

CORTICAL NETWORK MODULATION DURING PACED ARM MOVEMENTS

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ABSTRACT

In this paper we investigate task-related changes in brain functional connectivity (FC) by applying different methods namely event-related desynchronization (ERD), coherence and graph-theoretical analysis to electroencephalographic (EEG) recordings. While ERD provides an estimate of the differences in power spectral densities between task and rest conditions, coherence allows assessing the level of synchronization between the recorded signals and graph analysis enables the estimation of the functional network topology. EEGs were recorded on 10 subjects during left/right arm movements. Conventional analysis showed a significant ERD in both alpha and beta bands over the sensorimotor cortex. Connectivity assessment highlighted that stronger connections are those involving the motor regions for which graph analysis revealed reduced accessibility and an increased centrality during the movement. This highlights that network analysis brings complementary knowledge with respect to established approaches for modeling motor-induced FC.

Index Terms— EEG power, ERD, functional connectivity, coherence, graph analysis

1. INTRODUCTION

Brain functional connectivity (FC) is among the hottest topics in neurosciences as well as in clinical sciences. In the last two decades the study of brain networks both at rest and in relation to the execution of specific tasks has been gaining increasing attention [1] and new approaches have been proposed [2, 3]. FC studies ground on the investigation and modeling of the relationships between brain regions and their functional properties of correlations in neural activity. An increasing number of theoretical and empirical studies approaches modeling of FC from a network perspective. The analysis of brain networks is made feasible by the development of new tools from graph theory and dynamical systems. FC can be derived from different imaging modalities including electroencephalography (EEG). In particular, EEG power spectral density (PSD) is shown to decrease over motor activated cortical areas in alpha (8-12 Hz) and beta (13-30 Hz) bands, a phenomenon termed *event-related desynchronization (ERD)* [4].

The signal synchronization can be estimated by a coherence function, often interpreted as a measure of coupling between two brain regions. Coherence, as a measure of FC, reveals aspects of the brain network organization which complement the information obtained by power spectral analyses.

More recently, graph-based methods have been proposed for the analysis of EEG data [5]. Graph-based methods constitute a simple model for elucidating network structures. The network topology can be described at both local and global levels through properties such as *strength*, *clustering*, *accessibility*, *centrality* and *efficiency*.

The aim of this study was to provide a proof of concept that FC modulations during a motor task can be captured and characterized by network analysis, complementing and integrating the information provided by classical FC analysis methods. To this end, interregional coupling was assessed using (i) spectral (or magnitude-squared) coherence between scalp EEG electrodes and (ii) graph-theoretical approaches. Results provide evidence that network analysis is an alternative approach for the estimation of FC that is complementary to classical methods and provides a new probe for studying neural mechanisms related to motor tasks.

2. METHODS

2.1. Experimental setup and paradigm

The experimental set-up consisted of a synchronous video-EEG GEM 100 digital system (EBNeuro - ATEs Medica Device, Italy) equipped with one camera. EEG data were acquired at a sampling rate of 250 Hz on 10 right-handed healthy subjects (7 men; mean age 26.3 years, standard deviation 4.0 years) using a cap (SEI EMG s.r.l, Italy) with 21 electrodes (reference anterior to Fz and ground posterior to Pz) positioned according to the international 10-20 system of electrode placement. All subjects gave written informed consent for participating in the study in accordance with the Declaration of Helsinki. The study design and protocol were approved by the Local Ethics Committee of the Verona University Department and Hospital. Two EEG recordings were performed: self-paced flexion of right or left arm, metronome paced at a frequency of 0.5 Hz. Six blocks of rest alternated

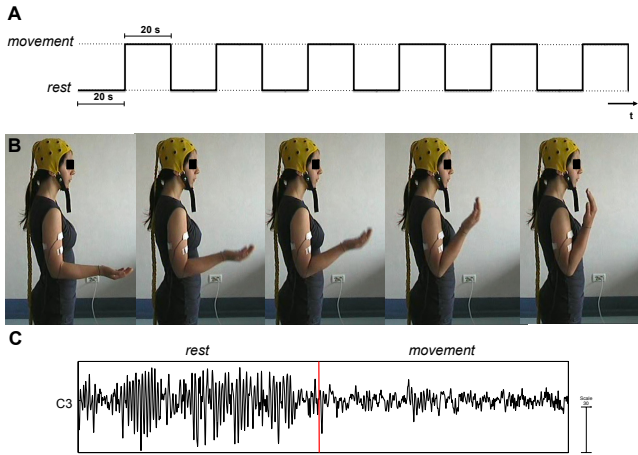


Fig. 1. (A) Protocol for EEG data recording during the experiment. Six blocks of rest alternated with six blocks of task lasting each 20 s. (B) Snapshots from the video recording. (C) Example of EEG (signal channel C3) acquired during the rest condition (left box) and the arm movement (right box).

with six blocks of task were performed in both left and right movement sessions (each block consisted of 10 consecutive trials with a total duration of 20 s) (Figure 1A). Subjects were standing with one arm flexed at the elbow at 90° (rest condition). At the start of the task they performed, with each arm separately, a self-paced flexion at the elbow from 90° to maximal contraction and vice versa. The forearm is pronated and the hand open (Figure 1B). The synchronization between the EEG (Figure 1C) and the movie was ensured by the video-EEG system.

2.2. Event-related desynchronization

Data were preprocessed in Matlab 7 (MathWorks, Natick, MA) as in [6]. EEG segments were divided into 10 epochs of 2s each. Fast Fourier transform (FFT) was applied to non-overlapping epochs, for each electrode and experimental condition, and then averaged across epochs under the same condition. Power spectral density PSD ($\mu V^2/Hz$) was estimated for alpha and beta frequency ranges in the two experimental conditions and used to calculate the ERD as follows:

$$ERD^\alpha = \frac{PSD_{task}^\alpha - PSD_{rest}^\alpha}{PSD_{rest}^\alpha} \times 100 \quad (1)$$

where the symbol α indicates the alpha band. The derivation of the corresponding equation for beta band is straightforward.

A topographic map showing the changes in ERD for each subject in alpha and beta bands and the mean map over all subjects were computed. A paired sample two-tailed t -test was performed for identifying significant differences between the PSD in the rest and task conditions, respectively ($p <$

0.05 , $|t| > 2.262$). Post-hoc paired t -test adjusted for multiple comparisons (i.e. number of electrodes) with Bonferroni method was used ($p < 0.05$).

2.3. EEG functional connectivity analysis

Spectral coherence represents the level of synchronization between pairs of EEG channels in a given frequency band. Spectral coherence, or magnitude-squared coherence, $Coh^\omega(x, y)$ is given by

$$Coh^\omega(x, y) = \frac{|PSD^\omega(x, y)|^2}{PSD^\omega(x) \times PSD^\omega(y)} \quad (2)$$

where $PSD^\omega(x)$ and $PSD^\omega(y)$ are the power spectral densities of two given signals x and y , $PSD^\omega(x, y)$ is the cross power spectral density of x and y and ω is the reference frequency band. The Welch averaged modified periodogram method was applied to each data segment divided into eight equal sections with 50% overlap. The resulting values were averaged across trials. Synchronization values were calculated from the average of $Coh^\omega(x, y)$ values in the alpha (8-12 Hz) and beta (13-30 Hz) frequency bands between all channel pairs, obtaining a connectivity matrix with entries accounting for all the channels.

Considering each electrode as a node, the FC resulted in a 19×19 adjacency matrix for each subject. The connectivity matrices of all subjects in the rest and task conditions were then separately averaged, resulting in one connectivity matrix for each condition.

In order to reduce the impact of inter-subject and inter-electrode-pair variability of absolute coherence values, the differential parameter task-related coherence ($TRCoh^\omega(x, y)$) was obtained as follows

$$TRCoh^\omega(x, y) = Coh_{task}^\omega(x, y) - Coh_{rest}^\omega(x, y) \quad (3)$$

$TRCoh^\omega$ allows eliminating task-unrelated spurious contributions that could affect both task and baseline recordings [7].

Finally, a paired sample two-tailed t -test was performed for detecting significant differences between the spectral coherence in the rest ($Coh_{rest}^\omega(x, y)$) and active ($Coh_{task}^\omega(x, y)$) conditions, respectively, for the 10 subjects and independently for each frequency band. T -matrices were computed and thresholded at $p < 0.05$ ($|t| > 2.262$) and the positive/negative binary matrices were extracted. In order to highlight the spatial topology of connections, positive and negative overthreshold links were displayed on the scalp.

2.4. Network analysis

Graph theoretical analysis was used for assessing the network model properties [2]. The brain network was constructed based on the unthresholded spectral coherence values of the 19 electrodes/nodes, using the corresponding $Coh^\omega(x, y)$ as the weight of the edge connecting x and y nodes. After

constructing the complete weighted graph, five network parameters were extracted:

1. Node strength (S) of the i -th node, defined as the sum of weights along edges connecting to the node i .
2. Weighted local clustering coefficient (CC), defined as the average "intensity" of triangles around a node.
3. Accessibility (A) of a node, calculated as a function of velocity at which the information flows across the connectivity pattern in terms of random walks [5].
4. Betweenness centrality (BC) of the i -th node, defined as the fraction of all shortest paths in the network that pass through the node. BC reflects the extent to which communication between nodes in a network depend on a given node.
5. Eigenvector centrality (EC), defined as the principal Eigenvector of the adjacency matrix of the graph. EC favours nodes that are connected to nodes that are themselves central.

Graph parameters were calculated subject-wise by using an open-source toolbox (Brain Connectivity Toolbox, BCT, <https://sites.google.com/site/bctnet/Home>) with the exception of accessibility that was calculated using a publicly available toolbox (<https://sites.google.com/site/fr2eborn/download>) as well as in-house software (Matlab).

The individually computed graph parameters were averaged across the subjects to obtain a scalp map for each condition. In order to obtain statistical inference regarding group differences in network parameters between rest and active conditions a paired sample two-tailed t -test, $p < 0.05$ ($|t| > 2.262$), was performed. Then, the two-dimensional t -map was computed for each parameter and each band from the t -values to detect the topographical distribution of the significance. Post-hoc paired t -test adjusted for multiple comparisons (i.e. number of electrodes) using the Bonferroni correction was applied ($p < 0.05$).

3. RESULTS

3.1. Event-related desynchronization results

The *ERD* was derived for all subjects and used for both individual and group analysis.

During LAM, the mean alpha and beta maps showed an *ERD* over the bilateral sensorimotor areas, with right hemispheric predominance in both the alpha and beta bands. The t -maps showed significant *PSD* changes over the same regions with highest values over the right sensorimotor regions ($p < 0.05$, not significant after Bonferroni correction) (Figure2A).

Similarly, during RAM the mean alpha and beta maps showed an *ERD* over contralateral and ipsilateral sensorimotor regions in both alpha and beta, but predominantly over the left hemisphere. The t -maps showed a significant *PSD* difference in both bands that was prominent over the left sensorimotor regions ($p < 0.05$, not Bonferroni corrected) (Figure2B).

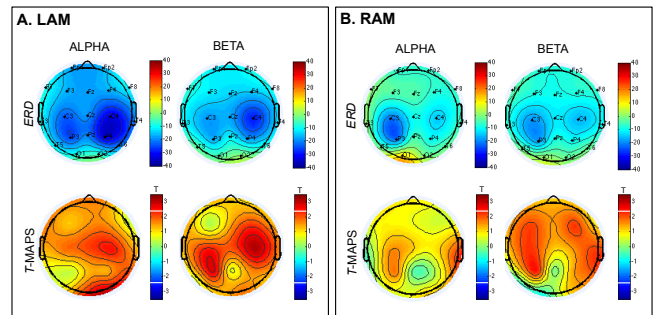


Fig. 2. Grand-average *ERD* topographies and relative power t -maps in alpha and beta bands during LAM (A) and RAM (B). Negative/blue colors indicate reduced activity during task with respect to rest; t -maps were thresholded at $p < 0.05$ ($|t| > 2.262$).

3.2. Functional connectivity results

During both LAM and RAM a strong and significant decrease of connectivity in the alpha and beta frequency bands was observed. Figure3 shows the connectivity pattern obtained from the LAM and RAM for the group. In particular, the *TRCoh*-based connectivity matrices, the binarized t -maps (after hard thresholding) and the statistically significant FC links are illustrated for both the LAM and RAM and frequency ranges.

In the figure, channels are the row and column indices of the connectivity matrices and the corresponding matrix ele-

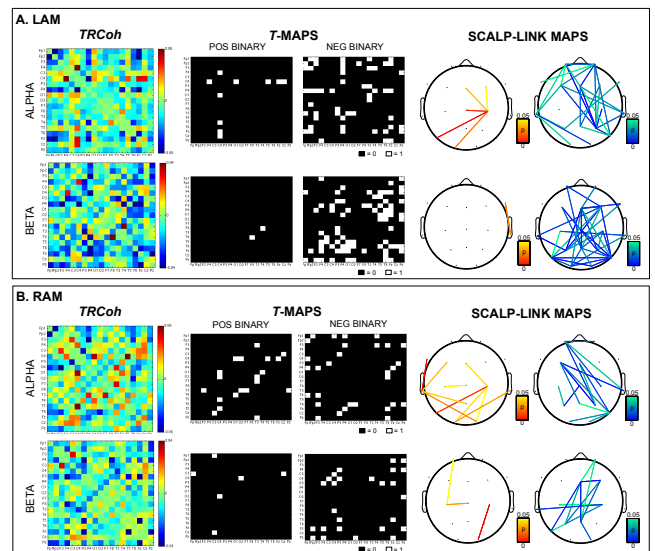


Fig. 3. Grand-average results for LAM (A) and RAM (B). First column: *TRCoh*-based connectivity matrices; second column: binarized t -maps; third column: statistically significant FC links for positive (left) and negative (right) p values ($p < 0.05$; $|t| > 2.262$), respectively.

ment provides the color-coded corresponding $TRCoh$ value, as indicated by the colorbar on the right. Significant increments/decrements in $TRCoh$ are displayed on the scalp maps as color-coded ‘links’ where the red lines (hot scale) indicate that coherence during the task (active condition) is significantly higher compared to resting state, and the blue lines (cool scale) indicate that it is significantly lower.

During LAM an increase in $TRCoh$ was observed in alpha band between the right sensorimotor and frontal, central, temporal and occipital regions (Figure3A).

During RAM results demonstrated an increase in EEG coherence involving the channels over the central/temporal regions versus frontal, parietal, and occipital ones in alpha, whereas in beta the few significant connections involved the motor channels (Figure3B).

3.3. Network results

Standard network indices [2] averaged across subjects were computed in order to infer the network topology in all the considered conditions as well as to detect and quantify the connectivity changes at node level when switching from one experimental condition to the other.

Figure4 illustrates the results for LAM (A) and RAM (B), respectively. The behaviour of network parameters across conditions is shown in the different rows (from top to bottom: strength (S), accessibility (A), clustering coefficient (CC), betweenness centrality (BC), and Eigenvector centrality (EC)). For all parameters the difference (Δ) between the active and rest conditions is shown, with the exception of accessibility for which the ratio in \log scale in the two conditions (RA) is provided.

During LAM, RA maps showed a significant decrease over the central sensorimotor and supplementary motor areas in both bands. The same trend was observed for strength (S) and clustering coefficient (CC) featuring a significant decrease mainly concerning the frontal and posterior regions in both bands (few electrodes were significant after the Bonferroni correction and only in beta band) as well as a significant increase over bilateral sensorimotor areas in alpha and over the supplementary motor area in beta. A different pattern was observed for betweenness centrality (BC) and Eigenvector centrality (EC). In particular, betweenness centrality showed a significant increase over the right motor cortex in alpha and over the supplementary motor area and right motor-temporal cortex in beta (not significant after Bonferroni correction), whereas Eigenvector centrality increased significantly bilaterally over the motor regions in both bands with right predominance in alpha (Figure4A).

A similar pattern of network modulation was observed during RAM, even though some differences could be discerned. In particular, alpha and beta maps showed a significant (not significant after Bonferroni correction) decrease in accessibility (RA) between the rest and task conditions over

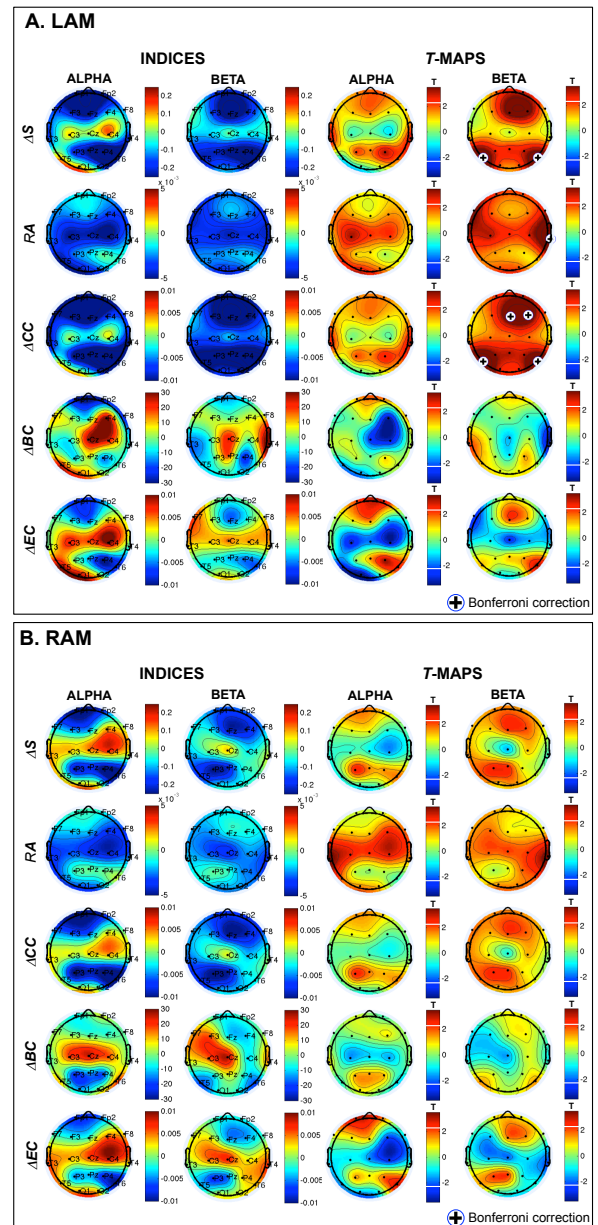


Fig. 4. Task-induced modulation in network parameters in LAM (A) and RAM (B). In each subfigure, the first two columns represent the parameter values and the second two show the corresponding t -maps. In the t -maps, the threshold was $p < 0.05$ ($|t| > 2.262$) and (+) indicates significance after Bonferroni correction.

motor areas, more bilaterally in alpha and principally over the supplementary motor area in beta. Increase in betweenness centrality (BC) appeared to be more bilateral showing high values over the motor cortex in alpha while involving the left area in beta (Figure4B). The similarity in network modulation between LAM and RAM was particularly evident for the

majority of the network parameters namely A , S , CC and EC , all showing a quite similar pattern of variation in both conditions.

4. DISCUSSION

So far, EEG-based mapping of arm movement is still under-investigated [8]. One possible reason could be that it generates a more widespread and less specialized cortical activity. However, its decryption holds a great potential for clinical usage especially in case of patients having difficulty in performing fine movements. This study is the first to investigate the brain functional network in EEG recordings in long-lasting repeated tasks evoked by paced-arm movements. Different analysis tools were exploited in order to investigate their respective descriptive power and complementarity in decrypting the modulation of the FC network during paced-arm movement.

Traditional ERD and $TRCoh$ are essentially competing analyses for describing the same neural process evoked by the task, placing emphasis on different aspects. ERD can be modulated by increasing or decreasing activity at any region, $TRCoh$ by enhancing or suppressing functional coupling between any pair of regions. During unimanual hand movements, a bilateral ERD was observed in both bands. Nonetheless, ERD was prominent over the contralateral central regions and, secondarily, the ipsilateral motor and mesial regions, with slightly larger values in alpha. $TRCoh$ showed an increased FC involving the motor regions associated with a decrease in functional coupling of other regions. However, the two different analysis approaches to the assessment of cortical activity might partially diverge during the execution of a motor task because the cortical network might modulate inter-regional coupling even without obvious changes in regional activation.

The main contribution of this work is the assessment of the modulation of the functional network using graph-based analysis highlighting a decreased accessibility in combination with an increased centrality of the motor regions recruited during the task. The central/motor areas became less accessible, i.e. “busier”, and more “central” during movement, suggesting that the execution of a task is related to a coordination of different brain regions involving both alpha and beta. Indeed, the accessibility index revealed a similar pattern in the network estimated during the LAM and RAM tasks. Strength and centrality indexes revealed an unilateral preference of the motor areas in alpha and a more distributed high strengths and Eigenvector centrality indices over the central electrodes in beta during LAM. During the RAM, high values for strength and centrality measures were revealed more contralaterally over the motor areas in beta.

The observed increase in clustering coefficient of the same nodes during both LAM and RAM could indicate that the neighboring nodes tend to synchronize stronger with each

other during the active condition. Functional network analysis also revealed that both tasks exhibit hubs. The increase of centrality indexes underlines that motor regions acted as hubs for information flow in both tasks, implying that removal of such areas from the estimated patterns would cause a collapse of the whole functional network.

In view of these findings the inference of the changes in the topological organization of the functional network during the execution of simple tasks by a cohort of healthy subjects has a potential as the benchmark for the assessment of the functional connectivity alterations due to pathological conditions.

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