Heart Sound Segmentation using Empirical Mode Decomposition

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***Abstract*— Heart sound segmentation method detects and extracts first (S_1) and second (S_2) sounds from phonocardiogram. Heart sounds are processed using Empirical Mode Decomposition (EMD). Intrinsic Mode functions (IMFs) obtained from EMD is selected based on energy, frequency and kurtosis based criterion. These select IMFs are analyzed by its kurtosis features. Kurtosis estimate of IMFs that lie outside of Gaussian distribution are selected for reconstruction of heart sounds. S_1, S_2 systolic and diastolic murmurs components are grouped separately.**

Keywords—Empirical Mode Decomposition, Estimator Intrerval I(N,q), First heart sound (S_1), Gaussian distribution, Intrinsic Mode Function, Kurtosis, Second heart sound (S_2).

I. INTRODUCTION

Heart sounds heard through stethoscope are essential for medical diagnosis of patient and provide heart rate and rhythm, valve functioning, and anatomical defects of heart [1]. This process called as heart auscultation. Now electronic stethoscopes are developed which captures heart sounds and convert them into electronic signal. These sounds can be processed with signal processing algorithm. This will help doctors for diagnosis instead going for ECG result which are large hardware. Developing such algorithm which will help in diagnose based on heart sounds features is done here.

Functioning of heart is periodic by repeating cycles of systole and diastole. Systole represents ejection of blood from heart and diastole represents filling of heart chambers with blood. First heart sound (S1) represents beginning of systole and second heart sound represents (S2) beginning of diastole [1]. This periodic functioning produces vibration which are propagated through chest walls and become audible. Only presence of S1 and S2 means normal functioning of heart. In abnormal conditions sounds present between S1 and S2 are called murmurs. These murmurs represent dysfunctions of heart valves. Murmurs loudness, its location in PCG wave, frequency decides dysfunction. Aortic stenosis and mitral regurgitation are well known murmurs. PCG is visual representation of heart sounds. In Fig 1 PCG wave of normal, aortic stenosis and mitral regurgitation is shown. S1, S2 and murmurs locations are shown in figure 1.

In heart sound segmentation S1, S2 and murmurs are extracted using Empirical Mode Decomposition (EMD). EMD decomposes signal into oscillations that are present in signals [6]. These oscillations are called Intrinsic Mode Functions (IMF). These IMF are analyzed based on kurtosis which indicates changes in signal. Among IMFs some corresponds to S1 S2, others correspond to murmurs. These IMFs are separated as per requirement of desire segments.

The rest paper is structured as Mathematical Background,

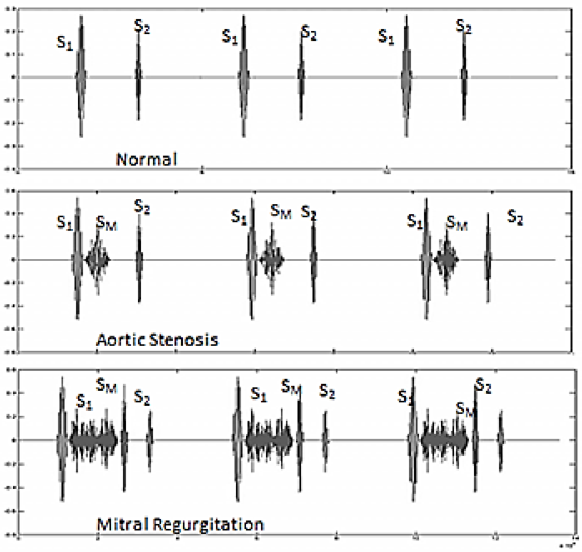

Fig.1. PCG of Normal heart sound, Aortic Stenosis and mitral regurgitation.

proposed approach and obtained results.

II. MATHEMATICAL BACKGROUND

A. *Empirical Mode Decomposition*

Empirical mode decomposition (EMD) decomposes signal into fast oscillation and slow oscillation [2]. It is iterative process until all oscillations are extracted. These finite numbers of oscillation are called as Intrinsic Mode Function (IMF). IMFs are obtained from signal by algorithm called as sifting algorithm sown in fig 2[3]. Sifting algorithm is based on two constraints: each IMF has same number of zero-crossing and extremes, and also has symmetric envelope defined by the local maxima, and minima respectively. Furthermore it assumes that the signal has at least two extremes [2]. So, for any 1-D discrete signal I_{ori}, EMD can be represented with following representation:

$$I_{ori} = \sum_{j=0}^{J} IMF\,(j) + I_{res} \quad \ldots \quad (1)$$

Where IMF (j) is the j[th] mode (or IMF) of the signal, and I_{res} is residual trend. The sifting procedure generates a finite number of IMFs that are nearly orthogonal to each other [3].

B. Intrinsic Mode function

EMD decomposes signal into zero mean band limited oscillatory components, simply called IMFs. Each IMF satisfies two basic conditions [4]:

i) In whole data set the number of extreme and number of zero crossings must be same or differ at most by one

ii) At any point, the mean value of the envelope defined by the local maxima and envelope defined by local minima is zero.

IMF defined by first condition ensures instantaneous frequency will not have redundant fluctuations. IMF defined by the zero oscillations involves one mode of oscillations, no complex riding waves are allowed. IMF is not restricted to narrow band signal; it can be both amplitude and frequency modulated, also it can be non-stationary [2].

The idea of finding IMFs relies on subtracting the highest oscillations from signal step by step process, which is called the sifting process.

C. Kurtosis[2]

Kurtosis of a fourth-order stationary, zero-mean, stochastic process x(t) is defined as the fourth order cumulant for zero-lag. Kurtosis is signal length dependent. Thus, the kurtosis estimate exists in a confidence interval, which is determined by the probability properties of the estimator. Estimator is having probabilistic lower and upper bound depends on the first statistics of estimator. For the X random process ($X \in x(t)$) of mean μ and standard deviation σ. Chebyshev inequality gives this interval using equation (2) [2].

$$\left\{X \in \left(\mu - \frac{\sigma}{\sqrt{1-q}}, \mu + \frac{\sigma}{\sqrt{1-q}}\right)\right\} > q \ \ldots (2)$$

Where, $q = 1 - (\sigma^2/\epsilon^2)$, ε >0, and $\frac{\sigma^2}{\epsilon^2}$ is sufficiently small. Let x(n) be zero-mean, N –sample observation from random variable X. The kurtosis estimate $\widehat{\gamma_4}$ of x(n) is given by (3)

$$\widehat{\gamma_4} = (N-1)\frac{\sum_{n=1}^{N} x^4(n)}{(\sum_{n=1}^{N} x^2(n))^2} \ldots (3)$$

Additionally if we assume X be the Gaussian, Then

$$\hat{m} \approx \frac{6}{N} \text{ and } \hat{s}^2 \approx \frac{24}{N} \ldots (4)$$

Where $\hat{m}$ and $\hat{s}^2$ are the mean and standard deviation estimates of $\widehat{\gamma_4}$. Substituting expression (4) in (2) yields in

$$P\{\widehat{\gamma_4} \in I(N,q)\} > q \ \ldots (5)$$

Where,

$$I(N,q) = (6/N - \sqrt{(24/N(1-q)}\,,)\ 6/N + \sqrt{(24/N(1-q)}\,)) \ldots (6)$$

It states that if the kurtosis estimate of N-sample observation x(n) lies outside I(N,q), then it does not lie in Gaussian distribution. It could be hypothesized that heart sounds do not follow Gaussian distribution. This hypothesis is applied to heart sounds [1]; parts of PCG which lies outside Gaussian distribution correspond to heart sound. The IMFs which lies outside Gaussian distribution are used to reconstruct heart sounds. This is main concept behind EMD for heart sound segmentation. Extracting IMF from original signal, then applying kurtosis hypothesis and reconstructing oscillations correspond to heart sound.

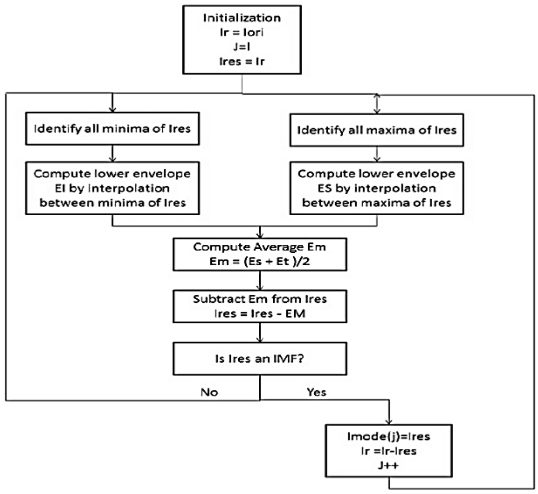

Fig.2. Sifting Algorithm to extract IMF from signal [3]

III. PROPOSED APPROACH

A. Preprocessing

Heart sound segmentation is based on statistics parameter kurtosis so it necessary to make zero-mean signal, then signal is filtered using third order median and followed by tenth order butterworth filter with cutoff frequency 250 Hz. As major part of heart sound lies between 20-250 Hz. This filtered signal $x_f[n]$ is analyzed using EMD. Before filtration signal is down sampled to 12 kHz.

B. EMD and Selection of IMFs

Filtered signal xf[n] (n=1, 2 …N) is decomposed into L IMFλ[n] (n=1, 2…N) using sifting algorithm. Each sequential IMF contains lower frequency oscillation than previous extracted. Fig 3 shows filtered signal and first four IMF. This is signal contains S1, S2 and systolic murmur.

Some of these extracted IMF correspond to heart sounds and few may not. So selection of IMFs is important. Selection criterions are Shannon energy of IMF, instantaneous frequency of IMF and kurtosis of IMF lies outside the Gaussian distribution.

i) Shannon energy based criterion

IMFs which contains energy correspond to heart sound are selected based on (7) [1].

$$n_\lambda = \frac{E\{\sum_{\lambda=1}^{M_n} IMF_\lambda[n]^2\}}{E\{x_f[n]^2\}} \ldots (7)$$

n_λ Calculated until cumulative energy do not cross threshold energy here threshold is 0.9999. So IMFs up to energy threshold value are selected.

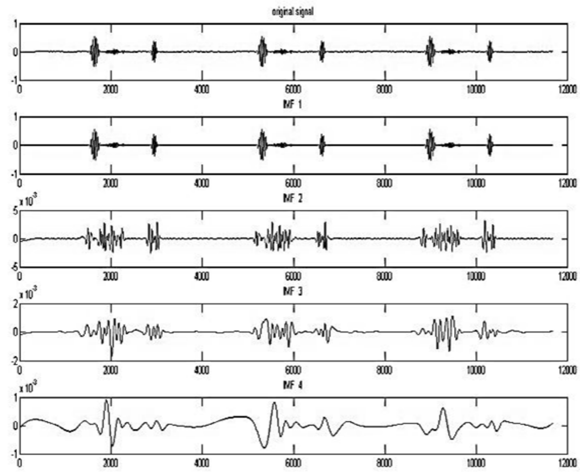

Fig.3. First waveform is Heart sound with S1 S2 and systolic Murmur next four waveforms are 4 IMF out of 7

ii) Instantaneous Frequency criterion [2][5]
Instantaneous frequency of each IMF is calculated using Hilbert Transform. If mean of instantaneous frequency is less than 250 Hz that IMFs are selected.

iii) Kurtosis Based criterion [1]

As previously discussed probabilistic interval in (6) is Gaussian distribution. Calculate kurtosis of each IMF based on Bootstrap concept. If it lies outside Gaussian distribution means IMF correspond to heart sound.
In such way on three criterion IMFs are selected. IMF which does not follow one of them is rejected. Selected IMF are noted as sIMFλ[n].

C. S1 and S2 Detection

sIMF are processed using windowing followed by kurtosis estimate. This is done to locate S1 and S2 in heart sound. lw (w = 1, 2 . . W) = Fs/50: Fs/50: Fs/10 where Fs is samplingfrequency of signal. As each signal down sampled to 12 kHz i.e. Fs.

Each IMF undergoes windowing with different windows and one sample shifting. Kurtosis of each windowed section is estimated using (8).

$$\hat{\lambda}_4^{m,lw} = (lw-1)\frac{\sum_{n=1}^{lw} \mathrm{sIMF}_m{}^4(n)}{(\sum_{n=1}^{lw} \mathrm{sIMF}_m{}^2(n))^2} \,..\,(8)$$

Where lw is window and m is sIMF number. $\hat{\lambda}_4^{m,lw}$ Matrix is of M x W dimension. M is number of selected IMFs and W is number of windows.
$\hat{\lambda}_4^{m,lw}$ Follows probability so values of each kurtosis which lies inside Gaussian distribution are rejected, means window ofcorresponding kurtosis is rejected. Probabilistic interval I(lw, q) for each window is calculated using (6). $\hat{\lambda}_4^{m,lw}$ Vector is selected if maximum absolute value lies outside I(lw, q) along direction J. new three dimensional matrix is developed $\hat{\lambda}_{4,j}^{m,lw}$ where J < M x W.

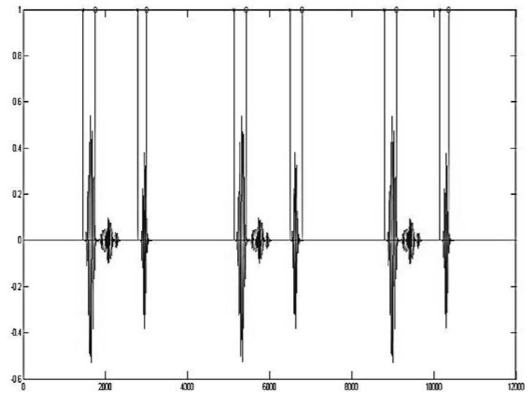

Fig.4. Starts and End points of S1 and S2 (x marked lines shows starting points and o marked shows ending points)

Start and ends of S1 and S2 are determined using$\hat{\lambda}_{4,j}^{m,lw}$. Kurtosis can detect sudden changes in signal, so S1 and S2 suddenly rises at point where it starts. Stating points are STARTS find using (9).

$$\mathrm{START} = \text{Location of Max}\,[\text{diff}\,\prod_{j=1}^{J}\hat{\lambda}_{4,j}^{m,lw}[k]]\,..\,(9)$$

Similarly END points detected using (10).

$$\mathrm{END} = \text{Location of Max}\,[\text{diff}\,\prod_{j=1}^{J}\hat{\lambda}_{4,j}^{m,lw}[k+lw]]\,...(10)$$

This start and ends detects sound location in signal. This is shown is fig 4.

Discrimination between S1 and S2 is important. In cardiac cycle systolic duration is smaller than diastolic duration. Calculate difference between detected sounds using (11).

$$k_{loc}(2i+1) - k_{loc}(2i) < k_{loc}(2i+3)k_{loc}(2i+2)\;....(11)$$

If (11) the area $k_{loc}(2i+1){:}\,k_{loc}(2i+2)$ belongs to S2 area else belongs to S1.

IV. Results

Empirical mode decomposition gives IMFs as shown in fig 3. Four IMFs are shown here for systolic murmur signal. Actually total seven IMFs are obtained. Number of IMFs also depends on sampling frequency of signal. For 12 kHz 7 IMFs and for 44.1 kHz 57 IMFs obtained.

While selection of IMFs energy criteria gives first IMF to Mn means its reject last IMFs while frequency based criterion reject initial IMFs as contains higher frequency oscillation. Selection of IMFs is as shown in fig 5.

While estimating Gaussian interval using (6) q = 0.9999 [1], higher q value ensures Gaussian distribution curve. q is adjusted such that at least one IMFs must be selected by kurtosiscriterion. lw = Fs/50: Fs/50: Fs/10 is used such that smaller window will look at fast oscillation and larger window will look at slower oscillation.

Detection of S1 and S2 is shown in fig 4. Segments of signal after complete process are sown in fig 6. Different S1, S2 and murmurs are separated from signal.

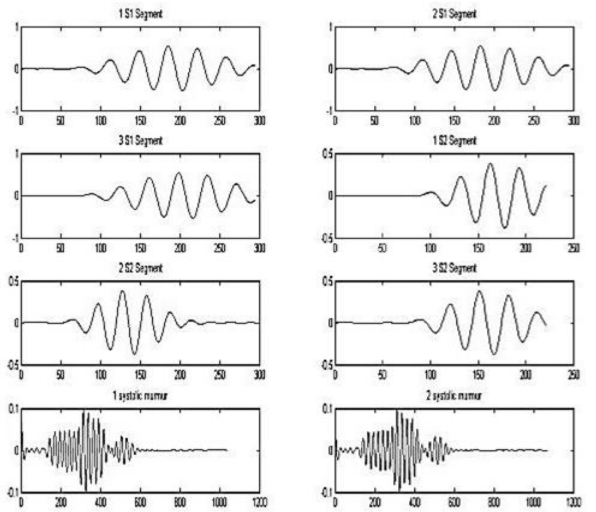

Fig.5. Segments of systolic murmur signal after complete EMD and kurtosis analysis. (1, 2, 3 … represent number first, second of segment)

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