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Dynamic frequency feature selection based approach for classification of motor imageries

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ABSTRACT

Electroencephalography (EEG) is one of the most popular techniques to record the brain activities such as motor imagery, which is of low signal-to-noise ratio and could lead to high classification error. Therefore, selection of the most discriminative features could be crucial to improve the classification performance. However, the traditional feature selection methods employed in brain-computer interface (BCI) field (e.g. Mutual Information-based Best Individual Feature (MIBIF), Mutual Information-based Rough Set Reduction (MIRSR) and cross-validation) mainly focus on the overall performance on all the trials in the training set, and thus may have very poor performance on some specific samples, which is not acceptable. To address this problem, a novel sequential forward feature selection approach called Dynamic Frequency Feature Selection (DFFS) is proposed in this paper. The DFFS method emphasized the importance of the samples that got misclassified while only pursuing high overall classification performance. In the DFFS based classification scheme, the EEG data was first transformed to frequency domain using Wavelet Packet Decomposition (WPD), which is then employed as the candidate set for further discriminatory feature selection. The features are selected one by one in a boosting manner. After one feature being selected, the importance of the correctly classified samples based on the feature will be decreased, which is equivalent to increasing the importance of the misclassified samples. Therefore, a complement feature to the current features could be selected in the next run. The selected features are then fed to a classifier trained by random forest algorithm. Finally, a time series voting-based method is utilized to improve the classification performance. Comparisons between the DFFS-based approach and state-of-art methods on BCI competition IV data set 2b have been conducted, which have shown the superiority of the proposed algorithm.

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1. Introduction

Besides the neuromuscular system, brain-computer interface (BCI) has provided a substitute way to convey the intention of the brain [1–3]. For the patients who have lost controllability over the body, BCI technique can recognize the signals sent by the brain and send control order to the external assistive devices which can help the patients in their daily life [4]. For healthy people, BCI technique can greatly improve the experience in multi-media and video games which have promising commercial value [5]. Different techniques have been developed to observe the brain, including Electrocorticography (ECoG) [6], Near infrared Spectroscopy (NIRS) [7], magnetoencephalography (MEG) [8], electroencephalography (EEG) [9], and functional Magnetic Resonance Imaging (fMRI) [10] and so on. Among all these methods, ECoG is invasive and thus is not widely employed due to its high risk. The cost of MEG and fMRI is quite high. NIRS is more robust to noise than EEG, while the spatial and temporal resolution of NIRS are both moderate [11]. EEG is the most widely used technique in BCI field thanks to its good temporal resolution [11], low cost equipment, and less environment restriction [12], even though the spatial resolution of EEG is low. Some previous studies have also combined different modalities of brain signals in BCI applications [13,14]. Motor imagery classification is an important branch of BCI research, and many BCI systems are built based on motor imagery analysis [15–17]. The EEG signals are recorded when the subject is imaging specific movement, e.g. movement of the tongue, hand or foot, based on which classification could be performed. The band power of EEG signals recorded over the motor cortex area during motor imagery changes in accordance to different imageries, which is known as event-related synchronization (ERS) and event-related desynchronization (ERD) [18]. The classifications of motor imaginaries are mainly based on the characteristics of ERS and

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ERD in the sensorimotor rhythm. The ERS and ERD could be evaluated both in time domain and frequency domain in terms of different criteria.

Temporal features and frequency features have both been employed to analyze EEG signals in previous research. For temporal features, Vourkas et al. [19] combined the Hjorth parameters (namely activity, mobility, and complexity) [20,21] of the EEG signals and artificial neural networks (ANN) to deal with mental-task discrimination. Blankertz et al. [22–25] developed multiple common spatial pattern (CSP) based approaches with subject-specific parameters (including different band-pass filters, varying time interval of EEG signals related to certain imaginary motor, and selection of subset of CSP filters) to implement the classification of imaginary motor tasks. In frequency domain, power spectral density (PSD) [26,27], bispectrum (BSP) [28] and wavelet packet decomposition (WPD) [29,30] based features are widely used in EEG analysis.

Typically, ERD/ERS in frequency band of 8–30 Hz is considered to be related to imaginary motors [31–34]. To select discriminative features out of this band, Shahid and Prasad [28] proposed a simple and robust feature extraction technique based on bispectrum for a motor imagery-based BCI. Specifically, the EEG signals from channels C3 and C4 are band-pass filtered to μ-band (8–14 Hz) and β-band (14–27 Hz). The hidden conditional random fields (HCRFs) based approach [35] select α-band (8–13 Hz), Σ-band (11–15 Hz), low β-band (18–23 Hz), high β-band beta (21–26 Hz) and low γ-band gamma (25–35 Hz) which are known to be associated with execution of motor tasks. Some other researchers considered for different subject features from different frequency band are more discriminable [22–25]. E.g., the (Filter Bank Common Spatial Pattern (FBCSP) [36] algorithm with specified frequency bands selected by MIBIF or MIRSR algorithm for each subject performed best among all submitted algorithms on the BCI competition IV datasets 2a and 2b. The quantum neural network-based EEG filtering method using both frequency and temporal features showed excellent performance [37] where the best subject-specific frequency band is selected by a two-step inner-outer fivefold cross-validation method. Obviously, a good selection of the frequency features for different subject can effectively improve the performance. However, these approaches, which used traditional feature selection method, only focus on the overall performance of all samples and pay no special attention to the samples misclassified multiple times, which could lead to unacceptable result.

To avoid the disadvantage mentioned above, we present a dynamic frequency feature selection (DFFS) approach. We introduce the idea of weighted training set into frequency feature selection for motor imagery classification where the weight means the importance of the samples. At first, the weights are initialized to the same setting. After a feature being selected based on all the samples, the weights of the correctly classified samples will be decreased, so the importance of the misclassified samples will be relatively increased in an implicit manner. With the updated weights, the feature selection procedure will be conducted again. As a result, the features selected in the next iteration are expected to perform better on those misclassified samples. The feature selection continues until a required number of features have been selected. In this way, DFFS approach considers every sample in the training set while the feature selection methods used in the BCI field before only focus on the overall performance of all samples and pay no special attention to the samples misclassified multiple times. And finally different frequency features are selected for different subjects. Furthermore, a time series voting method is employed to improve the performance. The proposed scheme is verified to be effective in motor imagery classification task.

This paper is organized as follows: Section 2 presents the DFFS approach. Section 3 gives the procedures of the proposed classification scheme for motor imagery classification which include wavelet packet decomposition, DFFS, random forest classifier and time series voting method. Section 4 discusses experimental results on BCI competition IV data set 2b. Section 5 is conclusion.

2. Dynamic frequency feature selection approach

2.1. Why we need DFFS

Wavelet packet decomposition (WPD) based technique has been widely used for transient and non-stationary signal analysis [38]. Because of the good performance of WPD in analysis of time-frequency domain and noise reduction [39,40], it is selected to extract features from the EEG signal. It has been shown that subject-dependent selection of the frequency bands provides a better performance than simple application of the traditional frequency band 8–30 Hz [22–25,36,37]. In order to test whether the WPD features of specified frequency band for different subject are helpful for classification, each frequency component is used to classify the data from BCI competition IV data set 2b simply based on one threshold. The details of feature extraction and the data set will be given in Section 3 and 4.

According to the discoveries about event-related desynchronization (ERD) and event-related synchronization (ERS) phenomena [18,31], if a subject is imaging the movement of the left hand, the right side of the sensorimotor area will be activated and the amplitude of the EEG signal will decrease (i.e. ERD). On the contrary, ERS will present in the left side of the sensorimotor area accompanying an increase of EEG amplitude. Considering that the coefficients of the WPD indicates the energy of different frequency band, a threshold can be used to detect the ERD/ERS phenomena and classify the EEG samples. Briefly speaking, a threshold is chosen for each frequency component to distinguish two classes based on the ERS/ERD phenomena. The classification error based on each frequency feature is shown in Fig. 1. From Fig. 1, several observations could be made. For subject 4 session 3 channel c3 (Fig. 1(a)), the features in 17–23 Hz failed in separating the EEG into two classes and for subject 5 session 3 channel c4 (Fig. 1(d)), the features near 50 Hz on the other hand show good discrimination power.

Comparing the classification error using single WPD feature of different frequency, it could be concluded that:

1) Not all the features in frequency band 8–30 are helpful for the classification.

2) Some features outside the frequency band 8–30 are also valuable for the classification.

3) Each subject is sensitive to different frequency bands.

Therefore, to select the specified frequency bands of WPD features for different subjects that are helpful for classification, the DFFS approach is proposed.

2.2. Description of DFFS

To explain how DFFS works, we need to understand the idea of the weighted training set first. Every sample in the weighted training set has an associated weight $w_j \geq 0$ which measures its importance. When sample j is misclassified, the final classification error rate contributed by this sample is w_j.

Before we start to choose the first feature, the weight of all samples is initialized as

$$w_j = \frac{1}{N}, j = 1, \ldots, N \quad (1)$$

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