Feature Extraction of Ballistocardiogram Signal

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***Abstract*—Cardiac arrest and other heart related diseases have become common in today's modern life style. It is at most important to detect the abnormalities before the damage is caused. Ballistocardiogram (BCG) is a non-invasive method used to detect the health of heart. Ballistocardiography (BCG) is a plot of repetitive motion of human body arising from the ejection of blood into the blood vessel. BCG is used to detect the Cardiac Output which is defined as "The amount of blood pumped by the heart in a minute". BCG Signal is obtained from the sensors placed near the aorta which is the main artery, originating from left ventricle of extending down to the abdomen. BCG is found to be the promising method to detect the cardiovascular diseases. The data obtained from the sensors contains vibrations due to respiration, body movements and other disturbances. It is a plot of repetitive motion of human body arising from the ejection of blood into the blood vessel. Each BCG wave contains GHIJKLMN peaks. The features of BCG signals such as the amplitude of the peak and the distance between the H, I, J, K and L peaks are calculated. The delay between the BCG Signal and the ECG signal is found by finding the interval between the dominant peak 'J' of BCG signal and the dominant peak 'R' of ECG.**

***Index Terms*—Ballistocardiogram, Feature Extraction, Wavelet Transform, Signal processing**

I. INTRODUCTION

Biomedical signals involve in measuring the physiological activities of organisms, protein and cardiac rhythms. Biomedical signals are used to detect the abnormalities in the health of heart, quality of sleep and other irregularities involved in patient's body. Biomedical signal processing has wide scope in today's competitive world. Extracting significant information from the recorded biomedical signals is referred to as biomedical signal processing. These biomedical signals are measured using sensors, which convert the physiological data to electrical signals. The recorded signals contains distortions and interferences. Biomedical signal processing involves in removing these distortions and obtaining pure signals. The features of a healthy person is extracted and the values are recorded and standards are set. The analysis is performed on patient and the specialist compares it with the standard values. On extracting the required information, the specialist decides if the patient's characteristics is normal or not by comparing it with the standard values. Different biomedical signals involved in the detection of heart health are Electrocardiography (ECG), Ballistocardiography (BCG) and Seismocardiography (SCG) etc. [1]

BCG is a non-invasive method used to measure the health of heart by making patient lie on bed/ chair in supine position. Here wires/sensors are not placed on the patient's body. The EMFi sensor is integrated in bed or chair. Another method is by inserting optic fiber in the mattress and the fiber length is changed by the heart and breathing activity. BCG records the body movements such as (a) Head to foot deflection, (b) Aentero-posterior vibrations and (c) Cardiac ejection. In bed/ chair based BCG systems head to foot deflection is measured. It is preferable to use microgravity environment for measurement and analysis of BCG signals. [1]

BCG wave represents repetitive motions of the human body due to the sudden ejection of blood into the blood vessels from the heart, with frequency 1-20 Hz. The BCG signal consists of eight points (G, H, I, J, K, L, M and N) as shown in Fig.1. The H wave is associated with contraction of heart is an upward deflection which is small. During heart disease amplitude its amplitude might become large, equal or exceeding the height of the J wave. The peak J corresponds to the end of rapid ejection of blood by both the ventricles. I-J amplitude is the force of contraction of left ventricle and I-J period reflects the contractility. The K and L wave reflects deceleration of blood flow and closing of the aortic valve. Diastolic wave (KL and MN) reflects the peripheral circulation. The influence of arteries wall stiffness and peripheral resistance has greater influence on the diastolic waves. [1]

In detection of cardiac diseases, BCG Feature Extraction plays a significant role. Feature extraction is used to determine the amplitudes and intervals in signal of BCG which is as shown in fig.1. The amplitudes and intervals of the BCG wave determine the health of heart. There are several techniques for the analysing the biomedical signal. Other methods are based on Fuzzy Logic, Wavelet transform, Fourier Transform, and other analysis techniques. All the above techniques has its own pros and cons. [2]

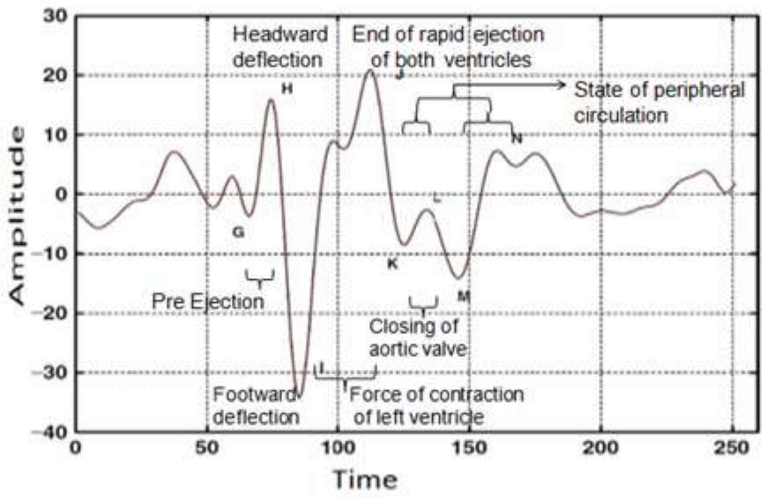

Figure 1: Ballistocardiogram wave

II. LITERATURE SURVEY

Feature extraction of biomedical signals are being studied since long back and many advanced methods are proposed with greater accuracy. Following are the various methods and transformations used in the extraction of features of biomedical signals.

Feature extraction can be done using techniques such as wavelet transform and few other support vector machines. The feature extraction process can be classified into 3 components which includes, signal pre-processing, feature extraction and classification. The wavelet transform method is to be employed to obtain the transform coefficients as the features of segments of the signal. Simultaneously, autoregressive modelling (AR) is also applied to realize the structure of biomedical waveform. Later the support vector machines with Gaussian kernel is used to classify the rhythms of heart and find if it is normal or not. The performance of this approach has reached an accuracy of 99.68%. [3]

Wavelet Transform (WT) is a robust method used in the field of recognition and diagnostics of signal. It will compress the time varying data signal that contains several data points to a parameter, which represents the signal. For non-stationary signals such as biomedical signals, WT is the suitable way for feature extraction. Using time-frequency domain method like WT, the features of the data signal can be extracted. WT is one of the spectral estimation technique where, any general function is expressed as infinite series of wavelets. In WT, designers are flexible to use variable size windows. [4]

There are two categories in which the WT analysis can be performed and are explained below. [4]

- **Continuous Wavelet Transform (CWT)**

CWT is given by the equation

$$\mathrm{CWT}(a,b) = \int_{-\infty}^{\infty} x(t)\,\psi_{a,b}^{*}(t)\,dt \qquad (1)$$

Where, unprocessed signal is given by x(t), dilation is given by 'a' and translation factor is given by 'b'. Factor $\psi_{a,b}(t)$ denotes the complex conjugate given by equation

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

Where $\psi(t)$ is the wavelet. The problem involved in CWT is that translation parameter and scaling parameter varies over time.

- **Discrete Wavelet Transform (DWT)**

Another alternative to CWT, discrete wavelet transform (DWT) which can define multi scale feature representation. The relationship between WTs and low pass filter is represented as follows

$$H(z)H\left(z^{-1}\right) + H(-z)H\left(-z^{-1}\right) = 1. \qquad (3)$$

Here, the filter h's z-transform is represented by H(z). The complementary z-transform of the high-pass filter is expressed as

$$G(z) = zH\left(-z^{-1}\right). \quad (4)$$

By absolutely depicting the components of the signal segment inside a predetermined domain of frequency and confined time domain properties, there are a many advantages that overcomes the disadvantages of the conventional convolution based implementation such as high computational and memory requirement.

Feature extraction of biomedical signal is useful to recognize the abnormal heart beats. The advantage of using wavelet transforms is that it can be used both in frequency and time domains. The most important step in extracting features is to de-noise the input signal. The appropriate mother wavelet is selected from the wavelet bank. The biomedical signal is decomposed into the vector by using suitable wavelet function. Thus obtained decomposed signal will be similar to the biomedical signal. The coefficients are divided into smaller segments and hence features can be obtained. [5]

For automatic extraction of features from ECG and classify it into normal or abnormal, we can use combination of artificial neural network (AAN) techniques and linear discriminant analysis (LDA). The features can be generated automatically using automatic algorithm. The overall signal is divided into segments and the features can be obtained. [6]

Fourier Transform is a transformation technique which is used to calculate the changes between time domain and frequency domain. The short-time Fourier transform (STFT) is a transform method similar to Fourier transform which is used to find the frequency and phase of a continuous signal. The STFT method uses segmented algorithm to analyse a continuous time signal. Using the moving window method, the signal can be decayed into segments and each decomposed fragment is processed by the conventional Fast Fourier transform (FFT) algorithm. The drawback of this method is that, once the window size is chosen, it remains constant for all frequencies. Most of the signals need an approach, where the size of the window is flexible and can determine the signal features more accurately either in time/frequency domain [7].

III. METHOD EMPLOYED

The ballistocardiogram contains few noise and it is required to be removed before the feature is extracted. Then the base line wandering has to be removed to extract the required features.

The 50Hz power line interface is removed from raw BCG signal using a simple notch filter. The wavelet based denoising is performed to suppress the baseline wander. The continuous wavelet transfer method is applied and particular levels of wavelet is selected and the maxima, minima pairs are selected. Zero crossing of the signal is detected and the location of the J wave is found. After the detection of J wave, the location of H, I, K and L waves is detected. Thus the features of the signal is extracted.

♦ SIGNAL PREPROCESSING

- **Power line interface removal**

  The power line interface in the BCG Signal can be easily eliminated by using a Simple notch filter of 50Hz.

- **Wavelet based de-noising**

  The noisy BCG signal is decomposed using Discrete Wavelet Transform (DWT). This is done by selecting an appropriate mother wavelet. DWT produces detail and approximate coefficients corresponding to low and high Frequency components of the signal respectively. Here 'coef5' is used as mother wavelet, as it shows better de-noising results for the BCG signals.

- **Baseline Wander Removal**

  The isoelectric line shift of the BCG signal due to motion artefacts and respiration is called as baseline wander. It is eliminated by applying following

  1) The BCG signal is passed through a median filter of 200ms to eliminate IJK complex and H waves.

  2) The signal obtained in (1) is passed through a median filter of 600ms to remove L wave, hence only wandered baseline is left out.

  3) The signal obtained from (2) if subtracted from the original BCG gives baseline wander free BCG signal.

The raw BCG signal, wavelet based de-noised BCG signal, the baseline wander removed BCG signal and the noise extracted are plotted and is shown in figure 2.

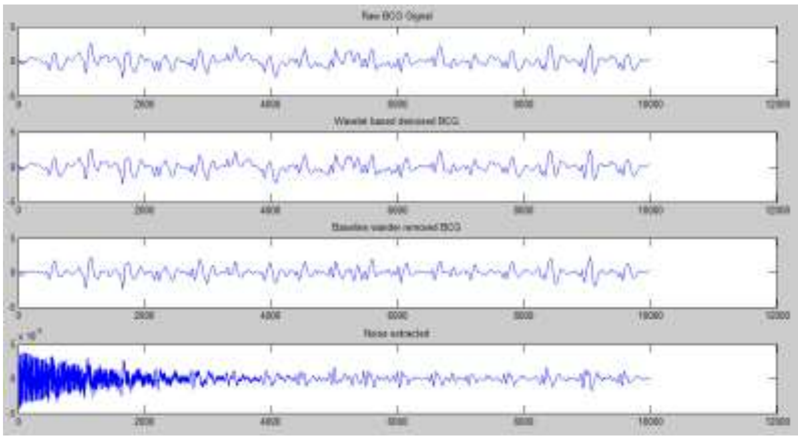

Figure 2: Pre-processed BCG signal

- **CONTINUOUS WAVELET TRANSFORM (CWT)**

In BCG signal, J-Peak has the highest amplitude and is the most significant peak. The pre-processed BCG signal was decomposed from 2^1 to 2^5 levels using CWT which is shown in figure 3. The mother wavelet selected for this purpose was 'db6'. Out of the above decompositions, 2^5 level is more significant because it gives the maximum amplitude at the J peak of BCG signal.

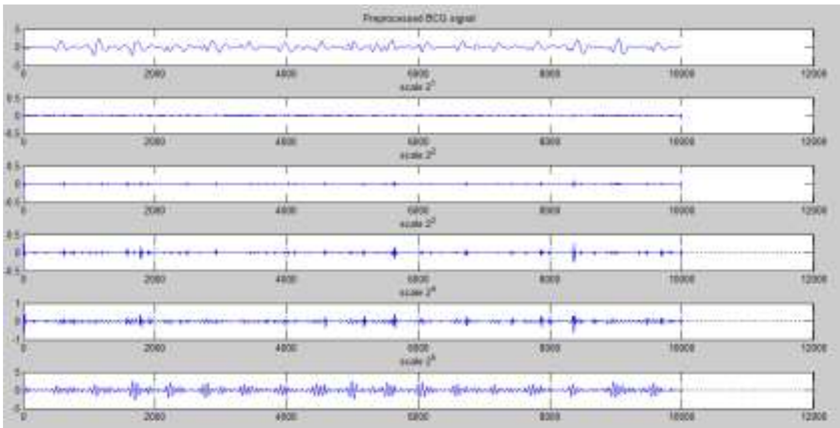

Figure 3: CWT decomposition of pre-processed BCG Signal

- **MAXIMA AND MINIMA PAIR SELECTION**

2^5 level wavelet was selected as it resembles similar to normal BCG Signal. Level 2^5 was selected to detect J peak as the maximum energy of IJK complex is noticed at this level. Thresholds thmax, thmin were set to extract only the significant maximas, minimas as below:

$$th_{max}=0.45*\max(w^5) \quad (4.5)$$

$$th_{min}=0.45*\min(w^5) \quad (4.6)$$

Where, w^5 is CWT of the signal at level 2^5.

Redundant maximas and minimas were discarded by eliminating the repeated locations while searching for maxima and minima by using the respective thresholds.

Zero crossings between pair of significant modulus maxima were detected which correspond to J peaks in time plane. For the accurate localization of J peak in time domain, a small sized search window about the location provided by zero crossing of Wavelet Transform Modulus Maxima (WTMM), can be further applied.

♦ ZERO CROSSING AND J PEAK DETECTION

Finally, zero crossings between pair of significant modulus maxima were detected which correspond to J peaks in time plane which is shown in figure 4. Amplitude of J peaks and Inter-beat intervals between two consecutive J peaks were noted.

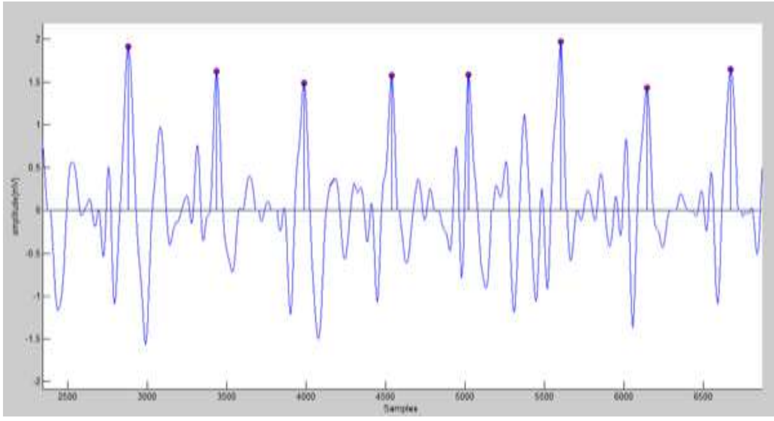

Figure 4: J peak detection

♦ DETECTION OF OTHER SIGNIFICANT PEAKS

Once the J peak is detected, all other peaks (H, I, K, and L) were detected by applying search window method about the location of J peak. The size of the search window is dependent over the J-J intervals of the signal obtained once J peaks are localized. A simple algorithm with range of corresponding search windows for the detection of characteristic peak locations is given below

- J_J=array of inter-beat intervals
- Hloc=array of H peak locations
- Iloc=array of I peak locations
- Jloc=array of J peak locations
- Kloc=array of K peak locations
- Lloc=array of L peak location
- Range_I=[Jloc(i)-0.20*J_J(i-1):Rloc(i)]
- Iloc=search_min[Range_I]
- Range_H=[Rloc(i)-0.30*J_J(i-1):Iloc(i)]
- Hloc=search_max[Range_H]
- Range_K=[Jloc(i):Jloc(i)-0.20*J_J(i+1)]
- Kloc=search_min[Range_K]
- Range_L=[Jloc(i)-0.25*J_J(i-1):Kloc(i)]
- Lloc=search_max[Range_L]

Using the above data, we find all the peaks of the BCG signal which is shown in figure 5.

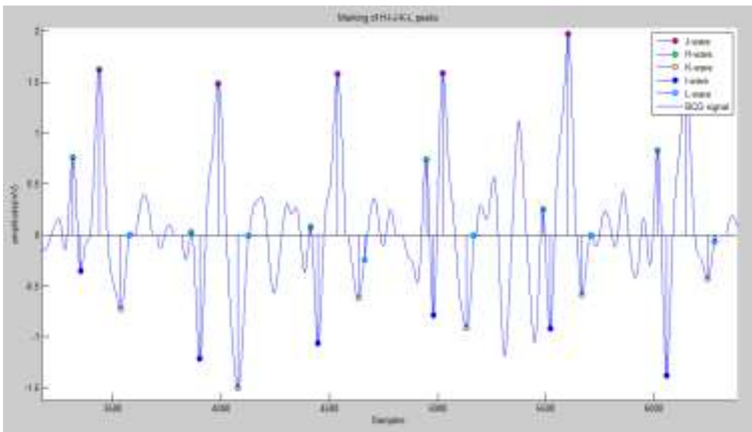

Figure 5: Detection of all the significant peaks of BCG Signal.

♦ FEATURE EXTRACTION

The operations performed in the above steps gives the features such as the number of J peaks denoted by length(Jloc), maximum J-J interval denoted by max(jj), minimum J-J interval denoted by min(jj), maximum amplitude of J denoted by max(Jamp) minimum amplitude of J denoted by min(Jamp), maximum amplitude of H denoted by max(Hamp), minimum amplitude of H denoted by min(Hamp), minimum amplitude of I denoted by min(Iamp), maximum amplitude of I denoted by max(Iamp), minimum amplitude of K denoted by min(Kamp), maximum amplitude of K denoted by max(Kamp), maximum amplitude of L denoted by max(Lamp), minimum amplitude of L denoted by min(Lamp), maximum time interval of IJK segment denoted by max(ijk_width), minimum time interval of IJK segment denoted by min(ijk_width), maximum interval between K and L denoted by max(k_l) and minimum interval between K and L denoted by min(k_l).

IV. R-J Interval Detection

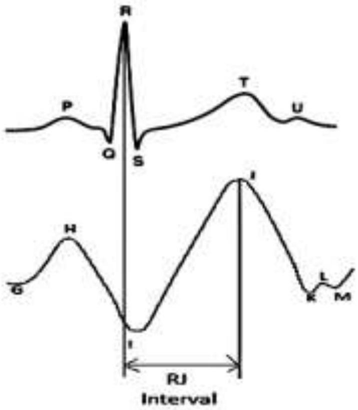

Figure 6: R-J interval

To find the interval between the J peak of BCG signal and R peak of ECG signal shown in figure 4.8, we need to extract ECG and BCG of the same person at the same time. The significant peak of the ECG signal, R peak and the significant peak of the BCG signal, J peak are detected (Shown in figure 7) and the difference between the adjacent peaks are calculated.

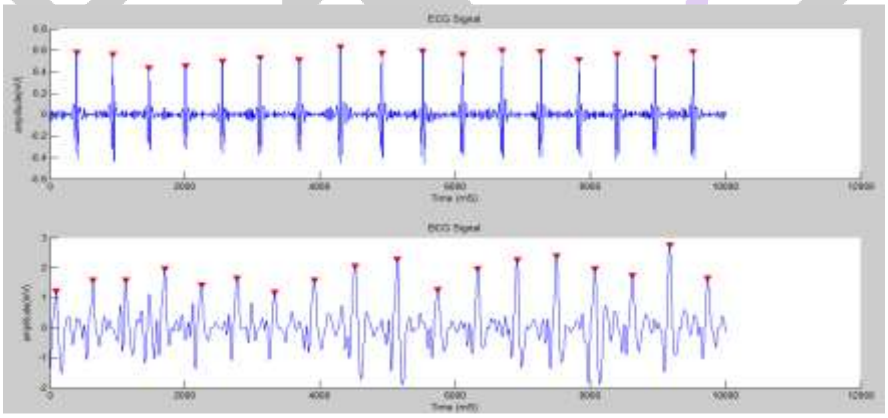

Figure 7: R and J peak detection

V. Results and Discussion

The features of the Ballistocardiogram signal is extracted and their corresponding values are tabulated in table 1.

Table 1: Extracted features of BCG signal

Sl. No.	Feature	Value
1.	No. of J peaks detected	16
2.	Max. J-J interval (mS)	1142
3.	Min. J-J interval (mS)	194
4.	Max. Amplitude of J (mV)	2.3
5.	Min. Amplitude of J (mV)	0.9
6.	Max. Amplitude of H (mV)	1.8
7.	Min. Amplitude of H (mV)	0
8.	Max. Amplitude of I (mV)	0

9.	Min. Amplitude of I (mV)	-2.3
10.	Max. Amplitude of K (mV)	0
11.	Min. Amplitude of K (mV)	-1.9
12.	Max. Amplitude of L (mV)	0.9
13.	Min. Amplitude of L (mV)	-0.4
14.	Max. IJK width (mS)	248
15.	Min. IJK width (mS)	128
16.	Max. KL width (mS)	0.0739
17.	Min. KL width (mS)	0

The Distance between the R peak of the ECG signal and the J peak of the BCG signal is calculated and is tabulated in table 2.

Table 2: R-J interval

Sl. No.	Feature	Value
1.	No. of R-J peaks detected	17
2.	Max. R-J interval (mS)	188
3.	Min. R-J interval (mS)	241
4.	Average R-J interval (mS)	225

Thus ECG signal leads the BCG signal.

VI. Conclusion

The Ballistocardiogram signal is preprocessed by removing the noise and the baseline wandering. The features are extracted, the amplitude of the peaks of HIJKL and the interval between them are found. The time interval between the ECG and BCG is calculated.

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