SEGMENTATION OF HEART SOUNDS USING SIMPLICITY FEATURES AND TIMING INFORMATION

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ABSTRACT

Automatic analysis of heart sounds aid physicians in the diagnosis of abnormal heart valve conditions. Segmentation, i.e. identification of first (S1) and second (S2) heart sounds, is the first step in the automatic analysis. In this work, we have proposed a segmentation method which uses energy-based and simplicity-based features computed from multi-level wavelet decomposition coefficients. This method utilizes timing information of S1 and S2 based on biomedical domain knowledge. Proposed method has been evaluated on several normal and abnormal heart sounds for identification of S1 and S2 and compared with windowed energy-based and simplicity-based approaches individually. The proposed method is an efficient and robust technique for identification and gating of S1 and S2, and yields better results than the above approaches.

Index Terms— Heart sounds, segmentation of phonocardiogram, wavelet transform, simplicity, windowed energy

1. INTRODUCTION

Auscultation, listening to sounds emanating from human organs, is a primary routine for screening and diagnosing many pathological conditions of the heart. Various mechanical events occurring during the functioning of heart produce different heart sounds. There is definite pattern of heart sounds for normal people and any deviation from that pattern clearly states the presence of underlying heart pathology.

A normal heart cycle consists of two major sounds: the first heart sound, S1 and the second heart sound, S2. Murmurs on the other hand are noise-like events, which can appear between S1 and S2 (known as systole) or between S2 and S1 (known as diastole) representing obviously various different cardiac pathologies. So, the first step in automatic analysis of heart sounds or phonocardiogram (PCG) is to identify S1 and S2 sounds and extract one heart cycle. This is not a trivial problem as heart sounds are normally superimposed by environmental, sensor and other noises.

Many techniques use electrocardiogram (ECG) as a reference for the segmentation of PCG. One of these techniques was proposed by Lehner and Rangayyan [1], in which the beginning of S1 is estimated by the onset of the R wave in the ECG and the beginning of S2 is estimated by using the Dicrotic Notch in the carotid pulse. However, acquiring ECG requires additional hardware, which may not be available. Another disadvantage of using ECG as a reference is that the timing between electrical and mechanical activities in a heart cycle are not constant for all patients because of a variety of pathological conditions [2]. This prompts researchers to investigate segmentation techniques which do not use ECG.

Liang et al [3] have proposed an envelogram based approach for detecting S1 and S2, which is calculated using Shannon energy. They have also presented improvements in their algorithm by using the quantized values of the spectrogram of the PCG. A model-based approach was proposed by Reed et al [4], where the occurrence of S1 and S2 are modeled by a pair of impulses which are convolved with the thoracic transfer function to yield S1 and S2. Gamero and Watrous [5] proposed a probabilistic approach for detecting S1 and S2 by employing Hidden Markov Models (HMM) to model the systole and diastole periods.

Vivek Nigam and Roland Priemer [2] have presented a simplicity-based method for PCG segmentation, which uses inherent complexity of the heart sound components. The advantage of this method is that it is robust to amplitude variations of the PCG due to background noises and various murmurs. Samit Ari et al [6] proposed a method which uses biomedical domain features to detect S1 and S2 from the energies of short time windows. This method reduces the computation complexity and is thus suitable for real-time analysis.

In this paper, we propose a method which combines the advantages of both the above methods, i.e. robustness of simplicity-based approach and biomedical domain features of window-based method. Proposed method uses multi-level wavelet decomposition to decompose heart sounds into approximation and detail components. We compute simplicity features from approximation coefficients obtained from first level decomposition and energy based features are computed for those obtained from second and third level decomposition.

2. PREVIOUS APPROACHES

Before discussing proposed segmentation method, windowed energy-based and simplicity-based approaches are described in this section.

2.1. Windowed Energy-based Approach

This time domain method was proposed in [6], is based on the use of frequency content present in the signal, calculation of energy in time windows and timing relations of signal components. This algorithm exploits various medical domain features e.g. normal split-sound duration, frequency content of S1 and S2 etc. The steps in the algorithm are as follows:

1. **Normalization & Filtering** : The amplitude of the input signal is normalized, then 10^{th} order low pass butterworth filter with 150 Hz cut-off frequency is applied on the normalized signal.

2. **Energy calculation** : A weak dynamic threshold is applied to the filtered signal based on the average amplitude in one heart cycle. The duration of the heart cycle is calculated from heart signal by autocorrelation method. Energy is computed for each non-overlapped segments of 10 ms.

3. **Detection of S1 & S2** : Another threshold is applied on the energy plot to remove low intensity energy peaks. If two peaks are within the duration of 50 ms, the one with low amplitude is removed by hypothesizing this scenario as split sound. Then detection of S1 & S2 are based on two domain features: the duration of diastole is greater than the systole and the systole period generally remains constant as compared to the diastole period.

2.2. Simplicity-based Approach

This approach, proposed in [2], exploits the complexity of various components in the heart sound signal, e.g. S1 and S2 are less complex as compared to murmurs and background noise.

Let $x(t)$ be the N-length time series representing the heart sound signal and a delay vector with window of size m can be formed as,

$$x_i(t) = [x(t), x(t-\tau), \dots, x(t-(m-1)\tau)] \tag{1}$$

where $\tau = 1/$(Sampling Frequency). By shifting one sample time increment towards the right in the analysis window, $P = N-(m-1)$ vectors are created. These vectors construct an embedding matrix $\mathbf{X}$,

$$\mathbf{X} = \frac{1}{\sqrt{P}} \begin{pmatrix} x_1^T \\ x_2^T \\ . \\ . \\ x_P^T \end{pmatrix} \tag{2}$$

The complexity of the embedding matrix is measured by first calculating its correlation matrix given in [7]:

$$\mathbf{C} = \mathbf{X}^T\mathbf{X} \tag{3}$$

Then, an eigen value decomposition of $\mathbf{C}$ is performed and diagonal matrix, $\mathbf{D}$ is formed with descending order of eigen values,

$$\mathbf{D} = diag(\lambda_1, \lambda_2, ..., \lambda_m) \text{ such that } \lambda_1 \geq \lambda_2 \cdots \geq \lambda_m \tag{4}$$

which defines the singular spectrum of the embedding matrix. The singular values are first normalized,

$$\hat{\lambda}_j^i = \frac{\lambda_j^i}{\sum_{k=1}^{m} \lambda_k^i} \tag{5}$$

Then the entropy, H is calculated from the normalized eigen values,

$$H(i) = -\sum_{j=1}^{m} \hat{\lambda}_j^i \log \hat{\lambda}_j^i \tag{6}$$

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

$$\Omega^i = 2^{H(i)} \tag{7}$$

Then the simplicity is defined as the inverse of Eqn. 7. For each window of size N, we get a corresponding value of simplicity. We then move by one sample increment and repeat the above steps. As heart sounds are less complex (and less random) than murmurs and noise, we get relatively high values of simplicity for the heart sounds and these can then be identified and gated. Simplicity of the wavelet decomposed heart sound signal is measured for segmentation in [8]. This method was tested with stenosis and regurgitation heart sounds for murmur boundary identification and obtained high sensitivity and specificity.

3. PROPOSED METHOD FOR SEGMENTATION

The proposed method combines the simplicity and energy-based features for segmentation, which are found to complement each other. The block diagram of this method is shown in Fig. 1.

First, the heart sound signal is normalized against amplitude variations due to age, physiology, etc. Then we applied first level wavelet decomposition on the normalized signal. The Daubechies-6 (db6) wavelet was used because of

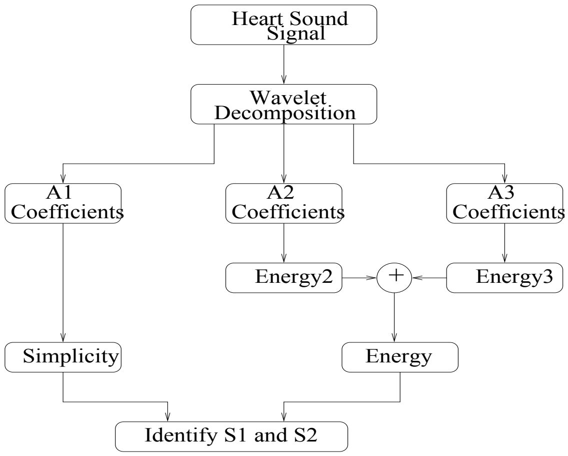


Fig. 1. Block diagram of proposed segmentation algorithm

its similarity to S1 and S2 sounds. Simplicity features were computed from the approximation coefficients obtained from wavelet decomposition. These features were smoothed using a median filter.

Low amplitude regions in the simplicity plot were removed using thresholding. Then peaks are identified using the Peak Pealing Algorithm (PPA) described in [9]. The parameter to the PPA is taken as function of standard deviation of simplicity. The signal is further decomposed to levels 2 and 3 using the same 'db6' wavelet. Then energy is computed from 2nd and 3rd level approximation coefficients only as most of the energy of S1 & S2 lies below 400 Hz.

Identification and gating of S1 and S2
The steps involved are as follows:

1. Combine the two energy plots using weighted mean and normalize the weighted energy. The weight for second level decomposition is high as the energy decreases for higher levels of decomposition.

2. The larger regions which are not broken up by the PPA, are split up into smaller regions, which are treated as gates. Pruning is done in subsequent steps to get correct gates.

3. Now use the energy information to complement the simplicity plot. We give lesser weight to the regions which are still larger than 180 ms. Then, we consider each simplicity gate and increase the amplitudes of the gates having higher energy.

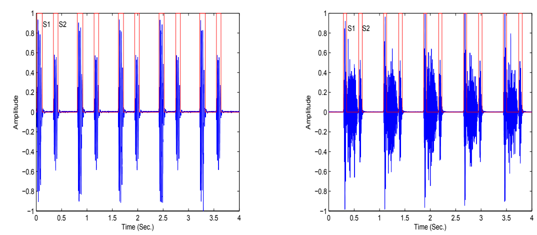
4. Next, the simplicity gates are increased by a factor which is exponential to the mean of the simplicity region in the gate. This helps to apply a hard threshold so that the lower peaks are removed.

5. A threshold is applied on each of the gates, based on the mean value of the gate, and gates having mean value below a certain cut-off are removed.

6. The remaining gates are sorted using the timing information that was used to identify S1 and S2, as in [6]. Actual labeling of S1 and S2 is based purely on the interval durations between consecutive gates.

4. DATABASE AND EXPERIMENTS

We have collected data from various web resources, e.g. eGeneral Medical, Cardiosource, BioSignetics, Texas Heart Institute. The data samples from the training CDs also been used for testing segmentation algorithms. Fig. 2(a) shows segmentation of a normal heart sound and gates of S1 & S2. Similarly, segmentation of a very complex abnormal heart sound is shown in Fig. 2(b). Our segmentation algorithm correctly detected S1 & S2 in the presence of systolic murmur (aortic stenosis).



(a) (b)

Fig. 2. Identification and gating of S1 and S2 in (a). normal heart sound, (b). abnormal heart sound (Aortic Stenosis)

Fig. 3 shows the identification of S1 (red 'o') & S2 (green '*') in the case of mitral stenosis using windowed energy-based method, where we can see a few wrong S1 & S2 detections. Also, we got wrong segmentation using simplicity approach as shown in Fig. 4. However, proposed method yields correct identification and gating of S1 & S2, was shown in Fig. 5.

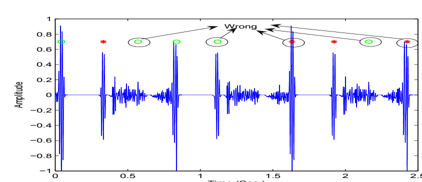


Fig. 3. Identification of S1 ('o') and S2 ('*') using windowed energy-based method

Three methods, namely windowed energy-based, simplicity-based and our proposed technique, were compared for identification of S1 & S2 in various normal and abnormal (stenosis & regurgitation murmur) heart sounds. Table 1 presents

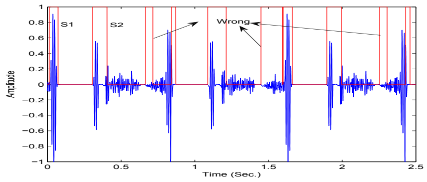


Fig. 4. Identification and gating of S1 and S2 using simplicity-based approach

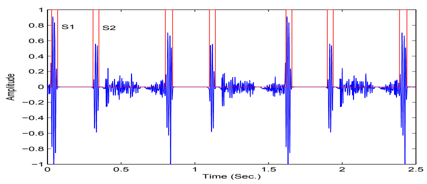


Fig. 5. Identification and gating of S1 and S2 using proposed method

the number of cycles for each pathological condition and the number of cycles where S1 & S2 are detected correctly for the three methods. Proposed method has significantly more number of correct detections of S1 and S2, 140 out of 166 i.e. an accuracy of 84%, compared to 72% and 44% obtained with energy and simplicity based methods respectively.

Heart condition	No. of data samples	Performance of Segmentation (no. of detected)		
		Energy	Simplicity	Proposed
Normal	6	6	6	6
Aortic Stenosis	34	26	17	**34**
Mitral Regurgitation	61	41	27	**53**
Mitral Stenosis	46	31	12	**32**
Pulmonary Stenosis	13	**13**	5	11
Tricuspid Regurgitation	6	2	**6**	4
All conditions	166	119	73	**140**

Table 1. Performance comparison of three segmentation algorithms for S1 & S2 detection in various heart sound signals, highest number of detections are in bold.

5. CONCLUSIONS

We have presented a new segmentation method for identification of first and second heart sounds. This method first decomposes heart sounds using multi-level wavelet decomposition and computes simplicity features from approximation coefficients obtained from first level decomposition. The energy-based features are then computed from the approximation coefficients obtained after second and third level decomposition. These features are complementary to each other and improve the overall performance of the segmentation as seen in the results. Proposed method in addition uses biomedical domain knowledge about duration of S1, S2, systole and diastole.

In the future work, we will investigate probabilistic techniques to combine energy-based features and simplicity values. Also efficient means to incorporate morphological features into segmentation algorithm will be explored.

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