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# Autoregressive spectral analysis in Brain Computer Interface context

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*Abstract:*
**Over the past decade, a number of studies have evaluated the possibility that scalp-recorded electroencephalogram (EEG) activity might be the basis for a brain-computer interface (BCI), a system able to determine the intent of the user from a variety of different electrophysiological signals. With our current EEG-based communication system, users learn over a series of training sessions to use EEG to move a cursor on a video screen: to make this possible users must learn to control the EEG features that determines cursor movement and we must improve signal processing methods to extract from background noise the EEG features that the system translates into cursor movement. Non-invasive data acquisition, makes automated feature extraction challenging, since the signals of interest are `hidden` in a highly noisy environment. It was demonstrated that the spatial filtering operations improve the signal-to-noise ratio ([6]). On the contrary, autoregressive modeling has been successfully used by many investigators for EEG signals analysis in BCI context (e.g. [3-4]), but to our knowledge no clear guidelines exist on how to choose the parameters of the spectral estimation.**
**Here we present an analysis of the dependence of BCI performance on the parameters of the feature extraction algorithm. In order to optimize user performances, we observed that a different model order value had to be chosen correspondently to different EEG features used to control the system, according to the differences in the spectral power content of alpha and/or beta bands.**

*Keywords*— **Brain Computer Interface, EEG, Motor Imagery, Feature Extraction, Autoregressive Modeling**

## I. INTRODUCTION

The development of a Brain-Computer Interface (BCI) aims to provide a communication channel from a human to a computer that directly translates brain activity into sequences of control commands as tools for communicating solely by intentions that are reflected in brain signals.

A lot of scientists works to determine the best algorithms for discrimination between different brain states and translation of these signals into device commands (e.g. [1-2]).

Non-invasive data acquisition, makes automated feature extraction challenging, since the signals of interest are `hidden` in a highly noisy environment, so it is important to strive for robust signal processing methods that are as invariant as possible against such distortions (e.g. [3]). It was demonstrated that the spatial filtering operations improve the signal-to-noise ratio ([6]). On the contrary, autoregressive modeling has been successfully used by many investigators for EEG signals analysis in BCI context (e.g. [3-4]), but to our knowledge no clear guidelines exist on how to choose the parameters of the spectral estimation.

The aim of the present study is to perform a systematic analysis of the dependence of BCI performance on the parameters of the feature extraction algorithm, in order to improve both the accuracy and the generalization ability of the feature extraction.

## II. METHODS

### *A. Recordings*

Eight healthy subjects, 26-30 years old, participated to the study. Subjects training consists in 6-10 recording sessions (weekly acquired for each subject) according to standard procedures of mu-based BCI training: they sat in a reclining chair facing a video screen, were asked to remain motionless during performance and to perform hands or feet movement imagination to bring up or down the cursor for correspondingly top or bottom targets.

Each session consisted of eight 3-min runs of 29 trials.

An EEG system (Vision, Brain products GmbH, Germany) was used to record electrical potentials from 59 electrodes disposed on the scalp by means of an electrode cap (reference electrode on the right ear, band-pass 0.1-50 Hz before digitization). A subset of channels (Cz/CPz or/and C4/Cp4 or/and C3/Cp3 dependently on the subject), re-referenced to the common average reference (CAR), were used to control cursor movement. The cursor moved horizontally across the screen at a fixed rate, while the user controlled vertical movements towards appearing targets

using *bci2000* framework with 2 targets covering half screen. (BCI2000 framework [3], D2box task).
The cursor moves as a function of an EEG control signal, which is usually the amplitude of mu rhythm activity (8–12 Hz activity) or the amplitude of higher frequency (e.g., 18–30 Hz) beta rhythm activity, both focused over sensorimotor cortex.

### *A. Real Data Off- Line Analysis*

For the purpose of the study, a cross-comparison was performed between different autoregressive models by varying model order and the length of EEG segment data, according to the attitude of the estimated EEG segments to predict the target. Data are reported in term of topographical and spectral analysis of $r^2$ values, a measure proved very useful for extracting mu- or beta-rhythm signal features [3].
$R^2$ value represents the level of correlation between user intent and the signal features the BCI employs to recognize that intent, so it's computed as the correlation between the amplitude of the signal spectrum used to control cursor movement and target position. Perfect correlation produces an $r^2$ value of 1.00.
We estimated the EEG signal's spectrum by using time epochs up to of 1 second (2 Hz bin resolution), a 33% overlap and 200 ms windows. We averaged each window result to obtain the estimation of EEG signal's spectrum in each bin frequencies. We evaluated performances for four epoch lengths: 200 ms, 250 ms, 500 ms e 1 s and than for the 1 sec. epoch length that maximize performances we ranged model order from a minimum of 10 to a maximum of 40, in order to approximate control signal's non parametric PSD (Welch PSD). (Fig. 1)

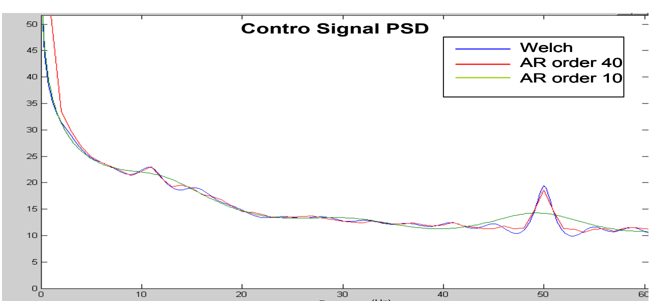


*Fig.1*. Different Power Spectral Density estimations of a typical control signal (Subject 3 Control Signal on channel C3) by means of Matlab SPtool

### *A. Synthetic Data Generation and Analysis*

We hypothesize that differences in model order selection are not related to the topographic localization of the EEG signals over sensorimotor areas: best performances were obtained for lower model order in both cases of bilateral desynchronization and mesial synchronization in beta band, so we hypothesize that differences are due to signal's frequency components rather then to sensorimotor components. In order to validate this hypothesis we also conducted simulations of the effects of model order selection using a simple model of participant EEG control signals. We reconstructed 5 different synthetic control signal's spectra that represent respectively three Hz alpha band desynchronization, three or six Hz beta band desynchronization or the two simultaneous alpha and beta desynchronization, in order to find differences for model order selection due to the "shape" of the different control signals. For each of them we test the model order we had to select to optimize user's performances in the ideal case he had to control the system by means of the "built" synthetic signal.

## III. RESULTS

The comparison of the distribution of r2 values at the most responsive frequency/channel revealed the best model order varied among subjects depending on the features used to control cursor movement: whose subjects with showed the highest values and most localized topographies in alpha band over bilateral sensorimotor cortex (condition A) achieve the best performances with an higher order (the best order varied from 22 to 28 among subjects (Fig2); subjects whose control signal is over mesial sensorimotor cortex in beta band, in both cases of mesial (condition B) and bilateral (condition C) desynchronization, maximize their performances by using a lower model order, from 10 to 20 among subjects. (Fig. 3)

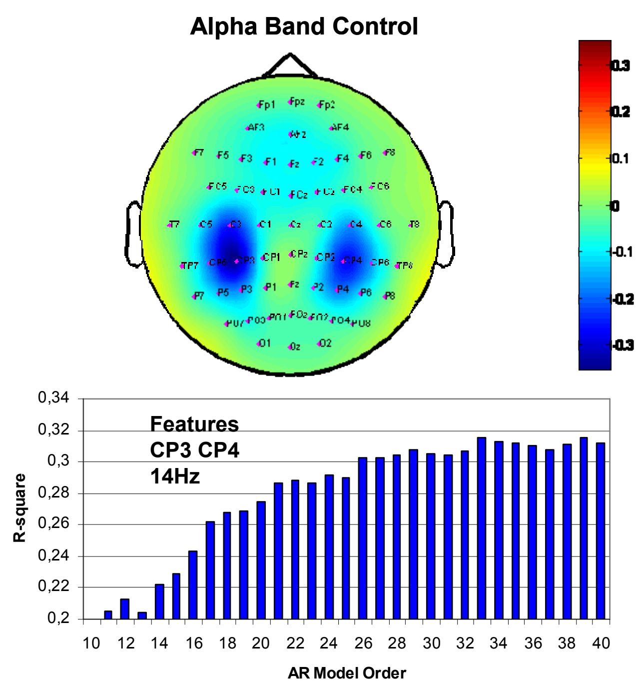


*Fig.2* Topographical distributions of $R^2$ values for a representative subject who controls the system by a desynchronization of mu-rhythm in alpha band, over sensorimotor cortex. The histogram represents $R^2$ peaks on control channels (Cp3 or CP4) varying the autoregressive model order.

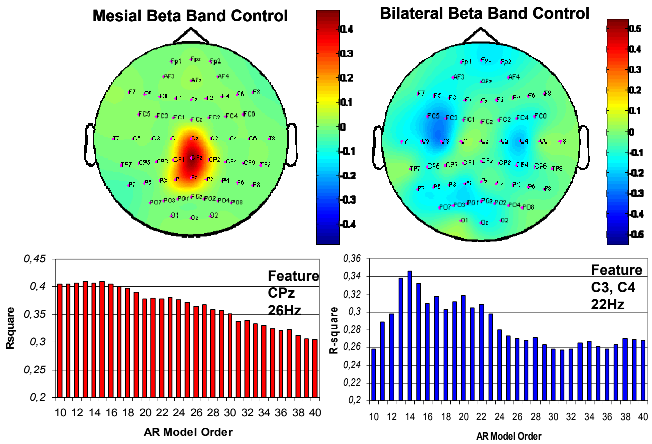


*Fig.3* Topographical distributions of $R^2$ values for two representative subjects who control the system respectively by a desynchronization of beta-rhythm over mesial (left figure) or bilateral (right figure) sensorimotor cortex (Conditions C and B, Beta Band Control). The histogram represent $R^2$ peaks on control channels (CPz for mesial control, C3 and C4 for bilateral control) varying the autoregressive model order.

The analysis of synthetic data confirmed real data results: the best order in terms of r-square maximization for desynchronization of mu-rhythm is 32 (Fig. 4).
We didn't find appreciable differences between different beta bands control signals: the best order in terms of r-square maximization varied from 20 to 22 among different kind of beta desynchronization (Fig. 5)

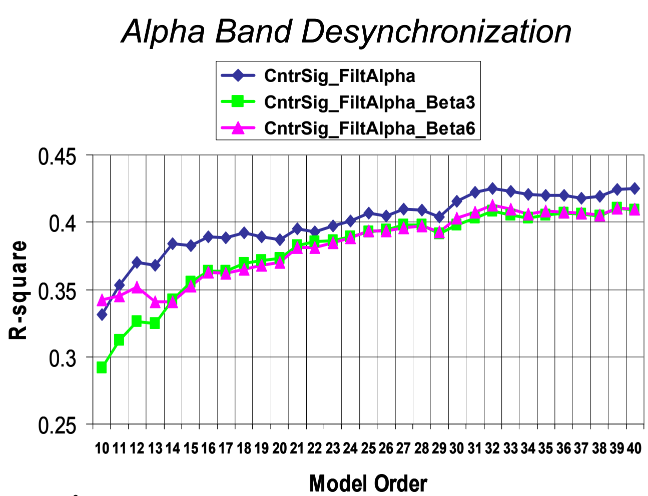


Fig. 4 $R^2$ values varying the autoregressive model order for built synthetic signals in the cases of 3 Hz alpha band desynchronization (blue line), and simultaneous alpha and 3/6 Hz beta band desynchronization (green line/ violet line)

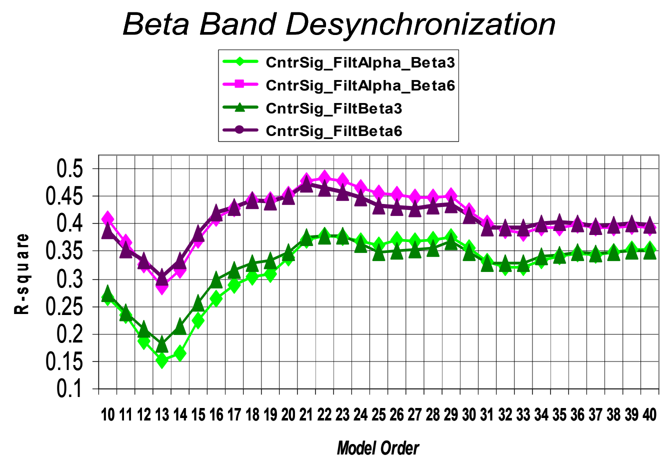


Fig. 5 $R^2$ values varying the autoregressive model order for built synthetic signals in the cases of 3 Hz beta band desynchronization (dark green line), 6 Hz beta band desynchronization (dark violet line), simultaneous 3 Hz alpha and beta band desynchronization (light green line), simultaneous 3 Hz alpha band and 6 Hz Beta band desynchronization (light violet line). Labels represent the maximum value for each curve.

We finally report a synthetic view of averaged results: conditions A, min 0,17 (model order 10), max 0.33 (model order 33); conditions B, maximum 0.3855 (model order 13), min 0,33 (model order 36); conditions C, max 0.259 (model order 13), min 0.19 (model order 40; Fig. 6).

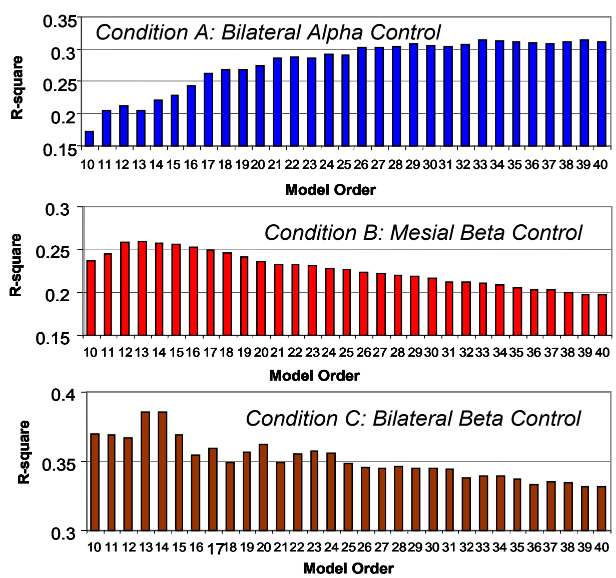


Fig. 6 R-square values varying the autoregressive model order for averaged real data in conditions A (desynchronization in alpha band over bilateral sensorimotor cortex), B (desynchronization in beta band over bilateral sensorimotor cortex), and C (desynchronization in beta band over mesial cortex),. For condition A and B we average results of 15 training sessions from 5 different users whose control was on bilateralsensorimotor cortex; for condition B we average results of 9 sessions from the other three users whose control was on mesial sensorimotor cortex).

## IV. DISCUSSION

A statistical study, using about 200 training sessions, was performed to find a relationship between r2 values measured on EEG data off-line and accuracy gained from users during on line sessions. According to this study the increase of r-square value obtainable by optimizing model order selection corresponds in a different increase of performances related to the ability of the users: the increase of r-square value we can obtain by varying model order is between 0,05 and 0,1, that means an increase of the classification range from 5% to 15%.

These findings show that the performance of a BCI classifier can be enhanced by tuning to the individual subject the parameters for the feature extraction - a concept that is already well known for spatial selection of the features. Future work will extend this study to alternative (e.g. non-parametric) feature extraction algorithms.

## REFERENCES

[1]Wolpaw J.R., Birbaumer N., McFarland D.J., Pfurtscheller G., Vaughan T.M., Brain–computer interfaces for communication and control. Invited Review. (2002) Clinical Neurophysiology, 113 (6), pp. 767-791.

[2] Schalk G, McFarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. BCI2000: a general-purpose brain-computer interface (BCI) system. IEEE Trans Biomed Eng. 2004 Jun;51(6):1034-43.

[3] Lemm S., Blankertz B., Curio G. and Müller KR., Spatio-Spectral Filters for Improving the Classification of Single Trial EEG, IEEE Trans Biomed Eng., 2005 Sep; 52 (9): 1541-8.

[4] Pfurtscheller G, Neuper C, Schlogl A, Lugger K. Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters. IEEE Trans Rehabil Eng. 1998 Sep; 6(3):316-25.

[5] Fabiani GE, McFarland DJ, Wolpaw JR, Pfurtscheller G. Conversion of EEG activity into cursor movement by a brain-computer interface (BCI).IEEE Trans Neural Syst Rehabil Eng. 2004 Sep;12(3):331-8.

[6] McFarland DJ, Lynn M. McCane S., David SV., Wolpaw JR., Spatial filter selection for EEG-based communication, Electroencephalogr. Clin. Neurophysiol., 103(3):386-394, 1997.