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ANALYSIS OF BALLISTOCARDIOGRAM WITH MULTIWAVELETS IN EVALUATION OF CARDIAC FITNESS

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ABSTRACT

This paper aims at providing efficient and accurate analysis of the cardiac activity of patient acquired from Electrocardiogram and Ballistocardiogram (BCG) signals using discrete multiwavelets de-noising analysis. The functioning of heart is studied from the Electrocardiogram (ECG), a noninvasive technique recorded by using skin electrodes and from BCG, an electrode-less technique that calculates the fitness of the heart. The setup of BCG and ECG was successfully made. The corresponding signals acquired, to calculate the cardiac output with respect to the parameters like R peak of ECG, J peak of BCG and R-J interval. Efficient analysis of ECG and BCG were done after removing the baseline drift and power line interference. Coiflet, Daubechies wavelets and multiwavelets were used to study the performance for better denoising and pre-processing to extract the features. Multiwavelet was found to be a better choice for finding the optimum performance of heart activity. 20 subjects (Normal life style adults and athletes) recordings have been taken for study and analysis on heart rate and cardiac output were made for each subject. The analyses were made 2 times a day (Morning and Night) to determine the index in evaluating the fitness of the heart. Cardiac output of athletes was found to be better than normal subjects.

Keywords – *Ballistocardiogram, ECG, wavelet, Multiwavelet filter*

1. INTRODUCTION

Ballistocardiography (BCG) is a tool for diagnosing, monitoring and managing myocardial disorders related to heart disease. The force exerted by BCG while cardiac ejection is compared to the recoil of the gun. The amplitude of the ballistocardiogram has been shown to have some relationship to cardiac output, and characteristic BCG patterns show correlation with certain pathological conditions [1][2]. The presence of any abnormal disorders in the BCG confirms heart diagnosis with ailment, which sometimes can be confused with other disorders because of some special situation for subject producing similar disturbances in BCG. However, there is yet no clear understanding of the causal relationship between specific cardiovascular events and corresponding ballistic waves. Hence, our main goal of this work is to find the cardiac fitness of a subject from their BCG signals under two groups, healthy subject (athletes) and subject having normal life style. We propose a new method of BCG features extraction using multiwavelet denoising.

BCG and ECG waveforms were to be taken simultaneously for the different group of healthy adults and adults with normal life style. Here the ECG signal is used in segmentation stage as a reference signal, which is only for extraction of BCG templates not for classification purposes.

1.1 Overview

This work includes the BCG signal acquisition technique using EmFi film sensor which is discussed in section 2, Signal pre-processing in Section 3, BCG signal extraction with reference of ECG - QRS detected waveform using Wavelet and multiwavelets de-nosing in section 4, HIJ peak detection and measurement of cardiac output in Section 5, performance of ECG to BCG and

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Result discussion in Section 6. The overview of the work is given in Fig. 1.

2. THE BCG CHAIR DESIGN

2.1 Sensor Unit

The EMFi sheet sensor used in our work is the L-series sensor.

The EMFi sensor is placed at the bottom of the flat seat surface chair with a backrest to see that the subject is sitting relaxed. The sensor has very high sensitivity; even a small movement of the subject can affect the BCG waveform.

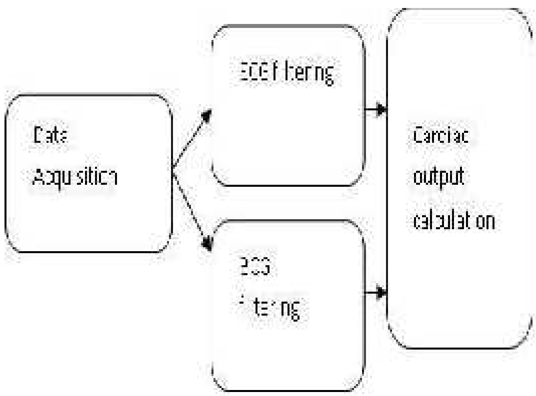

Figure1. Overview of Cardiac Fitness calculation

The Sensitivity of the EMFi sensor is 25pC/N and the size of the sensor is 30cm x 30cm as shown in Fig. 2.

2.2 Amplifier Unit

The EMFi sensor converts the small charge variations to corresponding voltage with the help of an operational amplifier (Op-amp) with a capacitive feedback.

Figure 2. The sheet type EMFi sensor.

To avoid noise originating from power supply, this set up is designed as a battery operated device. The Op-amp used for this circuit is Texas Instruments TL082 which requires low power and has a high slew rate of 13 V/μs.

2.3 Filter Unit

The acquisition of the signal was made using Data card NI DAQ 6008. The black legend waveform shown in Fig. 3, represent the BCG signal and the blue one represent the ECG signal.

BCG signal contain the useful information in the 0-30Hz frequency band, hence a low-pass IIR Butterworth digital filters characterized by fc=30Hz, N=20 (N-filter order) was implemented [2] as part of the signal processing software.

For some hefty subjects, the BCG signal was a bit difficult to interpret which is visible in BCG 2 of Fig. 4. On analyzing the BCG signals we found overlapping signals which is a result of reverberations caused in the body due to respiration [6]. In addition, the amplitude of the signal increased when the subject breathed in and reduced when the subject breathed out. The EMFi sensor seemed to be very sensitive and so the subject has to be very still when sitting on the chair.

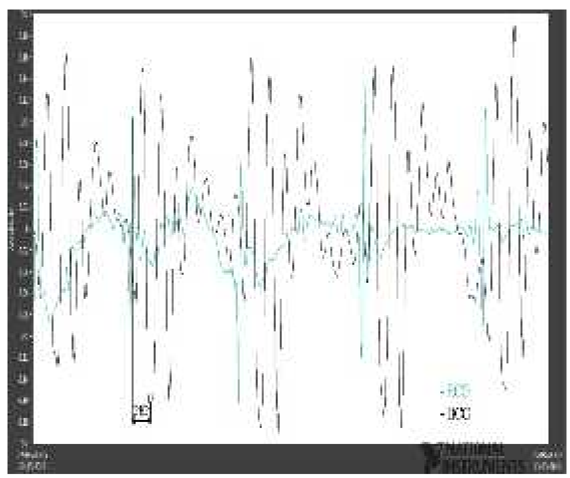

Figure 3. ECG versus BCG; taken in LabView. Time stamp shows an interval of 5s.

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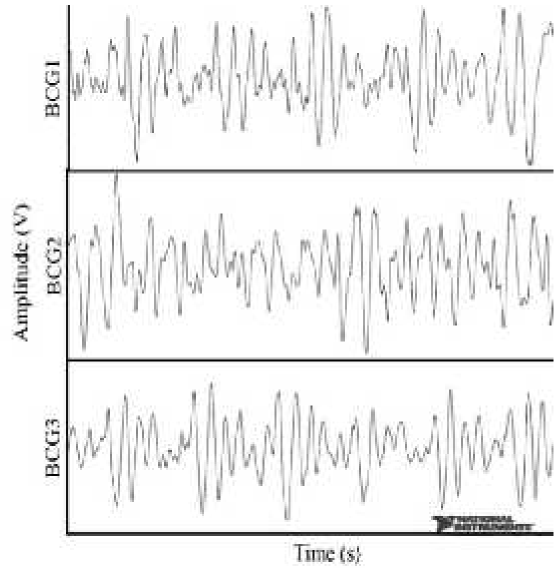

Figure 4. The BCG readings of three subjects; taken in Labview.

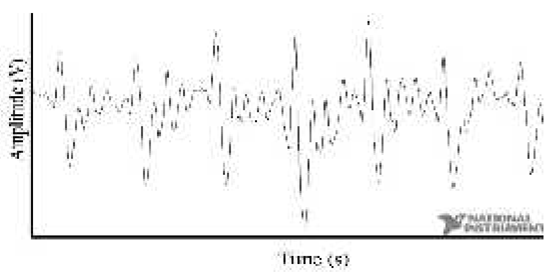

Figure 5: BCG signal.

The setup was taken to Amrita Vishwa Vidyapeetham, Bio-medical Research Laboratory (AMBE) and tested on a vibration free platform. Significant difference was found when the setup was placed in a vibration free platform; the signal obtained was clear and ready to analyze. A subject's signal taken on the vibration free floor is shown in Fig. 5, for a visual comparison with that given in Fig. 4.

3. SIGNAL PREPROCESSING

ECG and BCG signals are corrupted by noises such as muscle artifacts and floor noise, even respiration of subjects can also induce artifacts during acquisition, and hence it is required to remove noise before features extraction. The Pre-processing procedure of the signal is very much important in preserving the information of the signal and removing the artifacts [3][4]. The baseline drift and power line interference were removed with cutoff frequency 0.5Hz for the low pass filter and 60Hz for high pass filter as shown in Fig. 6, the blue legend waveform represent ECG and the red one represent the BCG signal

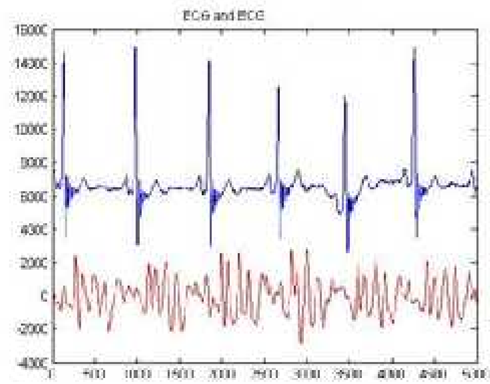

Figure 6. ECG Vs BCG data Acquisition

4. BCG SIGNAL EXTRACTION

Heart rate was measured calculating the number of R-peak detection with peak detectors, QRS complex the most prominent wave in ECG signal [5] is detected by selecting suitable windows size of 50 samples, before and after the R peaks.

4.1 Derivative Method

The derivative operator shows the result of the rate of change of the ECG signal which has the advantage to suppressing the slow moving P and T wave of the ECG signal and the second derivative; results in QRS complex detection.
The derivative of a signal in discrete domain can be the difference between the consecutive samples.

$$D[n] = x[n] - x[n-2] \qquad (1)$$

Then take the second derivative of the signal by the same procedure to get the QRS complex as in Eqn. 2.

$$D_1 = x[n] - 2x[n-2] + x[n-4] \qquad (2)$$

Then the two results are weighted and combined as in Eqn. 3.

$$D_2[n] = 1.3D[n] + 1.1D_1[n] \qquad (3)$$

Then a threshold is set and whenever the threshold is crossed it is counted as a peak which means the R wave in the ECG signal.

4.2 Denoising

The body movements and Respiratory artifacts contaminates the signals [7] therefore there is a need for efficient denoising of signals.

Table 1. Heart rate obtained by different methods

4.2.1 Discrete Wavelet Transform (DWT)

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Method	Heart rate computed (bpm)		
	S1	S2	S3
Reference ECG R peak	52	68	41
Coif 3	41	66	35
Db4	45	67	38
Db6	52	67	40
Multiwavelets	52	67	41

The BCG signal shown in Fig. 5, can be better represented minimizing the noise with wavelet decomposition [8] as sum of coefficients of the scaling function Φ_0 and detail function Ψ_0. Given any multi-resolution V_j, we can represent the signal using the scaling and detail coefficients with dilation factor 2. The wavelet function works by scaling and translating the mother wavelet with respect to the original wave, which is to be decomposed.

The decomposed scaling and detail function are given by

$$\Phi\left(\frac{x}{2}\right) = \sqrt{2}\sum h(n)\Phi(x-n) \qquad (4)$$

$$\Psi\left(\frac{x}{2}\right) = \sqrt{2}\sum g(n)\Phi(x-n) \qquad (5)$$

Where h(n) and g(n) are recursion coefficients.

In general, the decomposition can be expressed completely as given below

$$d_{j+1}(p) = \sum g(n-2p)a_j(n) \qquad (6)$$
$$a_{j+1}(p) = \sum h(n-2p)a_j(n) \qquad (7)$$

a_j represents the approximation of the signal at resolution 2^{-j} and d_j represents the details lost in approximation at resolution 2^{-j}.

The Preprocessed BCG signal is transformed using standard wavelets, decomposed [9] to 5 levels, In this work Coif3, Db4, and Db6 shown in Figs. 7–9 are used to obtain the parameters of BCG. Heart rate obtained is shown in Table 1.

By a proper threshold selection, BCG is detected from the Wavelet coefficient.

4.2.2 Multiwavelets

The main difference with Multiwavelets is considering the dilation factor m rather than 2. With m>2, we have m-1 wavelets functions and one scaling function.

Where Φ is the scaling function and $\psi^{(1)}$, $\psi^{(2)}$, $\psi^{(3)}$.. $\psi^{(m-1)}$are the wavelets.

$$\Phi(x) = \sqrt{m}\sum H(n)\Phi(mx-n) \qquad (8)$$

Similarly,

$$\Psi^{(n)}(x) = \sqrt{m}\sum G(n)\Phi(mx-n) \qquad (9)$$

where H(n) and G(n) are recursive coefficients

The feature extraction was performed by using multiwavelet denoising [10][11] and is shown in Fig 10,11.

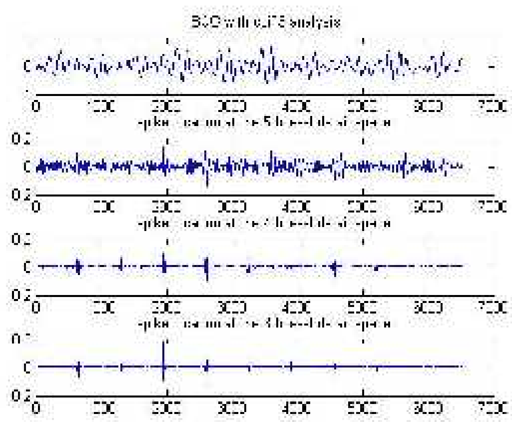

Figure 7. BCG decomposition using Coif3 wavelet

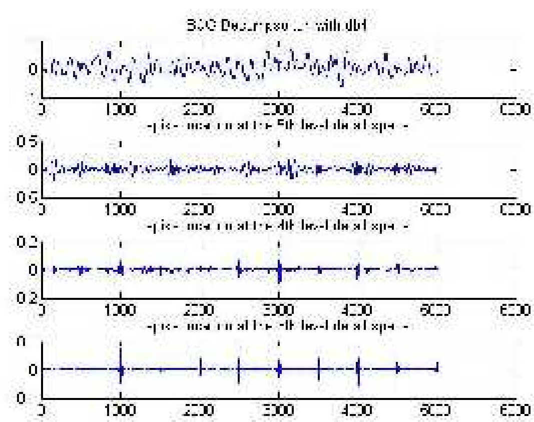

Figure 8. BCG decomposition using Db4 wavelet

With dilation factor m=4, denosing is performed for 20 subjects, 90% of the obtained heart rate were found to be close to the annotations of heart rate obtained by ECG R peak.

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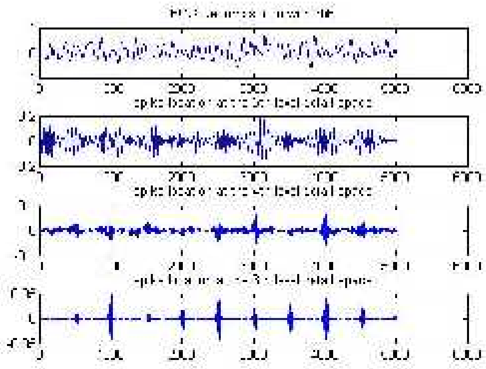

Figure 9. BCG decomposition using Db6 wavelet

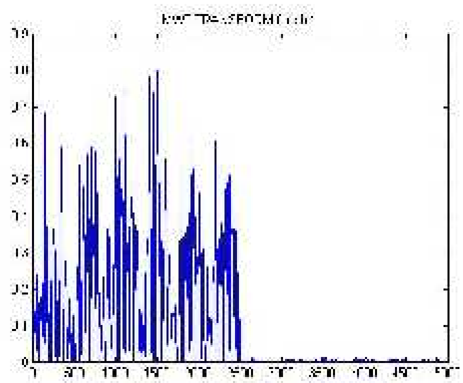

Figure 10. BCG decomposition using Multiwavelets with Phi1

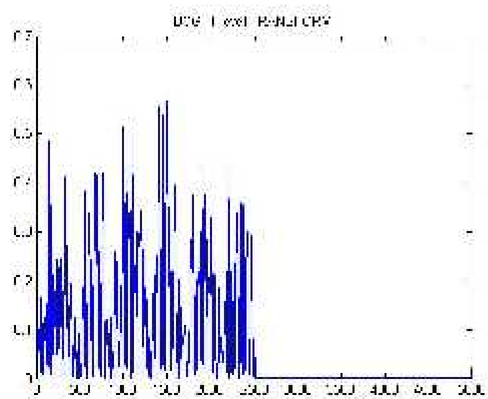

Figure 11. BCG I level decomposition using Mutliwavelets

BCG signal corrupted by various noises discussed above are removed with the help of multiwavelets. Standard wavelets and multiwavelets are compared with number of segments that accurately give the heart rate in correspondence to the heart rate obtained by ECG signal. It is significant to point out from Table 1 that the heart rate parameters obtained by multiwavelets were close to the actual values than that by other wavelets used for denoising.

5. BCG- HIJ PEAK DETECTION

With the reference of the R- peaks from ECG signal, the corresponding segmentation of BCG complex are taken as features for evaluating the fitness of the heart.

For, each subject a constant peak detect was set for the filtered ECG data, for all the 20 subjects, and the detected peaks of the ECG data were automatically located and annotated as R-waves. BCG beats [12] were segmented by windowing the BCG signals around the R-spikes.

5.1 BCG Segmentation

The BCG cycles of the subject are segmented using ECG signal [13] as a reference point. At first, the R peak of the ECG signal is identified and a uniform window with length of 400 samples was used to extract individual cycles of BCG of both normal and athlete subjects as shown in Fig. 12 and 13.

5.2 Performance of BCG And ECG

The BCG and ECG signals were taken together and compared.

The BCG was found to lag ECG by 0.15 - 0.3 seconds. This lag is actually due to the activity of the heart and it is known as PEP or Pre-Ejection Period(PEP) as shown in Fig. 3. This factor is important in determining the blood pressure variables of a person

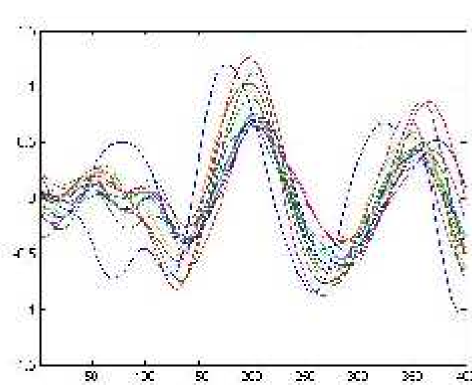

Figure12. Extracted BCG cycles from Healthy Athletic subjects

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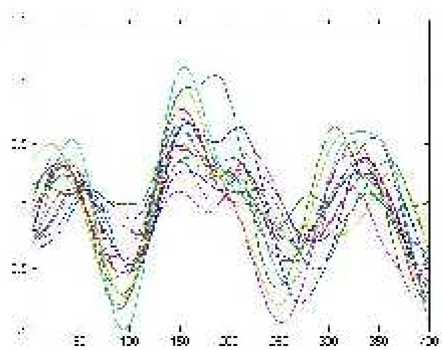

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Figure13. Extracted BCG cycles from Normal Subjects

5.3 Measurement of Cardiac Output

Step I: Analyze the BCG signal and determine the Maximum peak value (MAX) and minimum peak value (MIN)

Step II : Calculation of force applied
Force applied = NC ÷ Sensitivity of sensor (10)
where NC is the number of charge displayed.
Step III: Calculation of pulse pressure
Pulse pressure = (FA(Max) –FA(Min)) ÷ Area of artery (11)
where FA(Max) is the force applied by first peak MAX given in Step I and FA(Min) is the second peak of MAX due to systolic and diastolic activity of heart.
Step IV: Calculation of stroke volume
Stoke volume = pulse pressure x constant (12)
This constant was found to be 3.33 calibrated from echocardiogram of 2 subjects.
Step V: Calculation of Cardiac output(Litre/min)
Cardiac Output (CO) is measured from the BCG signal.
CO is termed as,
CO = Stroke Volume (SV) * Heart Rate (HR) (13)
The R-J interval is the time difference between the R peak of the ECG signal and the J peak of the BCG signal. From Table 2, the interval range was found to be between 0.15-0.3s. The standard deviation taken from the readings show that the interval does not vary much with time and even from person to person.

Table 2. Average and Standard deviation of the R-J interval of 3 Subjects.

	Subject 1	**Subject 2**	**Subject 3**
Average R-J interval (s)	0.193407	0.19447	0.176643
Standard Deviation	0.004341	0.006812	0.006459

6. RESULT AND DISCUSSION

6.1 Performance of BCG

Readings of Cardiac output are taken from the same subjects in the morning and evening (N1, N2 etc => normal life style subject and E1,E2, etc => Athletes).

It is evident from Table 3 that the variation of cardiac output for day and night reading for subjects are almost same but there was increase in cardiac output for athletic subjects than the normal life style subjects. The cardiac output was determined for 10 normal life style subjects with age group 20-25year and athletic subjects with age group of 20-23 years. Cardiac output was found to be around 4-5 l/min for normal life style subjects whereas 5.7 – 6.3 l/min for athletic subjects.

Table 3. Cardiac Output for Day and Night

Subject No.	**Day Reading**	**Night Reading**
N1	5.75	5.22
N2	4.65	4.37
N3	4.45	4.32
E1	6.4	6.18
E2	5.73	5.3
E3	4.94	4.81
E4	6.23	5.95

It is also observed from Table 1 that multiwavelets denoising is preferred than standard DWT as the heart rate calculated by the former is close to ECG R peak heart rate calculation.

7. CONCLUSION

We presented a setup which can measure BCG in sitting position using a flexible, light-weight polypropylene film sensor EMFi on a normal looking chair. The properties of EMFi sensor have been mentioned, and its suitability to this application has been verified. We have also made a simple setup of ECG for validation purposes. For cardiac output measurement, heart rate was determined from ECG and calculation of the same is difficult in BCG and complicated. BCG lagged ECG on an average of 0.1-0.3 s. We have taken the reading of 20 subjects and compared the resultant BCG cardiac output for normal life style subjects and athletes. The BCG differed for every

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individual due to various factors like strength of heart beat, vibration conductivity of the body, amount of fat in the body, weight of the person etc.

The future work can include respiratory analysis with a accelerometer sensor around the chest to cancel out the noise. This system could also be improved by transmitting these signals to a computer using wireless mode and sending them to a doctor for analysis, in case of an emergency; which may require further signal processing steps. The hospital can also be alerted when the variations are of the heart parameters indicate an upcoming heart abnormality conditions.

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