Research Paper

A contralateral channel guided model for EEG based motor imagery classification

Lei Sun [a], Zuren Feng [a], Badong Chen [b], Na Lu [a,c,*]

[a] *State Key Laboratory for Manufacturing Systems Engineering, Systems Engineering Institute, Xi'an Jiaotong University, Xi'an, Shaanxi, China*
[b] *Institute of Artificial Intelligence and Robotics, Xi'an Jiaotong University, Xi'an, Shaanxi, China*
[c] *Beijing Advanced Innovation Center for Intelligent Robots and Systems, Beijing, China*

A R T I C L E   I N F O

A B S T R A C T

Objective: A novel and effective EOG correction method is proposed to improve the motor imagery (MI) classification performance.
Methods: A new normalization model with one contralateral EOG channel is developed to retain the MI-related neural potentials and avoid the redundant influence among the EOG channels. By using the Hjorth features, the sub-optimal weights of our normalization model are learned for the MI classification of evaluation data.
Results: The proposed method was applied on BCI Competition IV dataset 2b and 2a, and one dataset collected in our laboratory. As a result, the proposed method obtained an average kappa of 0.72 for the dataset 2b, 0.53 for the dataset 2a and 0.47 for the collected dataset.
Conclusions: The proposed method could exclude interference among the EOG channels and the cross-interference between the EOG and EEG channel. The results proved that the EOG signal does have certain useful information for MI classification. The proposed method could emphasize ERD/ERS features, and improve MI classification performance.
Significance: Compared to the regression method, the raw data based and the ipsilateral EOG channel based methods, the proposed method has significantly improved the MI classification performance. In addition, compared to other state-of-the-art methods, our approach also has obtained the best performance.

1. Introduction

The brain-computer interface (BCI) system analyzes brain activities and sends effective signals or commands directly to ambient intelligent devices. BCIs can aid patients with motor neurons disease (MND) to interact with the external world. As a data recording method for BCIs, Electroencephalogram (EEG) has several advantages, including non-invasion, convenience, low cost, and low power consumption. In practice, BCIs can collect EEG signals of motor imagery (MI) through electrodes placing on the patient's scalp, and analysis of the MI-related EEG signals is one way to help patients who suffer from neuromuscular disorders. Therefore, researchers have developed many classification methods to dis-

criminate the MI tasks such as the left hand, right hand, foot, or tongue [1,2]. However, the EEG signal for MI classification could be easily contaminated by various noises, especially the electroculographic (EOG) artifacts [3]. Taking the disturbance of EOG artifacts into account, the proposal of an efficient EOG correction method for MI classification has become a major challenge.

The MI task triggers event-related neural potentials (ERPs) typically in alpha (8–13 Hz) and beta (13–26 Hz) frequency bands. These ERPs represent as decrease or increase of the EEG signals power, which are respectively called event-related desynchronisation (ERD) or event-related synchronization (ERS) [4,5]. ERD/ERS phenomena reflects the coordination of the underlying neuronal networks in the sensorimotor area. Based on the generation mechanism of ERD/ERS that the MI tasks of the right and left hands will invoke the ERD of the contralateral hemisphere and ERS of ipsilateral hemisphere [5], numerous MI classification studies have been proposed. Common spatial patterns (CSP) algorithm [6] provides a spatial filter to uncover ERD/ERS effects thereby classifying the

EEG signals. Ref. [7] proposes a feature extraction method based on bispectrum (BSP) to increase classification accuracy. This study gives more separable ERD/ERS related bispectral features to the classifier. In time domain, Ref. [5] gives a band power method to classify the MI tasks of the right and left hands. This method calculates the instantaneous power of the bandpass filtered EEG signals, and quantifies ERD/ERS as the percentage of power change. Comparing to the band power method, Hjorth algorithm [8] shows highly improved performance in regards to classifying brain states. Moreover, the Hjorth algorithm has better feature quality, higher classification stability, and computational simplicity. This algorithm produces three parameters, which evaluate the magnitude of the mean power, the mean frequency and the bandwidth of the EEG signal with the temporal computation. Many papers employ the Hjorth algorithm for MI classification [9,10]. For instance, Ref. [10] utilizes quantum neural network (RQNN) to find EEG signal characteristics, and then combines the Hjorth parameters with band power to separate two-class MI tasks. Despite the performance of the Hjorth algorithm, EOG artifacts still can influence the quality of Hjorth features, thereby biasing the results of MI classification. Therefore, an EOG correction method should be adopted before extracting the Hjorth parameters for MI classification.

EOG artifact stems from the change of electric fields around the eyes [3]. According to the direction of the eye movement, EOG artifact could be categorized into three orthogonal components (vertical, horizontal and radial). Each EOG component is computed by subtracting two EOG channels, which are placed around the eyes [11]. EOG signal is highly random and has large magnitude, which leads to serious influence on the EEG signals in lower frequency bands including delta (0.5–4 Hz) and theta (4–8 Hz) bands [11]. Therefore, many articles [11,3] employ bandpass filters to remove the influence of EOG artifacts. However, some studies [12–14] also report that the EOG signal could be found in alpha and beta bands, and thus directly disturbs the performance of MI classification.

To date, various methods of EOG correction are employed for purifying the EEG signals. For instance, some popular methods for correcting EOG artifacts use the wavelet algorithm to detect EOG signals before employing the traditional linear model, which obtains the true EEG signal by subtracting certain proportion of EOG signal from the contaminated EEG signal. Ref. [15] uses the wavelet based adaptive threshold algorithm to extract EOG zones, and applies the linear model based regression method to correct EOG artifacts. Ref. [16] develops a wavelet neural network (WNN) method to help the linear model based regression method correcting EOG artifacts. Also, many papers apply independent component analysis (ICA) algorithm to extract EOG signals for enhancing the efficiency of EOG correction with linear model. Ref. [3] combines ICA with multivariate empirical mode decomposition (MEMD) to detect EOG signals. Ref. [17] corrects EOG artifacts using a combination of ICA, wavelet neural network and the linear model based regression method. However, first, some of the above works use the three EOG components in the linear model for EOG correction. According to the presence of neural potentials in EOG signals, the EOG component could blur the features of ERD/ERS by subtraction of two EOG channels due to the unforeseeable difference of neural potentials between two EOG channels [12]; second, the linear model used in most of the above works not only causes the loss of the MI-related neural potentials, but also introduces the interference from the EOG channels. Additionally, the regression method could also include more cross-interference from the EEG and EOG channels [11,12]. Hence, the application of three EOG components and the linear model based regression method are no efficient enough to correct EOG artifacts for improving MI classification.

In this paper, we propose a novel and efficient method for EOG correction towards improving MI classification. Firstly, the raw EEG data is filtered through a fourth-order Butterworth bandpass filter

at alpha, beta and gamma bands to remove the major EOG artifacts; secondly, a new normalization model for each EEG channel based on one contralateral EOG channel is developed to minimize the influence of EOG artifacts and enhance ERD/ERS features; thirdly, the Hjorth algorithm is used for feature extraction with the normalized data; then, the sub-optimal subject-specific weights in our model are trained from labeled training data with a support vector machine (SVM) through comparing the maximum and average classification accuracy of different weight settings within the search space; finally, the Hjorth features of evaluation data is classified by applying these sub-optimal subject-specific weights into our proposed model. The proposed method is applied on BCI competition IV dataset 2b and 2a, and the dataset collected in our BCI laboratory. The results demonstrate superior performance of the proposed method compared to other state-of-the-art works, including HCRF [18], RQNN [10] and BSP [7].

2. Methods

2.1. EOG correction

Considering that the magnitude of EOG signal is usually larger than that of the EEG signal, EOG signal can affect every EEG channel distributed over the scalp [19]. In this case, EOG signal could be assumed as an additive noise within the recorded EEG signal [16]. Ref. [19] proposes that the recorded EEG signal follows a linear model as below:

$$Y_{T \times M} = S_{T \times M} + U_{T \times N} B_{N \times M},\tag{1}$$

where $Y_{T \times M}$ is the recorded EEG signal, $S_{T \times M}$ is the true EEG signal, $U_{T \times N}$ denotes the recorded EOG signal, $B_{N \times M}$ is the backward propagated weights from each EOG channel to each EEG channel, T is the number of time points, M is the channel number of the EEG, and N is the channel number of the EOG. Based on this linear model, the key to extract the true EEG signal from the recorded EEG signal is to find the sub-optimal weights B.

Regression method holds some advantages for EOG correction, being simple and applicable for any number of EEG channels. Thus, some articles use the regression algorithm to obtain B [18,19]. In the regression algorithm, B can be calculated as below:

$$\left(U^T S\right) = \left(U^T Y\right) - \left(U^T U\right) B,\tag{2}$$

where $(\cdot)^T$ is the matrix transpose. Without loss of generality, it could be assumed that the true EEG signal and the EOG signal are uncorrelated. Thus we have $\left(U^T S\right) = 0$, and it could be obtained that

$$B = \left(U^T U\right)^{-1} \left(U^T Y\right).\tag{3}$$

Then, the true EEG signal S could be simply calculated through Eq. (1) as

$$S = Y - UB.\tag{4}$$

However, the weights B are hard to estimate precisely from Eq. (3) owing to the cross-interference caused by the matrix product of the EOG and EEG channels with the regression method [3]. On the other hand, the linear model in Eq. (1) also has several problems addressing MI classification. First, the EOG channels disturb each other when the EEG electrodes are placed at the sensorimotor area [11]. Second, the true EEG signal could be miscalculated with Eq. (1) due to the loss of the MI-related neural potentials incorporated in the recorded EOG signal. Some MI-related neural activities could also be collected by the EOG channels, the recorded EOG signal thus is composed of the MI-related neural potentials and eye movement EOG [11]. In addition, the recorded EEG signal also includes the true