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Optimizing Low-Frequency Common Spatial Pattern Features for Multi-Class Classification of Hand Movement Directions

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Abstract— **Recent studies have demonstrated that hand movement directions can be decoded from low-frequency electroencephalographic (EEG) signals. This paper proposes a novel framework that can optimally select dyadic filter bank common spatial pattern (CSP) features in low-frequency band (0-8 Hz) for multi-class classification of four orthogonal hand movement directions. The proposed framework encompasses EEG signal enhancement, dyadic filter bank CSP feature extraction, fuzzy mutual information (FMI)-based feature selection, and one-versus-rest Fisher's linear discriminant analysis. Experimental results on data collected from seven human subjects show that (1) signal enhancement can boost accuracy by at least 4%; (2) low-frequency band (0-8 Hz) can adequately and effectively discriminate hand movement directions; and (3) dyadic filter bank CSP feature extraction and FMI-based feature selection are indispensable for analyzing hand movement directions, increasing accuracy by 6.06%, from 60.02% to 66.08%.**

I. Introduction

Advances in neuroscience and engineering have made it possible for the human brain to directly communicate and control an external device [1]. The brain-computer interface (BCI) monitors electrical brain activity, detects and processes brainwave patterns generated by the user, and translates the patterns into control commands, without using any peripheral nerves or muscles. Such an interfacing system can aid individuals with physical disabilities, improving their quality of life and lowering social costs [2].

Most BCI systems use electroencephalogram due to its portability, inexpensive, and non-invasive nature. Since each human body part can be represented in a specific somatosensory cortical area [3], electroencephalographic (EEG) signals are usually acquired and analyzed during real or imagined movements of right hand, left hand, foot, and tongue, each corresponding to one control command. Although it is convenient to employ EEG signals of various body parts, the number of separable classes or control commands can be limited. It also seems unnatural and not intuitive to imagine different limb movements for controlling kinematics (e.g., direction and speed) of one limb.

Recent studies have shed light on classifying or decoding hand movement directions from EEG signals [4-9]. Low-frequency band (≤ 7 Hz) was strikingly found to be more efficient in decoding movement directions and limb trajectories than beta band (10-30 Hz) and high-gamma band (62-87 Hz) [5,6]. Waldert *et al.* [5] decoded joystick movements in a four-target center-out paradigm and reported an accuracy of 55%. Demandt *et al.* [7] conducted four center-in arm reaching tasks and observed slightly above-chance decoding accuracy for center-in and center-out paradigm separately. Clauzel *et al.* [8] examined joystick movements in orthogonal and diagonal directions, and obtained an average binary classification accuracy of roughly 71%. This accuracy (≈ 71%) was also reported by Robinson *et al.* [9] after using a regularized wavelet common spatial pattern (CSP) to distinguish one orthogonal direction from another direction. This paper proposes a novel framework that can optimally select dyadic filter bank CSP features in low-frequency EEG band (0-8 Hz) for multi-class classification of four orthogonal hand movement directions. In doing so, we hope to improve the accuracy of classifying multiple hand movement directions, thereby providing more control commands and enhancing the naturalness and intuitiveness of brain-computer interaction.

This paper is organized as follows. Section II systematically describes the proposed framework, which includes EEG signal enhancement, dyadic filter bank CSP feature extraction, fuzzy mutual information-based feature selection, and one-versus-rest Fisher's linear discriminant analysis. Section III presents the multi-class classification results of this study and several comparison tests, followed by a discussion with concluding remarks in Section IV. All analysis was performed via MATLAB (version 2011b) unless otherwise stated.

II. Methods

A. Data Acquisition

EEG and electrooculographic (EOG) signals were acquired from seven healthy right-handed male subjects at the Institute for Infocomm Research, Singapore, using a 128-channel amplifier (Neuroscan SynAmps) sampling at 250 Hz. To ensure precise hand position during data acquisition, a MIT-MANUS robot [10] was adopted. Target cues and feedback were also provided on a computer screen, as exemplified in Fig. 1 for the 'east' or 'right' hand movement. At the end of each rest period, a target cue, which was symbolized by a circle located in any of the four orthogonal directions (north, south, east, and west, or equivalently, up, down, right, and left), was displayed. This cue allowed the subject to prepare and execute his/her hand movement immediately the center circle disappeared. After the

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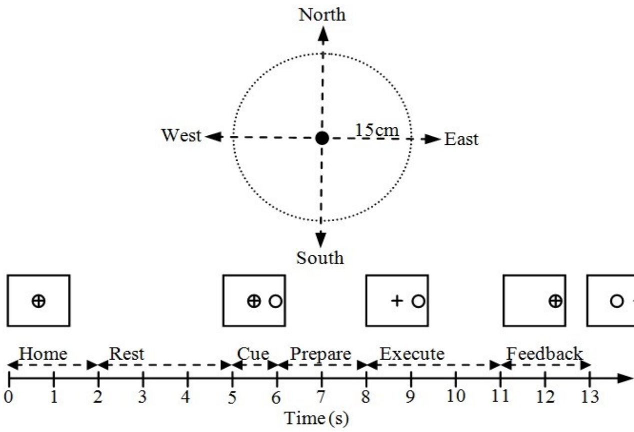

Figure 1. Experimental protocol and timeline

execution, a cross appeared at the target, which served as a feedback to the subject. A successful trial was indicated by reappearance of the center circle. The display then returned to home screen, and this cycle was repeated. Each subject underwent two sessions of 50 cycles each. Each cycle consisted of four orthogonal directions presented in a randomized order. Upon data acquisition, signals from 34 EEG channels, covering the frontal, central, parietal, and occipital regions, as well as two EOG channels were studied.

B. Electroencephalographic Signal Enhancement

To improve the quality of the acquired EEG signals, we eliminated three environmental and biological artifacts embedded in the signals. Firstly, power-line interference at 50 Hz was reduced using a 2nd-order infinite impulse response notch filter. Next, eye movements and blinks were minimized through Infomax independent component analysis [11], which maximizes the joint entropy of EEG and EOG signals while lowering their statistical dependence. A stopping weight change of 10^{-8} was set in the analysis for better output signals. Lastly, electromyographic (EMG) activity during hand motion was suppressed using a surface Laplacian spatial filter [12]. The filter, which amplifies localized EEG activity and dampens diffused EMG activity, was estimated by a finite-difference method that subtracts the mean activity of neighboring electrodes from the electrode of interest [12].

C. Common Spatial Pattern Feature Extraction

Upon signal enhancement, we segmented the lengthy signals into two-second segments, each containing information on the last one second of preparation and the first one second of execution, giving over a hundred single-trials for each subject. For each single-trial, the enhanced signal was downsampled to 128 Hz in order to reduce the computation cost and then decomposed using causal digital filters, namely Butterworth (4th-order, zero-phase lag) and Chebyshev Type II (passband ripple 3dB, stopband attenuation 20dB) that are extensively utilized in BCI [5,7,8,13]. We configured the Butterworth and Chebyshev filter banks in a dyadic manner such that dL1 = 32-64 Hz, dL2 = 16-32 Hz, dL3 = 8-16 Hz, dL4 = 4-8 Hz, dL5 = 2-4 Hz, dL6 = 1-2 Hz, and dL7 = 0-1 Hz. In comparison to the wavelet filtering technique used in [9], the present technique processes faster, which favors real-time implementation.

Subsequently, the subband filtered signals were spatially filtered using CSP algorithm [14], which augments the difference between variances of two classes with respect to the brain topographic mapping. The spatial filtered signal of ith trial in bth subband is $\mathbf{Z}_{b,i} = \mathbf{W}_b^T \mathbf{E}_{b,i} \in \Re^{c \times u}$, where $\mathbf{W}_b$ is the transformation matrix, $\mathbf{E}_{b,i}$ is the subband filtered signal, c is the number of channels, u is the number of samples per channel, and T is the transpose operator. The transformation matrix is obtained by solving the eigenvalue decomposition problem

$$\mathbf{C}_{b,1}\mathbf{W}_b = (\mathbf{C}_{b,1} + \mathbf{C}_{b,2})\mathbf{W}_b\mathbf{D}_b\,, \tag{1}$$

where $\mathbf{C}_{b,1}$ and $\mathbf{C}_{b,2}$ are the covariance matrices of two classes of hand movement directions, and $\mathbf{D}_b$ is the diagonal matrix containing $\mathbf{C}_{b,1}$ eigenvalues. Next, m pairs of CSP features of ith trial in bth subband are given by

$$\mathbf{v}_{b,i} = \log\left(\mathrm{diag}\left(\widetilde{\mathbf{W}}_b^T \mathbf{E}_{b,i}\mathbf{E}_{b,i}^T \widetilde{\mathbf{W}}_b\right) \Big/ \mathrm{tr}\left[\widetilde{\mathbf{W}}_b^T \mathbf{E}_{b,i}\mathbf{E}_{b,i}^T \widetilde{\mathbf{W}}_b\right]\right), \tag{2}$$

where $\mathbf{v}_{b,i} \in \Re^{1\times 2m}$, $\widetilde{\mathbf{W}}_b$ denotes the first m and last m columns of $\mathbf{W}_b$. In this study, we chose a typical value of m = 3 because, if m is too small, the classifier may fail to fully capture the discrimination of two classes; conversely, if m is too big, the classifier may overfit the training data, lessening its predictive accuracy [15]. Accordingly, the dyadic filter bank CSP feature vector for low-frequency band of ith trial is constructed by

$$\mathbf{v}_{0-8\mathrm{Hz},i} = \left[\mathbf{v}_{\mathrm{dL4},i}, \mathbf{v}_{\mathrm{dL5},i}, \mathbf{v}_{\mathrm{dL6},i}, \mathbf{v}_{\mathrm{dL7},i}\right] \in \Re^{1\times 4*2*3}. \tag{3}$$

CSP feature vectors for wider frequency bands (0-16 Hz, 0-32, and 0-64 Hz) were also formed to verify the sufficiency and effectiveness of low-frequency band in classifying hand movement directions.

D. Fuzzy Mutual Information-based Feature Selection

To alleviate the curse of dimensionality and optimize class separability, we discarded irrelevant and redundant CSP features from the estimation of intrinsic relation between EEG attributes and control commands using fuzzy mutual information (FMI) between each CSP feature f and class label L across all n training trials,

$$I(f;L) = H(f) + H(L) - H(f,L), \tag{4}$$

where $$H(f) = -\sum_{l=1}^{2}\left(\left(\sum_k \mu_{l,k}/n\right)\log\left(\sum_k \mu_{l,k}/n\right)\right) \tag{5}$$

is the marginal entropy of each feature,

$$H(L) = -\sum_{l=1}^{2}(n_l/n)\log(n_l/n) \tag{6}$$

is the marginal class entropy, n_l is the number of training trials belonging to lth class, and

$$H(f,L) = -\sum_{l=1}^{2}\left(\left(\sum_{k\in A_l}\mu_{l,k} \Big/ n\right)\log\left(\sum_{k\in A_l}\mu_{l,k} \Big/ n\right)\right) \tag{7}$$

is the joint fuzzy entropy satisfying the De Luca-Termini axioms [16,17], and A_l is the set of training trials belonging to lth class.

$$\mu_{l,k} = \left(\left\|\tilde{\mathbf{y}}_l - \mathbf{y}_k\right\|_\sigma \Big/ \left(\max\left\|\tilde{\mathbf{y}}_l - \mathbf{y}_k\right\|_\sigma + \varepsilon\right)\right)^{-2/(\lambda-1)} \tag{8}$$

is the fuzzy membership of kth trial vector in lth class, with a fuzzification parameter λ = 2, ε = 2.22×10^{-16} to avoid singularity, and a standard deviation σ for calculating Euclidean distance between the mean of training trials belonging to lth class and the training trials in kth vector.

We sorted CSP features in descending order of FMI and removed the last r features that have less discriminatory power, retaining useful CSP features for robust classification. Hence, CSP feature vector for low-frequency band of ith trial is reduced to $\mathbf{v}_{0-8\text{Hz},\text{FMI},i} \in \Re^{1\times(4*2*3-r)}$.

E. One-versus-rest Fisher's Linear Discriminant Analysis

As this study involves classifying four orthogonal hand movement directions (right, left, up, and down), we modeled four binary Fisher's linear disciminant (FLD) classifiers, each separating one class from the rest of the classes [18]. Each binary classifier possesses a functional form $g(\mathbf{x}_i) = \mathbf{w}^T\mathbf{x}_i + \sigma$ where $\mathbf{x}_i$ is the ith training trial with selected CSP features. $\mathbf{w} = \mathbf{S}^{-1}(\tilde{\tau}_1 - \tilde{\tau}_2)$ is the weights, and $\sigma = 0.5(\tilde{\tau}_1 + \tilde{\tau}_2)\,\mathbf{S}^{-1}(\tilde{\tau}_1 - \tilde{\tau}_2)$ is the threshold, which together depict the position and orientation of the decision surface from the origin. $\tilde{\tau}_1$ and $\tilde{\tau}_2$ are the mean of the training trials belonging to lth class, whereas

$$\tilde{\mathbf{S}} = \frac{1}{n_1 + n_2}\sum_{l=1}^{2}\sum_{j\in A_l}\left(\mathbf{x}_j - \tilde{\tau}_l\right)\left(\mathbf{x}_j - \tilde{\tau}_l\right)^T \tag{9}$$

is the within-class covariance matrix [19]. Given four FLD binary classifiers, the final classification was executed by assigning $\mathbf{x}_i$ to the classifier with the highest confidence. To better appraise the performance of the FLD classifiers for multi-class classification, we conducted five consecutive times of five-fold cross-validation and noted the average accuracy value.

III. Results

Based on our dataset of seven subjects, Table I summaries the average multi-class classification accuracies for different filtered signals without and with enhancement. It can be seen that EEG signal enhancement boosts the classification accuracy by at least 4%. A low-frequency band of 0-8 Hz (delta and theta) is also found to be adequate and more effective (mean accuracy about 1% higher) in discriminating hand movement directions than wider frequency bands containing alpha, beta, and/or gamma, which supports the findings in earlier studies [4-9].

TABLE I. Performance of Multi-Class Classification for Different Filtered Subband Signals without and with Enhancement

	Multi-class classification accuracy (%)				
	Without signal enhancement	With signal enhancement			
Filter types	0-8 Hz	0-8 Hz	0-16 Hz	0-32 Hz	0-64 Hz
Butter	47.93 (8.43)	54.88† (8.73)	53.66 (8.57)	53.99 (8.59)	54.84 (8.37)
Cheby	55.91 (8.30)	60.02† (8.57)	59.01 (8.49)	58.44 (8.46)	58.90 (8.69)

Values are presented as mean and standard deviation in parentheses. Symbol † indicates the maximum value in column. Butter and Cheby refer to 4th-order Butterworth filter and Chebyshev Type II filter, respectively.

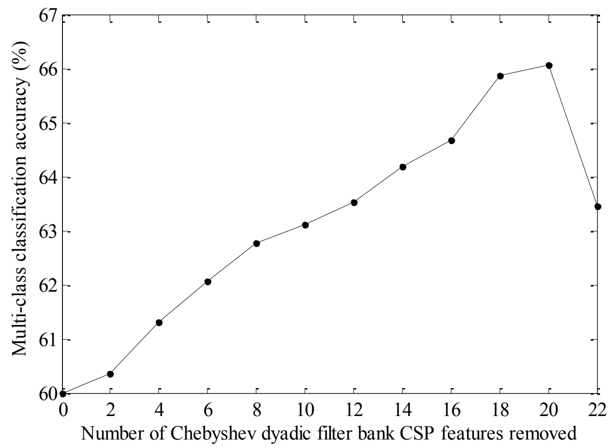

Figure 2. Performance of multi-class classification for different number of Chebyshev dyadic filter bank common spatial pattern (CSP) features removed at low-frequency band (0-8 Hz)

Moreover, CSP features extracted from Chebyshev Type II dyadic filter bank consistently outperform that from Butterworth dyadic filter bank by an average of 4.75% (range 4.06% to 5.35%), which is likely attributed to its frequency response characteristics that can well capture the properties of EEG signals. At 0-8 Hz, Chebyshev CSP achieves an accuracy of 60.02%, whilst Butterworth CSP yields only 54.88%.

The separability of hand movement directions can be further improved by the FMI-based feature selection. As illustrated in Fig. 2, the average classification accuracy substantially rises by 6.06%, from 60.02% to 66.08%, after removing 20 out of 24 Chebyshev dyadic filter bank CSP features at low-frequency band, which is equivalent to retaining or selecting the four most informative CSP features for classification. A close inspection of Table II also reveals that the FMI-based feature selection can increase the classification accuracy of every subject, in the range of 2.43% to 9.38%.

To further appraise the performance of the proposed framework, we compared its classification accuracy (66.08%) with that of a typical framework consisting EEG signal enhancement, low-pass filtering at 8 Hz using

TABLE II. PERFORMANCE OF MULTI-CLASS CLASSIFICATION FOR LOW-FREQUENCY BAND (0-8 HZ) CHEBYSHEV DYADIC FILTER BANK CSP FEATURES WITHOUT AND WITH FMI-BASED FEATURE SELECTION

Subject	Multi-class classification accuracy (%)	
	Without FMI-based feature selection (r = 0)	With FMI-based feature selection (r = 20)
1	79.63 ± 8.17	86.38 ± 5.84
2	54.25 ± 11.26	61.13 ± 7.97
3	72.13 ± 7.16	78.13 ± 9.59
4	56.25 ± 8.41	65.63 ± 8.84
5	46.25 ± 8.51	51.50 ± 7.66
6	68.75 ± 8.88	74.50 ± 10.51
7	42.86 ± 7.58	45.29 ± 8.29
Average	60.02 ± 8.57	66.08 ± 8.39

Values are presented as mean ± standard deviation. CSP refers to common spatial pattern; FMI, fuzzy mutual information; r, number of Chebyshev dyadic filter bank CSP features removed.

Chebyshev Type II filter, CSP feature extraction at m = 1, 2, 3, 4, or 5, and one-versus-rest FLD discriminant analysis. Using the same dataset, comparison results confirm that the proposed framework, which encompasses dyadic filter bank CSP feature extraction and FMI-based feature selection, is superior to the typical one whose accuracies are 53.32%, 59.07%, 61.82%, 62.08%, and 62.39% for corresponding m = 1, 2, 3, 4, and 5 pairs of CSP features.

IV. DISCUSSION

This study proposes a novel framework that can optimally select dyadic filter bank CSP features in low-frequency EEG band (0-8 Hz) for multi-class classification of four orthogonal hand movement directions, which was not considered in the earlier studies, to the best our knowledge. The framework encompasses EEG signal enhancement, dyadic filter bank CSP feature extraction, FMI-based feature selection, and one-versus-rest FLD analysis. Experimental results first highlight the importance of enhancing EEG signals by discarding both environmental and biological artifacts prior to signal analysis; the classification accuracy is improved by at least 4% after the EEG signal enhancement.

In addition, dyadic filter bank CSP feature extraction and FMI-based feature extraction are indispensable for analyzing hand movement directions, which information can be found in low-frequency band (0-8 Hz). The FMI can play a vital role in estimating the intrinsic relation between EEG attributes and control commands, thus optimizing the selection of CSP features for more desirable outcomes (accuracy 6.06% higher). Moreover, computational cost for estimating mutual information using fuzzy membership, as in this study, is lesser than histogram estimators and Parzen kernel density estimators [16], making it more suitable for real-time applications.

Moving forward, we attempt to enlarge the pool of subjects for more convincing results, implement the proposed framework in real-time, and extend this study to imagined hand movement directions.

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