Connectivity Modulations induced by Reaching&Grasping Movements

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***Abstract*—Functional neuroimaging enables the assessment of the brain function in both rest and active conditions. While traditional functional connectivity studies focus on determining distributed patterns of brain activity, the analysis of pair-wise correlations in the time series associated to brain regions allows a paradigm shift to graph theory making available a whole set of parameters for the analysis of the functional network. Then, the study of the properties of the networks as well as of their modulations can be performed in the space of the so-identified features potentially leading to the detection of condition-specific (static or dynamic) fingerprints. Following this guideline, this study is a first attempt to using graph-based measures for capturing task-specific signatures of a reach&grasp movement. The weighted clustering coefficient (CW), characteristic path length (SW) and small-worldness (SW) were considered and performance was assessed against classical measures (event-related (de)synchronization). Neurophysiological data were collected through high-density EEG and a stereophotogrammetric system was used for capturing the onset and end of the movement. Though not reaching statistical significance, these preliminary results witness the modulation of the function network due to reach&grasp and provide evidence in favour of the possibility of capturing such a modulation through graph-based properties. This would allow to shed light on the movement-induced reorganization of the network, which has a clear translational impact for the assessment of the recovery of patients after acute stroke.**

***Index Terms*—High-density EEG, Brain connectivity, Motor function, Graph theory**

I. Introduction

The mechanisms that the central nervous system employs to control the movement performed with the upper limbs are still matter of research [1], [2]. The present work proposes a neurophysiological approach to decode the electrical activity during the reaching and grasping movements [3] compared to a resting state condition. Some evidence demonstrate that finger tasks modulate cortical desynchronization mainly in α and β frequency bands [4], [5] and that flexo-extension task with upper limbs determines changes of EEG synchronization and functional networking [6]. However, a method which allows to simultaneously monitor and measure brain functioning and the execution of a finalistic task as reaching and grasping is not yet available. Nevertheless, this would allow to evaluate the upper limb kinematic features during the recovery process after stroke as well as to understand the pathophysiological processes which can promote or negatively condition the clinical improvement. Here we describe a method which relies on the assessment of the synchronization between high-density electroencephalography (EEG) and the data gathered by a stereophotogrammetric system. The results of this study could be particularly relevant for the evaluation of the mechanisms of functional recovery of finalist movements, such as reaching and grasping, involving not only motor cortex in patients with acute stroke.

II. Methods

A. Population

Ten healthy subjects were recruited (40.2 $\pm$ 7.4 years). The research was approved by the local ethics committee and complies with the Helsinki Declaration. Written informed consent was obtained for each subject.

B. Experimental Design

The motor performance during reaching and grasping (left/right arm) was simultaneously assessed by an optoelectronic system equipped with 8 infrared cameras and a high-density EEG equipped with 64 channels (NEURO PRAX EEG, neuroConn). The net was adjusted so that Fpz, Cz, Oz, and the preauricular points were correctly placed according to the international 10/20 system. The data were recorded at a sampling rate of 512 Hz. The motor task consisted in the execution of reaching&grasping movements for 15 times (trials) for each arm while the subject was seated in a relaxed position. Each reaching&grasping task was preceded and followed by a rest period of 10 s, namely Rest1 (pre-movement), and Rest2 (post-movement). The EEG recording was carried out under three different experimental conditions: Rest1 (pre-movement), Rest2 (post-movement) and Movement ("reach&grasp" movement). Rest (10 s) and Movement (2-4 s) blocks were interleaved and separated by event-markers. The

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motor performance during reaching and grasping was recorded by placing 18 markers on anatomical landmarks in accordance with a validated upper limb and trunk biomechanical model (RAB model - modified) [7].

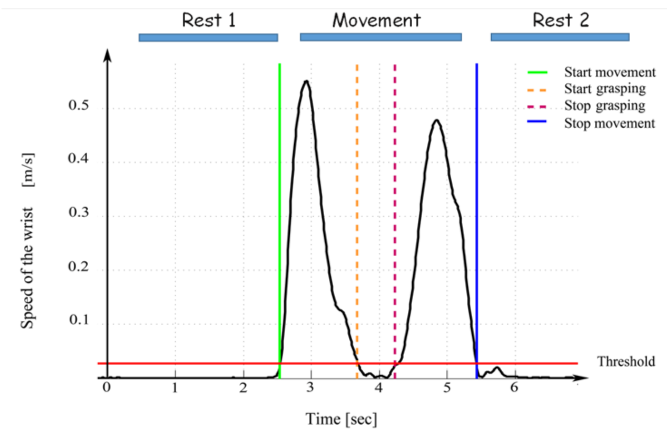

Fig. 1: Speed of the wirst during the reaching&grasping cycle. The red line indicates the 5% threshold used for marking the starting and ending time-points of the movement.

C. Movement Analysis

A threshold on the wrist marker velocity was used to detect the beginning and end of the reach&grasp cycles. The onset of movement from the initial position was identified as the instant when the velocity of the wrist marker exceeded 5% of peak reaching velocity. Similarly, the end of the cycle was associated to a decrease in wrist marker velocity to less than 5% of the maximum velocity upon returning the arm to the initial position (Fig. 1). Using the synchronized systems, it was possible to identify on the EEG recording the events as detected by this analysis in order to define the different blocks (Rest1, Movement and Rest2).

D. EEG Data Analysis

Data were preprocessed in Matlab R2014b (MathWorks, Natick, MA) using scripts based on EEGLAB 12 (http://www.sccn.ucsd.edu/ eeglab), as well as dedicated in-house code. The EEG recordings were band-pass filtered from 1 to 47 Hz. Visible artifacts (i.e. eye movements, cardiac activity, and scalp muscle contraction) were removed using independent component analysis (ICA) [8] and data were processed using a common average reference. EEG segments were divided in epochs of 2 s each. For each electrode and experimental condition, Fast Fourier Transform (FFT) was applied to non-overlapping epochs, and then averaged across epochs under the same condition. A non-overlapping 2-s Hamming window was used to avoid spectral leakage. The event-related synchronization/desynchronization method (ERS/ERD) was used for quantifying the task-related changes in brain activity in α and β frequency bands [4]. ERD/ERS values were defined as the percentage decrease/increase of the power spectral density (PSD ($\mu V^2/Hz$) during task (Movement) with respect to the baseline value (pre-movement, Rest1 and post-movement, Rest2), as follows:

$$ERD^{\alpha} = \frac{PSD^{\alpha}_{task} - PSD^{\alpha}_{rest}}{PSD^{\alpha}_{rest}} \quad (1)$$

where the symbol α indicates the alpha band. The derivation of the corresponding equations for ERD and δ, θ and β bands are straightforward. Accordingly, event-related PSD decrements representing a decrease in synchronization of the underlying neuronal populations and indicating cortical activation resulted in negative values. Finally, the Wilcoxon test with Bonferroni correction ($p < 0.05$) was performed to detect significant differences between PSD in Rest and Movement, respectively.

E. EEG Source Imaging and Functional Connectivity

EEG data were processed using standard low-resolution brain electromagnetic tomography (sLORETA) software for localizing the cortical sources (http://www.uzh.ch/keyinst/NewLORETA/LORETA01.htm). The EEG cross-spectra and the corresponding 3D-cortical distribution of the electric neuronal generators were computed for each frequency band (δ: 1-4 Hz, θ: 4.5-7.5 Hz, α: 8-12.5 Hz, β: 13-20 Hz), under the three conditions and for each subject separately [9], [10]. The solution space was restricted to the cortical gray matter and the Montreal Neurologic Institute average MRI brain (MNI152) [11] was used as a realistic head model.

Lagged linear connectivity, i.e. excluding coherences with zero phase lag, "lagged coherence" [12], was calculated for each epoch in the same frequency ranges and a whole-brain Brodmann areas (BAs) atlas was used for selecting the 42 BAs in each hemisphere as regions of interests (ROIs) for performing the functional connectivity (FC) analysis between pairs of ROIs. ROIs were sorted according to their functional role as somatosensory, motor, executive, emotional regulation, memory, attention, sound, visual, olfactory and not well studied [13]. The resulting values were averaged across epochs. The connectivity matrices of all subjects in the Rest1, Rest2 and Movement were then separately averaged, resulting in one connectivity matrix for each condition and arm.

F. Graph Analysis of Network Topology

Graph-theoretical analysis was used for assessing the network model properties [14]. The brain network was constructed based on the unthresholded values of the corresponding lagged coherence values as the weight of the edge connecting each pair of ROIs (nodes) [15]. After constructing the complete weighted graph, network parameters were calculated. Graph theoretical analysis was performed by using the open-source BCT toolbox (Brain Connectivity Toolbox, BCT, https://sites.google.com/site/bctnet/Home).

The local topological properties of the brain networks were calculated: weighted clustering coefficient (CW) and weighted characteristic path length (LW) as a measure of segregation and integration of the network, respectively. In each subject, the values of CW and LW of each band were normalized

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to the respective global mean value obtained after averaging each such parameter through the four bands (δ, θ, α, β). The measure of network small-worldness (SW) was defined as the ratio between CW and LW

$$SW = \frac{CW}{LW} \tag{2}$$

Finally, for each EEG frequency band the Friedman test was performed to detect significant differences between CW, LW and SW across the three different experimental conditions (Rest1, Rest2, Movement) and separately for the left or right arm.

III. Results

A. ERD/ERS Results

The ERD maps were derived for all epochs, frequency bands, arms and subjects and used for both individual and group analyses (Fig. 2). The mean maps revealed an increase of ERD over the sensorimotor cortex in α and β, comparing Movement vs. Rest1 and Movement vs. Rest2 for both right and left arm. The desynchronization was maximum over the contralateral central areas and, secondarily, over the ipsilateral motor areas for both arms (most clearly for Rest2). Moreover, Rest2 highlighted a more prosperous activity in α and β frequency band compared to the pre-movement condition.

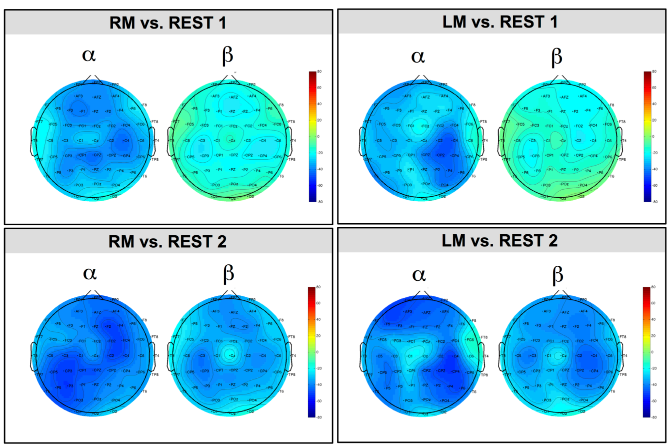

Fig. 2: Event-related desynchronization in α and β, comparing Movement vs. Rest1 and Movement vs. Rest2; RM = right arm movement, LM = left arm movement.

B. FC and network results

Figure 3 illustrates the connectivity matrices in the four considered frequency bands (δ, θ first row, α, β second row) for the Rest2 (a) and Movement (b) conditions, respectively. In Figure 3(b) the matrix was obtained for the movement of the right arm, but the same trend was observed for the left one. As it can be visually appreciated, the movement induces a decrease in connectivity. Such a behaviour was observed for both arms, in all frequency bands but stronger in α and β and with respect to both rest conditions (Rest1 and Rest2).

The topological parameter comparisons for the three conditions at different frequency bands and the statistical results are shown in Tables I and II. The Friedman test showed only a reduced LW in Rest2 versus Rest1 in β band during movement with left arm ($p = 0.04$), while no statistically significant difference was observed during movement with right arm ($p = 0.06$). For CW and SW no significant difference was found among Rest1, Rest2 and Movement in right and left tasks.

IV. Discussion

During movement, electrical changes are elicited in both the contralateral and ipsilateral somatosensory and motor areas, as well as in the frontal and occipital areas, bilaterally. Comparing the Rest2 (post-movement resting) and Movement conditions, arm movement of the dominant hand is accompanied by a more pronounced ERD in the contralateral hemisphere compared to the ipsilateral side in both α and β bands, whereas movement of the non dominant arm is characterized by a less lateralized ERD. Different PSD patterns of Rest1 and Rest2 have been observed in the α and β frequency bands. In particular, PSD of Rest2 was greater than that of Rest1. As consequence the ERD of Movement vs. Rest2 was greater than ERD of Movement vs. Rest1. These results are probably related with the mu-rhythm suppression in Rest1 reflecting the motor planning and with the post-movement power rebound which is probably related with the motor inhibition in Rest2 [4]. Although the significance for CW and the "small world" properties has not been reached during movement and rest conditions, except for LW as discusses above, many changes with different frequency bands were observed. The limitation in terms of statistical significance could be identified in the low number of subjects that were investigated [16]. In consequence, our preliminary results on functional connectivity and network analysis do not allow further speculations besides the observation that both lagged coherence analysis and LW analysis are concordant in highlighting a greater functional connectivity in β band during Rest2 after left movement. Indeed, the graph analysis showed that Rest2 is characterized by a greater integration of the global network with respect to Rest1. On the other side, after right movement the graph analysis showed no significant difference among Rest1, Rest2 and Movement, while functional connectivity analysis showed results similar to those observed after left movement. This different behaviour could be related with the requirement of a greater effort for performing the task with the non-preferred arm (left side in our sample) [17], [18].

V. Conclusion

Though preliminary, these data shed light on the possibility of detecting and interpreting the activity changes induced by acute pathologies, such as stroke, and for monitoring the modulation of electrical brain activity by the motor performance over time, setting the basis for identifying the neurophysiological processes underlining recovery.

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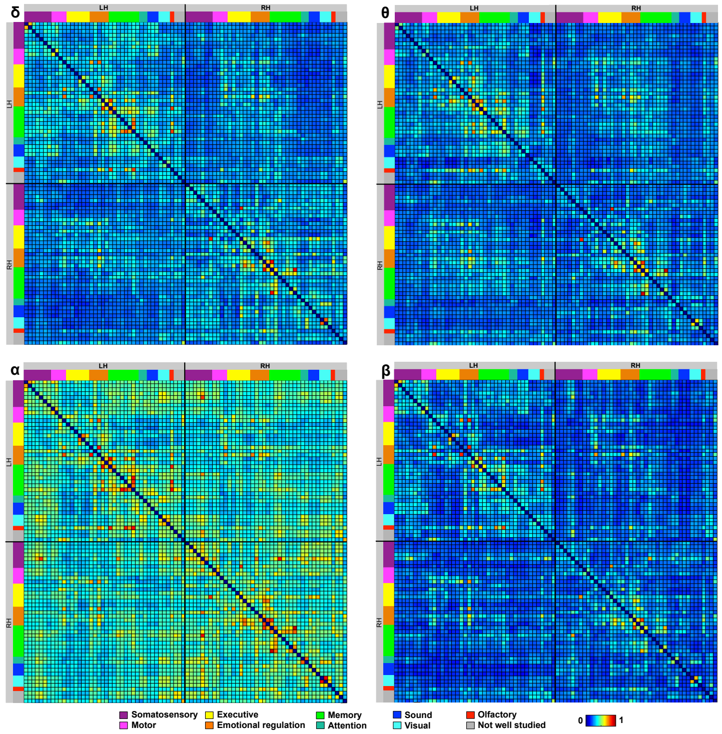
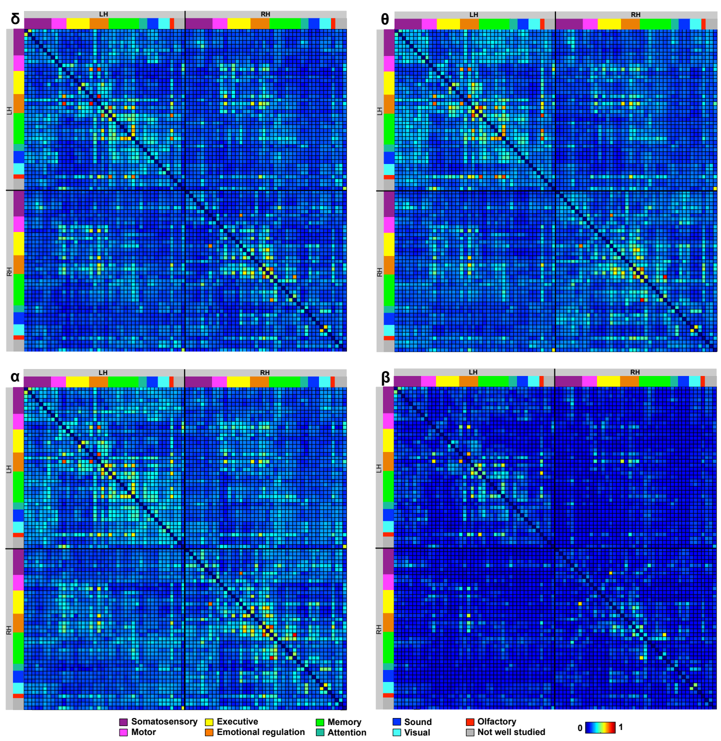


(a)



(b)

Fig. 3: Functional connectivity in Rest2 (a) and Movement (b) conditions averaged across subjects in δ, θ, α and β frequency bands. LH, left hemisphere; RH, right hemisphere. Regions are the row and column indices of the connectivity matrices and the corresponding matrix element provides the color-coded linear lag coherence value, as indicated by the color bar.

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TABLE I: Friedman test for CW, LW and SW between the three different experimental conditions (Rest1, Rest2 and Movement) for each EEG frequency band during the trials performed with the right arm.

RIGHT ARM												
	CW				LW				SW			
	Rest1	**Rest2**	**Movement**	**pvalue**	**Rest1**	**Rest2**	**Movement**	**pvalue**	**Rest1**	**Rest2**	**Movement**	**pvalue**
Delta	0.077	-0.13	0.212	0.41	-0.138	0.193	-0.173	0.49	-0.36	0.25	-0.486	0.9
	-0.648	-0.751	-0.465		-0.485	-0.805	-0.534		-2.007	-2.902	-0.886	
Theta	0.103	-0.064	0.427	0.27	-0.227	0.086	-0.326	0.27	-0.581	-0.664	-1.094	0.49
	-0.604	-0.823	-0.73		-0.487	-0.897	-0.619		-1.043	-1.084	-0.614	
Alpha	0.756	0.783	0.248	0.15	-0.686	-0.712	-0.405	0.74	-1.207	-0.933	-0.568	0.27
	-0.918	-0.872	-0.948		-0.896	-0.745	-0.901		-1.391	-0.818	-0.928	
Beta	-0.936	-0.588	-0.887	0.07	1.05	0.433	0.904	0.06	-0.593	-1.219	-1.476	0.27
	-0.281	-0.492	-0.7		-0.483	-0.71	-0.782		-0.851	-2.576	-1.563	

TABLE II: Friedman test for CW, LW and SW between the three different experimental conditions (Rest1, Rest2 and Movement) for each EEG frequency band during the trials performed with the left arm.

LEFT ARM												
	CW				LW				SW			
	Rest1	**Rest2**	**Movement**	**pvalue**	**Rest1**	**Rest2**	**Movement**	**pvalue**	**Rest1**	**Rest2**	**Movement**	**pvalue**
Delta	0.025	-0.05	0.156	0.67	-0.194	-0.033	-0.19	0.67	-0.533	-0.587	-1.111	0.3
	-0.554	-0.608	-0.851		-0.411	-0.65	-0.705		-0.999	-1.123	-2.408	
Theta	-0.025	-0.186	0.189	0.49	-0.064	0.227	-0.172	0.12	-0.16	-0.796	-0.654	0.9
	-0.704	-0.62	-0.692		-0.727	-0.705	-0.721		-2.896	-1.184	-1.01	
Alpha	0.941	1.076	0.649	0.49	-0.847	-0.996	-0.702	0.49	-1.328	-1.348	-0.898	0.49
	-0.646	-0.564	-0.629		-0.447	-0.435	-0.369		-0.684	-0.828	-0.498	
Beta	-0.941	-0.84	-0.994	0.49	1.105	0.802	1.064	0.04	-0.574	-0.352	-0.788	1
	-0.379	-0.387	-0.32		-0.486	-0.589	-0.548		0.86	-1.601	-0.673	

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