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Segmentation of Heart Sound and Classification of Murmurs Using Empirical Wavelet Transform

Abhina G N[1], Paul Thomas[2]
Department of ECE, MBCET, Thiruvananthapuram, Kerala
Corresponding Author: Abhina G N

Abstract: Phonocardiogram (PCG) are used for the study of heart sound and heart murmur. Heart sounds are consist of prominent systole (s1) and diastole (s2) and less prominent s3 and s4. Cardiac arrhythmias can be detected and diagnosed using the heart sound and heart murmur information. In this paper, we propose an Empirical Wavelet Transform (EWT) based decomposition of PCG signal and further classification of murmurs. Shannon entropy envelope and instantaneous phase of the signal are calculated for the identification of heart sounds. After identifying s1 and s2, cardiac cycle is calculated and from the cardiac cycle, heart rate is computed. Performance analysis shows that this proposed method achieves sensitivity (Se) of 96%, specificity (Sp) of 94% and overall accuracy of (OA) 95%. Murmurs are classified according to location and time of the occurrence of the heart sound. The PCG signal used in this work are taken from standard database of PhysioNet/CinC Challenge database.

Keywords: Phonocardiogram, heart sound, heart murmur, heart rate.

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I. INTRODUCTION

Phonocardiogram (PCG) is a biological signal related to cardiac sounds originating from the human heart. These biological signals are used to detect the malfunctioning of heart through the cardiac sounds and murmurs extracted from these signals. Segmentation of a PCG signal into individual cardiac cycles is a necessary step before murmur analysis and diagnosis. This is due to the fact that the temporal order of a murmur at intervals is a very important feature for the diagnosis of cardiac health disorders.

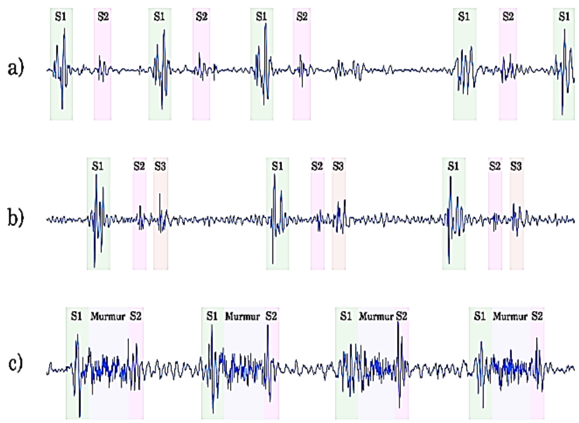

Fig -1: *Sample PCG signal recordings: a) Normal signal b) with third heart sound s3 c) Signal with heart Murmur.*

PCG taken from a healthy adult, there are mainly two sounds are present, S1 called systole (lub sound) with low pitch and S2 called diastole (dub sound) with high pitch with time duration of 150 ms and 120 ms respectively. Systole is due to the heart muscle contraction, while diastole is due to the heart muscle relaxation. But in children and individuals with thin thoraxic walls there is extra two sound- S3 and S4 with very low frequency.

Heart murmurs are sound produced by heart during the blood flow between heart chambers, which are loud enough to produce noise. Aortic stenosis and aortic regurgitation are the main reason behind the abnormal heart murmurs. The heart sound murmurs can be classified by the occurrence of their timing, i.e., as systolic murmur, diastolic murmur and continuous murmur. This classification is based on the occurrence of murmur that is heard in the part of the heartbeat.

II. EXISTING METHODS FOR HEART SOUND SEGMENTATION

PCG signal analysis technique can be broadly split into two classes. First one mainly aimed in the identification of heart events like heart sounds, systole and diastole. And then segment the PCG signal. The other method mainly aimed in finding the presence of heart murmurs and, thereby the cardiac arrhythmias. Both methods are interconnected to each other because both method share common base signal and the same signal processing tools. Existing heart sound segmentation methods can be broadly categorized into four groups [2]: Envelope feature based methods [6], [20], features based methods [4], [5], machine learning methods [9], [10] and HMM based methods [7], [8]. Identification of the locations of s1 and s2 is the important step for finding systolic period and diastolic period. It is essential for murmur classification and heart rate estimation.

The structure of this paper is as follows: Section 3 discuss the methods employed for the segmentation of heart sound, classification of murmurs and heart rate estimation in detail. Section 4 shows the experimental result of proposed technique.

III. PROPOSED METHOD

Figure 2 shows simplified block diagram of segmentation of heart sound and classification of heart murmur technique. This section details various components of the proposed technique.

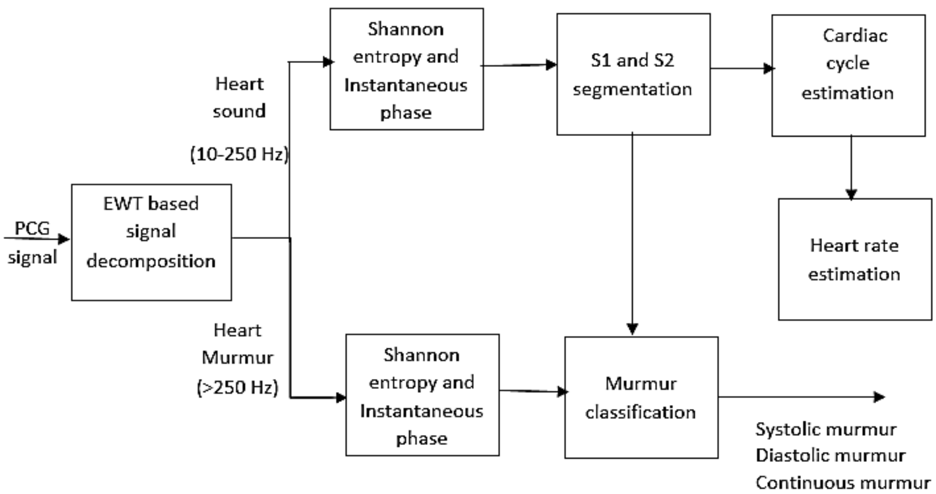

Fig -2: *Block diagram of proposed method*

In addition to s1 and s2, heart produce two more sounds, third (s3) and fourth (s4) heart sound. These are low amplitude sounds. S3 occurs during early diastolic period and normally seen in young people and athletics. But in old people, it may be symptom of congestive heart failure. S4 occurs during before systole and it is an indication of diastolic heart failure or active ischemia. However identification of s1 and s2 is difficult task when the PCG signal contains s3 and s4. By comparing the PCG signal with corresponding ECG signal, we can easily identify the first heart sound (s1), because R peaks of ECG signal corresponds to starting of first heart sound (s1) of PCG signal. In this work, we are not considering the presence of s3 and s4.

3.1 Phonocardiogram Database

Phonocardiogram signal is obtained from ePhysioNet/CinC Challenge database. It includes normal as well as pathological PCG signal. Abnormal PCG signal is obtained from people with heart valve disorders and coronary artery problems. The length of signal varies from 5 sec to 120 sec. So all the signals are time limited to 5 sec for further processing.

3.2 Empirical Wavelet Transform (EWT)

Empirical wavelet transform (EWT) is a new technique which is based on adaptive wavelet decomposition method. It is capable of constructing wavelet functions and scaling functions based on the information content present in the processed signal. This technique does not need any prior information of the signal. The main idea is to extract Amplitude Modulated (AM) –Frequency Modulated (FM) components [3] present in the signal, which having compact support Fourier spectrum. EWT decompose the signal into different

modes. This mode separation is similar to segment the Fourier spectrum and then perform filtering corresponding to each detected support. Low frequency components are captured in first mode, while high frequency components are captured by last modes.
Fourier transform of empirical scaling function is given by,

$$\hat{\Phi}_n(\omega) = \begin{cases} 1 & , |\omega| \le (1-\gamma)\omega_n \\ \cos\left(\frac{\pi}{2}\beta\omega_1\right) & , (1-\gamma)\omega_n \le (1+\gamma)\omega_n \\ 0 & , \text{Otherwise} \end{cases} \tag{1}$$

Where $\omega_1 = \frac{1}{2\gamma\omega_n}\left(|\omega| - (1-\gamma)\omega_n\right)$ and ω_n represents the support boundaries.
Fourier transform of empirical wavelet function is given by,

$$\hat{\psi}_n(\omega) = \begin{cases} 1 & , (1+\gamma)\omega_n \le |\omega| \le (1-\gamma)\omega_n \\ \cos\left(\frac{\pi}{2}\beta\omega_2\right) & , (1-\gamma)\omega_{n+1} \le |\omega| \le (1+\gamma)\omega_{n+1} \\ \sin\left(\frac{\pi}{2}\beta\omega_2\right) & , (1-\gamma)\omega_n \le |\omega| \le (1+\gamma)\omega_n \\ 0 & , \text{Otherwise} \end{cases} \tag{2}$$

Where,

$$\omega_2 = \frac{1}{2\gamma\omega_n}\left(|\omega| - (1-\gamma)\omega_{n+1}\right) \tag{3}$$

And $\beta(x)$ is an arbitrary function such that,

$$\beta(x) = \begin{cases} 0 & , x \le 0 \\ 1 & , x \ge 0 \\ x^4\left(35 - 84x + 70x^2 - 20x^3\right) & , x \in [0,1] \end{cases} \tag{4}$$

And

$$\beta(x) + \beta(1-x) = 1\,;\ \forall\, x \in [0,1] \tag{5}$$

The empirical mode function, f_k is given by,

$$f_0(t) = W^{\varepsilon}_f(0,t) \star \phi_1(t) \tag{6}$$

$$f_k(t) = W^{\varepsilon}_f(k,t) \star \psi_k(t) \tag{7}$$

Where $W^{\varepsilon}_f(k,t)$ and $W^{\varepsilon}_f(0,t)$ are detailed and approximation coefficients respectively and is given by,

$$W^{\varepsilon}_f(k,t) = \langle f, \psi_k \rangle = \int f(\tau)\, \overline{\psi_k(\tau - t)}\, d\tau \tag{8}$$

$$W^{\varepsilon}_f(0,t) = \langle f, \phi_1 \rangle = \int f(\tau)\, \overline{\phi_1(\tau - t)}\, d\tau \tag{9}$$

The algorithm of EWT is given by,

- Take Fourier transform of the signal.
- Find the set $\{\omega_n\}$ by computing the local maxima of signal on $[0, \pi$.
- Segmentation of Fourier spectrum into N segments
- Build the filter bank.
- Filter the signal to get each component.
- Modes are output of filter bank.

Compared to similar decomposition technique such as Empirical Mode Transform (EMD), EWT is robust to estimating the number of modes present when prior information of the signal is not provided. Also EMD exhibits too many modes and is difficult to interpret. EWT works in frequency space and have a strong mathematical background. This method is able to distinguish heart sound and murmurs even in the presence of other background noises. The efficiency of EWT method changes with the number of modes taken, i.e., number of expected filter banks.

3.3 Segmentation of Heart Sound

Segmentation of heart sound refers to identifying the heart sounds (systole and diastole). Also systolic period (time interval between systole and diastole) and diastolic period (time interval between diastole and systole) is measured. To determine these terms, Shannon entropy is used and calculated as follows.

$$s(n) = -\hat{x}_{hs} \log \hat{x}_{hs} \tag{10}$$

Where s(n) denotes Shannon entropy of the heart signal and $\hat{x}_{hs}$ is given by,

$$\hat{x}_{hs} = \begin{cases} |x_{hs}| & ,|x_{hs}| > \eta \\ 0 & ,Otherwise \end{cases} \tag{11}$$

Where, η is the noise level threshold computed as,

$$\eta = \frac{median(\mu)}{0.6745} \tag{12}$$

And μ denotes mean estimate of the heart signal. A zero phase filtering is used as smoothing filter to eliminate the multiple peaks and to obtain smooth candidate envelope.

Instantaneous phase is employed for identifying the starting and ending of the heart sounds. Instantaneous phase is computed as,

$$\phi(n) = \tan^{-1}\left(\frac{\hat{s}(n)}{s(n)}\right) \tag{13}$$

Where ŝ(n) the Hilbert transform of s(n).

3.4 Detection of Heart Murmur and Classification

Heart murmur is classified by timing and location of their occurrence. If murmurs are detected in the systolic cycle, then the murmur is categorized as systolic murmur. Similarly, if the murmur occur at diastolic period, it is classified as diastolic murmur. For that, beginning and ending of each peaks are identified. Then according to their properties, they are segmented as s1 and s2. In this paper segmentation of s1 and s2 are done according to their area, interval and duration. Also from the literature survey, it is clear that duration of diastole (time interval between s2 and s1) is larger than that of systole. Also amplitude of s1 is more than amplitude of s2. The features used for segmentation [1] of s1 and s2 obtained from the heart signal for the segmentation are described below.

- Interval (I): It is the time difference between beginning of $(i+1)^{th}$ segment and i^{th} segment.
- Duration (D): It is the time difference between end point of i^{th} segment and start point of i^{th} segment.
- Area (A): It is the integral of absolute amplitude over the segmented heart sound signal.

Using these features, s1 and s2 are segmented and thereby systolic period and diastolic period are identified. Then comparing with the timing and location of murmur sound, murmurs are classified as systolic murmur, diastolic murmur and continuous murmur.

3.5 Estimation of Heart Rate

Heart rate is estimated by calculating cardiac cycle and it is measured by beats per second (bpm). Cardiac cycle is the total time taken by systolic period and diastolic period. Systolic period is the time difference between adjacent systole (s1) and diastole (s2). Diastolic period is the time difference between adjacent diastole and systole. Heart rate is given by,

$$\text{Heart rate} = \frac{60}{\text{Cardiaccycle}} \tag{14}$$

Heart rate of a normal human ranges from 60-100 bpm

IV. RESULTS

The experiment is conducted using MATLAB tool, version R2018b software simulations. PCG signals are taken from PhysioNet/CinC 2016 Challenge database [12]. This database contains both normal and abnormal PCG signals. For analyzing the performance of the proposed method, 200 PCG signals which are taken from 2016 PhysioNet/CinC challenge database and PASCAL Heart Sounds Challenge database are used. Out of these, 100 signals are normal and 100 signals are abnormal PCG signals containing murmurs. Performance of the method is analyzed by using the parameters Sensitivity(Se), Specificity(Sp) and overall accuracy(OA), which are calculated by,

$$Se = \frac{TP}{TP + FN} \tag{15}$$

$$Sp = \frac{TN}{TN + FP} \tag{16}$$

$$OA = \frac{TP + TN}{TP + FP + TN + TP} \tag{17}$$

Where TP denotes true positive, FP denotes false positive, TN denotes true negative, and FN denotes false negative. The proposed method achieves Sensitivity of 96%, Specificity of 94% and Overall Accuracy of 95%.

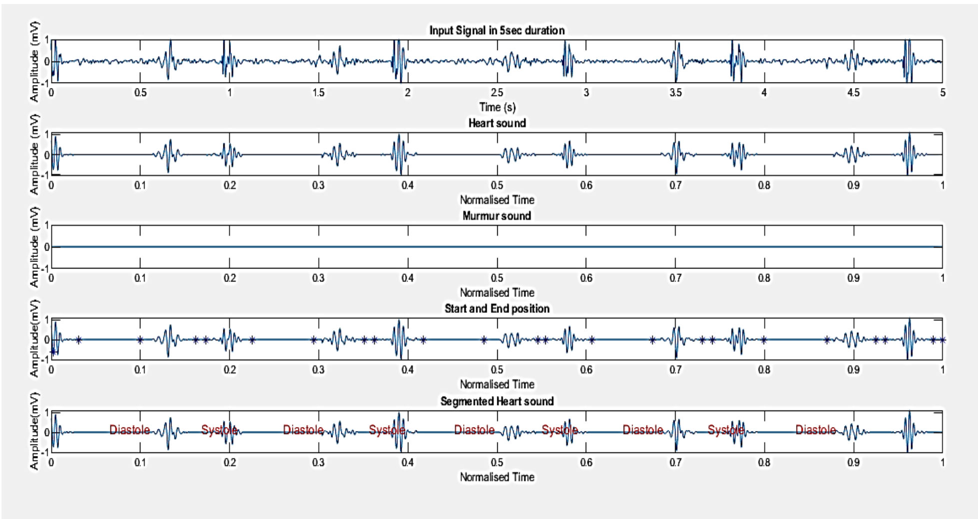

Fig -3 : *Result of normal PCG signal*
Heart rate estimated from figure 3 :- 70 bpm

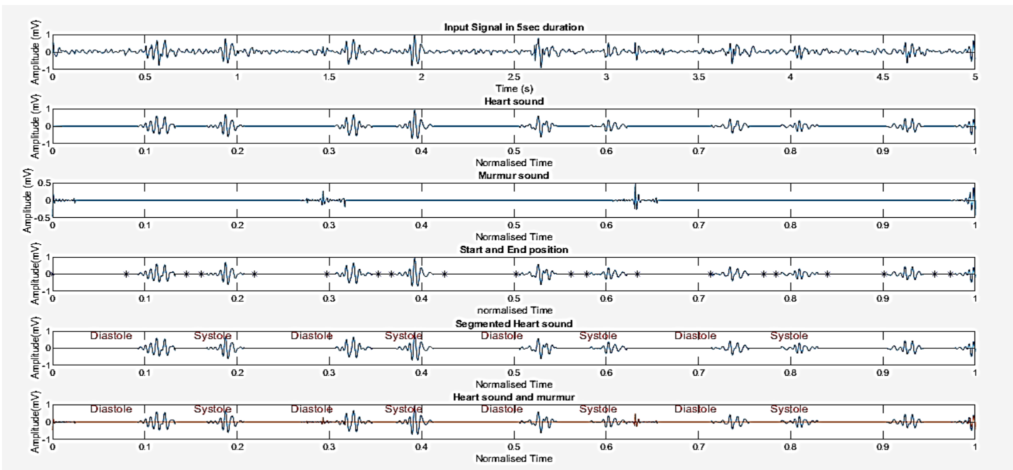

Fig -4 : *Heart sound and murmur of a PCG signal with diastolic murmur*
Heart rate estimated from figure 4 :- 72 bpm

V. CONCLUSION

In this paper, a study on phonocardiogram signal segmentation and classification of murmurs is presented. The proposed method provides proper segmentation of heart sound and classification of murmurs. Empirical Wavelet Transform (EWT) is used to separate heart sound from low frequency noise and high frequency murmurs. For segmenting heart sound from PCG signal, Shannon entropy method is incorporated. Instantaneous phase signal is used for the identification of starting and end points of the heart sound. Using these starting and end points, interval, duration and envelope area is calculated, and systolic period and diastolic period is identified. From that we can calculate the cardiac cycle and thereby the heart rate. Murmurs are then classified according to timing and location of their occurrence.

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