Task Identification Using Fluctuation Analysis

E. R. Bojorges-Valdez[1], J. C. Echeverría[1], O. Yáñez-Suárez[1]
[1] *UAM-I, Mexico City, Mexico*

Correspondence: E.R. Bojorges-Valdez, Universidad Autónoma Metropolitana, col. Vicentina, del. Iztapalapa, C.P. 09340, Mexico D.F., México, Ed.T-227. E-mail: erbv@xanum.uam.mx

Abstract. Task identification processes for motor control routines were performed using a fractal index. EEG data from 40 healthy subjects were analyzed. The main finding is the identification of significant changes in such index from electrodes near to the motor cortex, which support the utilization of this index as input for a BCI paradigm.

Keywords: DFA, EEG, Task Identification

1. Introduction

Fractal indexes as derived from EEG or ECoG signals have been used in different neurological studies such as sleep stage identification, anesthesia monitoring, etc. Recently the utilization of such indexes as input for a BCI has also gained interest [Reza and Moradi, 2004]. Yet, changes detected by fractal indexes have not been found consistent or in agreement with physiological phenomena. Fractal indexes can be estimated via different methods such as Higuchi, box counting, DFA (Detrended Fluctuation Analysis), among others [Eke et al., 2002]. In this work DFA was used to identify the realization of tasks that involve motor control [Pfurtscheller and Silva, 1999].

2. Material and Methods

Forty healthy subjects were recruited to perform an attentional task, which consisted in pushing a button when a visual stimulus was detected. Recordings of 20 channels EEG for each subject were performed in two conditions: *passive*, stimulus presentations without subject response; and *active*, stimulus presentation with response

Epochs of 2 seconds synchronized with the stimulus presentation were selected, and for each epoch of each channel, a fractal index (α) was estimated using DFA [Peng et al., 1994]. For each subject two sets of indexes per channel were conformed, α_p and α_a corresponding to *passive* and *active* periods respectively.

2.1. Statistical Test

Mann-Whitnney tests for each channel of each subject were performed to probe median changes between the two sets of motor activity indexes described before. Population results were averaged to find the top five channels which presented major differences between both activities. The corresponding α values of these channels were used as inputs for task identification using a Support Vector Machine with Gaussian kernel (SVM) [Burgess, 1998].

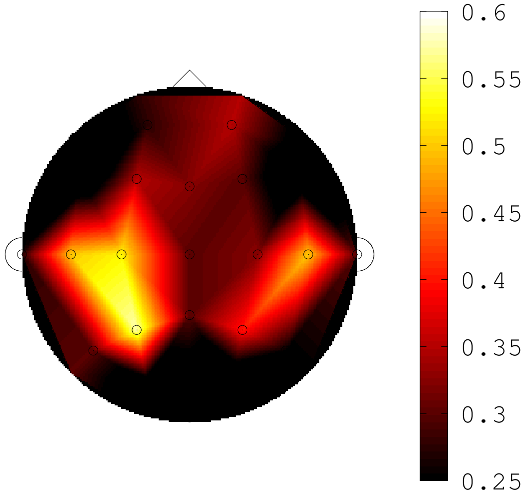
2.2. Task Identification

Task Identification was evaluated using a 20-fold cross-validation routine, assessing accuracy and area under ROC curve (AUC) for each subject. Cross-validation process consisted in taking 70 % of the total number of epochs for each subject (randomly) to construct a classifier and to test it over the remaining 30 %. Accuracy and AUC values were estimated and averaged for each subject. The summary of these results are shown in the next section.

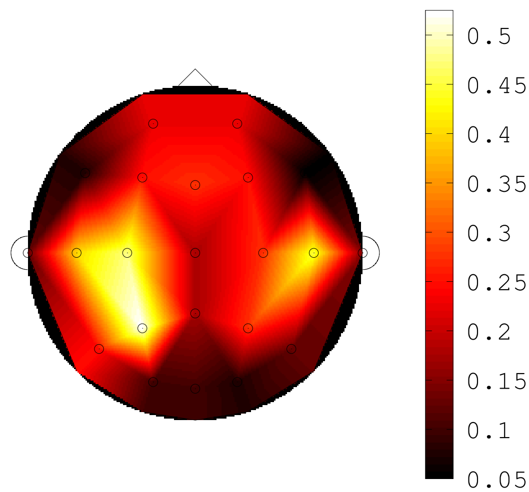
3. Results

3.1. Statistical Tests

The scalp distribution on figure 1 (a) shows in terms of population ratio which channels have a significant statistical differences at $p < 0.05$ for $H_o : \alpha_p = \alpha_a$, whereas figure 1 ($b$) shows the ratio with $p < 0.025$ for $H_o : \alpha_p > \alpha_a$.



(a) $\alpha_p = \alpha_a$



(b) $\alpha_p \leq \alpha_a$

Figure 1: *Scalp distribution of population ratio at* $p < 0.05$ *for* (a) $H_o : \alpha_p = \alpha_a$ *and* $p < 0.025$ *for* (b) $H_o : \alpha_p \leq \alpha_a$

3.2. Task Identification

Table 1 shows mean values of accuracy and AUC from the top 5 channels selected as suggested by the statistical analysis. Note that these values of AUC are above the chance line (i.e. 0.5).

Table 1: *Mean Values for Task Identification analysis*

index	value
AUC	0.72474 ± 0.19103
Accuracy	0.65441 ± 0.15586

4. Discussion

The main finding of this study is the identification of significant changes in the fractal index α as derived from EEG data collected from those electrodes near to motor cortex (in both hemispheres). In addition, the task identification, accuracy and AUC values suggest that this index could be used as input for a BCI application. The mean time for estimating the α index over a series of 256 sample is 5.1 (1.1) ms using a non-optimized algorithm (Intel Core 2). Given that α values were apparently larger for *passive* periods, these findings seem in accordance with the consideration that neurons become desynchronized during realization of motor control routines [Pfurtscheller and Silva, 1999].

Acknowledgments

First author acknowledges to Mexico's National Council of Science and Technology (CONACyT) for supporting his PhD studies (via scholarship 168498) and the Institute of Science and Technology of Mexico City (ICyTDF) for providing financial aid to attend this conference, and finally to the Autonomous Metropolitan University (UAM).

References

Burgess, C. J. C. (1998). A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, 2:121–167.

Eke, A., Kocsis, L., and Kozak, L. R. (2002). Fractal characterization of complexity in temporal physiological signals. *Physiol Meas*, 23:R1–R38.

Peng, C.-K., Buldyrev, S., Simons, M., Stanley, H., and Goldberger, A. (1994). Mosaic organiztion of DNA nucleotides. *Phys Rev E*, 49(2):1685–1689.

Pfurtscheller, G. and Silva, F. L. D. (1999). Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clin Neurophysiol*, (110):1842–1857.

Reza, B. and Moradi, M. H. (2004). A new approach in the BCI research based on fractal dimension as feature and adaboost as classifier. *J Neural Eng*, (1):212–217.