An Empirical Evaluation of Short-Term Memory Retention Using Different High-density EEG Based Brain Connectivity Measures

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***Abstract*—It is very vital to identify the variations in the brain activations and visualize the extent of interaction between brain areas to come up with logical interpretations regarding neuronal dynamics during higher-order cognitive functioning. Most cognitive functions are based on interactions between neuronal assemblies distributed across different cerebral regions. In this paper, we evaluate two traditional methods (Squared Coherence Spectrum (SCS) and Directed Transfer Function (DTF)) and one novel approach based on information theory (Phase Transfer Entropy (PTE)) based on the extent to which they can depict the information flow between distant brain regions during a standard visual short-term memory task. Results revealed that PTE was able to depict the performance and visualize the information flow better compared to the traditional techniques. These results demonstrate the applicability of functional brain connectivity measures in determining and visualizing higher-order cognitive functions. We plan to extend the use of these measures in assessing the neural underpinnings of executive functions as well.**

Keywords—Functional Connectivity; Squared Coherence Spectrum; Directed Transfer Function; Phase Transfer Entropy;

I. INTRODUCTION

The desire to study pathological and cognitive functions to identify variations in brain activation and the subsequent interaction within the different brain areas has escalated over the past few years [1]. It is vital to identify active brain regions also functional interactions among the neuronal assemblies distributed across different brain regions (also referred to as functional segregation and integration) [1]. Brain connectivity analysis examines how neuronal regions influence each other's activity. According to [2], brain connectivity is of three types: structural, functional and effective. Structural connectivity refers to tracking the fiber pathways over extended regions of the white matter of the brain. The objective of functional connectivity is to elucidate the temporal correlation (i.e., a statistically significant dependence between distant brain regions) among the activity of different neural assemblies [2]. Effective connectivity refers to quantifying the influence one neuronal system exercises on another [2]. Since EEG possesses a better temporal precision (<1ms), and functional and effective connectivity techniques are largely dependent on calculating the correspondence of neural signals over time, it can be more efficiently used for calculating these metrics [2]. In theory, large clusters of neurons interact and influence each other dynamically to undertake perceptual and cognitive functions [3]. EEG spectral analysis has been one of the most important approaches for studying human information processing and cognitive functioning. But this doesn't reveal how different frequencies are synchronized and what is their functional significance, mainly because most properties associated with the origin of EEG signals are probably non-linear [3]. Pioneering research in functional/effective connectivity started off with the application of cross-correlation function in the time domain [3] and the coherence function in the frequency domain after Fast Fourier transform [3] was applied for the study of the propagation of intracerebral EEG data [4]. The magnitude squared coherence, the linear connectivity metric in the frequency domain, allowed spatial correlations between signals to be measured and visualized in different frequency bands [2]. But the disadvantage was that if either power or phase changed in one of the signals, the overall coherence value was affected. Coherence doesn't elucidate direct information on the true relationship between the two signals, but only the stability of this relationship concerning power asymmetry and phase [2]. On the contrary, distant areas in the brain may activate in response to a particular cognitive task, and the way co-ordination is achieved has not been resolved yet [5,6]. Henceforth, many methods and measures based on mutual information [7], nonlinear regression [6] and phase synchronization methods [8] have been applied to quantify the information flow and the interaction between distant regions in the brain. Dynamic causal modeling (DCM) [1] and Granger Causality [9,10] are the relatively modern measures through which bidirectional/unidirectional coupling can be quantified. Granger causality (a time domain concept) has been applied in the frequency domain and gradually generalized from multivariate to univariate signals [10]. In 1991, [11] proposed a full multivariate spectral measure, called the directed transfer function, which was used to establish the directional influences between any given pair of electrodes in a multivariate autoregressive (MVAR) model predicted from EEG recordings of all the electrodes. This method has been applied to a number

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of biological and neurobiological signals [11]. Recently, a new method for depicting and visualizing the information flow between two regions, called PTE was proposed [12]. PTE quantifies the transfer entropy between the phase time series extracted from neuronal signals [12]. But a heuristic evaluation comparing this information-theory based method of brain connectivity with the other conventional methods is lacking and much needed in literature. In this study, SCS, DTF and PTE and how they elucidate the interaction and influence between different brain regions during a simple spatial short-term memory retention task was explored. We hypothesized that the PTE method would describe the neuronal oscillations and the underlying dynamic influences better than the traditional methods.

II. MATERIALS AND METHODS

In this section, we detail an experiment we conducted to identify different neural correlates for spatial short-term memory derived by three different brain connectivity measures from high-density EEG acquisition.

A. Participants

A total of 30 healthy participants (17 males & 13 females; mean age = 22.44 years) took part in the study. Participation was entirely voluntary and written consent was sought from all participants before they started the experiment. All participants had normal/corrected to normal vision, and no one reported a history of neurological disorders.

B. The Task

All participants undertook the computerized version of the Corsi-Block Tapping Task, a standard psychological test widely used for assessing visuospatial short-term working memory [13]. The computerized version of the test was designed using Inquisit software [14]. The task consisted of nine blocks on the computer screen. An arbitrary sequence of blocks flash on the screen which the participant must repeat in the correct sequential order. By increasing the length of the sequences, the capacity of the visuospatial short-term memory can be measured [13].

C. Procedure

The participant was seated in front of a computer screen. Initially, an instruction screen appeared containing a detailed explanation of the task at hand. Then the subject started the task by tapping a sequence of two blocks. Two trials were given per block of the same length. If this was repeated correctly, the next two trials consisted of a sequence of increasing length. Only a completely correct sequence was scored as correct; self-corrections were permitted in the computer screen.

D. EEG Acquisition

The EEG data was recorded through Ag/AgCl electrodes from 64-electrode locations, conforming with the extended 10-20 system. A eego$^{\text{TM}}$sports EEG system (ANT Neuro, Enschede, Netherlands) was used. The EEG signals were sampled at 1024 Hz and the impedance was kept to lower than 5 KΩ. EEG was acquired for both resting state (baseline) and during task.

E. EEG signal analysis

MVAR models can represent the various interactions between EEG signals in a linear difference form. Apart from the direction of information flow between the electrodes, the MVAR model also gives the extent of direct or indirect influences [11, 14-18]. Data was analyzed offline in MATLAB 2014b using custom scripts and Brainstorm [19], a user-friendly plug-in for MATLAB for EEG/MEG analysis. The data was band- pass filtered from 0.5 to 100 to remove the linear trends in the data. Ocular artefacts were rejected using signal-space projection method [20].

a. Time-varying MVAR parameter estimation

ARFIT [21] algorithm was used to estimate the time-varying parameters of the MVAR model. Akaike Information Criterion [22] was used to evaluate the optimum order. A surrogate data method with 100 realizations/iterations was then used to select the most significant values at a confidence interval of 95%. All causal relationships between the signals were removed by randomizing the samples for surrogates.

A time varying N-channel AR process can be represented as:

$$\begin{bmatrix} x_1(n) \\ \vdots \\ x_N(n) \end{bmatrix} = \sum_{k=1}^{p} A_k(n) \begin{bmatrix} x_1(n-k) \\ \vdots \\ x_N(n-k) \end{bmatrix} + \begin{bmatrix} u_1(n) \\ \vdots \\ u_N(n) \end{bmatrix} \quad (1)$$

where, $\boldsymbol{u_i(n)}$ is the prediction error and p is the model order. The matrix $\boldsymbol{A_k}$, known as the coefficient matrix, is given by:

$$A_k(n) = \begin{bmatrix} a_{11}(k,n) & \cdots & a_{1N}(k,n) \\ \vdots & \ddots & \vdots \\ a_{N1}(k,n) & \cdots & a_{NN}(k,n) \end{bmatrix} \quad (2)$$

for k ranging from 1 to p. A number of time-varying connectivity measures can be defined based on the transformation of the coefficient matrix $A_k(n)$ to frequency domain. The transformation can be represented as:

$$A(f) = I - \sum_{k=1}^{p} A_k(n) e^{-j2\pi fk} \quad (3)$$

Therefore, equation (1) can be represented in the frequency domain as:

$$A(f)X(f) = U(f) \quad (4)$$

where, $X(f)$ and $U(f)$ are the frequency domain representations of the input and the prediction error matrices respectively.

$$X(f) = A^{-1}(f)U(f) \quad (5)$$

$$X(f) = H(f)U(f) \quad (6)$$

where $H(f)$ is called the transfer matrix of the system.

Now, Power spectral matrix of the signal is given by:

$$S(f) = X(f)X^*(f) \quad (7)$$

which can be expanded as:

$$S(f) = H(f)U(f)U^*(f)H^*(f) \quad (8)$$

Equation (8) can be simplified as

$$S(f) = H(f)\Sigma H^*(f) \quad (9)$$

where, $\sum$ is the noise covariance matrix of $U(f)$.

b. DTF

DTF portrays the existence of directional signal propagation when the signal travels through intermediate structures rather than through an immediate direct causal path [23]. Hence DTF measures the connectivity between different regions in an indirect manner.
Mathematically, DTF is represented as:

$$DTF_{j\to i}^2(f) = \frac{\left|H_{ij}(f)\right|^2}{\sum_{m=1}^{N}\left|H_{im(f)}\right|^2} \quad (11)$$

Where $H(f)$ is the transfer matrix given in the equation (6).

b. SCS

SCS is formed on the basic premise that EEG signals are generated from a bidirectional model, formulated from a MVAR model.
SCS is given as:

$$\gamma_{ij}^2(f) = \frac{\left|S_{ij}\right|^2}{\sum_{m=1}^{N}\left|S_{im}\right|^2} \quad (10)$$

which gives the normalized directional coherence from channel i to channel j.

c. PTE

PTE quantifies the transfer entropy between phase time series extracted from neuronal time series by filtering-for-instance [12]. PTE is an excellent metric for extensive analyses of phase specific directional connectivity in EEG as it evaluates the direction and strength of the connectivity even in the presence of the noise and even when signals are linearly mixed. PTE quantifies directional phase interactions with high computational efficiency with a single parameter [12].

For a given frequency band, the instantaneous phase, $\theta(t)$, of the time-series of the signal $x(t)$ is represented as in:

$$S(t) = A(t)e^{-i\theta(t)} \quad (12)$$

where $S(t)$ is obtained by using Hilbert transform. PTE for a given analysis lag, δ, is given by:

$$\begin{aligned} Phase\ TE_{X\to Y} = {} & H\left(\theta_y(t), \theta_y(t')\right) \\ & + H\left(\theta_y(t'), \theta_x(t')\right) \\ & - H\left(\theta_y(t')\right) \\ & - H\left(\theta_y(t), \theta_y(t'), \theta_x(t')\right) \end{aligned} \quad (13)$$

$ft' = t - \delta$ such that: $\theta_x(t') = \theta_x(t-\delta)$ and $\theta_y(t') = \theta_y(t-\delta)$. And the marginal joint entropy is defines as [24]:

$$\begin{aligned} & H\left(\theta_y(t), \theta_y(t')\right) \\ & = -\sum p\left(\theta_y(t), \theta_y(t')\right)\log p\left(\theta_y(t), \theta_y(t')\right) \end{aligned} \quad (14)$$

$$\begin{aligned} & H\left(\theta_y(t'), \theta_x(t')\right) \\ & = -\sum \begin{matrix} p\left(\theta_y(t'), \theta_x(t')\right) \times \\ \log p\left(\theta_y(t'), \theta_x(t')\right) \end{matrix} \end{aligned} \quad (15)$$

$$H\left(\theta_y(t')\right) = -\sum p\left(\theta_y(t')\right)\log p\left(\theta_y(t')\right) \quad (16)$$

$$\begin{aligned} & H\left(\theta_y(t), \theta_y(t'), \theta_x(t')\right) \\ & = -\sum \begin{matrix} p\left(\theta_y(t), \theta_y(t'), \theta_x(t')\right) \times \\ \log p\left(\theta_y(t), \theta_y(t'), \theta_x(t')\right) \end{matrix} \end{aligned} \quad (17)$$

III. RESULTS AND DISCUSSION

The most significant values for the brain connectivity measures at a confidence level of 95% after the application of surrogate data technique are shown in Figures 1 through 6. The measures were illustrated by visualizing them on the Desikan Killiany Atlas [25], which is an automated labeling system for dividing the human cerebral cortex into regions of interest.
Behavioral analysis of the data was conducted by taking into consideration three different behavioral measures collected during the task: Corsi Span, Latency and Total Score. These scores were taken into consideration for classifying the participants as good performers and poor performers. All the figures from (1) to (6) depict the brain connectivity measures for individuals who had performed well and for individuals who had underperformed relatively. Figures (1) and (2) depict the SCS measure, where it is evident that though there is a no distinguishable difference between the connectivity graphs of the two groups. The DTF measures (as seen in Figures (3) and (4)), too don't give out any discernible difference between the two groups. Some differences can be seen between the measures, those can be attributed to the false positives, as EEG, even though cleaned, is a linear mixture of signals from different sources. As seen in Figure (6), a higher number of active electrodes were found for the individual who had performed badly. A higher number of active electrodes usually represents additional connections to the neural network, with each added connection depicting an incremental cost regarding wiring volume and resources and mental workload utilized to carry out the task. On the contrary, Figure (5), represented an efficient network topology (utilization of the optimum cognitive workload). PTE also highlighted the high intensity connectivity difference between the temporal hemispheres between the good performers and poor performers. Due to its model-free and assumption free-nature, PTE was able to depict the information flow between corresponding neuronal regions better than the other two methods.

IV. CONCLUSIONS

In the present study, three different measures of brain connectivity were compared viz. SCS, DTF and PTE and based on the extent to which they are being able to depict the information flow between distant brain regions during a standard visual short-term memory task. Out of the three measures, we found that the information theory-based PTE provided better and more accurate depiction and visualization of information flow compared to the other two measures. As expected, PTE was found to be less susceptible to external noise elements and linear mixing of components. These

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results demonstrate the applicability of functional brain connectivity measures in determining, depicting and visualizing higher-order cognitive functions. We plan to extend the use of these measures in determining the neural underpinnings of higher order executive functions and dynamic decision making tasks as well.

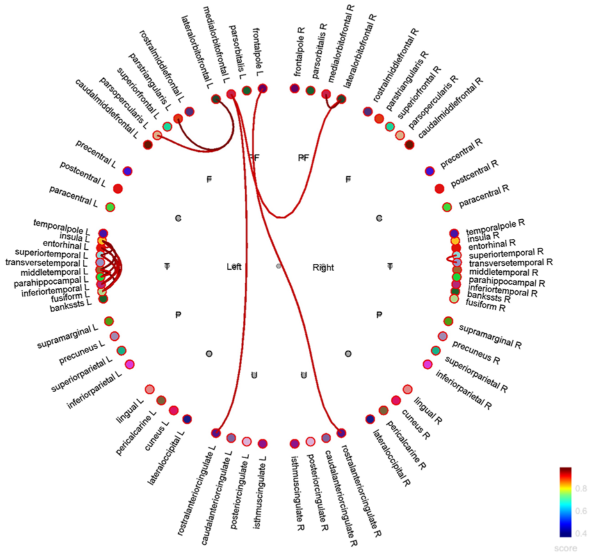

Figure 1: Squared Coherence Spectrum during the Corsi-Block Tapping Task using the Desikan-Killiany atlas for good performers

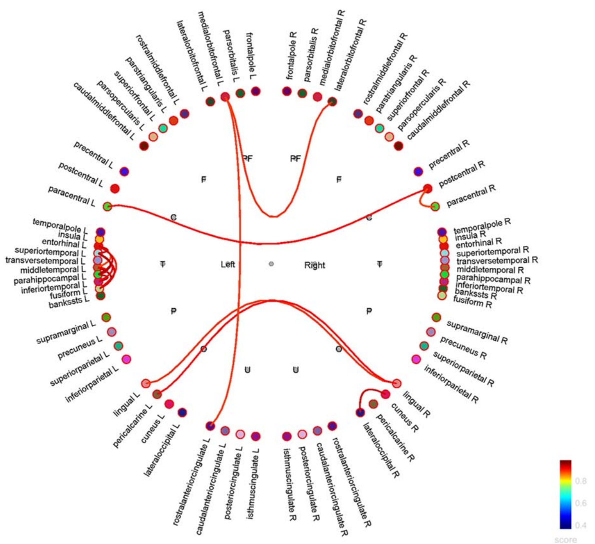

Figure 2: Squared Coherence Spectrum during the Corsi-Block Tapping Task using the Desikan-Killiany atlas for participants who performed relatively poor

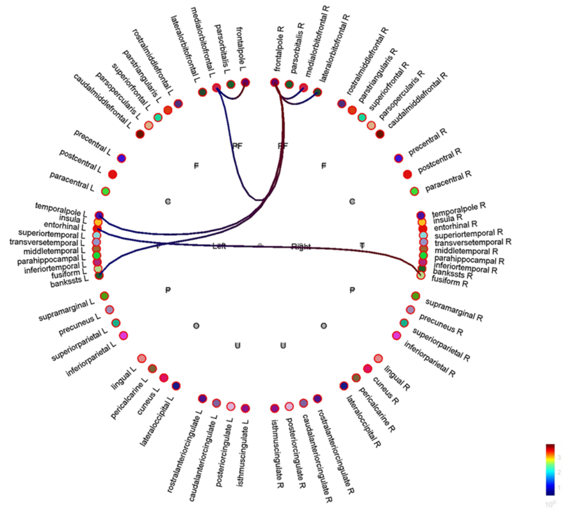

Figure 3: Directed Transfer Function during the Corsi-Block Tapping Task using the Desikan-Killiany atlas for good performers

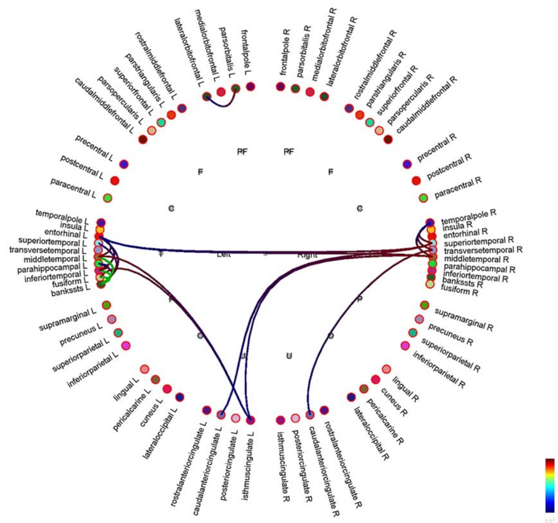

Figure 4: Directed Transfer Function during the Corsi-Block Tapping Task using the Desikan-Killiany atlas for participants who performed relatively poor

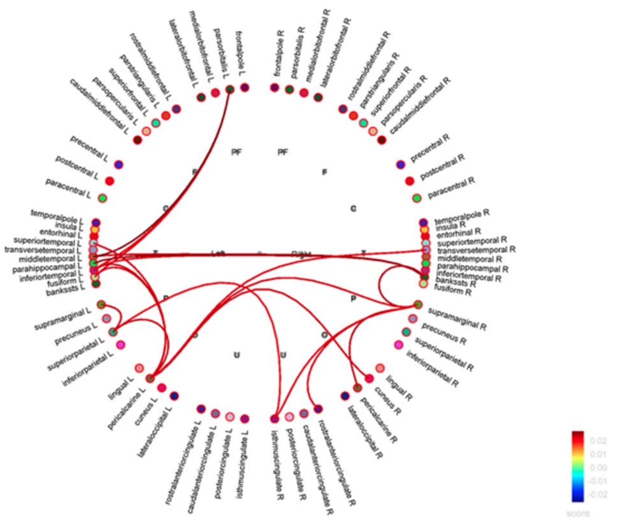

Figure 5: Phase Transfer Entropy visualized using the Desikan-Killiany atlas during the Corsi-Block Tapping Task for good performers

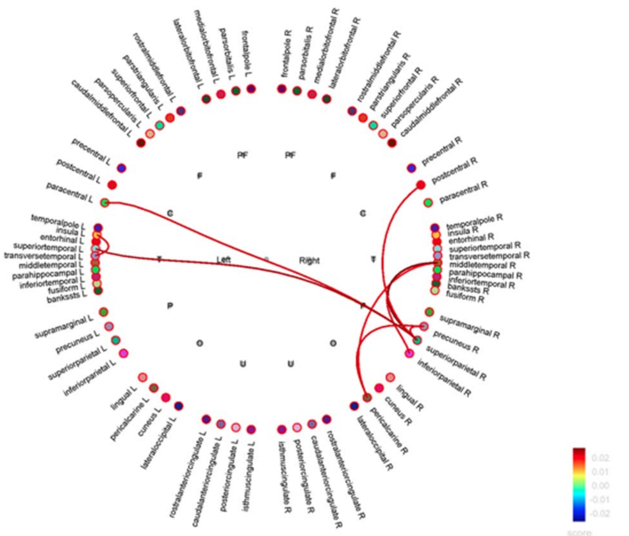

Figure 6: Phase Transfer Entropy visualized using the Desikan-Killiany atlas during the Corsi-Block Tapping Task for participants who performed relatively poor

V. REFERENCES

[1] K. J. Friston, "Modalities, modes, and models in functional neuroimaging," *Science,* vol. 326, pp. 399 - 403, 2009.

[2] V. Sakkalis, "Review of advanced techniques for the estimation of brain connectivity measured with EEG/MEG," *Computers in Biology and Medicine,* vol. 41, pp. 1110 - 1117, 2011.

[3] M. A. Brazier, "Spread of seizure in epilepsy: Anatomical and electrophysiological considerations," *Experimental Neurology,* vol. 36, pp. 263 - 272, 1972.

[4] J. W. Cooley and J. W. Tukey, "An algorithm for the machine calculation of complex Fourier series," *Mathematics of Computation,* vol. 19, pp. 297 - 301, 1965.

[5] F. Wendling, K. Ansari-Asl, F. Bartolomei, and L. Senhadji, "From EEG signals to brain connectivity: a model-based evaluation of interdependence measures," *Journal of Neuroscience Methods,* vol. 138, pp. 9 - 18, 2009.

[6] P. J. Uhlhaas and W. Singer, "Neural synchrony in brain disorders: relevance for cognitive dysfunctions and pathophysiology," *Neuron,* vol. 52, pp. 155 - 168, 2006.

[7] N. J. Mars and F. H. Lopes da Silva, "Propagation of seizure activity in kindled dogs," *Electroencephalography and Clinical Neurophysiology,* vol. 56, pp. 194 - 209, 1983.

[8] J. Bhattacharya, "Reduced degree of long-range phase synchrony in pathological human brain," *Acta Neurobiologiae Experimentalis,* vol. 61, pp. 309 - 318, 2001.

[9] C. W. J. Granger, "Investigating causal relations by econometric models and cross-spectral methods," *Econometrica,* vol. 37, pp. 424 - 438, 1969.

[10] J. F. Geweke, "Measurement of linear dependence and feedback between multiple time series," *Journal of the American Statistical Association,* vol. 77, pp. 304 - 313, 1982.

[11] M. J. Kamiński and K. J. Blinowska, "A new method of the description of the information flow in the brain structures," *Biological Cybernetics,* vol. 65, pp. 203 - 210, 1991.

[12] M. Lobier, F. Siebenhühner, S. Palva, and J. M. Palva, "Phase Transfer Entropy: A novel phase-based measure for directed connectivity in networks coupled by oscillatory interactions," *Neuroimage,* vol. 85, pp. 853 - 872, 2014.

[13] R. P. Kessels, M. J. van Zandvoort, A. Postma, L. J. Kappelle, and E. H. deHaan, "The Corsi Block-Tapping Task: Standardization and Normative Data," *Applied Neuropsychology,* vol. 7, pp. 252 - 258, 2000.

[14] L. A. Baccalá and K. Sameshima, "Partial Directed Coherence: A new concept in neural structure determination," *Biological Cybernetics,* vol. 84, pp. 463 - 474, 2001.

[15] L. A. Baccalá, K. Sameshima, G. Ballester, A. C. DoValle, and C. Timo-Iaria, "Studying the interaction between brain structures via directed coherence and granger causality," *Applied Signal Processing,* vol. 5, pp. 40 - 48, 1998.

[16] L. A. Baccalá, K. Sameshima, and D. Y. Takahashi, "Generalized Partial Directed Coherence," presented at the 2007 15th International Conference on Digital Signal Processing, Cardiff, UK, 2007.

[17] A. Korezeniewska, M. Mańczak, M. Kamiński, K. Blinowska, and S. Kasicki, "Determination of information flow direction among brain structures by a modified directed transfer function method," *Journal Neuroscience Methods,* vol. 125, pp. 195 - 207, 2003.

[18] C. Schmidt, B. Pester, N. Schmid-Hertel, H. Witte, A. Wismüller, and L. Leistritz, "A multivariate granger causality concept towards full brain functional connectivity," *PLOS ONE,* vol. 11, 2016.

[19] F. Tadel, S. Baillet, J. C. Mosher, D. Pantazis, and R. M. Leahy, "Brainstorm: A user-friendly application for MEG/EEG analysis," *Computational Intelligence and Neuroscience,* vol. 2011, 2011.

[20] M. A. Uusitalo and R. J. Ilmoniemi, "Signal-space projection method for separating MEG or EEG into components," *Medical and Biological Engineering and Computing,* vol. 35, pp. 135 - 140, 1997.

[21] C. Vidaurre, T. H. Sander, and A. Schlögl, "BioSig: The free and open source software library for biomedical signal processing," *Computational Intelligence and Neuroscience,* vol. 2011, 2011.

[22] H. Akaike, "A new look at the statistical model identification," *IEEE Transactions on Automatic Control,* vol. 19, pp. 716 - 723, 1974.

[23] L. A. Baccala, D. Y. Takahashi, and K. Sameshima, "Directed Transfer Function: Unified asymptotic theory and some of its implications," *IEEE Transactions on Biomedical Engineering,* vol. 63, pp. 2450 - 2460, 2014.

[24] K. Hlaváčková-Schindle, M. Paluš, M. Vejmelka, and J. Bhattacharya, "Causality detection based on information theory approaches in time series," *Physics Reports,* vol. 441, pp. 1 - 46, 2007.

[25] R. S. Desikan, F. Ségonne, B. Fischl, B. T. Quinn, B. C. Dickerson, D. Blacker, *et al.*, "An automated labelling system for subdividing the human cerebral cortex on MRI scans into gyral based regions of interest," *Neuroimage,* vol. 31, pp. 968 - 980, 2006.

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