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# EEG2EMG-Net: A Deep Learning Framework for Continuous EEG-to-EMG Estimation for Real-World Applications

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ABSTRACT: Estimating muscle activity from invasive neural recordings has been researched for decades with encouraging results. Such brain-computer interfaces (BCIs) are promising, as they offer an alternative pathway for motor control in patients with spinal cord injury. However, this application remains largely unexplored with non-invasive techniques, such as electroencephalography (EEG). Current non-invasive approaches typically rely on within-subject training, requiring both input (EEG) and output (electromyography, EMG) signals for calibration. This strategy is impractical for paralyzed patients unable to produce the required EMG. To address this, we developed EEG2EMG-Net a deep learning framework for continuous EEG-to-EMG estimation tailored for real-world clinical use. Our approach introduces a subject-adaptation strategy using synthetic EMG templates, eliminating the need for patient-specific muscle recordings during calibration. Results from 20 healthy participants show that the fine-tuning method allows accurate estimation of the EMG (pearson correlation coefficient: $0.69 \pm 0.32$) while suppressing spurious activations during resting-state. These findings open new research avenues for non-invasive BCI alternatives aimed at assisting motor function in individuals with severe impairments.

## INTRODUCTION

Brain-computer interfaces (BCIs) hold significant potential in the field of neurorehabilitation. By decoding the kinetic and kinematic parameters of movements from neural activity, BCIs provide a pathway to re-establish functional motor control in individuals with paralyzed or weakened muscles. While a kinematic BCI decodes brain signals into control commands such as position or velocity [1], a kinetic BCI aims to estimate the muscle activation patterns that would result from voluntary motor intention [2]. This kinetic approach is particularly valuable as the predicted muscle activation can serve as an input to stimulate muscles through functional electrical stimulation (FES), yielding the desired movement.

The continuous estimation of muscle activity from neural recordings for neurorehabilitation applications has been researched in the BCI field for decades. This kinetic decoding has been primarily explored using invasive techniques, demonstrating that high-fidelity muscle activation patterns can be extracted from the primary motor area (M1) to reconstruct movements in non-human primates [3, 4] and patients with spinal cord injury (SCI) [2]. In addition, arm and finger electromyography (EMG) signals have been decoded using electrocorticographic (ECoG) signals in humans [5].

Electroencephalography (EEG) is an appealing recording technique, as its non-invasive nature avoids the inherent risks associated with the surgeries required for invasive recording. However, EEG signals are characterized by limited spatial resolution and a low signal-to-noise ratio (SNR) due to volume conduction. Accordingly, BCI aimed at predicting muscle activity for neurorehabilation applications have not been as extensively explored within the non-invasive domain as its invasive counterparts. Despite these challenges, EEG offers high temporal resolution, which is pivotal for capturing the fast, non-stationary dynamics of motor intent [6] and the corresponding muscle activation patterns. By leveraging a wide range of decoding strategies, from classical linear estimators to advanced signal processing and deep learning (DL) algorithms, EEG to EMG decoding is emerging as a compelling strategy for non-invasive neurorehabilitation devices.

In the literature, early works aimed at predicting muscle activity from various upper limb muscles relied on linear estimators, often fed by EEG spectral features. These linear estimators include multivariate linear regression [7, 8], sparse linear regression [7], Wiener filters [9] and generalized linear models [10]. These studies demonstrated the feasibility of decoding muscle activity in a continuous manner from non-invasive signals. However, the

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use of linear approaches prevented the estimators from capturing the complex and inherent non-linear association between EEG and EMG signals. Consequently, these models were vulnerable to outliers and struggled to decode complex movements. To address such limitations, recent studies have focused on non-linear methods, including the Unscented Kalman Filter [11] and various DL architectures [8, 12].These studies yielded superior performance over linear estimators, with the CNN-LSTM architecture in [12] standing out as the best EEG-based muscle activity estimator to date.

Despite these promising advances in non-invasive muscle activity decoding, several limitations limit their clinical translation for real-world neurorehabilitation. First, existing linear and non-linear estimators typically rely on a pure within-subject training strategy. This requires synchronous EEG and EMG data from the user to calibrate the model. However, in a clinical scenario, patients with SCI or paralysis are often unable to produce the necessary ground-truth EMG signals, making these calibration-dependent models impractical. Furthermore, several approaches rely on non-causal estimation by mapping concurrent EEG and EMG windows [12]. In practice, this introduces a significant algorithmic latency, as the system must process the entire window before generating an output. These accumulated delays prevent real-time execution, which is critical for the proper integration of sensory feedback and the overall efficacy of closed-loop BCI systems.

The aim of this exploratory study was to design and validate a DL-based muscle activity estimator that addresses a critical real-world constraint: the lack of ground-truth EMG signals in paralyzed patients. We developed a cross-subject model trained to estimate muscle activation patterns (EMG envelopes) using only EEG signals as input. To enhance performance, we introduce a novel fine-tuning strategy that adapts the pre-trained model to the individual's neural dynamics using synthetic EMG templates, thus eliminating the need for users to generate these signals. To the best of our knowledge, this is the first EEG-based BCI designed to operate exclusively on past neural information (i.e., causal), which makes real-time implementation feasible, while enabling accurate cross-subject muscle activity estimation with minimal and clinically realistic adaptation.

## MATERIALS AND METHODS

*Dataset and experimental protocol:* A total of 20 healthy participants (aged 25.5 ± 4.8 years, 12 males, 8 females) participated in this study. All gave informed consent prior to the experiment. Each participant completed a single session consisting of a five-minute eyes-open resting-state recording, followed by active ME trials. The recordings were performed using the "Cross recorder" application within the MEDUSA© ecosystem [13]. The active ME recordings comprised 10-s 60 trials, during which participants were required to actively extend their right wrist and return it to the neutral position within a random 1 to 2-second interval. To ensure synchronization, a rotation cue was employed, consisting of a rotating cross overlaid on a stationary reference. Participants were instructed to initiate the movement exactly when the rotating cross aligned with the stationary one.

EEG and EMG signals were recorded using an actiCHamp system (*Brain Products GmbH, Germany*) at a sampling rate of 500 Hz. EEG data were acquired from 60 active electrodes distributed across the scalp following the international 10-05 system, referenced to the amplifier's internal common reference. The ground electrode was placed at FPz. Simultaneously, EMG activity was recorded using two passive electrodes in a bipolar configuration, placed over the extensor digitorum muscle of the right forearm.

*Signal processing:* EEG signals were processed using a band-pass filter (0.1–60 Hz) and a 50 Hz notch filter. Afterwards, signals were re-referenced to the common average reference (CAR). In parallel, EMG signals were high-pass filtered above 20 Hz and full-wave rectified by taking the absolute value. The EMG envelopes were then extracted via a 4 Hz low-pass filter [14]. Then, both signals were downsampled to 100 Hz to reduce computational cost. To maintain synchronization, the group delay introduced by the filtering stages was calculated, revealing a relative shift of 11 samples (110 ms) of the EMG envelopes with respect to the EEG signals. This latency was compensated in the subsequent signal processing step. The continuous recordings were segmented into 2-s epochs. An automatic artifact rejection method based on signal statistics was applied, followed by a visual inspection. Finally, muscle activity epochs were baseline-corrected by subtracting the 2nd percentile of the amplitudes and normalized to the 90th percentile of the ME-related EMG envelopes [14].

*Training dataset construction:* To prepare the data for the model, the previously segmented 2-s epochs were subdivided using a sliding window approach. Specifically, each EEG epoch was divided into smaller input examples of $L$ ms, with a stride of 10 ms between consecutive windows. To ensure the causality of the prediction, each EEG window included only past and current neural dynamics ($\boldsymbol{X}[t-L,t]$). The corresponding target was defined as an EMG envelope window of $H$ ms ($\boldsymbol{Y}[t+p,t+p+H]$), where $p$ represents the physiological delay between the neural and muscle signals [15]. This procedure yielded a comprehensive dataset of input-target pairs that ensures causal, continuous decoding independent of trial structures. The parameters $L$, $p$ and $H$ were subsequently tuned to optimize the estimator's performance. Each input example was standardized using the z-score. This ensures that standardization only takes into account the statistics of the present and past samples.

*Deep learning-based estimator:* The architecture of our EMG estimator, EEG2EMG-Net, was based on EEG-Inception [16], optimized for continuous and causal muscle activity prediction. While retaining the multi-scale

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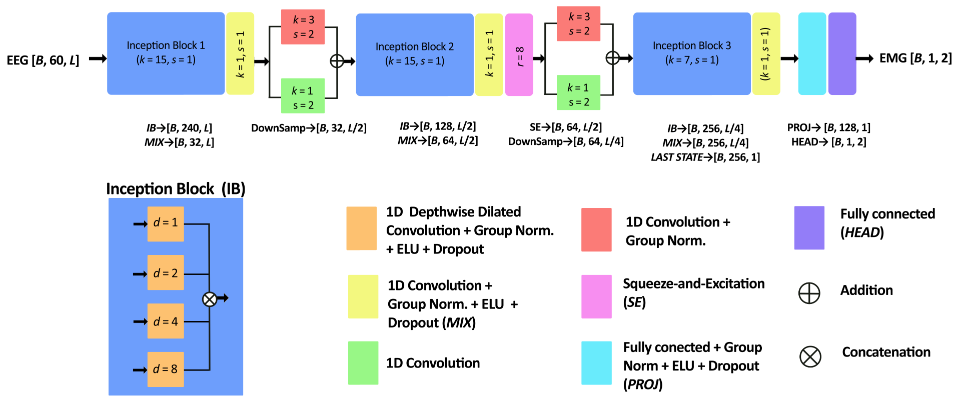


Figure 1: Overview of EEG2EMG-Net: Parameters $k, s, d$, and $r$ denote kernel size, stride, dilation, and the Squeeze-and-Excitation reduction ratio, respectively. Tensor dimensions are expressed as $[B, C, L]$ (Batch, Channels, Length).

spatio-temporal extraction capabilities of the original model, EEG2EMG-Net introduces several key structural modifications. First, strict causal padding was implemented before each Inception and downsampling blocks to ensure real-time compatibility. This restricts the receptive field to past samples and prevents future-data leakage during prediction. Second, we employed dilated convolutions with a fixed kernel size to achieve an exponentially larger receptive field and high temporal resolution without increasing the model parameters. Furthermore, temporal downsampling was performed via strided convolutions rather than fixed pooling layers, enabling the model to learn complex, data-driven strategies for information synthesis. Additionally, Squeeze-and-Excitation (SE) blocks and residual connections were integrated to enhance feature extraction and training stability. Finally, the output stage was redesigned to map the latent features onto a regression horizon of $H$ muscle activity samples. To achieve this, we extracted the last temporal step, referred to as the “Last State", from the final convolutional block. This operation collapses the temporal dimension by selecting the most recent feature vector, which encapsulates the cumulative receptive field of the causal network, before passing it through the projection and fully connected layers for the final estimation. A detailed overview of the EEG2EMG-Net architecture and its implementation parameters is provided in Figure 1.

*Hyperparameters optimization:* The hyperparameters $L$, $d$, and $H$ were optimized using a grid search within a five-fold cross-validation scheme. The search space for each parameter was defined as follows: $L \in \{200, 300, \ldots, 600\}$ ms; $p \in \{20, 30, \ldots, 50\}$ ms; and $H \in \{10, 30, \ldots, 200\}$ ms. To ensure that our model was cross-subject, the data split was performed at the subject level: all samples belonging to a single participant were assigned exclusively to either the training or the validation set in any given fold. Specifically, in each iteration, 80% of the subjects were used for training, while the remaining 20% were reserved for validation. The model was trained with a batch size of 128, a learning rate of 0.001, and a dropout rate of 0.25. We used the Mean Squared Error (MSE) between the real and the predicted muscle activity as loss function. Following the grid search, the optimal parameters for EMG decoding were identified as $L = 500$ ms, $p = 20$ ms, and $H = 20$ ms.

*Training procedure:* The training procedure comprised two sequential stages: a Leave-One-Subject-Out (LOSO) cross-validation to establish a subject-independent baseline, followed by a novel subject-adaptive phase. During each LOSO iteration, the model was trained using data from 19 subjects (15 for training and 4 for validation). The hyperparameters and loss function were kept identical to those described in the previous section. To prevent overfitting, an early stopping was performed if the validation loss failed to improve for 10 consecutive epochs.

Following the LOSO evaluation, we introduced a novel subject-adaptation process. While fine-tuning typically allows a pre-trained model to account for the inherent inter-subject variability of neural signals, its implementation in clinical settings is often limited by physiological constraints. In this sense, in a real-world clinical scenario, patients with SCI can generate motor intent EEG signals, but lack the ability to produce the corresponding ground truth EMG activity during ME attempts Consequently, these signals are typically unavailable for subject-specific estimator adaptation. To overcome this limitation, we simulated the missing muscle activity by generating synthetic EMG templates derived from the healthy cohort. Specifically, the corresponding EMG trials of the remaining 19 subjects were temporally aligned to compute a grand average and its standard deviation. During the fine-tuning phase, the real EMG targets of the test subject were substituted with these synthetic templates. To introduce natural physiological variability and prevent the model from collapsing to a single static prediction, random noise (scaled by the computed standard deviation) was added to the grand average. This synthetic dataset generation was applied exclusively to the training and validation sets used during fine-tuning. The adaptation process was evaluated using a five-fold cross-validation scheme, where the data were partitioned into 80% for training/validation and 20% for testing. This ap-

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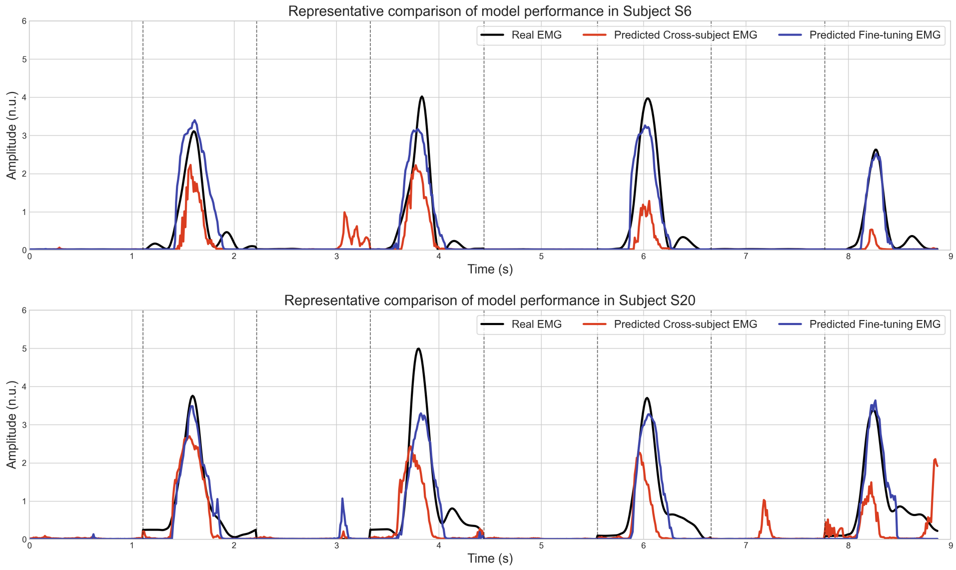


Figure 2: Representative EMG estimation examples for subjects S6 (top) and S20 (bottom). Temporal profiles show the real EMG envelope (black) compared against the estimations from the cross-subject model (red) and the subject-adaptive fine-tuned model (blue). Resting-state and motor execution epochs are delimited by vertical dashed lines.

proach ensures a comprehensive evaluation by allowing every trial to be utilized for both optimization and performance assessment. Importantly, as the input examples were generated using a highly overlapping sliding window, a standard random split would result in data leakage. Therefore, the data split was strictly performed at the event level (trial-wise), ensuring that all sliding windows originating from the same ME or resting-state event were grouped together in the same fold.

*Evaluation metrics:* To evaluate the estimator, condition-specific metrics were applied. During resting-state periods, performance was assessed using root mean squared error (RMSE) to identify spurious activations in the absence of motor intent. For the active ME condition, both Pearson correlation coefficient (PCC) and RMSE were employed. PCC enables to evaluate morphological fidelity while RMSE provides a complementary measure of magnitude accuracy relative to the real muscle contractions.

## RESULTS

Representative estimation examples under the different training conditions are shown in Figure 2. Note that the different reconstructed epochs (delimited by dashed vertical lines) are the result of concatenating the output of several consecutive EEG inputs. Furthermore, Figure 3 provides a comprehensive comparison of the estimator's performance across the cross-subject (red) and subject-adaptive (blue) modes. To evaluate the impact of the fine-tuning process, a paired one-tailed Wilcoxon signed-rank test was performed for each subject, with the False Discovery Rate controlled via the Benjamini-Hochberg (FDR-BH) procedure ($\alpha = 0.05$). Our analysis revealed that subject-adaptation significantly enhanced estimator performance across the entire cohort for all evaluated conditions. During ME trials, the fine-tuning process yielded a statistically significant improvement in both RMSE and PCC for all 20 subjects. Importantly, this enhancement extended to the resting-state condition, where RMSE values were also significantly reduced for every participant. Furthermore, this superior performance was consistently maintained in the group-level analysis. These performance metrics, averaged across trials and subjects, are summarized in Table 1.

Table 1: Muscle activity estimation performance across subjects and trials (mean $\pm$ standard deviation). Lower RMSE and higher PCC indicate better performance.

| Metric | Cross-subject | Fine-tuned |
|---|---|---|
| RMSE (Rest) | $0.138 \pm 0.185$ | $\mathbf{0.072 \pm 0.149}$ |
| RMSE (ME) | $1.108 \pm 0.345$ | $\mathbf{0.821 \pm 0.385}$ |
| PCC (ME) | $0.443 \pm 0.392$ | $\mathbf{0.694 \pm 0.324}$ |

## DISCUSSION

Our findings, aligned with previous research in the field [8, 11, 12], proved that EEG signals encode sufficient information to directly estimate muscle activity from cortical dynamics. Notably, the performance of the cross-subject estimation demonstrated the ability of DL-based estimators to capture generalized neural-to-motor mappings shared across individuals.

Regarding the proposed subject-adaptation, our results showed that the novel approach significantly enhanced estimator performance. Specifically, RMSE values significantly decreased in the 20 subjects. Low RMSE values in estimating resting-state muscle activity are key for clinical safety, as unintended stimulation in the absence

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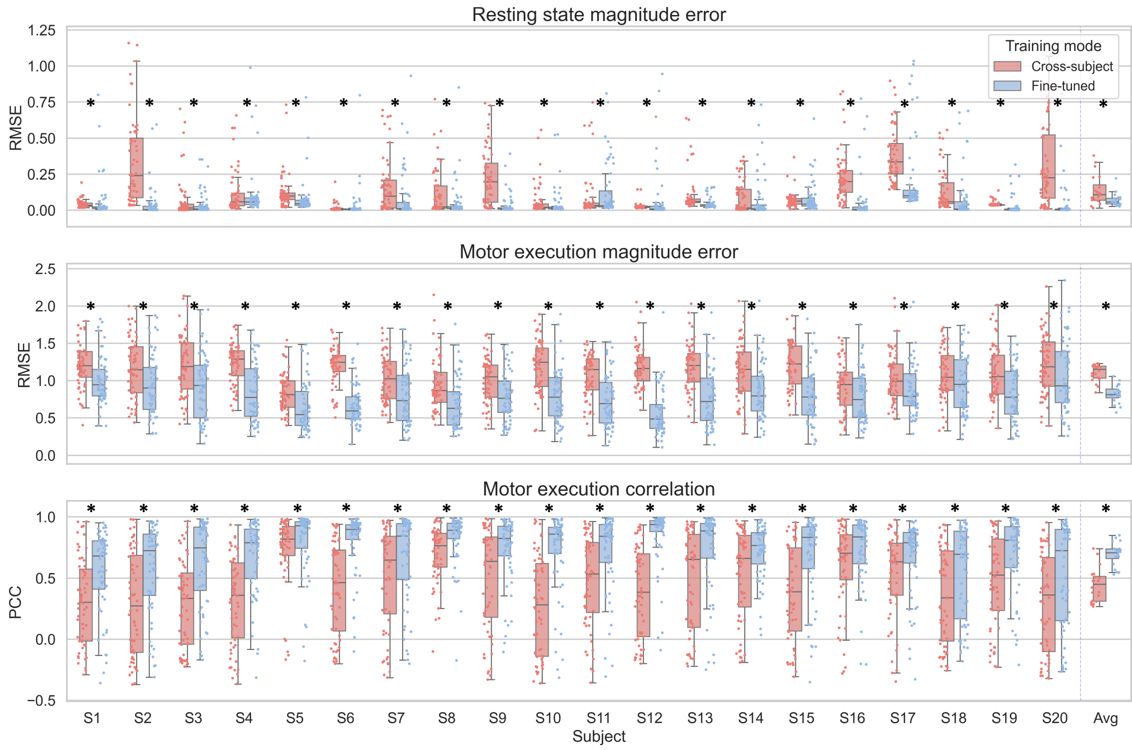


Figure 3: Performance comparison between cross-subject training and subject-adaptive fine-tuning. Distributions per subject are shown for resting-state RMSE (top), motor execution RMSE (middle), and Pearson Correlation Coefficient (PCC, bottom). The last column (AVG) presents the group-level performance averaged across all subjects. Boxplots indicate the median and interquartile range, with individual points representing single trials. Statistical significance between training modes was assessed per participant using a paired one-tailed Wilcoxon signed-rank test; asterisks denote significant differences after False Discovery Rate (FDR-BH) correction ($p < 0.05$).

of motor intent must be strictly avoided. Furthermore, despite the use of synthetic EMG templates instead of real muscle recordings, the fine-tuning process enabled the estimator to better capture the temporal coupling between neural motor intent and muscle activation. This was evidenced by a significant increase in PCC values during ME trials, indicating a better alignment between the ground truth and the estimated envelopes. However, despite yielding a significant reduction in RMSE during ME trials, the magnitude error after the fine-tuning process remained relatively high. This is a likely result of the fact that synthetic templates do not account for individual-specific EMG magnitudes. Thus, these RMSE results may reflect the intrinsic amplitude mismatch between the generalized templates and the participant's actual muscle activity.

When compared to state-of-the-art EMG estimators, our subject-adapted model achieved performance levels comparable to existing EMG estimators. For instance, Sburlea *et al.* (2021) [11] reported a median PCC of 0.20 across 33 grasp conditions, with a maximum of 0.35. Similarly, Amiri *et al.* (2025) [12] and Kumarasinghe *et al.* (2021) [10] achieved mean PCC values ranging from 0.50 to 0.65 across multiple muscle groups and one specific movement. However, it should be noted that, unlike previous studies, our results were obtained without relying on the participants' actual EMG signals. This highlights the potential of the proposed approach for clinical applications where ground-truth EMG is unavailable. Furthermore, to the best of our knowledge, no previous research has incorporated a resting-state condition in this context. We believe that accounting for the absence of motor intent from EEG signals is fundamental for ensuring safety and reliability in self-paced real-world applications.

Despite these promising results, we acknowledge several limitations in the present study. Due to the exploratory nature of this research, the current analysis was restricted to a single movement type and a single EMG channel. Consequently, future work should evaluate the proposed approach in more complex scenarios, such as multi-joint movements or high-density EMG recordings. Scaling this framework to multiple movements would represent a significant step toward practical motor control. Furthermore, while the proposed adaptation strategy was implemented using data from healthy participants, its application to clinical populations requires further validation. Although research indicates that patients with SCI engage similar motor cortical areas during motor attempts [17], it is also well-documented that post-injury cortical reorganization can alter these activation patterns [17]. Therefore, the real-world feasibility of our synthetic

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template-based adaptation must be tested with SCI patients to ensure the estimator remains robust despite the specific EEG patterns induced by the injury.

## CONCLUSION

To the best of our knowledge, this is the first study to explore the feasibility of an EEG-based muscle activity estimator specifically designed to adapt to real-world requirements. In this regard, we developed a causal and continuous DL model capable of estimating muscle activity without relying on a pure within-subject training strategy, as explored in previous studies. We found that while the cross-subject estimator achieved relatively good performance, it was significantly improved by following a novel subject-adaptation approach. By not relying on the real muscle activity of the testing subject, our fine-tuning approach could meet the requirements for use with SCI patients. These results pave the way for future BCI-based FES systems in neurorehabilitation.

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