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Classification and feature extraction strategies for multi channel multi trial BCI data

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Abstract. The techniques involved in the development of the brain computer interfaces require the validation of results on data recorded from a number of channels for a number of repetitions. But the sheer volume of data in this case calls for a simpler approach and the necessary skill to handle the data. The paper discusses the various techniques such as common spatial patterns (CSP) and evaluates the performance of these techniques in the light of BCI goals.

Keywords: Brain Computer Interface (BCI), Multi layer perceptron (MLP), Common spatial patterns (CSP)

1. Introduction

The current state of the art techniques for the development of brain computer interfaces (BCI) involve the recovery of the task relevant activity from the EEG/ECoG data. This recovered activity is then classified to open a communication channel between the brain and the outside world. Scalp EEG based BCIs are widely investigated because they are quick to setup and facilitate mobility but invasive electrodes implanted to decode the neuronal activity, have been professed to be advantageous for the translational algorithms, to devise this communication channel. Multi class ECoG data recorded using BCI paradigms have been suggested to be robustly classifiable [Leuthardt et al., 2004]. In this paper, event related synchronization/desynchronization (ERS/ERD) maps are used to investigate the spectral properties while combination of common spatial patterns (CSP) and Multi-layer Perceptron (MLP) is employed for the feature extraction and classification.

2. Data and Methodology

The data used is from dataset I of the BCI Competition 2005. Either in this motor imagery experiment of the left small finger or the tongue, ECoG was recorded by using 8x8 ECoG platinum electrode grids, placed on the contralateral motor cortex. Data was sampled at 1000Hz with trial length of three seconds.

2.1. ERS/ERD Maps

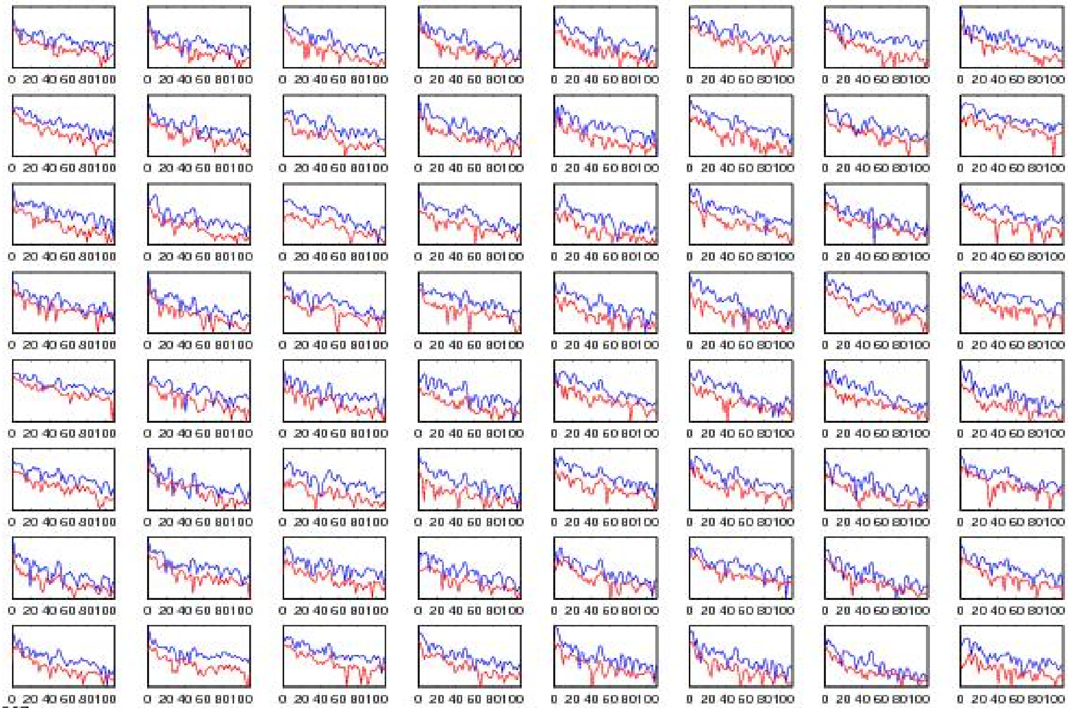
Analysis of event related EEG invokes event related potentials (ERPs) methods, which are phase locked as opposed to ERD/ERS, which are time locked and specific to a frequency band. It is advantageous to visualize EEG activity in the time frequency plane to display any significant power increase or decrease in a predefined frequency band, thereby, representing clear and easy visualization of the movement-related behavior of the induced activity averaged over several trials. Averaging over trials has been employed to deal with evoked potentials to improve the SNR; assuming the ongoing base brain activity as noise. Mathematically, ERD/ERS is represented as ratio of power calculated after averaging over all the trials to the power within a reference interval expressed in terms of percentage.

2.2. Common Spatial Paterns

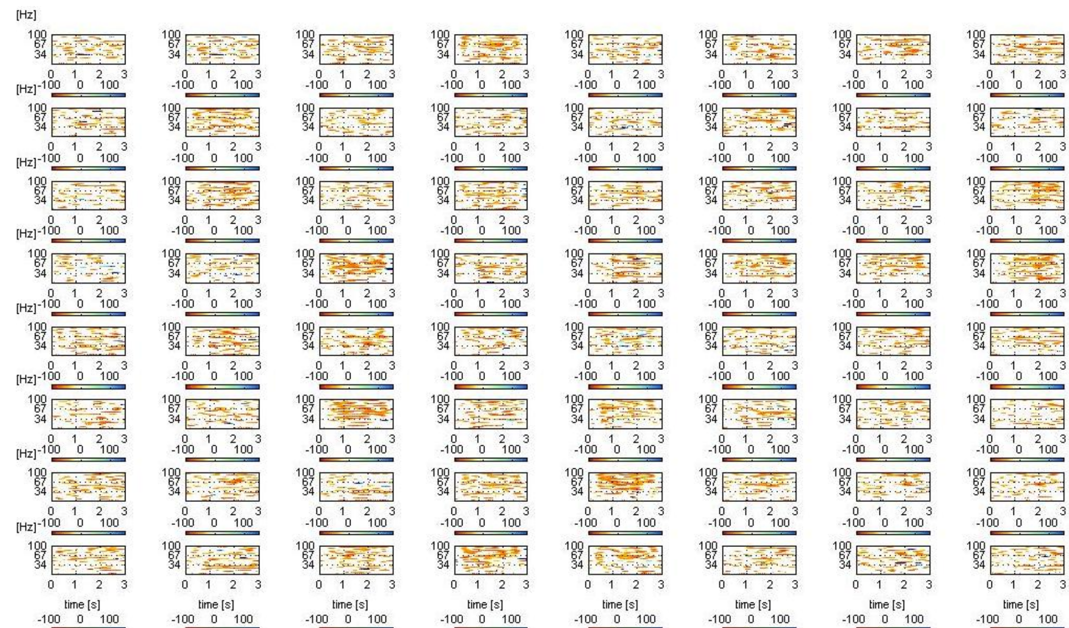
Common spatial patterns (CSP) and their derivatives are used in the BCI research for the feature extraction procedure [Lee et al., 2005], essentially, due to their ability to incorporate spatial information in the algorithm. Reduction in the dimensionality of the data can be done by either optimizing the number of electrodes or reducing the trials. The use of an electrode grid implies that closely placed electrodes have high correlation. In addition, the spatial information is valuable due to certain electrodes able to pick up more relevant information for BCI tasks. CSP reduces the dimensionality of the data by projecting it on a low dimensional feature space. For a two-class problem, it minimizes the variance of one class and maximizes the variance of the other class. Mathematically, this process is better known as joint diagonalization of the covariance matrices obtained from the ECoG data for the two classes.

3. Results, Discussion and Future work

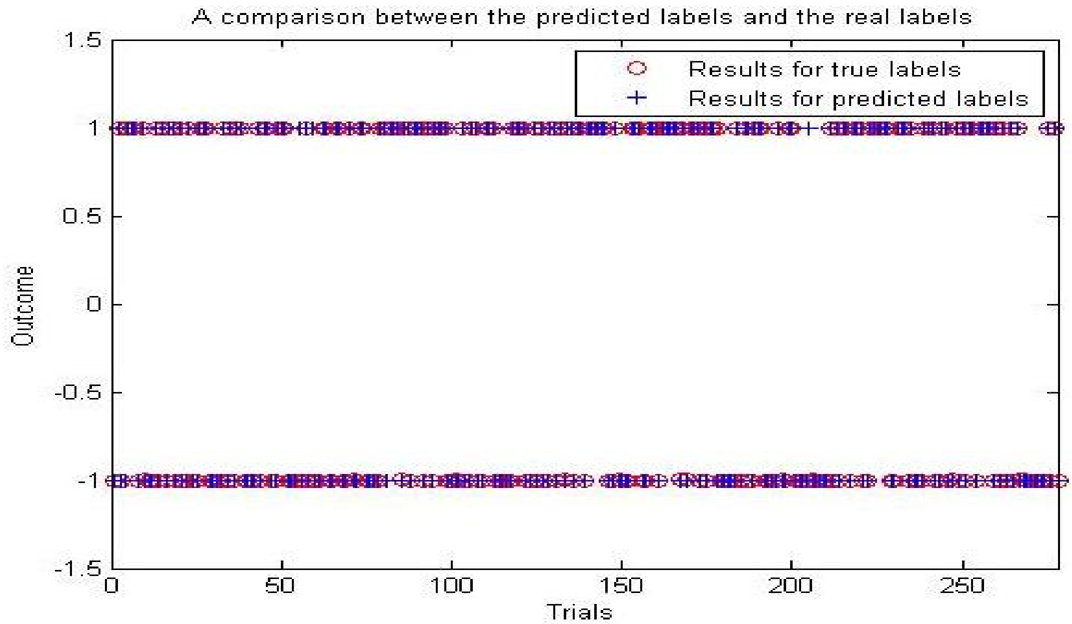
It is clearly observed from the spectra maps Fig 1(a) that unlike EEG, higher frequencies are quite relevant for the ECoG. ERS/ERD maps were therefore plotted within a band of 6-100Hz. A bootstrap value (alpha = 0.05) is used to reject the irrelevant ERD/ERS values. This helps to improve clarity and only the significant patterns are displayed. Even though the cue was presented 0.5s before the recording started, there are some traces of visually evoked potentials in the first few milliseconds of each trial. A reference interval of 1s is used. ERD values are depicted in red and blue color depicts ERS in Fig 1(b).



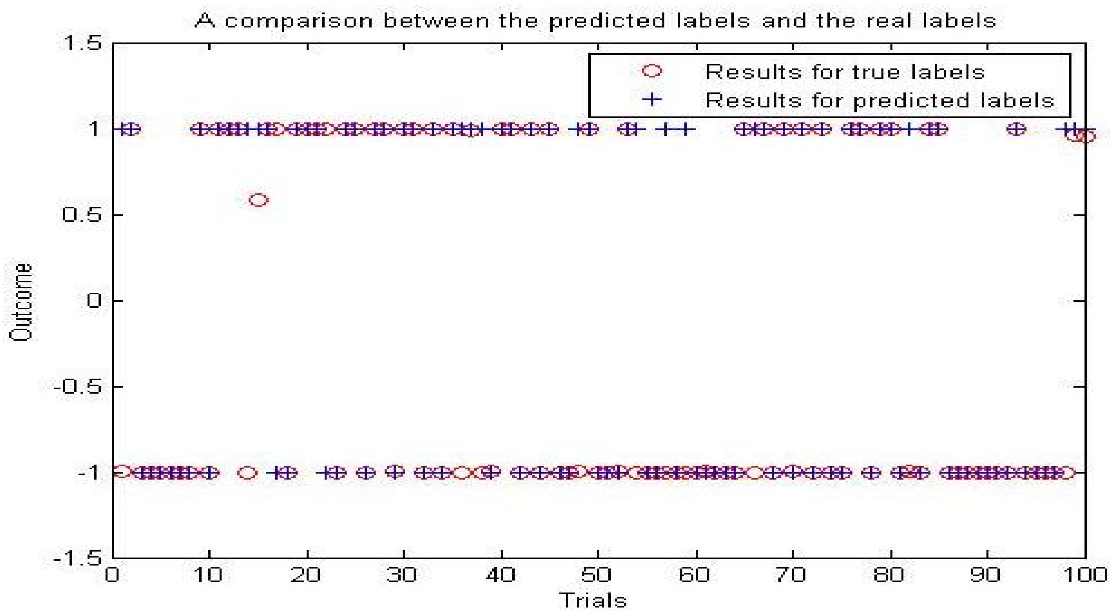
(a)



(b)



c)



d)

Figure 1. *Figure (a) shows the spectra of all channels for class I (b) show the ERD/ERS maps within frequency range 6-100Hz, white spaces indicate non significant values as bootstrapped by the factor alpha (0.05). (c) and (d) show the number of correctly classified trials indicated by the overlapping points for the test and training data.*

The projection matrix for the CSP was obtained using all the training data of 278 trials. The classification algorithm employed here was MLP with back propagation. The accuracy for the training data was 97 % and 86 % for the test data. Figures 1(c) and 1(d) are depictions of the correctly classified trials for the training and test data respectively.

In the previous work, the use of Principal Component analysis (PCA) on this data suggested that there is a need of some spatial analysis [Singh, 2006]. CSP did achieve some success but to have high accuracies of classification, it is perceived that some initial preprocessing algorithm will fine tune the process of feature extraction. Spectrally weighted spatial patterns may be able to achieve more accurate class distinction. Comparative analysis with other classification methods like linear discriminant analysis (LDA) will help to understand the performance of these methods better.

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