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Subject transfer BCI based on Composite Local Temporal Correlation Common Spatial Pattern

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ABSTRACT

In this paper, a subject transfer framework is proposed for the classification of Electroencephalogram (EEG) signals in brain–computer interfaces (BCIs). This study introduces a modification of Common Spatial Pattern (CSP) for subject transfer BCIs, where similar characteristics are considered to transfer knowledge from other subjects' data. With this aim, we proposed a new approach based on Composite Local Temporal Correlation CSP, namely Composite LTCCSP with selected subjects, which considers the similarity between subjects using Frobenius distance. The performance of the proposed method is compared with different methods like traditional CSP, Composite CSP, LTCCSP and Composite LTCCSP. Experimental results have shown that our proposed method has increased the performance compared to all these different methods. Furthermore, our results suggest that it is worth emphasizing the data of subjects with similar characteristics in a subject transfer diagram. The suggested framework, as demonstrated by experimental results, can obtain a positive knowledge transfer for enhancing the performance of BCIs.

Contents

1. Introduction

The automatic classification of movement-related Electroencephalogram (EEG) signals is one of the most challenging fields of brain–computer interfaces (BCIs). In a BCI system, users can manipulate the system just by thinking about what they want it to do within a limited set of choices. There are several types of EEG-based BCIs that include mental tasks [1], P300 [2], neural responses elicited during visual stimulus flickering [3] and motor imagery [4]. In the BCIs based on responses to mental tasks, different non-movement mental tasks lead to different EEG patterns associated with these mental tasks. In a P300-based BCI, in order to trigger a P300 waveform in a subject's brain activity, the subjects must focus their attention on a specified stimulus that randomly appears among many others. By detecting

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the P300 component, the system is enable to recognize the demanded stimulus and hence the demanded command. Some BCIs use visual evoked potentials (VEPs), which are electrical potential-differences originating from the scalp after a visual stimulus flickering like a flash-light. The aim of the VEPs-based BCIs is to identify this frequency reliably with high accuracy. Motor imagery based BCIs use Sensory Motor Rhythms (SMR) information to translate a subject's motor intention into a control signal to have efficient control over an output device such as a neuroprosthesis, a wheelchair, or a computer. Motor imagery tasks are associated with an increase or attenuation of localized brain rhythms activity called Event-Related Synchronization (ERS) or Event-Related Desynchronization (ERD) [5]. Fig. 1 shows the basic scheme of a general EEG-based BCI system. One of the most popular and efficient techniques to extract ERD/ERS related features is the Common Spatial Pattern (CSP), which is widely used for motor imagery BCI designs [6,7]. The CSP method aims to find spatial projections (filters) that simultaneously maximize the variance of one class while minimizing the variance of the other class [8,9]. Despite the efficiency and popularity of CSP in designing BCIs, this algorithm has two inherent drawbacks, one is the high sensitivity to potential outliers and artifacts and the another is the overfitting with small training sets [10]. Traditional CSP considers each time point of all EEG channels as a vector in the feature space and maps it into another space using the average covariance matrix of all EEG signals [11]. In such a situation, the temporally local structure of the EEG signals is not considered and the covariance matrix of all EEG signals is affected by the noise of one tiny time slot, which makes errors in estimating spatial filters [11]. To overcome the above-mentioned inconvenience of traditional CSP, the Local Temporal Common Spatial Patterns (LTCSP) method has been proposed [12]. LTCSP considers temporally neighboring samples and uses the local temporal information by making a time-dependent adjacency graph. Like CSP, this method is computationally simple, but it is less sensitive to noise and artifacts. Wang and Zheng demonstrated that in a two class motor imagery based BCI problem, LTCSP achieves more discrimination compared to the CSP method. Another extension of CSP in the literature which considered the local structure of EEG signals is Local Temporal Correlation Common Spatial Patterns (LTCCSP). LTCCSP uses local temporal correlation information to further improve the estimation of covariance matrices. Compared to CSP and LTCSP, the LTCCSP method has shown the best performance under outlier condition [13]. In the LTCSP method, the Euclidean distance between different N-channel EEG recording vectors at different time points is calculated to construct a weight matrix for the covariance matrices while in the LTCCSP, the correlation measure is used to construct the weight matrix. Correlation is introduced as a more reasonable measure to construct the weight matrix [13].

Most of the proposed CSP-based techniques in the literature use subject-specific covariance matrices to construct user-specific spatial filters. Limited and user-dependent training samples may lead to overfitting or suboptimal spatial filters and decrease the performance of BCIs. To overcome such inconveniences, one idea is to add a priori information to the CSP process using regularization terms [10,14]. In this case, the useful information obtained from other subjects (named as source subject group) involving the same task is transferred to the target subject (the subject whose brain signals would be classified), which is called subject-to-subject transfer [15]. Fig. 2 presents a proposed schedule for subject transfer based BCIs. With this aim, different regularized CSP methods have been proposed in the literature. Kang et al. proposed a regularized CSP method called Composite CSP, which aims to perform subject-to-subject transfer by the regularization of the covariance matrices using the other subject's information [15]. Their suggested regularized method used linear combination of covariance matrices calculated from the other subjects' data. One approach was regularized CSP with generic learning proposed by Lu et al. [14]. This method attempts to shrink the covariance matrix into both the generic and identity matrix, where the generic matrix is calculated using the covariance matrices of other subjects. Another regularized method that was used in the BCI literature is invariant CSP, which tries to find the filters invariant to a given source of noise [16,10]. All the mentioned regularized CSP methods have shown higher performance than traditional CSP, especially for subjects with small training samples [10]. In all of the above methods, the data of each subject from the source subject group has the same role in regularization of the covariance matrix. Indeed, the similarity between the signal characteristics of the target subject and all other subjects is not considered in the regularization process. However, owing to the inter-subject variability, it is unreasonable to easily add the other subject's data to the training data of the target subject. Indeed, if data from a large group of subjects is available, it may not be the best option to use all of them in regularizing the covariance matrix due to the large

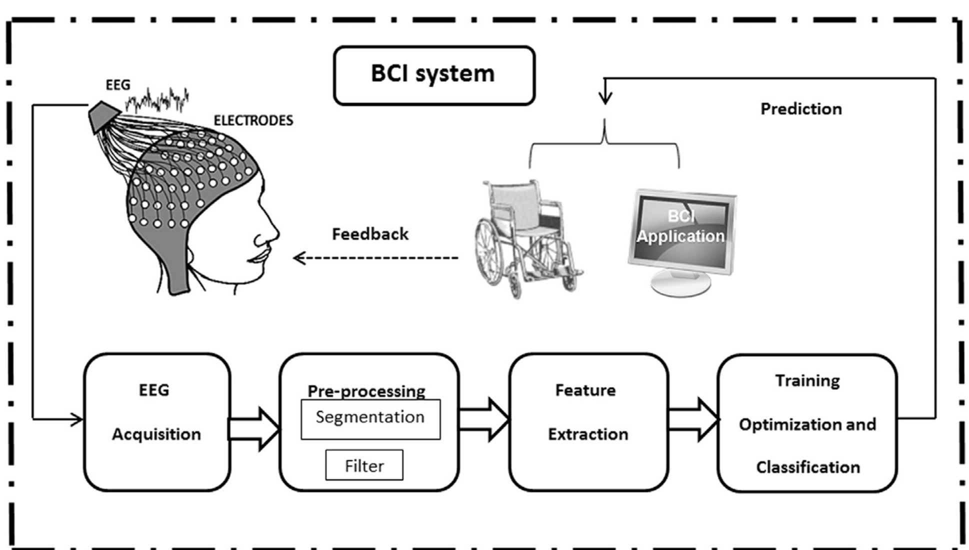

Fig. 1. Basic scheme of a general EEG-based BCI system. While a user performs mental tasks, the EEG signals are acquired and pre-processed. With feature extraction and classification stages, as parts of a machine learning system, the user intentions are predicted. These predictions can be used for controlling output devices.