

Automatic Heart Sound Signal Analysis with Reused Multi-Scale Wavelet Transform

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Abstract - The heart sound signal recorded from normal adults usually contains two distinct tones S1 and S2 that occur in each heartbeat. Their respective and relative time latencies are important parameters for the monitoring of cardiac functions, diagnosis, and improved treatment. In this paper, we propose a method to locate S1 and S2 heart sound features effectively using a multi-scale wavelet transform and a threshold decision to increase the precision of the detection process. The effectiveness of the framework to extract the features is evaluated in our experiments on 35 patients presenting various cardiac conditions. The proposed algorithm reaches an accuracy of about 92% on abnormal heart sounds and 100% on control cases with respect to the ground truth established by the clinicians.

Keywords - feature extraction, heart sound, multi-scale wavelet transform, reuse

1. INTRODUCTION

The continuous characterization of the heart function and its change in dynamics is an important clinical problem to detect critical variations and eventually improve the treatment of patients admitted with heart problems. A low-cost, noninvasive alternative to electrocardiography (ECG) is to describe the heart activity using its sound wave, as recorded externally by placing a stethoscope on the chest. Typically, the heart sound is made of two distinct sounds S1 and S2. It has been shown^[1] that for healthy subjects. The amplitude ratio between the first heart sound S1 to the second S2 is commonly used as a quantitative indice of human cardiac function (or malfunction). The ratio of diastolic D (S2-S1 inter-phase) to systolic S (S1-S2 inter-phase) can also be used to detect insufficiency of cardiac blood supply^[1]. The amplitude of S1 is also closely related to the myocardial contractility ability^[1]. In addition, the absolute value of the latency of S1 and S2 are important to determine the heart sound type and detect abnormal heart sounds^[2]. Therefore, the correct analysis of the heart sound signal and the effective extraction of its characteristics are essential to estimate cardiac function.

The normal frequency range of the first heart sound S1 is typically between 20-150Hz, and its latency value is between 0.1-0.16s; while the frequency range of second heart sound S2 is between 50-250Hz, and its latency value is 0.06-0.12s^[3]. During the acquisition process, the heart sound signal is inevitably mixed with noise and various artifacts due to the respiratory movements of the patient, for example. In order to extract features from the heart sound effectively, the noise has to be removed firstly. To do so, low-frequency noises caused by breathing, movements and environmental factors are first eliminated. Then, the process has to separate the high-frequency noises (e.g.: in the form of heart murmurs) which can interfere with the further envelopment analysis of the signal. Several techniques have been used and developed recently for the automatic analysis of heart sound signals. The most representative methods are Hilbert-Huang transform(HHT)^[4-6], wavelet

transform^[7,8], average Shannon energy^[9], time-frequency analysis methods such as short-time Fourier transform and matching tracking method^[10-12], and methods based on neural networks^[13]. HHT is effective in extracting the envelope of narrowband carrier signal but it performs poorly on heart sound signal because the extraction of the high-order harmonic interferes with the determination of heart sound signal envelope. By highlighting intermediate signal intensity and weakening low and high signal intensity, Shannon energy transform can detect intermediate and high signal intensity in advance, and make heart sounds envelope quite smooth, but it is easily affected by murmurs. Short-time Fourier transform has a simple principle and fast computing speed, but its results depend on the window function. To get a better envelope, it may require different window functions for different signals, which may be difficult in practice. Wavelet transform is featured by a good time-frequency localization characteristic and multi-resolution characteristic. It takes advantage of decomposition and reconstruction of multi-resolution wavelet and can effectively extract the information hidden in S1 and S2 spectrums by choosing appropriate sub-bands for reconstruction. By taking advantage of this characteristic, this paper introduces a reused multi-scale wavelet transform and thresholding decision algorithm for heart sound signal feature extraction. The proposed approach extracts heart sound signal time door, detects the accurate positioning of S1 and S2, and improves the precision of the characteristic parameters calculation which are beneficial for the evaluation of clinical cardiac function.

II . Method

The proposed method is based on reused multi-scale wavelet transform and thresholding decision methods. The algorithm is developed to locate the S1 and S2 components in the heart sound signal accurately to improve the computation precision of feature parameters of heart sound signal. Finally, from the extracted S1 and S2 features it will be possible to assess the cardiac functions of the patient. By reusing multi-scale wavelet transform, not only the noise presents in the heart sound signal can be removed effectively, but the features of time gate can also be highlighted, which could be helpful to extract the features of heart sound signal.

2.1 Wavelet transform

The wavelet transform is a popular technique in pattern recognition that offers the following characteristics: (1) multi-scale; (2) the ability of denoting local signal characteristics in both time domain and frequency domain, while offering a constant quality factor (3). During the wavelet transform, a range of scales can be specified and will influence the results. For example, the use of smaller scales makes the observation range of time axis shorter and provides a high-resolution (i.e. finer observations) thanks to a higher frequency. In contrast, a larger scale makes the observation range longer in the time domain, which is equivalent to obtain a general observation using low-frequency filter^[14].

Formally, the wavelet transform WT of the signal $x(t)$ is defined as:

$$WT_x(\tau, a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \overline{h\left(\frac{t-\tau}{a}\right)} dt = \sqrt{a} \int_{-\infty}^{+\infty} x(at) \overline{h\left(t - \frac{\tau}{a}\right)} dt \quad (1)$$

Where the signal $x(t)$ is analyzed by a mother wavelet function $h(t)$. This function is transformed in the time domain to select the signal parts to be analyzed. The selected signal parts are then extended or shrunk by a scale parameter a , which is similar to the frequency. In WT, the analysis for high frequency components uses a more

responsive time resolution than for low-frequency components. When analyzing the complex non-stationary signal such as biomedical signal, this characteristic is often very useful.^[15]

2.2 Heart sound feature extraction

In this section, the proposed algorithm for the extraction of S1 and S2 features is described as a process that includes preprocessing (1), multi-scale wavelet transform (2), signal reconstruction (3), computation of the time gate signal (4), reused wavelet transform (5), computation of the time gate signal (6) and extraction of the features (7). The main novelty is to reuse the wavelet transform and to exploit a thresholding decision to denoise and extract the feature of the heart sound signal.

(1) Preprocessing

The common sampling frequencies of the heart sound signal are 11,025Hz or 22,050Hz, while the heart sound features S1 and S2 are located between 20-250Hz. To reduce the amount of data in the subsequent signal processing steps of the algorithm and to increase the processing speed, the signal is down-sampled to $x(n)$, where n is the down-sampled points. In this work, the down-sampling frequency f_s is set to 2000Hz.

(2) Multi-scale wavelet transform

The signal $x(n)$ is then processed with a L -layer multi-scale wavelet transform to get the approximated and detailed signal, with a total of $L + 1$ sub-frequency band.

Based on the sampling theorem^[16], the maximum frequency of the heart sound signal can be set to $f_s/2$ on the condition of sampling frequency f_s ,

$$\left[0, \frac{f_s}{2}\right] = \left[0, \frac{f_s}{2^{L+1}}\right] \cup \left[\frac{f_s}{2^{L+1}}, \frac{f_s}{2^L}\right] \cup \dots \cup \left[\frac{f_s}{2^2}, \frac{f_s}{2}\right] \quad (2)$$

Let $x_L^a(n), x_L^d(n), \dots, x_2^d(n), x_1^d(n)$ be the sub-band signals after multi-resolution wavelet decomposition, their relationship with the original signal is written as:

$$x(n) = x_L^a(n) + \sum_{j=1}^L x_j^d(n) \quad (3)$$

where $x_L^a(n)$ represents the approximated signal, and $x_L^d(n), \dots, x_2^d(n), x_1^d(n)$ are the detailed signals after the multi-scale decomposition and L denotes the number of decomposition layers. In this paper, $L=6$.

(3) Heart sound signal reconstruction

The sub-bands $x_6^d(n), x_5^d(n), x_4^d(n), x_3^d(n)$ used to construct heart sounds signal are chosen according to the expected frequency range of the S1 and S2. The frequency range of $x_6^d(n), x_5^d(n), x_4^d(n), x_3^d(n)$ are respectively 15.625-31.25Hz, 31.25-62.5 Hz, 62.5-125Hz and 125-250Hz. The sets cover the frequency components of S1 and S2. The reconstructed heart sounds signal is written $x'(n)$ and defined as:

$$x'(n) = x_6^d(n) + x_5^d(n) + x_4^d(n) + x_3^d(n) \quad (4)$$

The reconstructed heart sound signal contains the information of S1 and S2 frequency bands, and eliminates the unwanted high and low frequency signal components of the original signal.

(4) Compute the time gate signal $e(n)$ of the heart sound signal $x'(n)$

The heart sound signal is then thresholded to obtain the time gate signal $e(n)$ as follows:

$$\text{If } \text{abs}(x'(n)) < \text{Th1}, e(n)=0; \text{ else } e(n)=1, n=1, 2, \dots, N \quad (5)$$

(5) Decompose time gate signal $e(n)$ by reusing the multi-scale wavelet transform

The time gate signal $e(n)$ acquired in step 4 still contains irrelevant high frequency variations. We remove them by reusing the multi-scale wavelet transform using a 6-layers decomposition and use its approximation signal $e_6^a(n)$ in place of $e(n)$.

(6) Compute the time gate signal $e'(n)$ of heart sound signal $x'(n)$

The approximated signal is thresholded to extract the time gate signal $e'(n)$:

$$\text{If } e_6^a(n) < \text{Th2}, e'(n)=0; \text{ else } e'(n)=1, n=1, 2, \dots, N \quad (6)$$

The threshold values Th1 and Th2 were chosen so that they reduce the impact of slight signal fluctuations. In this paper, Th1 value is 0.2 and Th2 is 0.1. But they did not appear to be critical during the extraction process, and we can adjust the values to try to obtain the best analysis results in practice.

(7) Extract heart sound signal features

According to the heart sound signal envelope curve $e'(n)$, we determine the start-stop points of S1 and S2, calculate the latency and amplitude of S1 and S2, and then obtain the durations of S1-S2 interval (systolic S) and S2-S1 interval (diastolic D), as shown in Fig.1. These feature parameters can be used to evaluate the cardiac function.

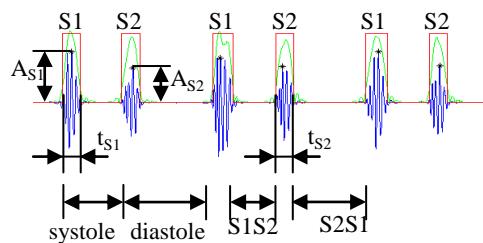


Fig.1 feature parameters of heart sound signal

III. Experiments

The proposed algorithm is evaluated on 15 cases of heart sound signals from clinical monitoring, which were recorded with the exercise heart monitor instrument, the sampling frequency is 11025Hz and a quantitative value of data acquisition is 8 bit. The 15 cases include 10 men and 5 women, their average age is 26 varying from 18 to 32, and they were in normal conditions. Furthermore, 20 additional cases from open heart sounds database^[17] were also analyzed, which includes aortic stenosis, heart sounds split, diastolic aortic backflow, gallop rhythm, and other kinds of abnormal heart sounds data.

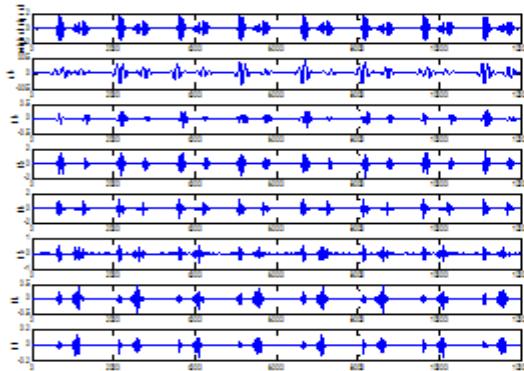


Fig.2 the multi-resolution wavelet decomposition of heart sound signal

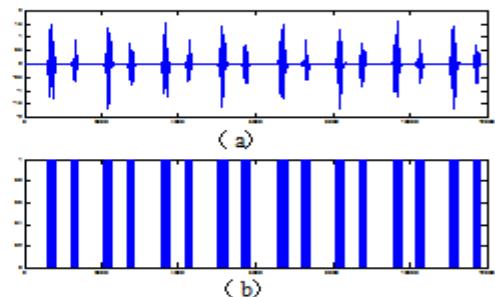


Fig.3 (a) de-noised heart sound signal with multi-resolution wavelet transform ;(b) the time gate signal with the first time threshold value judgment

An example of original signal is shown in Fig.2. The heart sound signal with murmur presents a delayed period of systolic. According to the developed algorithm, the wavelet base "db5" was chosen to make the first time multi-resolution wavelet decomposition. The results are also shown in Fig.2. After selecting the sub-frequency bands d6, d5, d4 and d3 to reconstruct the signal, the result shown in Fig.3 (a) is obtained. It could be seen that the murmur sound has been effectively eliminated by comparing with the original signal in Fig.2.

By applying the step 4 of the algorithm, we could obtain the time gate signal e(n), shown in Fig.3(b). Based on the step 5 of the algorithm, the multi-resolution wavelet transform was reused to decompose the gate signal e(n), shown in Fig.4, and the approximation signal a6 was taken to replace e(n), shown as the red curve in Fig.5(a). By

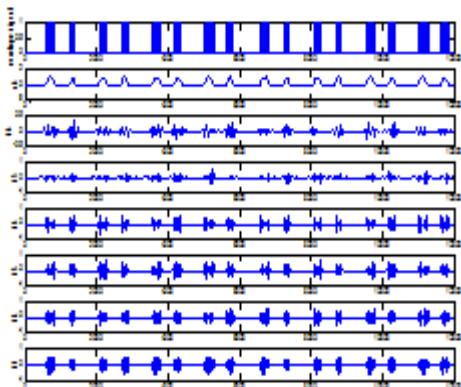


Fig.4 the results by reusing multi-resolution wavelet transform

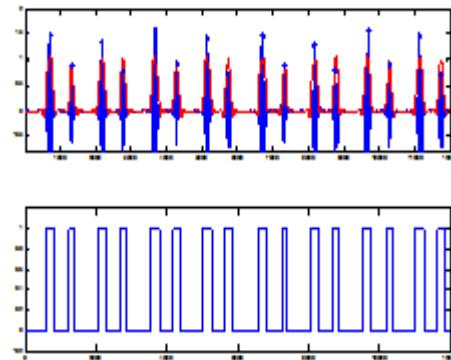


Fig.5 the time gate signal with the second time threshold value

applying the step 6 of the algorithm, the time curve of heart sounds signal was obtained, shown in Fig.5 (b). The start-stop points of S1 and S2 could be determined in an accurate fashion. And thus, the feature parameters of heart sound signals, such as the amplitude, time duration, systolic and diastolic interval, can be effectively extracted. Fig.6 illustrates another example. The data “*diastolic ventricular gallop S3.wav*” originates from the open heart sounds database. We can see from Fig.6 (a), the original heart sound signal has 4.5×10^4 points, after being down-sampled, the points are reduced to 9000 points, which is helpful to subsequent signal processing and analysis. The heart sound signal not only includes S1 and S2, but also includes S3 components. In this example, all of the three components are identified effectively by the proposed method. The original heart sound signal is shown in Fig.6(a), while Fig.6(b) is the down-sampled signal, Fig.6(c) is the reconstructed signal after the first WT, Fig.6(d) is the $e(n)$ signal, Fig.6(e) is the signal $e_6^a(n)$, Fig.6(f) and Fig.6(g) show that S1、S2 and S3 components have been identified effectively.

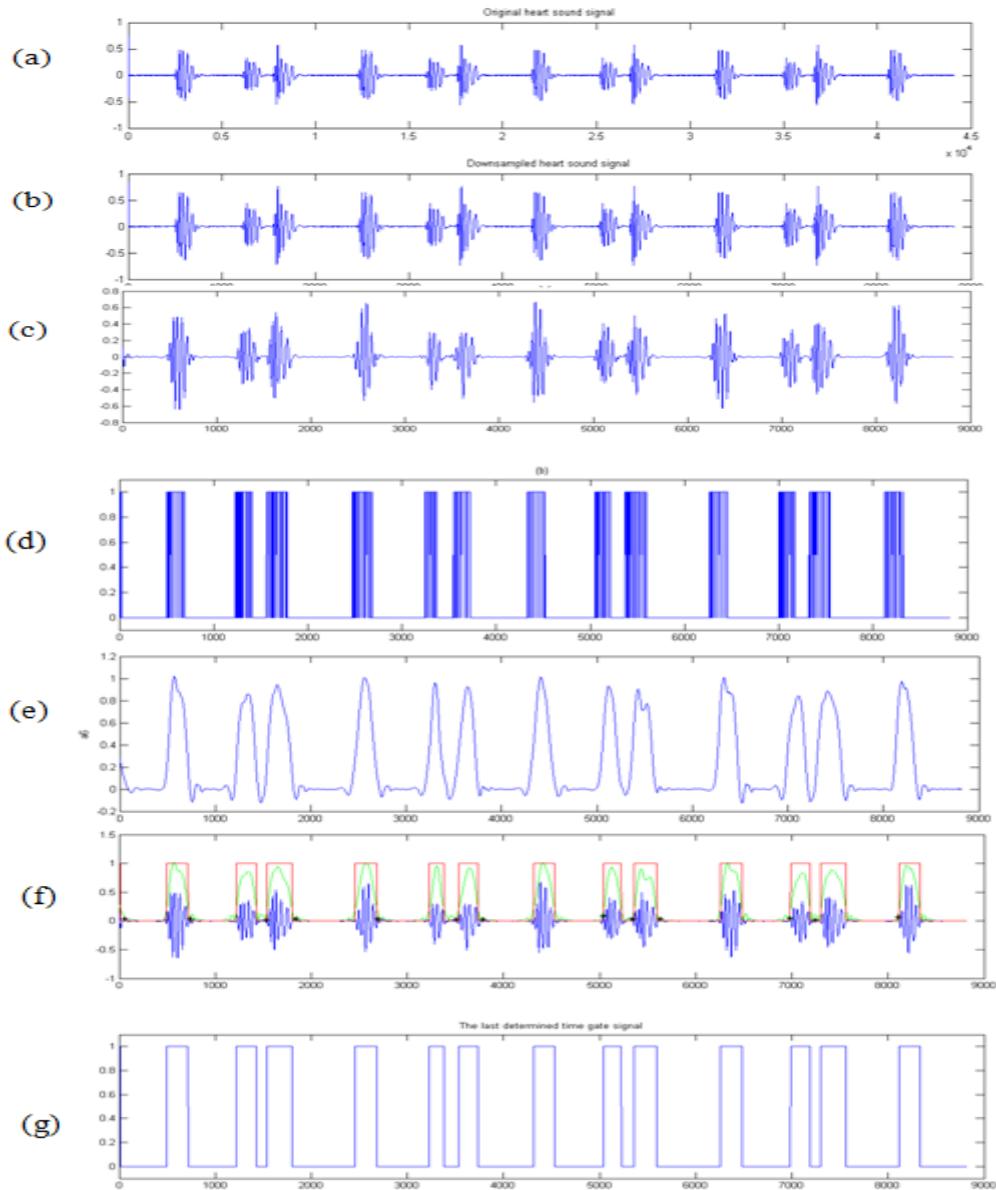


Fig.6 another example for feature extraction of heart sounds with the algorithm

IV. Results And Discussion

Compared with the clinical doctors' diagnosis results, the results of the feature extraction on normal heart sounds reach an accuracy of 100% with the proposed algorithm. The analysis of the abnormal heart sounds shows the correct position of S1 and S2. The algorithm can only identify two divisions in three S2 splits of the original 6s data. The reason is that the transition between the two unidentified S2 divisions is not obvious, and these can be identified by adjusting the threshold value Th2 in step 6 of the algorithm. The algorithm cannot

extract S1 and S2 in "critical systolic aortic stenosis.wav" and "diastolic pericardial friction rub.wav" from the heart sounds open database, due to the continual high intensity murmurs in these two heart sound signals, which filled with the whole heart sound cycles. For the rest of abnormal heart sound data, the analysis shows an extraction rate of 92.31%. The causes of errors are due to the existence of sustained heart murmurs that affected the final identification of S1 and S2. By the way, the threshold values of Th1 and Th2 could be adjusted to get the better analysis results. The limitation of the algorithm is that the threshold values could not be self-adaptive to the characteristic of the analyzed signals.

V. Conclusion

The effective extraction of S1 and S2 is an important problem for the calculation of heart sound characteristics and the application of taking these parameters as cardiac evaluation index. The proposed was evaluated on heart sound data from clinically recorded signals and an open database. Results indicate that with the proposed reusing multi-resolution wavelet transform algorithm, it is possible to locate the start-end points of S1 and S2 more accurately, and the heart sound features could be extracted effectively. Limitation occurs under the circumstances that the murmurs are continuous and severe, which is also an unresolved problem that would require further research.

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