

Co-Adaptive MRCP-based BCIs: Modulation of Cortical Potentials by Enhanced Classifier Performance

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ABSTRACT: Movement-related cortical potentials (MRCPs) reflect voluntary motor intentions and are widely used as control signals in asynchronous brain-computer interfaces (BCIs). However, the extent to which task engagement and feedback influence MRCP dynamics remains unclear. We analyzed MRCPs across two identical online speller sessions to examine how task context and classifier reliability relate to preparatory brain activity. Healthy participants controlled a row/column speller by performing right-hand gestures, first using a classifier trained on cue-aligned offline data and subsequently using a classifier retrained on data collected during the online task. Trials segmented into four task stages of increasing complexity showed no significant differences in MRCP amplitudes, suggesting limited within-session effects. In contrast, MRCP amplitudes were significantly higher in the second session following retraining. This pattern suggests an association between improved classifier performance, task success, and enhanced MRCP expression, supporting a co-adaptive interpretation and highlighting the importance of session-wise factors in MRCP-based BCI operation.

INTRODUCTION

Brain-computer interfaces (BCIs) enable direct communication between the brain and external devices, allowing individuals with severe motor impairments, such as amyotrophic lateral sclerosis, to interact with technology using neural activity alone [1]. Among non-invasive approaches, EEG-based systems that decode movement intention are particularly promising [2-3]. A central neural correlate in this context is the movement-related cortical potential (MRCP), a slow cortical potential that begins up to two seconds before voluntary movement and peaks at movement initiation [4]. MRCPs are tightly time-locked to motor preparation, making them an attractive control signal for asynchronous BCIs. Despite their potential, MRCP-based BCIs face a major challenge: cortical signals are inherently non-stationary. Even during repeated performance of the same motor task, neural activity can vary substantially. Traditionally, this variability has been attributed to noise, fatigue, or nonspecific cognitive fluctuations. However, increasing evidence suggests that internal states, such as attention, motivation, expectancy, perceived agency, and reward processing, can modulate cortical potentials. This issue is

particularly relevant in co-adaptive BCI systems, where both the classifier and the user continuously adapt to each other [5-6]. Adaptive algorithms optimize decoding by updating decision boundaries or feature weights, while users adjust cognitive strategies, effort, and engagement based on perceived control and feedback reliability. In this bidirectional loop, subtle changes in classifier behaviour can influence the subjective experience of control: reliable detection enhances motivation and engagement, whereas inconsistent feedback reduces it. These cognitive-motivational adjustments can directly affect MRCP amplitude, slope, and spatial distribution, creating a dynamic interaction between neural signals and system performance. Another important consideration is that offline calibration data often do not fully capture the neural patterns that arise during interactive BCI use. In real-time speller tasks, participants experience continuous feedback, interface dynamics, and time pressure, which can modulate MRCPs in ways that are not present during calibration [7-8]. As a result, classifiers trained solely on offline data may underperform when deployed online, highlighting the need for retraining on task-relevant neural activity. In our previous work [2] with the same MRCP-based BCI spelling paradigm, retraining the classifier with online task data significantly improved system performance, measured in characters per minute (CPM). This raises the question: does enhanced control also alter the underlying neural signals? We hypothesize that differences in MRCP characteristics between sessions reflect attentional engagement and adaptation to the interface within the co-adaptive human-machine loop, which may subsequently enhance user motivation, rather than mere variability. Changes in classifier dynamics may influence perceived controllability, expectancy, and cognitive investment, reshaping preparatory cortical activity. Understanding how classifier properties affect cortical potentials is crucial for developing robust MRCP-based BCIs. If neural signals systematically depend on the interactive context, training and retraining strategies must consider these bidirectional effects. Examining session-to-session modulation under controlled task conditions is therefore a critical step toward separating technical adaptation from genuine neurocognitive changes in co-adaptive BCI systems.

MATERIALS AND METHODS

A. Participants and Setup

This study presents a subset of data drawn from a larger experiment involving 21 healthy volunteers (12 males; average age 26.3 ± 5.8 years). Brain activity was recorded using a 64-channel actiCAP EEG system (Brain Products GmbH, Gilching, Germany) with a sampling rate of 500 Hz. Sixty electrodes were positioned according to the 10-10 system on the head to capture EEG signals, while the remaining four electrodes recorded electrooculography (EOG), placed horizontally at the outer canthi of both eyes and vertically above and below the left eye. The reference electrode was set at FCz, with the ground on the right mastoid. To capture movement onsets, a self-developed motion capture system (Logitech HD Pro C920) at the institute was used. A marker attached to the participant's index finger enabled movement tracking. The device operated at a sampling rate of 30 Hz. Synchronization between EEG/EOG and motion capture data was achieved via the Lab Streaming Layer protocol.

B. Experimental Paradigm

The main study comprised both offline and online phases. This contribution focuses mainly on the online phase, which comprised two consecutive sessions. Sessions were separated by a short break of approximately 15 minutes, allowing participants to rest between sessions. In Session 1, participants controlled an online speller matrix using a classifier trained on cue-aligned offline data. During this offline session, EEG was recorded while participants executed 5 different hand gestures each collecting 150 trials. In those cue-based runs, a continuously rotating cross superimposed on a static fixation cross served as the visual cue, rotating 90° clockwise every 3-4 seconds [9]. We then performed a self-paced run for each gesture which was used as a test set to evaluate which gestures performs the best and this gesture was then selected for detecting clicks in Session 1. In Session 2, the same spelling task was repeated, however, the classifier was retrained using the online data collected during Session 1. In this session, we aligned the movements to the expected onsets during the online speller task. During both sessions, participants were instructed to spell the identical set of predefined goal words and sentences using a row/column scanning matrix, ensuring full comparability between sessions. Each session started with 2 easy goal words, followed by a break then we started with 2 medium words and at the end 2 full sentences. All were ordered randomly to avoid repetition. The matrix was arranged in a 5×6 grid, with rows and columns highlighted sequentially for 1.6 seconds each. Movement execution at target fields was detected by the classifier. An ESC field in each row allowed participants to exit incorrectly selected rows, and

a DEL field provided the option to correct spelling mistakes. The detailed procedure of the paradigm, including cue presentation, gesture selection, classifier training and retraining as well as the online speller task, is described in full in [3]. Figure 1 provides an overview of the experimental setup and an explanation of the two sessions classifier calibration and the online speller matrix.

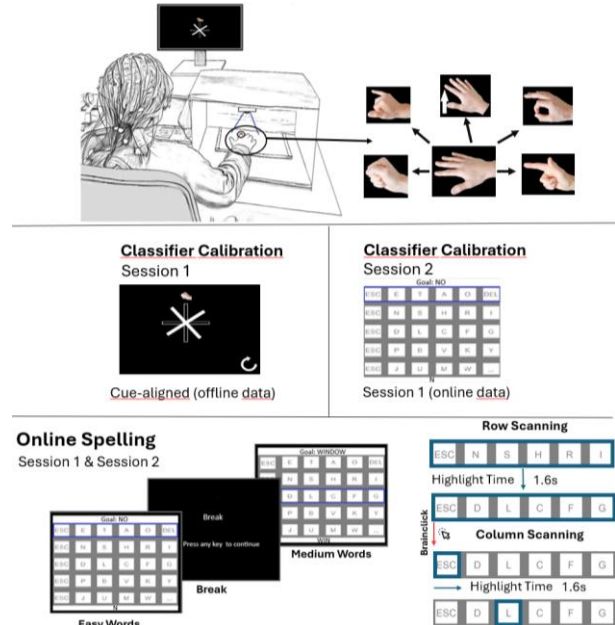


Figure 1: Experimental Setup. During offline phase 5 different right-handed gestures were performed. Session 1 used the best performing gesture (tested on test-set) for classifier training and control an online speller. Session 2 performed identical task, but the classifier was retrained on Session 1 data. Adapted from [3].

C. Data Processing & Online Classification

The signal processing pipeline included the following filtering steps: the EEG data was first band-pass filtered between 0.5 and 70 Hz to remove slow drifts and high-frequency noise. After this step, EOG artifacts were corrected using an eye-movement correction matrix [10]. The signals were then low-pass filtered at 3.5 Hz, downsampled to 10 Hz, and re-referenced to a common average reference. For filtering we used a 4th-order Butterworth IIR filter. To ensure methodological consistency, the offline data was processed using the same pipeline as applied during real-time operation, including the use of causal filters. All preprocessing and decoding procedures were implemented in BOLT (Brain Out-LeT), a Python-based framework for real-time neural decoding developed at the Wyss Center and built on the ezmsg architecture (<https://github.com/ezmsg-org/ezmsg>). For classification, a binary shrinkage linear discriminant analysis classifier was trained to detect movement onsets [11-12]. The calibration procedure followed the methods described in [2] and [3]. Specifically, the classifier for Session 1 was trained using

three cue-based runs consisting of 150 movement trials, while the Session 2 classifier followed the same procedure, using only the online data from Session 1 segmented into three runs.

D. Analysis

The analysis focused on MRCPs across Session 1 and Session 2 to assess neurophysiological and temporal characteristics. As the online speller task conditions were identical across sessions and only the decoder differed, additional analyses examined changes in MRCP characteristics and their relationship to behavioural performance. Low-frequency EEG amplitudes corresponding to MRCPs were used as features, and grand-average MRCPs were computed within a ± 2 s window around movement onset, pooling both sessions. Electrode C1 was selected for grand averages as it showed the strongest activity. Standard Error (SE) was included to reflect inter-subject variability. Significant differences between sessions (Session 1 - Session 2) were assessed using Wilcoxon rank-sum tests and corrected for multiple comparisons using the Benjamini-Hochberg procedure. Temporal variability between cue onset and movement onset was quantified by comparing cue-locked and movement-locked responses for each trial and participant. Session differences were evaluated to assess changes in MRCP amplitude, spatial distribution, and CPM at the single-subject level. Performance was quantified as CPM, where only characters that exactly matched the corresponding target position in the presented target words or sentences were counted as correct. Because scanning speed was fixed, CPM differences primarily reflect selection accuracy and efficiency. To examine within-session dynamics, trials were divided into four sequential stages (start, early, middle, late), each comprising 25% of trials. Grand-average MRCPs were computed for each stage across participants to assess potential learning or adaptation effects.

RESULTS

The grand-average MRCPs across all participants revealed significant differences between sessions at electrode C1 (Figure 2A). In particular, Session 2 showed a significant stronger negative peak amplitude ($-2.2 \mu\text{V}$) compared to Session 1 ($-1.2 \mu\text{V}$). The topographical analysis revealed significant differences at time points around movement onset (0 ms) and 125 ms (Figure 2B). These differences are primarily located over the contralateral side (right-handed movement execution) of the motor cortex as well as central motor areas. The subject-wise performance in CPM demonstrates an overall improvement when using the retrained classifier (Figure 3A). Nineteen out of the twenty participants showed an increase in CPM during Session 2, while only one participant did not exhibit a substantial improvement. Analysis of the temporal differences of the timing of movement execution relative to the cue onset

revealed reduced variability in Session 2 (Figure 3B). The interquartile range (IQR) for the movement onset relative to the cue was 0.18 s in Session 1 and 0.27 s in Session 2. For most subjects the timings in Session 2 are more centred around 0. The analysis of subject-wise MRCP amplitudes showed that most participants exhibited an increase in negativity during Session 2 (Figure 3C). The average values at C1 showed $-2.2 \mu\text{V}$ for Session 2 and $-1.2 \mu\text{V}$ for Session 1. The MRCP variability showed on a participant level a general pattern that the variability decreases for Session 2 (Figure 3D). Average values for Session 1 were $0.53 \mu\text{V}$ and $0.47 \mu\text{V}$ for Session 2. When comparing MRCP amplitudes between sessions, the calculated effect size was Cohen's $d = -0.5$, in contrast, the reduction in temporal variability showed a smaller effect size of $d = 0.27$. A comparison of the four stages of MRCP progression during Session 1 and Session 2 revealed stage-dependent differences in mean amplitude, although none reached statistical significance (Figure 4). In Session 1, the strongest negative MRCP amplitude was observed in the early stage ($-1.38 \mu\text{V}$), followed by the start stage ($-1.35 \mu\text{V}$) and the late stage ($-1.21 \mu\text{V}$), whereas the middle stage showed the weakest negativity ($-0.95 \mu\text{V}$). In Session 2, the strongest negative MRCP amplitude occurred in the middle stage ($-2.35 \mu\text{V}$), followed by the late stage ($-2.27 \mu\text{V}$) and the early stage ($-2.20 \mu\text{V}$), while the start stage exhibited the weakest negativity ($-1.98 \mu\text{V}$). However, statistical analysis revealed no significant differences between stages within either session.

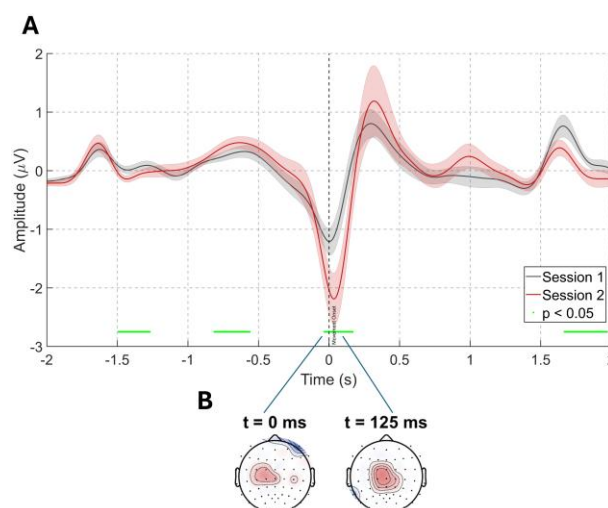


Figure 2: (A) Grand average MRCPs at electrode C1 for Session 1 (dark grey) and Session 2 (red), including SE, aligned to movement onset (-2 to +2 s). Significant differences between sessions are indicated in green. (B) Topographical distribution of significant differences between Session 1 and Session 2 from 0 ms to +125 ms relative to movement onset.

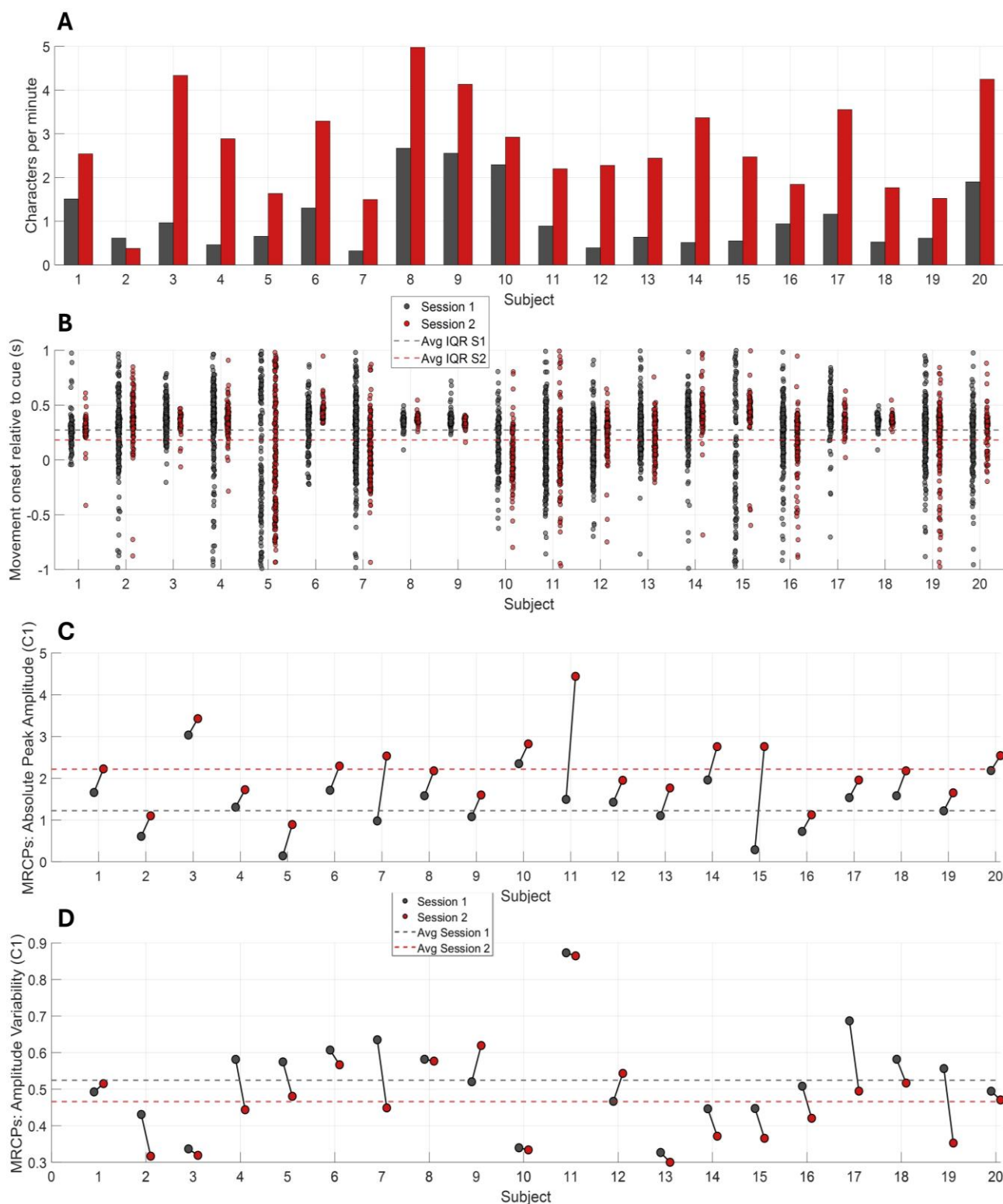


Figure 3: A) CPM per subject for Session 1 and Session 2. B) Time difference between movement onset and cue for both sessions per participant. The dashed dark-grey line shows the average IQR for Session 1, and the dashed red line shows the average IQR for Session 2. C) Subject-wise average MRCP peak amplitude for Session 1 and Session 2. D) MRCP amplitude variability per subject for both sessions. In all panels, Session 1 is shown in dark grey and Session 2 in red. The dashed lines in panel B indicate the average IQR for each session, while those in panels C and D indicate the average Amplitude/Variability for each session.

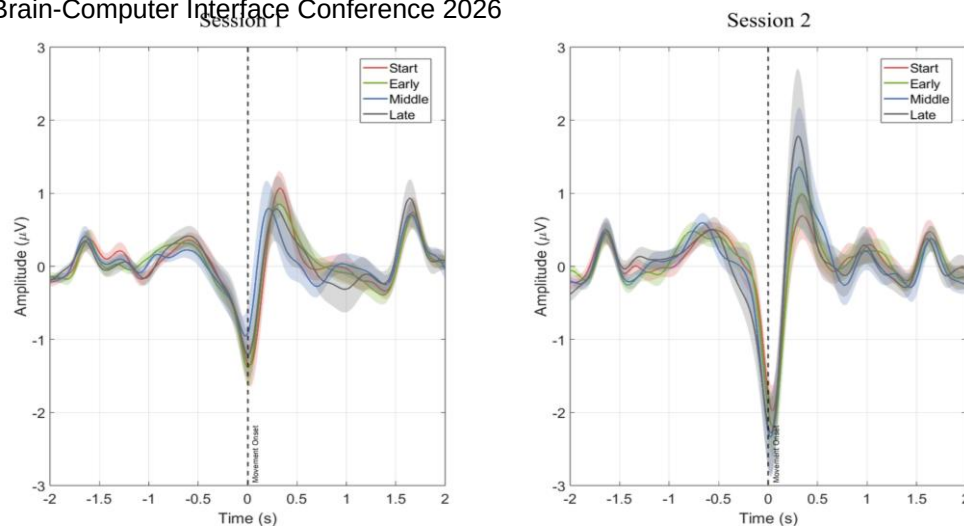


Figure 4: Grand average MRCPs of 4 different stages at electrode C1 for Session 1 and Session 2 including SE.

DISCUSSION

We observed a significant difference in motor-related brain activity between Session 1 and Session 2. Overall, the results indicate stronger and more consistent motor activation during the second session. This pattern is evident across multiple analyses. The grand-average MRCPs show a significantly stronger negative peak amplitude in Session 2 compared to Session 1 at electrode C1. Topographical maps further support this finding, revealing a larger negative MRCP amplitude at movement onset (0 ms) in Session 2. At 0 ms, the significant differences are primarily located over the contralateral motor cortex, with an additional effect at C4. At -125 ms relative to movement onset, the negative difference remains present but becomes more centrally distributed over the motor cortex. These spatial and temporal patterns are consistent with previous findings in the literature. Earlier work on slow cortical potentials and contingent negative variation (CNV) in BCI contexts has interpreted amplitude increases as correlates of learning and adaptive control, providing a framework for understanding preparatory brain activity changes in BCI systems [13]. An additional observation concerns the evolution of MRCP amplitudes across experimental stages. In Session 1, the strongest negative MRCP amplitude was observed during the early stage, followed by the start and late stages, while the middle stage showed the weakest negativity. In Session 2, the strongest MRCP amplitudes occurred during the middle and late stages, whereas the start stage showed the weakest negativity. However, these differences were not statistically significant in either session. Overall, the stage-wise analysis did not reveal a systematic evolution of MRCP amplitude within sessions, suggesting that within-session learning effects were minimal. Importantly, the increase in MRCP amplitude observed in Session 2 occurred after the classifier had been retrained and updated. Session 2 retraining used data recorded during the actual speller task, thereby improving alignment between training and testing distributions. This suggests an association between classifier adaptation, feedback reliability, and changes in motor-related brain activity. One possible explanation is

that more reliable feedback may support more stable and well-timed motor-related activity during task execution, potentially enhancing neural preparation and engagement compared to conventional feedback paradigms [14-16]. At the same time, it is also plausible that changes in neural activity and signal structure contributed to improved classifier performance, indicating a bidirectional relationship between neural dynamics and decoding accuracy. The results are therefore consistent with a co-adaptive process in which user and system mutually influence each other over time. In addition, psychological factors such as attention, engagement, and motivation may have contributed to the observed effects. Previous work has shown that these variables can modulate both BCI performance and neurophysiological signals suggesting a role in shaping MRCP dynamics alongside neural and system-driven factors. At the individual level, most participants showed stronger negative MRCP peaks in Session 2, although the magnitude of change varied across subjects. While most participants exhibited small increases in MRCP negativity, a few showed larger changes. Despite this variability, the overall effect size for the amplitude difference was moderate (Cohen's $d = 0.5$), while the reduction in variability showed a smaller effect ($d = 0.27$), supporting a general trend toward more consistent motor-related activity in Session 2. Several limitations should be considered when interpreting these findings. First, the direction of the relationship between MRCP modulation and classifier performance cannot be conclusively determined, as improved neural signal quality may also contribute to better decoding performance. Second, although sessions were conducted consecutively on the same day, factors such as task familiarity, attention, or fatigue may have influenced the results. Third, variability across participants suggests that the effects are not uniform and may depend on individual strategies or neural characteristics. Future work should address these factors by systematically manipulating feedback reliability and classifier performance. We acknowledge that a dedicated control condition in which Session 2 used the same classifier as Session 1 was not included. However, the within-session stage analysis did

not reveal systematic MRCP changes over time, suggesting that gradual learning effects within a session are unlikely to fully explain the between-session differences. Taken together, these findings suggest that MRCP modulation in BCI tasks is influenced by a combination of neural preparation, feedback characteristics, and learning-related processes. Rather than reflecting a single underlying mechanism, the observed effects likely emerge from the interaction between these factors within a co-adaptive BCI framework.

CONCLUSION

The present study suggests that motor-related brain activity became stronger and more consistent in the second online BCI session. This was reflected in increased MRCP amplitudes, reduced MRCP variability, decreased variability in movement timing relative to cue onset, and more stable motor activation patterns across participants. Crucially, these changes emerged after the classifier was retrained on task-related data, consistent with a co-adaptive interpretation of the system. In this framework, improved classifier performance may enhance the quality and interpretability of feedback, which in turn could support participants' engagement and more consistent motor preparation. At the same time, it is also plausible that increases in MRCP stability and amplitude contribute to improved classifier performance, suggesting a bidirectional relationship between neural signal quality and decoding accuracy. Together, these findings indicate that additional rounds of classifier retraining may further refine both neural modulation and classification performance, potentially increasing CPM by leveraging progressively more stable and discriminable neural signals. This co-adaptive interaction is particularly relevant for MRCP-based BCIs, which rely on self-initiated movements rather than externally driven visual stimuli. This design reduces visual demand and may facilitate a more natural interaction between user and system. Overall, the findings highlight the potential of adaptive BCI systems that continuously update classifiers based on task-related neural activity, enabling an interaction loop in which neural signals and decoding performance mutually influence each other over time.

ACKNOWLEDGEMENTS

This project is funded by the European Union's HORIZON-EIC-2021-PATHFINDER CHALLENGES program under grant agreement No 101070939 and by the Swiss State Secretariat for Education, Research and Innovation (SERI) under contract number 22.00198.

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