Regularised Common Spatial Patterns Algorithms for EEG Analysis

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Introduction

The basic steps of implementing a Brain Computer Interface (BCI) system can be seen in the figure below:

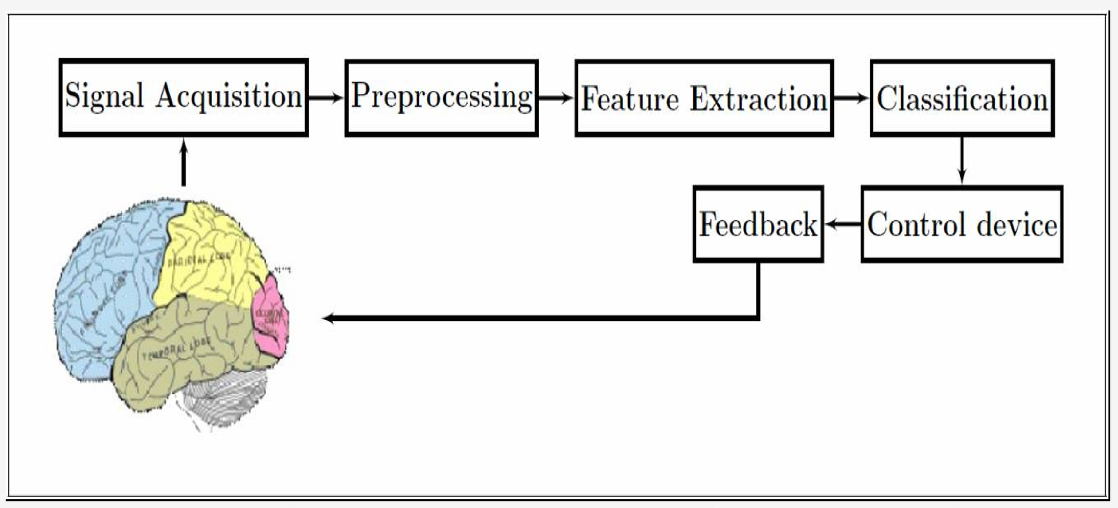

Figure 1: The main steps in BCI system design.

We focus on the stage of feature extraction of EEG signals and especially the use of spatial filters that maximize the discriminability of different brain conditions. The method that is used to estimate spatial filters includes the Common Spatial Patterns (CSP) algorithm and its variations.

Brain Activity

A BCI system "identifies" the user's mental state using a subject's electroencephalogram (EEG). Different types of brain motor leads to stimulation of different parts of the brain. For example, imagining a right hand movement causes event-related desynchronization in the μ and β rhythms on the left motor cortex. Consequently, the discrimination of movements can be related with the somatotopic arrangement of the modulation of the above sensorimotor rhythms [8]. However, the recorded EEG signal is a combination of many cortical activities that are not related directly to the signal of interest and the signal-to-noise ratio is low. In order to solve this problem, spatial filters are used.

Methods

Common Spatial Patterns (CSP) method is used to determine spatial patterns/filters which are extracted from two classes of EEG signals (e.g. left vs right hand movement), by simultaneously diagonalizing the covariance matrices of the EEG signals from each class [3]. The goal of this method is to maximize the first class variance while the second class's variance is being minimized. This algorithm is very sensitive to noise, artifacts and overfitting. For this reason many variants have been proposed. Most of them make use of regularization techniques. Regularized CSP algorithms can be divided into those that regularize the covariance matrix and others that regularize the objective function [1]. The first type includes algorithms that use other subjects' data in order to estimate the covariance matrix, such as Composite CSP(CCSP) [9] and Regularized CSP with Generic learning(GLRCSP) [4] algorithms or the Regularized CSP with Selected Subjects(SSRCSP) algorithm [1] that uses a subset of related subjects unlike the first two which use the whole set of available subjects. In this way the computation of the covariance matrix can be more representative of each class, especially in cases that the training set is small. Another type of algorithm of this kind is Regularized CSP with Diagonal Loading(DL), where the covariance matrix shrinks towards the identity matrix [1].

In the second type algorithms, the objective function is regularized by adding a penalty term in order to penalize the spatial filters. Such algorithms are Tikhonov Regularized CSP(TRCSP) and Weighted Tikhonov Regularized CSP(WTRCSP) [1]. The latter makes also use of the importance of each channel for a BCI system. Additionally, in Spatially Regularized CSP(SRCSP) algorithm [6], the objective function is regularized in order for the spatial location of channels to be taken into consideration.

In most cases, regularized variations of CSP are more robust than the Common Spatial Patterns algorithm.

Mathematical Background

A raw EEG signal of a single trial is represented as an $n_{ch} \times t_{spl}$ matrix X, where n_{ch} is the number of channels and t_{spl} is the number of samples per channel. We compute the covariance matrix of EEG using:

$$C = \frac{(XX^T)}{trace(XX^T)} \tag{1}$$

We calculate the covariance matrix of both of the classes (e.g. left and foot motor imagery).
The objective function to be extremized in order to compute spatial filters w is:

$$J(w) = \frac{w^T X_1 X_1^T w}{w^T X_2 X_2^T w} = \frac{w^T C_1 w}{w^T C_2 w} \tag{2}$$

Solved by the generalized eigenvalue problem [1]. The spatial filters that extremize the above equation are the eigenvectors which correspond to the largest and smallest eigenvalues of $M = C_2^{-1} C_1$.

Future Work

One parameter that should be considered in regularized CSP algorithms is the sparsity of EEG signals in the sensorimotor rhythms.

References

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