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A Graph-Based Dynamical Characterization and Inference in Hybrid BCIs

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***Abstract*—The accurate characterization of the underlying dynamics of neural responses across various neuroimaging modalities is pivotal to enhancing the performance of hybrid brain-computer interfaces (hBCIs). While unimodal electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) neuroimaging modalities for motor imagery (MI) have been successfully decoded for BCI applications, to date, conventional feature extraction schemes have not yet provided satisfactory performance improvements. In this context, a paramount research question is whether the conventional EEG spectral features are sufficient to express the underlying MI neural dynamics fully, maximizing the synergy with fNIRS characteristics. In this study, we explore a graph-based feature extraction method that integrates the nonlinear dynamics of MI-based EEG responses and its contributions to hBCIs for amyotrophic lateral sclerosis patients (ALS) who need these systems for communication and control. Our results demonstrated that while there is a slight performance improvement using EEG nonlinear features, there is a substantial increase (~15%) in the contribution of EEG features to the total number of selected fused features indicating better synergy with fNIRS features at a multimodal level, when compared with the classical features. The extracted graph-based features can add a new informative dimension for an efficient integration with MI-based fNIRS responses.**

Keywords—Hybrid brain-computer interface (hBCI), multimodal data fusion, nonlinear dynamics, motor imagery (MI), graph-based feature extraction, recurrence quantification analysis (RQA)

I. Introduction

Improving the performance of brain-computer interface (BCI) systems is a challenging research problem. These innovative systems need to realize their unfulfilled promise of being a practical efficient neural-based means of communication that severely disabled patients and their caregivers can rely on. Electroencephalography (EEG)-based motor imagery (MI)-BCI systems that rely on the classification of μ (8–12 Hz) and β (13–25 Hz) frequency bands' sensorimotor oscillatory variations during MI tasks, suffer from relatively low performance and are highly dependent on individual discrepancies in the MI patterns. Particularly for patients suffering from motor impairments such as amyotrophic lateral sclerosis (ALS), potential disease-specific neural alterations affect these patients 'electrical responses which imposes additional challenges on extracting discriminative features from their EEG responses [1,2]. Hybrid MI-based BCI systems rely on combining complementary discriminative features form EEG and other portable neuroimaging modalities such as functional near-infrared spectroscopy (fNIRS) for performance improvement [3,4]. However, these systems rely on conventional spectral analysis methods to classify the sensorimotor rhythms dynamics modulated in EEG during MI tasks and combine those features to fNIRS features for performance improvement. Considering the high discriminative ability of fNIRS features and the promising results for unimodal fNIRS-based MI-BCIs for ALS patients [5], a research question is raised regarding the hybrid performance being dominated by fNIRS modality especially for these patients. Novel analysis methods are required to exploit the underlying neural dynamics embedded in complex EEG signals and decode MI neural responses fully, in a way that maximizes the synergy between EEG and fNIRS modalities and optimizes the performance in a hybrid BCI context. Recurrence quantification analysis (RQA) has been successfully applied as a powerful nonlinear analysis tool to measure the complexity of numerous biological signals, especially when traditional techniques fail [6–9]. Recent evidence from our group and others suggested that nonlinear RQA features are sensitive to transitions between motor tasks and rest in EEG which represents a new information dimension for MI-BCI performance improvement [10,11]. However, these features have not been yet evaluated for MI-based hBCIs for ALS patients, for whom these systems are originally designed. This study evaluates a multimodal graph-based data fusion framework to decode and represent MI neural responses for hybrid BCI performance improvement. The proposed framework relies on graph-based recurrence quantification analysis (RQA) features to characterize the nonlinear dynamics of MI and complement the conventional linear spectral EEG features and fNIRS features combined traditionally in MI-based hBCIs. Simultaneous EEG-fNIRS data were recorded from five participants with ALS while performing MI-Rest tasks. Graph-based RQA and complex network theory features were extracted to decode the nonlinear dynamics within the μ and β frequency bands. The graph-based nonlinear features were extracted from the recurrence plots (RPs) reconstructed from each μ- and β-filtered one-dimensional EEG time series measured at each channel and its adjacency matrix reinterpretation. Classical linear spectral features were extracted using the mean power spectral density over the corresponding frequency bands. The fNIRS response's temporal characteristics were captured using various features extracted from fNIRS HbO_2 and HbR. To overcome the challenge of high-dimensional multimodal feature vectors, the framework adopts a fused feature selection approach based on the least absolute shrinkage and selection operator (LASSO) to decode a discriminative holistic representation from the high dimensional multimodal features. Three types of EEG-fNIRS data fusion were evaluated to analyze the effect of characterizing the nonlinear dynamics on the performance of hybrid MI-BCI. The performance of the unimodal techniques was evaluated further for comparison through a 5-fold cross-validation procedure

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using a linear support vector machine (SVM). We hypothesize that the proposed graph-based dynamical characterization of MI EEG neural responses will increase the synergy between EEG and fNIRS MI responses towards an optimized inference performance in MI-based hBCIs for patients with ALS.

II. Methods

A. Data Acquisition, Participants, and Experimental Protocol

EEG and fNIRS signals were recorded simultaneously using a single cap mounted with both EEG electrodes and fNIRS optodes. EEG was recorded from 13 Ag/AgCl electrodes (i.e., channels) referenced to the left earlobe and amplified using a g.USBamp amplifier (g.tec medical engineering). The signals were digitized at 256 Hz and zero-phase bandpass filtered (1–45 Hz). The EEG channels covered the pre-motor (FC3, FC4), primary motor (C1, C3, Cz, C2, C4), sensorimotor (CP1, CP3, CP2, CP4), and parietal (P3, P4) areas of the brain according to the 10–5 system. An additional electrode was placed at FCz as the ground electrode. fNIRS data were recorded using NIRScout (NIRX Inc.), with two near-infrared light wavelengths (760 nm and 850 nm) to acquire HbR and HbO_2 responses. The signals were digitized at 15.6 Hz, and the optode montage was configured using 16 probes, 8 sources, and 8 detectors, with a separation distance of ~3 cm to maintain acceptable signal quality and sensing depth. The fNIRS probe layout resulted in 14 fNIRS channels covering the pre/frontal cortex in addition to the primary motor cortex. Data acquisition for EEG and fNIRS and the design of the MI paradigm were handled by BCI2000 software [12] and NIRStar software (NIRX Inc.).

Five ALS patients, with varying degrees of disability, assessed using the ALS functional rating scale-revised on a 48-point scale [13] attended two MI data recording sessions on separate days. The data recording was performed in the NeuralPC Lab, University of Rhode Island (URI) with Institutional Review Board (IRB) approval. Each session contained three runs separated by approximately 5 minutes of rest, and each run consisted of 40 trials of MI task or Rest (20 trials each) based on a visual on-screen queue. The MI task involved imagining the left- or right-hand movement, and each MI trial was followed by a Rest trial. Each trial lasted for 10 seconds. None of the participants had previous BCI experience. The first session was used to familiarize the subjects with the task and the second session was used for data analysis. Table I shows the patients' demographics information.

TABLE I.
Participant's Demographic Information

Participant No.	*Age*	*Sex*	*ALSFRS-R (max 48)*	*Disease Duration (years)*
ALS-1	29	M	0	4
ALS-2	55	M	4	11
ALS-3	67	M	7	2
ALS-4	69	F	23	11
ALS-5	52	M	22	3
Mean±SD	54.4±16.0	-	11.2±10.6	6.2±4.4

B. Data Preprocessing

Eye movement artifacts were removed from EEG data using the extended Infomax Independent Component Analysis (ICA) algorithm using the EEGLAB toolbox [14]. The artifact-free signal was then reconstructed after removing the predominant artifactual components identified by visual inspection. The data were then zero-phase bandpass filtered into the μ (8–12 Hz) and β (13–25 Hz) frequency bands for further analysis. EEG data were re-referenced offline using a common average reference (CAR). For fNIRS data, the modified Beer-Lambert Law was used to calculate changes in the concentrations of HbO_2 and HbR using recorded alterations in the reflected light attenuation [15]. fNIRS data were then band-pass filtered at 0.01-0.09 Hz to eliminate physiological noise caused by respiration (~0.3 Hz), cardiac activities (~1 Hz), and Mayer waves (~0.1 Hz). As fNIRS signal quality can be heavily compromised by poor coupling of optodes to the head, due to optical interference from dense and heavily pigmented hair, the quality of the signal was automatically evaluated through the signal-to-noise-ratio (SNR) of each channel using NIRScout. Further, an exclusion criterion was considered based on a correlation threshold between HbO_2 and HbR, indicating a high-level physiological motion artifact [16]. The data from both modalities (i.e., EEG and fNIRS) were segmented into 10-sec trials synchronized with the appearance of the visual stimulus cues (Rest/LMI/RMI). Individual MI trials that contained artifacts were automatically rejected based on subject-specific thresholds from both modalities. For MI vs. Rest classification, the trials were combined to form two sets with 60 trials for each condition of MI and Rest representing the two classes.

C. Data Analysis

1) Linear Data Analysis

For the classical linear EEG spectral features, the average power spectral density (PSD) was calculated using Welch's method from the filtered EEG signals giving PSD-μ and PSD-β extracted from each channel. This resulted in a total of 26 linear EEG spectral features extracted from each trial from all the 13 EEG channels from both frequency bands [17]. The characteristics of the MI hemodynamic response were captured using seven discriminative features extracted from each HbO_2 and HbR response, corresponding to MI and Rest trials [5]. This resulted in a total of 196 fNIRS features extracted from each trial from both HbO_2 and HbR (i.e., seven features were extracted from each fNIRS concentration change from each of the 14 channels). The features were extracted from several window sizes as follows: For EEG, [0-2], [0-5], and [0-10] sec post-stimulus windows were considered for each frequency band. For slower hemodynamic response in fNIRS, [0-5], [2-7], [4-9], and [0-10] sec post-stimulus windows were considered for both fNIRS concentration variations. The optimized response windows were then selected for each modality based on the global peak of a nested 5-fold cross-validation classification procedure as explained in section II.D.

2) Graph-based Recurrence Quantification Analysis and Complex Network Features

In order to approximate the nonlinear neural dynamics underlying the MI and Rest tasks within each μ and β frequency bands separately, the bandpass filtered one-dimensional EEG signal measured at each frequency band, each channel, and each 10-sec MI/Rest trial was projected to a multi-dimensional phase space based on Takens' theorem of time-delay embedding [18] using the following equation [19]:

$$X_k = \left(x_k, x_{k+\tau}, \ldots, x_{k+(m-1)\tau}\right) \quad (1)$$

where X_k is the reconstructed phase space vector based on the observation x_k of the bandpass filtered EEG time series $(x_1, x_2, \ldots, x_L)$, L is the number of samples in the EEG time series, τ is the time delay, and m is the embedding dimension. The time-delay parameter (τ) and the embedding dimension (m) were estimated using the average mutual information (AMI) and the false nearest neighbor (FNN) methods respectively [20]. The time delay τ and the embedding dimension m, were directly calculated for μ and β frequency bands using only the training set of each of the 5 cross-validation folds as explained in section II.D. The phase space reconstruction can be represented as an $N \times m$ trajectory matrix $X = (X_1, X_2, \ldots, X_N)^T$ where $N = L - (m-1)$ is the number of states in time, and L is the number of samples in the EEG time series. Next, the recurrence plots (RPs) were created to visualize and quantify the recurrence patterns of the m-dimensional phase space trajectory X corresponding to each trial within each frequency band in a 2-dimensional plot [20]. RPs were constructed by considering an ε-neighborhood of states in phase space as follows:

$$RP_{i,j}(\varepsilon) = \Theta\left(\varepsilon - \left\|X_i - X_j\right\|\right) \quad i,j = 1, \ldots, N \qquad (2)$$

where RP is the $N \times N$ recurrence plot, N is the number of states in time, Θ is the Heaviside function, ε is the recurrence threshold determining the size of the neighborhood in state space, $\|\blacksquare\|$ is the Euclidean norm, and X is the reconstructed phase space vector. The recurrence exists when $RP_{i,j}$=1, (i.e., when the state space vectors at time i and j are within the same ε-neighborhood). The choice of the ε-neighborhood threshold was based on previous studies' recommendation and should not exceed 10% of the maximum phase space diameter [18]. Therefore, the value of ε was optimized for each participant by choosing from four different thresholds, namely 3%, 5%, 7%, and 10% of the maximum phase space diameter, for each frequency band, based on the global peak of a nested 5-fold cross-validation classification procedure as explained in section II.D. Features characterizing the recurrence patterns in each trial were extracted using graph-based RQA and complex network representations of the recurrence plots were reconstructed from each one-dimensional EEG time series measured at each channel. As it is common to find small distances between points in the reconstructed phase space that are close in time, the Theiler window in this study was set to a value of $(m-1)\tau$ so that only points that are farther than $(m-1)\tau$ from the diagonal were taken into account in the evaluation of the RQA measures [21]. The recurrence patterns were quantified using the vertical and diagonal line structures of the *RPs* using the nonlinear RQA features. twelve RQA features were extracted , namely, recurrence rate (*RR*), determinism (*DET*), the mean length of a diagonal line (*LMEAN*), the maximum length of a diagonal line (*LMAX*), the maximum vertical length (*VMAX*), the trapping time (*TT*), the laminarity (*LAM*), the entropy of diagonal line length distribution (*ENTR*), the entropy of vertical line length distribution (*ENTRV*), the recurrence time entropy (*RTE*), and the recurrence times of first type (*RT1*) and second type (*RT2*) [18,22,23]. In addition, two features from complex network theory, namely the global clustering coefficient (*CC)* and transitivity (*T*), were extracted from the adjacency matrix reinterpretation of the RP to include the topological characteristics of the recurrence patterns [24]. The features were extracted from the *RP* corresponding with μ and β frequency bands separately. This resulted in a total of 364 nonlinear graph-based RQA and complex network features extracted from each EEG trial from both μ and β frequency bands (i.e., 14 features were extracted from 2 frequency bands from each of the 13 channels) to quantify the nonlinear dynamics underlying the MI-Rest tasks. All RQA related computations were performed using custom MATLAB (R2016b) code adapted from the CRP Toolbox [23]. The features were extracted from several window sizes, similar to linear EEG features, and the optimized response window was selected within each frequency band based on the global peak of a nested 5-fold cross-validation classification procedure as explained in section II.D.

D. Data Analysis Multimodal Feature Fusion and Classification Procedure

Three types of EEG-fNIRS data fusion were evaluated; namely, EEG (linear)-fNIRS, EEG (nonlinear)-fNIRS, and EEG (linear+nonlinear)-fNIRS. For comparison, the performance of each of the three types of extracted features, i.e., EEG (linear), EEG (nonlinear) and fNIRS, were individually evaluated. Linear SVM was used to evaluate performance for each subject using a nested 5-fold cross-validation procedure to avoid biased estimation of the generalization error. Hyper-parameter optimization was performed independently for each of the 5 outer-folds based on the global peak of the nested 5-fold cross-validation procedure (i.e., inner-folds) within each of the 5 outer-folds. The nonlinear RQA parameters as well as the classification parameters were estimated and simultaneously optimized using only the training set of each of the outer-folds within the nested 5-fold cross-validation procedure. As the MI response dynamics vary across modalities (EEG/fNIRS), feature types (linear/nonlinear), frequency bands for EEG (μ/β), and fNIRS signal types (HbO_2/HbR) for fNIRS, the response windows were optimized independently for EEG (linear), EEG (nonlinear) and fNIRS features for both the unimodal and hybrid classification procedures. Features were extracted from various post stimulus windows as previously explained in section II C within each modality then concatenated to constitute a single unimodal (i.e., EEG (linear)/EEG (nonlinear)/fNIRS) or multimodal (i.e., EEG (linear)-fNIRS/EEG (nonlinear)-fNIRS/EEG (linear+nonlinear)-fNIRS) feature vector. The constructed feature vectors combine all extracted features from all the channels and all the combined response windows within the same modality for unimodal classification and across modalities for hybrid classification respectively. All the possible combinations of response windows were considered in the hyper-parameter optimization. For EEG (linear)-fNIRS, 24 possible response window combinations were considered (i.e., 6 EEG response windows × 4 fNIRS response windows = 24 multimodal response windows). For EEG (nonlinear)-fNIRS and EEG (linear+nonlinear)-fNIRS, the value of ε for the nonlinear analysis was considered for optimization simultaneously with the response window resulting in 384 possible multimodal feature vectors corresponding to all possible combinations of parameters (i.e., 6 EEG response windows × 4 fNIRS response windows × 16 possible combinations of ε-neighborhood threshold for μ and β frequency bands). In addition, due to the high dimensionality of the constructed feature vectors, we adopted the LASSO feature selection scheme for its proven performance efficiency for MI-BCIs especially for relatively small datasets [25]. Therefore, an optimized fused multimodal EEG-fNIRS representation of the MI response was selected to decode the discriminative oscillatory and/or nonlinear dynamics from EEG along with

TABLE II.
AVERAGED 5-FOLD CROSS-VALIDATION ACCURACY FOR OPTIMIZED UNIMODAL CLASSIFICATION PERFORMANCE AND MEDIAN OF THE OPTIMIZED NUMBER OF SELECTED FEATURES ACROSS FOLDS

Participant No.	*fNIRS*	*Optimized #features (median)*	*EEG (Linear)*	*Optimized #features (median)*	*EEG (Nonlinear)*	*Optimized#features (median)*
ALS-1	84.6	9	53.8	17	60.0	17
ALS-2	92.3	15	95.4	11	96.9	21
ALS-3	98.6	7	85.7	13	85.7	17
ALS-4	97.5	5	71.3	11	66.3	13
ALS-5	95.3	13	90.6	15	89.4	9
Mean±SD	93.7±5.6	9.8±4.1	79.4±16.9	13.4±2.6	79.7±15.8	15.4±4.6

the temporal characteristic of the hemodynamic response from fNIRS for hybrid classification. Similarly, for unimodal classification, the discriminative features were selected using LASSO from the constructed unimodal feature vectors to optimize the selected features within each unimodal technique. The hyper parameters (i.e., response window, number of selected features optimized in a range from 5 features to 23 features in steps of 2, and nonlinear analysis parameters if applicable) were optimized based on the global peak of the nested 5-fold cross-validation procedure for both the unimodal and hybrid classification. Finally, the optimized classification results for each subject were averaged over all the 5 outer cross-validation folds and reported for all types of unimodal and hybrid classifications.

III. RESULTS

Table II shows the optimized classification performance for each subject, comparing the fNIRS, EEG (linear), and EEG (nonlinear) unimodal classification illustrating the averaged 5-fold classification accuracy (outer-folds) for optimized unimodal classification performance and the median of the optimized number of selected features across folds for all feature types. The reported results are based on the optimized classification parameters for each fold (i.e., the response window, the number of selected features and the nonlinear RQA parameters if any) related to each subject's MI neural response in each modality. As shown in Table II, the obtained average accuracies were 93.7%±5.6%, 79.4%±16.9%, and 79.7%±15.8% using fNIRS, EEG (linear) and EEG (nonlinear) features respectively. Overall, the classification outcomes show that the performance of fNIRS features is superior in discriminating the MI neural response when compared to EEG (linear/nonlinear) features with ~14% average performance improvement over both EEG (linear) and EEG (nonlinear) features. This highlights the important role of discriminative fNIRS features in classification accuracy and MI neural characterization. On average, the classification performance of EEG (nonlinear) features did not improve the classification performance over classical EEG (linear) features for ALS patients, however, it did not degrade the performance either. . For ALS-1, and ALS-2, EEG (nonlinear) improved the classification accuracy by ~6% and 2% respectively when compared to EEG (linear) features while for ALS-3 and ALS-5 there was no major difference, and for ALS-4, EEG (nonlinear) decreased the performance. This indicates that the nonlinear features encompass discriminative information complementary to the classical EEG (linear) features and might complement the fNIRS features in a synergistic complementary representation of MI responses in a hybrid BCI framework. Table III shows the optimized hybrid multimodal classification performance for each subject, comparing the EEG (linear)-fNIRS, EEG (nonlinear)-fNIRS, and EEG (linear+nonlinear)-fNIRS types of hybrid classification. This table illustrates the averaged 5-fold classification accuracy (outer-folds) for optimized multimodal classification performance related to each subject's MI neural response in each type of fusion and the median of the optimized number of selected features across folds for all feature types.. As shown in Table III, the obtained average accuracies were 93.9%±5.9%, 95.3%±6.9%, and 93.8%±5.0% using EEG (linear)-fNIRS, EEG (nonlinear)-fNIRS and EEG (linear+nonlinear)-fNIRS fused features respectively. Although the discrepancies between the multimodal performances were marginal, these results support the main hypothesis of this study and highlight the importance of decoding a holistic electrical-vascular MI neural response representation to achieve the maximum performance in a hBCI framework. Overall, the classification outcomes show that the hybrid EEG-fNIRS multimodal classification performs better than the unimodal EEG classification. Fusing linear EEG features to fNIRS features improved performance by ~15% over linear EEG alone, however, it did not improve the classification performance over fNIRS. This highlights the effect of potential disease-specific abnormalities that affect ALS patient's electrophysiological responses and emphasizes on the importance of fNIRS in characterizing MI hemodynamic response for an improved MI-BCI for this group of patients. This was particularly evident in the percentage of contribution of EEG features to the total number of selected fused features in EEG (linear)-fNIRS fusion

TABLE III.
AVERAGED 5-FOLD CROSS-VALIDATION ACCURACY FOR OPTIMIZED MULTIMODAL EEG-FNIRS FUSION CLASSIFICATION PERFORMANCE AND MEDIAN OF THE OPTIMIZED NUMBER OF SELECTED FEATURES ACROSS FOLDS

Participant No.	*EEG (linear)-fNIRS Fusion*	*Optimized #features (median)*	*%of EEG (linear) features*	*EEG (nonlinear)-fNIRS Fusion*	*Optimized #features (median)*	*%of EEG (nonlinear) features*	*EEG (linear + nonlinear)-fNIRS Fusion*	*Optimized #features (median)*	*%of EEG features*
ALS-1	84.6	11	0.0	83.1	17	17.0	86.2	13	13.4
ALS-2	92.3	9	48.9	96.9	15	70.4	92.3	17	70.8
ALS-3	98.6	13	46.3	100.0	15	58.1	94.3	13	61.3
ALS-4	98.8	13	10.8	98.8	15	30.7	97.5	17	32.5
ALS-5	95.3	11	49.5	97.6	11	55.5	98.8	11	59.8
Mean±SD	93.9±5.9	11.4±1.7	31.1±23.8	95.3±6.9	14.6±2.2	46.3±21.8	93.8±5.0	14.2±2.7	47.6±23.8

(31.1%) which reflects how fNIRS is relatively dominating the fused representation of MI response when using conventional linear spectral features. Interestingly, fusing the nonlinear EEG features to fNIRS improved the performance by ~16% over nonlinear EEG features alone and ~2% over fNIRS features. This performance improvement was accompanied by a substantial increase in the percentage of contribution of nonlinear EEG features (46.3%) to the total number of selected fused features resulting in ~15% increase of EEG features in EEG (nonlinear)-fNIRS fusion when compared to the percentage of contribution of EEG features in EEG (linear)-fNIRS fusion (31.1%). This suggests that these graph-based features are contributing towards discriminative synergistic EEG-fNIRS representation of MI response when the nonlinear dynamics of MI are considered. This highlights the importance of decoding the graph-based EEG features to complement the fNIRS features for improved performance of MI-based hBCIs. Considering the fusion of linear EEG, nonlinear EEG and fNIRS, the classification accuracy did not improve over EEG (linear)-fNIRS and EEG (nonlinear)-fNIRS. This suggests that adding EEG (linear) features did not add discriminative information to EEG (nonlinear) features for this group of patients and further highlights the importance of characterizing the nonlinear dynamics for ALS patients for potentially enriching the information dimension extracted from their EEG signals and compensating the overall observed reduction in their oscillatory responses during MI.

IV. Conclusion

This paper suggest that graph-based nonlinear RQA and complex network features represent a valuable information dimension that increases the synergy and complementarity between EEG and fNIRS for performance improvement in MI-based hBCIs for ALS patients. The performance evaluation of hybrid EEG (nonlinear)-fNIRS MI-BCI revealed an average performance improvement of ~16% and ~2% over unimodal EEG and fNIRS features respectively. The proposed features increased the hybrid performance of ~1% over the conventional EEG-fNIRS hybrid classification relying on spectral EEG features. However, this improvement was accompanied by a substantial increase in the percentage of contribution of EEG features to the total amount of selected fused features (~15%) which highlights the importance of characterizing the nonlinear dynamics of the MI neural response in EEG, and suggest that nonlinear graph-based and fNIRS features are valuable information dimensions that can be exploited to improve hybrid MI-BCI performance.

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