ISSN: 0976-9102 (ONLINE)
DOI: 10.21917/ijivp.2020.0325

LOW POWER FAULT TOLERANT SYSTEM FOR BALLISTOCARDIOGRAM SIGNAL

B.M. Manjula[1], H.S. Prashantha[2] and M.A. Goutham[3]

[1,2]Department of Electronics and Communication Engineering, Nitte Meenakshi Institute of Technology, India

[3]Department of Electronics and Communication Engineering, Adichunchanagiri Institute of Technology, India

Abstract

Ballisto-CardioGram is an upcoming technique to detect the health of the heart. Basically it measures the force in the blood vessels. It is one of the noninvasive technique for producing a graphical representation of repetitive motions of the human body arising from the sudden ejection of blood into the great vessels with each heartbeat. The paper proposes an efficient architecture for BCG signal filtering using different types of FIR filter architecture such as direct form FIR, Transposed form of FIR, LMS adaptive filter and DLMS adaptive filter. Different filter architectures are implemented to minimize the power consumption. Performance parameters like mean square error (MSE), Mean Absolute Error (MAE) and Power Supply Rejection Ratio (PSRR) are considered for evaluation. The architecture is implemented for 2, 3, 4, 5, 6-Tap filtering scheme using Xilinx ISE simulator. The paper concludes with comparing the results of different sensors and also able to achieve different peaks of BCG signal. With the results obtained, the author concludes that minimum three sensors are required to detect all the peaks of the BCG signal and to state whether the signal is normal or abnormal.

Keywords:

Ballisto-CardioGram, Adaptive Filter, Hear Beat, Signal Filtering

1. INTRODUCTION

T Bio medical signals are the observations of physiological activities of living beings that can be continually measured and monitored. Bio-medical signal processing aims at extracting significant information about the bio medical signal. The information can be extracted through physiological instruments that measure heart rate, blood pressure, oxygen saturation levels, blood glucose, nerve conduction, brain activity and so-on [1].

Some of the biomedical signals include Ballistocardiography (BCG), Electrocardiography (ECG) and Electroencephalography (EEG). The work presented here focuses on Ballistocardiogram signal. BCG also one of the important signals just like ECG signals to measure the health of the heart. This paper focuses on Low power by designing DLMS adaptive filter. Signal separation and artifact removal is presented using ICA algorithm and finally by analyzing each sensor output it is possible to analyze the health of the heart and requirement of implantation. The Ballisto-cardiograph (BCG) is a measure of ballistic forces on the heart [1]. Ballistocardiography is a technique for producing a graphical representation of repetitive motions of the human body arising from the sudden ejection of blood into the great vessels with each heart beat [2].

There are many challenges in designing a bio medical processing system. Some of them are low power and low voltage circuit design, fault tolerant, pre-processing, Interpolation, portability and compact size, noise and artifacts. Low power has become necessary in biomedical signal processing, as most of the embedded systems run on batteries. The objective is to extend battery life [3]-[6] as long as possible without sacrificing too much performance and also cost incurred for the system. The design of fault-tolerant enables a system to continue its operation at a reduced level, when some part of the system fails.

During signal acquiring stage, the vibrations are induced in the original signal it is because of user’s motion. If vibrations are large, then the quality of the signal is very poor, which affects the results. So signal can have noise and artifacts. Preprocessing is the initial stage required for biomedical [7] signal analysis.

Physiological signals are extracted using electrodes or sensors. Different types of electrodes are available to extract the Electro Cardiogram (ECG) signals and also varieties of sensors are available to extract the Ballistocardiogram (BCG) signal. Both the signals adapts noninvasive method for extraction [4]-[5]. Non-invasive is the procedure that does not require incision into the body or the removal of tissue. Now a days to measure the continuous health both ECG and ECG signals are used. Noise and artifacts plays an important role in diagnosing the health of the heart. Various approaches have been proposed in recent years for BCG measurement. These approaches include table, bed, chair, weighing scale and electromagnet [3]. These systems using weighing scales have various advantages in terms of ease of use, reliability etc.

But these devices having some disadvantages for measurement of BCG due to motion artifacts and vibrations of floor. The motion artifacts are induced due to subject’s movement during signal recording, similarly during recording the floor vibration also induces vibration in to the original signal. During recent years several approaches have been proposed to remove the artifacts. ICA based artifact removal method is proposed in this work. The mean square error is calculated and also source signals are extracted and separated both BCG and ECG signal from the extracted signal. From extracted BCG peaks and amplitudes of BCG signals are calculated to identify healthy or unhealthy person [6]-[8].

2. RELATED WORK

The most recent work proposed for the artifact removal from BCG signal using various filtering techniques is presented in this section. The work carried out is divided in following steps.

2.1 PREPROCESSING AND INTERPOLATION

Pedro et al. [8] proposes a sampling theorem as an interpolation method. Here the author highlighted the relationship between piecewise linear approximation and the sampling theorem by the use of triangular pulses instead of sampling functions. A comparison of linear interpolation with a series on a non-orthogonal basis composed of equally spaced triangular pulses is presented. Carlos et al. [9] proposed an algorithm used to detect the beat-to-beat heart rate of Ballistocardiogram (BCG) signal obtained from seated subjects. The developed algorithm is based on the continuous wavelet transform with splines. The algorithm includes learning phase in which the first four heartbeats in the BCG are detected to define search windows, initial thresholds, and interval limits. To evaluate the results from the algorithm and the heart rate obtained from the ECG, a Bland–Altman plot has been used to compare them for seven seated subjects. Solovjova et al. [10] introduced an algorithm which is based on the cubic spline interpolation method for function reconstruction. The authors also explore its several modifications, ranging from the basic, when small amounts of data are extracted from the original function, to more precise and efficient approaches [11]-[14].

2.2 BCG SIGNAL FILTERING

Since the BCG signal is very sensitive by nature, mixing of a small level of noise in the original signal leads to significant changes in clinical diagnosis. The signal voltage level is low and it is susceptible to artifacts that comparatively large. The frequency components of a human BCG signal falls in the range of 10 to 50Hz. The muscle movements, power line interference and electro-magnetic interference due to electrode contact noise are the main causes of artifacts in the signal. Hence filtering is one of the important issues, as data that is corrupted with noise must either filter or discarded. Nayak [15] – [17] proposed the use of filtering techniques that have been used in ECG signal pre-processing in a wide variety of systems in recent research work. These techniques use the wavelet transform technique which is an effective way to remove the base line wandering. Power line interference which is caused due to improper grounding of ECG equipment can be eliminated by using notch filter. Baseline Wander and Power line Interference can also be suppressed using digital IIR filter. Total power consumption required is 25mw.

2.3 ARTIFACT REMOVAL AND SIGNAL SEPARATION

Many algorithms for the removal of artifacts are based on Independent Component Analysis (ICA) and Principal component analysis (PCA), which is well known computational and transformation methods to separating multi-rate signal into additive subcomponents. ICA is a recently developed method in which the goal is to find a linear representation of non-Gaussian data so that the components are statistically independent, or as independent as possible. Srivastava et al. [18]-[20] made a comparative study of the average subtraction method and the ICA-based method, and concluded that the ICA-based method removes BCG artifact more effectively. Nakamura et al. [21] tested several different ICA algorithms for removing BCGs from EEG data, and evaluated their results with objective indices. To obtain better filtering, the work in [22]-[24] proposed the removal of BCG artifacts from simultaneously recorded EEG data using the ICA method. The performance of the model is evaluated in terms of power delay and frequency. After successful elimination of noise signal, the authors propose an ICA-based artifact removal method. Power spectrum is computed based on Independent components and k-means clustering is applied, the result of which is detection and removal of the artifact [25].

2.4 FEATURE EXTRACTION AND ANALYSIS

The QRS complex is a name for the combination of three of the graphical deflections of electrocardiogram (EKG or ECG). QRS corresponds to the depolarization of the right and left ventricles of the human heart. The Q, R, and S waves occur in rapid succession, do not appear in all leads, and reflect a single event, and are usually considered together. A Q wave is a downward deflection after the P wave. An R wave follows as an upward deflection, and the S wave is any downward deflection after the R wave [26]-[27]. Abdullah et al. [27] proposed a low cost algorithm implemented using FPGA for analysis of the ECG signal. As per the authors, determination of QRS complex is very important. Due to its characteristic shape, QRS detection in an ECG signal is necessary for efficient extraction of beat-to-beat time intervals (R-R). The proposed (FPGA) algorithm can detect the occurrence of R peak, measure the R-R time intervals and extract features from ECG signals. Xilinx ISE 14.6 package is used for implementation. Simulation. Extraction of J peak of BCG signal is proposed by Clapers et al. [28]. The paper conclude that, in order to reduce J peak time uncertainty below the measured intrinsic uncertainty of about ±2ms, the minimal bandwidth should be from 1.5 Hz to 22.5 Hz; and the sampling frequency can be decreased up to 50 Hz . Yu Hen Hu and Willis J. Tompkins describe the use of neural networks, specifically the feed forward multilayer perceptron architecture, with a dual purpose. First, they use it to detect QRS complexes in order to extract 51 samples centered on the QRS peak [29].

3. RESEARCH METHODOLOGY

The data set comprises of male and female data set. During signal acquisition, users were instructed to stand still for 60 s in an erect position on force plate measurement. Next, the users performed stepping exercise for 60s duration and after that they were told to stand on the scale for 5 min to analyze their full recovery. The data set also includes the data of the person at rest on chair and on bed. The dataset contains data of total 17 healthy users, which includes 10 male and 7 female users with the age range of 23.6±4.5 years, with height variations of 172.8±9.9 cm and weight variations of 70.7±11.3 kg. Preprocessing and Interpolation of these extracted signal is done using different techniques such as linear interpolation, cubic spline interpolation and spline interpolation. The results obtained conclude that the spline interpolation is suitable for biomedical signal.

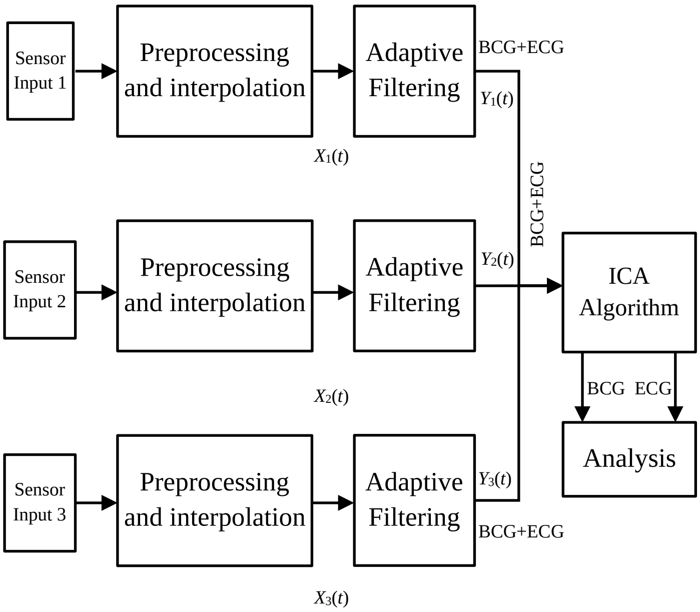


Fig.1. Block diagram of proposed work

In Fig.1, $x_1(t)$, $x_2(t)$, $x_3(t)$ are the signals obtained after preprocessing and interpolation. Among different types of Interpolation techniques Spline Interpolation is best suited for peak retention in biomedical signal.

This signal is a combination of both ECG and BCG. Preprocessing of BCG signal is performed. Spline interpolation is one such technique which has given satisfactory results of the BCG data. Data from any one sensor is considered at a time for processing. The preprocessed data is given as input to adaptive filter. Proposed architecture consists of FIR filter and error computation blocks. In this work author has used 2-tap, 3-Tap, 4-Tap, 5-Tap and 6-Tap filtering scheme for filtering. The thesis proposes different FIR filter structure to obtain efficient results in terms of error computation and achieves the better weight update parameters corresponding to the original filtered signal. 80% of noise is removed from the input signal. Low power is achieved using DLMS adaptive filter. In order to address the issue of artifacts the thesis proposes an independent component analysis (ICA) based approach. Proposed design is implemented using MATLAB, and experiment is carried out for various user data sets. The result shows artifact removal in terms of mean and standard deviation. This method shows better filtering performance. The proposed ICA algorithm separates ECG and BCG signal. This data is analyzed to identify the normal and abnormal state of the person using peaks of BCG signal. The abnormal state of the patient gives an indication for need of implantable devices.

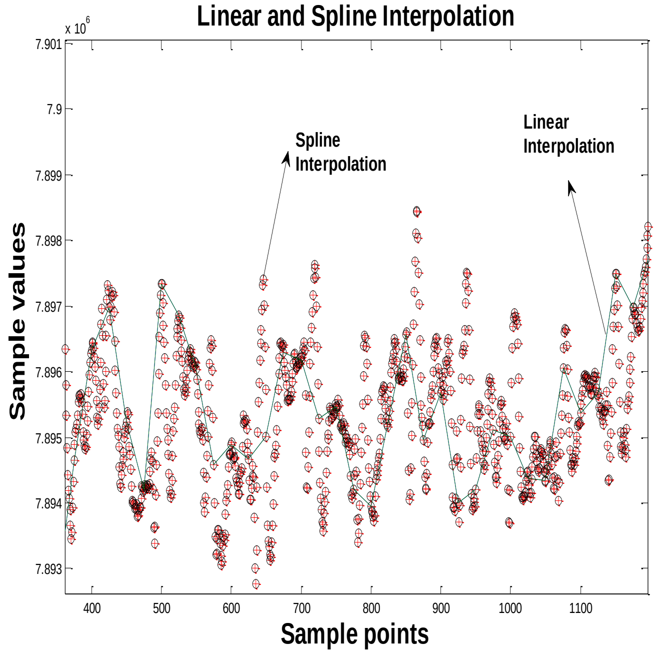


Fig.2. Spline and Linear Interpolation

Heart related problems are increasing every day. Electrocardiogram (ECG) is more commonly used method for vital signal monitoring and measurement of the cardiac activity. Hence this thesis proposes an alternative method that is Ballistocardiogram (BCG) to measure the cardiac action. The problem associated with biomedical signals is separation of the required signal from artifacts and noises. Noises are caused due to muscle artifacts, baseline wandering, and power line interference and electrode artifacts. In order to separate the signal from noise and artifacts varieties of digital filters are used. Author proposes an FPGA implementation of Pipelined direct form FIR filter, Transposed FIR filter and Adaptive filter scheme for signal filtering of Ballistocardiogram signals. BCG data is obtained from three different sensors and it is preprocessed using preprocessing technique. The preprocessed data is plotted using spline interpolation technique. This is given as input to the filter. The thesis presents different FIR filter structure to eliminate the noise [30]-[31]. The research work includes the implementation of Normal FIR filter, direct form pipelined architecture and transposed FIR filter. As per the result obtained the author concludes that the adaptive filter with pipelined architecture is best suitable for eliminating noise in the biomedical signal. Simulation results obtained are presented in result section.

The maximum sampling frequency of the filter can be estimated as

$$F_{sampling} = 1/(T_{mult}+3T_{add}) \tag{1}$$

3.1 ADAPTIVE FILTER

This paper proposes an Adaptive algorithm to eliminate the noise present in the data. An adaptive filter tries to model the relationship input signal in an iterative manner. It has two inputs are x(n) and d(n).

The basic operations of an adaptive filter include two processes

- *Filtering*: In this process, Output of the filter is in response to the given input signal
- *Adaptation*: The aim is to adjust the filter parameters to the environment. DLMS adaptive filter with pipelined architecture gives better results.

3.1.1 Least Mean Square Adaptive Filter:

LMS is one of the most basic forms of adaptive filter. Adaptive filter mimics the desired filter by calculating filter coefficients for which the error due to mean square is least. Here error is due to difference of desired and actual signal. The obtained difference is used to update the weights of the filter in every iteration. During nth iteration, the updated weight of LMS algorithm is shown in Eq.(2)-Eq.(4). The advantage of LMS algorithm is fast convergence; it is easy to design and is reliable.

$$y(n) = W_n^T \cdot X(n) \tag{2}$$

$$e(n) = d(n)\text{-}y(n) \tag{3}$$

$$w_{n+1} = w_n.\beta.x(n).e(n) \tag{4}$$

where

$$X(n) = [x(n), x(n\text{-}1), x(n\text{-}2),\ldots,x(n\text{-}N_1)]^T \tag{5}$$

$$W_n = [w_n(0), w_n(1), w_n(2)\ldots w_n(N\text{-}1)]^T \tag{6}$$

For an LMS filter of order N and step size β

$$e(n) = d(n)\text{-}w(n).x(n) \tag{7}$$

where,

$x(n)$ - filter input

$d(n)$ - desired input signal

W_n - N^{th} order LMS adaptive filter weight at t_n^{th} iteration

$y(n)$ - Output of the filter at the nth iteration

N - Order of LMS filter

B - Step size or convergence-factor.

$e(n)$ - Error computed during nth iteration

The disadvantage of LMS algorithm is lengthy critical path. Pipelining is introduces to overcome this critical path delay. This modification of the LMS algorithm produces the DLMS algorithm that supports pipelined operations.

3.1.2 DLMS Adaptive Filter:

To achieve reduced delay for adaption and lower power consumption, an optimized pipelining based scheme across the combinational DLMS algorithm is used. This is done by reducing the delay required for updating the weights of the input sample. This scheme is implemented for 2 to 6 Tap filtering schemes using Xilinx ISE simulator. The optimal results are obtained for 4-tap filtering. The filter performance is evaluated in terms of power.

The proposed algorithm uses delayed error $e(n\text{-}m)$ to update the weight and this error is due to $(n\text{-}m)^{th}$ iteration. Equation for weight-update is given by,

$$w_{n+1} = w_n.\beta.x(n\text{-}m).e(n\text{-}m) \tag{8}$$

$$e(n\text{-}m) = d(n\text{-}m) - y(n\text{-}m) \tag{9}$$

Here m is the delay due to adaptation; delayed LMS adaptive filter is as shown in Fig.2.

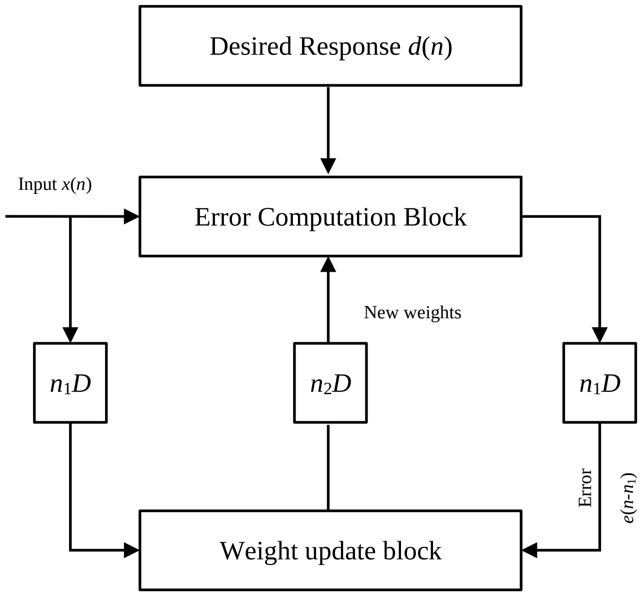


Fig.3. Proposed delayed LMS filter

In proposed DLMS filter algorithm, instead of considering, adaptation delay as a single entity, it is considered as decomposed two parts. One part is due to the FIR filtering and other is due to weight adaptation. Based on the result total delay and error is calculated. Here if n_1 cycle is the latency or delay of computation of error, then the error computed by proposed structure at the n^{th} cycle is denoted by $e(n\text{-}n_1)$, Which is obtained by the input samples delayed by n_1 cycles. This is used to generate the weight-increment term.

3.1.3 Updating the Weight using Delayed Error:

To update the current weight delayed error is used in the proposed DLMS adaptive algorithm. The weight update process is given by,

$$w_{n+1} = w_n.\beta.x(n-m).e(n-m) \tag{10}$$

As per the proposed design, the architecture can be presented in two parts: (i) pipeline architecture to reduce the delay and (ii) updating the weight.

The weight update of proposed LMS adaptive algorithm is written as:

$$y(n) = W_{n-n_2}^T \cdot X(n) \tag{11}$$

$$\underline{e}(n-n_1)=d(n-n_1)-y(n-n_1) \tag{12}$$

$$w_{n+1} = w_n.\beta.x(n-n_1).e(n-n_1) \tag{13}$$

The proposed DLMS algorithm performs the weight update and error computation.

3.1.4 Mean Square Error Optimization:

The Optimal mean square error w_{opt} can be computed as:

$$H_{xx}\, w_{opt} = P_{xd} \text{ and } w_{opt} = H_{xx}^{-1} \cdot P_{xd} \tag{14}$$

where $H_{xx} = (X(n).X^T(n))$

$$P_{xd} = (X(n)).d^T(n) \tag{15}$$

Here H_{xx} is the correlation matrix associated with $X(n)$ and P_{xd} is the cross-correlation matrix between $d(n)$ and $X(n)$.

$$X(n)=[x(n), x(n-1), x(n-2),\ldots, x(n-N+1)]^T \tag{16}$$

3.2 SIGNAL SEPARATION AND ARTIFACT REMOVAL USING ICA ALGORITHM

Artifacts in the signal due to vibration, head movement, muscle movement, motion artifacts and eye blinking during extraction. The thesis proposes ICA algorithm to minimize the artifacts which are present in the data and to separate the BCG and ECG signal. ICA model for three sensors can be written as

$$F_1(n) = a_{11}s_1(\mathrm{n})+a_{12}s_2(n)+ a_{13}s_3(n) \tag{17}$$

$$F_2(n) = a_{21}s_1(\mathrm{n})+a_{22}s_2(n)+ a_{23}s_3(n) \tag{18}$$

$$F_3(n) = a_{31}s_1(\mathrm{n})+a_{32}s_2(n)+ a_{33}s_3(n) \tag{19}$$

The equation can be expressed as below using vector-matrix notation,

$$F = As \tag{20}$$

where, $F = \begin{bmatrix} F_1 \\ F_2 \\ F_n \end{bmatrix}$ and $S = \begin{bmatrix} s_1 \\ s_2 \\ s_n \end{bmatrix}$

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \tag{21}$$

F is the random vector of mixture,

s is the random vector of sources $s_1,s_2,\ldots,s_n$

A is the mixing matrix with elements a_{ij}. It can be written as

$$F = \sum_{i=1}^{n} a_i s_i \tag{22}$$

The research work considers only three sources for experiment. ICA is similar to Blind source separation (BSS) problem [28]. In order to extract the source the author proposes equation [22] – [24].

$$z_1(t)=w_{11}F_1(n)+ w_{12}F_2(n)+ w_{13}F_3(n) \tag{23}$$

$$z_2(t)=w_{21}F_1(n)+ w_{22}F_2(n)+ w_{23}F_3(n) \tag{24}$$

$$z_3(t)=w_{31}F_1(n)+ w_{32}F_2(n)+ w_{33}F_3(n) \tag{25}$$

$$\mathrm{s}=\mathrm{A}^{-1}F \tag{26}$$

where, $s = WF$ and It can be written as

$$z=WF \tag{27}$$

where,

F is the random vector of mixtures $F_1\ldots,F_n$,

S is the random vector of sources $s_1,s_2,s_3\ldots,S_n$

A is the mixing matrix with elements a_{ij},

W is un-mixing matrix.

3.2.1 Block Diagram of ICA

For experimental purpose the author considers BCG data of single person by keeping three sensors on bed in supine position. The same experiment is carried out for all 17 available BCG data with different conditions. The output of the adaptive filter is given as input to ICA block to eliminate the artifacts if any present in the data and also to separate the source signal. Each of these sources have two main components that is BCG and ECG. The ICA block separates the two components and also eliminates the artifacts present in the data. The proposed work is shown in Fig.3.

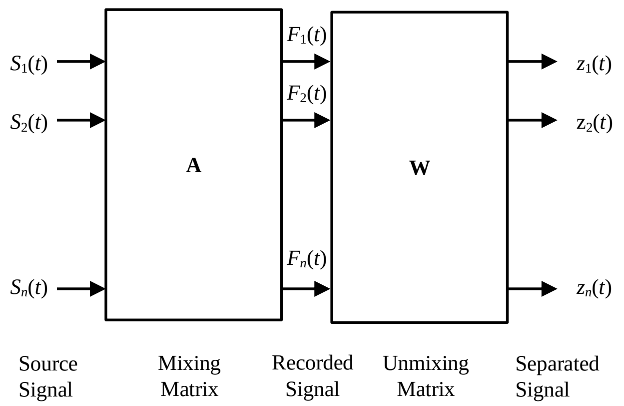


Fig.4. ICA block diagram for n number of sources

In Fig.4, $s(t)$ is the output of an adaptive filter, $F(t)$ is the recorded signal, $z(t)$ is the estimation of sources, A is the mixing matrix and W is the un-mixing matrix.

Here the author considered adaptive output $y(t)$ as input to ICA block which is denoted by $s(t)$, and obtained BCG and ECG separated data as ICA output. Mixing matrix is assumed as 2×2 square matrix. It can be obtained randomly by using MATLAB tool. The initial value of mixing matrix A is considered as

$$A = \begin{bmatrix} 0.3344 & 0.8040 \\ -0.1199 & -0.0680 \end{bmatrix}$$

$$W = \begin{bmatrix} 12.8522 & -2.3792 \\ -5.1441 & -2.4126 \end{bmatrix}$$

The un-mixing matrix W is obtained by inversing the matrix A. The value of W is output z is the separated estimation of the input. Mixing and un-mixing matrix is updated continuously up to 100th iterations [32]-[35].

3.3 ICA GRADIENT ASCENT

To obtain gradient ascent the entropy of the components $U=g(z)$ will be by definition:

$$H(Z) = H(F) + E\left\{\sum_{i=1}^{n} \ln P(z_i)\right\} + \ln|W| \tag{28}$$

where $z_i = w_i^T F$ is the i^{th} component which is extracted by i^{th} raw of the un-mixing matrix W. By definition the pdf p of variable is the derivative of that variable cdf g.

$$P(z_i) = \frac{dg(z_i)}{dz} \tag{29}$$

where this derivative is denoted by $g(z_i) = p(z_i)$ so that it can be written as:

$$H(Z) = H(F) + E\left\{\sum_{i=1}^{n} \ln g'(z_i)\right\} + \ln|W| \tag{30}$$

The un-mixing matrix W that maximizes the entropy of Z. The function $h(Z)$ which maximizes the entropy is given by

$$h(Z) = E\left\{\sum_{i=1}^{n} \ln g'(z_i)\right\} + \ln|W| \tag{31}$$

The initial stage of the research work considers random value of mixing matrix A and un-mixing matrix W. It can be updated by using the formula

$$W_{new} = W_{old} + \alpha\left(W^{-T} - \frac{2}{N}\sum_{k=1}^{N} \tanh(z^k)\left[F^k\right]^T\right) \tag{32}$$

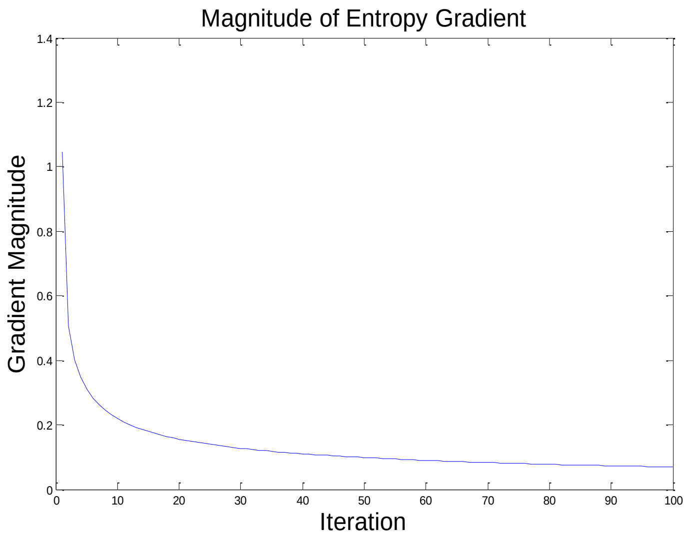
where,

α is the small constant, $k=1,2,\ldots,N$

W_{new} is the updated value of un-mixing matrix

W_{old} is the old value of un-mixing matrix

Around hundred iteration gradient magnitudes have come to zero.



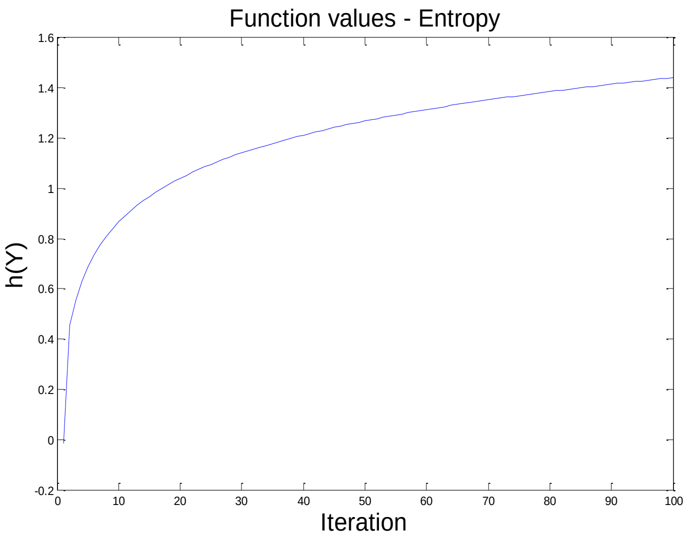


Fig.5. Magnitude of Entropy Gradient and Function Value-Entropy

Graph of h during the gradient ascent. This approximates the entropy of the signals

$$Z = g(z), \text{ where } z = WF. \tag{33}$$

The correlation matrix is:

1.0000	0.0046	0.0757	-0.9964
0.0046	1.0000	0.9975	0.0806
0.0757	0.9975	1.0000	0.0095
-0.9964	0.0806	0.0095	1.0000

The diagonal indicates extracted signals are close to source signal. The initial and final correlation between source signal and estimated signals are:

$$R_{initial} = \begin{bmatrix} 0.9416 & 0.9964 \\ 0.3440 & 0.0920 \end{bmatrix}$$

$$R_{Final} = \begin{bmatrix} 0.1609 & 0.9934 \\ 0.9882 & 0.1072 \end{bmatrix}$$

The result of final correlation matrix indicates that the original source signals are extracted successfully.

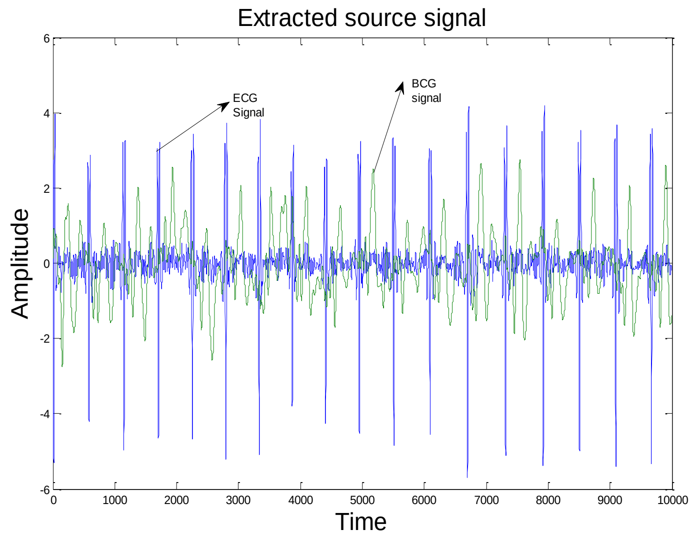


Fig.6. Separated ECG and BCG signal

3.3.1 *Feature Extraction:*

Feature extraction is very important to monitor health of the heart continuously. ECG is one of the method to monitor the heart continuously. Recent advances in bio medical field show that ECG signal can be replaced by BCG to measure the health of the heart. I-J-K is most critical part of waveform. I-J-K complex can be obtained by Pan–Tompkins algorithm. The formula used to calculate heart rate is given as:

$$\text{Heart rate} = (60/RR) \text{ intervals in seconds} \quad (34)$$

72 beats per minute is the average rate of heart beat for a normal person, it is in between seventy to eighty (70-80) beats per minute for normal person. During normal sinus rhythm, resting heart rate below 60 bpm is called as Bradycardia and heart rate above 90 beats per minutes (bpm) is called as tachycardia. Based on the ECG peak value BCG peak vales are calculated.

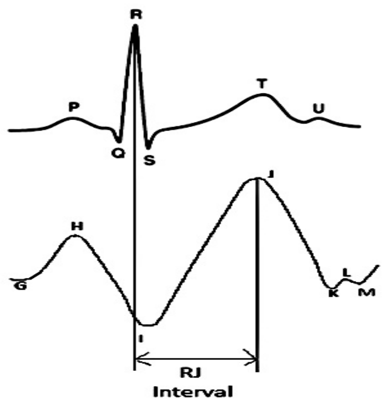


Fig.7. RJ interval Calculation

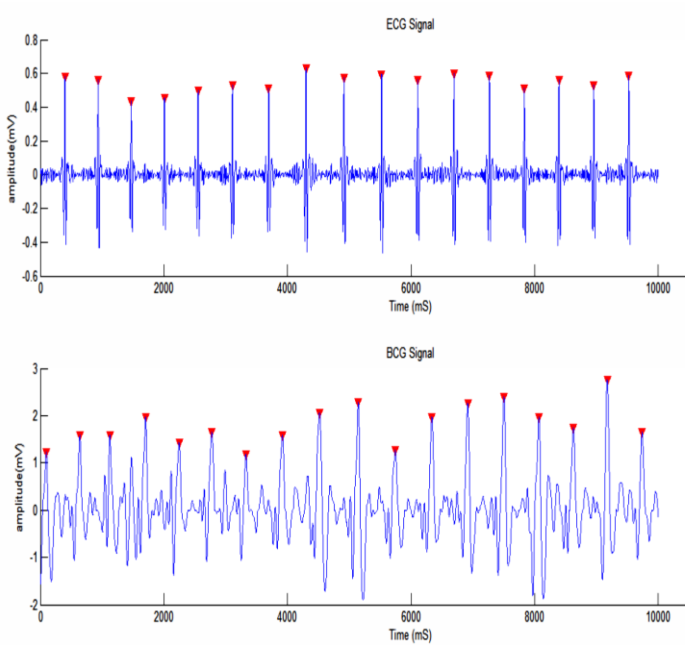


Fig.8. R and J peak detection

4. RESULTS AND ANALYSIS: FILTER DESIGN RESULTS

Experiments are conducted for different set of data obtained from different sensors of the preprocessing unit. The results are presented in Table.1 – Table.3.

Table.1. FPGA Synthesis results for Pipelined Direct form FIR Filter

Parameters	2-Tap	3-Tap	4-Tap	5-Tap	6-Tap
MSE	0.5332	0.4536	0.03383	0.0278	0.0182
MAE	0.1202	0.1532	0.1795	0.215	0.2160
PSNR	25.63	35.69	40.90	42.36	42.52
Total Supply power (Watts)	1.536	1.542	1.550	1.553	1.556
Dynamic	0.058	0.064	0.071	0.074	0.074
Static Power	1.478	1.478	1.478	1.478	1.478

Table.2. FPGA Synthesis results for Transformed FIR Filter

Parameters	2-Tap	3-Tap	4-Tap	5-Tap	6-Tap
Slice Registers	32	65	99	99	134
Flip-Flops	32	65	99	99	134
Slice LUTs	33	67	102	138	175

Occupied cells	17	26	35	44	54
LUT FF pairs	65	99	134	170	207
IOBFs	50	51	52	53	54
Average fan out	1.36	1.57	1.63	1.68	1.71
MSE	0.0152	0.0215	0.0254	0.0302	0.398
MAE	0.105	0.125	0.159	0.15	0.168
PSNR	30.25	39.25	41.17	42.3	42.65
Total Supply power(W)	1.518	1.539	1.546	1.55	1.553
Dynamic	0.040	0.061	0.068	0.07	0.075
Static Power	1.478	1.478	1.478	1.47	1.478

Table.3. FPGA Synthesis results for DLMS Filter

Parameters	**2-Tap**	**3-Tap**	**4-Tap**	**5-Tap**	**6-Tap**
Maximum Frequency MHz	528.513	528.513	528.513	528.513	528.513
Arrival time of input before clock in ns	3.702	3.702	3.702	3.702	3.702
Maximum output required time after clock in ns	0.682	0.682	0.682	0.682	0.682
Maximum Combinational path delay in ns	7.286	8.366	9.446	10.3	11.52
Slice Registers	60	86	113	138	164
Flip-Flops	60	86	113	138	164
Slice LUTs	150	200	267	317	367
Number used as Logic	145	194	259	295	347
Total Supply power (W)	1.481	1.48168	1.482	1.482	1.483
Dynamic	0.0050	0.0055	0.0058	0.0059	0.0057
Static Power	1.476	1.476	1.476	1.476	1.476

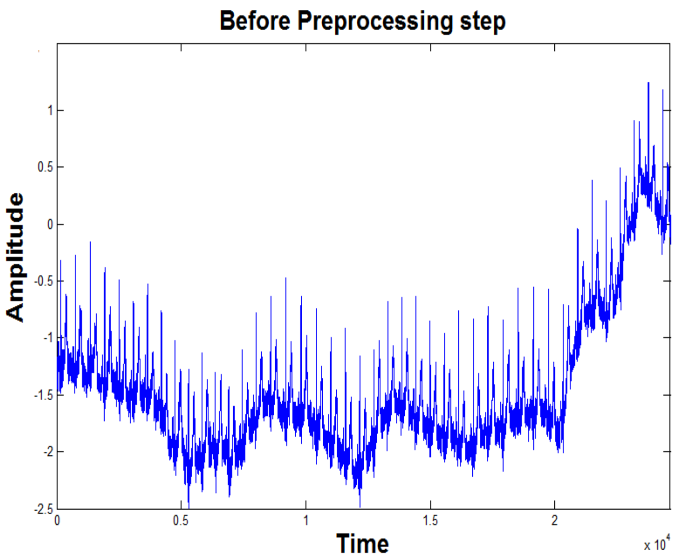


Fig.9. Extracted Raw Data of sensor1

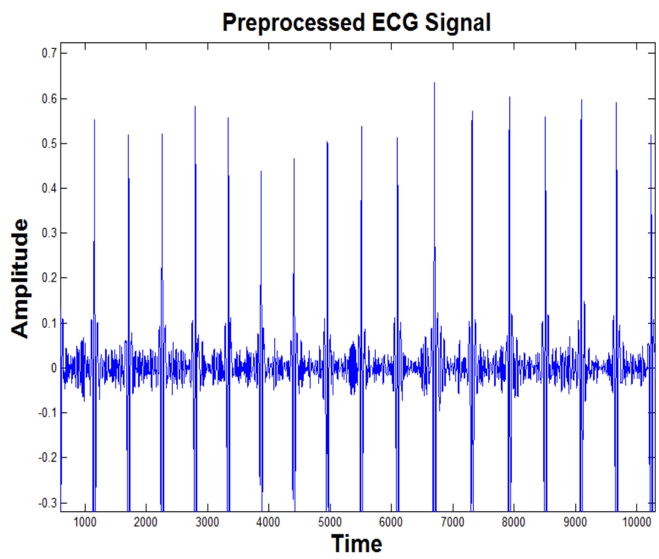


Fig.10. Pre-processed

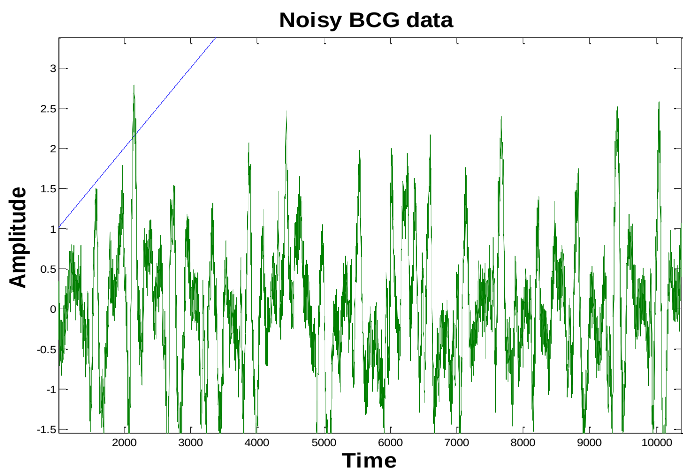


Fig.11. Noisy BCG Data

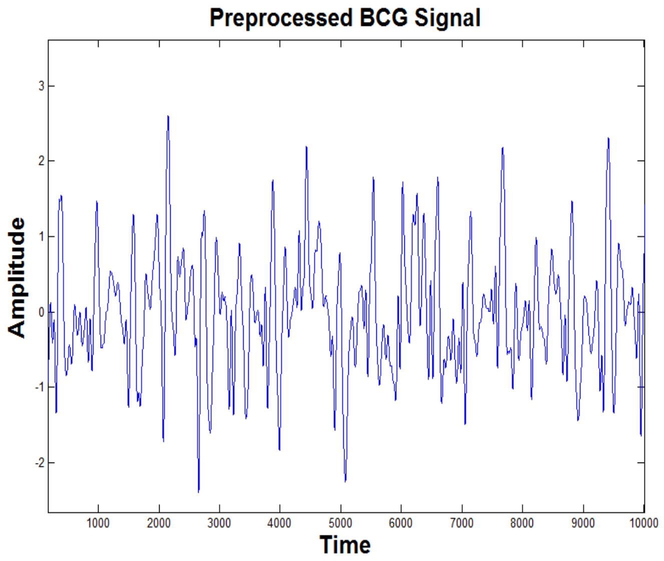


Fig.12. Pre-processed BCG signal

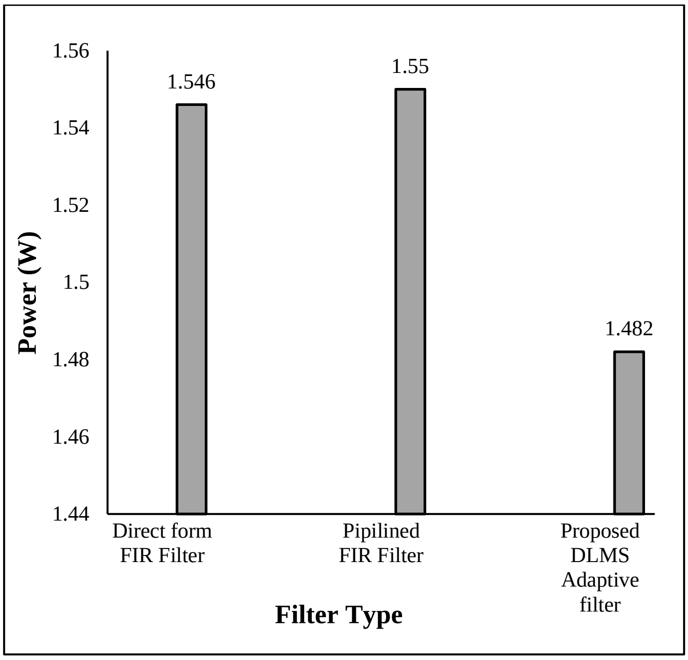


Fig.13. Power Consumption results for 4-Tap filter

The author concludes that proposed DLMS filter is best suitable for eliminating the noise content present in the data. The proposed design mainly concentrates on the weight update process for the given undistorted data in order to achieve the filtered data.

Table.4. Important parameters for 4 Tap filter

Parameters	Transposed FIR	Pipelined Direct form FIR	Proposed DLMS Adaptive Filter
MSE	0.0582	0.03383	0.0063
MAE	0.2413	0.1795	0.0792
PSNR	42.60	38.96	42.61

Thus the output obtained from the adaptive delayed LMS filter almost eliminates the noise. But there may be a possibility of artifacts which is caused by subject movement during extraction of the BCG signal, which can be eliminated by applying a concept of independent component analysis.The results obtained for statistical parameter analysis of female subject using ICA algorithm is presented. Mean and standard deviation are calculated and presented in Table.5 - Table.7.

Table.5. Statistical Parameter of female observed BCG signal

User 1	Mean	Standard Deviation
Female subject (168 cm height and 68 kg)	0.0072	2.0165

By comparing the mean and standard deviation it can be concluded that the deviation in the data is reduced which shows the stability in the signal and removal for unwanted signal.

Table.6. Pre-processed BCG data

User 1	Mean	Standard Deviation
Female subject (168 cm height and 68 kg)	0.0020	1.4378

Table.7. Filtered Output Results

Female subject (168 cm height and 68 kg)	Mean	Standard Deviation
Existing System	-0.0862	1.0347
Proposed System	-1.1842	1.0355

Similarly, it is possible to compute the performance of proposed model by considering Male BCG signal data. According to simulation study and analyses, the author concludes that proposed model is capable of removing artifact present in the BCG signals. The experimental analysis of artifact removal is presented for two users male and female in the thesis. Artifact removal method is compared with presently existing approach which shows better performance.

Table.8. IJK interval, JJ duration and HR Considered for abnormal patient

Signal	1	2	3	4
J-J interval (seconds	0.791	0.6	0.931	0.51
Obtained Heart rate (beats/min)	75.84	100	64.59	117.64
IJK interval (s)	0.094	0.025	0.035	0.022
R-J Interval	0.18	0.201	0.214	0.191
I-J interval	0.072	0.059	0.058	0.214
I-J amplitude	1.56	1.22	2.01	0.05
Status	Standard	Abnormal	Abnormal	Abnormal

Similar to Table.8, it is possible to calculate for normal patient.

Table.9. Normal Data-Unhealthy Person (Considering sensors)

Sensors	Condition	Faulty Sensors	Inference
1,2	Supine position	3	Able to detect Heart rate, I, J, K Peaks
2,3	Supine position	1	Able to detect Heart rate, I, J, K Peaks
1,3	Supine position	2	Able to detect Heart rate, I, J, K Peaks
1,2,3	Supine position	-NIL-	Able to detect Heart rate, H, I, J, K Peaks.

The results obtained is compared with timing references to those obtained from the ECG. J-J intervals and IJK intervals and different peaks are calculated using the Pan-Tompkins algorithm [17] and the results were manually inspected to guarantee the different peaks. Based on the results obtained the author concludes the normal and abnormality of the dataset and requirement of implantable devices based on the heart rate observed. Hence this works as faults tolerant system by considering any two sensors. The experiments are carried out with two sensors and also with three sensors and concludes that H peak information is not plays an important role in making normal and abnormal dataset decision which we get by considering all three sensors together. BCG signal filtering approach is implemented using IEEE standard VHDL. Xilinx I.S.E is used for synthesis and simulation. Proposed filter architecture is simulated by using Xilinx I.S.E 14.3.For simulation study Virtex–V family is used which contains the device XC5VSX95T, package FF1136 and speed grade of -2.

5. CONCLUSION

Ballistocardiogram is a type of biomedical signal which provides lot of important information to doctors or to physicians for diagnosis. It gives the information on physical conditions which helps to record the biomedical data for a longer period of time. In order to identify the abnormality it is required to consider the data for longer duration and it is important to identify different peaks and features of BCG data.

The problem associated with signal extraction is noise and artifacts. The extracted biomedical signals are usually in A/D form which is not possible to analyze these data. It has to be converted in to some readable form. To convert A/D data in to voltage level preprocessing techniques is applied. In preprocessing 23 bits are used to achieve the voltage range of 5V.The work presented here considers 8 bit,16bit,24 bit and 32 bit for preprocessing and obtained the voltage range of 161890.1,630.38,2.47 and 0.00965 respectively. The author proposes Linear Interpolation, Spline Interpolation and cubic Spline interpolation techniques to fill the missing data point with the available discrete set of known data point and also to smoothen the obtained BCG wave. The results obtained concludes that Spline Interpolation method is best method to retain I, J and K peaks of BCG wave.

In order to eliminate the noise in the data and to minimize the power consumption and to high operating frequency the author proposes different FIR filter structures such as pipelined direct form FIR and transpose FIR filter. An Adaptive filter is implemented which includes FIR filter and error computation block. Better convergence parameters are obtained by designing DLMS adaptive filter. DLMS algorithm is simple and power of 1.428W is obtained .The important parameters such as MSE, MAE and PSNR is calculated for all types of FIR filter structure. To update the weights and to eliminate the noise, pipelining architecture is used. The designed architecture is simulated and implemented using Xilinx I S E simulator to measure performance of the architecture in terms of operating frequency, slice logic used and power consumption. This scheme of signal filtering is used to filter the BCG signal. Efficient performance of designed architecture in terms of frequency, for 2-tap, 3-tap, 4-tap, 5-tap and 6-tap filtering scheme, operating frequency is achieved 528.513 MHz is presented in the result.

Artifacts present in the data can be eliminated by designing an ICA algorithm. ICA algorithm is also used to separate BCG and ECG signal present in extracted data set. For bio-medical application, author has considered BCG signal and addressed the issue of artifact removal. Magnitude of entropy gradient and function Value-Entropy is also calculated for the BCG data. Results show that around 100th iterations magnitude of entropy almost reaches to zero. The correlation matrix for BCG data is also presented. Results obtained in diagonal matrix indicate that the input and output of ICA are correlated to each other. Output of ICA is an estimation of source signal at the input. Analysis is done on the extracted BCG signal. Different peaks and intervals of BCG signals are detected using Pan-Tompkins algorithm and concluded that any two sensors are enough to detect the peaks and heart rate and to analyze the BCG signal. The work presented here works as fault tolerant scheme, to analyze normal abnormal state of the patient. Hence the work focuses in the area of low power fault tolerant system for biomedical implants for BCG signal and the thesis focuses on developing a proof of concepts for low power fault tolerant system for biomedical implants [37]-[39].

REFERENCES

[1] US National Library of Medicine Medical Subject Headings (MeSH), "Ballistocardiography, A Bibliography", Technical Report, NASA Server, pp. 1-120, 2011.

[2] *D.C.* Mack, J.T. Patrie, R.A. Felder and P.M. Surrat, "A. Sleep Assessment using a Passive Ballistocardiography-Based System: Preliminary Validation", *Proceedings of 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 4319-4322, 2009.

[3] O.T. Inan, M. Wiard Etemadi and L. Giovangrandi, "A. Robust Ballistocardiogram Acquisition for Home Monitoring", *Physiological Measurement*, Vol. 30, No. 2, pp. 169-185, 2009.

[4] S. Junnila, A. Akhbardeh, A. Varri and T. Koivistoinen, "An EMFi-Film Sensor based Ballistocardiographic Chair: Performance and Cycle Extraction Method", *Proceedings of IEEE Workshop on Signal Processing Systems Design and Implementation*, pp. 373-377, 2005.

[5] S. Sprager, D. Donlagic and D. Zazula, "Monitoring of Basic Human Vital Functions using Optical Interferometer", *Proceedings of IEEE International Conference on Signal Processing*, pp. 1-4, 2010.

[6] I. Starr and F. C. Wood, "Studies with the Ballistocardiograph in Acute 963 Cardiac Infarction and Chronic Angina Pectoris", *American Heart Journal*, Vol. 25, No. 9, pp. 81-101, 1943.

[7] L.D. Peres Pedro, Ivanil S. Bonatti and Walter C. Borelli, "The Linear Interpolation Method: A Sampling Theorem Approach", *SBA Control and Automation Journal*, Vol. 14, No. 4, pp. 1-16, 2003.

[8] Carlos Alvarado-Serranoa, Pablo Samuel Luna-Lozanob and Ramon Pallàs-Areny, "An Algorithm for Beat-to-Beat Heart Rate Detection from the BCG based on the Continuous Spline Wavelet Transform", Technical Report. Instrumentation Sensors and Interfaces Group, Universitat Politècnica De Catalunya, pp. 1-158, 2013.

[9] Viktorija Solovjova, "A Modified Spline Interpolation Method for Function Reconstruction from Its Zero-Crossings", Master Thesis, Department of Computer Science and Information Technologies, University of Latvia, pp. 1-132, 2010.

[10] L. Giovangrandi, O.T.I.S. Kulkarni and Supriya O. Rajankar, "Preprocessing Techniques of Electrocardiogram", *International Journal of Engineering and Computer Science*, Vol. 5, No. 6, pp. 16746-16748, 2016.

[11] Abdul Q. Javaid, Andrew D. Wiens, N. Forrest Fesmire, Mary A. Weitnauer and Omer T. Inan, "Quantifying and Reducing Posture-Dependent Distortion in Ballistocardiogram Measurements", *IEEE Journal of Biomedical and Health Informatics*, Vol.19, No. 5, pp. 1549-1556, 2015.

[12] L. Givoangrandi, O.T. Inan and R.M. Wiard, "Ballistocardiography: 974 A Method Worth Revisiting", *Proceedings of Annual International Conference on Engineering and Medicine*, pp. 4279-4282, 2011.

[13] Seema Nayak, M.K. Soni and Dipali Bansal, "Filtering Techniques for ECG Signal Processing", *International Journal of Research in Engineering and Applied Sciences*, Vol. 2, No. 2, pp. 114-126, 2012.

[14] A. Yasoubi and M. Modarressi, "Low-Power Online ECG Analysis using Neural Networks", *Proceedings of International Conference on Digital System Design*, pp. 547-552, 2016.

[15] Nitesh and B.M. Manjula, "Data Processing of Ballistocardiogram Signal using Adaptive Filter", *International Journal of Innovative Research in Electrical, Electronics, Instrumentation, and Control Engineering*, Vol. 4, No. 5, pp. 254-257, 2016

[16] Jeong Gih Sung Chung, Jeong Su Lee and Kwang Suk Park, "Wakefulness Estimation only using Ballistocardiogram: Nonintrusive Method for Sleep Monitoring", *Proceedings of Annual International Conference on Engineering in Medicine and Biology Society*, pp. 1-6, 2010.

[17] O.T. Inan, M. Etemadi, B. Widrow and G.T.A. Kovacs, "Adaptive Cancellation of Floor Vibrations in Standing Ballistocardiogram Measurements using a Seismic Sensor as

a Noise Reference", *IEEE Transactions on Biomedical Engineering*, Vol. 57, No. 3, pp. 722-727, 2010.

[18] G. Srivastava, K.M. Lau, G.H. Glover and V. Menon, "ICA-Based Procedures for Removing Ballistocardiogram Artifacts from EEG data Acquired in the MRI Scanner", *NeuroImage*, Vol. 24, pp. 50-60, 2005.

[19] W. Nakamura, K. Anami, T. Mori, O. Saitoh, A. Cichocki and S. Amari, "Removal of Ballistocardiogram Artifacts from Simultaneously Recorded EEG and fMRI Data using Independent Component Analysis", *IEEE Transactions on Biomedical Engineering*, Vol. 53, No. 7, pp. 1294-1308, 2006.

[20] P. Adhikary, "A Novel Approach to Find Out QRS Complex for ECG Signal", Proceedings of Annual International Conference on Information Technology, Electronics and Mobile Communication, pp. 1-5, 2016.

[21] A.D. Wiens, M. Etemadi, S. Roy, L. Klein and O.T. Inan, "Toward Continuous, Noninvasive Assessment of Ventricular Function and Hemodynamics: Wearable Ballistocardiography", *IEEE Journal of Biomedical and Health Informatics*, Vol. 19, No. 4, pp. 1435-1442, 2015.

[22] B.M. Manjula and C. Sharma, "BCG Artifact Removal using Improved Independent Component Analysis Approach", *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 4, No. 2, pp. 373-382, 2016.

[23] M.M. Butt, M.U. Akram and S.A. Khan, "Classifying Normal Sinus Rhythm and Cardiac Arrhythmias in ECG Signals using Statistical Features in Temporal Domain", *Proceedings of International Conference on Electronics and Mobile Communication*, pp. 28-31, 2015.

[24] H.N. Abdullah and B.H. Abd, "A simple FPGA System for ECG R-R Interval Detection", *Proceedings of International Conference on Industrial Electronics and Applications*, pp. 1379-1382, 2016.

[25] H.S. Javaid and S.A. Sheikh, "ECG as Biometric using Autocorrelation of Normalized R-R Interval", *Proceedings of International Conference on Intelligent Systems*, pp. 698-701, 2016.

[26] R.R. Perez, A. Marques and F. Mohammadi, "The Application of Supervised Learning through Feed-Forward Neural Networks for ECG Signal Classification", *Proceedings of International Conference on Electrical and Computer Engineering*, pp. 1-4, 2016.

[27] A. Mahadevan, D.H. Mugler and S. Acharya, "Adaptive Filtering of Ballistocardiogram Artifact from EEG Signals using the Dilated Discrete Hermite Transform", *Proceedings of International Conference on Engineering in Medicine and Biology Society*, pp. 2630-2633, 2008.

[28] Kara N. Bocan and Ervin Sejdi Kara N. Bocan and Ervin Sejdic, "Review Adaptive Transcutaneous Power Transfer to Implantable Devices: A State-of-the-Art Review", Master Thesis, Department of Electrical and Computer Engineering, Swanson School of Engineering, pp. 1-175, 2009.

[29] Ganesh R. Naik and Dinesh K Kumar, "An Overview of Independent Component Analysis and Its Applications", *Informatica*, Vol. 35, No. 2, pp. 63-81, 2011.

[30] C. Jutten and J. Karhunen, "Advances in Blind Source Separation (BSS) and Independent Component Analysis (ICA) for Nonlinear Mixtures", *International Journal of Neural Systems*, Vol. 14, No. 5, pp. 267-292, 2004.

[31] A.J. Bell and T.J. Sejnowski, "An Information Maximization Approach to Blind Separation and Blind Deconvolution", *Neural Computing*, Vol. 7, No. 6, pp. 1129-1159, 1995.

[32] T. Koivistoinen, S. Junnila, A. Varri and T. Koobi, "A New Method for Measuring the Ballistocardiogram using EMFi Sensors in a Normal Chair", *Proceedings of International Conference on Engineering in Medicine and Biology Society*, pp. 2026-2029, 2004.

[33] Shashi Kant Sharma and Rajesh Mehra "LMS and RLS based Adaptive Filter Design for Different Signals", *International Journal of Emerging Technologies and Engineering*, Vol. 4, No. 3, pp. 141-156, 2014.