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Technical note

Composite kernel support vector machine based performance enhancement of brain computer interface in conjunction with spatial filter

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ABSTRACT

For Motor imagery Brain Computer interface, a large number of electrodes are placed on the scalp to acquire EEG signals. However, the available number of samples from a subject's EEG is very less. In such a situation, learning models which use spatial features obtained using common spatial pattern (CSP) method suffer from overfitting and leads to degradation in performance. In this paper, we propose a novel three phase method CKSCSP which automatically determines a minimal set of relevant electrodes along with their spatial location to achieve enhanced performance to distinguish motor imagery tasks for a given subject. In the first phase, electrodes placed on brain scalp are divided among five major regions (lobes) viz. frontal, central, temporal, parietal and occipital based on anatomy of brain. In the second phase, stationary-CSP is used to extract features from each region separately. Stationary-CSP will handle the non-stationarity of EEG. In the third phase, recursive feature elimination in conjunction with composite kernel support vector machine is used to rank brain regions according to their relevance to distinguish two motor-imagery tasks. Experimental results on publically available datasets demonstrate superior performance of the proposed method in comparison to CSP and stationary CSP. Also, Friedman statistical test demonstrates that the proposed method CKSCSP ($\mu \neq 0$) outperforms existing methods.

1. Introduction

Communication is a basic human need which involves more than just speaking and listening. However, severe neurological disorders like amyotrophic lateral sclerosis (ALS), brainstem stroke, locked-in condition, etc. restrict a person's ability to communicate their emotions, thoughts and basic needs. Such patients usually have an active brain with normal brain activities. These people rely on alternative ways of communication. Since 1960s, there have been several efforts to develop machine learning techniques to analyze bio-signals and provide physicians with quick and precise means of diagnosis [1]. The research works [2,3,34] have emphasized the potential of a symbiotic relationship between human and computer. On the basis of this symbiotic relationship, a brain computer interface (BCI) is developed that interprets neuronal activity to derive user commands and thus creates a direct communication pathway between a brain and a device without involving the brain's conventional output pathways such as muscles or peripheral nerves. BCI has been found of profound interest to researchers as it helps persons with severe motor disabilities to control devices such as computers, speech synthesizers, assistive appliances and neural prostheses [4–8], which can provide faster communication.

The electrical signals generated in the brain due to neuronal activity are used in BCI for the purpose of communication. Among the various brain signals, EEG signal is most widely used for analysis of brain states due to its low measurement cost, high resolution and non-invasive nature. Typical EEG based BCI paradigms includes P300, visually evoked potential, sensory motor rhythms (motor imagery) [9] etc. Among these, motor-imagery based BCIs, which involve thinking or imagination of movement of a specific body part, have gained more attention among the research community [10,11]. Imagination or execution of limb movement induces variations in rhythmic activity recorded over the Sensorimotor Cortex [9], which are detected on the scalp by EEG. These are oscillations in electric brain activity recorded over post frontal and anterior parietal areas of the brain. The amplitude of SMRs decreases during motor execution or imaginary. This decrease in rhythmic activity is called as "Event-Related Desynchronization" (ERD) and the subsequent increase in the rhythmic activity immediately after

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the movement is called as "Event-Related Synchronization" (ERS) [9,12–14].

In general, a large number of electrodes (∼10–256) are utilized for an EEG based BCI device [15]. The process of placing electrodes on the scalp is strenuous and time consuming. Hence, sometimes practitioners prefer to use a smaller number of relevant electrodes even at the cost of little reduction in accuracy. Extraction of information from these electrodes is also a challenging task as relevant brain activity is smaller in amplitude as compared to artifacts and background activity. To subside the aforementioned effect, features are extracted using signal processing techniques such as bandpass filter and spatial filter [16–18]. These signal processing techniques rely upon task-specific and subject-specific parameters. In order to deal with the subject or task specific parameters, data driven techniques have been used in literature [16] which aim at extracting the discriminating features. Common spatial pattern (CSP) is one of supervised spatial filtering techniques which help in estimating spatial filters to analyze multichannel data [19,20]. CSP is sensitive to noise and non-stationarity of EEG signals which may arise due to artifacts, the loose electrode positioning, placement of electrode during different sessions, concentration of the person and other reasons during signal acquisition [21]. Hence, instead of extracting relevant features corresponding to a task, features extracted using CSP may be noise driven. In such a situation, CSP suffers from overfitting [22] and thus lead to performance degradation. To handle the non-stationarity of EEG data, Stationary CSP, a variant of CSP is suggested in literature [23]. However, the penalty parameter used in stationary-CSP method has to be determined using cross-validation for each subject, which requires more computation time.

CSP and its variants involve computation of the covariance matrix and Eigen decomposition of EEG data. However, these methods suffer from the small sample size (SSS) problem [43,49] as the number of electrodes is usually large and the number of sessions to acquire task related EEG from a subject is very less. Under this situation, Eigen decomposition is computationally expensive and may not be accurate. To overcome this problem, there is a need to determine a reduced set of relevant electrodes.

To obtain a reduced set of relevant electrodes, evolutionary algorithms have been employed where classification accuracy is optimized using a small number of electrodes [15,24–26]. However, evolutionary algorithms are computationally intensive. Also, these methods require tuning of more number of parameters such as kind of selection, crossover operator, population size, fitness function to achieve optimal solution. Hence, evolutionary algorithms are not suitable for real time BCI application.

As different brain regions are responsible for different tasks of the body, neurological information can be utilized to determine the relevant brain region(s) for a given task. For example, C3 and C4 electrodes are well known brain locations for the detection of hand motor imagery. However, relevant brain region(s) may vary depending on the given task [16]. Hence, there is a need to automatically learn relevancy of brain region(s) for a given motor-imagery task of a subject.

In this paper, we propose a novel three phase method which automatically determines a minimal set of relevant electrodes along with their location to achieve enhanced performance to distinguish motor imagery tasks for a given subject. In the first phase of the proposed method, electrodes placed on brain scalp are divided among five major regions (lobes) viz. frontal, central, temporal, parietal and occipital based on anatomy of brain. In the second phase, we used stationary-CSP [23] which handles non-stationarity problem of EEG to extract relevant features from each region separately. Motivated by the research work [27], in the third phase, we used recursive feature elimination in conjunction with composite kernel support vector machine (SVM) to identify discriminative brain regions to distinguish two motor-imagery tasks. The proposed method provides better performance and a reduced set of relevant electrodes along with their brain location.

To check the efficacy of the proposed method, experiments are performed on two publically available BCI competition III dataset IVa and BCI competition IV dataset Ia. Performance is measured in terms of classification accuracy. Experimental results are compared with CSP and stationary CSP.

The major contributions of the present study are: (i) to best of our knowledge, the proposed method, for the first time in BCI, utilizes information of neurological anatomy to divide the electrodes placed on brain scalp among five major lobes of brain cortex. This division allows us to determine the relevancy of each of the anatomically segmented regions to distinguish two given motor imagery tasks; (ii) it alleviates small sample size problem and non stationarity problem which are faced by existing CSP method and its variants; (iii) the proposed method utilized recursive feature elimination in conjunction with composite kernel support vector machine (SVM) to rank brain regions according to their relevance to distinguish motor-imagery tasks and thus provides user dependent and task related relevant brains regions.

The rest of the paper is organized as follows: Section 2 includes the relevant work. Section 3 describes the proposed method along with its basic components such as stationary CSP and composite kernel SVM. Further, the experimental setup, dataset description and the obtained results are discussed in Section 4. Finally section 5 includes conclusion and future research directions.

2. Related work

In the area of motor imagery BCI, CSP is one of most commonly used spatial filtering techniques. The performance of CSP is influenced by the spatial resolution of EEG data. It also suffers from the problem of non-stationarity of EEG signals arising from artefacts generated from eye movements, electromyographic activity or any other muscular activity, session to session transfer, brain cortical folding etc. [16,23]. Some of the limitations of the CSP method have been overcome by its variants like common spatio-spectral pattern (CSSP) which includes time delay embedding. Common sparse spectral spatial pattern (CSSSP) is another variant of CSP which considers optimization of an arbitrary frequency impulse response filter along with time delay embedding. To reduce the effect of non-stationarity, stationary common spatial pattern [23] has been proposed which introduce penalty term in the CSP's target function. In research work [28], non-homogenous spatial filters are used to take care of non-stationary and variable nature of EEG signals. A generalized CSP framework [29] has also been suggested to estimate spatial and spatio-spectral filters using a specific target function and optimization constraint to improve classification accuracy and minimize instability to handle non-stationarity of EEG signals. In another research work [46], to deal with noise and inter subject variability, subject transfer based composite local temporal correlation CSP has been proposed. In their work, local temporal based covariance matrices have been used to increase robustness to noise and composite approach based subject transfer has been utilized to avoid overfitting and inter subject variability.

However, CSP and its variants suffer from the SSS problem [43,49] due to presence of large number of EEG electrodes and scarcity of number of samples available for analysis of MI data. Many research works uses dimensionality reduction to handle this problem for motor imagery BCI. The research work [30] used unsupervised fuzzy Hopfield neural network clustering technique to obtain reduced sized flexible clusters of multi-resolution fractal features for the classification of non- stationary EEG signals. In the research work [31], unsupervised and supervised dimensionality reduction techniques (principal component analysis and