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Spatio-temporal discrepancy feature for classification of motor imageries

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ABSTRACT

Brain-computer interface (BCI) is an alternative pathway for communication between the brain and the outside world. Electroencephalography (EEG) records electrical signal that can reveal the mental state of the brain. EEG-based motor imagery classification is an important branch of BCI research. ERS (event-related synchronization) and ERD (event-related desynchronization) based features have been widely employed to classify motor imageries. Meanwhile, various methods derived from ERP (event-related potential) have been developed. Previous studies have demonstrated that ERP and ERD could provide complementary information about brain activity, so approach combining them is expected to give better performance for motor imagery classification. In this study, a novel variant of ERP called spatio-temporal discrepancy feature (STDF) is proposed, which evaluates the difference of the EEG signals from the left and the right sensorimotor area. With STDF, the noise which affects the left brain signal and the right brain signal simultaneously could be suppressed and the signal difference between the left and the right sensorimotor areas could be enhanced, which will certainly benefit the left vs. right motor imagery classification. STDF as a temporal feature is then combined respectively with three kinds of frequency features describing the ERD/ERS phenomenon to further improve the classification performance. Experiments on BCI competition IV dataset 2a and 2b have been conducted. Different features and state-of-the-art methods have been compared and the proposed STDF based method has obtained the best performance.

1. Introduction

Brain-computer interface (BCI) is an alternative pathway to connect the brain with the outside world besides the neuromuscular system [1] and has promising application prospect in both treatment of the disabled people and entertainment [2,3]. Classification of motor imagery is an important branch of BCI [1]. It aims to recognize different mental imaginations of movements. Specifically, the motor imageries include, but not limited to, hand movement [2], tongue movement, foot movement [4,5], fist movement [6], limb movement [7] and wrist movement [8].

From previous study, it could be concluded that there are three factors determining the efficiency of a BCI system: (1) the equipment and techniques used to record the brain signals; (2) the features extracted from the brain signal; (3) the algorithms applied to classify the brain signal with the extracted features [1].

Many techniques have been applied in BCI to record the brain signal, such as Magnetoencephalography (MEG) [9], Electrocorticography (ECoG) [10], Near-infrared Spectroscopy (NIRS) [11], functional Magnetic Resonance Imaging (fMRI) [12] and Electroencephalography (EEG) [13]. Among them, EEG is the most widely applied technique in BCI field, because it is non-invasive, of low cost and has high temporal resolution [14]. In this paper, the EEG based motor imagery classification is studied.

Motor imagery, similar to motor execution, causes changes of EEG over sensorimotor areas [15]. So BCI could discriminate different kinds of neural activities following the appearance of specific motor imageries according to EEG. Motor imagery based BCI has been proved as an efficient way of rehabilitation and complex movement related research [16]. Studies about the classification of EEG based motor imagery mainly focus on features used to describe the signal and classification algorithm used to make prediction.

Numerous classifiers have been applied in classification of motor imagery, such as Linear discriminant analysis (LDA) classifier [17], support vector machine (SVM) [18], Bayesian classifier [19], neural network [17,19] and combination of classifiers [20]. Reviews

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about comparisons among classifiers employed in BCI field could be found in [7,21]. For EEG based BCI applications, the SVM algorithm turned out to be more efficient and accurate than other classifiers [18,21]. In addition, the combination of classifiers [20] and dynamic classifiers also obtained good performance [21].

Feature extraction is another crucial procedure. Certain event (such as sensory stimuli and motor imagery) causing localized power change in EEG rhythm is a result of increased and decreased excitability of cortical neurons [22]. The power changes in frequency domain of the EEG signals are time-locked and can be detected using frequency analysis technique [23]. The frequency power increasing is called event-related synchronization (ERS) and the power decreasing is called event-related desynchronization (ERD) [13,24]. For example, motor imageries of the left or the right hand lead to ERD in contralateral sensorimotor area, and simultaneously ERS appears in ipsilateral sensorimotor area. After that, ERS appears in the contralateral sensorimotor area [24]. Researchers have discovered the specific frequency bands which are closely related to the motor imagery induced ERD/ERS [16]. The actual effective frequency bands are influenced by the subjects' mental state, the deployment of the electrodes and the signal processing procedure. The frequency band of 8–30 Hz in EEG is widely employed in studies of motor imagery based BCI [25,26]. Different methods have been applied to describe the ERD/ERS phenomenon including, but not limited to, power spectral density [27], autoregressive model [28], common spatial pattern (CSP) algorithm [4,13] and time-frequency analysis [29]. Shahid and Prasad [27] extracted simple and robust bispectrum-based features in the μ-band (8–14 Hz) and β-band (14–27 Hz). More frequency bands (over 8–35 Hz) features extracted by autoregressive model are selected by the Hidden Conditional Random Fields (HCRFs) based approach [28]. Some other studies tried to choose different frequency bands with respect to different subjects in order to get more discriminative features [30]. For example, the filter bank common spatial pattern (FBCSP) approach [4] used mutual information-based best individual feature (MIBIF) and mutual information-based rough set reduction (MIRSR) to select specific frequency features, which won the championship of the BCI competition IV on datasets 2a and 2b [31].

Event (sensory stimuli, imagery and so on) related brain activity could evoke time-locked response in EEG electrical potentials which is known as event-related potentials (ERP) [24,32]. ERP is usually extracted by a simple averaging technique in the time domain [32]. When someone is imaging a movement, the state of the neurons in the sensorimotor area will change and the amplitude of the EEG signal will increase (deactivated) or decrease (activated) [32]. ERP is another widely used feature to analyze the brain state and also called movement-related potential (MRP) when employed for motor event analysis. Lu et al. have developed a variety of motor imagery classification algorithms via ERP analysis [33,34]. However, the ERP has been demonstrated that it cannot fully reveal the characteristics of the brain state [35]. And some researchers verified the hypothesis that MRP and ERD could provide complementary information about the brain state accompanying the preparation and execution of volitional finger movement [36]. Therefore, how to efficiently combine the information from ERD/ERS and ERP becomes an important direction to further improve the performance of motor imagery classification. Considering the ERP is featured in time domain while the ERD/ERS is detected in frequency domain, the combination of ERP and ERD/ERS can also be interpreted as the combination of time domain feature and frequency domain feature, which is suggested in [37,38] to improve the performance.

In this paper, a new ERP derived feature called spatio-temporal discrepancy feature (STDF) is proposed. For the left hand vs. right hand two-category motor imagery classification problem, the difference between the left and right sensorimotor areas EEG is calculated to evaluate the brain signal variation over the scalp and time. In this way, the noises affecting the left and right sensorimotor area simultaneously are suppressed and the signal differences between the left and the right sensorimotor area are enhanced. Signal integral method is then used to extract spatio-temporal discrepancy feature (STDF) from the EEG difference signal. The STDF have shown advantages on different subjects compared with the ERD/ERS-based frequency features in our experiments. Various spectral analysis algorithms have been employed for frequency feature extraction, including Welch's power spectral density estimate [39], autoregressive power spectral density estimate based on Burg's method [40] and wavelet packet decomposition [41] based approach. These frequency features are then respectively combined with ERP-based STDF (time domain feature) to accomplish the motor imagery classification. Experiments on BCI competition IV dataset 2a and 2b have been conducted to verify the efficiency of the proposed method.

This paper is organized as follows: Section 2 describes the STDF. Section 3 presents the combination features and the experiment scheme. Session 4 discusses the experiments and results. Conclusion is drawn in Section 5.

2. Spatio-temporal discrepancy feature

2.1. Spatio-temporal discrepancy signal

ERPs are contralateral preponderant [24], and this is a basic feature used for motor imagery classification. However, due to the low signal to noise ratio (SNR) of EEG recording, the amplitude change of the signal could not be observed directly. Therefore, how to enhance and extract discriminant feature from the EEG signal remains a challenge for motor imagery classification.

In order to obtain enhanced feature, the discrepancy signal between contralateral EEG channels has been obtained as:

$$D = S_l - S_r \tag{1}$$

where S_l is the EEG signal recorded from left sensorimotor area, S_r is the one from the right sensorimotor area. Considering the term D evaluates the difference over both the space and the time, it is called spatio-temporal discrepancy signal.

The noise (especially the volume noise) is supposed to influence all the EEG channels over the scalp simultaneously. Therefore, the above defined discrepancy term could suppress the noise shared by the left and the right sensorimotor areas. Meanwhile, the contralateral difference of the EEG signals could be enhanced.

2.2. Spatio-temporal discrepancy signal analyses on BCI competition IV dataset 2b

Analyses have been conducted to verify the efficiency of spatio-temporal discrepancy signal D for the left vs. right two-category motor imageries classification. BCI competition IV dataset 2b [2,31] is used, which presents a two-category (left hand and right hand) motor imagery classification problem. There are 9 subjects and 5 sessions per subject in this data set. According to the competition rules, sessions 1, 2 and 3 are used as training set and sessions 4 and 5 are testing sets. Considering only the trials in sessions 3, 4 and 5 have included feedback procedure, so session 3 is set as the training set and sessions 4 and 5 are set as the testing set in our experiment. EEG recorded from 3 channels (channel C3, Cz and C4) is collected with sampling frequency of 250 Hz. The signal range of the feedback session is $-50\,\mu$V to $50\,\mu$V. The data is filtered using a bandpass filter (0.5 Hz to 100 Hz) and a notch filter (50 Hz). The artifacts inspected by experts are marked. The length of each trail is