Proceedings of the
7th Graz Brain-Computer Interface Conference 2017 DOI: 10.3217/978-3-85125-533-1-04

ELECTROENCEPHALOGRAPHY (EEG)-DERIVED MARKERS TO MEASURE COMPONENTS OF ATTENTION PROCESSING

A. Anzolin[1,2], L. Astolfi[1,2], J. Toppi[1,2], A. Riccio[2], F. Pichiorri[2], F. Cincotti[1,2], D. Mattia[2]

[1] Dept. of Computer, Control, and Management Engineering, Sapienza University of Rome, Italy
[2] IRCCS Fondazione Santa Lucia Hospital, Rome, Italy

E-mail: anzolin@dis.uniroma1.it

ABSTRACT: Although extensively studied for decades, attention system remains an interesting challenge in neuroscience field. The Attention Network Task (ANT) has been developed to provide a measure of the efficiency for the three attention components identified in the Posner's theoretical model: alerting, orienting and executive control. Here we propose a study on 15 healthy subjects who performed the ANT. We combined advanced methods for connectivity estimation on electroencephalographic (EEG) signals and graph theory with the aim to identify neuro-physiological indices describing the most important features of the three networks correlated with behavioral performances. Our results provided a set of band-specific connectivity indices able to follow the behavioral task performances among subjects for each attention component as defined in the ANT paradigm. Extracted EEG-based indices could be employed in future clinical applications to support the behavioral assessment or to evaluate the influence of specific attention deficits on Brain Computer Interface (BCI) performance and/or the effects of BCI training in cognitive rehabilitation applications.

INTRODUCTION

Attention is fundamental for human cognitive processing. As such, it includes a wide class of processes related with the ability of a subject to interact with the external environment. According to Posner's theoretical model [1], this is possible through a sustained state of alertness (alerting), the selection of the important information in a noisy context (orienting) and the ability to control a situation and solve conflicts (executive control). When the complex mechanism at the basis of attention is altered, e.g. following a stroke event, consequences may affect a wide range of behavioural and social aspects. Several neuroimaging and neurophysiological studies have employed the so-called Attention Network Task (ANT), a behavioural task which allows to disentangle the three components (alerting, orienting and executive control) as described by Fan et al. in [2]. The available evidences indicate that the three attention components are independent [3], involve different anatomical areas (functional magnetic resonance imaging, fMRI, studies) [4] and each of them has a distinct oscillatory activity and time course (EEG study) [5].

In this study, we applied modern methodologies for effective connectivity estimation and graph theory approaches with the aim to define stable and reliable descriptors of the dynamic brain circuits underpinning the attentional components in terms of directed relationships between the brain areas and their frequency content. Currently available brain connectivity studies on attention are based on structural networks (anatomical connectivity) [6] or functional networks extracted from fMRI data [7]. We were interested in extracting markers of the brain circuits elicited by the ANT performed by healthy volunteers while recording high density EEG (hdEEG) and thus, exploiting its high temporal resolution, low invasiveness and cost-effective. To this purpose we explore whether connectivity-based indices would correlate with behavioural data in order to strengthen their relevance as measure of attention processing for future applications. [8], [9].

MATERIALS AND METHODS

Experimental Design: Data (60 EEG channels + 4 EOG channels, reference at linked mastoids and ground at Fpz, Brain Products) were recorded from 15 healthy volunteers (10 female, age 27.2 ± 2.5) during the execution of the ANT [5] (Fig.1). They had no history of neurological or psychiatric disorders. The experimental protocol was approved by the local Ethical Committee. Participants were seated in front of a computer screen; a row of 5 black arrows pointing left or right was presented in the middle part of the screen. Subjects were asked to indicate the direction of the central arrow (target stimulus) as quickly and accurately as possible with the left arrow keyboard or the right arrow keyboard button according to the direction of the target, using their right hand. Trials were defined as *Congruent* if the 4 lateral *flankers* and the central arrow had the same direction, *Incongruent* if the flankers pointed at the opposite direction. In addition there were three cue (an asterisk sign) conditions: *No cue*, *Center cue* (in the center of the screen for alerting), and *Spatial cue* (at the target location, above or below a fixation cross, for alerting plus orienting) [3]. The timeline of the paradigm is showed in Fig.1. The contrast between the different experimental conditions (72 trials each condition) allowed to extract the three attention components: i) *Center cue* and *No cue* conditions define the alerting, ii) *Spatial cue* and *Center* *cue* the orienting, iii) *Incongruent* and *Congruent* the executive control.

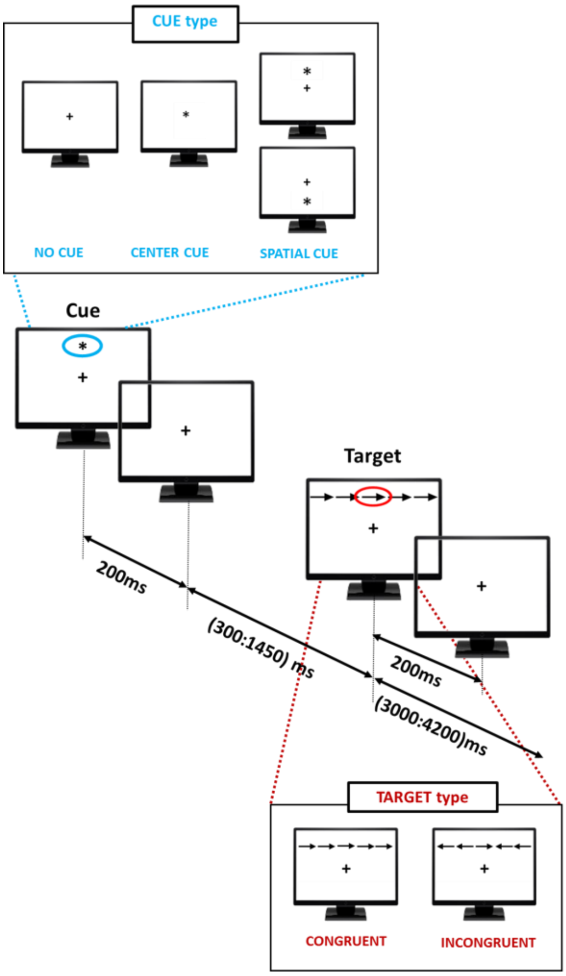

Figure 1: Timeline of the ANT paradigm. In each trial, a cue (asterisk) may appear for 200 ms in the center of the screen (center cue condition) or in the semi-space in which the target will appear (spatial cue). After a variable duration (300–1450ms), the target and the flankers (congruent or incongruent) are presented. The participant indicate the direction of the central arrow within a time window of 2000 ms. The target and flankers disappear after the response is made.

Behavioral Data: As behavioral index for each attention component we used the efficiency measure introduced in [2]. Alerting efficiency (Eff_{Al}), orienting efficiency (Eff_{Or}) and executive control efficiency (Eff_{EC}) are defined as the difference between the mean reaction times (RT) in specific experimental conditions:

$$Eff_{Al} = RT_{No} - RT_{Center} \tag{1}$$

$$Eff_{Or} = RT_{Center} - RT_{Spatial} \tag{2}$$

$$Eff_{EC} = RT_{Incong} - RT_{Cong} \tag{3}$$

EEG Data Analysis and Connectivity Estimation: EEG scalp data were band-pass filtered in the range [1-45] Hz and ocular artifacts were removed through Independent Component Analysis (fast-ICA algorithm). EOG channels were also included in the ICA decomposition. Signals were segmented in different time windows defined as [0 - 500] ms according to the *cue* onset and [0-400] ms according to the *target* onset. Residual artifacts were removed by means of a semi-automatic procedure based on a threshold criterion (±80 µV). Connectivity patterns were estimated through Partial Directed Coherence (PDC) [10] and averaged in four frequency bands (Theta, Alpha, Beta and Gamma) defined according to the Individual Alpha Frequency (IAF) [11]. We obtained a network for each frequency band, each experimental condition and each subject. A statistical comparison (unpaired t-test, p<0.05, False Discovery Rate, FDR, correction) was performed between appropriate conditions (according to ANT theory) in order to isolate the networks associated with each of the three attention components. In particular, we compared: i) *center cue* vs *no cue* for alerting, ii) *spatial cue* vs *center cue* for orienting and iii) *congruent* vs *incongruent* for executive control. Graph theory indices were extracted from the networks underlying the three attention components with the aim to synthetize their main global and local properties. In this study, we adopted the following indices:

<u>*Global Indices*</u> to describe the general properties of the entire network [12]:

- Clustering: to measure the tendency of the network to segregate the information in subnetworks;
- Path Length: to measure efficiency of the communication between the nodes on the basis of the shortest paths between them.

<u>*Local Indices*</u>: to quantify the involvement of a specific sub-network and/or investigating the relation between different sub-networks. In particular as sub-networks we considered left (Fp1, AF7, AF3, F7, F5, F3, F1, FT7, FC5, FC3, FC1, T7, C5, C3, C1, TP7, CP5, CP3, CP1, P7, P5, P3, P1, PO7, PO3, O1) and right (Fp2, AF4, AF8, F2, F4, F6, F8, FC2, FC4, FC6, FT8, C2, C4, C6, T8, CP2, CP4, CP6, TP8, P2, P4, P6, P8, PO4, PO8, O2) hemispheres, anterior (Fp1, Fp2, AF7, AF3, AFz, AF4, AF8, F7, F5, F3, F1, Fz, F2, F4, F6, F8, FT7, FC5, FC3, FC1, FCz, FC2, FC4, FC6, FT8) and posterior (TP7, CP5, CP3, CP1, CPz, CP2, CP4, CP6, TP8, P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO7, PO3, POz, PO4, PO8, O1, Oz, O2) areas [13]. We computed the following indices:

- Density: to quantify the percentage of existing connections with respect to the totality of possible links. It has been adapted as in the following formula to quantify the percentage of connections relative to a specific area:

  $$sub - Density = \frac{n_{subnet}}{n_{TOT}}$$

  Where n_{subnet} is the number of existing links connecting only the nodes (electrodes) belonging to the considered subnetwork and n_{TOT} is the number of all the existing connection of the entire circuit.
- Divisibility - Modularity: to measure the level of interaction between subnetworks in terms of inter

(divisibility) and intra (modularity) connections: strict interconnection or isolation [14].

- Influence: to measure a prevalence in the direction of inter-connections linking two spatial regions [13].

Connectivity indices extracted for each attention component were then correlated with the relative behavioral parameters (Eff_{Al}, Eff_{Or}, Eff_{EC}) by means of Pearson's correlation ($p<0.05$). FDR correction was applied to take into account errors due to multiple correlations.

RESULTS

Results are reported separately for each component of the ANT paradigm.

Alerting: as shown in Figure 2, we found significant negative correlations between the efficiency Eff_{Al} and i) the path length index in beta band (Fig. 2, panel a) and ii) the left/right influence index in theta band (Fig. 2, panel b). Such correlations pointed out a relation between the behavioral performances and the speed in the exchange of information between network nodes in the alerting phase (low path length) in beta band. Moreover, an efficient alerting is associated to a communication between the two hemispheres in theta band with a prevalence of the information flows directed from right to left (negative values for left/right influence).

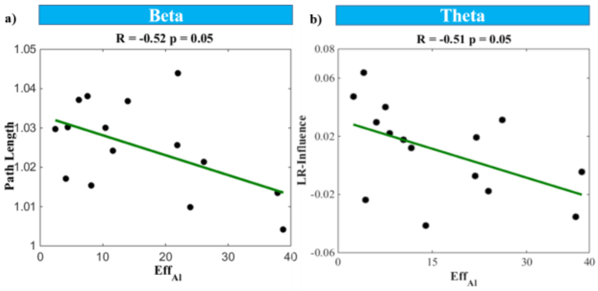

Figure 2. Alerting: statistical correlations between the efficiency Eff*$_{Al}$ *(y-axis) and the connectivity indices (x-axis): path length in beta band (panel a) and left/right influence in theta band (panel b). As in all figures, dots correspond to the values obtained for each of the 15 subjects involved in the study. The green line represents the linear fitting computed on the data. The associated values of correlation (R) and significance (p) are reported on the top of the figure.

Orienting: as shown in Figure 3, a positive correlation was found between the efficiency Eff_{Or} and i) the right density (Fig. 3, panel a) and ii) the left/right divisibility (Fig.3, panel b) in the theta band.

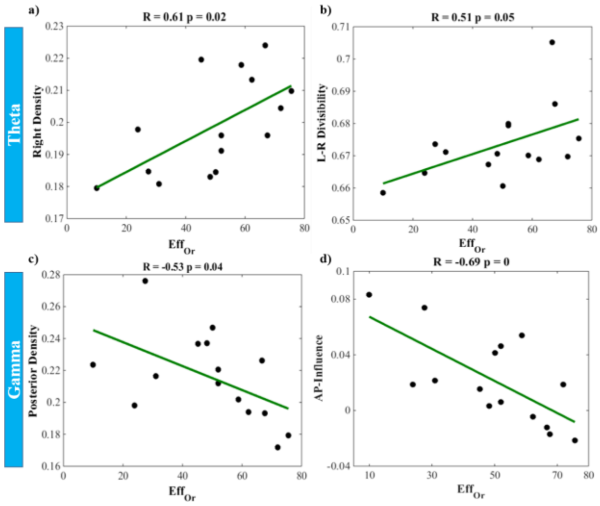

Figure 3. Orienting: statistical correlations between the efficiency Eff*$_{Or}$ *(y-axis) and the connectivity indices (x-axis) right density (panel a) and Left/Right Divisibility (panel b) in theta band, posterior density (panel c) and Anterior/Posterior Influence (panel d) in gamma band.

In particular, such results pointed out how an efficient orienting process is associated to a strong segregation of the information flows within the right hemispheres (high right density) and a low integration of the two hemispheres (high left/right divisibility) in theta band. Furthermore, we found that the parameter Eff_{Or} negatively correlated with the posterior density index (Fig.3, panel c) and the anterior/posterior influence index (Fig.3, panel d) in the gamma band.

This indicates that an efficient orienting process is associated to a low involvement of the posterior scalp regions (low posterior density) and to the establishment of a communication between anterior and posterior regions with a prevalent direction from posterior to anterior.

Executive Control: Figure 4 shows a significant positive correlation between executive control efficiency Eff_{EC} and both the Path Length (Fig.4, panel a) and the Clustering indices (Fig.4, panel b) in the gamma band. Significant correlations were also found between efficiency Eff_{EC} and left/right divisibility (Fig.4, panel c), left/right modularity (data not shown; R=0.53, p=0.05) and left/right influence indices (Fig.4, panel d) in the alpha band. In particular such results indicated how a reduction in the time required for solving the conflict (low Eff_{EC}) is associated to a high communication speed between the electrodes (low path length) and to a less tendency of the network to create clusters (low clustering). Moreover, an efficient (i.e. correlated with high behavioural performance) executive control is explained by a high integration of the two hemispheres (low left/right divisibility) with information flows directed from right to left (negative values of left/right influence).

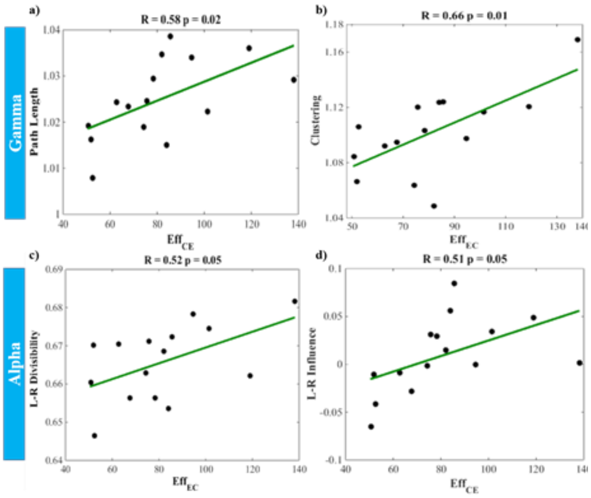

Figure 4. Executive control: statistical correlations between the efficiency Eff$_{EC}$ (y-axis) and the connectivity indices (x-axis) -Path Length (panel a) and Clustering (panel b) in gamma band -Left/Right Divisibility (panel c) and Left/Right Influence (panel d) in alpha band.

DISCUSSION

In the present study, we used advanced techniques for EEG signals processing to extract the cortical connectivity patterns (causal relationship between scalp areas) associated with the 3 attention components as elicited by the ANT paradigm (i.e. alerting, orienting and executive control) performed by healthy subjects. Some indices, derived from the graph theory, allowed the quantitative description of the relevant local and global properties of the 3 different causal connectivity networks in specific EEG frequency bands as they correlated with the behavioural performance (i.e. correlated with *Eff$_{Al}$*, *Eff$_{Or}$*, *Eff$_{EC}$)*. According to our findings, the estimated *alerting* network was described mainly by a negative relationship between the behavioral efficiency (*Eff$_{Al}$*) and Path Length index in the beta band, (ie, the higher efficiency the shorter Path Length) and the left/right Influence index in the theta band (ie, the higher efficiency the higher interhemispheric connection from right-to-left; negative values for left-right influence index).

The phasic alerting improves the speed of target response by changing the internal state of preparation for perceiving a (visual) stimulus [5]. Our results indicate that an efficient alerting function (higher speed to target response) is associated with a global network organization characterized by a shorter average Path Length which corresponds to a high efficiency information transfer [15]. As yet, the entire network appears to be characterized by a prevalent exchange of information directed from right to left hemisphere. Such prevalence might reflect the role of the right hemisphere to sustain alertness that was already stressed in previous studies in which lesions of the right frontal and parietal areas were associated to reduced ability in maintaining the alert state [16]. The above discussed index modulation occurred in beta and theta band, respectively. This finding is in line with previous EEG evidence of a relationship between these frequency oscillations and the alerting function [5].

The efficiency of the *orienting* function was in our study, described by a set of network indices which correlated with behavioral performance *(Eff$_{Or}$)*. First, we found that the higher performance efficiency the higher right Density and left-right Divisibility in the theta band. In addition, higher orienting efficiency also correlated to both lower posterior Density and anterior/posterior Influence (prevalence for post-to-ant) in the gamma oscillations. Together, these results indicate a prevalent role of the right hemisphere versus the left (higher connectivity density) and poor communication between hemispheres (higher divisibility). About the frontal and parietal areas, results indicate a prevalence of connections from posterior to anterior areas (higher anterior/posterior influence and lower posterior density). This is in line with previous evidence of the (right) parietal and frontal areas involved in orienting function which enables for the selection of specific information from a number of sensory inputs [3],[16][4]. The above discussed index modulation occurred in the theta and gamma frequency oscillations that may be in line with the evidence in favour of the contribution of the theta oscillation to long-range communications for cognitive processing by phase-locking to high gamma power (Fries, 2015).

Finally, an efficient *conflict* resolution (ie, *executive control*) was described mainly by a positive relationship between the behavioral efficiency (*Eff$_{EC}$*) and both the Clustering and Path Length indices in the gamma band, (ie, the lower time to solve the conflict (low *Eff$_{EC}$*) the lower tendency to clustering and shorter Path Length) and both the left/right Divisibility and Influence indices in the alpha band (i.e., the higher efficiency the higher interhemispheric connection with a prevalent right-to-left direction flow; negative values for left-right influence index). Altogether these results reflect the highly integrative nature of the conflict processing which requires more integration than segregation of information flow which are originated from several partially overlapping networks [18].

Future studies conducted at cortical and subcortical level (i.e. using source localization techniques like sLoreta [19]) should clarify the effective brain networks properties and their relationship with the currently available knowledge on anatomical and functional connectivity of attention networks. Such further step mightvalidate the proposed indices as neuro-physiological correlates of attention components for future applications.

CONCLUSION

Advanced EEG signals elaboration based on time-varying connectivity estimation and graph theory were applied to extract direct and weighted connectivity patterns elicited by the ANT paradigm at scalp level. Correlation results pointed out a set of EEG-based indices able to synthetically describe each of the three attention components in the different frequency bands and to follow the variations in the corresponding behavioural measures. Such preliminary results could be used in the near future to: i) support the neuropsychological assessment in healthy subject and people with attention impairments; ii) clarify the role of specific attention components in BCI contexts (P300- and SMR-based BCI) and eventually improve the design of BCIs targeting attention rehabilitation; iii) increase the knowledge on attention brain networks elicited by the ANT paradigm. Altogether, our findings at the scalp level might have a strong impact on several clinical/non clinical applications related to the BCI field.

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