

# An Approach for Estimation of Obstructive Sleep Apnea Syndrome from EEG

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**Abstract**— Sleep is a corporeal mechanism which achieves recuperative functions for the brain and the body. To maintain a healthy status for most living organisms sleep is an essential criteria. Being a naturally recurring state it is characterized by reduced or absent consciousness, relatively suspended sensory activity, and inactivity of nearly all voluntary muscles. After the middle age, the upper respiratory tracts of some of individuals could shrink and which leads to obstruction of the nasal passages and snoring during sleep. This situation called apnea, could affect the quality of sleep and health when it occurs frequently, and may even cause death in severe cases. Obstructive sleep apnea syndrome is a situation where repeatedly upper airway stops off while the respiratory effort continues during sleep at least for 10 s. Bispectral analysis is an advanced signal processing technique particularly used for exhibiting quadratic phase-coupling that may arise between signal components with different frequencies. In this project, a new technique for recognizing patients with OSAS was introduced using bispectral characteristics of EEG signal and an artificial neural network. The amount of quadratic phase coupling in each sub band of EEG namely; delta, theta, alpha, beta and gamma, was calculated over bispectral density of EEG. Then, the obtained quadrature couplings are fed to the input of the designed ANN. The recommended technique could be used in the development of an automatic OSAS identification system which will improve medical service and diagnostic capability.

**Keywords**— EEG, Quadrature coupling, OSAS, Bispectral analysis, ANN.

## I. INTRODUCTION

The increasingly recognized as an important health issue in the last two to three decades is mainly concerned about obstructive sleep apnea syndrome (OSAS). The frequent episodes of upper airway collapse during sleep which causes recurrent arousals, intermittent hypoxemia, sleep fragmentation and poor sleep quality are the main characteristics of OSAS. There is accumulating evidence that OSA is being considered as an independent risk factor for hypertension, glucose intolerance, diabetes mellitus, cardiovascular diseases and stroke, leading to increased cardio metabolic morbidity and mortality. The prevalence rates of OSA have been estimated in the range of 2 to 10 per cent worldwide. The main risk factors for obstructive sleep apnea are advanced age, male sex, obesity, family history, craniofacial abnormalities, smoking and alcohol consumption. Heavy snoring, witnessed apneas and daytime hyper somnolence are common clinical symptoms which would help to identify the affected individuals.

Early recognition and treatment of obstructive sleep apnea may prevent from adverse health consequences. The main contribution of the project is to research and develop this as a practical tool and to prove that an inexpensive test can provide early warnings to sleep apnea conditions, thus saving the health care system significant cost. The enhancement and automated analysis of the EEG signal would constitute a significant advancement in diagnostic EEG applications. So this breakthrough to analyze, classify and characterize the normal and abnormal EEG signal using bispectral analysis is introduced. Biomedical signals like EEG signals commonly change their statistical property over time and are highly non stationary signals. For the analysis of this kind of signals bispectrum is a power tool. Electroencephalogram (EEG) is the tool used for the diagnosis of sleep apnea disorder.

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Automatic detection of disorder is the fundamental requirement. Sleep is essential for humans although its basic physiological function remains obscure. Disturbance of the normal breathing process can cause the development of severe metabolic, organic, central nervous and physical disorders. Bispectral analysis is an advanced signal processing technique particularly used for exhibiting quadratic phase-coupling that may arise between signal components with different frequencies. From this perspective, in this study, a new technique for recognizing patients with OSAS was introduced using bispectral characteristics of EEG signal and an artificial neural network (ANN). The amount of Quadratic phase coupling (QPC) in each subband of EEG (namely; delta, theta, alpha, beta and gamma) was calculated over bispectral density of EEG. Then, these QPCs were fed to the input of the designed ANN. The neural network was configured with two outputs: one for OSAS and one for estimation of normal situation.

The EEG signal is an indicator of sleep apnea. The software has the capability of calculating bicoherence of EEG signal which gives a measure of quadrature coupling in the signal and indicates if the patient is having high risk of sleep apnea as in [11]. An EEG signal, during an OSAS exposes higher bispectral peaks than in the normal EEG signal, before OSAS. The finding through this particular method might imply that brain activity involves much complex or chaotic processes during OSAS that generally emerges an EEG with different signal components in different frequency bands which cause a higher degree of phase coupling. In other words, as the patient goes through the apnea the nonlinearity in the brain dynamics increases compared to the EEG before OSAS. Since bispectrum conveys more information about a time-varying signal than power spectrum, this technique can offer more potential for clinical utility. A correlation between inter-frequency phase-coherence of cortical EEG and levels of consciousness may reflect phase coherent synchronization over large spatial regions mediated by deeper brain structures.

### II. SYSTEM METHODOLOGY

#### A). Bispectral analysis

In the analysis and handling of random signals, the first and second order statistics have gained significant importance and is used in a wide variety of applications. For many signals, which are generated from nonlinear processes, second order statistical methods are not sufficient for analysis. Many of the

naturally occurring signals deviate from Gaussianity and linearity. Hitherto, such signals were considered Gaussian or near Gaussian signals and analysis were conducted, which has resulted in loss of valuable information. For these reasons, higher order statistical methods have been developed, which can handle non-Gaussian as well as non-linear signals. Phase information is not available in the second-order measures such as the power spectrum and autocorrelation functions because of which, non minimum phase signals and certain types of phase couplings, associated with nonlinearities, cannot be correctly identified by second order statistics. The Gaussian signals can be completely characterized by its mean and variances. Different types of nonlinearities results in different types of phase couplings. If a signal composed of two sinusoids is passed through a non linear system, then the output will contain components at the sum and difference frequencies as well. Quadratic Phase Coupling is the term used to describe the coupling which results from such type of nonlinearities.

The traditional power spectrum is the Fourier transform of the autocorrelation sequence, while the bispectrum is the Fourier transform of the third-order cumulant sequence or the autobicorrelation sequence. The bispectrum is a member of the category of higher order spectra, or polyspectra and can provide additional information than the power spectrum. Among the higher order spectra, the third order polyspectrum or the bispectrum can be computed very easily and hence is attracting more and more researchers as in [4]. The bispectrum can be thought of as a frequency decomposition of the third-order cumulant and it follows that the process skewness  $Y_3$  which is the zero-lag cumulant  $C_3(0,0)$  is equal to the bispectrum summed over all the frequencies. This can be compared with the way in which the variance of a process is related to its power spectrum and second-order cumulant or autocorrelation function. Bispectral analysis can reveal the deviation of the processes from Gaussianity, since all polyspectra of order greater than two is identically zero for Gaussian process. The bispectrum is asymptotically consistent.

Bispectral analysis makes use of phase information by detecting whether the phase of signal components at frequencies and are interdependent. Furthermore, the degree of dependence is quantified so that a high bispectrum correlates to a signal with highly interdependent frequency components. It is the Fourier transform of the second-order cumulant,  $R(t_1, t_2)$ , (the autocorrelation function). In contrast to power

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spectrum, bispectrum reveals a non-Gaussian and nonlinear information which allows the detection of nonlinear characteristics and characterization of nonlinear mechanisms such as brain. It produces time series through phase relations of their harmonic components. For a discrete, stationary and zero-mean random process,  $x(n)$ , the third-order cumulant sequence  $R(m,n)$  has been defined in terms of its third-moment sequence as:

$$R(m,n)=E[x(k)x(k+m)x(k+n)] \quad (1)$$

where  $E[.]$  denotes the expectation operation. Transforming the third-order cumulant into frequency domain yields the bispectrum,

$$B(\omega_1, \omega_2) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} R(m,n)W(m,n)e^{-j(\omega_1 m + \omega_2 n)} \quad (2)$$

where  $W(m,n)$  is a two-dimensional window function employed to reduce the variance of the bispectrum. Eq. (2) can equivalently be expressed in terms of the Fourier transform of  $x(n)$  as:

$$B(\omega_1, \omega_2) = E(X(\omega_1) X(\omega_2) X^*(\omega_1 + \omega_2)) \quad (3)$$

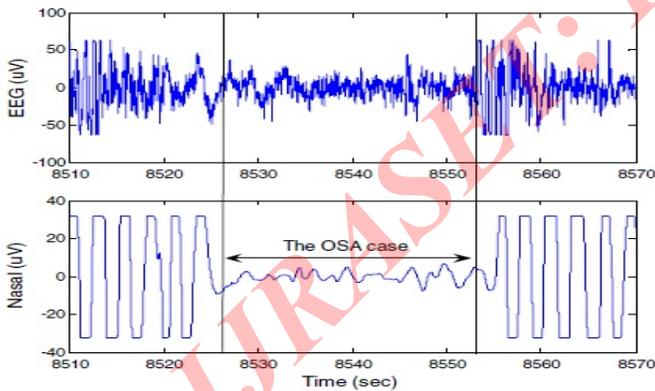


Fig.1 The signal characteristic of OSAS

Each EEG sample taken for analysis was with 10 s duration (that is the minimum obstruction duration for an OSAS) and consequently 2560 samples which require a big

number of input nodes for NN. To minimize the number of data to be input to NN the EEG samples were first evaluated through the bispectral analysis and/or bicoherence through the pre-processing module. In the calculation of bispectras a Hanning window having a width of 0.1 s was used. The obtained bispectra were appraised over the triangular holding the whole spectral information. This triangular region was segmented as:

Delta ( $\delta$ ) 0.5–4 Hz, i.e.,  $0.5 \text{ Hz} < (f_1, f_2) < 4 \text{ Hz}$ ,

Theta ( $\theta$ ) 4–8 Hz, i.e.,  $4 \text{ Hz} < (f_1, f_2) < 8 \text{ Hz}$ ,

Alpha ( $\alpha$ ) 8–13 Hz, i.e.,  $8 \text{ Hz} < (f_1, f_2) < 13 \text{ Hz}$ ,

Beta ( $\beta$ ) 13–32 Hz, i.e.,  $13 \text{ Hz} < (f_1, f_2) < 32 \text{ Hz}$ ,

Gamma ( $\gamma$ ) 32–64 Hz, i.e.,  $32 \text{ Hz} < (f_1, f_2) < 64 \text{ Hz}$ .

The QPC energy remaining under the delta, theta, alpha, beta and gamma frequency bands of EEG were quantified and the developed computerized image scanning program. These quantified relative data were then given as inputs to the classification module.

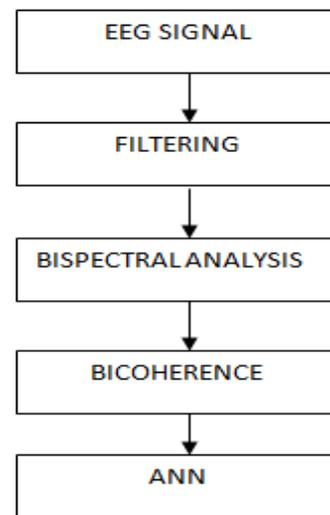


Fig.2 Structure of Proposed Method

As shown in figure 2 the data points of EEG are taken from the MIT Polysomnograph database from physionet. The duration of each signal sample was 10 s (2560 data points) which is the minimum obstruction duration for an OSAS. The

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whole spectral information of the signal can be attained in the triangular region defined as  $0 \leq \omega_2 \leq \omega_1$ . Other regions in  $B(\omega_1, \omega_2)$  are just the symmetric copies of this particular region. If a well concentrated peak does emerge at frequency  $\omega_1 + \omega_2$  in this triangular region, due to the nonlinear quadratic dependency, this peak is called quadratic phase coupling (QPC) at frequencies  $(\omega_1, \omega_2)$ . If two smooth peaks do emerge at frequencies  $\omega_1$  and  $\omega_2$  it suggests that there is not such a phase coupling as shown in figure 4.3. The phase coupled components contribute to the third-order cumulant sequence of a process, and give extra information about the signal. This unique property of bispectrum is a useful tool that can be used to detect and quantify the possible existence of QPCs in the EEG signals, and possibly differentiate the normals from OSAS patients.

### B). Bicoherence

The bicoherence measure is the normalized version of the bispectrum, extensively used to study the correlation between two simultaneously measured signals in frequency domain. Bicoherence is an auto-quantity which can be computed from a single time signal. While the one dimensional coherence function provides a quantification of deviations from linearity between the input and output measurement sensors of the system, the bicoherence measures the proportion of the signal energy at any bifrequency that is quadratically phase coupled.

In order to reduce the computation time the bispectrum estimation mostly performed through the direct method that uses Fast Fourier Transform algorithm. In the bispectrum pattern, as mentioned above, the main frequency in different frequencies can concentrate at any region on  $(f_1, f_2)$  where  $f_1 \neq f_2$ . The bispectrums obtained from the EEG of patients, which could be with OSAS, was segmented into subbands which usually standardized to EEG spectrum as Delta, Theta, Alpha, Beta and Gamma, and then the QPC associated to these regions were quantified and used for detection of patients with OSAS.

### III. RESULTS

The pathologic conditions usually modulate EEG signal, as in this case, can be detected by signal processing means. An EEG signal, during an OSAS exposes higher bispectral peaks than in the normal EEG signal, before OSAS. The finding through this particular method might imply that brain activity

involves much complex or chaotic processes during OSAS that generally emerges an EEG with different signal components in different frequency bands which cause a higher degree of phase coupling. In other words, as the patient goes through the apnea the nonlinearity in the brain dynamics increases compared to the EEG before OSAS. The high rate of phase coupling detected in the bispectrum, which particularly concentrated over the region of the interest was successfully used for OSAS estimation.

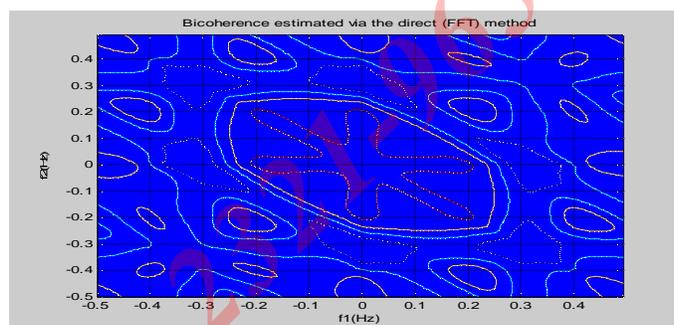


Fig.3 Bispectrum for normal EEG

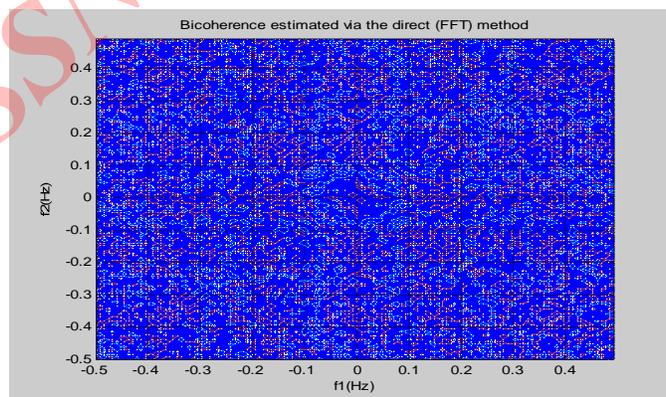


Fig.4 Bispectrum for OSAS

During normal and abnormal cases the EEG recorded at 256kHz. The input signal is filtered and denoised in the pre-processing stage. During deep sleep EEG frequency will be very less and hence the quadrature coupling existing components will be less and bispectrum of the corresponding signal will be concentrating in the origin. It will also be symmetric about origin, whereas in the abnormal case the quadrature coupling will be maximum and bispectrum will be scattered around the axes as shown in figure 3 and 4 respectively.

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### IV. CONCLUSION

Bispectral analysis has not been widely applied to EEG analysis because of being technically more difficult than the conventional power spectral analysis to implement. Also the interpretation of bispectrum is quite difficult. Since bispectrum conveys more information about a time-varying signal than power spectrum, this technique can offer more potential for clinical utility. A correlation between inter-frequency phase-coherence of cortical EEG and levels of consciousness may reflect phase coherent synchronization over large spatial regions mediated by deeper brain structures.

The artificial neural network has to be implemented for the automatic detection of OSAS classification. The system can be improved by further studies and an automated system can be designed. It also can be integrated into the present polysomnographs for automatic OSAS identification which may reduce the diagnosis time and improve the medical service efficiency.

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