

Estimation of Graph-Varying Indexes from High-Resolution EEG Recordings during a Voluntary Motor Act

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Abstract— In this work, a novel approach is proposed in order to capture relevant features related to the structure and organization of the functional brain networks estimated in the time-frequency domain. To achieve this, we used a cascade of computational tools able to estimate first the electrical activity of the cortical surface by using high-resolution EEG techniques. Then, on the cortical signals from different regions of interest, we estimated the time-varying functional connectivity patterns by means of the adaptive Partial Directed Coherence. Such time-varying connectivity estimation returns a series of causality patterns evolving during the examined task, which can be summarized and interpreted with the aid of mathematical indexes based on the graph theory. The combination of all these methods is demonstrated on a set of high-resolution EEG data recorded from a healthy subject performing a simple foot movement.

I. INTRODUCTION

THE importance of objectively comprehending the relationships among the differently specialized brain structures is assuming a relevant role in the Neuroscience [1]. Several methods able to estimate functional connections among such structures have been proposed and discussed in literature [2],[3]. Among these, the use of multivariate autoregressive (MVAR) models for the estimation of cortical connectivity is of particular interest since they characterize at the same time direction and spectral properties of the interaction between different brain signals and require only one model to be estimated from all the time series [4]. However, classical utilize of these methods requires the stationarity of the signals and transient pathways of information transfer could remain hidden because the

estimation of a unique model on the entire time interval. To overcome this limitation, different algorithms for the estimation of MVAR with time dependent coefficients were recently developed [5]. Anyway, the interpretation of such functional brain connectivity patterns remains an open issue, because often-estimated functional cerebral networks have a relative great size and complex structure. Recently, it was realized that functional connectivity networks estimated from EEG or MEG recordings can be analyzed with tools that have been already generated for the treatment of graphs as mathematical objects [6]. Anyway, empirical results demonstrate that purely topological models, which neglect the weight of connections, are inadequate to explain the rich and complex properties observed in real systems [8]. According to this observation, emergent models proposed for weighted and directed graphs have been employed in this study to naturally achieve the available broad scale distributions and topology-weight correlations among the units.

II. METHODS

A. Time-Varying Connectivity

A time-varying formulation of Partial Directed Coherence (PDC) based on an adaptive MVAR (AMVAR) model is employed in this study. Time dependent parameter matrices were estimated by means of the recursive least squares (RLS) algorithm with forgetting factor, as described in [5], [9]. Time-varying PDC allows for the observation of transient influences among different cerebral regions during the execution of a task and provides the evolving patterns of connectivity in particular frequency contents.

B. Weighted Graph Analysis

1) *Strength*. This quantity has to be split into in-strength s_{in} and out-strength s_{out} , when directed relationships are being considered. The strengths integrate the information on the number (degrees) with the weights of the links, thus representing the total amount of intensity outgoing or incident into a node.

3) *Efficiency*. The efficiency is a quantity recently introduced in [10] to measure how efficiently the nodes of the network communicate if they exchange information in parallel. At global scale, it measures the overall communication among the units while at local scale it represents the tendency to form clusters that mutually share functional connections.

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III. RESULTS

In this work, we would like to show the suitability of the time-varying graph approach illustrating the cortical dynamics obtained from a representative healthy subject. He was asked to perform a dorsal flexion of his right foot.

A. Strength.

The analysis of the “strength” indexes put in evidence a particular subset of regions, which receives a growing amount of information as time elapses. Both the cingulate motor areas (CM_L and CM_R), altogether with the contralateral supplementary motor area (SMp_L) and contralateral primary motor area (MF_L) form the strongest nucleus for the whole incoming information. Instead, the outgoing information places itself more uniformly among the cortical regions during time advancing.

B. Efficiency.

The study of the efficiency indexes showed how the brain network changes its structure and organization according to the different functional necessities during the performance of a simple movement. At one second from the onset, cortical regions of interest show low levels of global and local efficiencies leading to a weak communication pattern. As time gets near the execution of the movement, local properties arise and local efficiency increases steering the network towards an ordered and well organized configuration. In proximity of the execution (about 200 ms before the onset), global and local efficiency reach their highest value and the cortical network assumes a clear Small-World (SW) [7] configuration which interpolate between the characteristics of a regular lattice and a random graph. After the onset, the cortical network seems to return to its initial state, showing mostly low values of global and local efficiency and therefore lower level of communication.

IV. DISCUSSION

The extraction of relevant features from complex evolving graphs allowed for the generation and testing of particular hypotheses on the physiologic nature of the functional networks estimated from high-resolution EEG recordings. Moreover, the time-varying adaptation of such mathematical indexes is particularly suitable to capture the dynamics of the cortical networks and represents a promising tool to be integrated in several on-line procedures, ranging from clinical to brain-computer interface applications.

REFERENCES

[1] Horwitz B. “The elusive concept of brain connectivity”. *Neuroimage* 19:466-470, 2003.
[2] Lee L, Harrison LM, Mechelli A. “The functional brain connectivity workshop: report and commentary”, *Neuroimage* 19:457-465, 2003.
[3] David O, Cosmelli D, Friston KJ. “Evaluation of different measures of functional connectivity using a neural mass model.” *Neuroimage* 21(2):659-73, 2004

[4] Kaminski M, Blinowska K. “A new method of the description of the information flow in the brain structures”. *Biol Cybern* 65:203-210, 1991.

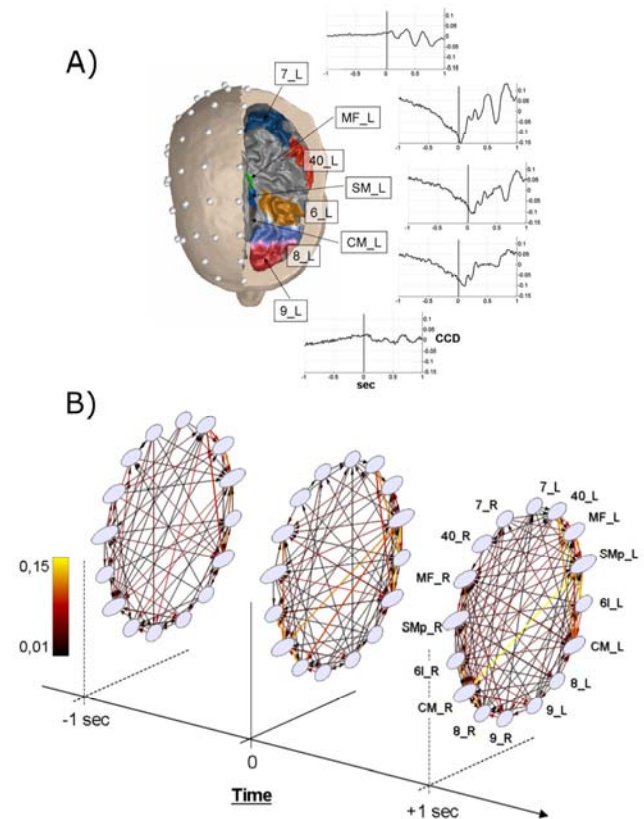


Fig. 1A) Head model employed for the cortical activity estimation. Time waveforms are shown for particular ROIs that are represented in color on the cortex.

1B) Representation of time-varying networks in the Beta frequency band. Three instants, 1 second before the movement, the onset and 1 second after the movement are illustrated for representative purposes. The influence from an area X to Y is represented by an arrow; the intensity of such a relationship is coded by its size and color according to the color-bar

[5] Moeller E, Schack B, Arnold M, Witte H. “Instantaneous multivariate EEG coherence analysis by means of adaptive high-dimensional autoregressive models.” *J Neurosci Methods* 105:143-58, 2001.
[6] Stam CJ. “Functional connectivity patterns of human magnetoencephalographic recordings: a ‘small-world’ network?” *Neurosci Lett* 355:25-8, 2004.
[7] Watts DJ, Strogatz SH. “Collective dynamics of ‘small-world’ networks”. *Nature* 393:440-2, 1998.
[8] Boccaletti S, Latora V, Moreno Y, Chavez M, Hwang DU. “Complex networks: structure and dynamics.” *Physics Reports*. 424:175-308, 2006.
[9] Hesse W, Möller E, Arnold M, Schack B. “The use of time-variant EEG Granger causality for inspecting directed interdependencies of neural assemblies”. *Journal of Neuroscience Methods* 124:27-44 2003.
[10] Latora V and Marchiori M. “Efficient behaviour of small-world networks”. *Phys Rev Lett* 87:198701 2001.