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Classification of Brain Signals Associated with Imagination of Hand Grasping, Opening and Reaching by Means of Wavelet-based Common Spatial Pattern and Mutual Information

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Abstract— **An important issue in designing a practical brain-computer interface (BCI) is the selection of mental tasks to be imagined. Different types of mental tasks have been used in BCI including left, right, foot, and tongue motor imageries. However, the mental tasks are different from the actions to be controlled by the BCI. It is desirable to select a mental task to be consistent with the desired action to be performed by BCI. In this paper, we investigated the detecting the imagination of the hand grasping, hand opening, and hand reaching in one hand using electroencephalographic (EEG) signals. The results show that the ERD/ERS patterns, associated with the imagination of hand grasping, opening, and reaching are different. For classification of brain signals associated with these mental tasks and feature extraction, a method based on wavelet packet, regularized common spatial pattern (CSP), and mutual information is proposed. The results of an offline analysis on five subjects show that the two-class mental tasks can be classified with an average accuracy of 77.6% using proposed method. In addition, we examine the proposed method on datasets IVa from BCI Competition III and IIa from BCI Competition IV.**

I. Introduction

Different types of mental tasks have been investigated in designing brain-computer interface (BCI) including left-hand, right-hand, foot, and tongue motor imagery, mental arithmetic task, hand grasping imagery, imagination of right bank, left bank, right roll, and left roll maneuvers in an imagery flight, mental rotation, word association, auditory imagery, mental subtraction, spatial navigation, imagery of familiar faces, and repetitive squeezing a ball, and wrist extension. To date, the potential applications of some of these mental activities for online control of a computer or a neuroprosthesis have been explored [1]-[9]. Pfurtscheller et al. used foot movement and left hand movement imagination to control grasping and opening the hand in a patient with tetraplegia using functional electrical stimulation [2]-[4]. Leeb et al. [5] used imagination of the left and right hand movement to control the left and right movement direction in a virtual apartment. Scherer et al. [1] used the imagination of the left-hand, right-hand, and foot or tongue to navigate through the freeSpace. Left-/right-hand motor imagery was used for rotation to the left/right whereas foot or tongue for forward motion. Moreover, the imagination of the left and right hand movement has been also employed for controlling the direction of the robot arm movement [6], balancing a simulated inverted pendulum [7], 2-D controlling of a virtual wheelchair [8], and 2-D cursor control [9].

In all above mentioned works, the mental tasks are different from the actions to be controlled by the BCI. It is desirable to choose a mental task to be consistent with the desired action to be performed by the BCI. The intended action is to be what the subject imagines. For example, to control a robotic arm by a BCI, it is natural to control the reaching, hand grasping and opening by imagination of hand reaching, hand grasping and hand opening, respectively. The main goal of this paper is to investigate the discrimination of the hand motor imageries including imagination of hand reaching, hand grasping and hand opening.

Feature extraction is an important issue in designing a BCI. CSP is a popular discriminative feature extraction method in multichannel EEG data involving motor imagery task [10], [11]. Recently, CSP is combined with wavelet transform [12]. First, wavelet transform was employed to decompose the EEG data of each channel, and then the CSP was applied to the reconstructed signals using each wavelet coefficient.

In the current study, we propose a method for feature extraction based on wavelet packet transform, CSP, and mutual information.

II. Methods

The diagram of the proposed method for feature extraction is depicted in Fig. 1. The method is based on combination of wavelet packet transform, CSP and mutual information. First, wavelet packet transform is applied to the EEG signals recorded from each channel. Then, CSP is used to extract features from each related coefficient. Finally, mutual information is employed to select features which jointly have the largest dependency on the target class and minimal redundancy among themselves.

A. Wavelet Packet

The wavelet transform is well-suited to analyze the irregular structures and transient phenomena in signals. By decomposing the signals into elementary building blocks that are localized both in space and frequency, the wavelet transform can characterize the local regularity of the signal. Due to the multiresolution property of the wavelet transform, we applied the CSP to the signal reconstructed from each building block.

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In this work, the EEG data is decomposed up to level 6 using Daubechies mother wavelets. Since the EEG data is sampled at 256 Hz, the last level spanned the whole frequency range by approximately 2 Hz bandwidth, which cover all mu and beta rhythmic components. All packets from all levels which span the frequency range of 0.5-60 Hz (the frequency range of the band-pass filter in preprocessing of EEG) were selected.

B. Common Spatial Pattern with Tikhonov Regularization

The purpose of common spatial patterns is to design filters that maximize variance of the filtered signal for one class and minimize it for another class simultaneously [10]. The filter obtained by this algorithm should maximize or minimize the following cost function [10]:

$$J(w) = \frac{w^T X_1^T X_1 w}{w^T X_2^T X_2 w} = \frac{w^T C_1 w}{w^T C_2 w} \tag{1}$$

where T denotes transpose, C_i is the covariance matrix of class i, and X_i is the data matrix for class i. It has been shown that the CSP filters are the eigenvectors of matrix $M = C_2^{-1} C_1$ which correspond to its largest and lowest eigenvalues [10]. Despite the popularity and efficiency of CSP, it is highly sensitive to noise and to severely overfit with small training sets [10]. To address these drawbacks, several approaches based on regularization scheme were proposed. In [10], the performance of 11 different regularized CSP (RCSP) filters were compared and concluded that the best RCSP algorithm was CSP with Tikhonov regularization.

C. Mutual Information Based Feature Selection

One of the most effective approaches for optimal feature selection is the mutual information (MI). MI measures the mutual dependence of two or more variables [13]. Assume a random variable F representing feature vectors, and discrete-valued random variable C representing the class labels Mutual information is defined by

$$I(F;C) = \sum_{c \in C} \int_f p(\mathbf{f}, c) \log \frac{p(\mathbf{f}, c)}{p(c)p(\mathbf{f})} d\mathbf{f} \tag{2}$$

where $p(c)$ and $p(\mathbf{f})$ represent the probability of the class $\boldsymbol{C}$ and feature, respectively. If the mutual information between two random variables is large, it means two variables are closely related. The MI is zero if and only if the two random variables are strictly independent. In terms of mutual information, the purpose of feature selection is to find a feature set S with m features that jointly have the largest dependency on the target class C. However, it is not always easy to get an accurate estimation for probability density functions $\left(p(f_1 ... f_m), p(c)\right)$ and to perform the integration. An alternative method to select the features is based on the minimal-redundancy-maximal-relevance criterion (mRMR) [13]. A feature is selected which cannot be predictable from the already selected features and must be informative about the target class. Given a set of already selected feature S_{m-1}, the algorithm chooses the mth feature from the set $F - S_{m-1}$ as the one that maximizes the information about the class with minimal redundancy by optimizing the following condition:

$$\max_{f_j \in F - S_{m-1}} \left[I(f_j; c) - \frac{1}{m-1} \sum_{f_i \in S_{m-1}} I(f_j; f_i) \right] \tag{3}$$

III. Experimental Setup and Data Set

A. BCI Competition Data Set

Before applying the classification method to our motor imagery data, the algorithm was applied to datasets IVa from BCI Competition III [14] and IIa from BCI Competition IV [15]. Dataset IVa includes EEG data from five subjects recorded using 118 channels. In each session the subjects were directed to perform right hand, left hand, and foot motor imagery tasks. Dataset IIa comprises EEG signals of nine subjects recorded using 22 channels. With visual cues, the subjects were directed to perform one of the four motor imagery tasks: left hand, right hand, feet, or tongue.

B. Experimental Setup

The experiments were carried out with five able-bodied volunteer subjects. The monopolar EEG signals were recorded at a sampling rate of 256 Hz from positions F3, F4, Fz, C3, C4, Cz, P3, P4, and Pz by Ag/AgCl scalp electrodes placed according to the International 10–20 system. The EEG signals were recorded with a bipolar EEG-amplifier (g.USBamp, g.tec, Guger Technologies, Graz, Austria) and were filtered with a 0.5–60 Hz bandpass filter using a Butterworth filter of order 4.

All recording channels were referenced to the left earlobe and one electrode on the forehead served as a ground electrode. A real-time adaptive neural filter was used to remove eye-blink artifact [16].

The experiment consisted of 2 sessions for each subject. Each session was conducted on a different day and consisted of 30 trials for each task. Fig. 2 shows the structure and timing of each trial of experiments. Depending on the visual cue which was appeared on the monitor of the computer, the subject imagined hand grasping, hand opening, or hand reaching.

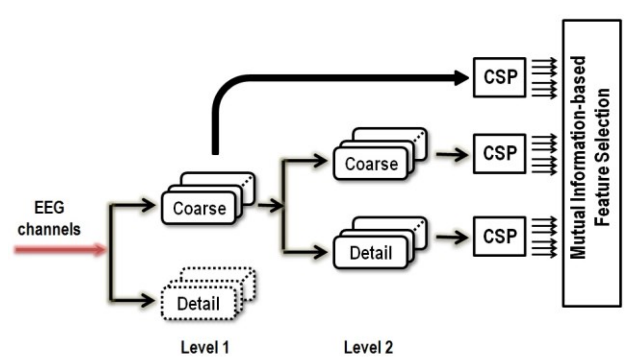

Fig. 1. Diagram of the proposed method for feature extraction

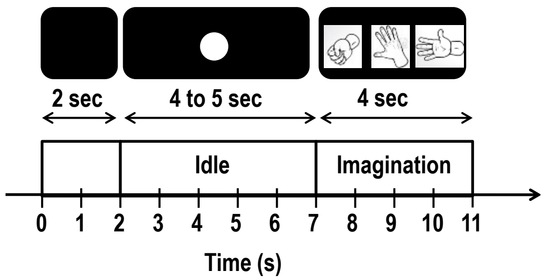

Fig. 2. The structure and timing of an experiment during one trial.

IV. Results

A. Time–frequency Analysis

Fig. 3 (a) shows the time–frequency distribution of EEG signals in subjects ZB during imagination of hand grasping and hand opening. The EEG spectra computed during grasping imagery was considered as the baseline spectra. A narrow-banded event-related desynchronization (ERD) of mu rhythm in frequency around 10 Hz is observed during hand opening imagery with respect to hand grasping. Furthermore, a weak ERD of lower beta band in frequency around 20 Hz can be also observed at the F3, Fz, and C3 sites and a weak ERD of upper beta band over the C3, Cz, and C4 positions during opening motor imagery. In addition, a weak event-related synchronization (ERS) of gamma activity in frequency around 35 Hz exits. Fig. 3(b) shows the average of the mu rhythm ERD over all subjects at 11 Hz for the imagination of hand opening with respect to grasping. Fig. 4 shows the ERD/ERS responses during imagination of grasping with respect to reaching. The mu and beta rhythms demonstrate a relatively wide-spreads ERS activity.

B. BCI Competition Data

The EEG data were band-pass filtered using Butterworth filter from 0.5 to 60 Hz. The wavelet transform of the filtered EEG signals from the training set were used to train the CSP. Subsequently, the wavelet transform of the EEG from all channels were spatially filtered using the first and last three spatial filters of the trained CSP. The features were extracted from the time segment located from 0.5 to 2.5 s after the cue instructing the subject to perform the mental task. The variance of the spatially filtered signals constituted the original feature set. Finally, the relevant features were selected according to the mutual information criterion and applied to the SVM classifier. The classification accuracy with different sizes of feature set was obtained and the best accuracy was reported.

Table I summarizes the results of classifying right and left hand motor imagery tasks for each data set. It is observed that an average accuracy of 77.1% is achieved for data set IVa from BCI competition III and 81.8% for data set IIa from BCI competition IV. The results show that the proposed method outperforms TRCSP by almost 2.2% and CSP by nearly 3.2%.

C. Imagination of Hand Reaching, Grasping and Opening

The EEG data was continuously recorded and the eye blink artifacts were removed online during each run of experiment. The feature vectors were extracted from 2-s windows with 1 s overlap during 4-s motor imagery phase.

Table I. Classification Accuracies obtained for Each Subject Using the Proposed Method in This Paper, Standard CSP, and TRCSP.

Data	**Subject**	**Method**		
		Proposed method	**TRCSP [10]**	**CSP [11]**
BCI competition III (data set IVa)	A1	72.5	71.4	74.3
	A2	96.6	96.4	94.3
	A3	58.1	63.3	49.3
	A4	77.0	71.9	77.1
	A5	81.3	86.9	72.8
	Mean	77.1 ± 14.0	78.0 ± 13.4	73.6 ± 16.1
BCI competition IV (data set IIa)	S1	86.6	88.9	91.0
	S2	72.0	54.2	56.2
	S3	96.1	96.5	96.5
	S4	72.1	70.8	72.9
	S5	68.2	62.5	63.9
	S6	67.0	67.4	63.9
	S7	85.1	81.3	79.9
	S8	97.3	95.9	97.2
	S9	92.1	91.7	91.7
	Mean	81.8 ± 12.1	78.8 ± 15.6	79.2 ± 15.6
Overall	**Avg.**	**80.1 ± 12.5**	**78.5 ± 14.3**	**77.2 ± 15.4**

Table II. Classification accuracies (%) Obtained Using Proposed Method for Five Subjects (mean and Standard Deviation)

Subject	**Day**	**Task**		
		Grasping/ Opening	**Reaching/ Grasping**	**Reaching/ Opening**
BA	1	70.2 ± 1.6	77.6 ± 1.9	76.1 ± 1.8
	2	77.2 ± 1.0	82.0 ± 1.0	80.2 ± 0.8
MM	1	75.2 ± 1.8	74.0 ± 1.5	73.0 ± 1.1
	2	78.6 ± 1.1	78.5 ± 0.7	77.1 ± 0.6
AS	1	74.2 ± 1.3	76.6 ± 1.1	76.5 ± 1.2
	2	78.5 ± 0.9	79.3 ± 0.9	80.0 ± 0.9
BS	1	71.0 ± 2.2	75.8 ± 2.9	76.0 ± 2.5
	2	73.3 ± 1.2	78.1 ± 1.2	77.8 ± 0.9
ZB	1	79.7 ± 1.4	83.4 ± 1.1	83.2 ± 0.9
	2	79.1 ± 0.9	83.3 ± 0.8	81.7 ± 0.6
Overall	**Avg.**	**75.7 ± 3.4**	**78.9 ± 3.2**	**78.2 ± 3.0**

From 90 feature vectors for each task, 45 vectors were randomly selected for training, while the rest was kept aside for validation purposes. Training and validating procedure was repeated 5 times and the results were averaged.

Table II summarizes the results of classifying different two-class mental tasks. The mean classification accuracies are 75.7%, 78.9%, and 78.2% for classifying grasping/opening, reaching/grasping, and reaching/opening imageries, respectively.

V. Conclusion

In this paper, we investigated the classification of the grasping imagery versus hand opening imagery, reaching versus opening, and reaching versus grasping. For this purpose, a method for feature extraction was proposed. The method is based on wavelet transform, CSP, and mutual information. The results show that the two-class mental tasks can be classified with an average accuracy of 77.6%.

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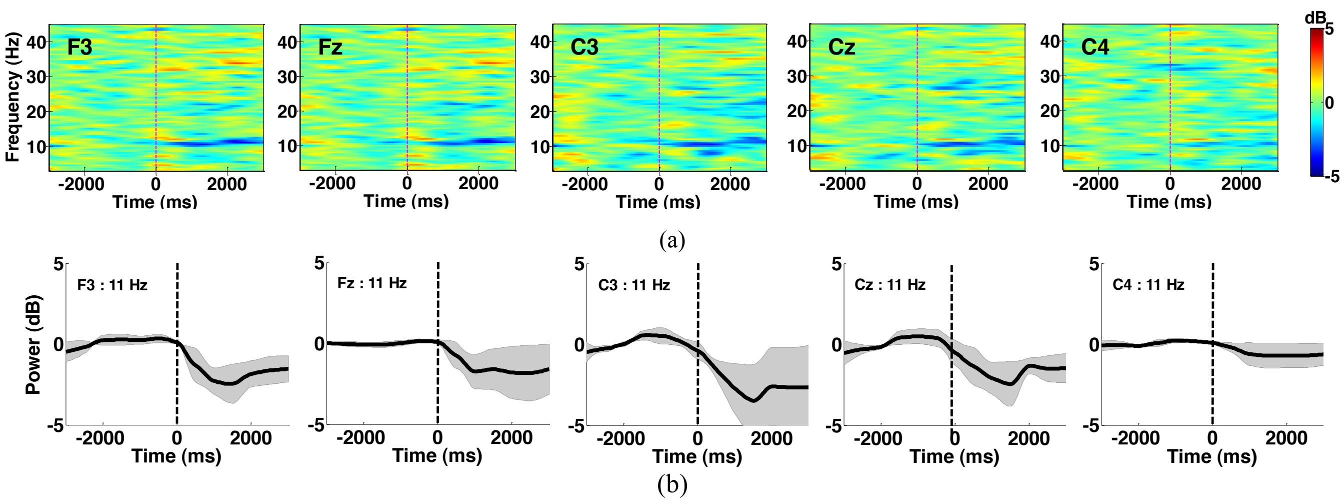

Fig. 3. The ERS/ERD maps for the subject ZB (a) and the average of the mu rhythm ERD over all subjects (b) during imagination of hand opening with respect to closing.

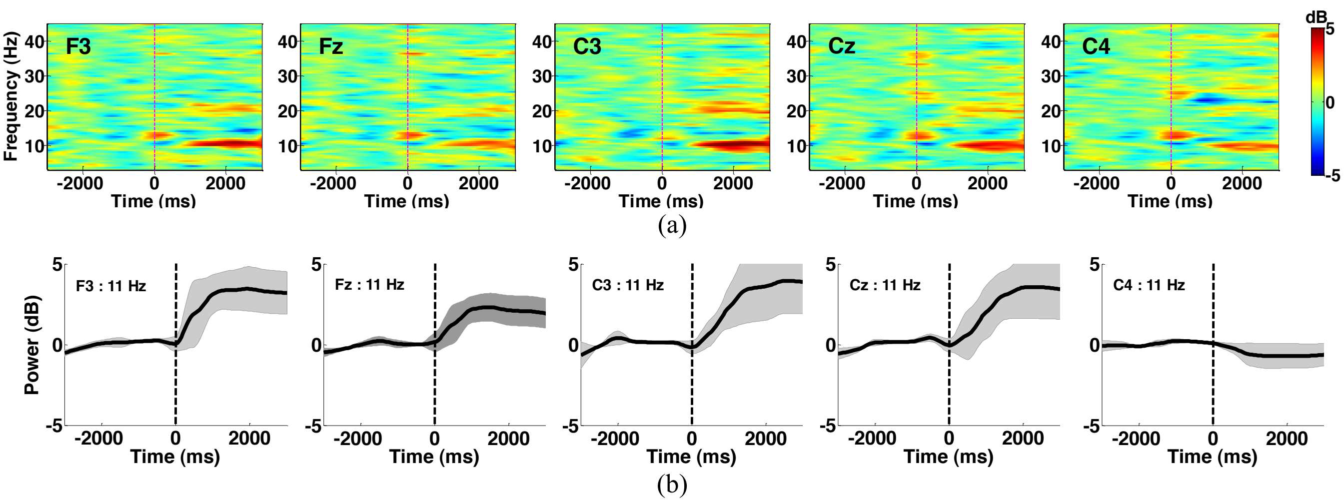

Fig. 4. The ERS/ERD maps for the subject ZB (a) and the average of the mu rhythm ERD over all subjects (b) during imagination of hand closing with respect to reaching.