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A Novel Heart Rate Detection Algorithm in Ballistocardiogram Based on Wavelet Transform

Jingjing Jin, Xu Wang and Shilong Li
School of Information Science & Engineering
Northeastern University
Shenyang, China
e-mail: dovejin@126.com

Yingnan Wu
School of Mechanic & Electronic
Eastern Liaoning University
Dandong, China
e-mail: wyingnan@163.com

***Abstract*—*The heart's mechanical activity while pumping out blood causes the vibration of physical and the object connecting with physical. The vibration is rhythmically with the heart rate and record as ballistocardiogram (BCG) on the spinal axis of the body. It is able to know human's heart rate by measuring the vibration. BCG is weak non-stationary random signal and contains a lot of noise caused by the impact of human and equipment. So heart rate detection from the original acquisition BCG is difficult. Through discrete sequence wavelet transform, BCG is preprocessed by translation invariant method based on adaptive threshold wavelet shrinkage. Choosing proper wavelet base and adaptive threshold function, estimating the noise variance are done at the same time. The characteristics of BCG are retained while eliminating noise. Based on de-noised BCG, the heart rate of subject is detected by using pseudo-period detection method. A single channel ECG is recorded synchronously to test the veracity. The result shows that it is the same as heart rate gained from ECG.*

Keywords-heart rate; ballistocardiogram; wavelet transform; pseudo-period detection

I. INTRODUCTION

Ballistocardiogram (BCG) is a physical vibration signal relative to mechanical activity of the heart. When the heart pumping out blood a certain force exerts to amount of blood, according to Newton's third law, the blood exerts reaction to body and caused physical synchronous vibration with the heart. The vibration corresponds to the heart rate and should be an effective tool to inspect and evaluate the cardiac function. BCG can be measured on the spinal axis of the body by some sensitive force sensor [1]. Such measurement is low-cost and no electrode contacting with body, the heart rate of subject can be gained by measuring the vibration of objects holding up subject without felling. It provides condition to home screening procedure.

The original acquisition BCG contains a lot of noise components caused by the impact of equipment and the human unconscious activities, such as deep breathing, unintentional activities. BCG is weak, low signal-to-noise ratio, non-stationary random signal and contains more singular characteristics. In order to remove noise, while retaining the BCG characteristics and gain heart rate accurately, in this paper, through discrete sequence wavelet transform, translation invariant method based on adaptive threshold wavelet shrinkage is used to preprocess original acquisition BCG. Proper wavelet base and adaptive threshold function choice together with noise variance estimation are also discussed. The heart rate of subjects is extracted from de-noised BCG by using a new pseudo-period detection method.

II. DISCRETE SEQUENCE WAVELET TRANSFORM AND FAST ALGORITHM

$f(t)$ is discretely sampled to N points discrete signal f(n), n=0,1, ⋯ ,N-1.The discrete sequence wavelet transform (DSWT) is:

$$W_f(j,k) = 2^{-\frac{1}{2}} \sum_{n=0}^{N-1} f(n)\varphi\left(2^{-j} n - k\right) \tag{1}$$

In application, equation (1) is too complex to calculate and wavelet function $\Psi(x)$ is usually no explicit expression, so recursive methods of wavelet transform is gained from two-scale equation:

$$S_f(j+1,k) = \sum_m h(m-2k) \cdot S_f(j,k) \tag{2}$$

$$W_f(j+1,k) = \sum_m g(m-2k) \cdot S_f(j,k) \tag{3}$$

In equation (2) and (3), m=0,1,⋯,N-1.

Corresponding reconstruction equation is：

$$S_f(j-1,m) = \sum_k S_f(j,k) \cdot h(m-2k) + \sum_k W_f(j,k) \cdot g(m-2k) \tag{4}$$

In equation (4), $W_f(j,k)$ is wavelet coefficient, simply marked to $\omega_{j,k}$. $S_f(j,k)$ is scale coefficient, and $S_f(0,k)$ is original signal $f(k)$. h and g are low pass filter and high pass filter corresponding scale function $\Phi(x)$ and wavelet function $\Psi(x)$ separately. j is decomposing layer. This algorithm was first brought forward by Mallat, so called Mallat algorithm [2].

III. WAVELET TRANSLATION INVARIANT DENOISING BASED ON ADAPTIVE THRESHOLD

Signal's wavelet coefficient increases but the noise's decreases with the scale increases. According to the characteristics of signal and noise coefficients in every scale,

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signal and noise could be separated. Donoho and Coifman put forward wavelet shrinkage method based on this rule [3]. Choosing proper wavelet base, doing j layers wavelet transform, using per-determined threshold to process wavelet coefficient, reconstructing signal based on processed wavelet coefficient, then de-noised signal is gained. But at discontinuous points of original signal the de-noised signal has Pseudo-Gibbs phenomenon by using this method. Translation invariant is the improvement of wavelet shrinkage method. Because of restraining the Pseudo-Gibbs phenomenon, it is thoroughly studied and widely used [4].

A. Wavelet base choices

In the commonly used wavelet, considering of the orthogonality, vanishing moment and regularity of the wavelet function, Biorthogonal wavelet 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 scale function, the scale coefficient reflects the profile information of signal. If the shape of scaling functions is closer to the shape of signal, it will more benefit to retain the original signal characteristics in different scales. So the Sym8 wavelet whose wavelet function is symmetry and scale function is close to the shape of BCG is chosen to de-noise the original acquisition BCG.

B. Threshold selection and noise variance estimation

Threshold λ plays a decisive role in the de-noising process. If λ is too small, the processed wavelet coefficient will contain excessive noise component, and can't achieve the purpose of de-noising. By contrary, a part of signal components will be removed, resulting in the distortion of reconstructing signal. At present, the threshold selecting methods are fixed threshold, Rigrsure threshold, heuristic threshold and minimax threshold. Donoho presented a typical wavelet threshold selection method [5].

Set the original BCG is x(n), n=1,2,⋯,N. λ is:

$$\lambda = \sigma\sqrt{2\ln N} \tag{5}$$

σ is noise standard variance.

Because noise wavelet coefficient decreases with the increase of the scale, it is unreasonable to handle all scales wavelet coefficients by a threshold with uniform noise variance, as equation (5) shows. Therefore, it is necessary to estimate variances of different scales. Wavelet transform of signal has a higher center frequency in small scales. Especially in the two smaller scales, the signal wavelet coefficients drowned in noise wavelet coefficients. So the original BCG noise variance can be estimated from the two smaller scales [6].

Supposed σ is the standard variance of noise e and σ_j is the noise standard variance of scale j. According to DSWT filter algorithm:

$$\sigma_j = \sigma \cdot \left\| h_0 * h_1 * \cdots * h_{j-2} * g_{j-1} \right\| \tag{6}$$

$\|\bullet\|$ in equation (6) is the energy of limited energy sequence. The noise standard variance at scale j is:

$$\sigma_j = \frac{\sqrt{P\omega_1'/(N-k)} \cdot \left\| h_0 * h_1 * \cdots * h_{j-2} * g_{j-1} \right\|}{\|g_0\|} \tag{7}$$

In equation (7) $P\omega_1 = \sum_n (\omega_{1,k})^2$ is wavelet coefficients energy. The elimination number of large value points caused by acute change of signal is k.

C. Adaptive threshold function

Against the shortage of wavelet shrinkage method based on hard and soft threshold, [7] puts a new adaptive threshold function:

$$\tilde{\omega}_{j,k} = \begin{cases} \operatorname{sgn}(\omega_{j,k}) \left[|\omega_{j,k}| - \dfrac{\lambda_j}{\exp\left[\dfrac{|\omega_{j,k}| - \lambda_j}{N_p} \right]} \right] & |\omega_{j,k}| \geq \lambda_j \\ 0 & |\omega_{j,k}| < \lambda_j \end{cases} \tag{8}$$

In equation (8), N_p called adjustment factor is an arbitrary positive constant. New threshold function has the same continuity as the soft threshold function. The asymptote is $\tilde{\omega}_{j,k} = \omega_{j,k}$. $\tilde{\omega}_{j,k}$ approaches to $\omega_{j,k}$ along with the increase of $\omega_{j,k}$ gradually. When $|\omega_{j,k}| \geq \lambda_j$ the deviation between $\tilde{\omega}_{j,k}$ and $\omega_{j,k}$ isn't a constant, it overcomes the shortage of soft threshold approach. Equation (8) is equal to hard threshold approach when $N_p \to 0$, and equal to soft threshold approach when $N_p \to \infty$ The appropriate value of N_p can be determined by repeating experiment to make the de-noised reconstruction signal smoothness and preserve singular points characteristics at the same time.

D. Algorithm realization

The noisy signal is cycling translated by n times. The translated signal is averaged to avoid the Pseudo-Gibbs phenomenon at the discontinuities points caused by traditional wavelet shrinkage. It is called "translation–de-noising-average", the translation invariant (TI) wavelet de-noising.

Original BCG is $x(n)$, n=1,2, ⋯ ,N, translation cycle operator is S_h, translation range is $H_n = \{h | 0 \leq h < n\}$, and Ave denote average. So TI wavelet de-noising by cycling translated n times is:

$$\overline{T}\left(x, (S_h)_{h \in H_n}\right) = Ave_{h \in H_n} S_{-h}\left(T(S_h x)\right) \tag{9}$$

Translation invariant (TI) wavelet BCG de-noising procedure based on adaptive threshold wavelet shrinkage may therefore be achieved as follows:

(1) Set a translation range $H_n = \{h | 0 \leq h < n\}$ for original BCG $x(n)$, n=1,2,⋯,N and cycling translate $x(n)$ according to H_n.

(2) Do DSWT to the signal before and after translation. In order to ensure the number of decomposition coefficient unchanged, the type of wavelet transform is set to periodization.

(3) Save all the wavelet coefficients to a coefficients table. The low frequency coefficients of each resolution are saved in the first column of table. They aren't be updated until the low frequency coefficients of last decomposition are saved.

(4) Estimate the noise variance according to the wavelet coefficients of the highest resolution. Process every wavelet coefficients at all levels by using new adaptive threshold function based on typical wavelet threshold.

(5) Do IDSWT according to each resolution's wavelet coefficients of the coefficients table. The type is also periodization.

(6) The reconstruction signal is reversely cycling translated and averaged. Low frequency coefficients of each resolution are saved at the first column, until the final reconstruction signal is gained. The result is the de-noised BCG, $y(n)$, $n=1,2,\cdots,N$.

IV. HEART RATE DETECTION ALGORITHM

As Figure 2 shows, BCG changes periodically with cardiac cycle. But it's different from ECG that the period of BCG is not strict, so called pseudo-period. If the pseudo-period of BCG is identified, it is able to detect the heart rate. Reference [8] presents a method to calculate pseudo-period and extract heart rate by calculate the largest swing. This method requires calculating the local minimum and local maximum value of signal and preserving them and their coordinates. In this paper, the method is improved to only calculate and preserve the value and coordinates of local maxima to detect heart rate. The improved heart rate detection algorithm will be realized as follows:

(1) Search de-noised BCG sequence $y(n)$, $n=1,2,\cdots,N$, from left to right, the local maxima are saved as a sequence $l_{max}(n)$, $n=1,2,\cdots,N_1$.

(2) Arrange $l_{max}(n)$ by sort ascending and become the threshold sequence $threshold(i)$, $i=1,2,\cdots,N_1$.

(3) Search $l_{max}(n)$ from left to right, if $l_{max}(n)>threshold(i)$, save the value and coordinates of point n.

(4) In step (3), the interval between approaching two local maxima is recorded as pseudo-period. If the first local maximum's position is bigger than the biggest value of pseudo-periods, it is also recorded as one pseudo-period.

(5) Calculate the quotient of pseudo-period's standard deviation and average, and save as $q(i)$, $i=1,2,\cdots,N_1$.

(6) Return (3) until calculate all threshold. Choose threshold T which makes q least.

(7) Research $y(n)$ again. If $y(n)>T$, mark it with circle and calculate heart rate.

V. EXPERIMENT RESULT

The de-noising effect is shown in Figure 1.The upper is original BCG and its power spectral density (PSD). The lower is de-noised BCG and its PSD. In time domain, the de-noised BCG is smoother than the original BCG. In frequency domain the PSD of the de-noised BCG is smoother than the original BCG at high frequency. Through discrete sequence wavelet transform, adaptive threshold wavelet shrinkage translation invariant method based on typical wavelet threshold gains well effect in preprocessing original acquisition BCG.

Figure 2 shows the detected heart rate on de-noised BCG by using improved heart rate detection algorithm. The subject is a healthy young man. A signal channel ECG is recorded synchronously.

The circle presents the biggest BCG amplitude of one cardiac cycle, called 'J' wave, along with systolic wave [9]. Red line presents the threshold which is chosen automatically by heart rate algorithm. Every interval between two circles determines one cardiac cycle. The sample frequency of BCG and ECG are both 500Hz, so the heart rate of the subject calculated from BCG is 61 times per minute. The result is the same to gain from ECG.

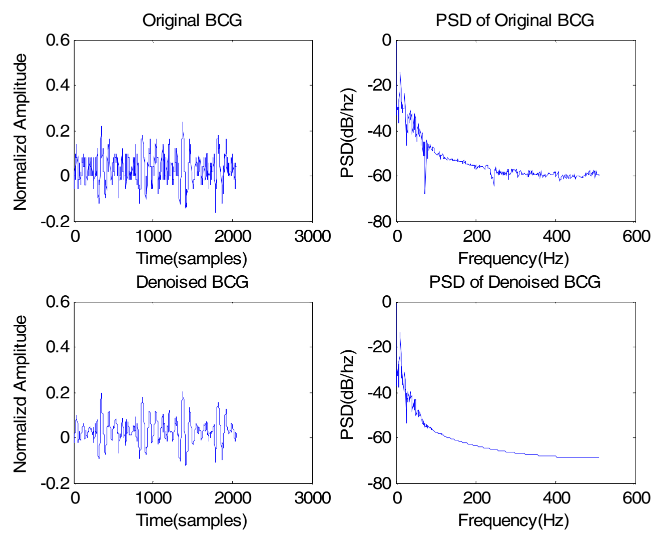

Figure 1. Original and de-noised BCG with their PSD

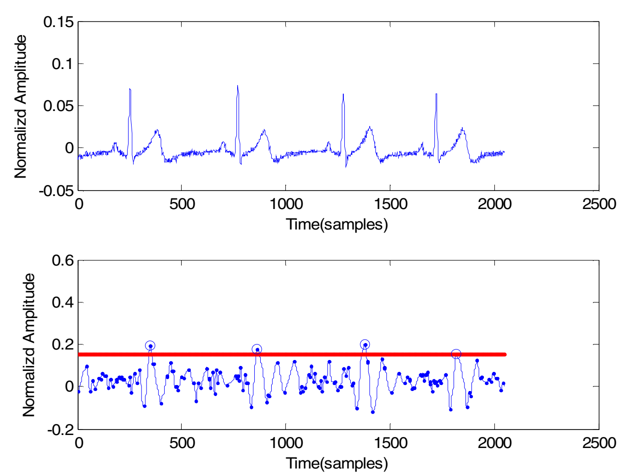

Figure 2. Heart rate detection on de-noised BCG compared with a signal channel ECG

VI. CONCLUSION

Through discrete sequence wavelet transform, this paper applies adaptive threshold wavelet shrinkage translation invariant method based on typical wavelet threshold in preprocessing original acquisition BCG, and this method gains well effect. The improved new pseudo-period is used to detecting the subject's heart rate, and gained the same result compared with a signal channel synchronous ECG.

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