The Effect of Obstructive Sleep Apnea on the Electrocardiogram Signals

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Abstract

In the present study, a nonlinear analysis that is bispectral analysis which is a family of the higher order spektrum was used to extract phase relations between the components of the electrocardiogram (ECG) signals before, during and after obstructive sleep apnea (OSA) episodes. The bispectrum analysis is a capable of extract the phase relations between the components of a signal, and this phase relations may contain important information about some abnormalities in the ECG rhythms. The OSA is the stoppage of the airflow at least 10 s during sleep. To extract the phase information in the ECG before, during and after OSA periods can give some important clues about electrocardiological diseases which are related with OSA.

Key words: Electrocardiogram, bispectrum analysis, obstructive sleep apnea.

1. Introduction

Electrocardiography (ECG) signals are electrical activity of the heart detected by electrodes that attached to the surface of the skin and recorded by a device with noninvasive. They are highly random in nature and may contain useful information about the heart state. They are basically non-linear and nonstationary in nature. Hence, important features can be extracted for the diagnosis of different diseases using advanced signal processing techniques. ECG signals are quite useful since they give off no radiation, are noninvasive, and are suitable for monitoring over long periods of time. In addition, useful ECG reference values are available for studying Obstructive sleep apnea (OSA). OSA is characterized as cessation of air through lung at least 10 s. There is an abrupt frequency shift in the ECG signal when sleep apnea starts and ends. OSA may occur for 10 seconds or more when a patient falls asleep during non-rapid eye movement (NREM) sleep. When breathing becomes normal, brain waves tend to shift to a relatively continuous frequency signal above delta, namely in the theta and alpha wave frequency bands [1,2]. If we compare ECG signals with nasal and oral airflow signals when symptoms of OSA, we see that the nasal and oral airflow signals are clearly reduced, and the bispectrum of ECG signal becomes lower in amplitude when an episode of OSA ends.

Bispectral analysis is an advanced signal processing method that quantifies quadratic nonlinearities (phase-coupling) among the components of a signal. Sigl and Chamoun [3] introduced the detailed principle and concept of bispectral analysis in 1994. Ning and Bmnzino [4] have studied the bispectral estimates of hippocampal EEGs under various stages of sleep such **as** quiet waking, rapid eye movement (REM) and slow wave sleep and have reported success in distinguishing between the different vigilant states. Muthuswamy et al. [5] reported the bispectral analysis of burst patterns in EEG. This analytic technique is also known as a core technology of the Bispectral Index System (BIS) monitor (Aspect Medical Systems, Natick, MA). Ye et al. [6] observed a distribute characteristics on the bispectral coupling of EEG according to depth of anesthesia using bispectrum analysis method in a type of nonlinear signal processing and Zhang et al. [7] analysed the bispectrum of focal ischemic cerebral EEG signal and indicate that the

EEG bispectrum analysis may be useful to distinguish the ischemic region from the normal one and to estimate the ischemic extent. Nonetheless, not much emphasis has been placed on the detection and characterization of nonlinear properties in the ECG signals for OSA patients. Although bispectral analysis involves complicated mathematics, today's computers are powerful enough for real-time bispectral analysis of ECG data. This paper investigates the presence of nonlinearities in ECG signals before, during and after OSA events by using bispectral analysis.

2. Materials and Methods

2.1. Subjects and database preparation

The polysomnograms of 40 OSA patients (mean ±SD) age 37±9 years, body mass index (BMI) 33±2 kg/m^2 were analysed. All subjects were free of any cardiac history. Diagnosis was based on clinical symptoms and polysomnographic (PSG) outcomes. PSG study included EEG, left and right electrooclugram, leg movements, body positions, thoracic and abdominal wall expansion (by respiratory inductive plethysmography), oronasal airflow (by Nasal pressure, Pnasal), arterial oxygen saturation SaO_2 (by pulse oximetry), submental electromyography (EMG) and electrocardiogram (ECG). All of the recordings were performed in accordance with the medical ethical standards [8]. The PSG was scored manually according to standard criteria [9, 10] by two experts with extended experience of interpreting sleep data and rated for OSA. A total of 3000 episodes were used in the experiment.

2.2. Bispectral Analysis

Bispectral analysis is a statistical process that measures the degree of phase coupling present in a time domain signal [3, 11]. The Fourier transform of the second-order cumulant, i.e., the autocorrelation function, is the traditional power spectrum. The Fourier transform of third-order cumulant-generating function is called the bispectrum or bispectral density. Applying the convolution theorem allows fast calculation of the bispectrum. They fall in the category of higher-order spectra (HOS), or polyspectra and provide supplementary information to the power spectrum. One of the disadvantages of using power spectrum is that it suppresses phase information in the signal. A third order spectrum or bispectrum preserves phase information.

Bispectral analysis has found success in the area of identifying phase relationship of signals between different frequency bands [12]. In contrast to power spectrum estimation, bispectrum estimation reveals the non-Gaussian and nonlinear information. This allows the detection and characterization of nonlinear mechanisms, the brain activity in this study, which produces time series through phase relations of their harmonic components.

Let x(k) be discrete, strictly stationary, zero-mean random process, and its third-order cumulant sequence $C_{3x}(n_1, n_2)$ will be identical to its third-moment sequence given by [12],

$$\begin{aligned} C_{3x}(n_1,n_2) &= cum\left\{x(k)x(k+n_1)x(k+n_2)\right\} \\ &= \left\langle x(k)x(k+n_1)x(k+n_2)\right\rangle \\ &\quad -\left\langle x(k)\right\rangle\left\{\left\langle x(k)x(k+n_1)\right\rangle+\left\langle x(k)x(k+n_2)\right\rangle+\left\langle x(k+n_1)x(k+n_2)\right\rangle\right\} \\ &\quad +2\left\langle x(k)\right\rangle^3 \end{aligned} \tag{1}$$

where $\langle . \rangle$ denotes the expectation operation.

Defining the *r*th order moment of function x(k) as,

$$m_{rx}(n_1,n_2,...n_{r-1}) = \left\langle x(k)x(k+n_1)...x(k+n_{r-1})\right\rangle \tag{2}$$

Then we can write Eqn.(1) as,

$$C_{3x}(n_1,n_2) = m_{3x}(n_1,n_2) - \left(m_x(m_{2x}(n_1)+m_{2x}(n_2)+m_{2x}(n_2-n_1)) - 2m_x^3\right) \tag{3}$$

Additionally, the third order cumulant can alternatively be written as,

$$C_{3x}(n_1,n_2) = m_{3x}(n_1,n_2) - m_{3x}^G(n_1,n_2) \tag{4}$$

Where $m_{3x}(n_1,n_2)$ is the third order moment function of x(k) and $m_{3x}^G(n_1,n_2)$ is the third order moment function of a Gaussian rondom process with the same first and second order characteristics of x(k).

$$m_{3x}^G(n_1,n_2) = m_x(m_{2x}(n_1)+m_{2x}(n_2)+m_{2x}(n_2-n_1)) - 2m_x^3 \tag{5}$$

An important result of Eqn.(4) is that for a Gaussian process, x(k), the third order cumulant is zero [12, 13].

$$\begin{aligned} &m_{3x}(n_1,n_2) = m_{3x}^G(n_1,n_2), \text{ then} \\ &C_{3x}(n_1,n_2) = 0 \end{aligned} \tag{6}$$

In addition, we note that for zero mean process, the third order cumulant and the third order moment operation are equivalent, thus Eqn.(4) simplifies to,

$$C_{3x}(n_1,n_2) = m_{3x}(n_1,n_2) \tag{7}$$

Wheras the autocorrelation examines the relationship between two points, the third order cumulant examines the relationship between combinations of three points within a time series. The third order cumulant have the following symmetry properties:

$$C_{3x}(n_1,n_2) = C_{3x}(n_2,n_1) = C_{3x}(-n_1,n_2-n_1) = C_{3x}(n_1-n_2,-n_2) \tag{8}$$

Transforming the third-order cumulant into frequency domain yields the bispectrum,

$$B(\omega_1,\omega_2) = \sum_{n_1=-\infty}^{\infty}\sum_{n_2=-\infty}^{\infty} C_{3x}(n_1,n_2)W(n_1,n_2)e^{-j(\omega_1 n_1+\omega_2 n_2)} \quad |\omega_1|, |\omega_2| \leq \pi \tag{9}$$

Where $W(n_1, n_2)$ represents a two-dimensional window function which is employed to reduce the variance of the bispectrum estimate. Eqn.(9) is equivalently expressed as an average over the Fourier transform $X(\omega)$ of x(k),

$$B(\omega_1,\omega_2) = \left\langle X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)\right\rangle \tag{10}$$

where $B(\omega_1,\omega_2)$ is the bispectrum of x(k). In general $B(\omega_1,\omega_2)$ is complex and a sufficient condition for its existence is that $C_{3x}(n_1,n_2)$ is absolutely summable. Using the properties of $C_{3x}(n_1,n_2)$, the following symmetry properties can be derived for the bispectrum:

$$\begin{aligned} B(\omega_1,\omega_2) &= B(\omega_2,\omega_1) \\ &= B^*(-\omega_2,-\omega_1) \\ &= B(-\omega_1-\omega_2,\omega_2) \\ &= B(\omega_1,-\omega_1-\omega_2) \end{aligned} \tag{11}$$

where * denotes complex conjugate. Also $B(\omega_1,\omega_2)$ is periodic in ω_1 and ω_2 with period 2π. $B(\omega_1,\omega_2)$ is a symmetric function, such that a triangular region $0 \leq \omega_2 \leq \omega_1,\ \omega_1+\omega_2 \leq \pi$ could completely describe the whole bispectrum. A peak observed in the triangular region indicates that the energy component at frequency $\omega_1+\omega_2$ is produced, likely due to the quadratic nonlinearity dependence, called quadratic phase coupling (QPC), at the bifrequency (ω_1,ω_2) [14]. On the contrary, a flat bispectrum at the two frequency components ω_1 and ω_2 suggests no such activities. Consequently, phase coupled components contribute extensively to the third-order cumulant sequence of a process. This unique capability of bispectral analysis becomes a useful tool to detect and quantify the possible existence of QPCs in the ECG signals of OSA patient.

The bispectral analysis was performed based on the direct method that uses Fast Fourier Transform algorithm to reduce the computation time for estimating the bispectrum [15].

There is a main frequency component of signal at frequency (f_1, f_2) where $f_1=f_2$ and there is a phase coupling at frequency (f_1,f_2) where $f_1 \neq f_2$. There are situations in which the interaction between harmonic components causes contribution to the power at their sum (or difference) frequencies. Such a phenomenon which gives rise to certain phase relations of the same type as the frequency relations is called quadratic phase coupling [12].

3. Experimental study

3.1. Bispectral Analysis of ECG Signals

In Figure 1, Figure 2 and Figure 3 for one patient (42-year-old male), it is shown the ECG signal, power spectrum, bispectrum and bispectrum in positive frequency for before, during and after an OSA event respectively. From the figures, it can be seen that the peak of phase coupling exist in frequency ranges of [0 – 50] Hz. However the most dominant peaks observed in [0 – 20] Hz for all choices. A lower phase coupling after an OSA occured for all samples of OSA episodes. This means that after an OSA period the ECG rhythms are more Gaussian and not complexer as compared with ECG signal during or just before OSA episodes. A strong phase coupling present in the signal shows the presence of harmonically related frequency components. Comparing power spectrum to bispectrum in positive frequencies; it can be seen that some peaks present, exist by phase coupling, in the bispectrum while they are not exist in the power spectrum and vice versa.

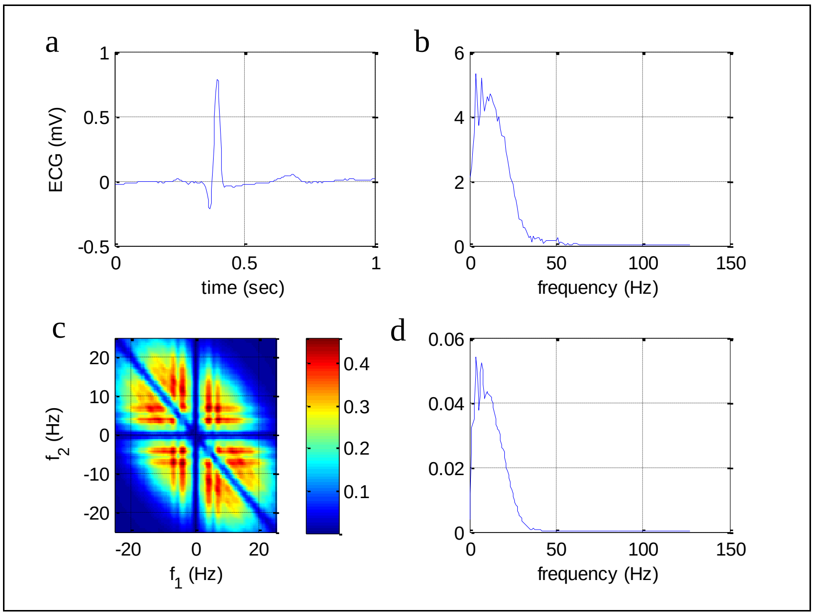

Figure 1. ECG signal before OSA; (a) ECG signal, (b) power spectrum of ECG signal, (c) bispectrum of ECG signal and (d)) bispectrum of ECG signal for positive frequency.

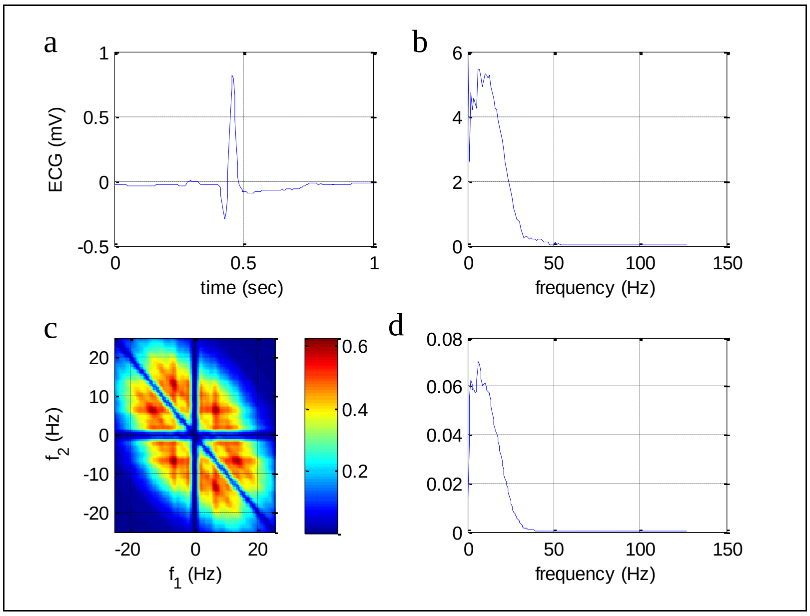

Figure 2. ECG signal during OSA; (a) ECG signal, (b) power spectrum of ECG signal, (c) bispectrum of ECG signal and (d)) bispectrum of ECG signal for positive frequency.

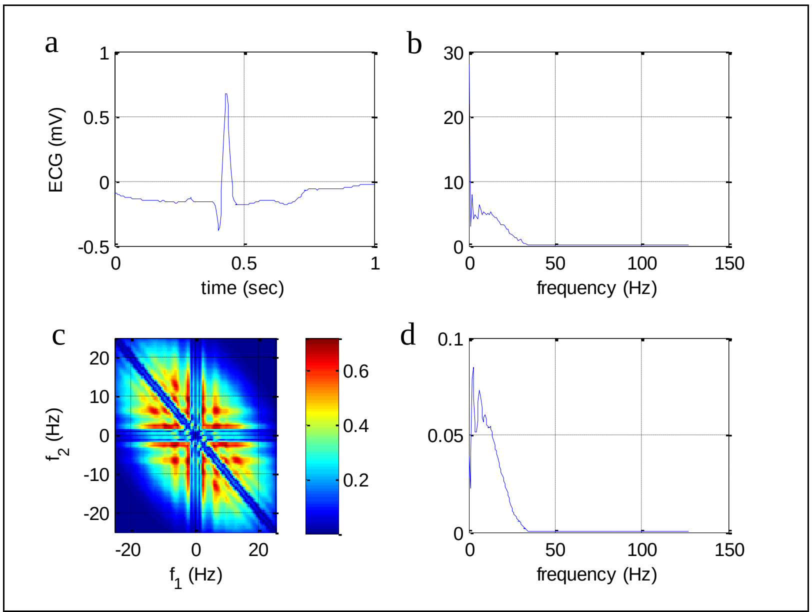

Figure 3. ECG signal after OSA; (a) ECG signal, (b) power spectrum of ECG signal, (c) bispectrum of ECG signal and (d)) bispectrum of ECG signal for positive frequency.

4. Discussion and Conclusion

An ECG signal just after an OSA have lower bispectral peak amplitude than ECG signal during OSA and before OSA. These findings might imply that ECG signal after OSA have lower degree of phase coupling, due to nonlinearities in the signals, than ECG during OSA and before OSA. Relating this to the pathology of OSA, the ECG signal after OSA has generally less different frequency components than the ECG during and before OSA. This means while the patient start to apnea till end of apnea the nonlinearity in the heart dynamics increase.

There is a high phase coupling present in the peaks, which appear in the bispectrum plot. The magnitude of the bispectrum can be used to estimate the amount of phase coupling present in the sample. A strong phase coupling present in the signal shows the presence of harmonically related frequency components.

Bispectral analysis has not been widely applied to ECG analysis because of being technically more difficult than the conventional power spectral analysis to implement. Also the interpretation of bispectrum is quite difficult. Bispectral analysis extracts more information about a time-varying signal than power spectral analysis, thus offering more potential clinical utility.

In the present study the identification of OSA has been exhibited by using bispectral analysis of ECG signals. The results could be useful in detecting OSA events or OSA related arousals to characterize sleep fragmentation from ECG signals.

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