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Dynamic analysis of EEG signals during spatial working memory used for either perception discrimination or planning of action

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Abstract— **We analysed multi-channel electroencephalographic (EEG) recordings during a spatial Working Memory (WM) task in order to test the hypothesis that segmentation of perception and action is present when the visual stimulus has been stored in spatial WM. To detect the interactions between different regions of the brain depending on the task we employed both Short Time Fourier Transformation (STFT) and the concept of Granger Causality (GC). Our computational analysis supports evidence that the Parietal Cortex (PC) is involved in WM processing.**

I. Introduction

Performing WM tasks causes an increase of neuronal activity in several brain regions, which suggests information exchange between them. An influential theory of WM proposes that this cognitive function is sub-served by different systems in the brain according to the type of stimuli being processed (verbal versus spatial etc) [1], [2]. Another theory on vision proposes the existence of two visual processing streams, one used in perception and one used for the planning and execution of movements [3], [4]. To test the above hypotheses, EEG recordings were obtained during four types of tasks: movement with two conditions (condition 1: memory, condition 2: no memory) and perception discrimination with the same two conditions, as will be described further in the next section.

The interactions between neuronal assemblies during cognitive tasks suggest that the analysis of the neuronal mechanism sub-serving a cognitive procedure in terms of causal networks is meaningful. One approach to investigate the causal relations between time series has been proposed by Wiener and formalized by Granger within the framework of linear regression models of stochastic processes [5], [6]. As has been shown in several studies, GC analysis can provide information about the dynamics, the directionality as well as the spectral properties of the signals obtained from electrophysiological recordings [7]-[16].

Previous studies have found a clear involvement of the PC in spatial WM tasks. This evidence has been supported mostly by functional magnetic resonance image processing [17], [18]. In addition, it has been also shown that PC damage is related to deficits in spatial WM [19], [20]. In this study we attempted to provide such evidence using both time-frequency analysis and GC network analysis from EEG data. Our aim is to test whether the segmentation of perception and action is present when the visual stimulus has been stored in spatial working memory, thus suggesting a further segmentation of spatial WM into two sub-systems.

II. Description of the Experiment

A. Participants

We recruited ten healthy right-handed volunteers (seven men and three women) between 29 and 44 years of age (with a mean 35), who had no history of major medical or psychiatric illness and had normal or corrected-to-normal vision.

B. Tasks and procedure

We investigated four types of WM tests: (a) movement and (b) perceptual discrimination tasks, each one consisting of two conditions. In the first condition, engaging WM, the subjects were asked to memorize the location of a target and act accordingly, while in the second condition, memorization was not required. Each test consisted of a set of 72 trials. At the beginning of each test, a small circle was displayed at the center of a monitor. The subject should point a joystick cursor on the central circle and keep the eyes fixed on the circle. The color of the circle denoted the task to follow: blue was used to indicate a movement-related task, while red was used to indicate a perceptual discrimination-related task. The trial started when the color of the monitor was changing from black to grey with the simultaneous appearance of a peripheral target (see figure 1). The location of the peripheral target was uniformly distributed among 36 possible positions, forming angles of 10 degrees and multiples of 10 degrees with respect to the horizontal axis. The presentation time of the target was set equal to 250ms common for every task. At the end of the presentation time,

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in the first condition (WM condition) the colour of the monitor background changed to the colour of the peripheral target thus masking the peripheral target while in the second condition (no WM) the colour of the background changed again so that the peripheral target remained visible. After a "delay period" randomly varied to minimize preparatory activity, ranging from 3500–4500 ms the central circle disappeared serving as a "go" signal. Then, the subject had either (a) to move the joystick cursor and place it on the target (movement task) or (b) decide whether the appearance of a second target was located at the same position as the first one, or not (discrimination task), by pressing one of two buttons.

The recording initiated during the baseline period lasting 1000ms, followed by the presentation of the peripheral target lasting 250ms. The minimum delay period where the peripheral target disappears or continues to appear - depending on the sought task was about 3250ms.

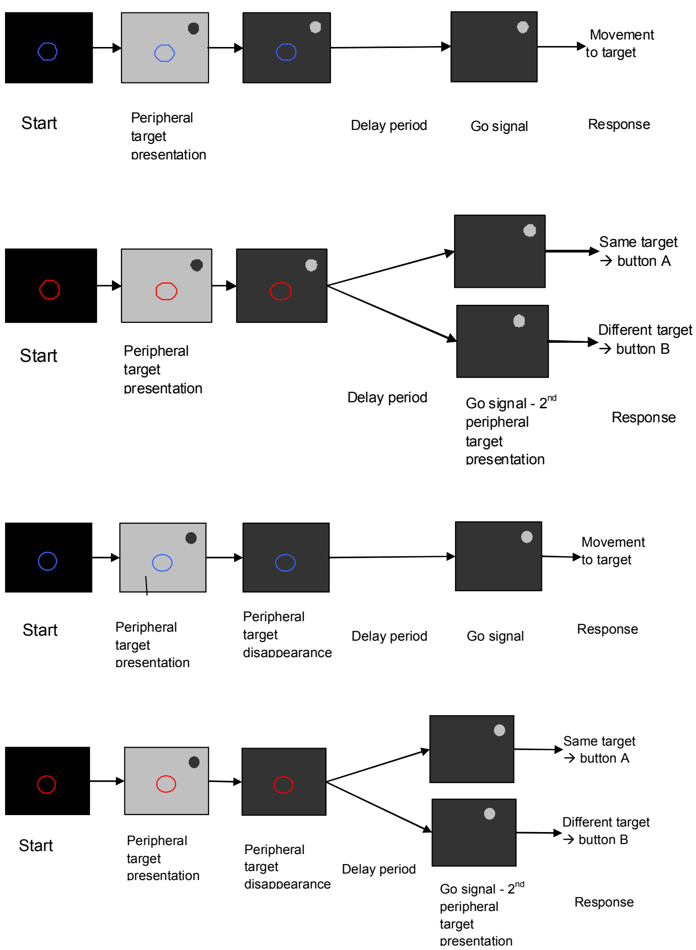

Figure 1. Schematic of the WM experiment.

C. *Equipment*

We recorded the EEG with 62 tin electrodes attached on the scalp using an electrode cap (Compumedics, 64 Channel Quik-Cap Electcrode System), at positions based on the official extended 10-20-20 system (American Electroencephalographic Society, 1994). Horizontal eye movements were recorded using one electrode for each eye using the Skalar IRIS Eyetracker (Cambridge Research Systems). The impedance of all electrodes during recording was kept below 5kΩ. Using a digital data acquisition system (ISO-1064CE and CONTROL-1164 Braintronics, the Netherlands), the EEG and IRIS signals were amplified with a 10 seconds time constant and a 100 Hz low pass filter and sampled at 1024 Hz from a data acquisition A-to-D card on a desktop PC. Simultaneously we recorded the signals produced by an analogue joystick sampled at 1024 Hz, as well as these produced by the joystick buttons used for the discrimination response. During the EEG measurements, the subjects were seated in a comfortable inclined position in a dimly lit, sound-attenuated electrically shielded room.

III. Methods

A. *Time-Frequency Analysis*

Spectral estimates were computed using Short-Time-Fourier transform using overlapping windows of 440ms width with a shift of 10ms. The data were first processed using a zero-phase Butterworth filter. The transformation was applied to each trial separately and then the power spectrum was averaged over all trials and over all persons at each channel.

B. *Granger Causality Analysis*

The concept of GC was developed in the context of autoregressive modeling (AR). A usually accepted definition is: "If the knowledge of the past of both $X_1(t)$ and $X_2(t)$ reduces the variance of the prediction error $E_1(t)$ of $X_2(t)$ in comparison with the knowledge of the past of $X_2(t)$ alone, then a signal $X_1(t)$ causes the signal $X_2(t)$ in Granger sense" [13].

For the linear case, the bivariate AR model can be written as

$$X_1(t)=\sum_{j=1}^{p}A_{11}(j)X_1(t-j)+\sum_{j=1}^{p}A_{12}(j)X_2(t-j)+E_1(t) \qquad (1)$$

and extending the above formula, for an arbitrary number of channels we get the multivariate AR model (MVAR) which can be expressed as

$$\mathbf{X}(t)=+\sum_{j=1}^{p}\hat{\mathbf{A}}(j)\mathbf{X}(t-j)+\mathbf{E}(t), \qquad (2)$$

where $\mathbf{X}(t)$ is the data vector at time t, $\mathbf{E}(t)$ is the vector of white-noise values, $\hat{\mathbf{A}}(j)$ are the model coefficients, and p is number of lags included in the MVAR model (model order). The criteria that are used to estimate the optimum model order is the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) [21], [22].
Solving the above system of equations and using the definition of Granger Causality for two channels X_1 and X_2, we say that X_1 causes X_2 if the coefficients $A_{12}(j)$ are not jointly significantly different from zero. The null hypothesis is tested via an F-test and the strength of each connection is estimated by the logarithm of the F-statistic.
The necessary precondition in order to apply the MVAR model is to have covariance stationary data. In order to achieve stationarity three steps of preprocessing the data were done according to the method proposed by Ding [10] and Seth [23]. The first step was the removal of the linear trend of the data, the second step was the subtraction of the ensemble mean and the division with the standard deviation and the third step was to differentiate the data.
To investigate the dynamical changes of the interactions between different brain regions during a cognitive task, we segmented the data into time windows each of 255 msec length. The preprocessing of the data and the Granger analysis were made using the freely distributed toolbox from Seth [23]. Finally the GC analysis for N data channels yields a NxN matrix which fully describes the brain network.

IV. RESULTS

Performing the above power spectrum analysis on the averaged over all trials and over all subjects signal we found significant increment of the spectral amplitude of the working memory perception discrimination task only in the Parietal Cortex (PC) within the band 5 to 10Hz. Figure 2, compares the differences of the power spectra between memory and no-memory conditions. Figure 2a shows the difference between the power spectra of the discrimination with memory (condition 1) and discrimination with no-memory (condition 2) as calculated at the band 5Hz-10Hz at the PC region. It is clearly shown that during the baseline period this difference fluctuates around zero while it is significant positive within the delay period. On the other hand, the same measure showed no significant deviation from zero on the Frontal Cortex (FC) (see figure 2b). The above evidence was also supported by some findings obtained with the GC analysis. In particular we performed a multivariate GC analysis over all trials and all subjects using a 220ms sliding window moved in time by 50ms.

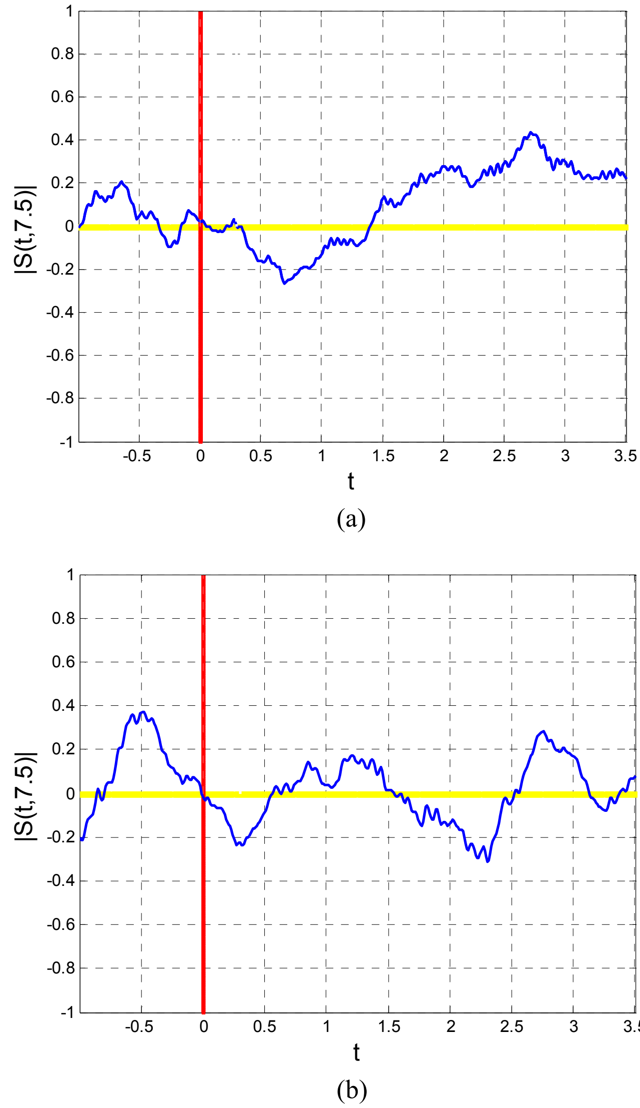

Figure 2. Difference of the power spectra between perception discrimination with memory (condition 1) and perception discrimination with no-memory (condition 2) for the PC region (a) and the FC region of the brain (b). The above responses have been obtained using STFT within the 5-10Hz band and averaging the powers of those frequencies. The red line marks the trigger onset.

For each window we computed the network connectivity measuring several statistical measures, such as clustering, mean path length, the in-degree and out-degree distribution, flow etc. Figure 3 shows an indicative snapshot of the in-degree intensity across all channels together with their links for one of the subjects. The snapshot was taken within the delay period for the test involving perception discrimination with working memory. Compared to the results obtained within the baseline period, the network analysis revealed a relatively increased EEG activity within the delay period at

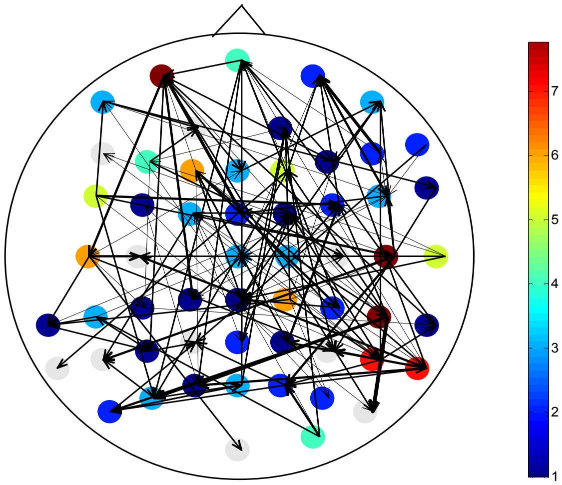

Figure 3. A snapshot of the in-degree intensity across all channels together with their links for subject number 2 within the delay period for the test involving discrimination with working memory.

the PC region. This work is still in progress in order to evaluate possible differences in the functional and effective connectivity between perception discrimination or planning of action.

V. CONCLUSIONS

Recent developments in the analysis of brain signals using EEG recordings in normal humans are currently being exploited in the study of the neural substrate of cognitive functions such as working memory (WM). An influential theory of WM proposes that this cognitive function is sub-served by different systems in the brain according to the type of stimuli being processed. Our aim was to analyse the EEG signals in order to test if different spatio-temporal patterns of EEG activity are related to spatial WM in a task of perceptual decision versus a task of movement planning and execution. For the analysis, we employed both Short Time Fourier Transformation and Granger Causality networking. Regarding discrimination tasks, the analysis showed evidence of increased activity in the PC associated with visual spatial processing. Such behaviour was observed only in the PC within the frequency band of 5-10 Hz. Our final objective is test whether the segmentation of action is also present when the visual stimulus has been stored in spatial working memory thus suggesting a further segmentation of the spatial WM into two sub-systems.

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