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Analysis of the connection redundancy in functional networks from high-resolution EEG: a preliminary study

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Abstract— **In the present study, we propose a theoretical graph procedure to investigate the communication redundancy in brain networks. By taking into account all the possible paths between pairs of cortical regions, this method captures the network redundancy i.e. a critical resource of the brain enhancing the resilience to neural damages and dysfunctions. As an example for its potential, we apply this procedure to the cortical networks estimated from high-resolution *EEG* signals in a group of spinal cord injured patients during the attempt of the foot movement. Preliminary results suggest that in the high spectral contents the effects due to the spinal trauma affect the expected redundancy attitude by suppressing mainly the longer alternative pathways between the cortical regions.**

I. Introduction

Recently, it was realized that the functional connectivity networks estimated from brain-imaging technologies such as Magnetoencephalography (*MEG),* functional Magnetic Resonance Imaging (*fMRI),* and Electroencephalography (*EEG*) can be investigated using graph theory [1-8].

Since a graph is a mathematical representation of a network that has been essentially reduced to nodes and connections between them, the use of a graph-theory approach is potentially relevant and useful, as first demonstrated on a set of anatomical brain networks [9,10]. In those studies, the researchers employed two characteristic features, namely the average shortest path L and the clustering index C to extract the global and local properties respectively of the network structure [11]. They found that anatomical brain networks exhibit many local connections (*i.e.,* a high C) and a few random long distance connections (*i.e.,* a low L), characterizing a particular model that interpolates between a regular lattice and a random structure. Such a topological property of the network (designated as *small-world*) has a strong impact in Neuroscience, since it is related to the optimal architecture for information processing and signal transmission among different cerebral structures [10,12]. The small-world concept in a complex network is strictly related to the length of the shortest paths within the network, which is given by the smallest number of edges needed to go from a starting vertex i to a target node j [13]. However, shortest paths just represent one possible way in which two nodes in the network can communicate and other existing pathways should be generally taken into account to characterize the connectivity pattern [14]. In particular, by neglecting the longer pathways important information is lost about the alternative trails that could connect any two nodes in a network. This information appears strictly related to the concepts of “redundancy” and “robustness”, critical resources for the survival of many biological systems as they provide reliable function despite the death of individual elements. Indeed, the presence of more than one path between two nodes in the graph tends to increase the interaction between them, while enhancing the resilience to damages. In particular, the human brain is supposed to exhibit a high level of alternative anatomical and functional pathways between adjacent regions and sites. This type of organization would allow the brain to reshape its physiologic mechanisms in order to compensate the critical consequences of possible diseases [15].

In the present study, we considered the “superedges” methodology [14] in order to obtain a detailed analysis of brain networks considering the concept of generalized connectivity. This approach allows characterizing the networks structure and dynamics by taking into account all the possible paths between pairs of nodes. In order to illustrate the potential of such a superedges approach to brain network analysis, we studied a set of high-resolution *EEG* signals from spinal cord injured patients and control subjects during the preparation of an intended motor act.

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II. METHODS

A. Experimental Design

The experimental subjects participating in the study were recruited by advertisement. Informed consent was obtained in each subject after the explanation of the study, which was approved by the local institutional ethics committee. The spinal cord injured group (*SCI*) consisted of five patients (age, 22-25 years; two females and three males). Spinal cord lesions were of traumatic etiology and located at the cervical level (C6 in three cases, C5 and C7 in two cases, respectively). The control group (*CTRL*) included five healthy volunteers (age, 26–32 years; five males). The experimental task for the *SCI* patients consisted in the performance of a brisk protrusion of their lips while they were attempting (volition task) the right foot movement; the same task was for the *CTRL* subjects but they had to execute the foot movement. The task was repeated every 8 seconds in a self-paced manner and 100 single trials were recorded. A 96-channel system (BrainAmp, Brainproducts GmbH, Germany) was used to record simultaneously the 64 *EEG* signals from the scalp and the *EMG* signals from the lips. Before the experiment, the structural MRI images of the head were taken for each experimental subject by means of a Siemens 1.5T Vision Magnetom MR system (Germany).

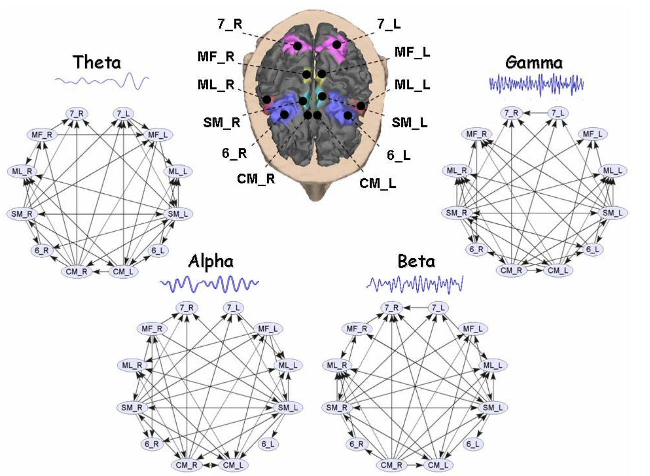

Fig. 1 Cortical networks estimated from the high-resolution EEG signals of a representative patient during the task. The functional relationships were evaluated in four main frequency channels, Theta (3-6 Hz), Alpha (7-12 Hz), Beta (13-29 Hz) and Gamma (30-40 Hz). Networks are represented as graphs. Each node corresponds to a particular ROI in the illustrated cortex model. Each directed edge corresponds to a significant causal relationship between the electrical activities of two ROIs.

B. Cortical Functional Connectivity

The cortical activity estimation from the 64 scalp *EEG* signals was obtained by using realistic head models and Linear Inverse procedures according to techniques described in previous papers [16-18]. By using the passage through the Tailairach coordinates system, twelve Regions Of Interest (*ROIs*) were then obtained by the segmentation of the Brodmann areas on each accurate cortical model consisting of about 5.000 triangles (*i.e.* electrical dipoles). The *ROIs* considered in this analysis are strictly involved in the information processing during motor acts. Eventually, the electrical activity in each *ROI* was obtained by averaging the single time series of the dipoles within the segmented area.

In order to study the preparation to an intended foot movement, a temporal segment of 1.5 seconds before the lips pursing (i.e. the event trigger) was analyzed. The resulting cortical waveforms were simultaneously processed for the estimation of functional connectivity by using the Directed Transfer Function (*DTF*) [19]. The application of this method to the *ROIs* waveforms yields a fully connected cortical network for each frequency band of interest: *Theta* 4-7 Hz, *Alpha* 8-12 Hz, *Beta* 13-29 Hz, *Gamma* 30-40 Hz. However, only those functional connections that resulted statistically significant ($p<0.001$) after a contrast with the surrogate distribution of *DTF* values obtained from a Montecarlo procedure were considered in the present study. Fig. 1 shows the functional networks of a representative *SCI* patient in the four characteristic ranges of *EEG* oscillations.

C. Superedge Approach

The theoretical representation of a network is the graph. A graph consists of a set of vertices (or nodes) and a set of edges (or connections) indicating the presence of some sort of interaction between the vertices. The adjacency matrix G contains the information about the connectivity structure of the graph. When a link connects two nodes i and j, the corresponding entry of the adjacency matrix is $a_{ij} = 1$; otherwise $a_{ij} = 0$.

Basically, the superedges methodology involves the partition of the network into three parts: (i) the input sub-network G_{in}, (ii) the output sub-network G_{out} and (iii) the superedge G_s that is the remainder of the network [14].

The effect of G_{in} on G_{out} can be quantified in terms of structure and dynamics, given G_s, which can be understood as a dynamical system. In our current approach, the G_{in} and G_{out} are individual nodes (cortical regions). Figure 2 presents an example of superedge approach. Note that the superedge framework also establishes a direct analogy with to the input/output representation adopted in dynamical systems theory. A suitable measurement to characterize the network structure is the number of outward paths of various lengths between G_{in} and G_{out}. These paths are alternative routes of communication between the input and output sub-networks, and they are fundamentally associated to the brain function. The number of outward paths of a node i with length h, $R_{outh}(i,)$, is given by the total number of paths of length h between that node and all other nodes in the network:

$$R_{out\,h}(i) = \sum_{j=1}^{N} R_h(j,i) \qquad 1)$$

where R_h is the number of outward paths of length h starting at i reaching the vertex j. When a vertex i concentrates many alternative paths to other common vertices this implies that the connections between such vertices present a high level of resilience against edge disruption. In fact, when an edge belonging to any of the paths between i and j is removed, the connection between these vertices are not interrupted. Therefore, the number of outward paths indicated the vertex importance in terms of long range connectivity and redundancy.

D. Principal Component Analysis

When a large volume of data is available, techniques of dimensionality reduction are necessary. A possible way to overcome these limitations can be obtained by identifying the principal component analysis methodology, which is a dimensionality reduction transformation that removes data redundancy in an optimal fashion [20]. Let $X = [x_1, x_2, ..., x_h]^T$ be a vector that represents a set of h measured variables. Let X_i, $i = 1, 2, ..., m$, be a sample vector of m observations of X. In our analysis, X would represent each individual and each measured variable, the number of outward paths or outward activation at distance h. Given $Z = [z_1, z_2, ..., z_h]$ the $h \times h$ orthogonal matrix constructed from the eigenvectors of the sample covariance matrix of X, then the elements of z_i give the contribution weight of each measurement for the *PCA* component i. The new feature vectors can be obtained from the original normalized feature vector by the following transformation [21]:

$$U = Z^T X \quad .$$

This transformation allows one to project the m x h dimensional feature into a new space with reduced dimensionality while yielding completely decorrelated new variables which correspond to linear combinations of the original features.

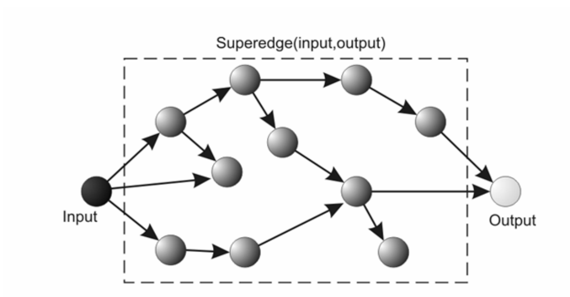

Fig 2. The sub-network inside the dashed region represents the super-edge, which acts as a dynamical system between the input vertex and the output vertex.

III. Results

The superedges approach was applied to the estimated cortical networks by considering path lengths ranging from *1* to *10* (*h=1,2…10*, where 10 is the maximum distance observed for such networks). Since the estimated cortical networks are directed, we considered the directed version of the algorithm described in Da Fontoura Costa and Rodrigues [14]. The current investigations about the structure of the cortical networks in spinal injured patients and healthy individuals consider the optimal statistical method i.e. Principal Component Analysis (*PCA*) for decorrelation of the heavily correlated measurements and dimensionality reduction. In particular, the number of measurements was the number of experimental subjects i.e. *m=10* (five healthy and five spinal cord injured) and the number of variables was the number of considered path lengths i.e. *h=10*. Eventually, we projected the $m \times h$ spaces of each frequency band into the main three-dimensional space. The results from the *PCA* analysis are presented in Fig. 3 for all the frequency bands. Each scatter plot shows the projections of the R_{out} values with respect to the first three main principal components (i.e. *PCA1, PCA2, PCA3*). While the separation between the *SCI* group and the *CTRL* group is well defined in the *Gamma* band (mostly due to the combination of the *PCA2* and *PCA3* components), the separation in the other bands is not clear. This implies that only in the *Gamma* band the *SCI* cerebral network deviates from the *CTRL* network with respect to its structure, which is quantified by the number of the outward paths distribution.

Figure 4 shows that the mean R_{out} values of both the populations have similar bell-shaped profiles, with a peak in correspondence of *h=5*. However, a comprehensible distinction is that the *SCI* network tends to have fewer paths across a narrow range of lengths *h* (i.e. $5 \leq h \leq 7$). This lower number of outward paths reflects a loss in terms of mid-range connectivity and redundancy in the cortical functional network.

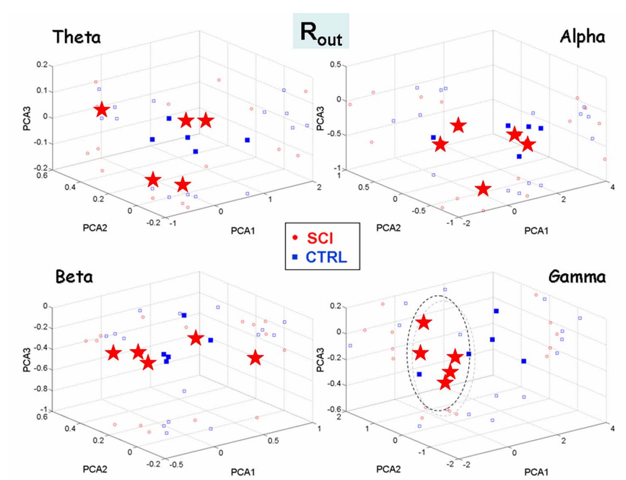

Fig 3. Scatter plot of the three main components obtained through the Principal Components Analysis from the outward paths R_{out} of length h=1… 10. Each subplot shows the results found in a different frequency band. Star symbols represent values from the SCI group; little squares stand for values from the CTRL group. Each value is also projected on the respective Cartesian planes (PCA1xPCA2, PCA1xPCA3, PCA2xPCA3).

IV. Discussion

The use of theoretical graph approaches have been widely demonstrated to provide important information about the structure and the architecture of complex brain networks [22]. Several works have investigated the *small-world* properties of anatomical and functional brain networks in pathological and physiological conditions. The *small-world* analysis relies on the estimate of two characteristic measures i.e. the path length and the cluster index. Both these indexes are computed from the shortest paths within the network. The organization of such optimal pathways is very useful as it reveals the level of information processing and signal transmission among different cerebral structures. However, the solely consideration of shortest path distances could provide for an incomplete characterization of networks, since complex connectivity systems with similar shortest paths distribution can indeed exhibit distinct structures and dynamics.

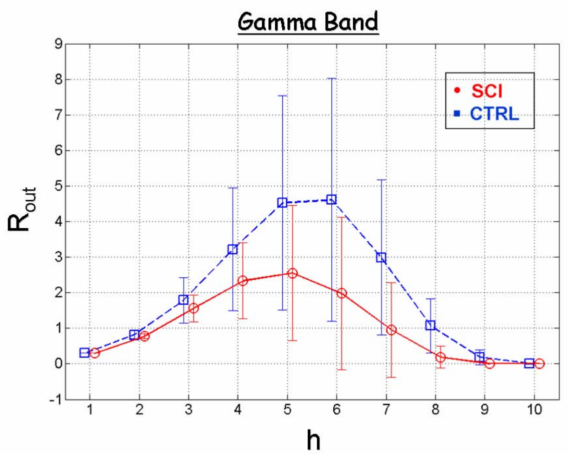

Fig 4. Profile of the number of outward paths R_{out} in the Gamma frequency band. The different lengths h are listed at the x-axis. Solid circles represent R_{out} mean values from the SCI group; Dashed squares stand for the R_{out} mean values from the CTRL group. Vertical bars indicate the respective standard deviation.

The obtained preliminary results suggest that the effects due to the spinal trauma affect the expected redundancy attitude of the cortical functional networks by suppressing mainly the longer alternative connections between the ROIs in the Gamma (30-40 Hz) frequency band.

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