Pseudo-Period Segment of Ballistocardiogram Based on Joint Time-Frequency Analysis

Jingjing Jin
School of Information Science and Engineering
Northeastern University
Shenyang, China
dovejin@126.com

Xu Wang
School of Information Science and Engineering
Northeastern University
Shenyang, China

Yingnan Wu
School of Mechanic and Electronic
Eastern Liaoning University
Dandong, China

Yanbo Yu
School of Information Science and Engineering
Northeastern University
Shenyang, China

***Abstract*—Heart beat causes the synchronous body vibration, which can be measured on the spine axis by sensitive force sensor called ballistocardiogram. Ballistocardiogram was a kind of non-stationary physiological signal, which couldn't be analyzed and processed by traditional signal processing method. The generation and acquisition method of ballistocardiogram were explained. As examples of bilinear and linear time-frequency distribution, the Cohen class distribution and wavelet transform were discussed and used in ballistocardigram pseudo-period segment. In addition, the frequency range of ballistocardiogram and the levels of wavelet decomposition were determined by Cohen class distribution, but the performance of exponential distribution is better than that of Wigner-Ville distribution and has a fine correspondence to time domain wave of actual ballistocardigram. The experiment results show that, bilinear and linear time-frequency distribution are both able to divide ballistocardiogram into pseudo-periods corresponding to cardiac cycle, but the segment performance of wavelet decomposition is better than that of Cohen class distribution, and the latter one is terser to realize.**

Keywords- heart beat; ballistocardiogram; time-frequency distribution; pseudo-period; segment

I. Introduction

Ballistocardiogram (BCG) is a noninvasive technology to record body synchronous vibration with heat beat. Recently research indicates that, BCG could be a potential technology to diagnose coronary artery disease and assist electrocardiogram (ECG) diagnose to enhance its capability [1]. At present, it mainly uses its time-domain wave or wavelet coefficient of a certain level by wavelet decomposed to analyze BCG [2]. Like other physiology signal, characteristic of BCG changes with time, and shows non-statistical features, so BCG is a kind of non-stationary random signal. Traditional signal analysis method is based on Fourier analysis, which describes frequency component with the whole signal, lacks of local information, and unable to analyze non-stationary random signal like BCG. Joint time-frequency analysis is a two-dimensionally joint expression of local signal by using time and frequency domain information. In this way, the frequency existed in the signal and its variety will be known [3]. In this paper, Cohen class distribution is used to acquire the feature of time and frequency domain of BCG. A proper wavelet base is used to decompose BCG, and the wavelet decomposition level is determined by Cohen class distribution. Both signals gained by two kinds of time-frequency analysis method are segmented to several pseudo-periods, and their effects are also compared.

II. GENERATION AND ACQUISITION OF BCG

Whether blood flows from the heart which mainly jets along up to the artery or returns to heart, major movement is along the axis parallel to the spine. Therefore, the main direction of movement is vertical. According to Newton's third law, the force exerted on blood by heart is equal but opposite to the force exerted on body by blood, that is $\vec{F}_{onblood} = -\vec{F}_{onbody}$. If the subject sat on the chair, when heart pumps the force may cause the body and chair move upward and downward. Sensitive accelerometer is installed under the chair to do measurement, and the acceleration of blood flow may be calculated by equation (1).

$$m_{blood} \cdot \vec{a}_{blood} = -m_{body+chair} \cdot \vec{a}_{body+chair} \tag{1}$$

The result measured by this method is called acceleration BCG [4]. Compared ECG which measures the electrical activity of the heart, BCG measures of movement caused by myocardial contraction, blood ejection and flow. BCG can be is conveniently used to determine the physiology cycle of heart, because no invasion is involved. In addition, it has a practical way to study cardiac blood with clear physiological and pathological meaning. There are three kinds of BCG corresponding to displacement, velocity and acceleration respectively. But BCG generated by displacement is concerned in this paper.

III. JOINT TIME-FREQUENCY ANALYSIS

Joint time-frequency analysis is a method to express and deal with non-stationary signals by using joint function of time and frequency. In order to overcome the overall transformation limitations of traditional Fourier transform, local transformation methods must be used to analysis and process non-stationary signal. That is joint time-frequency analysis method. According to the different time-frequency function, there are two basic types: bilinear and linear time-frequency distribution. Cohen class distribution and wavelet transform are representations of above two types.

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A. Cohen Class Distribution

Cohen found that many bilinear time-frequency distributions are deformations of Wigner-Ville distribution, and can be unified in the same form. In this condition Cohen class time-frequency distribution was proposed. Cohen class distribution of signal $s(t)$ is:

$$C_z(t,\Omega)=\frac{1}{2\pi}\iiint z\left(u+\frac{\tau}{2}\right)z^*\left(u-\frac{\tau}{2}\right)\cdot g(\theta,\tau)e^{-j(\theta t+\Omega\tau-u\theta)}dud\theta d\tau \quad (2)$$

In equation (2), $g(\theta,\tau)$ is kernel, $z(t)$ is the analytic signal of original signal $s(t)$, which can be gained by Hilbert transform. $A_z(\tau,v)=\int_{\infty}^{-\infty}z\left(u+\frac{\tau}{2}\right)z^*\left(u-\frac{\tau}{2}\right)e^{j2\pi tv}dt$ is the ambiguity function. This type of distribution is two-dimensional Fourier transform based on kernel weighted ambiguity function, so Cohen class time-frequency distribution is also called generalized bilinear time-frequency distribution. In equation (2), if $g(\theta,\tau)=1$, Cohen class distribution becomes Wigner-Ville distribution (WVD).

$$W_z(t,\Omega)=\int z\left(t+\frac{\tau}{2}\right)z^*\left(t-\frac{\tau}{2}\right)e^{-j\Omega\tau}d\tau \quad (3)$$

Wigner-Ville distribution has a good characteristic both in time and frequency domain and can be seen as time and frequency domain distribution of signal's energy. But there are always oscillations cross-terms, whose amplitudes are twice higher than that of auto-terms, because cross-weight of each component is different in multi-component signal, based on convolution theorem. The cross-term is mainly suppressed by designing kernel. Choi and Willarms proposed an exponent kernel, as equation (4) shows [5].

$$g(\theta,\tau)=\exp\left(-(\theta\cdot\tau)^2/\sigma\right) \quad (4)$$

The corresponding time-frequency distribution is called exponent distribution (ED) or Choi -Willarms distribution, as equation (5) shows.

$$C_z(t,\Omega)=\iint\sqrt{\frac{\sigma}{4\pi\tau^2}}\exp\left(-\frac{\sigma\cdot(\mu-t)^2}{4\tau^2}\right)\cdot z\left(u+\frac{\tau}{2}\right)z^*\left(u-\frac{\tau}{2}\right)e^{-j\Omega\tau}dud\tau \quad (5)$$

In equation (5), when θ and τ are not zeros at the same time, $g(\theta,\tau)<1$, but $g(0,0)=g(0,\tau)=g(\theta,0)=1$. σ is a constant. The greater value of σ, the faster signal changes in frequency and magnitude, and the higher resolution of auto-term. On the contrary, the smaller value of σ, the greater cross-terms suppress. Commended value of σ is between 0.1 and 10. When $\sigma\to\infty$, $g(\theta,\tau)\to 1$, ED is changed to WVD.

B. Wavelet Transform

Wavelet transform (WT) is also a kind of time-frequency analysis. To signal $s(t)$, there is a basic function $\phi(t)$, whose expansion and translation is recorded as equation (6).

$$\phi_{a,b}(t)=\frac{1}{\sqrt{a}}\phi\left(\frac{t-b}{a}\right) \quad (6)$$

In equation (6), $\phi_{a,b}(t)$ is a series of functions. The inner product of $s(t)$ and $\phi_{a,b}(t)$ is defined as wavelet transform, as equation (7) shows [6].

$$WT_s(a,b)=\int s(t)\phi^*_{a,b}(t)dt=\langle s(t),\phi_{a,b}(t)\rangle \quad (7)$$

If $a>1$, $\phi(t/a)$ presents $\phi(t)$ expanding on the timeline, else if $a<1$, $\phi(t/a)$ presents $\phi(t)$ compressing on the timeline. Smaller a is corresponding to high frequency component of signal. In this condition, time-domain resolution is fine but frequency-domain resolution is neglected. On the other hand, greater a is corresponding to low frequency component of signal. In this condition, frequency-domain resolution is fine but time-domain resolution is neglected. But WT can't describe transient power spectral density of signal. The relationship between WT and WVD is:

$$|WT_s(a,b)|^2=\iint W_s(t,\Omega)W_\phi\left(\frac{t-b}{a},a\Omega\right)dtd\Omega \quad (8)$$

In equation (8), $W_\phi\left(\frac{t-b}{a},a\Omega\right)$ is WVD of $\phi_{a,b}(t)$. WT is closely related to time-frequency analysis.

IV. SEGMENT OF BCG

A. Segment Based on ED

ED may be understood as the energy of signal in the window, which is set by $(t-\Delta t/2,t+\Delta t/2)$ and $(\Omega-\Delta\Omega/2,\Omega+\Delta\Omega/2)$ as equation (9) shows.

$$E_{\Delta t,\Delta\Omega}=\frac{1}{2\pi}\int_{-\Delta t/2}^{+\Delta t/2}\int_{\Omega+\Delta\Omega/2}^{\Omega+\Delta\Omega/2}C_z(t,\Omega)dtd\Omega \quad (9)$$

$E_{\Delta t,\Delta\Omega}$ reflects the energy distribution of signal. However, according to Heisenberg-Gabor uncertainty principle, a single on the $t-\Omega$ plane can't be explained as instantaneous energy of signal. But a lot of experiments show that, time center of the largest amplitude is corresponding to the peak of original BCG in time-domain after ED. According to this characteristic, samples with largest amplitudes of ED are extracted and segmented and the pseudo-periods are also segmented. The algorithm is as follows:

a) Calculate ED of original BCG. To all samples, extract the one has largest amplitudes in a certain time.

b) Do curve fitting for these maxima. Find local maxima of the fitting curve $l\max(n)$, $n=1\cdots N_1$. It is used to retain local maxima caused by BCG and eliminate ones caused by noise.

c) Order local maxima sequence from small to big. Set its threshold for the sequence $threshold(i)$, $i=1\cdots N_1$。

d) Search $l\max(n)$, if $l\max(n)>thshold(i)$, record the position of the point n. The length between two local maxima recorded as a pseudo-period, until all maxima are searched. If the length between the first local maximum and starting point longer than the maximum pseudo-period, it is also recorded as a pseudo-period.

e) Calculate and save the quotient of all pseudo-cycle standard deviation dividing average $q(i)$, $i=1\cdots N_1$.Return to step b), until all thresholds are calculated. Find the threshold T, which make q minimum.

f) Search $l\max(n)$ again, if, i is the maximum of one cardiac cycle, then record it. The central of two nearest maximum point is used as a point to divide BCG into two periods.

B. Segment Based on WT

1) Choice of wavelet base

Wavelet base isn't unique in wavelet transform. Different wavelet bases have different time-frequency characteristics. For some certain signal, analyzed by different wavelet base, the results may be different. But the optimal wavelet base should be the one which can produce the most near-zero wavelet coefficients. The ability of wavelet base is depended on orthogonality, regularity, vanishing moments, size of support and symmetry. Considering above five characteristics of wavelet function, Biorthogonal and Symlet wavelet are suitable to process BCG. However, the symmetry of Biorthogonal wavelet is poor. Symlet wavelet improved in symmetry, but it also lead to phase distortion of decomposition and reconstruction. From the view of scaling function, the scale coefficient reflects the profile information of signal. The shape of scaling functions closer to the shape of signal, it will more benefit to retain the original signal patterns in different scales. So the Sym8 wavelet whose function is symmetry and scale function is close to the signal shape is chosen as wavelet base.

2) Decomposition levels

$s(n), n=1\cdots N$, is a discrete sequence which is sampled from $s(t)$ by sampling frequency f_s. According to sampling theorem, $s(n)$ contains the frequency $[0, f_s/2]$. If decompose $s(n)$ to j level, the frequency of wavelet signal and scale signal are $[0, f_s/2^{j+1}]$ and $[f_s/2^{j+1}, f_s/2^j]$ respectively. Due to the restrictions of the signal length, the largest decomposition scale can't exceed $\log_2 N$. Considering above two reasons, the BCG whose frequency is about f_b, can be gained at j level:

$$j = \min\left\{\left\lfloor \log_2 \frac{f_s}{f_b} - 1 \right\rfloor, \lfloor \log_2 N \rfloor\right\} \tag{10}$$

In equation (10), $\lfloor \bullet \rfloor$ means down integral.Actual sampling frequency is 500Hz. The frequency of BCG is around10Hz, which is gained from ED of original signal, as figure3 shows. According to equation (10), the sixth level of wavelet decomposition is the actual BCG. The pass-band frequency of each level in wavelet decomposition is shown in table 1.

TABLE1. Each Level Pass-Band Frequency of Wavelet Decomposition

Wavelet Signal of Each Level	*Bandwidth（Hz）*
CD1	250-500
CD2	125-250
CD3	62.5-125
CD4	31.25-62.5
CD5	15.625-31.25
CD6	7.8125-15.625

3) Pseudo-Periods Segment Algorithm

Noise of original BCG mainly involves high-frequency noise arising from acquisition circuit and low-frequency noise arising from as well as man-made unconscious activities such as breathing. These noise isn't included in the 6 scale of wavelet decomposition. So extract the wavelet signal at sixth scale as actual BCG. It has advantage to avoiding the pre-processing, simplifying the calculation and improving the signal processing speed. In addition, the extracted signal doesn't contain pseudo-maximum points and has smooth waveform. The pseudo-period segment algorithm based on wavelet transform is as follows:

a) Choose Sym8 as wavelet base, and decomposition level is 6. Do wavelet decomposition to original BCG.

b) Extract the wavelet signal at the sixth level as actual BCG to be analyzed. $s(n), n=1\cdots N$. N is the signal length.

c) Calculate the local maxima of $s(n)$. $l\max(n), n=1\cdots N_1$.

The fourth and the seventh step of the algorithm is the same as that of algorithm based on ED.

V. RESULTS OF EXPERIMENT AND SIMULATION

The subject sits quietly on a familiar family chair fixed sensitive pressure sensors. Heart beat causes the vibration of human body as well as the chair and generates BCG. The sensor changes the vibration signal into electrical signals which are put into acquisition device. The original BCG is shown in Figure1b. Original BCG involves noise components, and its characteristic points aren't obvious. In order to verify the accuracy of BCG, a synchronous single-channel ECG was collected as a reference, shown in Figure1a. Sampling frequency of both signal are 500Hz. Compared with ECG, in each cardiac cycle, BCG changes with laws and a maximum amplitude point exists in systolic.

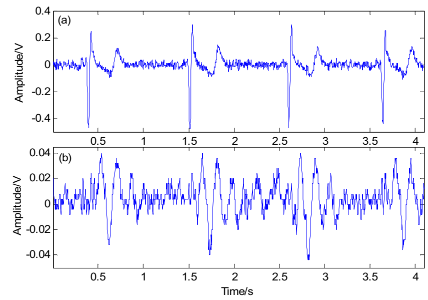

Figure 1. Original BCG and synchronous signal channel ECG.
(a) signal channel ECG;(b) Original BCG

Do WVD and ED for original BCG, and the vertical view are shown in Figure2 and Figure3 respectively. The result of ED is better than that of WVD, because cross-terms are obviously reduced and the amplitude of auto-terms became prominence.

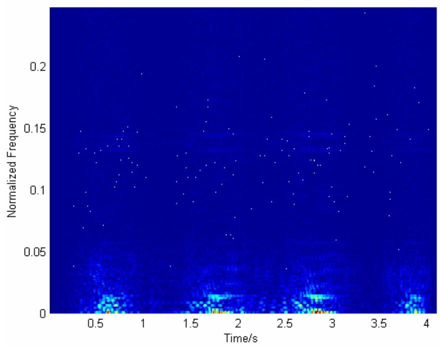

Figure 2. Wigner-Ville distribution of original BCG.

The range of wavelet signals on the sixth scale (CD6) is 7.8125~15.625Hz by sampled at 500Hz, as TABLE 1 shows. It can be concluded that the frequency range of BCG is around 10Hz from Figure3 which shows ED of original BCG [7].

Therefore, CD6 could be extracted directly as actual time-domain BCG. The comparison of actual BCG's time-domain waveform and original BCG's ED, is shown in figure4a and b respectively. Two waveforms have well correspondence at maxima.

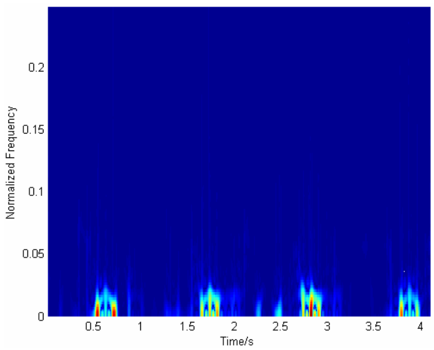

Figure 3. Exponent distribution of original BCG.

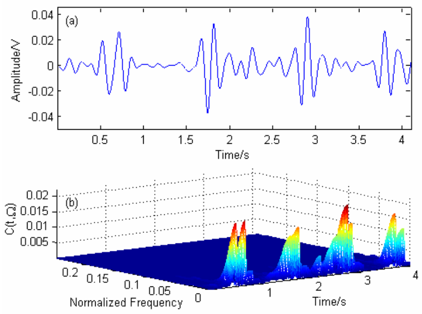

Figure 4. The sixth scale and exponent distribution of original BCG. (a) The sixth scale wavelet signal; (b) exponent distribution.

Figure5a and b shows threshold with red line and maxima with blue cycle of figure4a and b, though the BCG pseudo-period method based on ED and WT respectively. Compared with Figure5a, Figure5b marked minimum of each cardiac cycle, except the second one, in which the blue cycle marked the minimum. The demarcation of pseudo-cycle through ED exist error to a degree. The central point of the nearest two maxima is used to divide cardiac pseudo-period. The four divided pseudo-periods are shown in Figure 6a~d respectively. It can be concluded that, average cardiac cycle of the subject is 1.04s. The result is similar with that of ECG.

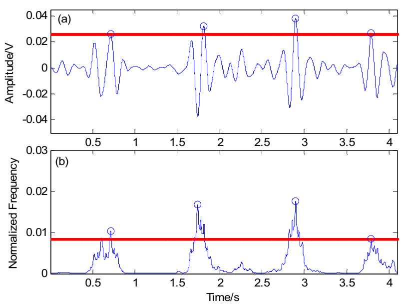

Figure 5. Threshold and maxima of exponent distribution and wavelet transform. (a) Wavelet transform; (b) Exponent distribution

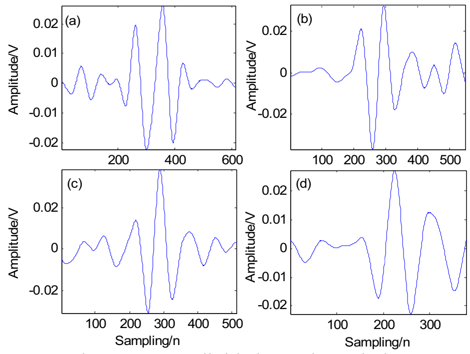

Figure 6. Four divided pseudo-periods.

VI. CONCLUSION

Generation principles and acquisition method of BCG were described in this paper. Bilinear (WVD and ED of Cohen's class distribution) and linear (wavelet transform) time-frequency distribution were discussed, and their relationship was explained. The experiment results showed that, the performance of ED is better than that WVD. In addition, ED of original BCG has well correspondence to time-domain waveform of actual BCG. Furthermore, from its ED, frequency range of BCG, which is around 10Hz and wavelet decomposition level, which is six, were gained. ED and WT were both used to segment BCG to pseudo-periods, and their algorithms were also presented. After comparison, the division results of WT slightly is better than that of ED, but the latter one is terser to realize. The average cardiac cycle of subject is also gained.

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