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Detection of delay time between the alterations of cardiac rhythm and periodic breathing

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Abstract

Analysis of time-series multichannel physiological data were performed using wavelets. Wavelet provides a time-scale description and lead us to decompose any signal into frequency bands. A better precision in the frequency domain is often necessary to detect stationary phenomena or characterize time–frequency structures. A natural idea is to combine wavelet analysis with local Fourier analysis using an appropriate strategy: the *wave packets*. In this paper, we apply trigonometric wave packets to determine the time lag between the start of the apneas in the breathing and the consistent disorder in the cardiac rhythm. We show that breathing dynamic drives the evolution of the cardiac rhythm.

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Keywords: Wave packet; Wavelet; Apneas; ECG

1. Introduction

Data set is a multivariable physiological time series, consisting of 4 h and 43 min of simultaneous heart rate, lung volume change, blood oxygen saturation and electroencephalogram (EEG) state. These data set were recored from a 49-year-old male in the Sleep Laboratory of Boston’s Beth Israel Hospital [1]. The patient suffered from extreme daytime drowsiness, as result of sleep apnea. When he starts to fall asleep,

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he stops breathing; his blood-oxygen concentration decreases and carbon dioxide increase. This increase in carbon dioxide in blood results in a reflex arousal, and the patient takes some short, quick breaths and awakes. This process is repeated as a pattern called Cheyne–Stokes breathing [2]. The signals were recorded with a multichannel instrumentation recorder, several channels of which were subsequently played back and digitized at 250 Hz.

A common problem in this kind of analysis is to extract the parameters of interest when these involve joint variations of time and frequency. The most popular way of performing frequency analysis has been the Fourier method, with the fast Fourier transform (FFT) algorithm. However, the FFT method assumes the stationary of the signal, and is insensitive to its varying features. Wavelet transform provides a similar time-scale description and lead us to decompose any signal into *frequency bands* [3]. However, wavelet analysis can be considered as a time-scale method, it gives its best performance when it is applied to detect short time phenomena, discontinuity or abrupt changes in a signal. On the other hand, a better precision in the frequency domain is often necessary to detect stationary phenomena or characterize time–frequency structures. This lack suggest to get some improvements. A natural idea is to combine wavelet analysis with local Fourier analysis using an appropriate strategy: the *wave packets* [4]. We apply *trigonometric wave packets* [5], to determine the time lag between the start of the apneas in the breathing and the consistent disorder in the cardiac rhythm from the time series. Roughly speaking, a wave packet is square integrable function with mean zero, well localized in both position and frequency. It may be assigned three parameters: frequency, scale and position. A family of wavelet packets is a collection of modulated waveforms, which corresponds to a covering the time–frequency domain. These elemental signals are localized with variable precision, and they are organized as a basis of $L^2(\mathbb{R})$. A family of wavelet packets is a collection of elemental signals obtained from appropriate linear combination of wavelets. They look as locally oscillating waveforms resembling modulated sines or cosines. Moreover, they can be organized in orthonormal basis for the space of finite energy signals. The remarkable advantage consists in the fact that using wavelet packets one can extend the standard wavelet analysis, using a flexible strategy. So, the description of the given signal can be well adapted according with the significative structures. Several families of wavelet packets have been proposed in the literature [4]. Here we will apply trigonometric spline wavelet packets, as it is exposed in Ref. [5]. Let us give a brief review of the proposed technique.

2. The wave packets

Denote $s_0(t)$ the finite energy signal to be analyzed. Using spline wavelet analysis, we successively decompose it in the form

$$s_{j+1}(t) = s_j(t) \oplus q_j(t) \tag{1}$$

for each scale $j = 0, -1, \ldots$. The components $s_{j+1}(t)$ and $s_j(t)$ resume the information of the signal corresponding with the frequency bands $|\omega| \leqslant 2^{j+1}\pi$ and $|\omega| \leqslant 2^j\pi$, respectively. That is, the decomposition at level j consists in to filter the component $s_{j+1}(t)$, coming away the details corresponding with the remained frequencies $2^j\pi \leqslant |\omega| \leqslant 2^{j+1}\pi$. The component $q_j(t)$ resume this information. We can describe the signal $s_0(t)$ in term of detail signals as

$$s_0(t) = \sum_{j<0} q_j(t) . \tag{2}$$

On the other hand, the detail component can be described in term of wavelets atoms

$$q_j(t) = 2^{j/2} \sum_k c_{jk}\, \psi(2^j t - k) . \tag{3}$$

Since each wavelet $\psi(2^j t - k)$ is well localized at the interval $2^{-j}k \leqslant t \leqslant 2^{-j}(k+1)$, the corresponding coefficient c_{jk} resumes the local information of the detail. However, as we above referred, these coefficients average all the involved frequencies $2^j\pi \leqslant |\omega| \leqslant 2^{j+1}\pi$. So, we have not explicit information about stationary structures. Now, we are interesting in to improve the frequency precision. The main idea is to decompose the component $q_j(t)$ in portions, each of one covering a longer interval. Then we can implement locally an appropriate frequency technique. Define any portion or local signal as

$$q_{jml}(t) = 2^{j/2} \sum_{k=l}^{l+2^m-1} c_{jk}\, \psi(2^j t - k) , \tag{4}$$

where the parameters m and l are choose, such that $q_{jml}(t)$ covers the full interval $2^{-j}l \leqslant t \leqslant 2^{-j}(l + 2^m)$. Note that this is a relative long interval, of length 2^{m-j}, corresponding with 2^m basic wavelets. Now define the set of *fundamental frequencies*

$$\omega_{mh} = \pi + \frac{2h\pi}{2^m}, \quad 0 \leqslant h \leqslant 2^{m-1} \tag{5}$$

and the associated Fourier matrix

$$M_m = 2^{-m/2} \begin{pmatrix} \sin[\pi(k+1/2)] \\ \cdots \\ 2^{1/2}\cos[\omega_{mh}(k+1/2)] \\ 2^{1/2}\sin[\omega_{mh}(k+1/2)] \\ \cdots \\ \cos[2\pi(k+1/2)] \end{pmatrix}_{0\leqslant k<2^m;\, 0<h<2^{m-1}} . \tag{6}$$

This is a 2^m-dimensional orthogonal matrix. Then, we can define the new set of elemental functions to expand $q_{jml}(t)$ as

$$(\theta_{jmln}(t))_{0\leqslant n<2^m} = 2^{j/2} M_m (\psi(2^j t - k))_{l\leqslant k<l+2^m} . \tag{7}$$

Clearly, these functions constitutes a new local orthonormal basis covering the analysis interval $2^{-j}l \leqslant t \leqslant 2^{-j}(l + 2^m)$. Therefore, we can give a second description for the local signal

$$q_{jml}(t) = \sum_{n=0}^{2^m-1} d_{jmln}\, \theta_{jmln}(t) \; , \tag{8}$$

where the corresponding coefficients are easily computed as

$$(d_{jmln})_{0 \leqslant n < 2^m} = M_m(c_{j(k+l)})_{0 \leqslant k < 2^m} \; . \tag{9}$$

The *trigonometric wavelet packets* $\theta_{jmln}(t)$ have zero mean, oscillate on the interval $2^{-j}l \leqslant t \leqslant 2^{-j}(l + 2^m)$ and decay with exponential ratio. Moreover, their wave-forms resemble modulate sines or cosines. In fact, we can demonstrate that each $\widehat{\theta}_{jmln}(\omega)$ is centered at the fundamental frequency ω_{mh}, when $n = 2h$ or $n = 2h - 1$. Moreover, $\widehat{\theta}_{jmln} = 0$ on the other fundamental frequencies and it has fast decay outside the range $2^j\pi \leqslant |\omega| \leqslant 2^{j+1}\pi$. In other words, the coefficients $\{d_{jmln}\}$ can be considered as the discrete Fourier spectrum for the local signal $q_{jln}(t)$. Summing up, we can resume in the double set of coefficients $\{c_{jk}\}$ and $\{d_{jmln}\}$ the time-scale-frequency information of the local signal $q_{jml}(t)$. Finally, to analyze the complete function $q_j(t)$, that is, the details at level j, we decide some partition in local components $q_{jm_il_i}(t)$, according the structure of the signal

$$q_j(t) = \sum_{m_i} q_{jm_il_i}(t) \; . \tag{10}$$

3. Results and discussion

Before 200 s, the system is in preapnea state. The apnea appear between 200 and 1200 s approximately. After 1200 s the state is intermittent apnea. We transformed the cardiac and chest volume time series to time–frequency domain by means of orthogonal discrete wavelet transform (cubic spline as a mother wavelet), obtaining in this way the wavelet coefficients [6]. Due to the cardiac rhythm at rest state is approximately around 1 Hz, we choose the wavelet level $j = -1$ for wave packet analysis. According with the theory exposed, we divide the corresponding $\Delta f = [0.5, 1]$ Hz interval in nine sections. The two principal frequencies, (in sense that carrier the most energy of this band), corresponding to 0.50 and 0.56 Hz, in both cases. In other words, frequencies greater than 0.6 Hz are negligible. Fig. 1a and b display the data set for the cardiac series and chest volume variation. The appearance of a peak at 200 s in the cardiac amplitude (energy) wave packets (Fig. 1c and e) correspond to the change in the dynamics, because the patient pass from to the preapnea to the apnea state. Note that the chest variance wave packet amplitude does not present this significant amplitude for this time, in spite of the fact that the breath dynamic drives the evolution of the cardiac rhythm. When the system leaves the apnea state, the presence of the principal peaks is in the breathing wave packet (around the 1200 s for 0.5 Hz) (Fig. 1d), and the heart rhythm presents an delay time of this event, around of 35 s (Fig. 1c). For

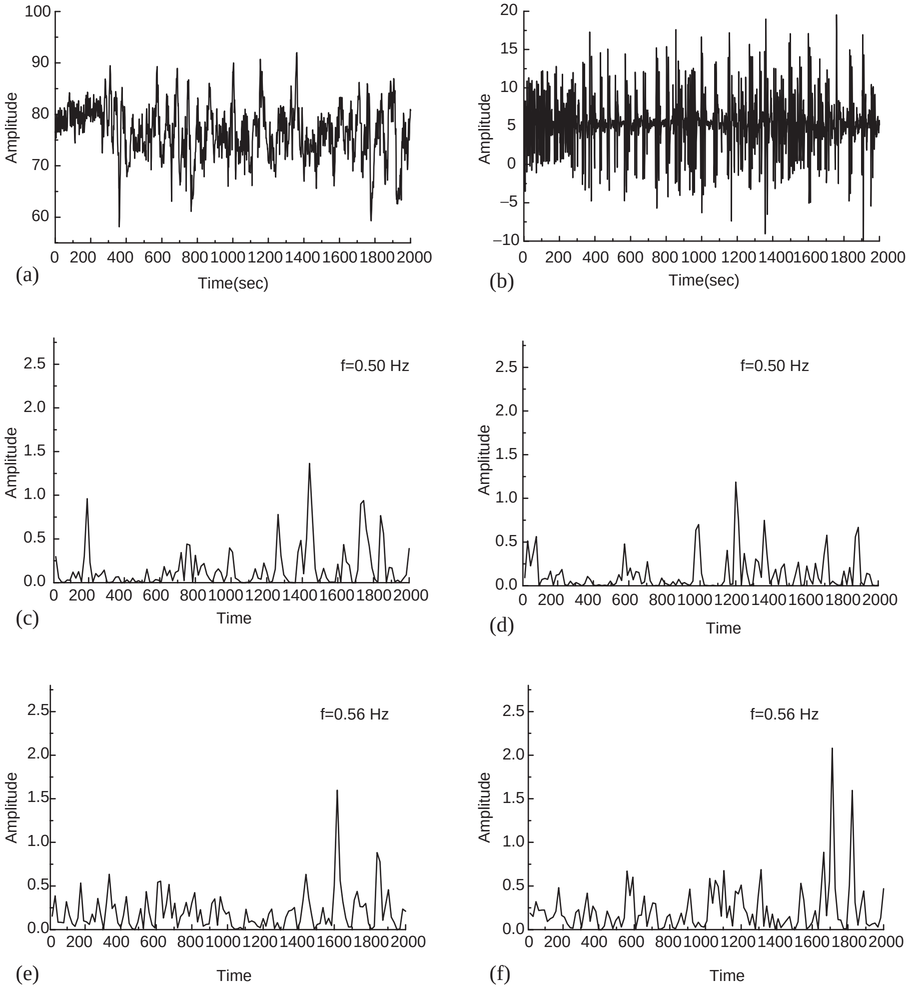

Fig. 1. Cardiac (a) and chest volume (b) time series. Amplitude (energy) wavelet packet center at frequency 0.50 Hz for cardiac (c) and chest volume (d), respectively. Amplitude wavelet packet center at frequency 0.56 Hz for cardiac (e) and chest volume (f), respectively.

the 0.56 Hz frequency, the principal peaks appear around 1700–1900 s (see Fig. 1e) for the chest volume variation packets and for the cardiac packets (see Fig. 1f). This peaks correspond to the intermittent state and are synchronized approximately. Similar results were obtained in other segments of the data series (apneas events).

From the results present in this work, we can conclude that the apnea behavior is triggered by breath dynamics and cardiac rhythm following it. When the normal breath activity is recovered, the cardiac system present a time delay in to achieved the normal behavior. This time delay in the behavior in the coupled dynamic cardiac–respiratory system can be measure by wavelet packets methodology.

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