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Abstract – Cognition is formed from networks between functionally specific but distributed brain regions. A very challenging issue in cognition is how to precisely track brain networks at very short temporal scales (often very short <1s). So far, very few studies have addressed this problem as it requires high temporal and spatial resolution simultaneously. Due to its excellent temporal resolution, Electroencephalography (EEG) is a key neuroimaging technique to access real-time information flow among large scale neuronal networks.

Here, we propose a new method based on EEG source connectivity to map large-scale networks at high temporal (in the order of ms) and spatial (~1000 regions of interest) resolution. We show clear evidence of the ability of EEG source connectivity to track brain networks with high time/space resolutions during picture naming task. Our results reveal that the cognitive process can be decomposed into a sequence of transiently-stable and partially-overlapping networks. Our qualitative and quantitative observations show that the identified brain networks are in accordance with results reported in the literature regarding involved brain areas during the analyzed task.

I. INTRODUCTION

Human cognition is a network phenomenon, requiring interactions of distributed neuronal clusters forming large-scale cognitive networks [1, 2]. These networks have to rapidly and dynamically self-organize and coordinate to allow the execution of mental processes. Accurate timing is then fundamental for the analysis of the information processing in the brain. However, much less is known about the dynamics of brain networks at hundreds of milliseconds temporal scales.

A significant challenge in today's cognitive neuroscience is the mapping of brain networks over very short duration [3], typically <1*s* for a picture naming task, for instance. It needs mainly the use of techniques with very high temporal resolution (on the order of *ms*) which is the case of the magneto/electro encephalography (M/EEG).

Many studies showed that the synchronization between the gamma oscillations (>30Hz) plays a crucial role in the cognitive tasks such as attention, perception and working memory. Yet, the interpretation of connectivity measures from sensor level recordings is not straightforward, as these recordings suffer from a low spatial resolution and are severely corrupted by effects of field spread [4].

The past years have witnessed a noticeable increase of interest for M/EEG to analyze functional connectivity at the level of brain sources reconstructed from scalp signals. The advantage is to provide an excellent temporal and very good spatial resolution [5-7].

The method involves two main steps: i) solving the M/EEG inverse problem to estimate the cortical sources and reconstruct their temporal dynamics (see [8] for review about inverse solution) and ii) measuring the functional connectivity to assess statistically significant functional relationships among the temporal dynamics of sources (see [9] for review about functional connectivity measures).

A critical step when realizing EEG source connectivity analysis is 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 Phase Locking Value (PLV) using high resolution EEG is the best combination among the tested combinations.

In this paper, we use this combination and apply it in a picture naming task. We show evidence about the proposed new method based on EEG source connectivity to identify brain networks involved in the information processing during the picture naming task.

II. MATERIALS AND METHODS

II.1. Data

Twenty one right-handed healthy volunteers (11 women and 10 men), 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) [10]. The images were selected from a database of 400 pictures standardized for French [11] and were used during session about eight minute. This study was approved by the National Ethics Committee for the Protection of Persons (CPP), conneXion study, agreement number (2012-A01227-36), promoter: Rennes University Hospital). The brain activity was recorded using hr-EEG 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 brain 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 45Hz. 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 [12].

II.2. **EEG source connectivity**

The whole process is described in figure 1. 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. Here, we use the weighted Minimum Norm Estimate (wMNE) combined with the Phase Locking Value (PLV) using dense EEG at it was shown to be the best combination among all the tested combinations [5, 6].

Technically, in the source model, we assumed that EEG signals are generated by macro-columns of pyramidal cells lying in the cortical mantle and aligned orthogonally with respect to its surface [13]. Thus, the electrical contribution of each macro-column to scalp electrodes can be represented by a current dipole located at the center of gravity of each triangle of the 3D mesh and oriented normally to the triangle surface. Using this source space, the weighted Minimum Norm Estimate (wMNE) method only estimates the moment of dipole sources.

The wMNE compensates for the tendency of classical MNE to favor weak and surface sources. This is done by introducing a weighting matrix $\mathrm{W_S}$:

$$\hat{\mathrm{D}}_{\mathrm{wMNE}} = (\mathrm{G}^{\mathrm{T}}\mathrm{W_S}\mathrm{G} + \lambda\mathrm{I})^{-1}\mathrm{G}^{\mathrm{T}}\mathrm{W_S}\mathrm{S}$$

where matrix $\mathrm{W_S}$ adjusts the properties of the solution by reducing the bias inherent to MNE solutions. Classically, $\mathrm{W_S}$ is a diagonal matrix built from matrix G with non-zero terms inversely proportional to the norm of the lead field vectors. The value of λ is computed relatively to the signal to noise ratio for each signal computed as the ratio between the post-stimuli period to the pre-stimulus (200 ms).

The sources were reconstructed for each trial and the functional connectivity was then computed between the reconstructed sources using phase synchronization approach. The first step for estimating is to extract the instantaneous phase of each signal. We are using the method based on Hilbert transform in our study. The second step is the definition of an appropriate index to measure the degree of synchronization between estimated instantaneous phases. Here, we used the phase locking value (PLV) method as described in [14]. For each sources pair, *x* and *y*, at time *t*, and for all the trials (*n=1*... *N*), PLV is defined as:

$$\mathrm{PLV}_{xy} = \frac{1}{N}\left|\sum_{n=1}^{N}\varphi_x - \varphi_y\right|$$

To compute synchronization values comparable between near and distant sources pairs, we applied a normalization procedure so that the PLV_{xy} values were compared with the 200ms baseline preceding the presentation of the image. Let μ_{xy} and σ_{xy} be the mean and standard deviation computed from a 200ms pre-stimulus baseline. The normalized PLV is then computed as $\mathrm{PLV}_{xy} = (\mathrm{PLV}_{xy} - \mu_{xy}) / \sigma_{xy}$. The functional connectivity was computed in the low gamma band (30-45Hz). This frequency band is highly relevant in the context of the considered cognitive task, as reported in [14-16].

II.3. **Regions of interest and network measure**

The functional networks presented here are the averaged networks over all participants. We used Freesurfer [17] to register a labeled mesh from an average brain, where each label corresponds to one of 148 anatomical cortical regions [18]. This output provides a standardized partition of the cortex into 148 regional areas. Each of these areas was then subdivided into a set of small sub-regions using Brainstorm [19], resulting in 1000 ROIs covering the whole cortex. This segmentation provided us with high resolution connection matrices (see figure 1). These ROIs were then considered as the nodes of our networks.

To characterize the networks, we computed the strength measure which is defined as the sum of all edge weights for each node. We used MATLAB ® (2007a, MathWorks Inc) in the entire process: from EEG preprocessing, source reconstruction, functional connectivity analysis, computation of the graph parameters and visualization of the brain networks.

III. **RESULTS**

In figure 2A, we show networks of a segment taken from 150-190 ms which typically corresponds to the period after the visual recognition of the stimuli and the access to the memory. This was achieved by using an algorithm developed recently in our team to segment such task into functional connectivity 'states' [20, 21]. In figure 2B, a typical example of the event Related Potentials (ERP) signal recorded during the task from the onset (presentation of the visual stimuli) to the motor response (beginning of the articulation) is shown. The whole process takes about 600 ms as illustrated in figure 2B.

In figure 3A, we quantify the networks by computing the strength of each node and order them in increasing way (from bottom to up). The results show the implication of different brain regions. Following [22], the horizontal red-colored bars denote the significant regions corresponding to the nodes with a strength value higher than mean+SD. We retain the bilateral inferior occipital gyrus and sulcus, the left occipital pole, the left temporal sulcus and the right anterior occipital.

In figure 3B, we show the significant regions identified in figure 3A. This representation was based on Destrieux Atlas [18] using Brainstorm Tool [19].

IV. DISCUSSION – CONCLUSION

The algorithm used here to track functional brain dynamics was originally applied to scalp EEG networks [20]. The results showed a 'global' information flow from occipital to temporal then frontal zones. However, due to the 'volume conduction' effects, the interpretation of the spatiality of such networks was very difficult and inaccurate, where the main contribution of the proposed method in this paper [20, 23].

In this paper, we showed the high capacity of the EEG source connectivity analysis to reveal brain networks involved in the visual processing and memory access during picture naming task. To our knowledge, this is the first study showing brain networks with such temporal and spatial precision.

Our findings corroborate already-reported results regarding the brain regions supposed to be involved in the considered cognitive task, but using other modalities, mainly fMRI and PET [24]. At the period (150: 190 ms), results also indicate a mainly occipital network but with an implication of the bilateral inferior temporal sulcus. This system is known to be related to lexical retrieval, lemma retrieval and lemma selection [25]. It is also involved in semantic working memory system when someone tries to remind the name of the objects [26].

In this paper, we focused on one time window related to the visual processing (120-150 ms). A natural perspective is the tracking of the brain dynamics from the presentation of the stimulus to motor response. We recently developed an algorithm to segment such very short cognitive task into different 'functional connectivity states' [20]. This will provide, to our knowledge, a unique methodological framework to track brain networks over very short time duration (hundreds of milliseconds).

We chose to keep only regions with strength values higher than mean+SD regardless the normality of the distribution, as reported in [22]. This choice does not affect the main conclusion of this part of the study. Nevertheless, we believe that this empirical choice can be improved to more advanced and accurate thresholding process.

To sum up, we have presented a complete novel framework based on dense EEG recordings to reveal brain networks involved in a cognitive task. The main originality of this work is the high temporal (ms scale, as brought by the EEG technique) and spatial (~cm² scale, as provided by the solution of the inverse problem) resolution of the identified networks. To our knowledge, this is the unique method that can track the spatiotemporal dynamics of functional brain networks at short duration cognitive task.

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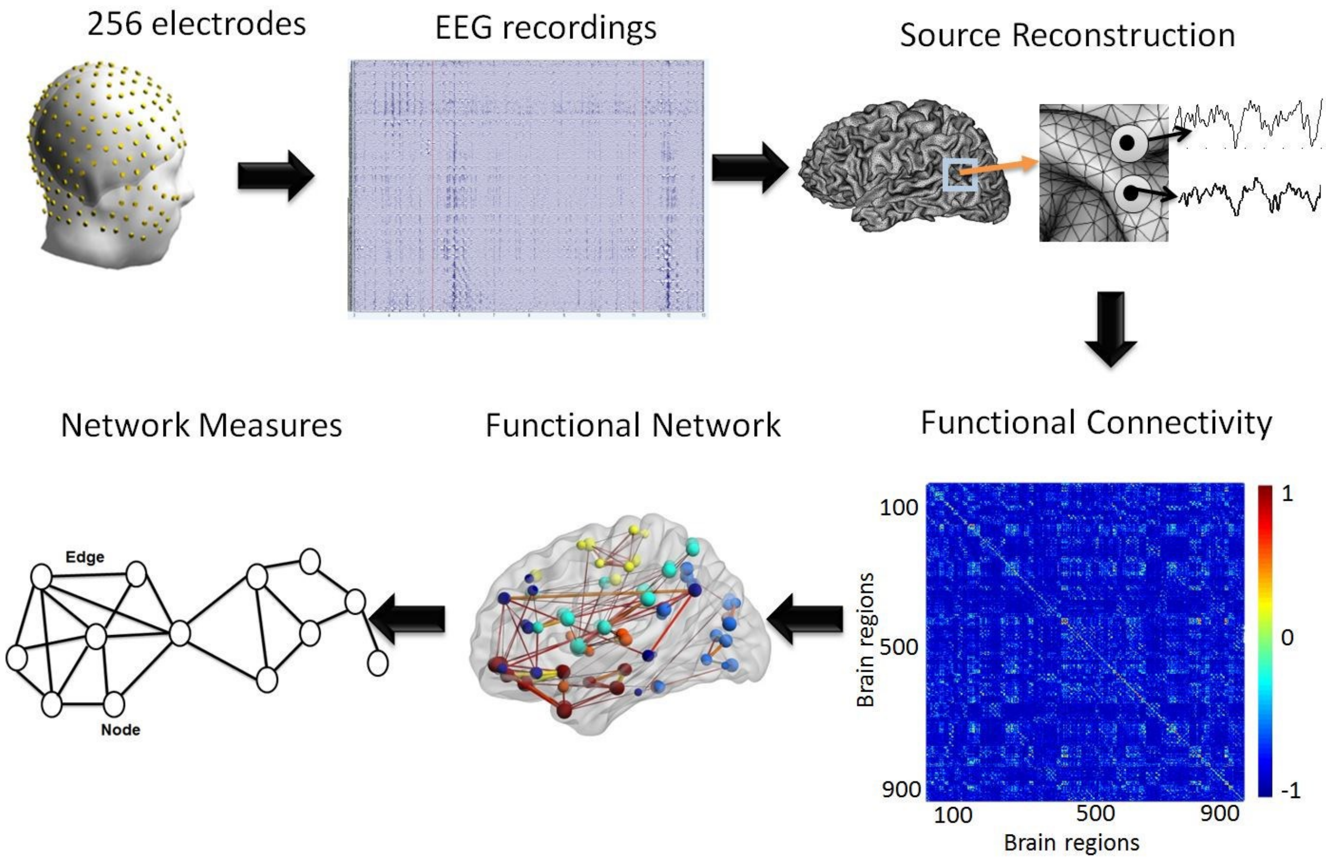

Figure1: Structure of the investigation. Dense EEGs were recorded during the picture naming task. The inverse problem was then solved by 3D head model using the weighted Minimum Norm Estimate method. The time series of the reconstructed sources were obtained. The functional connectivity between the reconstructed sources was computed using the Phase Locking Value method. A high resolution functional connectivity matrix was obtained and the corresponding functional brain network was visualized. Network measures were then extracted from the network using graph theory based analysis.

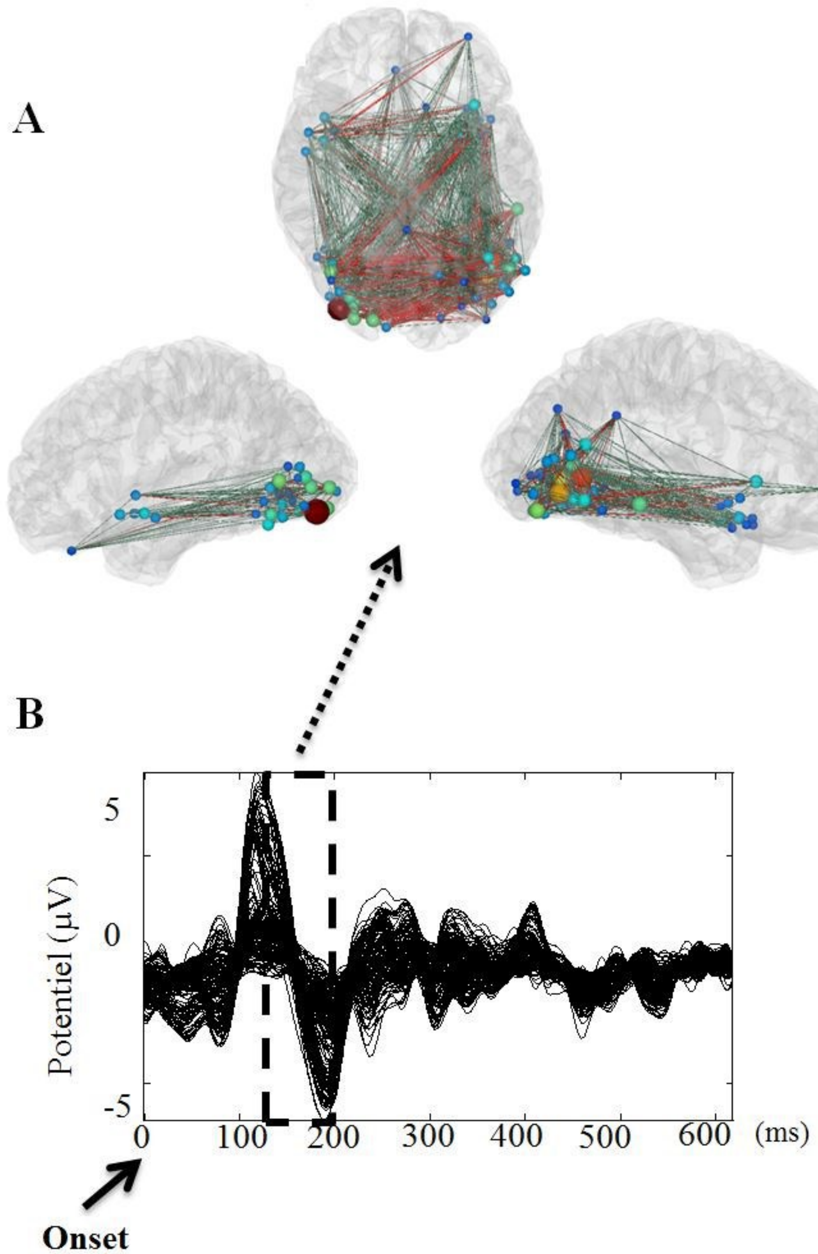

Fig.2. Identified brain networks. A) Different views of the brain network iden-tified at 120–150ms. Node size represents the strength. B) ERP signal obtained during the task. Dashed rectangle represents the period between 120ms and 150ms corresponding to the visual perception.

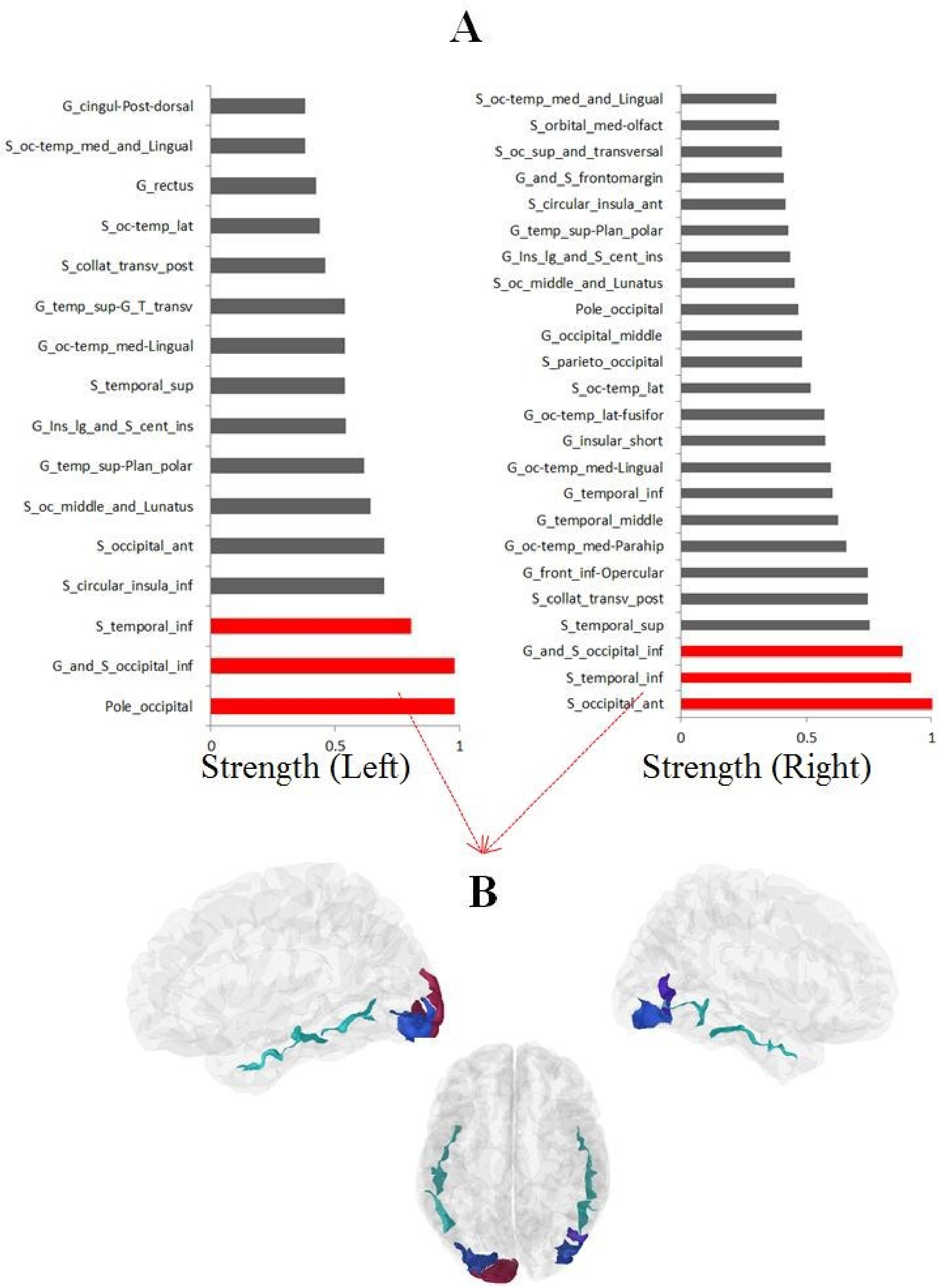

Fig.3. Network measures. A) The values of the average strength for each node in left and right hemispheres. Red bars indicate values greater than the mean+SD considered as significant ones. B) Visualization of the significant regions. Regions were color coded based on the anatomical parcellation of Destrieux Atlas using Brainstorm Tool. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)