns within a class), and rest distinctiveness (separation between task-related activity and the resting baseline). Because these measures are independent of a specific classifier, they provide a physiologically interpretable description of neural adaptation during MI-BCI training.

In the present study, we use Riemannian geometry-based metrics to investigate how neural representations evolve during MI-BCI training and how these changes relate to users' perceived performance. By integrating run-wise neural metrics with behavioral learning trajectories, we examine whether successful and unsuccessful MI-BCI learning are associated with distinct patterns of class stability, class distinctiveness, and rest distinctiveness. Through this framework, the study aims to provide a multidimensional characterization of neural adaptation during MI-BCI beyond traditional hemispheric laterality-based interpretations.

MATERIALS AND METHODS

Dataset and Participants: EEG data were obtained from the publicly available motor imagery dataset introduced by Cho et al. [10], designed to investigate inter-individual variability in SMR-based BCI performance. The dataset contains recordings from 52 healthy participants (19 females; mean age 24.8 ± 3.86 years) performing left- and right-hand motor imagery across 5–6 runs with 20 trials per class per run. After each run, participants reported their expected BCI performance and motor imagery difficulty. EEG was recorded using a 64-channel Biosemi ActiveTwo system at 512 Hz. Participants with incomplete questionnaire data or unusable EEG recordings were excluded, resulting in a final cohort of 44 participants.

EEG Preprocessing: EEG preprocessing was performed using MNE-Python [11]. Signals were restricted to the 64 scalp electrodes, followed by DC offset correction, linear detrending, band-pass filtering (0.1–50 Hz), and a 60 Hz notch filter. Artifact removal involved RANSAC-based channel repair, Artifact Subspace Reconstruction (ASR), and Infomax ICA. Components were automatically labeled using mne-icalabel [12], and those with artifact probability greater than 90% were removed. Noisy channels were interpolated, and signals were re-referenced to the common average reference.

Riemannian Geometry-Based Neural Metrics: EEG data were segmented into epochs from -1.99 s to 5 s relative to cue onset, baseline-corrected, and cropped to the 0–3 s motor imagery period. Signals were filtered into delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), gamma (30–45 Hz), and broadband (0.1–50 Hz) bands. Neural dynamics during motor imagery were quantified using classifier-independent Riemannian metrics proposed by Lotte and Jeunet [9], implemented using the PyRiemann toolbox [13]. Three metrics—class distinctiveness, class stability, and rest distinctiveness—were computed separately for each frequency band and run.

Table 1: Definitions and equations for the computed Riemannian neural metrics.

Metric	Definition & Equation
Class Distinctiveness	Separation between two task-related neural states (left vs right imagery). $classDis(A, B) = \frac{\delta_R(\bar{C}^A, \bar{C}^B)}{\frac{1}{2}(\sigma_{CA} + \sigma_{CB})}$ where $\bar{C}^A, \bar{C}^B$: geometric means; σ_{CA}, σ_{CB} : intra-class dispersions; δ_R : Riemannian distance.
Class Stability	Consistency of neural patterns within a class. $classStab(A) = \frac{1}{1 + \sigma_{CA}}$ where σ_{CA} : dispersion within class A.
Rest Distinctiveness	Separation between task-related neural activity and the resting baseline. $restDis(A) = \frac{\delta_R(\bar{C}^A, C_{rest})}{\frac{1}{2}(\sigma_{CA} + \sigma_{C_{rest}})}$ where C_{rest} : resting baseline covariance matrix.

Behavioral Performance Trajectories: After each run, participants reported their expected MI-BCI performance as a percentage score reflecting how accurately they believed they controlled the MI-BCI. Behavioral learning across runs was quantified using Ordinary Least Squares (OLS) regression (`np.polyfit`), where the slope represented the longitudinal change in expected performance (% change per run). Subjects were categorized as Improved, Worsened, or Unchanged based on the direction and magnitude of this slope.

Neural Adaptation Trajectories: To examine neural adaptation during training, slopes were computed for each Metric $\times$ Frequency Band combination, yielding 35 neural features per subject. Neural metrics were standardized using population-level z-score normalization, and outliers exceeding $|Z| > 2$ were removed. Slopes were then estimated using OLS regression across runs, with standardized neural metric values as the dependent variable and run index as the independent variable. Positive slopes indicated increasing neural modulation across runs, whereas negative slopes indicated decreasing modulation.

Statistical Analysis: To evaluate differences in neural adaptation between behavioral groups, the Kruskal–Wallis test was used. Statistical significance was validated using a permutation test (5000 iterations), and features with permutation-corrected $p < 0.05$ were considered significant. Significant features were further examined using Mann–Whitney U tests with Holm–Bonferroni correction.

One-vs-Rest Effect Size Analysis: To identify neural features uniquely associated with each behavioral group, a One-vs-Rest (OVR) analysis was conducted. Longitudinal slope distributions for each behavioral group were compared with the pooled distribution of the remaining subjects. Cohen's d quantified effect size, where positive and negative values reflected stronger or weaker run-wise neural trends relative to the remaining participants.

Classifier Benchmarking: To determine whether the behavioral groups were reflected in decoding performance, a Riemannian Minimum Distance to Mean (MDM) classifier implemented in PyRiemann was used. Classification was performed independently for each subject to distinguish left versus right motor imagery, with accuracy estimated using cross-validation across trials.

RESULTS

Results are first presented for stratification of participants based on their behavioral performance and their corresponding motor imagery difficulty trends across runs, thus characterizing their longitudinal learning behavior. This is followed by analyses of neural metric changes, frequency-specific relationships with performance, group-level slope differences, discriminative neural signatures, and classifier-based validation to examine how different dimensions of neural organization relate to MI-BCI learning trajectories.

Stratification of Participants based on Behavioral Performance Trajectories: Participants exhibited heterogeneous behavioral trajectories across the five runs. Based on the slope of reported BCI performance, subjects were categorized into Improved, Unchanged, and Worsened groups. The Improved group showed a progressive increase in performance from approximately 56% in Run 1 to over 72% by Run 5 (Fig. 1A). In contrast, the Worsened group declined from about 72% to 61%, while the Unchanged group remained relatively stable around 60–62%. Subjective imagery difficulty showed a different pattern (Fig. 1B). The Improved group reported moderate difficulty with a temporary improvement around Run 3, whereas the Worsened group reported relatively easy imagery throughout. In contrast, the Unchanged group consistently reported greater difficulty. These observations indicate that perceived imagery ease did not directly correspond to performance improvements. Reported BCI performance reflects subjective evaluation of MI-BCI control, whereas imagery difficulty reflects how difficult participants perceived the motor imagery task itself.

Longitudinal Evolution of Neural Representations: To examine neural adaptation across runs, Riemannian neural metrics were computed using the trial-wise pre-cue baseline as the resting reference. Although resting-state recordings were available, the pre-cue baseline was used to remain consistent with Lotte and Jeunet [9] and better capture run-wise MI training effects. Figure 2 shows longitudinal changes in neural metrics relative to Run 1. The Improved group showed increasing trends across rest distinctiveness, class stability, and left–right distinctiveness metrics, indicating progressively more separable and consistent motor imagery representations. The Unchanged group showed mild declining trends across class stability and left–right distinctiveness metrics, indicating limited longitudinal improvement in neural representations. The Worsened group showed mild increases in left–right distinctiveness and stability metrics but decreasing rest distinctiveness, indicating progressively structured representations with reduced separation from baseline neural activity.

Frequency-Specific Neural Correlates of Motor Imagery: To examine spectral contributions to performance, Spearman correlations were computed between behavioral performance and neural metrics across frequency bands (Fig. 3). Across runs, correlations strengthened particu-

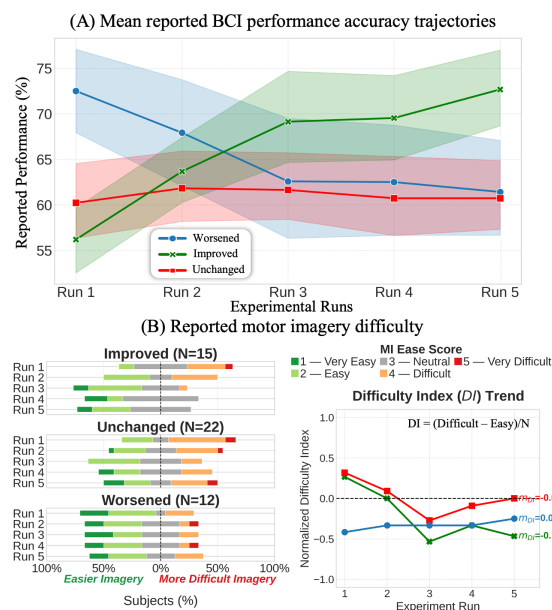


Figure 1: a) Average self-reported expected MI-BCI performance (%) across 5 runs, categorized by the slope of expected MI-BCI performance (Improved, Unchanged, Worsened). b) Distribution of reported motor imagery difficulty ratings and normalized Difficulty Index (DI) trends across 5 runs for each behavioral group, where $N_{difficult}$ and N_{easy} denote the number of difficult and easy responses, respectively. Positive DI values indicate greater perceived imagery difficulty, whereas negative values indicate easier imagery performance.

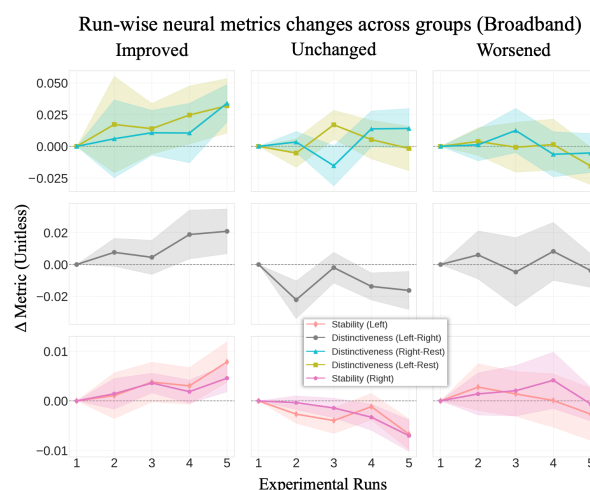


Figure 2: Run-wise changes in broadband neural metrics across behavioral groups relative to each subject's Run 1 baseline. Lines represent median changes across subjects, and shaded regions indicate SEM across subjects.

larly in beta and gamma bands, especially for rest-related distinctiveness and left–right separability. When stratified into behavioral groups, the Improved group showed stronger and more consistent correlations in lower frequency bands, whereas the Unchanged group exhibited weaker and more heterogeneous relationships. In the Worsened group, correlations were primarily observed in higher frequency bands, suggesting that spectral features alone may not fully explain the decline in performance.

Divergent Neural Adaptation Slopes Across Behavioral



Figure 3: Spearman correlation heatmaps between expected MI-BCI performance and neural metric values across frequency bands for a) all subjects and b) behavioral groups. Positive correlations indicate association with higher expected MI-BCI performance. Color intensity indicates correlation strength (Red = Positive, Blue = Negative). Asterisks denote significance (* $p < 0.05$, ** $p < 0.01$).

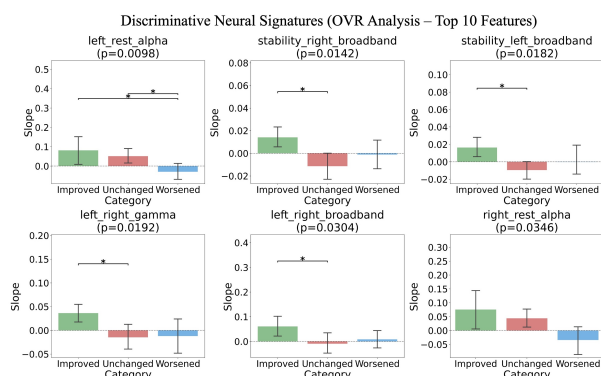


Figure 4: Divergent neural adaptation trends across behavioral groups. Subplots show mean slopes of neural metrics across training runs. p -values (titles) are derived from a permutation-based Kruskal-Wallis test (5,000 iterations); asterisks indicate significant post-hoc pairwise differences (Holm-corrected Mann-Whitney U, $p < 0.05$). Error bars represent ± 1 SEM.

Groups: To quantify longitudinal changes in neural metrics, slopes were computed for each metric across runs. Significant differences in neural adaptation slopes were observed among the behavioral groups (Fig. 4). Notably, alpha-band rest distinctiveness (left_rest_alpha and right_rest_alpha) showed positive slopes in the Improved group but negative or near-zero slopes in the Worsened group. Similarly, broadband stability metrics increased in the Improved group but decreased in the Unchanged group. Differences were also observed in left-right broadband distinctiveness and gamma-band separability, which increased in the Improved group but remained stable or decreased in the other groups. These results indicate that improvement in MI is associated with positive neural adaptation across multiple representational dimensions.

Neural Signatures of Behavioral Learning Trajectories: To identify neural features distinguishing each group, an OVR effect size analysis using Cohen's d was performed on the slopes of neural metric changes across runs (Fig. 5). The Improved group showed strong positive effect sizes for broadband stability and left-right separability,

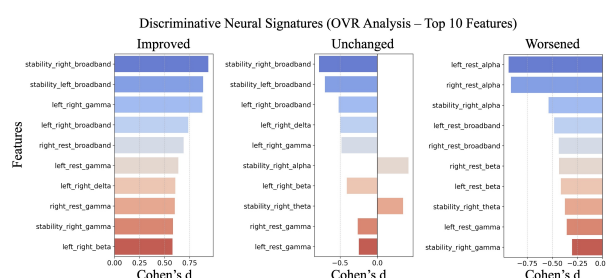


Figure 5: Discriminative neural signatures identified using one-vs-rest (OVR) analysis. Top neural metric slopes distinguishing each behavioral group, ranked by Cohen's d effect size. Positive values indicate stronger association with the target group relative to the remaining participants.

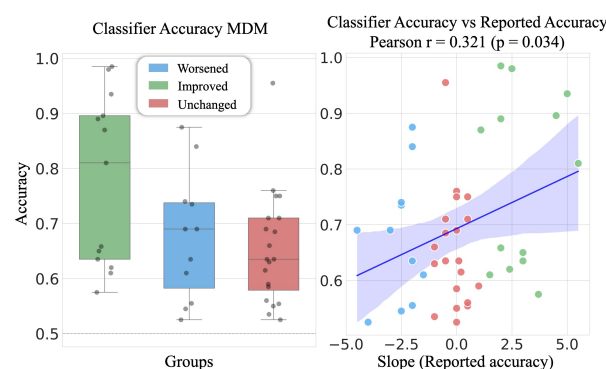


Figure 6: Relationship between classifier performance and behavioral learning trends. Left: Distribution of subject-wise MDM classification accuracy across behavioral groups. Right: Positive correlation between classification accuracy and behavioral performance slope (Pearson $r = 0.321$, $p = 0.034$).

indicating that increased neural consistency and class separability characterize successful learners. The Unchanged group exhibited negative effect sizes for stability and class-separability metrics, suggesting weaker neural structuring despite increased task-rest divergence. In contrast, the Worsened group showed large negative effect sizes for rest-related alpha and broadband metrics, indicating that reduced separation from baseline activity characterizes declining performance.

Classifier-Based Validation of Behavioral Groups: To determine whether these behavioral groups were reflected in decoding performance, a subject-specific Riemannian Minimum Distance to Mean (MDM) classifier was applied to classify left versus right motor imagery. Classification accuracy differed across groups (Fig. 6A). The Improved group achieved the highest median accuracy (~ 0.81), while the Worsened and Unchanged groups achieved lower accuracies (~ 0.69 and ~ 0.63 , respectively). Classifier accuracy was also positively correlated with behavioral learning slope (Pearson $r = 0.321$, $p = 0.034$; Fig. 6B), indicating that stronger behavioral improvement corresponded to greater neural decodability.

DISCUSSION

Motor imagery brain-computer interfaces (MI-BCIs) have traditionally been interpreted through the framework of hemispheric lateralization, where successful control arises

from contralateral modulation of sensorimotor rhythms during imagined movements [7]. In this classical view, improvements in BCI performance reflect increasingly strong lateralized neural activity that enables classifiers to distinguish between motor imagery classes. However, accumulating evidence suggests that this explanation alone cannot account for the variability observed in BCI learning outcomes [9]. In the present study, we examined neural adaptation during multi-run MI-BCI training using Riemannian geometry-based neural metrics and longitudinal slope analysis. Our results indicate that BCI learning cannot be explained solely by hemispheric lateralization but instead reflects the coordinated evolution of class stability, class distinctiveness, and rest distinctiveness. Class distinctiveness is closely related to hemispheric lateralization because it reflects the separability between left- and right-hand motor imagery representations. However, the present results showed that changes in class distinctiveness alone were insufficient to explain behavioral trajectories, as the groups also differed in the evolution of class stability and rest distinctiveness.

Consistent with previous reports highlighting substantial inter-individual variability in BCI performance [9, 14], participants in our dataset exhibited heterogeneous behavioral trajectories. Some individuals showed progressive improvements in classification accuracy across runs, whereas others displayed stable or declining performance. Importantly, these behavioral patterns were accompanied by distinct neural adaptation profiles. Participants in the Improved group exhibited simultaneous increases in class stability, class distinctiveness, and rest distinctiveness across runs. The neural dynamics observed in this group suggest a coordinated strengthening of motor imagery representations. Rest distinctiveness increased across runs, indicating that neural activity during motor imagery became increasingly separated from the resting baseline. At the same time, class distinctiveness increased, reflecting improved separability between the two imagery classes, while class stability increased, indicating more consistent neural patterns within each class. Together, these changes likely improve both the signal-to-noise ratio and the reliability of neural representations used for decoding, consistent with the higher classification accuracy observed in this group.

The Unchanged group exhibited a different neural profile. Participants in this group showed increasing rest distinctiveness but decreasing class distinctiveness and class stability across runs. This pattern suggests that although neural activity diverged from the resting baseline during the task, the neural patterns associated with the two imagery classes became less discriminable and less consistent over time. In other words, participants appeared to engage in task-related neural activity but failed to develop class-specific representations required for BCI control. This profile aligns with the concept of BCI illiteracy described in the literature [9, 14]. A particularly relevant study is the simultaneous EEG-fMRI motor imagery BCI investigation by Zich et al. [8], which identified three cate-

gories of users: BCI literate, illiterate, and pseudoilliterate. In their work, pseudo-illiterate users produced motor imagery activity detectable in fMRI but not EEG, suggesting that neural signals were present but not measurable by EEG due to neurophysiological factors such as dipole orientation. In contrast, BCI-illiterate users showed no clear motor imagery modulation in either EEG or fMRI. Because the present study relies solely on EEG recordings, pseudo-illiteracy cannot be identified. Instead, the Unchanged group likely corresponds to the true BCI-illiterate group, where participants fail to develop neural representations that differentiate motor imagery classes. The increasing rest distinctiveness observed in this group suggests engagement in task-related cognitive activity without recruitment of the neural circuits required for discriminable motor imagery patterns. This interpretation is also consistent with the greater subjective difficulty reported by this group.

The Worsened group exhibited yet another neural adaptation profile. In this group, class stability and class distinctiveness increased across runs, while rest distinctiveness decreased. This indicates that participants were able to generate structured neural patterns differentiating the two imagery classes, but the strength of these signals relative to the resting baseline diminished over time. One possible explanation is that these participants produced class-specific neural activity that was weak relative to baseline activity, reducing the reliability of signals used by the classifier. Unlike the Unchanged group, these users appear capable of generating class-specific neural patterns. Their declining performance may therefore reflect insufficient signal strength, fatigue, reduced engagement, difficulty identifying an effective motor imagery strategy, or recruitment of neural networks not optimally aligned with the intended MI task rather than an inability to perform motor imagery [15]. Such users may benefit from improved training protocols or personalized feedback strategies designed to strengthen task-related neural modulation [9].

Hence, these findings suggest that successful MI-BCI learning requires the simultaneous increase of class stability, class distinctiveness, and rest distinctiveness. Improvements in only one or two metrics appear insufficient for reliable MI-BCI performance. Increasing rest distinctiveness without increasing class distinctiveness produces the neural profile observed in the Unchanged group, whereas increasing class stability and class distinctiveness without rest distinctiveness leads to the pattern observed in the Worsened group. These results suggest that unsuccessful MI-BCI performance may arise from multiple neural failure modes rather than a single underlying limitation.

Recent studies have suggested that MI learning involves large-scale reorganization of functional connectivity and resting-state networks rather than isolated modulation of sensorimotor laterality alone. Resting-state functional connectivity changes have been reported in sensory-motor, visual, and default-mode networks following MI training, indicating that baseline neural dynamics evolve throughout learning [16, 17, 18]. In this context, the present

findings suggest that Riemannian metrics derived from covariance geometry may capture aspects of this broader network-level reorganization through changes in class stability, class distinctiveness, and rest distinctiveness.

Methodologically, this study demonstrates the value of Riemannian geometry-based neural metrics for analyzing motor imagery EEG signals [19]. By examining the covariance structure of multichannel EEG signals, these metrics capture changes in neural representations that are not easily detected using traditional canonical frequency band power-based measures. Analyzing the longitudinal slopes of these metrics across training runs allowed us to identify distinct neural adaptation trajectories associated with different behavioral outcomes.

Finally, classifier benchmarking further supports these findings. Participants in the Improved group achieved higher classification accuracy using a Riemannian Minimum Distance to Mean classifier, and classifier accuracy showed a positive relationship with behavioral learning slopes. This indicates that the behavioral grouping derived from performance trajectories reflects meaningful differences in the separability of neural representations within the EEG signal.

Future research should investigate whether these neural adaptation profiles generalize across different BCI paradigms and training protocols. Understanding these trajectories may help inform the development of adaptive training strategies and personalized feedback systems aimed at improving BCI learning outcomes.

CONCLUSION

This study investigated neural adaptation during motor imagery BCI training using Riemannian neural metrics. Our results show that successful learning is associated with simultaneous increases in class stability, class distinctiveness, and rest distinctiveness, whereas unsuccessful users exhibit partial or conflicting changes in these metrics. In particular, participants in the Unchanged group increased rest distinctiveness but failed to develop class-specific neural representations, consistent with the concept of BCI illiteracy described in previous studies [8, 9]. Overall, these findings demonstrate that MI-BCI learning cannot be explained by hemispheric lateralization alone, but instead depends on the coordinated evolution of class stability, class distinctiveness, and rest distinctiveness during training.

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