Wavelet Transform And Simplicity Based Heart Murmur Segmentation

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Abstract

This paper is aimed at the identification of the boundaries of murmur present in heart sound. Heart murmurs provide crucial diagnosis information for several heart diseases such as natural or prosthetic valve dysfunction and heart failure. In order to find the valuable information about abnormal heart behavior, segmentation of the heart murmurs has to be performed. In this work we solve this problem using the wavelet decomposition-simplicity filter. In this algorithm, simplicity of the wavelet decomposed heart sound signal is measured and adaptively thresholded in order to discriminate S1/S2 sounds from murmurs. The method has been tested with stenosis and regurgitation (aortic, mitral, pulmonary, tricuspid) heart sounds and 89.10% sensitivity and 95.50 % specificity have been achieved.

1. Introduction

Auscultation of the heart sound is performed namely for the heart valve disorders, heart failure and coronary artery diseases (CAD). This is the preferred method for the detection of heart valve (native or prosthetic) dysfunction; it exhibits 92% sensitivity over echophonocardiography and cinefluroscopy [1]. Usually, auscultation is performed by physicians who only focus on frequency features (such as the pitch) of the heart sound components. Besides these, morphological features, which may provide important indication of crucial heart disorders, may not be noticed by the human ear. A computer assisted automated heart sound analysis tool is required to perform heart sound acquisition as well as comparative study of changing characteristics. In the development process of automatic analysis techniques, it is important to first segment the heart sound into its main components, i.e. S1, S2 and murmur. The most important component in heart valve dysfunction identification is murmur. Therefore, correct boundary identification of murmurs is essential for feature extraction.

Heart murmurs are originated from the turbulent flow of blood in heart vessels. Audible murmurs are usually associated with pathological state. Two types of murmur can be observed during auscultation: pathological and normal. Pathological murmurs are much focus of attention to the cardiologists and researchers. Both murmurs can be further categorized into systolic and diastolic murmurs. Systolic murmurs appear between S1 and S2 sound; they start from the S1 end and terminate at start of the S2 sound. Diastolic murmurs are heard between S2 and S1 sounds. Some systolic murmurs, such as innocent murmur, are normal murmur and are generally found in children whereas diastolic murmur are always pathological. Systolic and diastolic murmur are subcategorised into several categories based on their morphological and frequency nature.

For murmur boundary identification, the boundaries of S1 and S2 heart sounds have to be precisely identified. To solve this problem, two main class of approaches can be found in literature: (i) using ECG as a reference signal and (ii) without ECG. In the first class of approaches, the precise heart murmur boundaries are demarcated using the QRS-complex and T-waves of ECG signals [2]. In the second class of approaches, many signal processing techniques are utilized. For example, auto regressive and auto regressive moving average spectral methods [3], power spectral density [3], wavelet transform [4], trimmed mean spectrogram [5], Wigner-Ville distribution and an ambiguous function [6]. Both classes of methods are involved with either intricate wiring system for the ECG recording or lack of suitable adaptivity for the vast variety of murmurs. In order to the efficient murmur segmentation, an algorithm is required that may independent of ambient or internal body noise.

In this paper, we propose a method for the boundary identification of S1 and S2 and subsequently heart murmur, using a wavelet decomposition and simplicity/complexity based adaptive filter. The heart sound samples are filtered using wavelet transform-simplicity (WT-S) filter for the precise boundary identification of S1 and S2 sound. Consequently, heart murmur between S1-S2 or S2-S1 are assessed.

The paper is structured in three main sections: first section briefly explains the proposed method, in the second section achieved results are addressed, and finally in section 3 some main conclusions are drawn.

2. Methodology

The proposed methodology involves heart sound boundary demarcation using wavelet transform-simplicity (WT-S) filter. Before the description of the applied filter, some mathematical backgrounds of the proposed simplicity measurement technique are summarized in this section.

2.1. Simplicity Measurement

Simplicity is computed by the eigen value spectrum method; being insensitive to additive noise, this technique is found superior over autoregressive and entropy for physiological signals [7]. Let $x(t)$ be the time series representing the heart sound signal, then a new delay vector is formed, $x_i(t) = [x(t), x(t-\tau), ..., x(t-(m-1)\tau))]^T$, where τ is delay and T is transpose. In the application of this method, two integer parameters (m, τ) are important to be suitably chosen. The application of an (m, τ) window to a time series of N data points results in a sequence of $P = N - (m-1)$ vectors. The delay vector $x_i \in \mathbb{R}^m, i = 1, 2, ...P$, is constructed by shifting one sample time increment towards the right in the analysis window. These sequences construct an embedding matrix X,

$$X = \frac{1}{\sqrt{P}} \begin{pmatrix} x_1^T \\ x_2^T \\ . \\ . \\ x_P^T \end{pmatrix}, \tag{1}$$

On suitable selection of (m, τ), the embedding matrix provides information about complexity of the heart sound signal. This is measured by calculating the correlation matrix,

$$C = X^T X, \tag{2}$$

where X^T is the transpose of the embedding matrix X. Let D be diagonal matrix with the eigen values of C correlation matrix sorted in descending order, i.e. $D = diag\{\lambda_1, \lambda_2, ...\lambda_m\}$, where $\lambda_1 \geq \lambda_2 \geq .... \geq \lambda_m$. The diagonal matrix D is defined as singular spectrum of embedding matrix X. The dynamic changes are exhibited in the eigen value spectrum which can be measured by calculating the entropy of the eigen values. Let H be the entropy of the calculated normalized eigen values $\hat{\lambda}_k^i$. The entropy is defined by,

$$H(i) = \sum_{k=1}^{m} \hat{\lambda}_k^i log \hat{\lambda}_k^i, \tag{3}$$

If the base of the logarithm term is taken as 2, then another representation of complexity can be given as,

$$\Omega^i = 2^{H(i)}, \tag{4}$$

Here, the objective is to first emphasize the low complexity (high simplicity) of S1 and S2 heart sound components. For the ease of application, simplicity is calculated in the further processing that is given by following equation,

$$S^i = \frac{1}{\Omega^i}, \tag{5}$$

In this work, the values of parameters m, τ and N are experimentally chosen, and fixed to 10, T_s and 44, respectively.

2.2. Wavelet Transform - Simplicity Filter

The wavelet transform-fractal dimension (a method for complexity/simplicity measurement) based adaptive filter was developed for the enhancement and separation of lung sound (LS) and bowel sound (BS) from background noise [8]. Likewise, in solving the problem of S1 and S2 heart sounds separation from the murmurs, simplicity is derived using aforementioned eigen value spectrum method of wavelet transformed heart sound signal which enhances the distinguishable peaks of S1 and S2 sounds. It has already been mentioned that heart murmurs usually exhibit high frequency content which is more complex compared to S1 and S2 sounds. Therefore, S1 and S2 heart sound peaks can be peeled using an adaptive iteratively threshold.

The WT-S filter encompasses wavelet transform based on multiresolution decomposition to initially decompose heart sound into approximation and detail coefficients. The mother wavelet db6 is chosen from Daubechies wavelet family due to resemblance in shape to S1 and S2 sounds waveforms. Subsequently, simplicity (S) is computed from the decomposed signal, i.e. the approximation coefficients. Heart sound S1 and S2 exhibit high S compared to murmur. The S peaks of S1 and S2 are identified using an iteratively applied threshold, which is found based upon the mean square error. Furthermore, the suitable depth of wavelet decomposition level is also iteratively found using the mean square error criterion. The entire algorithm of decomposing heart sound followed by S peak threshold identification is described in the following few steps.

Step1: Heart sound is decomposed by wavelet transform using db6 as the mother wavelet. Let MRD^l be the l^{th} level decomposition, where $l = 1....L$, and L is the final depth level used in filtering.

Step2: Simplicity is computed using the eigen value spectrum method described in the previous subsection (see in figure1(b)).

Step3: Peaks in simplicity curve of S1 and S2 sounds are picked using the peak peeling algorithm (PPA) described in [9]. PPA algorithm finds not only peaks of S1 and S2 sounds but also the duration of S1 and S2 sounds. This is accomplished by employing the mean square error criterion as the stopping criterion to iteratively finding threshold (see in figure1(b)).

Step4: Two binary thresholds are constructed and applied to the thresholded simplicity curve ($SSTH^l$) achieved from the previous step (see figure1(c)), first one is STh^l, which separates wavelet coefficients that are related to S1 and S2 sounds, whereas second one, i.e. MTh^l, keeps wavelet coefficients related with murmur sounds (see in figure1(d, e)). These two binary threshold are,

$$STh^l = \begin{cases} 1 & SSTH^l \neq 0 \\ 0 & SSTH^l = 1 \end{cases}, \tag{6}$$

$$MTh^l = 1 - STh^l, \tag{7}$$

These thresholds are multiplied with the wavelet coefficients. The outcomes of these multiplications consist of the WT coefficients that are related to S1 and S2 sound waveform and the WT coefficients that are related to the presence of murmur.

Step5: The wavelet coefficients related to murmur are reconstructed in order to achieve suitable decomposition depth. Let Y_M^l be the multiresolution reconstructed signal with murmurs, then the stopping criterion is found using the mean square error given in equation (8).

$$STC^l = \mid E\{(Y_M^l)^2\} - E\{(Y_M^{l-1})^2\} \mid < \epsilon \tag{8}$$

where $E\{.\}$ represents expected value, and $\epsilon \in (0, 1)$, in this work it is fixed to 0.1. If equation (8) is not satisfied then the algorithm jumps to step1, and is repeated until the stopping criterion is found. The Y_M^1 is initialized with the expected value of the original heart sound signal.

2.3. S1 and S2 Recognition

The murmur part of the heart sound is separated by the above described WT-S filter. The S1 and S2 sounds are recognized based upon a high frequency marker that we have previously introduced in [10]. This marker is physiologically motivated by the accentuated pressure differences found across heart valves, both in native and prosthetic valves, leading to distinct high frequency signatures of the valve closing sounds. From the functionality of heart it is known that S2 sounds are produced with relatively high pressure. Hence, typically S2 sounds are recognized using high frequency marker. Furthermore, all heart cycles are found based on S2 sounds. Subsequently, S1 sounds are classified using the knowledge regarding S1 sound between two S2 sounds, i.e. heart cycle.

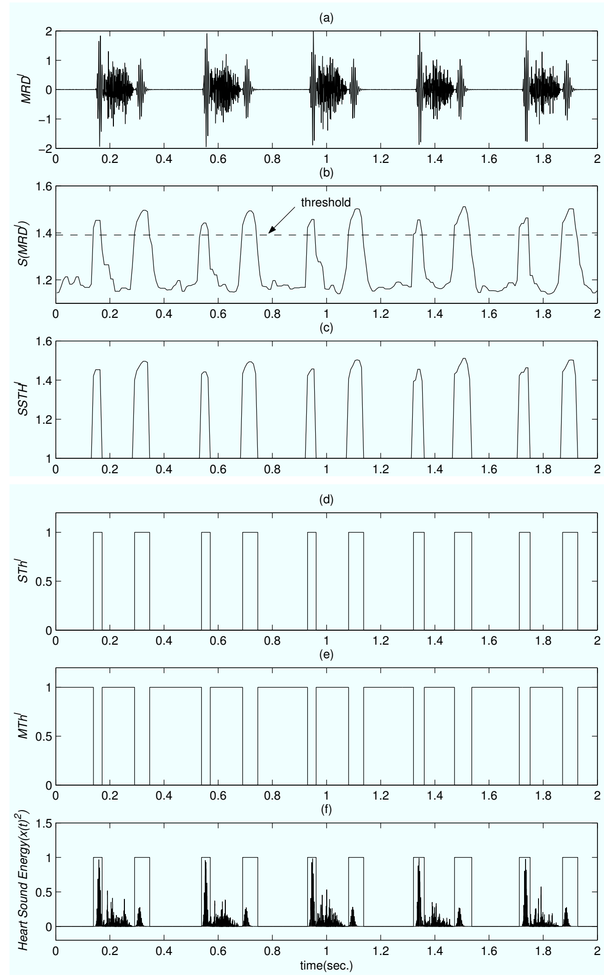

Figure 1. Steps involved in WT-S filter deployed on an aortic stenosis heart sound. (a) Wavelet-decomposition at 4^{th} depth level, (b) Simplicity and iteratively chosen threshold, (c) Thresholded highly simplicity component, (d) Binary thresholded components related to S1 and S2 sounds, (e) Binary thresholded components related to murmur sounds, (f) S1 and S2 sounds are demarcated using *STh*.

3. Experimental Results

The heart sound samples were collected from http://egeneralmedical.com/listohearmur.html. Some heart sounds possessing medium grade murmur were collected from the Cardiothoracic Surgery Center of the University Hospital of Coimbra. During acquisition, patients were asked to maintain silence and to make the least possible physical movements in order to maintain the integrity of heart sound samples. Recording was performed with an electronic stethoscope from Meditron. The stethoscope has an excellent signal to noise ratio and extended frequency range (20 - 20,000 Hz). Although ECG is not considered in the present work, it was also recorded simultaneously to assess the segmentation efficiency of the algorithm. All heart sounds were digitized using a 16-bit ADC at 44.1kHz sampling rate. Sound samples were recorded for the maximum duration of one minute.

Table 1. Some results of murmur boundary identification.

Murmur Type	Detected	Not-detected	Wrong-detected
Aortic stenosis	87	10	5
Aortic regurgitation	23	5	0
Innocent murmur	5	0	0
Pulmonary stenosis	18	3	0
Tricuspid regurgitation	12	0	0
Mitral stenosis	19	3	2
Mitral regurgitation	24	2	0

The algorithm has been tested on several class of murmurs possessing variable intensity grades (I-VI). Some achieved results are summarized in table1. The method achieved a sensitivity of 89.10% and a specificity of 95.50% for the tested heart sounds.

The performance of the method degrades in severe murmurs. In such situation heart murmurs overlaps S1 and S2 sounds, leading to difficulty in identifying the boundaries of the sounds. Severe mitral and aortic regurgitation are noted to be the worst heart sound samples for the proposed method.

4. Conclusions

This paper introduced a new method for heart sound segmentation that is applicable even in the presence of murmur. Wavelet transform is incorporated for multiresolution representation of heart sound which facilitates in significant discrimination between simpler S1, S2 sounds and more complex murmurs. The threshold for the separation of murmurs and S1, S2 sounds as well as the depth of wavelet decomposition are iteratively chosen using the mean square error as a stopping criterion. The method exhibits adaptability for vast varieties of population, which is one of the most prominent issues in heart sound segmentation.

The pathological murmur recognition in heart sound sample is targeted for future work. The recognition problem can be solved using supervised classification techniques, such as decision tree or support vector machine. In the way to accomplish this task, some discriminative morphology, time and frequency features of murmurs shall be extracted.

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