NeuroImage 54 (2011) 1930–1941

Contents lists available at ScienceDirect

NeuroImage

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

Tracking cortical activity from M/EEG using graph cuts with spatiotemporal constraints

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ARTICLE INFO

Article history:
Received 22 April 2010
Revised 20 September 2010
Accepted 28 September 2010
Available online 7 October 2010

Keywords:
Functional brain imaging
Tracking
Graph cut optimization
Magnetoencephalography (MEG)
Electroencephalography (EEG)

ABSTRACT

This work proposes to use magnetoencephalography (MEG) and electroencephalography (EEG) source imaging to provide cinematic representations of the temporal dynamics of cortical activations. Cortical activation maps, seen as images of the active brain, are scalar maps defined at the vertices of a triangulated cortical surface. They can be computed from M/EEG data using a linear inverse solver every millisecond. Taking as input these activation maps and exploiting both the graph structure of the cortical mesh and the high sampling rate of M/EEG recordings, neural activations are tracked over time using an efficient graph cut based algorithm. The method estimates the spatiotemporal support of the active brain regions. It consists in computing a minimum cut on a particularly designed weighted graph imposing spatiotemporal regularity constraints on the activation patterns. Each node of the graph is assigned a label (active or non active). The method works globally on the full time-period of interest, can cope with spatially extended active regions and allows the active domain to exhibit topology changes over time. The algorithm is illustrated and validated on synthetic data. Results of the method are provided on two MEG cognitive experiments in the visual and somatosensory cortices, demonstrating the ability of the algorithm to handle various types of data.

Introduction

Magnetoencephalography and electroencephalography (collectively denoted M/EEG) source imaging is a functional brain imaging modality that offers the possibility to measure non invasively the magnetic field and the electric potential generated by the electric activity of cortical neurons (Baillet et al., 2001; Hämäläinen and Ilmoniemi, 1994). The challenge that we propose to address in this contribution is the estimation, from M/EEG sensor measurements, of the location in space and also in time of the brain activations that have generated the signal. More precisely, we propose to estimate the spatiotemporal support of the active brain regions in order to sketch the cortical dynamics of event-related brain activity. This spatiotemporal support is binary information (active vs. non active) and can be understood as the spatiotemporal "mask" of the active domain. This new challenge supplements the purely spatial localization of specific brain areas involved in experimental tasks.

The linearity of Maxwell's equations show that what is measured by M/EEG sensors is a linear combination of the electromagnetic fields produced by all current generators, here fixed at the locations of the vertices of the cortical mesh. The linear operator, or "mixing matrix", predicts the fields measured by the M/EEG sensors due to an activation map (Hämäläinen and Ilmoniemi, 1994). Distributed inverse solvers seek to invert this linear operator. The number of generators however largely exceeds the number of M/EEG sensors, which makes this inverse problem ill-posed. To tackle this problem, one needs to use a priori knowledge on what a realistic activation map should be like.

The priors most commonly used in the M/EEG community are based on the ℓ_2 norm, leading to what is known as the Minimum Norm (MN) inverse solver (Hämäläinen and Ilmoniemi, 1994; Dale and Sereno, 1993; Pascual-Marqui, 2002). The solution is penalized with a squared ℓ_2 norm, assuming that an activation map should have a small ℓ_2 norm. This MN inverse solver leads to linear solutions, i.e., currents estimates are obtained by simple matrix multiplication, which makes the estimation extremely fast. The main reasons for the success of the MN inverse solver are that it is easy to implement, makes few assumptions on the solutions, is very fast to compute and relatively robust, considering the level of noise present in experimental M/EEG datasets. More importantly, it is used in the M/EEG community because it provides relatively accurate localizations. The dimensionality of the resulting signals is however overwhelming: patterns need to be extracted from the time series of thousands of elementary cortical sources. Most methodological approaches consist in detecting amplitude effects at some time latencies, *e.g.*, by constrasting two

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doi:10.1016/j.neuroimage.2010.09.087

experimental conditions. However little has been developed to extract the time-evolving patterns carried by the changes in amplitudes of the distributed source maps.

In this paper, we propose to post-process the spatiotemporal distribution of M/EEG cortical sources, with the purpose of tracking active regions over time. What is referred to as *tracking* in this contribution is the challenge that consists in locating activation "hot spots" defined over a triangulated cortical surface and over time. The difficulty of this problem is inherited from the complexity of neuroimaging data. With such data, amplitude changes can wander locally on the cortical ribbon via horizontal connections potentially exhibiting propagating waves (Prechtl et al., 2000; Ermentrout and Kleinfeld, 2001). Recent development on neural networks modeling has actually shown using bifurcation theory that equations with delays can produce oscillatory bumps and traveling waves (Roxin et al., 2005). Activations can also move rapidly from one part of the brain to another one via white matter tracts. While simulations of brain dynamics over such long range connections have also shown the emergence of waves (Izhikevich and Edelman, 2008), the activations within these white matter tracts are not captured by MEG or EEG. Also, during the processing of a cognitive task, the amplitudes of activations vary. The intensities and contrasts between active and non active regions change over time. Brain activations are not rigid objects, which imposes that the approach proposed should allow the topology and the shapes of the active brain regions to evolve over time. An approach based on the tracking of a single contour is therefore not adapted. The present contribution extends the application of relatively recent computer vision techniques to the fairly unexplored question (but see Lefèvre and Baillet, 2008 and Lefèvre and Baillet, 2009) of characterizing and tracking the cortical dynamics revealed by M/EEG source imaging.

Brain functional activation maps in the exposed framework are defined over a mesh and over time. As it will be detailed in this manuscript, our tracking approach boils down to the optimization of a Markov random field (MRF) defined over a mesh and over time. While tracking can be performed via the estimation of motion parameters and displacement fields, the problem is formulated here as a spatiotemporal regularization of activation maps.

For this purpose, a solver based on graph cuts is proposed. In the neuroimaging community, especially in functional MRI (fMRI), the MRF framework has been previously used for regularizing activation maps in order to help the detection of active voxels (Descombes et al., 1998; Ou and Golland, 2005; Woolrich and Behrens, 2006). The underlying assumption is that active voxels should be close in space as well as in time, leading to spatiotemporal clusters of active voxels. In this contribution, we make the same assumption. However, the intrinsically different nature of M/EEG data, compared to fMRI, motivates new developments. M/EEG source estimates are defined on meshes which do not have the regular structure of a 3D grid, and the temporal resolution of M/EEG, of the order of the millisecond, is not comparable with fMRI data where the signal of interest is captured a few seconds after the neural activation. The dynamics in the signal and the dimensions of datasets thus do not compare. Localizing spatiotemporally regular active regions from M/EEG data has already been explored. For example in Cottereau et al. (2007) and Valdés-Sosa et al. (2009), the inverse solvers consider the prior that active regions are expected to be spatially regular, hence the concept of *active patches* of cortex. The temporal smoothness of activations has also been investigated as prior (see Schmitt et al., 2001 for example).

The graph structure of a triangulated mesh supports the use a graph-based method in order to achieve fast and robust tracking of the cortical activations. Graph cut techniques are quite widely used in the computer vision community: for image restoration (Greig et al., 1989), for image segmentation (Boykov and Jolly, 2001; Wu and Leahy, 1993), and for video segmentation (Boykov and Jolly, 2001; Juan and Boykov, 2006; Xu et al., 2003). Similarly to Boykov and Jolly (2001), we design in this contribution a graph cut based approach that achieves global optimization, and takes as input the full temporal data. However, as stated earlier, in the current application, the domain is not a regular 3D grid of pixels but a mesh. Previous contributions in the domain of computer graphics, such as (Sinha et al., nd; Zhou et al., 2008), demonstrate that graph cut methods are well adapted for discrete optimization problems over meshes, which confirms the relevance of our solution to the problem of tracking brain activations over the triangulated cortical surface.

The rest of this contribution consists of three parts. Tracking with graph cuts on a triangulated surface section presents the optimization framework that is used to select coherent spatiotemporal activations defined over a triangulated mesh. A variational formulation of the tracking problem is introduced, and its discretization over a triangulation leads to an optimization problem that can be very efficiently solved using a graph cut algorithm. In the Tracking results with synthetic data section, the method is validated on synthetic datasets. The influence of the parameters is also investigated. Application to the tracking of cortical activations from M/EEG data section presents the application of the algorithm to MEG data with two datasets exhibiting activations in the primary visual cortex and the somatosensory cortex. Even if the results are only presented on MEG data, the method also applies directly to neural currents estimated from EEG measurements.

Tracking with graph cuts on a triangulated surface

From thresholding to tracking

Let f be a real valued function, defined over a domain Δ:

$$f : \Delta \rightarrow \mathbb{R}.$$

When Δ contains a temporal dimension, finding an "active" region, denoted Ω, vs. a "non active" region of Δ, denoted Ω^c can be viewed as detecting activity over time. The regions Ω and Ω^c form a partition of Δ, i.e., $\Omega \cap \Omega^c = \emptyset$ and $\Omega \cup \Omega^c = \Delta$ (cf. Fig. 1). The function f contains the information on how likely an element of Δ is to be active. It is assumed to take high values in active regions. Note that this assumption is not restrictive. With M/EEG data, regions are likely to be active if their activity deviates from the prestimulation period or the baseline. If the changes in activity are negative, taking their absolute value is a simple solution. When considering source models where two different sources can have opposite orientations, the sign of the activation cannot be reliably estimated. Taking the absolute value is also a way to bypass this estimation problem.

A coarse tracking result can be obtained by simple thresholding, i.e., $\Omega^* = \{x \in \Delta \text{ s.t. } f(x) \geq T\}$ where $T \in \mathbb{R}$ is the thresholding value. However results obtained by thresholding can be very noisy when f is corrupted by noise. Results are considered to be noisy if the border of the active region is irregular or if Ω consists of very small isolated active regions. This is illustrated in Fig. 2a. As noted in Boykov and Funka-Lea (2006), the result obtained by thresholding is the solution of the following variational problem:

$$\Omega^* = \arg\min_{\Omega} -\left(\int_{\Omega} f(x)dx + \int_{\Omega^c} T dx\right) = \arg\min_{\Omega} \mathcal{D}(\Omega). \tag{1}$$

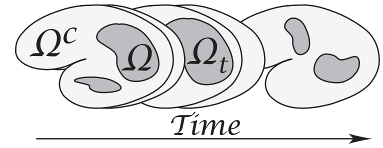

Fig. 1. Schematic illustration of spatiotemporal active cortical regions. Ω (resp. Ω^c) indicates the active (resp. non active region). Ω_t is the restriction of Ω to time t.