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Activity detection and causal interaction analysis among independent EEG components from memory related tasks

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Abstract—**Over the past few years there has been an increased interest in studying the underlying neural mechanism of cognitive brain activity related to memory. In this direction, we study the brain activity based on its independent components instead of the EEG signal itself aiming towards identifying and analyzing induced responses being attributed to oscillatory bursts from local or distant neural assemblies, with variable latency and frequency, in an auditory working memory paradigm. The contribution and functional coupling of independent components to evoked and/or induced oscillatory activities is investigated through the concept of the recently introduced partial directed coherence method, which can also reveal the direction of the statistically significant relationships. The results on read data from an oddball experiment are in accordance with previous psychophysiology studies suggesting increased phase locked activity most prominently in the delta/ theta band, while alpha is also apparent in measures of non phase-locked activity. Dynamic synchronization is inferred between the alpha and delta bands, whereas some influence of the theta band is also detected. This study indicates that functional connectivity during cognitive processes may be successfully assessed using spectral power measures applied on independent components, which reflect distinct spatial patterns of activity.**

I. INTRODUCTION

DURING electroencephalographic (EEG) activity time-locked to an event, neuronal assemblies at different topographic locations (either local or distant) self-organize into transient networks, which synchronize in time and frequency to produce bursts of oscillations contributing to the observable EEG characteristics. Such activity caused by an external or internal event can be categorized to either a phase-locked evoked response or a phase resetting of ongoing EEG activity, also referred to as induced response [1][2]. Thus, the transient oscillatory event-related activity, has been found to reflect the superimposed activity of several evoked and induced response sources, each having a distinct topographic organization [3][4][5]. Because of their neurophysiologic origins, phase-locked (evoked) and non phase-locked (induced) responses are different [1][6] and have different functional roles [3][5], even though they may reflect similar cognitive events and may correlate in their various parameters. Phase-locked evoked activity, also termed as event related potential (ERP) [2] and ongoing EEG rhythms of induced oscillations (such as event related (de)synchronization ERD/ERS [1]) may be considered as coupled processes progressing in time with different spatial localization of activated neuronal assemblies and partially overlapping frequency content [1][4][5]. In essence, pre-stimulus EEG activity may remain on post-stimulus response and can affect the characteristics (amplitude, latency, frequency) of the evoked and induced responses.

In this paper we study the involvement of several brain sources in performing a working memory cognitive task. Our working assumption is that the performance of the task triggers certain evoked and induced responses, as expressed by synchronization between different neural assemblies. Independent Component Analysis (ICA) [2] has been successfully applied on continuous or event related EEG to decompose it into a sum of spatially fixed and temporally independent components [1] that can lead in different spatial distribution patterns, which in turn may be directly attributed to underlying cortical activity. In this work, besides their study of their content, we consider the synchronization of important components by using the partial directed coherence (PDC), which is a linear method able to derive information on the “driver and response” relationship between observations [7].

II. METHODS

Event related brain dynamics entail a variety of activations and oscillations, from phase resetting of ongoing EEG activity in the alpha and theta bands [4] to phase-locked evoked and non phase-locked induced oscillations especially in delta, theta and gamma bands [1][8]. Their origins relate to multiple task conditions and many stimulus types engaged during the event presentation and execution of its consequent actions [5], which define distinct brain functions, some operating independently and some being coupled [6].

Since we are interested in identifying distinct signal components and analyzing their coupling, we focus on decomposing the EEG signal into ICA components stemming from different brain regions and then analyzing their time-frequency content throughout multiple trials.

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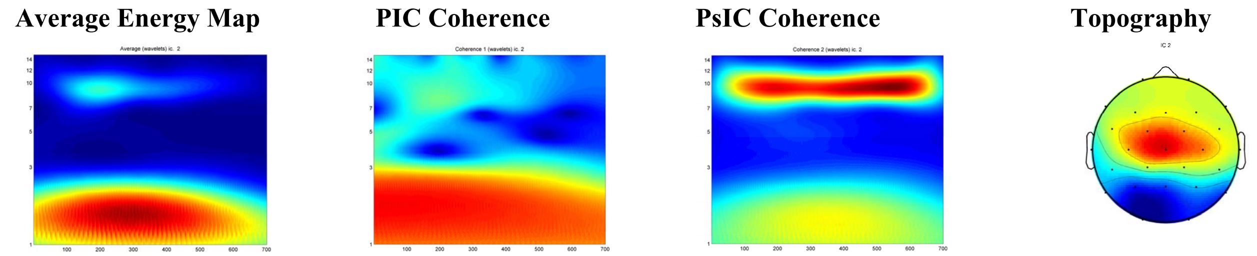
Average Energy Map **PIC Coherence** **PsIC Coherence** **Topography**

Fig. 1: Three inter-trial coherence measures of a particular component along with its scalp topography map. The first two measures, intended for phase-locked coherence, reflect intense delta mixed with some portion of theta-band activity. The third measure reflect non-phase locked alpha activity split into an early and a late part The topography shows central concentration, more closely associated with alpha band effects. The color-map is normalized from zero to one. The horizontal axis spans time from stimulus up to 700ms post-stimulus. The vertical axis spans frequencies from 1 to 14 Hz in a log scale.

More specifically, we address two aspects, one related to the repeatability of components across trials and the other related to the dynamic coupling of important components. The first aspect of analysis has been partially addressed with measures that can reveal phase locking effects [2][3]. Besides these measures, we introduce a metric for considering stimulus-locked but not phase-locked activity. The second aspect related to synchronization is addressed through the PDC measure to reveal coupling characteristics.

A. Data acquisition and test description

The EEG signals used in this work arise from two representative subjects out of 9 healthy participants (age: 37-74), who had no history of neurological or psychiatric disorder. The measurement involved 27 channels with linked ears (A1-A2) as the recording reference and electrode AFz as Ground. The signals were digitally sampled at 1024Hz, with a high pass filter of cut-off frequency 0.016Hz, a low pass filter of cut-off frequency 60Hz, and a notch filter at 50 Hz. Recordings were acquired from an auditory oddball experiment, where a stimulator provided 40 2 kHz target tones (20%) and 160 1 kHz non-target tones (80%). The inter-stimuli interval (ISI) was 1.29s.

B. Independent Component Selection

Instead of directly measuring the synchronization using the actual EEG traces, independent components (ICs) were first obtained and then identified based on their spatial and frequency properties. Under the assumption of spatially consistent sources, we perform Infomax ICA [2] decomposition in a concatenated trials scheme, with the EEG signal extended by one trial following the other, in the same way for each channel. Besides its increased stability and generalization capabilities, the concatenated trials approach has the add-on advantage of preserving the correspondence of components throughout the trials. In this way, the content of each ICA component can be analyzed in several perspectives including its topological origin, the time and frequency distribution, as well as its coherence over trials.

Following their derivation, the components of ICA are often organized (or clustered) by means of multiple spatiotemporal constraints on their structure [4][5]. In our approach, we first label components based on the phase locking attributes over trials. Some components may involve phase-locked evoked responses, others may capture time but not phase-locked induced responses, while others could engage both types [5][6]. The similarity of components across trials has been studied using their time-frequency energy distribution maps. However, the measure of average spectral energy does not necessarily reflect signal synchronization across trials, since a strong activity in just a few trials can induce significant spectral energy, but without providing any indication of synchronization among trials. In this paper, we employ another scheme based on phase synchronization of each component across trials. For phase locked synchronization we use the phase intertrial coherence (PIC) measure [3], whereas for non-phase locked activity we introduce the so-called shift-phase intertrial coherence (2). The former is based on the phase similarity of phase-locked components, whereas the latter is based on the power similarity of same structure but not phase-locked components across trials, which is an extension of the power measure used in ERD/ERS detection. If all trials are phase locked to the same shift, then the Phase Intertrial Coherence (PIC) [3] is defined as:

$$c_{PIC}[k] = \left|\sum_i X_i[k]\right| \Big/ \sum_i \left|X_i[k]\right| \le 1 \qquad (1)$$

with equality holding for perfect phase locking. This metric can easily be expanded to the time-frequency representation of a signal $X_i[k,n]$, with k and n indicating the frequency and time ticks, respectively.

In case of the same base signal with different shifts from trial to trial, we define a conceptually similar metric based on the power of band-selective activity instead of the signal itself. For phase-shifted responses, this metric eliminates the complex phase effects and compares the intertrial content only based on its power in specific frequency bands. More specifically, we introduce the so-called Phase-shift Intertrial Coherence (PsIC), which is defined as:

$$c_{PsIC}[k,t] = \frac{\sum_i \left|X_i[k,t]\right|^2}{\max\limits_{k,t} \sum_i \left|X_i[k,t]\right|^2} \le 1 \qquad (2)$$

where equality implies the same magnitude of *X[k,t],* even with different shifts at each trial.

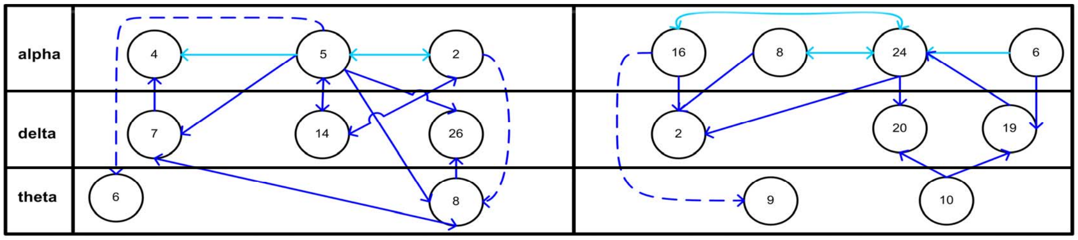

Fig. 2: The depicted networks of ICs reflect the synchronization maps of two representative subjects organized by means of the PDC of the band activity in Delta, Theta and Alpha. Apart from the synchronization itself, directionality is also identified. The bidirectional coupling indicates no single influence between the "cause" and "effect" relationship.

Both the phase and the shift-phase coherence factors can also be utilized as global metrics on a component, measuring its overall intertribal coherence. All three maps will be used for the characterization of relevant components as each one emphasizes on different aspects of synchronous activity.

C. *Partial Directed Coherence (PDC)*

Only those components associated with event-related activity (evoked or induced) are further analyzed in terms of their dynamic coupling through PDC, which is based on the commonsense idea that causes precede their effects in time and is formulated in terms of predictability. In a linear framework, Granger-causality [7] is commonly evaluated by fitting Vector Autoregressive Models. Suppose that a set of N simultaneously observed time series $\mathbf{x}(t)=\left[x_1(t),\ldots,x_N(t)\right]^T$ is adequately represented by a Vector Autoregressive Model of order p (MVAR(p)):

$$\mathbf{x}(t)=\sum_{k=1}^{p}A_k\mathbf{x}(t-k)+\mathbf{w}(t) \tag{3}$$

where $\boldsymbol{A_k}$ is the coefficient matrix at time lag k, and $\mathbf{w}(t)=\left[w_1(t),\ldots,w_N(t)\right]^T$ is the vector of model innovations. Let $A(\lambda)=\sum_{k=1}^{p}A_k e^{-i2\pi\lambda k}$ be the Fourier transform of the coefficient matrices, where λ is the normalized frequency in the interval [-0.5,0.5]. Then the PDC is defined [7] as:

$$\left|\pi_{i\leftarrow j}(\lambda)\right|=\frac{1}{\sigma_i}\left|\overline{A}_{ij}(\lambda)\right| \Bigg/ \left(\sum_{m=1}^{p}\frac{1}{\sigma_m^2}\overline{A}_{mj}(\lambda)*\overline{A}_{mj}^H(\lambda)\right)^{1/2} \tag{4}$$

where $\overline{A}(\lambda)=I-A(\lambda)$ and σ_i^2 refers to the variance of the innovation processes $w_i(t)$. PDC ranges between 0 (indicating independence) and 1 (maximum coherence).

III. RESULTS & DISCUSSION

The three intertrial coherence measures of a particular component are presented in Fig. 1. It is observed that the PIC measure expressed the existing phase-locked activity differently than the average energy spectrum, indicating an influence of the latter on factors irrelevant to phase consistency throughout the trials. The synchronization maps of two subjects are presented in Fig. 2, organized by means of the directed influence of the bands Delta, Theta and Alpha. Besides the strong synchronization among bands, these figures elucidate the order of functional activity in terms of the driver system. The oddball ERP response is mainly characterized by a positive peak 300ms after the stimulus, also known as P300, appearing in the target stimuli. P300 response forms a processing sequence that varies in time, topography and frequency. Studies on the topography of P300 response reveal both earlier anterior and later posterior contributions to P300 responses. Target stimuli involve parietal activations that vary with the degree of cognitive engagement. Anterior contributions were found in unexpected and novel stimuli; in general, infrequent task irrelevant stimuli produce earlier strong anterior activations [9]. A number of investigators have also evaluated ERP activity to novel and target stimuli using time–frequency methods, and findings suggest that the anterior to posterior processing sequence also varies in frequency. Specifically, the anterior activation is generally higher in frequency (e.g. theta) relative to the posterior activation (e.g. delta). Both theta and delta activities have been related to oddball target responses [10]. Delta activity (from 0 to 3Hz), has been most directly related to target P300 amplitude and the cognition as related to memory processing.

Theta activity (from 3 to 7Hz) has also been strongly implicated in oddball processing, related to attention, short-term memory and encoding of new information. Theta generally precedes delta in the P300 response, and is more anterior in topography, while delta is later and more posterior. Interestingly, theta is selectively enhanced during novelty stimulus presentations, linking it to the orienting processes associated with novelty processing [9]. Thus, the processing sequence involves an anterior theta response first, more closely tied to orienting, and then a posterior delta response more closely tied to cognitive processing. Sensory stimulation also induces phasic alpha ERD. In accordance to the neuronal inhibition hypothesis of stimulus processing, the P300 waveform may originate from a reduction and desynchronization of fast (alpha rhythm) non-phase locked oscillations, even though it is composed of phase locked delta and theta synchronized oscillations.

Alpha ERD is induced by task requiring cognitive processing with attention and memory components. Task induced alpha rhythms are associated with the above functional meaning, with an early slow (8-10Hz) alpha being associated to attention and late fast (10-12Hz) alpha linked to memory. The model proposed by [9] for the generation of P300 waveforms comprises an early process (P3a) localized in frontal working memory related to attention and a late stimulus-related process (P3b) driven by attention that relates to memory processing. Even though the relation of P3a to alpha ERD has not been verified, it is clear that P3b related to the late alpha frequency of the EEG.

The functional role of frequency components is also verified in this work. Two representative examples are presented in Figure 2, which depicts numbered components (ICs). Even though the control group involves a large variation in ages, it has been demonstrated that processes related to working memory have been found to weaken with normal aging, but in general follow the same patterns of activation [11]. This is also verified in Fig 2, with the two similar networks corresponding to subjects of different ages. The strong interaction in the alpha band is indicated by directed light-blue lines, whereas the weak influence of the theta band from the alpha band is indicated with dashed lines.

The independent components identified relate to the alpha, theta and delta bands on the basis of their (major) frequency activity (Fig. 2). The delta components (related to cognitive processing) strongly relate to the alpha components. In both cases, we can also observe two types of alpha components, an early one at lower alpha band and a late one at the fast alpha range, with the early one driving the late alpha. The early alpha associated with attention drives a delta component related to cognition, which in turn drives the late alpha component that also related to memory operations; this relationship in fig. 2 is observed as node influence from 5 to 7 to 4 in the left network and from 6 to 19 to 24 in the right network. This tendency supports the clear relationship of P3b (mostly activated in delta band) to the late alpha activity [9]. The theta components (related to episodic short-tem memory and attention) are also related to delta activity, with a tendency of theta to drive delta components. Instead, there is only weak relation between alpha and theta verifying the unclear relation of P3a (mostly associated to theta content) with alpha activity.

IV. CONCLUSION

Our study was able to identify and characterize the intertrial coherence of independent components involved in the multiple trials of the auditory odd experiment. Furthermore, it enabled the efficient visualization of established brain networks in three frequency bands, by means of the PDC synchrony measure. This study considered a population of nine control subjects. Two representative activation networks are presented, but the rest of the subjects are giving similar patterns of activation. Denoting the limitations of the study, which should be extended to a larger population sample, the initial results presented indicate that the proposed synchronization analysis framework is able to reflect not only the brain network topology during a certain mental task (like the working memory), but also the directional coupling between related brain regions.

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