Toward Automatic Feature Extraction in Brain–Computer Interfacing

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MEi:CogSci Conference 2013, Budapest

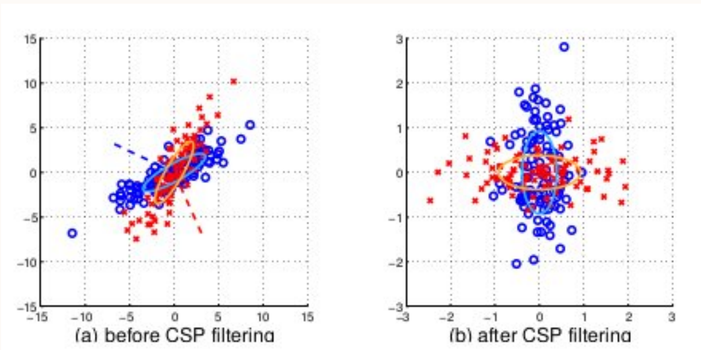
Introduction

People with severe motor disabilities have a new hope in the near future. Improvement of technologies brought many instances of gadgets that make life easier for them. However technically great are these prosthesis, they still lack some accurancy in functionality. Brain–computer interface (**BCI**) systems measure specific features of brain activity and translate them into device control signals, that can control prosthesis or wheelchair. Performance of BCI depends on many characteristics of the system, e.g. signal processing methods, characteristics of the user and others [1].

The goal for **cognitive scientists** is to find not only classifier, but also optimal features that would be able to distinguish the pattern of action, that a subject wants to perform. BCI2000 has its own classifier. Another successful method is adaptive LDA classifier, that can also be unsupervised [5]. This project aims at maximizing the success of classification by the CSP method by selecting the best features.

CSP

Common Spatial Patterns (CSP) method is a commonly used supervised linear feature extraction method used for maximizing discrimination of two conditions. Projections of the preprocessed EEG data (in terms of their spectral characteristics) are chosen in a way so as to maximize variance for one condition and minimize for the other [2].



(a) Ellipses show the estimated covariances and dashed lines show the direction of CSP projections. (b) Horizontal (vertical) axis yields the largest variance in the red (blue) class and the smallest in the blue (red) [4].

Mathematics behind CSP: The prerequisite for CSP is existence of two data sets X_1, X_2, both of dimension $n \times t$, n is the number of variables, t is the number of trials. Covariance matrices are computed for both data sets:

$$R_1 = \frac{X_1 X_1^T}{t}, R_2 = \frac{X_2 X_2^T}{t}$$

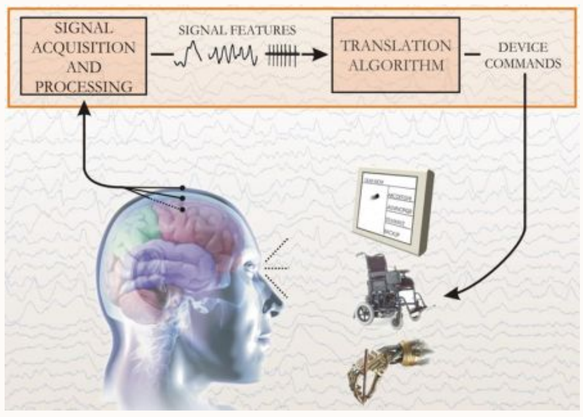
Matrix $P = [p_1, \ldots, p_n]$ of eigenvectors and diagonal matrix of eigenvalues $D = [\lambda_1, \ldots, \lambda_n]$, $\lambda_1 \geq \ldots \geq \lambda_n$, are found. Then first k eigenvectors is selected to create matrix W, $k/2$ for R_1, $k/2$ for R_2 such that $S = W^T E$, where $W \in \mathbb{R}^{k \times n}$ is the spatial filter matrix, $S \in \mathbb{R}^{k \times t}$ is the filtered signal matrix and $E = X_1 \cup X_2$ [2,4].

Acknowledgement

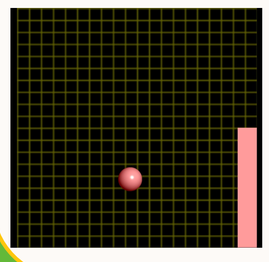
I would like to thank my supervisor doc. Igor Farkaš for his help, time and his very useful advice and overview in the field of this project.

BCI2000

In their non-invasive form, BCI systems use brain electrical signals recorded from the scalp (**EEG**) to control the environment. Open-source BCI2000 system consists of four modules: source, signal processing, user application, and operator interface [1]. BCI2000 can be be used in various online applications. In **motor imagery** paradigm, the user is instructed to perform specific motor imagery when a specific target appears on the screen and the signal features associated with this movement or imagery are evaluated and considered as the conditions.



BCI system - schema

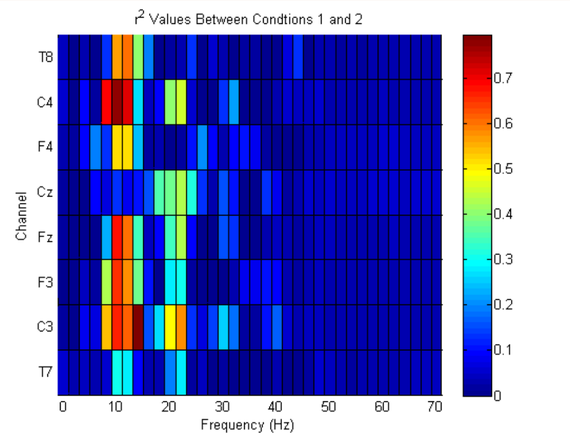


We can use various user applications

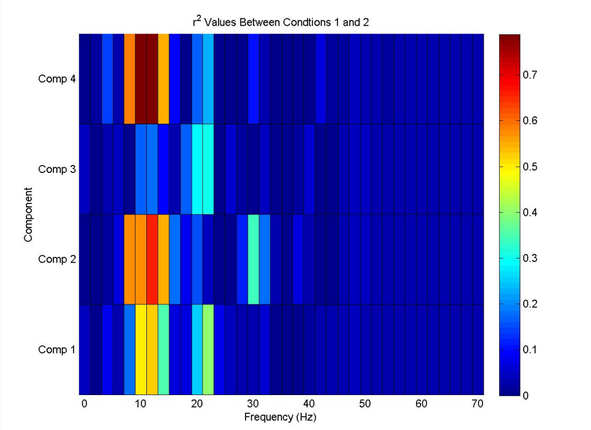
- wheel chair movement
- typing of words
- cursor movement

Using CSP in BCI2000

Method and Results: In BCI2000, feature selection is done by an offline analysis tool that shows the difference (in terms of the coefficient of determination) between the two conditions for each electrode and frequency range after a training session [3]. The selection of features is subject to human decisions. The project goal is to use CSP for automatical selection of electrodes and frequencies. Measured data from previous EEG experiments will be processed by standard BCI2000 offline analysis and by offline analysis using CSP. Their comparison shows the possibility to substitute the CSP filter for standard offline analysis. Using CSP online in the user application and comparison with other classfiers is desirable. We tried to extend usage of CSP in BCI2000 by: ***Component selection***: We projected the original signal from 8 dimensions into 4 components with the highest variance.

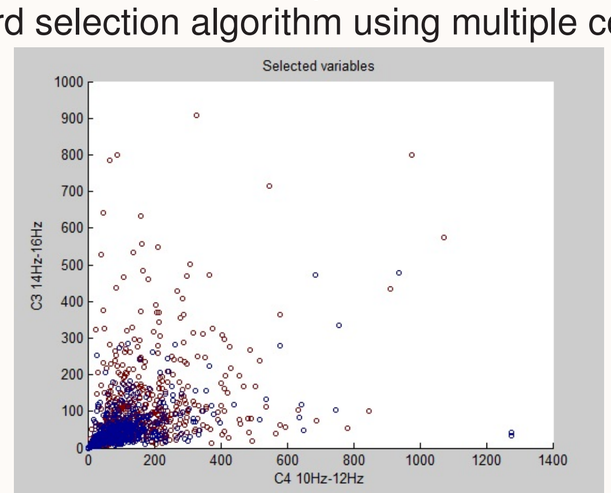


BCI2000 Offline Analysis using Common Average reference

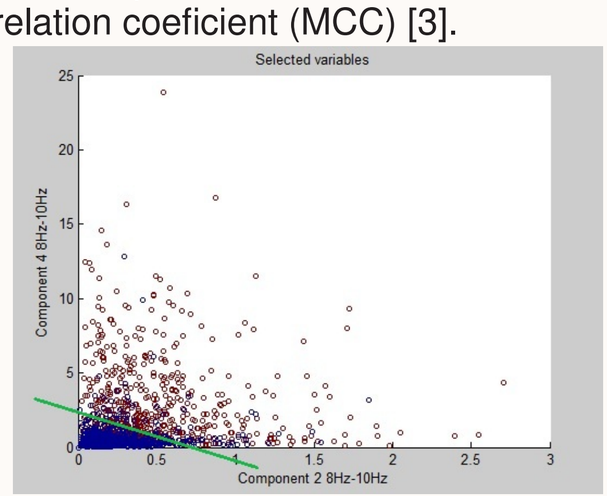


Offline Analysis after CSP filtering

Feature selection: Data from previous method was further processed with CSP method extended by backword selection algorithm using multiple correlation coeficient (MCC) [3].



Manually selected features after BCI2000 Offline analysis



Selected features after CSP with added separating line

Conclusion: Selected feature vectors are better separable by hyperplane, but selected features did not correspond exactly with features selected by offline analysis. This differnce could be caused by BCI2000 signal processing or the used CSP + MCC, so improvement of this method is possible.

References

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