cortex xxx (2015) 1–13

Available online at www.sciencedirect.com

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Journal homepage: www.elsevier.com/locate/cortex

Research report

Dynamic reorganization of functional brain networks during picture naming Q8

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ARTICLE INFO

Article history:
Received 10 April 2015
Reviewed 9 June 2015
Revised 6 July 2015
Accepted 27 August 2015
Action editor Jean-Francois Demonét
Published online xxx

Keywords:
Evoked potentials
Picture naming
Dense EEG
Brain dynamics

ABSTRACT

For efficient information processing during cognitive activity, functional brain networks have to rapidly and dynamically reorganize on a sub-second time scale. Tracking the spatiotemporal dynamics of large scale networks over this short time duration is a very challenging issue. Here, we tackle this problem by using dense electroencephalography (EEG) recorded during a picture naming task. We found that (i) the picture naming task can be divided into six brain network states (BNSs) characterized by significantly high synchronization of gamma (30–45 Hz) oscillations, (ii) fast transitions occur between these BNSs that last from 30 msec to 160 msec, (iii) based on the state of the art of the picture naming task, we consider that the spatial location of their nodes and edges, as well as the timing of transitions, indicate that each network can be associated with one or several specific function (from visual processing to articulation) and (iv) the comparison with previously-used approach aimed at localizing the sources showed that the network-based approach reveals networks that are more specific to the performed task. We speculate that the persistence of several brain regions in successive BNSs participates to fast and efficient information processing in the brain.

1. Introduction

Any cognitive process involves the activation of a large-scale functional brain network (Bressler & Menon, 2010). In visual, attentional and memory processes, this network is characterized by increased synchronization of cortical oscillations (in the gamma frequency range (Doesburg, Roggeveen, Kitajo, & Ward, 2008), in particular but not only) across distant neuronal assemblies distributed over distinct brain areas. Q2

The accurate tracking of the spatiotemporal dynamics of large-scale networks over the duration (often as short as a few hundreds of msec) of cognitive processes is still a challenging issue (Allen et al., 2012; Hutchison et al., 2013). A number of

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http://dx.doi.org/10.1016/j.cortex.2015.08.019
0010-9452/© 2015 Published by Elsevier Ltd.

theories have been elaborated to explain these spatiotemporal dynamics. It has been hypothesized that functional brain networks engage in fast transitions between transiently stable states, each characterized by a network with intrinsic dynamics and with specific functional relationships between neuronal assemblies (Hansen, Battaglia, Spiegler, Deco, & Jirsa, 2014; Sporns, 2010). According to this theory, the substrate of cognitive processes would correspond to a sequence of switches between networks and, thus, to time- and space-dependent fluctuations in the node and edge properties of the global network.

The validation of such hypotheses for task-related data requires the following of brain processes at the millisecond time-scale. This can barely be achieved using fMRI data for a simple and well-known reason: although they are characterized by an excellent spatial resolution, BOLD signals reflect the metabolic and hemodynamic response of neuronal assemblies (at voxel level). This slow response (sec) is obviously related to the fast dynamics of cortical oscillations taking place over interconnected neuronal assemblies and defining functional networks, but indirectly [i.e., through the neuro-glial-vascular coupling (Logothetis, Pauls, Augath, Trinath, & Oeltermann, 2001)].

In this study, we address this issue using electroencephalography (EEG) source connectivity analysis to track the spatiotemporal dynamics of large-scale networks associated with cognitive activity. We collected dense-EEG data from 21 subjects performing a picture naming task. We then reconstructed the functional networks in both their spatial and temporal dimension, over the entire duration of the cognitive process (from image perception to motor response) using a recently reported method (Hassan, Dufor, Merlet, Berrou, & Wendling, 2014) that combines i) the solution to the inverse EEG problem, ii) the estimation of brain connectivity from phase locking values (PLVs) and iii) the segmentation of functional networks using a clustering method (Mheich, Hassan, Khalil, Berrou, & Wendling, 2015) (see Fig. 1A). Our results reveal that the cognitive process can be decomposed into a sequence of transiently-stable and partially-overlapping networks. We consider, based on the state of the art of the picture naming task, that each network might be associated with a specific function (Levelt, Praamstra, Meyer, Helenius, & Salmelin, 1998) (visual percept computing, lexical concept activation, selecting the target word from the mental lexicon, phonological encoding, phonetic encoding, and initiation of articulation) of the whole cognitive process. The results show that dense-EEG can bring highly valuable information about cortical networks, with both high spatial (1000 cortical regions) and temporal (msec time-scale) resolution. We speculate that the identified brain network states (BNSs) contribute to fast and efficient information processing in the brain.

2. Materials and methods

2.1. Picture naming task

Twenty one right-handed healthy volunteers (11 women: mean age 28 year; min: 19, max: 40 and 10 men: mean age 23 years; min: 19, max: 33), with no neurological disease, were involved in this study. Participants were asked to name at a normal speed 148 displayed pictures on a screen using E-Prime 2.0 software (Psychology Software Tools, Pittsburgh, PA) (Schneider, Eschman, & Zuccolotto, 2002). The images were selected from a database of 400 pictures standardized for French (Alario & Ferrand, 1999) and were used during session about eight minute. They were controlled according to several parameters (see Table S1). All pictures were shown as black drawings on a white background. Order of presentation was randomized across participants. Naming latencies were determined as the time between picture onset and the beginning of vocalization recorded by the system. Oral responses were recorded and then analyzed with Praat software to set the voice onset time (Boersma, 2002). This study was approved by the National Ethics Committee for the Protection of Persons (CPP), *conneXion* study, agreement number (2012-A01227-36), and promoter: Rennes University Hospital. All participants provide their written informed consent to participate in this study. The ethics committee has approved the consent procedure. A typical trial started with the appearance of an image during 3 sec followed by a jittered inter-stimulus interval of 2 or 3 sec randomly. Most responses were given while the image was still present on the screen. Errors in naming were discarded for the subsequent analysis. A total of 2926 on 3108 events were considered. The fastest response time delay for an event was <600 msec (see Fig. S1 for the responses delays of all subjects).

2.2. Data

The brain activity was recorded using dense-EEG, 256 electrodes, system (EGI, Electrical Geodesic Inc.). The main feature of this system is the large coverage of the subject's head by surface electrodes allowing for the improved analysis of the intracerebral activity from non-invasive scalp measurements, as compared with 32- to 128- electrodes standard systems. EEG signals were collected with a 1 kHz sampling frequency and band-pass filtered between 3 and 45 Hz. Each trial was visually inspected, and epochs contaminated by eye blinking, movements or any other noise source were rejected and excluded from the analysis performed using the EEGLAB open source toolbox (Delorme & Makeig, 2004).

2.3. EEG source connectivity

A crucial step when realizing EEG source connectivity analysis is the choice of three factors: the method used to solve the inverse problem, the method used to compute the functional connectivity among the time series of the reconstructed sources and the number of electrodes used on the scalp. Very recently, we have described a comparative study of these factors and we showed that a combination of the weighted Minimum Norm Estimate (wMNE) with the PLV using high resolution EEG is the best combination among the tested combination (Hassan et al., 2014). This combination was used in the presented work.

According to the linear discrete equivalent current dipole model, EEG signals $\mathbf{S}(t)$ measured from Q channels can be