Pattern Recognition 43 (2010) 530 – 544

Contents lists available at ScienceDirect

Pattern Recognition

journal homepage: www.elsevier.com/locate/pr

Classification and interactive segmentation of EEG synchrony patterns

Alfonso Alba[a,*], José L. Marroquín[b], Edgar Arce-Santana[a], Thalía Harmony[c]

[a]Facultad de Ciencias, UASLP, Diagonal Sur S/N, Zona Universitaria, C.P. 78290, San Luis Potosí, SLP, Mexico
[b]Centro de Investigación en Matemáticas, Guanajuato, Mexico
[c]Instituto de Neurobiología, UNAM Campus Juriquilla, Querétaro, Mexico

A R T I C L E   I N F O

Article history:
Received 30 May 2008
Received in revised form 25 November 2008
Accepted 2 March 2009

Keywords:
Interactive segmentation
Seeded region growing
Bayesian regularization
EEG synchrony
Electroencephalograpy
Psychophysiological experiment

A B S T R A C T

This paper presents a novel methodology for the exploratory analysis of power and synchronization patterns in EEG data from psychophysiological experiments. The methodology is based on the segmentation of the time–frequency plane in regions with relatively homogeneous synchronization patterns, which is performed by means of a seeded region-growing algorithm, and a Bayesian regularization procedure. We have implemented these methods in an interactive application for the study of cognitive experiments, although some of the techniques discussed in this work can also be applied to other multidimensional data sets. To demonstrate our methodology, results corresponding to a figure and word categorization EEG experiment are presented.

1. Introduction

EEG measurements obtained from a scalp electrode consist of voltage signals which reflect the electrical activity of the underlying networks of neurons. During the execution of relatively complex tasks, such as adding two numbers or making a decision, several areas of the brain may interact together by means of reciprocal connections, forming what is called a *neural assembly* [6]. Even when these areas are distant to each other and perform specialized tasks, the interaction between them may be reflected as some form of synchronization or correlation between their corresponding EEG signals. According to Varela et al. [34], one of the most plausible mechanisms for neural integration is the formation of dynamical links which are reflected as phase-synchronization of the EEG signals. Another work, by David and Friston [7], introduces a mathematical model of the EEG dynamics based on the interaction of excitatory and inhibitory neural populations. The authors show that, under this model, a bidirectional coupling between two different areas of the brain will result in a phase difference of zero or π between the corresponding EEG signals, regardless of the distance between the two areas. This is supported by various experimental works in which it was observed that the distribution of the phase difference between two EEG signals concentrates around zero during the episodes of high synchrony [10,30].

Synchronization is typically measured between pairs of narrowband EEG signals corresponding to different electrodes. Various measures have been proposed in the literature, including coherence [27], and measures based on certain statistics of the phase difference, such as the circular variance [20,19], or the average magnitude [3]. Most of these measures yield values between 0 (no synchrony) and 1 (perfect synchrony); in practice, however, the differences between values at episodes of high synchrony and episodes of low synchrony are very subtle, thus a statistical analysis is usually required to determine the true significance of the observations. Neuroscientists are often interested in how a specific EEG measure (e.g., power or synchrony) changes with respect to a certain baseline. The baseline is usually obtained from the EEG data during a condition which is considered neutral, for example, previous to a treatment, or immediately before a stimulus is presented to the subject. In a cognitive experiment, one is usually interested in how these inter-electrode couplings change over time and frequency; this analysis may involve the computation of a relatively large data set, which specifies the degree of synchronization for each electrode pair, at each time sample and each frequency band. Therefore, one of the challenges in EEG synchrony analysis lies in the design of an adequate visualization system, which allows the neuroscientist to explore the synchronization dynamics across a wide time and frequency range.

For a fixed time and frequency range, one can show the synchronization between each electrode pair in form of a matrix; however, this solution is often undesirable because it cannot represent the spatial position of the electrodes, which is often meaningful. Another representation, which preserves the spatial position, consists of a graph with a vertex (dot) located at each electrode site, and edges

* Corresponding author. Tel.: +52 444 8262486x2906.
E-mail addresses: fac@fc.uaslp.mx, falbac@cimat.mx (A. Alba).

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doi:10.1016/j.patcog.2009.03.005

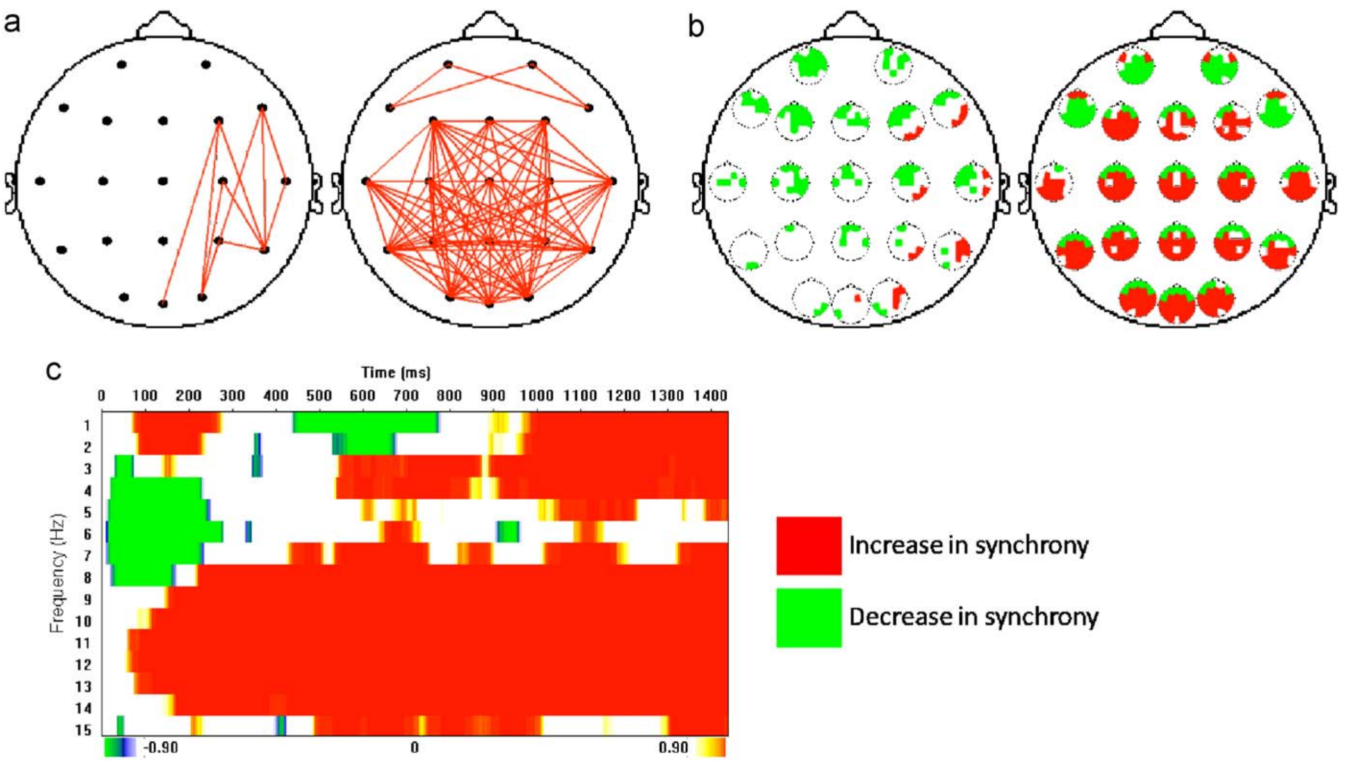

Fig. 1. Various types of display used in EEG synchrony analysis: (a) graph diagram showing significant synchrony increases, (b) multitoposcopic display showing significant synchrony increases and decreases, (c) time–frequency map of significant synchrony increases and decreases for a specific electrode pair.

(lines) connecting those electrodes whose synchronization index is significative (Fig. 1a). This representation has been used extensively (see, for example, [30,34,24,31]); however, it has two serious disadvantages: first, it may become too cluttered with complex synchronization patterns (SPs), and second, it does not show the dynamics of synchrony over time or frequency. The first disadvantage can be overcome with multitoposcopic displays (MDs) [3] (Fig. 1b), in which one head diagram is plotted at each electrode position; each head diagram shows the spatial distribution of the synchronization between the corresponding electrode and every other site. Graph diagrams and MDs are both useful for 10 or 20 EEG channels, but they may become too cluttered with high-density EEG (64 or more electrodes), although it is possible to use MDs for high-density EEG by grouping the electrodes in regions and plotting one head diagram for each region [3]. A recent work [33] proposes a different solution, which consists in finding spatially connected maximal cliques (i.e., groups of mutually synchronized electrodes); these cliques are referred to as functional units (FUs). The *strength* of an FU is defined as the sum of the coherences corresponding to the edges of the clique. The authors plot the FUs in a head diagram with a color scale representing the strengths. For each pair of significant FUs, an *inter-FU coherence* can also be computed as the average coherence between electrodes from one FU and electrodes from the other FU, and displayed as a line joining the centers of both FUs if the inter-FU coherence exceeds a given threshold. This method effectively reduces the clutter in a high electrode density display, producing diagrams which are easy to interpret; however, it is not suited for a typical montage with 10–20 electrodes, where each electrode already represents a large area of the cortex.

The visualization techniques described above only present a snapshot of the synchronous activity for a given time–frequency (TF) window, which may be adequate for certain studies, such as the analysis of EEG at rest. For cognitive studies, however, one is usually interested in the dynamics of the EEG properties (e.g., power and synchronization) over time and frequency. In this case, one usually computes a synchronization measure at each time sample, and for each frequency band of interest. This increases the dimensionality of the data by 2, which leads to serious visualization problems.

For a single electrode pair, one of the most straightforward ways to display dynamic synchronization data consists of a TF map (Fig. 1c), which is basically a 2D image in which the color or intensity at each pixel represents the degree of synchronization between both electrodes at the corresponding time and frequency. This type of representation is used in various works [34,17,31]; however, because it focuses on only one pair of electrodes, it fails to show the spatial distribution of the synchronous processes. In previous works [22,3], we introduced a time–frequency-topography (TFT) visualization system which was able to display significant changes in synchronization across a wide TF region either by reducing one spatial dimension (i.e., results were displayed for each electrode instead of each electrode-pair), or by averaging across relatively large TF windows (and thus reducing the resolution of the analysis). While this methodology produces useful results, it presents a few shortcomings: first, in order to obtain a comprehensive display of synchronization dynamics for all electrode pairs, one has to estimate a statistic of the synchrony changes across an arbitrarily chosen TF window (e.g., obtained from a regular partition of the TF plane), and it is assumed that the SP remains relatively constant across the window. Second, the amount of data presented in a TFT display may at first seem overwhelming to the neuroscientist, and the method does not attempt to detect any regions of possible neurophysiological interest in order to guide the exploration.

In this work, we refine our TFT visualization system by computing a segmentation of the TF plane in regions where the SP is relatively homogeneous. These regions may be related to specific neurological processes, and thus are also regions of interest. The segmentation is performed by means of a seeded region-growing (SRG) algorithm and a Bayesian regularization technique. The seeds may be specified