International Journal of Bioelectromagnetism
Vol. 9 No. 4, pp. 205 - 213, 2007
www.ijbem.org

Inferring brain connectivity subserving real and imagined movements from synchronization analysis

Anastasios Bezerianos[a], Maria Stavrinou[a], Laura Cimponeriu[b] and Liviu Moraru[a]
[a]*Department of Medical Physics, School of Medicine, University of Patras, Greece*
[b]*Institute of Physics, University of Potsdam, Am Neuen Palais, Potsdam, Germany*

Correspondence: A Bezerianos, Department of Medical Physics, School of Medicine, 26500, Rio Campus, Achaias Greece.
E-mail: bezer@patreas.upatras.gr, phone +30 2610 969145, fax +30 2610 992496

Abstract. In this paper we assess the connectivity among brain areas engaged in a real and an imagined finger tapping task from Electroencephalogram (EEG) measurements using linear and non-linear measures of synchronization. In the linear approach, connectivity is inferred using the measures of Coherence and Partial Coherence. Non-linear measures of connectivity are further employed using phase dynamics. Information encoded in the phase dynamics is quantified using measures of phase synchronization. Instantaneous phases of each single trial are calculated using time-frequency methods best fitted for non-stationary signals. Local phase extraction is performed using wavelet transform and a newly developed signal analysis technique based on the Hilbert-Huang transform. The inferred patterns of connectivity highlight similarities in the structural and functional organization of cortical networks involved in actual and imagined motor movement. The consistency of results produced by the various measures of functional connectivity employed here provides further evidence that synchronization analysis can be used for the detection of movement intention in EEG-based brain computer interface applications.

Keywords: EEG, Phase Synchronization, brain connectivity, Wavelet transform, Hilbert-Huang transform

1. Introduction

The detection of movement intention from brain signals is the primary task of Brain Computer Interface (BCI) applications. Successful operation of BCI systems allows restoring the communication between a disabled person and his environment, or controlling neuroprosthetic devices. Within this framework, the identification of similar patterns of activation between an actual motor task and its imagination can help detection of movement intention. Apart from movement related frequency modulations quantified using the ERD/ERS methodology [Pfurtscheler and da Silva, 1999; Pfurtscheller et al., 2006], the information encoded in the phases of brain signals has recently received attention in BCI research [Gysels and Celka 2004, Brunner et al., 2006, Stavrinou et al., 2007]. In our previous work we investigated whether connectivity patterns evaluated by synchronization measures can be used as extra features for the detection of movement intention. Until now, several methods have been implemented for assessing the connectivity between brain areas, that were based a) on the amplitude modulation of the recorded electrophysiological signals (Electrocorticography, or Electroencephalography, EEG), b) on the frequency content and, lately, c) based on the phase information contained in the signals.

A number of approaches developed within different theoretical frameworks have been used in the study of brain functional and effective connectivity from electrophysiological data [Quiroga et al., 2002]. According to Friston [Friston et al., 1993], functional connectivity is operationally defined as temporal correlations (dependencies) among spatially remote electrophysiological events while effective connectivity deals with the causal influence of one system over the other. Using the information in the frequency domain, the functional interactions between neural regions have been largely investigated using coherence and partial coherence analysis of multivariate neural signals [Baccala and Sameshima, 2001]. Moreover, the direction of information flow, thus effective connectivity has been investigated using linear methods like Partial Directed Coherence (PDC)

[Baccala and Sameshima 2001] and Directed Transfer Function (DTF) [Kaminski et al., 2001; Babiloni et al., 2005].

Lately, in the study of both functional and effective connectivity, nonlinear methods have been introduced (e.g., based on the concept of generalized synchronization [Schiff et al., 1996] or phase synchronization [Varela et al., 2001]. The dynamical interaction of brain electrical activity can be better characterized by non-linear interdependencies [Breakspear and Terry, 2002]. Nonlinear measures of interdependence using information theoretic concepts like entropy and mutual information have been used in the literature. Moreover, methods of nonlinear dynamical systems theory (e.g., nonlinear synchronization measures) have been used to evaluate dynamical interdependences in multichannel EEG data [Lachaux et al., 1999; Quian Quiroga et al., 2002; David et al., 2004]. The evaluation of phase synchronization is based on the calculation of instantaneous phases. Widespread approaches used for this procedure are either based on Hilbert transform [Tass et al., 1998], or the signal convolution with a complex wavelet [Lachaux et al., 2000]. Both methods were compared and found fundamentally equivalent for the study of neuroelectric signals [Quiroga et al., 2002].

In the present work we evaluated the functional connectivity among the brain areas dominantly engaged in the actual and imagination of the motor task. The aim of the present study is to compare and contrast linear and nonlinear synchronization measures for inferring neuronal connectivity sub-serving real and imaginery finger tapping from EEG data.

2. Materials and Methods

Four healthy volunteers participated in this study (2 males) with mean age 27.5 years, range 22-34 years. Subjects were strongly right-handed according to the Edinburgh Inventory [Oldfield 1971]. The protocol and experimental procedures were approved by the local ethics committee and were in compliance with the declaration of Helsinki. The experiments have been conducted in the EEG Laboratory of Neurophysiology Unit, Department of Physiology, Medical School, University of Patras, Greece.

Subjects sat on a comfortable armchair in an electrically isolated room, dimly illuminated. A small led light was adjusted on the wall in front of the subjects, in order to fixate their sight on it, so as to avoid excess of ocular movements. The experimental session consisted of four parts. In the first part, a median nerve stimulation of subject's right wrist was conducted, above the motor threshold where a definite twitch of the thumb was visible. The ISI of the electric stimulation was 1500 ms and stimulus duration 200 microseconds. For the second part the subject was instructed to make a right index finger tapping task, tapping a key of a keyboard, externally paced by an auditory signal (1000 Hz, dB max 64 arranged to be heard but not annoying to the subject, 50microseconds duration, and ISI 1500 ms). The next session consisted of a sub-session were the subjects practiced right index finger tapping for 250 trials before the right index finger imagery task begun. Subjects were instructed to imagine the right index finger tapping task with the auditory stimulation giving the pace. Subjects were instructed to imagine the kinesthetic of the movement and not the visual image of the movement itself. After training, approximately 130 trials of right index finger imagery were recorded. A control session consisted of an auditory stimulation, were the subject was instructed to hear passively the auditory stimulation without executing any movement, while being relaxed.

EEG signals were recorded with a sampling frequency of 1000 Hz from 60-electrodes mounted on an elastic cap (Electrocap International, Ohio, USA), and acquired with a SynAmps amplifier (Neuroscan, USA). The Neuroscan software was used for recording. Linked earlobes were used as a reference and AFZ electrode as ground. Impedances were kept bellow 5 KΩ. The signals were filtered between 0.1 and 200 Hz. The positions of all the electrodes as well as of four anatomical landmarks (nasion, inion and the two preauricular points) and points on the face and head were digitized with a 3D Digitizer (Pohlemus 3Dspace Fastrack, Colchester Vt, USA).

The datasets were visually checked for noisy epochs which were excluded from further analysis. Approximately 100 artifact-free trials were selected for each session and each subject for the actual finger tapping task and the imagery task. Each epoch consisted of a time window of 300 ms pre- and 1200 ms post- stimulus, while a -100 to -80 ms time interval was used for baseline correction. A cluster of ten electrodes above the sensorimotor cortex was selected for further analysis: FC3, FC1, FCZ, C5, C3, C1, CZ, CP3, CP1, CPZ, for the left (contralateral) hemisphere and for the right hemisphere FCZ, FC2, FC4, CZ, C2, C4, C6, CPZ, CP2, CP4. The datasets were preprocessed with a discrete Laplacian before continuing with the synchronization methods. The analysis is further focused on beta band (15-30 Hz) activity.

2.1. Reference dependency and reference – free data

In multi-channel EEG recordings, the choice of the reference electrodes plays an important role especially when coherence or phase synchronization index is computed. Some authors suggested that, the use of a common reference electrode confounds the recorded signals, as the activity at this electrode contributes to both signals involved in the coherence analysis, therefore it can influence the value of the coherence obtained. To follow that, it is assumed that signals should be reference-independent prior to their analysis for the coherence or phase content. Moreover, volume conduction affects the coherence and connectivity measures. For all these reasons, we calculated the discrete Laplacian-transformed time series before starting their analysis.

2.2. The Multivariate Autoregressive Approach

These measures of connectivity are based on the output of feeding the data to an autoregressive model and calculating the absolute Coherence and partial Coherence [Rosenberg et al, 1998, Schlogl and Supp, 2006].

We briefly describe the analysis steps involved in calculation of coherence and partial coherence within the multivariate autoregressive (MVAR) modeling framework. For a stationary time series, of D simultaneously measured signals (adjusted to have mean zero) $s_t \in \Re^D$, a MVAR model of order p , can is described by:

$$s_t = \sum_{k=1}^{p} A_k s_{t-k} + E_t,$$

where $A_k \in \Re^{D \times D}$ are the coefficient matrices of the model, and the noise term E_t is a D-dimensional independent and identically distributed sequence with mean zero and covariance matrix Σ . The autoregressive coefficients $a_{(i,j)(k)}$, with $i, j = 1,..., D$ represent the linear interaction effect of s_{t-k} onto s_t . Several numerical methods are available for estimating the parameters of the model. The coefficients for a particular data set have been estimated by solving a multivariate version of the Yule-Walker equations.

The spectral matrix of the fitted MVAR model is defined by:

$$S(f) = H(f)\Sigma_e H^H(f),$$

where the subscript $(.)^H$ denotes the Hermitian transpose and

$$H(f) = [I - A(f)]^{-1} = [\overline{A}(f)]^{-1}$$

is the transfer matrix of the system. $A(f)$ is given by the Fourier transform of the coefficients:

$$A_{ij}(f) = \sum_{k=1}^{p} a_{k,ij} \cdot e^{-i2pkf} .$$

A very important step is the calculation of the coefficients model order. The above estimation procedure can be carried out for any model order m. In the literature of multivariate linear models different criteria for model order estimation have been proposed e.g.: Final Prediction Error - FPE criterium [Akaike, 1969], Information Theoretic Criterion – AIC [Akaike, 1974], Autoregressive Transfer Function Criterium - CAT [Parzen, 1977].

Based on the experience gained by using these three criteria we have adopted the use of the AIC criterion. The correct m is determined by minimizing the Akaike Information Criterion (AIC) defined as

$$AIC(k) = N \cdot \log[\det(\hat{V}_e)] + 2p^2 m$$

where N is the number of experimental data points of the sampled signal, $\hat{V}_e$ is the estimated covariance matrix of the noise processes. $\hat{V}_e$ can be determined from the formula:

$$\hat{V}_e = \hat{R}(0) + \sum_{i=1}^{k} \hat{A}_i \hat{R}(i)$$

where $\hat{A}_i$, $\hat{R}(i)$ are the estimated matrix of coefficients and matrix of covariances.

2.2.1. Coherence Measures

Coherence analysis has been widely applied to multichannel EEG data as a tool for studying linear coupling between signals. Mathematically, coherence is analogous to a cross-correlation coefficient in the frequency domain and gives a measure of the synchrony between two signals at a particular frequency. Coherence measures take into consideration both amplitude and phase variations in order to calculate the interrelations between signals. High coherence values reflect the phase consistency between scalp areas, and it has been often interpreted as evidence for anatomical connections, functional coupling, information exchange, functional coordination or "temporal coordination" [Gray and Singer, 1989, Pfurtscheller and Andrew, 1999] between the cortical structures underlying these areas.

After fitting the MVAR model, we calculated the coherence (Coh) and the partial coherence (pCOh) at an interval of ±2 Hz around the individual peak frequency of the beta band identified from the wavelet time-frequency maps. The denoted coherence is the absolute value of the coherence derived from the multivariate power spectral density $S_{ij}(f)$ between two channels *i* and *j*:

$$C_{ij}(f) = \left| \frac{S_{ij}(f)}{\sqrt{S_{ii}(f) \cdot S_{jj}(f)}} \right|.$$

Partial Coherence (pCoh) is used to determine whether the relationship between two processes *i* and *j* is the consequence of a common input or whether there is an additional association between *i* and *j* [Rosenberg et al., 1998]. If this common influence existing between signals *i* and *j*, might be originating from a third generator *k* that drives them, the partial coherence will calculate the interaction between *i* and *j* that is not shared with *k* [Pereda et al., 2005]. In this way, the pCoh has a smaller value than the Coh, but is a better estimator in what regards the removal of the volume conduction effects. The pCoh between the channels i and j at a given frequency f is defined as:

$$pCoh_{ij}(f) = \frac{g_{ij}(f)}{\sqrt{g_{ii}(f) \cdot g_{jj}(f)}}, \text{ where } g_{ij}(f) = \left|g_{ij}(f)\right| = A(f) \textstyle\sum_x^{-1} A(f).$$

In other words, the partial coherence estimates the amount of additional improvement in predicting *j* from *i*. The limits for partial coherence are also between 0 and 1; 0 indicating that the linear time invariant relationship between channels i and j is entirely accounted for by their individual dependencies on another channel *k*, and 1 indicating that *i* perfectly predicts *j*, and neither can be perfectly predicted from k. However we must notice here, that pCoh is based on the assumption of linearity, that is, it removes linear interdependencies between signals. A possible non-linear interaction between signals is not depicted by this method. However, it is known that electrophysiological processes are non-linear processes, thus there is the need for nonlinear multivariate methods for the connectivity analysis.

2.3. The Phase Dynamics Approach

Quantification of the interrelation between phases of signals has started to become a very important tool in the analysis of neurophysiological data. Developed within the framework of weakly coupled nonlinear oscillator systems [Rosenblum et al., 1996; Pikovsky et al., 2001], the phase synchronization analysis can detect a weak form of nonlinear interaction between oscillator systems, which may be not revealed by cross-correlation or coherence. This owns to the fact that standard coherence measures cannot disentangle the contributions of phase and amplitude, and clearly discard the linear contribution of a third signal from the calculations. There are many cases in neuroscience research in which the signals can be strongly coherent, but with no actual synchronization of oscillatory processes present. Therefore, there is the need of a more strict measure that measures inherent characteristics of oscillators. For this purpose, it has been proposed the use of the non-linear phase synchronization measure to characterize the phase coupling between two given signals [Tass et al., 1998, Varela et al 2001].

This approach has been used recently to characterize connectivity and enhance low-resolution electromagnetic tomography, to characterize synaptic connectivity subserving plasticity [Palmero-Soler et al., 2007, Tass and Hauptmann, 2007] and its usage is becoming increasingly popular. In a previous work [Cimponeriu et al, 2003] it has been demonstrated the performance of phase synchronization analysis in identifying connectivity patterns between brain areas engaged in a paced finger tapping task. Here, we employed it to the analysis of functional connectivity in actual and imagined finger tapping by quantifying the inter-channel phase synchronization in the beta frequency range.

The first step of the phase synchronization analysis is the computation of phase from the recorded brain data. For this purpose, we made use of two time-frequency based methods for estimation of the local phase of a signal. The first one is based on the wavelet transform, whereas the second one uses the Hilbert-Huang transform. The two methods are described below.

Wavelet transform- based phase synchronization analysis

As a first approach, we used wavelet phase synchronization, taking the wavelet coefficients corresponding to the most reactive frequency in the beta range. After extraction of phases, the degree of synchronization between any two of the selected electrodes i and j, is evaluated, on a single trial basis, using a phase synchronization index (PSI) PSI_{ij}. The wavelet used is a complex Morlet wavelet $u(t, f_0) = A\exp(-t^2/2\sigma_f^2)\exp(2f\pi f_0 t)$, where $\sigma_f = 1/2\pi\sigma_t$ is the frequency resolution and σ_t is the time resolution respectively. $A = (\sigma_t\sqrt{\pi})^{-1/2}$ is a normalization factor (communication with Ole Jensen) is a normalization factor which ensures that the wavelet has unit energy [Tallon-Baudry et al., 1997]. We choose the complex Morlet wavelet as it yields a complex wavelet transform, containing information on both the amplitude and phase. The square magnitude of the convolution of the signal (each single trial) and the wavelet function, gives an estimation of the power (or energy) for each frequency analyzed: $E(t, f_0) = |u(t, f_0) * s(t)|^2$. This value is calculated for each single trial and each frequency and it is then averaged to produce the time – frequency plots.

Hilbert-Huang transform based phase synchronization analysis

As introduced by Huang and colleagues [Huang et al., 1998], the empirical mode decomposition (EMD) technique is capable of adaptively decomposing signals into oscillating intrinsic components. The EMD is an adaptive decomposition technique with which any complex signal can be decomposed into a definite number of high frequency and low frequency components by means of a process called sifting. These components are called intrinsic mode functions (IMF). These IMFs have well defined instantaneous attributes and are defined as functions that (1) have the same number of zero-crossings and extrema; and (2) the mean value of the upper and the lower envelopes is equal to zero. EMD offers an alternative, adaptive method of identifying intrinsic oscillations within data, providing a new method of identifying connection between neural assemblies [Sweeney-Reed and Nasuto, 2007]. The phase synchrony analysis is performed on the component corresponding to the beta range activity (IMF number 4). The original time history x(t) is finally expressed as the sum of the IMF components plus the final residue:

$$x(t) = \sum_{i=1}^{n} imf_i(t) + r(t)$$

where r(t) is the residue of the decomposition. The phase of each $imf_i(t)$ has been obtained using the Hilbert transform:

$$H_{imf_i}(t) = P.V.\left[\frac{1}{\pi}\int_{-\infty}^{\infty}\frac{imf_i(t')}{t-t'}dt'\right]$$

where P.V. stands for the Cauchy principal value for integral. The analytic signal is constructed to yield an amplitude function A(t) and a phase function $\phi(t)$,

$$\psi_i(t) = imf_i(t) + i * H_{imf_i}(t) = A_i(t)e^{i\varphi_i(t)}$$

The phase synchronization analysis of the dominant intrinsic modes can provide a useful indicator of the degree of interaction between coupled dynamical systems.

Phase synchronization quantification

Phase synchronization is encountered in weakly interacting oscillator system and it manifests by the occurrence of a relationship between the corresponding phases variables. The degree of synchronization between two EEG signals can be measured by a statistic on the distribution of their phase difference called the index of synchronization (PSI) [Pikovsky et al., 2001]:

$$PSI_{i,j} = \left|\frac{1}{T_p}\sum_{t_p=1}^{T_p}\exp\left(i\left(\phi_i(t_p) - \phi_j(t_p)\right)\right)\right|,$$

where $\phi_j(t_p)$ and $\phi_i(t_p)$ are the instantaneous phases of any two channels single trials or corresponding dominant EMD components, and T_p is the total duration of the trial or the segment used for the calculation of the PSI_{ij}. Here, we used a segment of 800 ms, starting from the 200 ms post-stimulus. PSI_{ij} takes values in the range from 0 (no phase synchronization) to 1 (perfect synchronization). Furthermore, PSI_{ij} values are averaged over all single trials selected for analysis.

3. Results and Discussion

In this work, we compare the results of the above mentioned methodologies for the purpose of Brain Computer Interface applications. We studied the connectivity in the hemisphere contralateral to the hand moves, within a cluster of electrodes above the sensorimotor area.

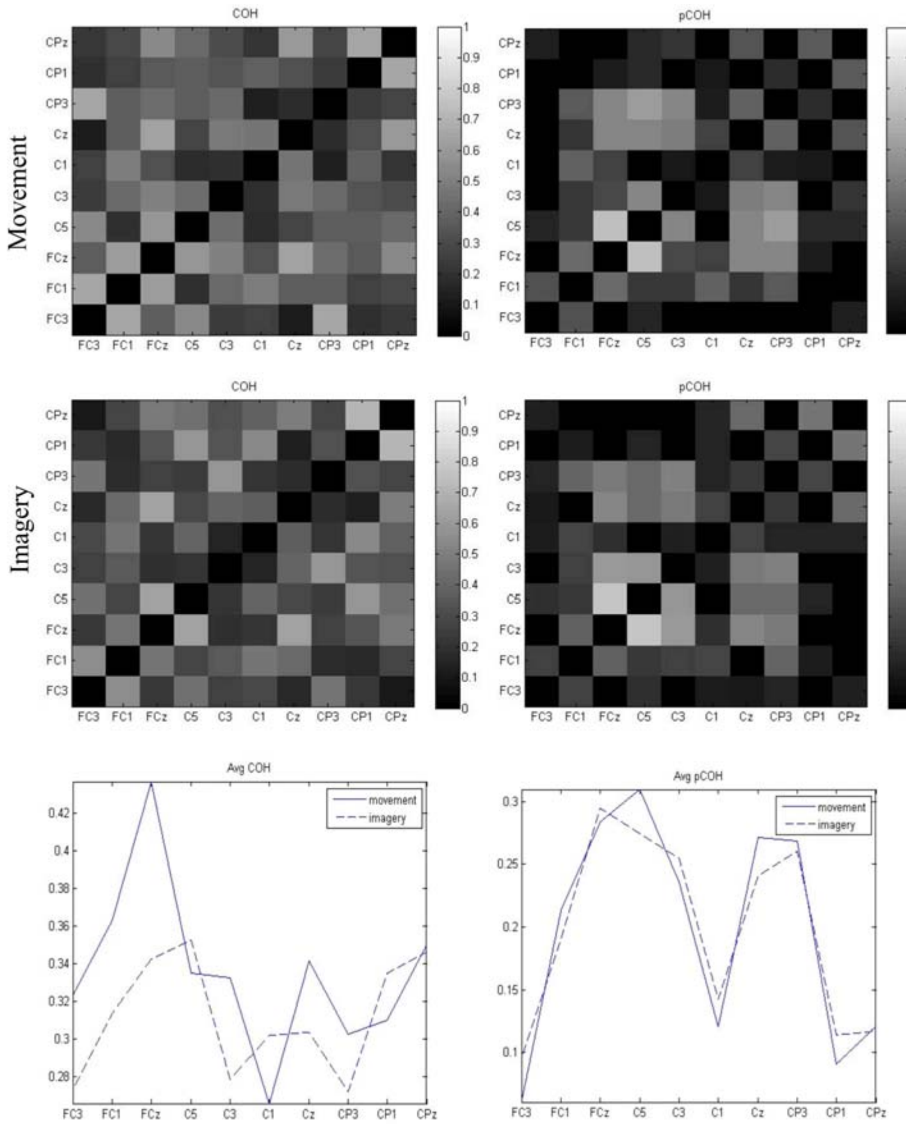

Figure 1. The output for the linear multivariate approach contains results of Coherence (Coh) (left column) for a representative subject, and the results of partial Coherence (pCoh) for the same dataset.. The upper plots show the connectivity patterns for the real and the bottom ones for the imagination of the movement. The results of coherence (Coh) analysis highlight the important role played by the FCZ channel. Partial coherence (pCoh) reveals a cross-talk between FCZ, C5, CP3 and Cz.

Previous results have shown that on the same group of electrodes on the ipsilateral hemisphere, similar connectivity patterns but without a prominent couple of interrelating electrodes. Moreover, a lack in bilateral coherence between post movement central mu and beta oscillations in the human electroencephalogram has been reported in the literature [Andrew and Pfurtscheller, 1997; van Leeuwen et al., 1978]. Here, we extracted connectivity patterns from the linear coherence measures and the non-linear phase synchronization measures. As we can see from Figure 1 the Coh results are different from the pCoh ones showing different degree of synchronization between the selected channels.

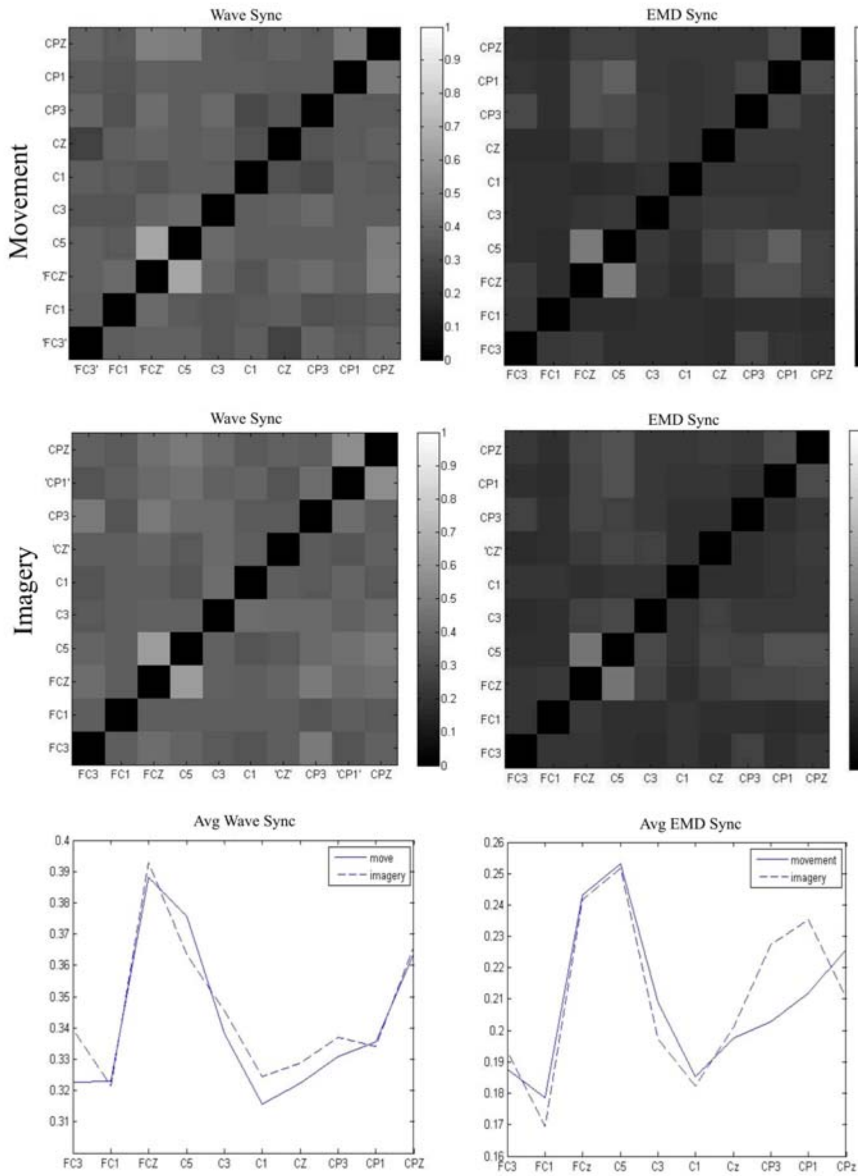

Figure 2. The output for the phase dynamics approach after the wavelet transform (left column) for the same dataset as in Fig.1, and the results of EMD approach for the same dataset as well. The upper plots depics the connectivity patterns for the real and the bottom plots for the imaginary of the movement. A prominent interrelation between C5 and FCZ is seen. The same pattern holds and for the EMD –based synchronization analysis.

However, the pCoh measure is more close to the results obtained with the phase approach, as can be seen from comparison of Figures 1 and 2. It is stated by other authors that to interpret coherence as cortical coupling could be misleading, because volume conduction and activity at the reference electrodes can result in erroneous high coherence values [Andrew and Pfurtscheller, 1997]. In this perspective, it is explained why pCoh provides more consistent results, as it expected to remove contribution from a third, common generator. However, these contributions could be extracted using the pCoh approach, only if they are linear [Pereda et al, 2005].

It is widely accepted that coherence cannot disentangle the contributions of amplitude and phase in the interrelations between the measured signals. In addition, the role of phase synchronization in the genesis of oscillations between cortical areas is becoming more prominent [Womelsdorf T et al., 2007]. The phase dynamics accounts for the non-linear interactions between the coupled oscillators. In addition, the phase synchronization should explain both local and distant binding, not only perceptual, but also the overall integration of all dimensions of a cognitive act [Lachaux et al., 1999].

Synchronized beta oscillations were found to bind multiple sensorimotor areas into a large scale network during a repeated motor task [Bovelli et al., 2004]. Thus, synchronization in the beta band might subserve binding of information processing regarding the preparation, intention and execution of a motor task, in the same way as gamma band is thought to be the binding mechanism for higher cognitive tasks [Lachaux et al, 1999].

We used first the instantaneous phase of the EEG signals obtained by the complex wavelet decomposition to quantify the inter-channel synchronization and evaluate the patterns coupling in the beta frequency range. Wavelets have been successfully and traditionally implemented for phase extraction from many authors in the past [Varela et al, 2001, Lachaux et al, 1999]. Our results show consistent high interrelation between the electrodes FCZ and C5 for this measure (see Figure 2, left column). This prominent connectivity between those two channels was preserved in imagery. A medial to lateral connectivity pattern underlying movement planning and execution has been reported in the literature [Michelon et al., 2006, Lotze et al, 1999].

In addition, we tested the results in synchronization of the newly developed method of Hilbert Huang transform. This technique adaptively decomposes a given data series, here the EEG datasets, into a number of elementary orthogonal modes with well defined instantaneous attributes (IMFs). These Imfs might be more accurate to represent the intrinsic oscillatory processes [Huang et al, 1998]. The instantaneous phase has been extracted by applying the Hilbert transform on the dominant oscillatory components identified by EMD. A possible advantage of such a transform over traditional time-frequency transforms, is that the nonlinearity of the signal may lead to leakage of energy into high frequency and hence results in spurious synchrony, which is avoided with EMD.

For the purpose of our analysis we checked the frequency content of the 4^{th} Imf used. The peak frequency for this Imf was inside the beta band. The results found with this method are similar with those of the wavelet transform as can be seen in Figure 2. The same lateral and medial network was revealed with the leading role to belong to FCZ and C5 EEG electrodes. Moreover, the similarity in this context of real movement with the imagery one was seen with this methodology as well. The reproducibility of the results using the EMD-based selection of beta range activity and the subsequent synchronization analysis, forward this method as an alternative, adaptive method of identifying intrinsic oscillations within data, providing a new way to determine the particular frequency bandwidths in which synchronization phenomena occur.

4. Conclusions

The symmetric and non-linear measures of interaction like the phase synchronization index may detect consistently patterns of connectivity between distinct neural populations. The results show consistency as various methods have been used in order to extract the phase from the signals. The reproducibility of the results indicate that phase indeed contains the information needed to code the connect connectivity and interrelations between neuronal populations and can be safely used as an extra input feature for BCI research.

References

Akaike H. A new look at the statistical model identification. *IEEE Transactions on Automatic Control.* 19(6): 716–723, 1974

Akaike H. Fitting autoregressive models for prediction, *Ann. Inst. Statist. Math.* 21:243–247, 1969.

Andrew C and Pfurtscheller G, Lack of bilateral coherence of post movement central beta oscillations in the human electroencephalogram, Neuroscience Letters 273:89-92, 1997

Babiloni, F., Cincotti, F., Babiloni, C., Carducci, F., Mattia, D., Astolfi, L., Basilisco, A., Rossini, P.M., Ding, L., Ni, Y., Cheng, J., Christine, K., Sweeney, J. and He, B. Estimation of the cortical functional connectivity with the multimodal integration of high-resolution EEG and fMRI data by directed transfer function. Neuroimage, 24:118-131, 2005

Baccala, L.A. and Sameshima, K. Partial directed coherence: a new concept in neural structure determination. Biol. Cybern, 84: 463-474, 2001

Breakspear, M. and Terry, J.R. Topographic organisation of nonlinear interdependence in multichannel human EEG. NeuroImage, 16: 822 - 835, 2002.

Brunner C, Scherer R, Graimann B, Supp G, Pfurtscheller G. Online control of a brain-computer interface using phase synchronization. IEEE Trans Biomed Eng. 53(12):2501-2506, 2006

Cimponeriu L, Rosenblum MG, Fieseler T, Dammers J, Schiek M, Majtanik M, Morosan P, Bezerianos A and Tass PA. Inferring asymmetric relations between interacting neuronal oscillators. Progress of Theoretical Physics Suppl. 150: 22-36, 2003.

David O, Cosmelli D and Friston KJ, Evaluation of different measures of functional connectivity using a neural mass model. NeuroImage, 2004, 21 :659-673.

Friston, K.J., Frith, C.D., Liddle, P.F. and Frackowiak, R.S.J. Functional connectivity: the principal component analysis of large (PET) data sets. J. Cereb. Blood Flow Metab, 13:5-14, 1993.

Gray CM, Singer W.Stimulus-specific neuronal oscillations in orientation columns of cat visual cortex. Proc Natl Acad Sci U S A. 86(5):1698-1702, 1989.

Gysels E, Celka P. Phase synchronization for the recognition of mental tasks in a brain-computer interface. IEEE Trans Neural Syst Rehabil Eng. 12(4):406-415, 2004

Huang N, Shen Z, Long S, Wu M, Shih H, Zheng Q, Yen N-C, Tung C, Liu H. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc. R. Soc. Lond. 454:903-995, 1998

Kaminski, M., Ding, M., Truccolo, W.A. and Bressler S.L. Evaluating causal relations in neural systems: Granger causality, directed transfer function and statistical assessment of significance. Biol. Cybern., 85: 145-157, 2001.

Lachaux J, Rodriguez E, Le van Quyen M, Lutz A., Martinerie J and Varela F. Int. J. Bifurcation Chaos Appl. Sci. Eng. 10: 2429, 2000

Lachaux, JP, Rodriguez, E, Martinerie, J., Varela F.J. Measuring phase synchrony in brain signals. Hum. Brain Mapp; 8: 194-208, 1999.

Lotze, M., Montoya, P., Erb, M., Hulsmann, E., Flor, H., Klose, U., Birbaumer, N. and Grodd, W. Activation of cortical and cerebellar motor areas during executed and imagined hand movements: an fMRI study. J. Cogn. Neurosci. 11: 491-501, 1999

Michelon P, Vettel JM, Zacks JM. Lateral somatotopic organization during imagined and prepared movements. J Neurophysiol. 95(2):811-822, 2006

Oldfield, R.C. The assessment and analysis of handedness: the Edinburgh inventory. Neuropsychologia.,9: 97-113, 1971

Parzen E. Multiple time series: Determining the order of approxi-mating autoregressive schemes. In: P. R. Krishnaiah, Editor, MultivariateAnalysis–IV. Amsterdam: North Holland, 1977, 283–295

Pereda E, Quiroga RQ, Bhattacharya J. Nonlinear multivariate analysis of neurophysiological signals.Prog Neurobiol. 77(1-2):1-37. 2005

Pfurtscheller, G. and Lopes da Silva, F.H. Event-related EEG/MEG synchronization and desynchronization: basic principles. Clin. Neurophysiol, 110: 1842-1857, 1999.

Pfurtscheller, G., Brunner, C., Schlogl, A. and Lopes da Silva, F.H. Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. NeuroImage, 2006, 31:153-9.

Pikovsky, A., Rosenblum, M. and Kurths, J. Synchronization: A Universal Concept in Nonlinear Sciences, Cambridge, Cambridge University Press, 2001.

Quiroga, R.Q., Kraskov, A., Kreuz, T. and Grassberger, P. Performance of different synchronization measures in real data: A case study on electroencephalographic signals. Phys. Rev. E, 65: 041903, 2002.

Rosenberg JR, Halliday DM, Breeze P, Conway BA.Identification of patterns of neuronal connectivity--partial spectra, partial coherence, and neuronal interactions. J Neurosci Methods. 83(1):57-72, 1998

Rosenblum, M.G., Pikovsky, A.S. and Kurths, J. Phase Synchronization of Chaotic Oscillators. Phys. Rev. Letters, , 76:1804-1807, 1996.

Schiff SJ, So P, Chang T, Burke RE, Sauer T.Detecting dynamical interdependence and generalized synchrony through mutual prediction in a neural ensemble.Phys Rev E Stat Phys Plasmas Fluids Relat Interdiscip Topics. 54(6):6708-6724, 1996

Schlogl A and Supp G, Analyzing event-related EEG data with multivariate autoregressive parameters., Progress in Brain Research, Neuper and Klimesh (Eds), Elsevier, Amsterdam 159:135-147, 2006

Stavrinou ML, Moraru L, Cimponeriu L, Della Penna S, Bezerianos A, Evaluation of cortical connectivity during real and imagined rhythmic finger tapping.Brain Topography, 19(3): 137 – 145., 2007

Sweeney-Reed CM and Nasuto SJ, A novel approach to the detection of synchronization in EEG based on empirical mode decomposition, Journal of Computational Neuroscience, 23:79-111, 2007.

Tallon-Baudry C, Bertrand O, Delpuech C and Pernier J. Oscillatory γ-Band (30-70 Hz) activity Induced by a Visual Search Task in Humans. J. Neurosci., 17:722-734, 1997

Tass P, Rosenblum M G, Weule J, Kurths J, Pikovsky A, Volkmann J, Schnitzler A and Freund H J Detection of *n*:*m* phase locking from noisy data: application to magnetoencephalography ***Phys. Rev. Lett.*** 81 3291–4, 1998

Tass PA, Hauptmann C. Therapeutic modulation of synaptic connectivity with desynchronizing brain stimulation. Int J Psychophysiol. 64(1):53-61. 2007

van Leeuwen WS, Wieneke G, Spoelstra P, Versteeg H. Lack of bilateral coherence of mu rhythm.Electroencephalogr Clin Neurophysiol.44(2):140-146, 1978

Varela F, Lachaux JP, Rodriguez E, Martinerie J.The brainweb: phase synchronization and large-scale integration.Nat Rev Neurosci. 2(4):229-239, 2001.

Womelsdorf T, Schoffelen JM, Oostenveld R, Singer W, Desimone R, Engel AK, Fries P., Modulation of neuronal interactions through neuronal synchronization. Science.316(5831):1609-12. 2007