Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

Narrowband vs. Broadband Phase Synchronization Analysis Applied to Independent Components of Ictal and Interictal EEG

Disha Gupta *Student Member, IEEE*, and Christopher J. James *Senior Member, IEEE*

Abstract—**This paper presents a comparison of the use of broadband and narrow band signals for phase synchronization analysis as applied to Independent Components of ictal and interictal scalp EEG in the context of seizure onset detection and prediction. Narrow band analysis for phase synchronization is found to be better performed in the present context than the broad band signal analysis. It has been observed that the phase synchronization of Independent Components in a narrow band (particularly the Gamma band) shows a prominent trend of increasing and decreasing synchronization at seizure onset near the epileptogenic area (spatially). This information is not always found to be consistent in analysis with the raw EEG signals, which may show spurious synchronization happening due to volume conduction effects. These observations lead us to believe that tracking changes in phase synchronization of narrow band activity, on continuous data records will be of great value in the context of seizure prediction.**

I. INTRODUCTION

PHASE SYNCHRONIZATION analysis in the analysis of neurophysiologic activity has gained momentum [1]-[4]. It was first introduced for the description of two coupled harmonic oscillators [5] and made possible the measurement of the strength of phase synchrony between two signals. It was also shown that these measures could be applied to noisy and chaotic signals [6]. Thus the concept of phase synchronization helped to measure the synchrony evolution while the amplitude of the signals remained uncorrelated. It should be noted that the underlying theory of phase synchrony assumes the signals to have a narrow frequency band and it has not been demonstrated whether or not it is appropriate to extend the same analysis for broad band data . This assumption is usually seen to be ignored in the context of biomedical signals like the electroencephalogram (EEG). This study aims to compare the broad band and narrow band phase synchronization analysis in the context of epileptic seizure detection and prediction. Here the obvious question that would be raised is how to determine what would be the optimum width of the narrow band for an analysis. The solution to this problem is not trivial but in the case of EEG signals we need not isolate signals at each frequency as phase synchronization measures synchrony within a range of mean frequencies (as long as this range of frequencies is not very large) [5]. In the present context we have used 20 Hz bands from 1-80 Hz of frequency to analyze changes in synchrony across a wide bandwidth, also they will roughly relate to bands of interest in EEG, such as beta (13-30 Hz), gamma (>60 Hz), etc.

Phase synchrony has long been considered as an important factor in the genesis of epileptic phenomenon [7]. Many studies suggest an underlying correlation between neuronal synchronization and seizure development and onset [3],[7]. We investigate the variability of the amount of phase synchronization in multivariate EEG data. In order to partially isolate the signals of interest in a particular area (spatially) from multivariate EEG data, we have used the concept of constrained Independent Component Analysis (cICA) [8]. EEG signals are contaminated by noise and artifacts that can be efficiently isolated and removed with ICA. Also due to volume conduction, EEG the signals on the scalp get spatially overlapped which may lead to spurious synchronization. This effect is removed by the use of ICA as it aims to isolate the source signals (i.e. ICA combats the effects of volume conduction).

II. THEORY

A. ICA and Spatially Constrained ICA

ICA is a statistical technique which performs Blind Source Separation (BSS) on linear mixtures of statistically independent sources. For a set of p random variables $\mathbf{v}(t)= [v_1,v_2,v_3....v_p]^T$ assumed to be a linear combination (represented by the mixing matrix $\mathbf{A}$) of m unknown statistically independent sources $\mathbf{s}(t) =[s_1,s_2,s_3, ..., s_q]^T$ where $q \leq p$, such that $\mathbf{v}(t) = \mathbf{A}\,\mathbf{s}(t)$. ICA aims to find the demixing matrix $\mathbf{W}$ such that $\mathbf{s}(t) = \mathbf{W}\,\mathbf{v}(t)$**.** The demixing matrix thus helps to find the sources $\mathbf{s}(t)$. To simplify the estimation we 'whiten' the mixtures (de-correlate), which makes the covariance matrix of $\mathbf{v}(t)$ diagonal and its components of unit variance. There are various implementations of ICA in the literature [8]-[11] and we have selected FastICA [10],[11] because of its ease of implementation and speed of operation.

In general, in ICA, there are two main limitations with the IC's obtained: 1) The sign of IC's cannot be determined and 2) there is no ordering of the IC's. This poses a problem in objective identification of the IC's of interest (seizure topographies in this case). This is the motivation of using *spatial constraints* in conjunction with ICA [8],[12]. Spatial constraints are references provided in the form of source

This work was supported in part by the Institute of Sound and Vibration Research, University of Southampton and the Life Science Interface, U.K.

D. Gupta is with the Signal Processing and Control Group, ISVR, University of Southampton, SO17 1BJ, UK (Tel: +44 (0)2380-592689; Fax: +44 (0) 23 8059 3190; email: disha@soton.ac.uk).

Dr. C. J. James is with the Signal Processing and Control Group, ISVR, University of Southampton, SO17 1BJ, UK (Tel: +44 (0)2380 593043; Fax: +44 (0) 23 8059 3190; e-mail: C.James@soton.ac.uk).

projections whose location in the source mixture model is specified *a priori*. It should be noted that constrained ICA partially relaxes the independence assumption for constrained sources, which are independent of the unconstrained sources but may be mutually dependent [8].

B. Phase Synchronization Analysis

Phase synchronization measurements require an estimation of instantaneous phases of the two signals, the variability of the phase difference is then measured at a certain time. Synchronization of signals is marked by an appearance of a horizontal plateau in the phase difference across time [5]. To quantify the amount of phase synchronization, we need to use an index. In the literature, a number of indices called Phase Locking Values (PLV) have been used for intracranial and scalp EEG, based on different concepts, such as: Mutual Information, Shannon entropy, and Mean Phase Coherence [1]-[4]. We have opted to use the Mean Phase Coherence. The PLV is calculated as follows:

1. Estimate the instantaneous phases of two signals using the Hilbert transform.
2. Find the phase difference for two signals across time.
3. Calculate the PLV value.

The instantaneous phase of a signal $x(t)$ is estimated by forming an analytical signal using the Hilbert Transform [6]:

$$A(t) = x(t) + i\tilde{x}(t), \tag{1}$$

where the imaginary part $\tilde{x}(t)$ is the Hilbert transform of $x(t)$ (P being the Cauchy principle value):

$$\tilde{x}(t) = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau . \tag{2}$$

The instantaneous phase is the 'unfolded' angle of the analytic signal, which is given by:

$$\phi(t) = \arctan \frac{\tilde{x}(t)}{x(t)}. \tag{3}$$

The phase synchronization is defined as the locking of the phases of two oscillating systems *a* and *b*:

$$n\phi_a(t) - m\phi_b(t) = const . \tag{4}$$

In this case, as we aim to measure the synchronization between signals from within the same physiological system (i.e. active brain regions), we assume that the phase locking ratio of *n:m*=1:1 as per [1] and using this bivariate data calculate the PLV using:

$$PLV = \left| \frac{1}{N} \sum_{j=0}^{N-1} e^{i\left[\phi_a(j\Delta t) - \phi_b(j\Delta t)\right]} \right|, \tag{5}$$

where $1/\Delta t$ is the sampling rate of the time series of length *N*. This can be expanded by Euler's formula as

$$PLV = \sqrt{\left(\left[\frac{1}{N}\sum_{j=0}^{N-1} Sin(\phi_a(j\Delta t) - \phi_b(j\Delta t))\right]^2 + \left[\frac{1}{N}\sum_{j=0}^{N-1} Cos(\phi_a(j\Delta t) - \phi_b(j\Delta t))\right]^2\right)} \tag{6}$$

From the above we can see that PLV is a normalized value, where a perfect synchronization corresponds to a value of one and no synchronization a value of zero. Here it should be noted that EEG signals are usually broadband (1-100Hz) and Hilbert Transform may not be able to correctly estimate the instantaneous phase of broadband signals (which is an ongoing research problem). This raises concern if the broadband phase synchronization analysis may mislead interpretation of the results.

C. Phase Locking Statistics

Phase Locking Statistics (PLS) is a statistical test to differentiate significant PLV values against background fluctuations [2],[3]. It tests the null hypothesis H_0 that the signals are not phase synchronized. It is based on a bootstrap technique which uses surrogate series [2],[3]. We use 'shift surrogates' as opposed to 'shuffled surrogates' as they preserve the inherent autocorrelations of the EEG signals and only destroys the cross-correlations [2]. 100 shift surrogates were generated by time shifting one series relative to the other by random lags and wrapping the extra values to the end. The PLV calculated between two signals was considered significant if the value was greater than two Standard Deviations from the mean PLV calculated on the surrogates.

III. Method

A. Epileptiform Data

We studied multi-channel ictal scalp EEG recordings of two patients (four seizures and twenty interictal background EEG recordings each) who were undergoing continuous scalp EEG monitoring for possible epileptic surgery. The EEG was in the form of segments of two minutes with gaps of fifteen minutes, throughout the day and night. The data was recorded using twenty-five electrodes placed on the scalp according to the International 10-20 electrode placement system, with reference FCz. The data was sampled at 200 Hz and digitally stored at 12 bit resolution. The interictal recordings consist of 120 seconds of non-ictal EEG, away from the seizures. The seizure recordings consist of some pre-ictal periods and are of variable lengths from 120 seconds to 300 seconds. We analyzed the data of each patient separately using a moving window technique with a window length of 600 samples (3 sec).

B. Time-Frequency Evolution of Phase Synchronization in EEG signals and Independent Components

FastICA was used to generate independent components (IC's) of the multivariate EEG signals. The EEG signals and the IC's were filtered in different frequency bands (1-20 Hz, 20-40 Hz, 40-60 Hz and 60-80 Hz) using a finite impulse response filter. The time-frequency evolution of phase synchronization was investigated on the multivariate EEG

signals and the corresponding IC's by calculating the PLV for each frequency band across time for all combinations of EEG electrodes and IC's. To apply the analysis to the problem of seizure onset detection, we partially isolate signals of interest in a particular spatial area (near epileptogenic focal area) with the help of spatially constrained ICA. The procedure followed for the selection of constraints has been explained in the following section.

C. *Selection of Constraints*

Constraints were selected using a template EEG data segment of the patient that exhibited sufficient pre-ictal and ictal periods (about 100 seconds each). IC's were estimated for this segment using FastICA and the topographies were plotted from the mixing matrix **A**. Then the PLV was calculated for all combinations of IC's. The ICs that showed maximum change at seizure onset (in a frequency band) were selected and their topographies were used as constraints. This in effect depicted that there was maximum change observed in phase synchrony between these spatial areas. The spatially constrained sources were found as explained in Theory section, for interictal and ictal data. These were then used to estimate the phase synchrony evolution over time across all frequency bands to assess if these areas (spatially) got involved before and at seizure onset.

IV. RESULTS

Discrepancy was seen between the broadband and the narrowband phase synchrony results for the spatially constrained IC's in case of both interictal and ictal data. This has been shown by an example as applied to a patient's ictal and interictal EEG data. The template used for estimating the spatial constraints and the constraint topographies that were selected have been shown in Fig. 1. The IC's that were found to show a prominent demarcation in the PLV levels at seizure onset appeared to be present only in the high frequency band. These topographies were then used as spatial constraints for estimating two spatially constrained sources on the patient's interictal and ictal data.

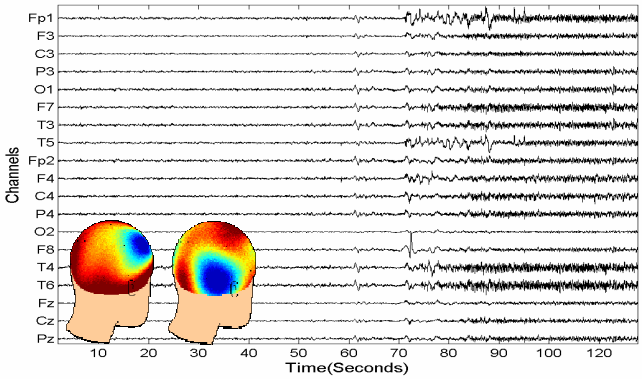

Fig. 1 Plot of ictal EEG used as template to derive the topography constraints (only a section has been shown here) and the selected topographies, to be used as constraints.

A. *Narrowband vs. Broadband Phase Synchronization*

The time-frequency evolution of the phase synchronization for the estimated IC's has been shown in Fig. 2 (upper plot) and the broadband phase synchronization for the same has been shown in Fig. 2 (lower plot). From Fig. 2 we can see that all the narrowband phase synchrony results do not match the broadband phase synchrony results.

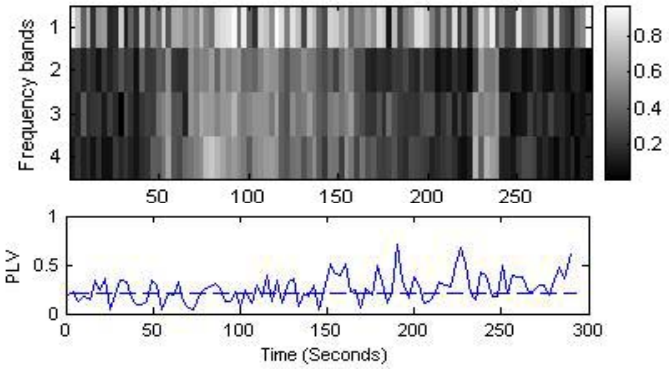

Fig. 2: Plot of time-frequency evolution of phase synchrony for spatially constrained IC's of ictal data (upper). Plot of broad band phase synchrony for the same signals (lower). Differences can be seen in the time window of 50-100 sec. Broadband PLV shows a lower value while narrow band PLV shows a higher value in band 1 and 4.

In Fig. 3 and Fig. 4 we compare the phase synchronization in broadband and a narrow frequency band in interictal and ictal data. The narrowband (60-80 Hz) selected for this example is for clarity and is the one that shows maximum difference between broadband and narrowband PLV's. Fig. 3 shows that in interictal segments the narrowband PLV remains consistently significant with a stable low value of PLV while the broadband PLV for the same interictal data is either at a higher or lower level and sometimes becomes non-significant. In Fig. 4, where the same is repeated for ictal data, narrowband phase synchrony is seen to reduce prominently to non-significant levels or 0.1 prior to the seizure onset and thereafter increase to higher levels of 0.7-0.8 at seizure onset. While with broadband PLV we do not see such a demarcated change in the amount of phase synchrony when evolving from interictal to ictal zone.

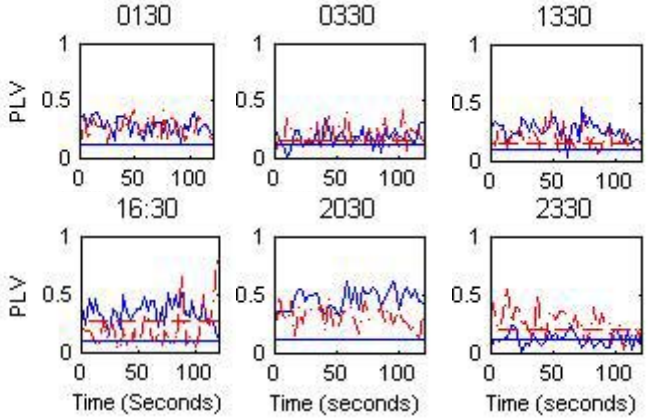

Fig. 3 Plots of inter-ictal PLV for narrow band (60-80 Hz) (solid) and broad band (dotted) at various times (01:30 – 23:30). Horizontal lines indicate corresponding PLS significance levels.

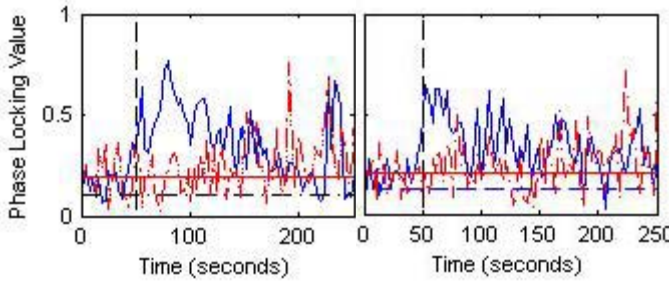

Fig. 4 Plots of ictal narrow band (60-80 Hz) (solid) and broad band (dotted) phase synchrony. Horizontal lines show PLV levels for narrow band (dotted) and broad band (solid). Vertical line indicate seizure onset

Also, in this study it was observed that there was inconsistency between the amount of phase synchronization seen at different frequency bands between the EEG electrodes and the corresponding IC's (to compare combinations of IC's and EEG electrode signals we use the spatial information of the IC's, i.e. IC's having the topography similar to that of the position of EEG electrodes). An example is shown in Fig. 5, where we see that the phase synchronization between EEG electrodes F3 and T3 for an EEG segment shows high phase synchrony in low frequency bands and the amount of phase synchrony in high frequency bands is comparatively lower. But the corresponding combination of IC's (selected by their similarity of topography to the positions of F3 and T3 electrodes) show high phase synchrony in low frequency bands as well as high phase synchrony in high frequency bands as opposed to the observation in the corresponding EEG electrode combination. This discrepancy may be attributed to the overlapping of signals in EEG channels which is removed in IC's. This observation further strengthens the concept that ICA demixes the scalp recorded data bringing the analysis a step closer to the underlying sources and removing the effect of overlapping of signals.

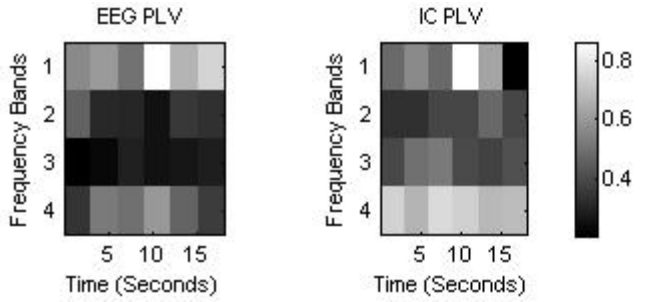

Fig. 5 Plots of Time Frequency evolution of EEG (F3, T3) and the corresponding IC's (matched to the location of EEG electrodes by their corresponding topographies).

With the above study it was also observed that the 60-80 Hz band was prominent in showing sudden increase in phase synchrony at seizure onset. Recent research has indicated some correlation of Gamma band (> 60 Hz) activity and epileptiform activity using intracranial EEG signals [13]. This information is sometimes not observed in the analysis of raw EEG signals, which may be due to appearance of spurious synchronization resulting from volume conduction effects.

V. Discussion and Conclusions

In this study the phase synchrony analysis of narrowband signals were found to reflect a trend that allowed demarcating the start of a seizure while the broadband signals failed to consistently reflect such a change. The broadband IC phase synchrony appears to depict an average of the individual narrowband phase synchronies. Such discrepancies can lead to incorrect interpretations in certain applications like seizure onset detection, when relying on broadband phase synchrony analysis; hence we conclude that the use of phase synchronization analysis on broadband signals should be performed with caution.

The observation of the existence of a prominent trend of decreasing and increasing phase synchronization in high frequency band (Gamma) > 60 Hz, at seizure onset, between least independent sources found near the epileptogenic focal area might be helpful for seizure prediction. Confirmation about the change in this frequency band synchrony prior to a seizure onset, (that may help to predict a seizure) will require prospective statistical evidence, which was currently not possible due to lack of continuous scalp EEG recordings. We will be exploring the changes in Gamma band synchrony prior to a seizure (including the effect of change in behavior or sleep and wake state on the phase synchrony levels prior to the seizure onset) further next, in the context of seizure prediction.

References

[1] W. De Clercq, P. Lemmerling, W. Van Paesschen and S. Van Huffel, "Characterization of interictal and ictal scalp EEG signals with the Hilbert transform", in *Proc. 25th Annu. International Conf. of the IEEE EMBS*. Vol. 3, pp. 2459- 2462, Sept. 2003,

[2] R. Q. Quiroga, J. Bhattacharya, "Nonlinear multivariate analysis of neurophysiologic signals", Prog. in Neurobiology 77, pp. 1–37. 2005.

[3] T.I. Netoff and S.J. Schiff, "Decreased Neuronal Synchronization during Experimental Seizures", The Journal of Neuroscience, 22(16), pp. 7297–7307, Aug. 2002.

[4] R. Q. Quiroga, A. Kraskov, T. Kreuz, P. Grassberger, "Performance of different synchronization measures in real data: a case study on electroencephalographic signals", Phys Rev E., 65, Apr. 2002.

[5] A. Pikovsky, M. Rosenblum, J. Kurths, "Synchronization: A Universal Concept in Nonlinear Sciences", Cambridge University Press, UK, 2001, ch. 3

[6] M. G. Rosenblum, A. S. Pikovsky, and J. Kurths "Phase Synchronization of Chaotic Oscillators", Phy. Rev. Let. Vol.76, No. 11, March 1996.

[7] M. Le Van Quyen, "Anticipating epileptic seizures: from mathematics to clinical applications", C R Biol., 328(2), pp. 187-98, Feb. 2005.

[8] C. W. Hesse and C. J. James, "The FastICA Algorithm With Spatial Constraints", IEEE Signal Proc. Letter, Vol. 12, No. 11, Nov. 2005.

[9] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution", Neural computation, 7, pp. 1129-1159, 1995.

[10] The FastICA MATLAB Package [Online]. Available: http://www.cis.hut.fi/projects/ica/fastica.

[11] A. Hyvärinen, and E. Oja, "A fast fixed-point algorithm for independent component analysis", Neural Computation, 9, pp. 1483-1492, 1997.

[12] J. James and C. W. Hesse, "Independent Component Analysis for Biomedical Signals", Physiol. Measurement, 26, R15-R39. 2005.

[13] A. V. Medvedev, "Epileptiform spikes desynchronize and diminish fast (gamma) activity of the brain. An anti-binding mechanism?", Brain res. bull. vol. 58, no 1, pp. 115-128, 2002.