Performing Bimanual Tasks with a BCI: Combining a Brain-Controlled Hand Exoskeleton with the Functional Limb

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***Abstract*— Brain-controlled robotic systems have shown promise as personalized assistive tools, yet current efforts largely focus on single-arm exoskeletons for basic functions, offering limited utility in real-world tasks that require bimanual coordination. This limitation is critical for individuals with motor impairments, who must combine brain-computer interface (BCI) control with overt motor actions in daily activities. Collecting calibration data is essential for training BCI decoders for online BCI control; however, gathering data for a wide range of complex bimanual tasks can be time-consuming and cognitively demanding, potentially hampering quality of calibration data and hence online BCI control in such settings. While unimanual flexion vs rest BCIs provide only limited degrees of freedom, combining BCI control with simultaneous movement of the functional limb can support a variety of bimanual tasks. Although the motor cortex supports simultaneous movements, non-invasive electroencephalogram based BCIs remain understudied in this context. In this study, we demonstrate that a unimanual hand-flexion BCI decoder can be reliably transferred to bimanual tasks across multiple sessions, thereby reducing task-specific calibration burdens. Furthermore, we show that multi-day closed-loop BCI training improves decoding performance, ultimately enabling more natural bimanual control. Our results pave the way for practical assistive BCI systems that enhance functional independence.**

***Index Terms*— Brain–Computer Interface (BCI), Assistive BCI, Motor Imagery (MI), Neuroprosthetics**

I. INTRODUCTION

BCIs hold great promise for personalized assistive devices, particularly for individuals with disabilities [1] [2] [3]. However, current efforts are mainly focused on single-arm exoskeletons [4] for rehabilitation or basic assistance [5]. These systems have limited utility in real-world tasks requiring bimanual coordination—such as holding a tray or opening a bottle. Individuals with an impaired limb have limited independence when relying solely on the functional arm, highlighting the need for BCIs that enable coordinated bimanual control for everyday use.

Few studies have examined BCI control alongside overt motor activity [6] [7] [8]. Those that do—mostly using invasive recordings—show the feasibility of simultaneous control but also reveal decoding challenges due to interference from ongoing movements. The invasiveness of these methods limits clinical adoption, whereas non-invasive EEG-based BCIs offer a more practical and accessible alternative. For example, Cheung et al. [9] demonstrated that participants could control a game cursor using right-hand MI while simultaneously moving a joystick with the left hand. However, this was evaluated over only two days with both BCI-only and combined-task conditions. Thus, there is a pressing need to study BCI control over multiple days in realistic, simultaneous BCI and functional task settings, and to understand how performance evolves when transitioning from BCI-only to combined tasks.

Calibration is a major challenge for BCIs supporting bimanual control, as simulating complex tasks is time-intensive and can confuse users, hindering the generation of reliable calibration data—even for common binary MI tasks like imagining hand flexion versus rest [10]. While binary BCIs enable only limited actions, such as triggering a grasp with a hand exoskeleton [11], combining them with voluntary movement of the functional limb enables more practical bimanual actions. For instance, a BCI can maintain a grasp while the other hand unscrews a bottle cap. However, even in such scenarios, collecting representative calibration data remains difficult due to the variability and coordination demands of real-world bimanual tasks.

A more scalable approach is to transfer the neural patterns and decoding models learned from simpler unimanual BCI tasks to more realistic bimanual scenarios involving simultaneous BCI control and functional hand use. This strategy minimizes the need to simulate a broad range of complex tasks for calibration and allows subjects to first build reliable BCI control in isolation before introducing the demands of dual-tasking. However, while prior work suggests that core MI patterns may remain stable during dual-tasking, the added complexity of functional hand use—engaging overlapping motor regions [12]—may introduce physiological interference and feature-space non-stationarities, further complicating calibration and potentially degrading BCI performance.

To address these challenges, we hypothesize that a decoding framework that minimizes non-stationarities and accounts for day-to-day variability in neural feature spaces—when paired with longitudinal closed-loop training—can enable effective BCI control in bimanual settings [13] [14]. In particular, we employ an incremental recentering-based decoder within a Riemannian geometry framework, which has demonstrated effectiveness in reducing non-stationarities

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and enabling robust decoding performance in online BCI settings across multiple sessions and different tasks [13]. Prior work underscores the importance of multi-day training for improving task performance and generating more robust, discriminative neural patterns [3] [13] [15] [16].

In this study, we show that training with a unimanual BCI decoder across multiple sessions allows users to generate distinctive neural patterns for BCI control while simultaneously using their functional hand, ultimately enhancing their BCI performance in bimanual tasks. Over five sessions with seven participants, we demonstrate successful transfer of a flexion-vs-rest decoder to bimanual tasks, with consistent gains in both unimanual and bimanual performance while generating increasingly discriminant feature spaces. Additionally, our post-hoc analysis further highlights the importance of adaptive decoding to mitigate non-stationarities in real-world applications.

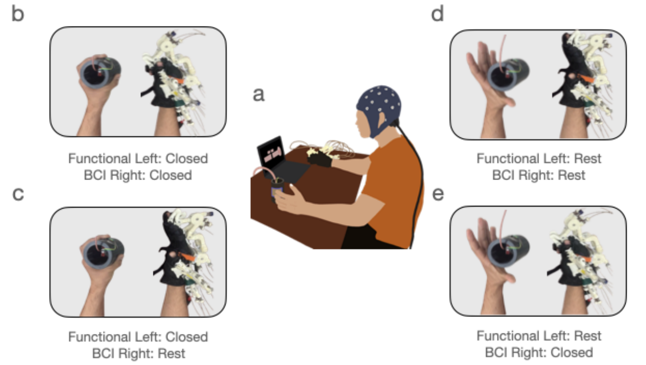

Fig. 1. **Bimanual experimental setup:** a) Subject is cued on screen to simultaneously control assistive robotic exoskeleton using MI-BCI (right hand flexion vs rest) while using their functional left hand for applying force (or rest) using a cylindrical grip. Different cues presented on screen for bimanual tasks are b) "Functional Left: Closed, BCI Right: Closed" c) "Functional Left: Rest, BCI Right: Rest" d) "Functional Left: Closed, BCI Right: Rest" e) "Functional Left: Rest, BCI Right: Closed"

II. Methods

A. *Experimental Protocol*

In this study, we recruited seven healthy participants with normal or corrected to normal vision. Five of the participants had prior experience with BCI systems, and one participant had previously used the assistive hand exoskeleton in a passive, non-BCI context. However, none had experience operating a BCI in conjunction with the exoskeleton. The experimental protocol was approved by the Institutional Review Board of The University of Texas at Austin, and all participants provided consent to participate in the experiment. EEG signals were recorded using a 32-channel ANT Neuro eego amplifier at a sampling rate of 512 Hz, following the standard 32-channel montage, except for the M1 and M2 electrodes. In addition to EEG electrodes, we also recorded EOG channels using the montage described in [13] [17] to detect online EOG activity and reject EEG samples potentially contaminated by EOG or facial movements.

The seven participants underwent longitudinal training over five online sessions on different days, with an initial offline session conducted on a separate day before the first online session to collect calibration data to build the decoder used for online feedback. During the offline session, subjects completed four runs of right-hand flexion imagery versus rest trials. Each run consisted of 20 trials, divided evenly between flexion and rest imagery. Trials were presented in a pseudo-random order to prevent anticipatory strategies during task performance.

During the offline runs, each trial began with a 2-second fixation period, followed by the presentation of a cue (flexion or rest imagery) for 1.5 seconds, and a 7-second task period where a progress bar guided the subjects in their imagery task. To mimic a realistic prosthetic operation, participants wore an assistive hand exoskeleton [11] programmed to perform a power grasp at the end of each flexion imagery trial. Participants also received sensory threshold neuromuscular electrical stimulation (StNMES) to provide naturalistic proprioceptive feedback throughout the task period and during the exoskeleton's grasping actions, which has been shown to enhance closed-loop BCI training [18] [10]. After each trial, there was a 3-second inter-trial rest period before the next trial began.

During the online unimanual sessions, subjects performed 20 trials that consisted right-hand flexion imagery or rest imagery. The task timeline was similar to that of the offline training runs; however, during the task period, subjects received real-time feedback (both visual via a progress bar and proportional feedback via StNMES) based on their imagery performance, using a decoder trained on the offline data. As described in the paradigms of [16] and [13], subjects were provided with target thresholds for both flexion and rest imagery, which they were required to achieve by correctly modulating their neural patterns. If they reached the threshold for the cued class, it resulted in a hit (correct command delivery), and they were instructed to continue imagining the corresponding class for an additional 7 seconds to sustain the imagery. Notably, a successful flexion imagery command triggered the exoskeleton to perform a power grasp. If subjects hit the threshold for the opposite class or failed to reach any threshold within the specified 7-second window, it resulted in a missed command or a timeout, respectively, ending the trial. For a detailed description of hits, misses, timeouts, and the online implementation of the BCI framework, please refer to [13] and [16].

During the bimanual BCI online sessions, subjects performed tasks in a cued synchronous BCI fashion (Fig. 1a). Similarly to the unimanual sessions, they were cued to perform different tasks; however, in contrast to the purely BCI tasks in the unimanual setting, bimanual session tasks included the use of both the subject's functional left hand and the BCI-controlled right hand exoskeleton. Each of the four online runs consisted of 5 trials for each of the following visual cues: Functional Left: Closed, BCI Right: Closed (Fig. 1b) ; Functional Left: Closed, BCI Right: Rest (Fig. 1c) ; Functional Left: Rest, BCI Right: Closed (Fig. 1d); Functional Left: Rest, BCI Right: Closed (Fig. 1e).

An additional bar feedback was displayed above the existing BCI bar feedback to indicate the amount of force applied by the functional left hand on a force sensor mounted on a cylindrical object. During the "Functional Left: Rest" condition, subjects were instructed to avoid applying any force to the sensor while keeping their left hand at rest. In contrast, during the "Functional Left: Closed" condition, they were required to apply a force within a specified range. Before each bimanual online session, subjects practiced using the force sensor to familiarize themselves with the required force levels and correct hand positioning.

Similar to the unimanual sessions, subjects were required to begin imagining the correct BCI cue, however they also were tasked to simultaneously perform a task with their functional hand. A BCI miss or timeout would end the trial, whereas a successful hit for both the BCI and functional hand tasks resulted in a correct command delivery, prompting the subjects to maintain the corresponding state for an additional 7 seconds.

Specifically, during the "Functional Left: Closed, BCI Right: Closed" condition, subjects needed to deliver a flexion imagery command and simultaneously grasp the force sensor within the specified force range to correctly execute the command. If successful, the exoskeleton performed a power grasp. In the "Functional Left: Rest, BCI Right: Rest" condition, subjects were instructed to keep their functional arm at rest and avoid applying any force while delivering a resting imagery command via BCI. In the "Functional Left: Closed, BCI Right: Rest" condition, subjects had to apply force with the functional left hand on the force sensor while imagining a rest imagery command for the BCI-controlled hand. Finally, in the "Functional Left: Rest, BCI Right: Closed" condition, subjects were instructed to keep their functional left hand at rest while performing flexion MI to close the exoskeleton.

B. Online Decoder

We utilized a minimum distance to mean decoder based on the Riemannian geometry framework for providing online feedback. Covariance features were extracted from the task period of the subjects' specific offline session data to build the decoder in the recentered space. During the online sessions, in order to address non-stationarities and shifts in the feature distributions, we implemented online incremental domain adaptation using the Generic Recentering (GR) framework introduced in [19] to minimize shifts in the feature spaces. The decoding parameters were consistent with those used in prior works [13], [16], where decoding was performed on the trace-normalised covariances of 1-second band-pass filtered EEG samples (8–30 Hz) with a step size of 1/16 seconds. For the decoding analysis, we utilized the 22 channel described in [13].

C. Event Related Desyncronisation

We performed an event-related desynchronization (ERD) analysis to visualize grand average patterns across different task conditions. EEG data contaminated by EOG artifacts were excluded, and the remaining signals were band-pass filtered in the mu band (7–13 Hz). Laplacian spatial filtering was applied to improve signal-to-noise ratio. The instantaneous power during the task period was estimated by squaring the band-passed signal and averaging it over the last 2 seconds of the task duration. To quantify ERD, the averaged instantaneous power from the task period was normalized using baseline data recorded 1 to 2 seconds after the fixation cue presentation in each trial. Only trials that resulted in successful hits for the corresponding tasks were utilized, thereby excluding trials where subjects may not have accurately performed the required imagery or combined imagery and functional tasks.

D. Pseudo Online Decoder Comparison

To observe the effect of between-session non-stationarities, as well as those potentially induced by background physiological activity from using the functional hand during bimanual tasks, we compared the online decoder, which incorporates incremental recentering to address non-stationarities, with a decoding model that does not include any adaptation for reducing non-stationarities, referred as *Fixed Decoder*. Specifically, the Fixed Decoder was built using the covariances of band-pass filtered EEG samples in the original space. During the pseudo-online decoding, there was no adaptation mechanism; the covariances of the online band-pass filtered samples were classified directly without any incremental recentering.

E. Feature Distinctivness

The separability of generated feature spaces during BCI tasks is a key factor in acquiring the necessary skill for robust BCI control [20] [21] [22] . In this work, we analyze the evolution of Riemannian distinctiveness of covariance features used for online decoding across different sessions during unimanual and bimanual online tasks. Riemannian distinctiveness, inspired by the theory of Mahalanobis distance, is estimated as the ratio of the distance between the Riemannian means of feature distributions for different classes to the sum of the spreads of the feature distributions for individual classes. For a detailed description of Riemannian distinctiveness, refer to [13] and [20].

III. Results

A. Online MI-BCI Performance

Fig. 2 illustrates the evolution of sample-level online performance across different subjects during the unimanual and bimanual sessions. The mean performance (Cohen's Kappa) and standard deviation across these sessions were as follows: Unimanual 1 (0.3016 ± 0.1997), Unimanual 2 (0.4406 ± 0.2323), Bimanual 1 (0.2171 ± 0.1577), Bimanual 2 (0.2405 ± 0.1531), and Bimanual 3 (0.3686 ± 0.2015). Post-hoc statistical analysis using paired t-tests revealed a significant improvement in performance between the first and second unimanual sessions (p = 0.0005) and between the first and last bimanual sessions (p = 0.0042). A comparison between the unimanual and bimanual BCI settings showed a

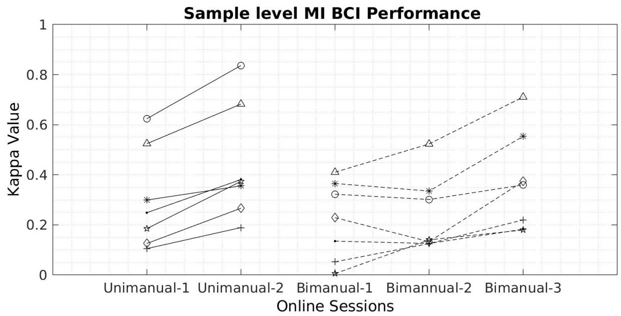

Fig. 2. **Bimanual BCI Control:** Session-level kappa value of MI classification performance for each session during unimanual and bimanual online sessions. Different markers represent individual subjects (n = 7) across the online sessions.

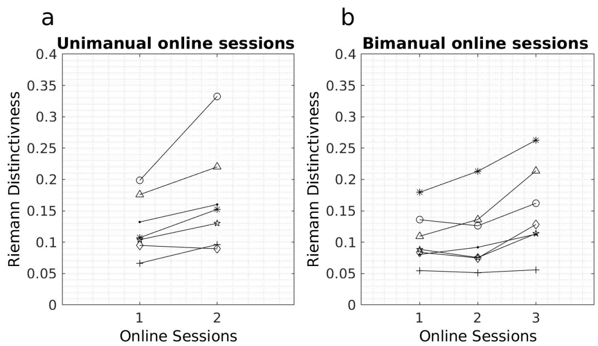

Fig. 3. **Feature Separability Analysis:** Session-level Riemannian distinctiveness illustrating the separability of feature spaces in (a) unimanual online sessions and (b) bimanual online sessions. Different markers represent individual subjects (n = 7) across the online sessions.

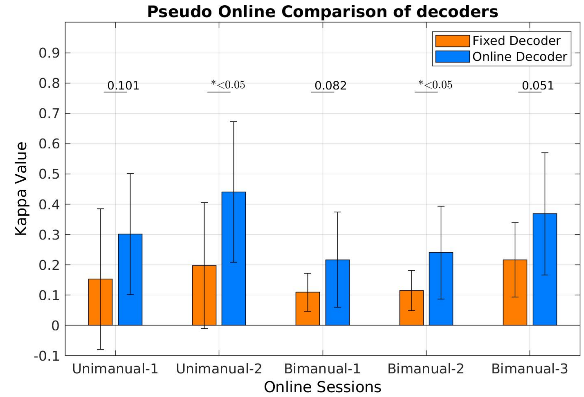

Fig. 4. **Pseudo Online Decoder Comparison:** Bar plot comparing different decoders across unimanual and bimanual online sessions. The bars represent the mean classification performance across subjects (n = 7) for each corresponding online session, with error bars indicating the standard deviation. The numbers above the bars show the p-values (paired t-test) for the comparison of kappa values between the fixed and used online decoders.

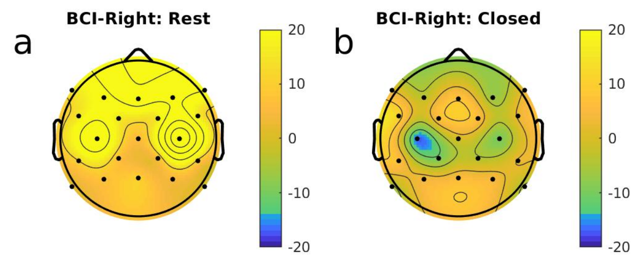

Fig. 5. **Event Related Desynchronisation During Unimanual Online Session:** Topographical analysis of the grand average event-related desynchronization (ERD) in the μ band [7, 13] Hz across all subjects (n = 7) and unimanual online sessions (n = 2) during (a) rest imagery and (b) right-hand flexion imagery.

significant decrease in performance when transitioning from unimanual to bimanual tasks (p = 0.0185). Notably, all seven subjects demonstrated an improvement in BCI classification performance in the final unimanual and bimanual sessions compared to their respective initial sessions.

B. Feature Distinctivness Analysis

Fig. 3 shows the evolution of Riemannian distinctiveness of the generated covariance features during the unimanual and bimanual online sessions. Similarly to the classification performance, we observe an improvement in the separability of the feature spaces during the unimanual online sessions, with distinctiveness values of Unimanual 1 (0.1256 ± 0.0468) and Unimanual 2 ($0.1688 \pm 0.0.0845$). A comparable trend is observed during the bimanual training sessions, where an increasing trend in feature distinctiveness is noted across the sessions: Bimanual 1 (0.1047 ± 0.0415), Bimanual 2 (0.1099 ± 0.0544), and Bimanual 3 (0.1500 ± 0.0695).

Post-hoc statistical testing reveals a a statistically significant improvement in feature distinctiveness from the first to the second unimanual online session (p = 0.0392). More importantly, subjects demonstrate a statistically significant improvement in feature distinctiveness from the start to the end of the bimanual online sessions (p = 0.0005).

C. Decoder Framework Comparison

Fig. 4 presents the pseudo-online comparison between a decoder without online incremental adaptation (Fixed decoder) and decoder with incremental adaptation (Used decoder). Across all online sessions, the decoder with incremental adaptation achieves higher mean classification accuracy across participants compared to the fixed decoder (Unimanual 1: Fixed - 0.1532 ± 0.2319, Online - 0.3017 ± 0.1997; Unimanual 2: Fixed - 0.1977 ± 0.2080, Online - 0.4407 ± 0.2323; Bimanual 1: Fixed - 0.1094 ± 0.0629, Online - 0.2172 ± 0.1577; Bimanual 2: Fixed - 0.1149 ± 0.0663, Online - 0.2406 ± 0.1531; Bimanual 3: Fixed - 0.2168 ± 0.1226, Online - 0.3687 ± 0.2016). Post-hoc paired t-tests between the two decoding frameworks did not reveal any statistically significant differences, except for the second unimanual ($p = 0.018$) and secondbimanual online session ($p = 0.015$).

IV. Discussion

Our findings demonstrate that a decoder trained on rest vs. flexion imagery for unimanual BCI control can be effectively transferred to a more realistic bimanual BCI setting, where subjects independently manipulate the other, functional hand.

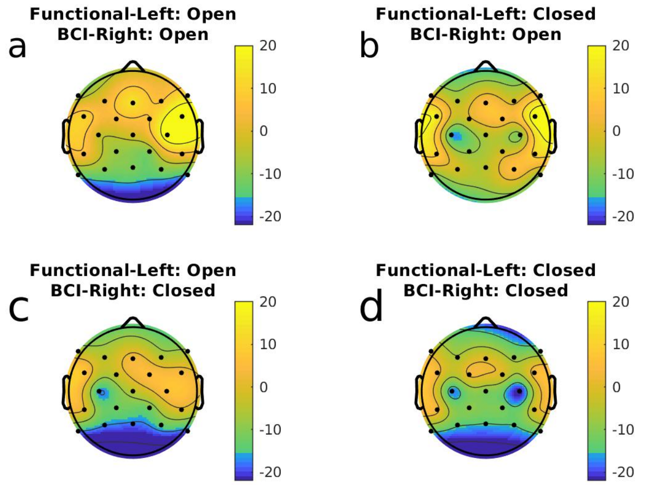

Fig. 6. **Event Related Desynchronisation During Bimanual Online Session:** Topographical analysis of the grand average event-related desynchronization (ERD) in the μ band [7, 13] Hz across all subjects (n = 7) during the bimanual online sessions (n = 3) for the following conditions: (a) functional left hand open with rest imagery, (b) functional left hand closed with rest imagery, (c) functional left hand open with right-hand flexion imagery, and (d) functional left hand closed with right-hand flexion imagery.

Notably, we observed that with training over multiple days, subjects improved their BCI control both in the BCI-only tasks and in the more complex simultaneous BCI tasks. Although an initial decrease in overall BCI performance was observed when transitioning to simultaneous control of the BCI and functional hand, performance steadily improved with continued multi-day training. Furthermore, our post-hoc pseudo-online analysis highlights the effectiveness of our online decoder adaptation framework. The decoder trained solely on unimanual BCI tasks without adaptation consistently showed lower mean classification performance across all online BCI sessions, highlighting the benefits of our adaptive approach.

Long-term validation of BCI systems is increasingly recognized as essential because of day-to-day neural variability—and the user's own learning curve in operating the BCI—can markedly alter performance. Demonstrating reliable operation across multiple days is therefore a prerequisite for translating BCIs into real-world, out-of-lab applications. Cheung et al. [9] demonstrated the feasibility of both unimanual BCI control (right-hand imagery) and simultaneous BCI control with overt movement (bimanual: right-hand imagery and joystick control with the left hand) over two separate days. Although their experimental protocol included only two online sessions, with both unimanual and bimanual tasks performed on the same day, they observed similar or reduced performance when transitioning from unimanual to bimanual settings (although on same day, unlike our protocol on different days) with slight improvement in performances on day-2 from day-1. On the other hand, our study demonstrates the reliability of a BCI system across five online sessions involving both unimanual and bimanual tasks over multiple days in a real-life functional task where subjects control an assistive exoskeleton using a BCI to operate one hand while simultaneously using their other hand.

Closed-loop decoder adaptation is essential for acquiring BCI skills and achieving improved control within a two-learner framework, where both the subject and the decoding model adapt in synchrony to optimize performance [8], [23]. This was evident in our study, where subjects not only demonstrated improved BCI performance (Fig. 2) but also generated a more discriminative feature space (Fig. 3) during BCI only tasks — a critical aspect highlighted in previous research for robust MI skill acquisition [3] [15] [13] [16].

Orsborn et al. [8] demonstrated that performing simultaneous motor tasks while controlling a BCI often leads to task interference due to overlapping cortical areas, resulting in decreased BCI performance. Additionally, studies using invasive BCIs [6], [8] have shown that training over multiple days can improve performance in tasks involving simultaneous motor activity and BCI control. Our findings corroborate these observations using non-invasive recordings: while BCI performance initially declines when transitioning from unimanual to bimanual settings, it recovers with training over multiple days. Notably, we observe not only an improvement in performance (Fig. 2) but also enhanced feature space discriminability over sessions (Fig. 3), suggesting that subjects learn to generate distinct neural patterns for different BCI tasks despite the presence of interfering activity.

The grand average visualization of desynchronization during unimanual tasks reveals event-related synchronization (ERS) during rest imagery (Fig. 5a) and bilateral desynchronization (Fig. 5b) over electrodes C3 and C4 during the imagination of right-hand movement. These findings are consistent with previous literature, which has reported ERS during resting or idling states [24] and bilateral desynchronization during MI tasks [25], [26].

In the bimanual tasks, we also observe synchronization during the "Functional Left: Rest, BCI Right: Rest" condition (Fig. 6 a), where both hands were at rest, and a more pronounced bilateral desynchronization during the "Functional Left: Closed, BCI Right: Closed" condition (Fig. 6 d). The synchronization observed during the resting conditions of both tasks can be attributed to ERS activity in the idle state. In contrast, the stronger bilateral desynchronization during the combined flexion imagery and functional hand closure (as compared to unilateral right hand MI) likely results from overlapping desynchronizations due to both the imagery of right-hand movement and the physical closing of the functional hand. Interestingly, during the "Functional Left: Open, BCI Right: Closed" condition, we observe contralateral desynchronization (Fig 6 c) with ipsilateral synchronization. Although this condition closely resembles the unimanual setting of "BCI Right: Closed" (Fig 5 b) the neural patterns display slight differences. Finally, in the "Functional Left: Closed, BCI Right: Open" condition, the grand average plots exhibit weak bilateral desynchronization (Fig. 6b). This pattern is likely driven by the widespread ERD elicited by closing the functional (left) hand, which counteracts the expected ERS associated with rest imagery of the BCI-controlled hand.

While our results demonstrate the efficacy of using adaptive decoders in closed-loop online feedback for enhancing BCI control during simultaneous functional tasks and MI, further validation with a larger population and extended training periods is needed to strengthen these findings. Additionally, we believe that the decoding model could be further optimized by fine-tuning with labeled data on bimanual tasks, similar to the PAR framework introduced in [13], as domain-specific training may enhance BCI performance. Future work should also focus on validating this protocol with people with disabilities, which is essential for extending the application of non-invasive BCI systems to real-world scenarios that involve simultaneous BCI control and functional tasks. Furthermore, integrating advanced machine learning techniques for adaptive decoding and tracking non-stationarities during dual-tasking, along with a deeper understanding of the neural mechanisms underlying dual-task learning, could help in enhancing BCI performance in complex, bimanual settings.

V. CONCLUSION

Our findings demonstrate that unimanual-trained BCIs can successfully transfer to bimanual tasks, with participants achieving better feature distinctiveness and decoding performance through multi-day training, despite initial performance drops during the unimanual-to-bimanual transition. Our analysis highlights the importance of longitudinal training for robust bimanual BCI control. Finally our study highlights the viability of transferring unimanual BCI decoders to bimanual tasks, paving the way for more natural and efficient assistive control that enhances real-world functional independence for individuals with motor impairments.

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