Principal Component Analysis (PCA) Approach to Segment Primary Components from Pathological Phonocardiogram

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***Abstract*— Heart auscultation (interpretation of heart sounds) is the primary tool used in screening patients for heart pathology, and they are usually found in the primary health care. In this paper, a method based on principal component analysis is proposed for segmenting heart sounds. Firstly, the signal is filtered to remove low frequency noises and decimated to consider only the frequencies which are of clinical significance. Then principal component analysis is used to extract the feature set which is envelope extracted using Shannon energy and sub-divided into individual cardiac cycles using variance based algorithm. Finally, the envelope is segmented by using cardiac periods of the signal. Any false segmentation is eliminated according to the subjective knowledge of the heart sounds. Experimental results show that the proposed statistical approach performs well for both normal and pathological heart sounds with segmentation accuracy of 97.7%.**

***Keywords:* Cardiac cycle, heart auscultation, principal component analysis, segmentation, Shannon energy.**

I. INTRODUCTION

Heart sounds (HSs) are generated by the beating heart and the resulting blood flow through it. However, the sounds reflect the turbulence created when the heart valves open and close. Any dysfunction in the valvular heart produces additional sounds called murmurs, along with the first and second heart sounds (S1 and S2) which have their own pattern (structure). Heart sounds have a certain structure while murmurs are more complex and noise has no structure at all [1]. These valvular dysfunctions may be caused due to valvular stenosis or valvular insufficiency (regurgitation). Auscultation of heart sounds is a fundamental tool in cardiac diagnosis. Research has demonstrated poor auscultation skills among health care physicians with correct diagnosis rates as low as 20%. So automatic analysis and diagnosis of HS is required and many researchers are paying more concentration on this field [2].

With the advancement of technologies in signal processing, many new segmentation methods are proposed by the scholars. In order to detect HS, it is necessary to extract appropriate features which depend on timing, morphology and spectral properties [3]. Even though cardiac murmurs are non-stationary and exhibit sudden frequency changes and transients, it is common to assume linearity of the feature sets extracted from the heart sounds [4]. In [5], Simplicity based HS segmentation algorithm is proposed, which gives the basic understanding of the complex nature of the murmur. [6], presents a HS envelogram approach which detects the primary components from murmurs. Time-frequency analysis does not work well in the cases where primary components and murmurs are inseparable, so a hidden Markov model (HMM) based probabilistic approach was proposed in [7] to model the systolic and diastolic intervals, which are used subsequently to detect the presence of S1 and S2. Model-based approach is sensitive in modeling (such as the choice of the wavelet) and model parameter estimation (like determining the parameters of an HMM). So a homomorphic filtering based self-organizing probabilistic model approach was proposed in [8] to identify and detect primary heart sounds.

In this paper, we proposed a robust segmentation algorithm using principal component analysis (PCA) which reduces the computational complexity. In order to extract cardiac cycles, preprocessing is done to remove low frequency noises by filtering (high pass filter) and further it is decimated. The preprocessed signal is wavelet analyzed to obtain a set of featured signals for key cardiac events at the highest temporal resolution. PCA is applied to the wavelet analyzed signal to acquire desired feature set and envelope is extracted to the set using Shannon energy. A variance based algorithm is performed on the PCA analyzed signal to obtain individual cardiac cycles which are used in validating and setting accurate boundaries of S1 and S2. Any false representations are eliminated at the segmentation time using two thresholds. The proposed algorithm promises for segmenting and detecting heart sounds (S1 and S2) accurately.

The rest of the paper is organized as follows. Section II gives details of the acquisition process; section III describes the preprocessing technique; section IV gives the theoretical knowledge of the methods used in this paper and envelope extraction; section V explains the segmentation process in detail and algorithms used followed by experimental results in section VI and conclusion in section VII.

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II. MATERIALS

The records used in this paper are sampled at 22050Hz sampling frequency which includes normal and abnormal records. Acquisition is done in such a way that the HS signal starts either with S1 or S2. The abnormal records consist of different kinds of heart valve diseases like aortic, mitral, tricuspid and pulmonary valve diseases. The records are taken at different auscultation positions and are further normalized.

III. PREPROCESSING TECHNIQUE

During acquisition there is a possibility of noise interference. The noises may be due to respiratory sounds, environmental disturbances, the measuring equipment itself, which are usually with frequency less than 50Hz. So a high pass filter with cut-off frequency of 50Hz is used, which removes all frequencies below the cut-off frequency (see Figure (Fig.1)). The primary components of HS have a frequency range from 50 to 200Hz and the murmurs due valvular diseases have frequency range up to 600Hz [9]. The frequencies more than this are not of clinical significance for analysis and diagnosis; hence the HS signal is decimated without losing any key events. Decimation employs an eighth-order low pass Chebyshev type I filter with cut-off frequency of 0.8*(Fs/2)/r, where Fs is the sampling frequency, r is decimation factor. Here 'r' is chosen to obtain sample rate of 700Hz. It filters the HS in both forward and reverse directions to remove all phase distortions.

IV. EXTRACTION OF HS ENVELOPE

i) Basic theory of wavelet analysis and PCA:

Wavelet analysis (WA) has become one of the useful tools for various signal processing applications because of its virtuous time-frequency resolution. Wavelets are capable of handling rapidly changing transient signals because of their scaling and translation property [5]. Wavelet transform can formally be written as:

$$\Psi(\tau, s) = \int x(t)\psi^*_{s,\tau}(t)\,dt, \qquad (1)$$

where $\psi^*_{s,\tau}(t)$ is the complex conjugate of $\psi_{s,\tau}(t)$, which is a wavelet function, s is scale parameter and τ is translation parameter. The wavelets are generated from mother wavelet $\psi(t)$ by scaling and translation:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \qquad (2)$$

where $\frac{1}{\sqrt{|s|}}$ normalizes the energy across different scales.

Principal component analysis (PCA) is a method for analysing data sets of high dimension, revealing patterns and highlighting the similarities and differences. Although PCA can be used for various types of analysis, here the emphasis is on data reduction and feature extraction. The purpose of using this is to remove redundant information and replace a group of variables which measures the same information with asingle new variable called principal component (PC). The calculation

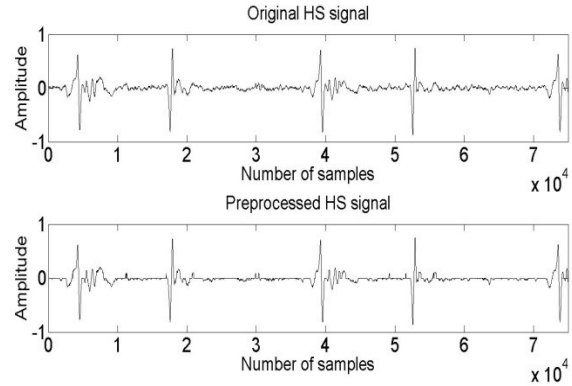

Fig.1. Original and preprocessed HS signal.

of the PC is essentially equivalent to performing the singular value decomposition (SVD) on a data set, X [10].

$$Z=\mathrm{diag}(\sigma_1, \sigma_2, \sigma_3 \ldots \sigma_m) \qquad (3)$$

$$PC = [PC_1\ PC_2 \ldots PC_m]$$

where $\sigma_1 > \sigma_2 > \sigma_3 > \ldots > \sigma_m$, PC_m is the Eigen vector corresponding to Eigen value σ_m and X is original data set.

Properties of PCA:

There are infinite number of ways to determine an orthogonal basis for a particular set of data. Based on its properties PCA provides great benefits in feature extraction problems. The properties of PCA are:

1) Each PC contains linear combination of original variables.
2) All the PCs are orthogonal to each other so there is no redundant information.
3) The PC's as a whole form an orthogonal basis for the space of the data.

Each principal eigen value measures the amount of information captured in the direction of a corresponding eigen vector. In this sense, the original data set is transformed so that it is expressed in terms of patterns between the variables. The transformation/projection can be expressed mathematically using following equation:

$$Y=PC^T \cdot X, \qquad (4)$$

where Y is transformed data set.

ii) Envelop extraction:

The preprocessed signal is wavelet analyzed using Daubechies-15 wavelet, 8th level wavelet decomposition is performed. The decomposed signal is further synthesized to achieve highest temporal resolution. The Daubechies (db) wavelet is chosen for its property of orthogonality and strong resemblance to the primary heart sounds. A linear combination of the synthesized feature sets are used to segment the cardiac events. This is done by using PCA. PCA extracts the best feature sets which highlights the two classes of cardiac events i.e. primary components and murmurs. The feature sets which highlights the corresponding component of HSs are observed and is shown in Table I.

From the observations on the feature sets given in Table I, we can conclude that most of the S1 and S2 HSs are

concentrated in 1st PC. So the 1st PC is only considered for further analysis. The envelope of the PC analyzed HS is identified using different methods like absolute value, squared energy, Shannon entropy and Shannon energy. Out of these Shannon energy is found to be best suited for its property of magnifying medium intensity values while diminishing high and low intensity values, shown in Fig.2.

Envelope extraction using Shannon energy is performed by dividing the PCA analyzed HS into short segments of 40msec window with 50% overlap. Shannon energy is calculated for each of these segments to obtain better time resolution and Shannon energy, E is given by [6].

$$E = -\frac{1}{N_{seg}}\sum_{n=1}^{N_{seg}} s^2(n)*\log s^2(n) \qquad (5)$$

where, s(n) is the 1st PC of HS signal, N_{seg} is the number of samples in the 40ms segment. Envelope positions are stored for further analysis. Fig.3 depicts the envelope of the HS where the amplitude level of the envelope has been scaled to 1 for better viewing purpose.

V. SEGMENTATION OF HS BASED ON CARDIAC CYCLE

After the extraction of the envelope it is necessary to validate S1 and S2 in both normal and abnormal conditions. Generally, amplitude thresholding doesn't work well in cases where, the primary components are dominated by murmurs energy and if the energy of the primary components less than the threshold. In those cases false representation of the HSs may occur and additional processing must be done to overcome those problems, which are complex and time consuming [5] & [6]. In order to combat such problems, segmentation based on cardiac cycle duration is proposed in this paper. Each cardiac cycle contains S1, systolic phase, S2 and diastolic phase. For obtaining cardiac cycle, the PCA analyzed signal is sub-divided into windowed segments and processed using a variance based algorithm. From the subjective knowledge the maximum heart rate in case of pathology is found to be 200beats per minute (bpm) in extreme cases and on an average the pathological heart rate is 150bpm. So for obtaining exact boundaries a heart rate of 150bpm is chosen and is used in the algorithm. The operation is performed for each windowed segment of the PCA analyzed HS and corresponding variances are computed. The consecutive windowed variances are subtracted from one another and compared with a threshold which is nothing but variance of the unsegmented PCA analyzed HS signal. If the difference is more than the threshold the succeeding window segment is subdivided again and repeat the same procedure of comparison with the above threshold till we obtain the accurate boundaries. If the difference is less than the threshold the variance of the succeeding window segment is subtracted from the window segment next to the succeeding window.

In this paper, we choose a 100msec window segment with a reduction factor of 10 up to 30msec and locate the Start and end positions and record the cardiac duration of each individual cardiac cycle. As heart sounds have person specific structure [1], the threshold varies from person to person. A representative signal in fig.4 shows the individual cardiac cycle obtained after applying above variance based algorithm.

TABLE I
SUMMARY OF PRINCIPAL COMPONENT ANALYSIS

Heart sound	Level(s) reflecting S1	Level(s) reflecting S2	Levels reflecting murmur
Normal	1	1	--
Aortic stenosis	1,2	1,2	2,3
Early Aortic stenosis	1	1	3,4
Late Aortic stenosis	1,2	1,2	3,4
Aortic regurgitation	1	1	3
Mitral stenosis	1	1	2,3
Mitral regurgitation	1	1	3,4
Pulmonic stenosis	1	1	3,4
Tricuspid stenosis	1	1	3

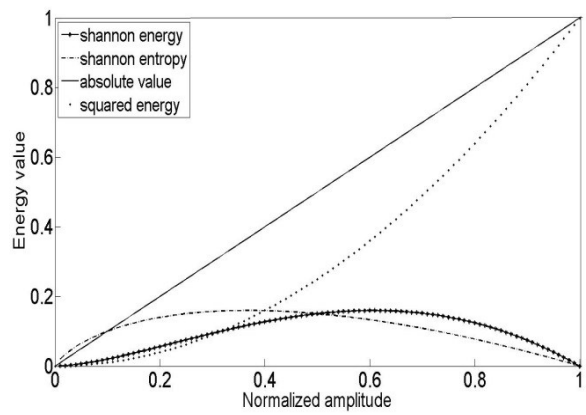

Fig.2. Comparison of different envelope methods.

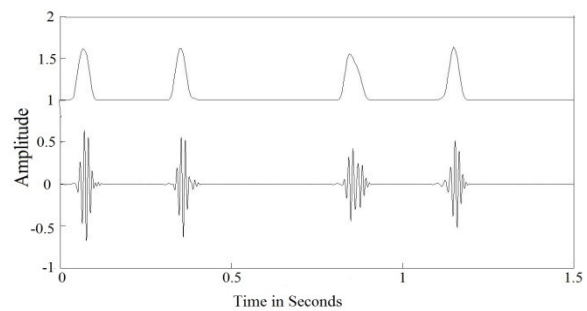

Fig.3. Shannon energy based envelope of HS.

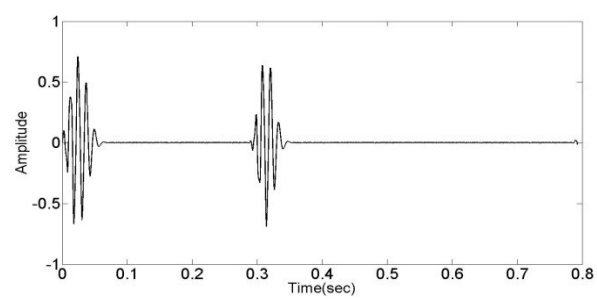

Fig.4. Cardiac cycle of a normal HS signal.

In order to separate out primary HSs i.e. S1 and S2 from PCA analyzed signal we use the above cardiac data and positions obtained from envelope extraction. Firstly, based on the cardiac data either S1 or S2 is validated. After validating S1 or S2, two thresholds are set using cardiac durations to validate the second HS i.e. S2 or S1. The purpose of using two thresholds is, in cases where murmur and primary HSs are close to each other a single threshold may not work properly and may lead in validating murmurs instead of primary HS. The two thresholds we calculate using the positions and individual cardiac duration of the HSs are expressed as:

$$Th1 = \frac{p(i)+((p(i+1)-p(i)/3)}{\text{Time period of particular cardiac cycle}} \quad (6)$$

$$Th2 = \frac{p(i)+((p(i+1)-p(i)/2)}{\text{Time period of particular cardiac cycle}} \quad (7)$$

where i = 1, 2… n, n = number of cardiac cycles, p (i) is the position of either S1 or S2s HS envelope.

The thresholds are also set by considering the subjective knowledge of 1) the diastolic period which will have the largest interval 2) the systolic period which is relatively constant compared to the diastolic period. In addition to segmentation, the two thresholds themselves help in eliminating false picking of HSs in abnormal cases. Fig.5 shows the patient with mitral stenosis. Here the diastolic murmur component is rejected by considering it as a non-primary HS.

After finding two HSs we have to identify S1 and S2. The identification is done based on the subjective knowledge. The longest time interval between two adjacent peaks is diastolic period and the signal at the start of the period is set as S2 and the signal at the end of the period is set as S1, then it follows. Fig.6 depicts the segmented and detected HS signal in case of abnormality (Mitral stenosis).

VI. EXPERIMENTAL RESULTS

A total of 479 cardiac cycles collected from 22 people in which 4 healthy and 18 suffering from valvular diseases are segmented and detected. The diseases include aortic stenosis, mitral stenosis, pulmonic stenosis, tricuspid stenosis, aortic and mitral regurgitation and atrial fibrillation, and the HSs are taken at different auscultation positions. The segmentation results are shown in Table II.

TABLE II
RESULTS FROM SEGMENTATION ALGORITHM

HS	correct	Incorrect	total	Percentage (%)
Normal	89	0	89	100
Abnormal	372	18	390	95.38
Total cycles	461	18	479	97.7

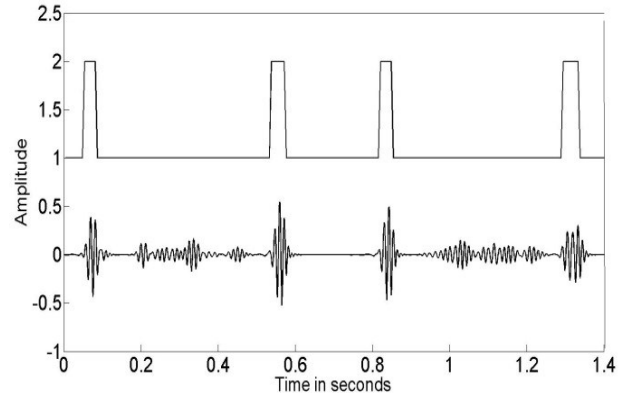

Fig.5. Validated S1 and S2 after thresholding.

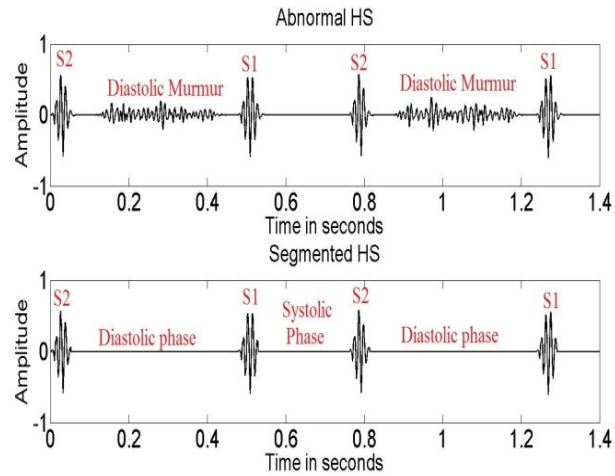

Fig.6. Segmented HS with S1 and S2 detection.

Incorrect detection of HSs is due to large variation of time periods as well as energy levels in the subsequent cardiac cycles in case of atrial fibrillation and high intensity of noise in case of critical aortic stenosis where S1 and S2 are unidentifiable.

VII. CONCLUSION

A robust method for segmentation of S1 and S2 is proposed based on PCA. The used records with interfered noise in both systolic and diastolic intervals are considered. So a preprocessing step is used to remove the low frequency noises and in order to concentrate only on frequencies of clinical interest, the signal is decimated further. PCA analysis is applied to extract feature set which gives no redundant information and highlights primary components. Envelope is extracted by using Shannon energy and cardiac periods are calculated to the extracted feature set (1st PC). Finally segmentation and detection is done using two thresholds derived from subjective knowledge and cardiac periods. Any false segmentation is eliminated by using two derived thresholds itself. The proposed method is simple and can be capable of picking low energy components without any additional effort. The results show that the proposed method is efficient and gives effective performance.

Future work will be to make the algorithm more sophisticated to pick S1 and S2 accurately even for greater cardiac irregular periods and noise dominated HSs.

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