A Novel and Robust Method for Segmenting Heart Sounds by Averaging Neighbors

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Abstract **- A novel method for segmenting heart sounds is proposed. The Algorithm composes of filtering the heart sound signal by Discrete Wavelet Transform(DWT), smoothing by moving average filters, detecting peaks with automatic threshold and Labeling of S1 and S2 sounds. In this study, the signal is normalized and decomposed using 'daubechies-30' wavelet. The algorithm handles High intensity murmurs and high background noise that lacks in Homomorphic Filtering and Shannon energy methods. The proposed method achieved better performances with 95% and 93% segmentation accuracies of S1 and S2.**

Keywords: PCG, Peak detection, Threshold, Segmentation of sounds, DWT.

I. INTRODUCTION

Reliable Authentication and Identification is becoming increasingly important in many fields where information security is facing issues on illegal copying and sharing of digital media. Knowledge-based or possession-based access control methods proved to be immortal. Biometric authentication system offers several advantages over traditional authentication at the time and point of authentication. It is difficult to forge biometric traits and they seem to be powerful. Each trait has its own strength and weakness and the choice depends on the Application.

Cardiac Auscultation uses natural signals called Heart sounds for health monitoring and diagnosis for thousands of years. Heart sounds contain great information to provide unique identity for each person. The heart produces two biological signals, the Electrocardiogram (ECG) and Phonocardiogram (PCG). Like ECG readings, these signals are difficult to disguise and therefore reduces falsification.

Heart sounds are discrete bursts of auditory vibrations of varying Intensity (loudness), frequency (pitch), quality and duration[1]. Two sounds namely S1 and S2 are normally generated as blood flows through the heart valves during each cardiac cycle. The first heart sound is low and associated with the vibrations set up by the sudden closure of the mitral tricuspid valve during the ventricles contract and pump blood with the aorta and pulmonary artery at the start of the ventricular systole[3,4]. The second sound S2 is a shorter high-pitched sound caused when the ventricles stop ejecting, relax and allow the aortic and pulmonary valves close just after the end of the ventricular systole. S1 has duration of about 0.15s and the frequency ranges from 25-45Hz. S2 has duration of about 0.12s and has 50Hz frequency. The signal has to be manipulated so as to

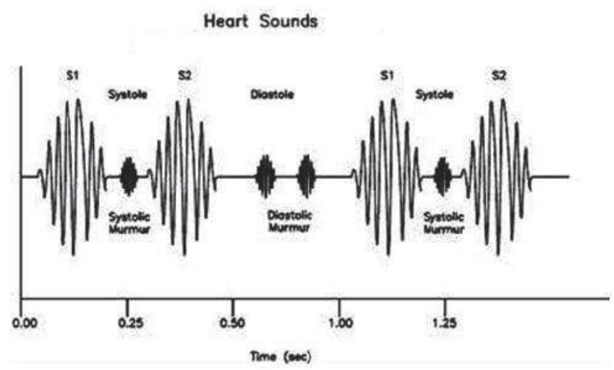

Fig. 1. Time-Frequency representation of Heart Sounds

gain useful features that have to involve for the process of identification.

II. EXISTING SYSTEM

Segmenting Heart sounds is a crucial task in the study of PCG signals for identification and authentication. Heart sound signals are decomposed into wavelet energies and an adaptive threshold is used to discriminate S1/S2 sounds from murmurs. Gupta et.al segmented using Homomorphic filtering and k-means clustering. This technique converts a non-linear combination by applying logarithmic transformation.

Liang et.al segmented heart sounds based on envelograms. Multi band wavelet Shannon energies are used. Olmez et.al segmented using wavelet energies. Bentley used polyfit function to fit that point and its neighborhood with parabola. It focused on the segmentation and classification based on wavelet decomposition combined with spectrogram analysis. When compared to the previous approaches, olmez's approach gave performance with a process time of 0.76s and achieved 91.47% success in segmenting S1 and 88.95% success in segmenting S2.

Segmentation by Homomorphic filtering and Shannon energy methods were slightly affected from noise. The envelope analysis approach needs elimination of the extra peaks while retaining the ones that correspond to the fundamental heart sound.

III. PROPOSED SYSTEM

Our aim is to increase the performance rate in segmenting S1 and S2. The overall authentication needs manipulation of the signal which involves signal capturing, amplification of the signal and remove noise, changing a signal to emphasize certain characteristics, training and Matching and Identity verification. Fig.2 shows the overall authentication process. This study exposes the pre-processing stage of the whole process. Accurate segmentation is needed for further processing.

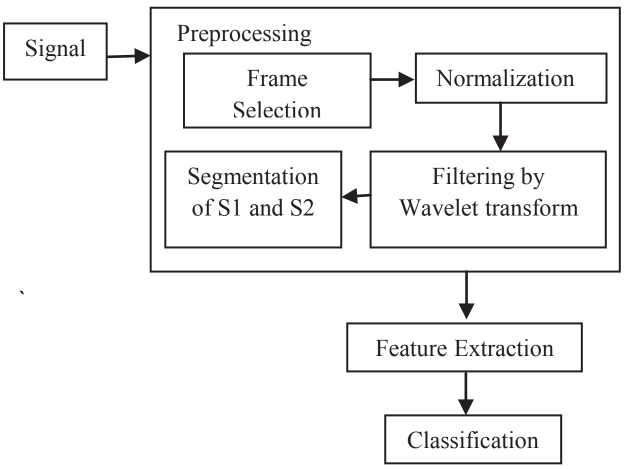

Fig. 2. Cardiac Biometrics Authentication Process

In this system, multi-pass moving average filters smooth the sum of the up-sampled third, fourth and fifth-level wavelet coefficients. A particular time-frequency representation commonly used in heart sound analysis is the discrete wavelet transform (DWT).

DWT based features are easy to implement. Moreover, the coefficients are unaffected by the type of envelope detection method used, since they are calculated directly from heart sound signals. The smoothed output gives an apparent output of the locations of S1 and S2.

The peaks are determined by calculating the average of the distance between its neighbors. The threshold value is automatically calculated. The locations of the heart sounds are computed with time intervals. The aim is to have a pathology-independent recognition system that is capable of separating sounds from murmurs.

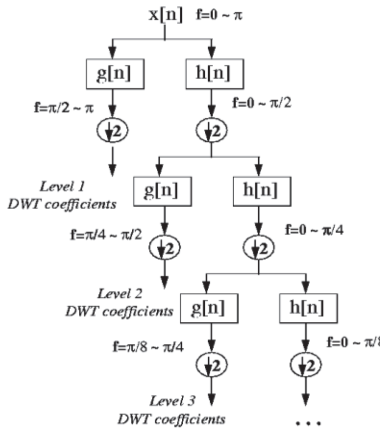

Fig. 3. Discrete Wavelet Transform

A. Windowing

Windowing is decomposing Heart signals into frames of length N ending at time m. For simplicity, Rectangular windowing function was used.

$$W(n) = \begin{cases} 1, & 0 \le n \le N-1 \\ 0, & \text{otherwise} \end{cases}$$

where N is the length of the window in samples. Each frame is chosen such that it has one full cardiac cycle with 20ms of frame length and 5ms of overlapping time.

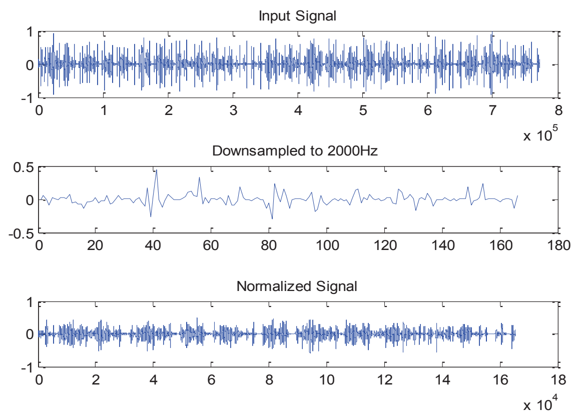

Fig. 4. Normalized Signal

B. Normalization

The windowed samples are normalized to remove offsets. The original signal was down sampled to 2000Hz and normalized by

$$x_{norm} = \frac{x_{2000}(t)}{\max(|x_{2000}(t)|)}$$

where $x_{2000}(t)$ is the value of the down sampled signal at time t. Fig. 4 shows the normalized signal after down sampling by 2000Hz.

C. Wavelet Energies

The DWT analyzes the signal at different frequency bands with different resolution. There are characteristics that define the wavelet Analysis: the irregularity and the asymmetry of the wavelet mother functions, and the variable length of windows to better adapt to the frequency components being analyzed. These characteristics make the wavelet analysis suitable for the surveillance related sound events, which frequently present a short duration and impulsive characteristics [2].

According to Nyquist's rule, the signal can be sub-sampled by two, simply by discarding every other sample as depicited in fig.3. The signal is decomposed by using daubechies 5th order wavelet method. The Daubechies wavelet family is selected because of its orthogonal property, accuracy and computational inexpensiveness. As S1 and S2 fall within the range of frequencies 30-250Hz and considering 2000Hz sampling frequency, fifth decomposition level detail coefficients produce the best output. Studies indicate that segmentation by wavelet energies show higher performance and Accuracy [4].

Heart sound features with the highest frequency are murmurs which are up to 600Hz [5]. So this decomposition, depicted in Table 1, removes high intensity murmurs which HMF algorithms fail to achieve. Table 1 describes the different frequency bands obtained through the transform.

TABLE I

DECOMPOSED LEVELS AND FREQUENCIES

Sub signal	Frequency Bands
1st level, D1	500-1000Hz
2nd level, D2	250-500Hz
3rd level, D3	125-250Hz
4th level, D4	62.5-125Hz
5th level, D5	31.25-61.5Hz
6th level, D6	15.6-31.25Hz

The detailed coefficients of 3, 4 &5th level (D3, D4 & D5) are taken for the amplification of the signal. The outputs are up-sampled and summed for emphasizing the difference between S1 and S2 sounds. Fig. 5 shows the output of the decomposition at level 5 which sums the detail coefficients D3, D4 and D5.

D. Segmentation

Multi-pass Moving Average Filters: *The Actual Heart sound signal still has very complicated patterns with numerous spikes that has little impact on diagnosis but may influence the location of S1 and S2[5].*

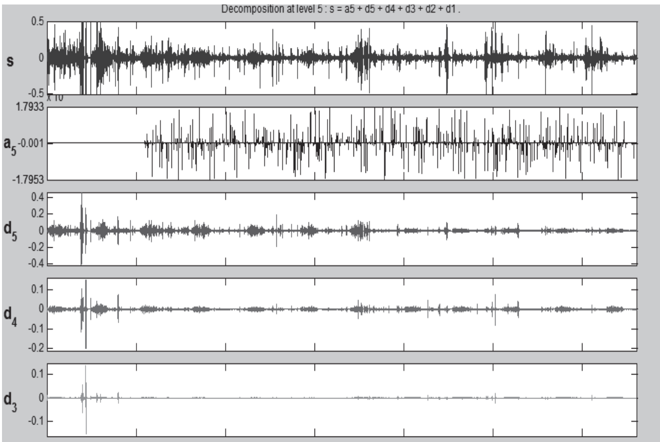

Fig. 5. Matlab Output for the 3rd, 4th and 5th Detailed Coefficients

Hence the signal is smoothed. If both signal and noise are present, these two can be partially separated by looking at the amplitude of each frequency.
One of the difficulties in implementing this and other is that the overlap-add method for filtering signal is not valid. A typical approach is to divide the original time domain signal into overlapping segments. After processing, a smooth window is applied to each of the overlapping segments before they are recombined. This provides a smooth transition of the frequency spectrum from one segment to the next. Moving Average Filters operate by taking the average of the number of points from the Input signal to produce each point in the output signal, given by the equation

$$y[i] = \frac{1}{M}\Sigma\sum_{j=0}^{M-1} x[i+j]$$

where M is the number of points in the average. The highest amplitude can be attributed and the noise can be discarded, it is set to zero. Multi-pass involves passing the input signal through a MAF two or more times. Two passes are equivalent to using a 'triangular' smoothing. This is explicitly good smoothing filters. The biggest difference in this filter when compared to others is execution speed. It is the fastest digital filter available.

2) Peak Detection by Averaging Neighbors: The Peak is the highest point between ‘valleys’. It means that there are lower points around it. Slopes greater than zero amplitude are taken into consideration. Let X=[x1, x2, … xi,… xN] be a given uniformly sampled signal containing periodic peaks, where N is the length of the signal. Let Y=[y1, y2, … yi,… yN] be their corresponding amplitudes. xi be the given ith point in X. The search exists till the length of the signal, from left to right. Let L be the set of k samples of highest amplitude, to the left of the ith point in xi in X. Let R be the set of highest amplitude to the right of the ith point of xi in X. The peak function is defined as the average of the maximum of L and R.

$$F = \frac{\max(L)+\max(R)}{2}$$

A given point xi in X is a peak if a function

F(i, xi) ≥ h,

Where h is a threshold value obtained by Ma, ven, Genderen and Beukelman(2005) [6]. They compute the threshold automatically as

h = (max+ abs_avg)/2+k*abs_dev

If the computed peak function F is greater than or equal to the threshold then it is considered a peak. For this one and a half cycle of heart sound, three peaks are found. Among different values, it is found that k=1, gives the best value.

```
if no. of peaks>1
{
Store peak_dist= current peak position-previous peak
        Position;
}
```

If the peak distance between the 1st and 2nd peak is greater than the time interval between 2nd and 3rd, then the peaks are named as S2-S1-S1 else it is S1-S2-S1, as the distance between a systole and a diastole is shorter than the distance between a diastole and a systole.

IV. EXPERIMENTAL EVALUATION

Heart sounds are recorded with Digital Stethoscope with 16-bit accuracy and a sampling frequency of 2000Hz. A database of 20 PCG sequences comprising of heart sounds of different pathologies from 20 people, both male and female, are taken for the study. Each sound is a .WAV file and is of 70s of length. The proposed algorithm gave higher accuracies of 95% of S1 and 93% of S2 segmentations.

The segmentation accuracies resulted when tested on a subset of Heart sound database. It is the result of the number of sounds segmented without errors to the total number of heart sounds in the database.

Multiple passes will be correspondingly slower, but still very quick. In comparison, Gaussian, triangular filters are excruciatingly slow, because they must use convolution. Not only is the moving average filter very

good for many applications, it is optimal for a common problem, reducing random white noise.

TABLE II

PERFORMANCE OF DIFFERENT METHODS

Method	**Process time**	**Performance**	
		S1	**S2**
Wavelet Energy Method	0.76s	91.47%	88.95%
Wavelet Shannon Energies	0.83s	84.94%	81.19%
Homomorphic Filtering Method	0.37s	85.64%	66.68%
Proposed Method	0.80s	95%	93%

V. CONCLUSION AND FUTURE WORK

In this paper we have explained a preliminary phase on the implementation of the Identification system with biological traits. Information taken from a single cardiac cycle plays an important role. So identifying a single cycle and its characteristics give accurate results for further study. We proposed a method to segment the heart sounds to identify S1 and S2 without the presence of murmurs. In the near future, automated verification system is to be implemented by emphasizing features of the heart sounds.

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