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BCG Artifact Removal Using Improved Independent Component Analysis Approach

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Abstract

Recent advancement in bio-medical field has attracted researchers toward BCG signal processing for monitoring the health activities. There have been various techniques for monitoring physical activities such as (SCG) Seismocardiography, Electrocardiography (ECG) etc. BCG signal is a measurement of reaction force applied for cardiac ejection of blood. Various measurement schemes and systems have been developed for BCG detection and measurement such as tables, beds, weighing scale and chairs. Weighing scales have been promising method for measurement of BCG signal because of less cost of implementation, smaller size etc, but these devices still suffer from the artifact which are induced due to subject movement or motion during signal acquisition or it can be caused due to floor vibrations. Artifact removal is necessary for efficient analysis and health monitoring. In this work we address the issue of artifact removal in BCG signal by proposing a novel method of signal processing. According to proposed approach raw signal is pre-processed and parsed to independent component analysis which provides the decomposed components and later k-means is applied to detect the components which are responsible for artifact and removed. Proposed approach is compared with existing method and shows better performance in terms of artifact removal.

Keywords: *BCG, SCG, artifact removal.*

1. Introduction

In recent years, extensive researches have been carried out in the field of biomedical signal processing to monitor and assessthe physical activities of human body. Using biomedical signals various physiological activities such as cardiac rhythms, blood pressure and heart rate etc. can be observed which provides important information for analysis. Process of information extraction from biomedical signal is called as biomedical signal processing. In order to perform the analysis and information extraction different signals are present which are used for activity analysis such as Seismocardiography (SCG) [1], Electrocardiography (ECG) [2] and Ballistocardiography (BCG) [3] etc. Following section briefs about these biomedical signal processing techniques and their advantages.

Seismocardiography (SCG) is a biomedical signal which provides the information about body vibrations caused by heartbeat. This signal contains information related to cardiac mechanism such as heart sound and cardiac output [4]. This technique was observed in 1961 and implemented first in 1991 [5] but the technique is older for body movement measurement so it was abandoned. Another biomedical signal technique is known as Electrocardiography (ECG) which is widely used for recording the electrical activities of heart using electrodes which are placed on human or patient’s body. These electrodes are able to measure a minute variation in skin surface which is induced by the heart muscle during heartbeat. This approach uses 10 electrodes which are placed on chest surface of patient’s body and magnitude of signals are recorded and stored for a specific period of time. Another technique for biomedical signal processing is termed as Ballistocardiography (BCG) which provides the information about recoil forces of human body during cardiac blood ejection with heart beat. This technique is the most recent and promising technique which helps to provide diagnosis, health monitoring and disorders which are related to heart diseases. Mechanical movement of heart and sudden disturbance in myocardial functions are the main components which induce disorders. Heart diagnosis is confirmed by BCG technique if any disorder is present in the BCG signal. Analysis of signal becomes difficult if similar disturbance is produced by another heart activity. In order to

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overcome this, various classification techniques have been proposed. These classification techniques includesingle channel and multichannel template matching schemes. Xinsheng Yu et al [6] proposed principle component analysis (PCA) based approach for bio-medical signal classification. Linear filtering autoregressive modeling [7], neural network [8] and support vector machine [9] etc.

These existing approaches provide better performance when motion artifacts, non-linear disturbance i.e. electronic device drift, noise induced during recording are not considered which causes misclassification during bio-medical signal processing. Noise induced in signal deteriorates the performance of BCG signal analysis. BCG signal measuring techniques also induces noise in the signal. Some of widely used techniques are mentioned below:

1. Wearable BCG measurement system

Various techniques for BCG measurement have been developed in recent years. According to this scheme, measurement sensors are placed on patient’s body using plastic mounting models and BCG is measured. Wiens et al. [10] proposed broad range wearable BCG measurement system. According to the method discussed in [10] an accelerometer device is affixed on the human body which enables continuous monitoring during the day.

2. Weighing Scale BCG

According to this method, weighing scales are used for BCG measurement where body weights and motion artifacts are built. BCG measurement using weighing scales is prone to the motion artifacts and noise caused due to floor vibrations.

3. Bed based BCG

According to this method, BCG measurement is carried out when patient is sleeping which helps to measure the quality of sleep and disorders which are related to sleep and during acquisition electrodes are not attached to patient’s body which reduces artifact during signal acquisition.

During signal acquisition, original signal get contaminated due to various aspects such as electrode movement or misplacement, floor vibrations, noise, body movement during acquisition etc. These issues affect the quality of bio-medical signal analysis. In order to overcome this issue various approaches have been proposed for different biomedical signals. Measurement of BCG signals can be carried out by using home weighing scale and myocardial and cardiac activities can be tracked. According to most of the existing methods, during acquisition or measurement patient’s need to stand still where user error, position errors and artifacts etc. are not considered [11].

In this work, we propose a new algorithm for artifact removal from acquired BCG signal. According to proposed approach, initially raw data is pre-processed by applying low-pass and filtering, pre-processed BCG data is given for ICA decomposition which gives the independent components and weights of BCG data. Based on Independent components, power spectrums are computed for each components and k-means clustering is applied which results in detection and removal of artifact. Rest of the paper is organized as follow: section II deals with literature survey, proposed approach is depicted in section III, experimental study is presented in section IV, section V provides concluding remarks of proposed artifact removal scheme.

2. Literature Survey

In this section of manuscript we describe most recent works presented in the field of bio-medical signal processing. Various methods have been developed for BCG measurement for home monitoring applications. These methods includetables, weighing machine, chair and beds etc. O.T. Inan et al [12] developed an adaptive noise canceller which reduces vibration effects, caused due to floor vibrations from BCG signal using a bathroom scale. In [13] D.W. Jung et al discussed about fragmentation sleep and its effect on daytime performance and reported that frequent awakenings are also one reason which affects daytime performance of human. In order to measure sleep quality, polysomnography (PSG) is widely used but due to inaccurate performance, BCG based monitoring has been discussed and analyzed. In today’s scenario, fMRI (functional magnetic resonance imaging) and EEG (electroencephalography) are recorded simultaneously and have attracted bio-medical researchers to analyze and study about nature of human body. Combination of EEG (with higher temporal resolution) and fMRI (with high spatial resolution) provides better insight which is helpful for analytical study of brain activities [14].

H.J. Baek et al [15] et al developed a new method to measure electrocardiogram (ECG), photoplethysmogram (PPG) and ballistocardiogram (BCG) which is contactless between instruments and skin.This experiment includes capacitive electrodes which contains high-speed amplifiers. In this work PPF also measured but it doesn't provide better efficiency when motion artifact, body movement and vibrations are considered. This issue of motion artifacts and vibrations remains challenging task for researchers. In another work, Y. Yao et al [16] reported that measurement of ballistocardiogram using bed based methods provides better efficiency for measurement. Acquired signals with the help of bed measurement system are a combination of two components i.e. cardiac and respiratory components.

Ferdows et al [17] proposed a novel approach for ballistocardiogram removal named as source extraction technique. This approach performs BCG artifact removal from simultaneous recording of EEG and fMRI. This approach uses linear prediction based technique which is based on semiblind source extraction scheme. In order to extract BCG sources from the recorded signal, cost-function is defined. Main aim of this work is to modeling of temporal structure and prior information extraction from BCG sources with the help long-term prediction method. Another method for BCG artifact removal from EEG-fMRI is discussed in [18]. According to this work in bio-medical signal processing spectral overlap and nonstationary overlap time issues are caused due to BCG which results in signal suppression. To overcome this issue discrete Hermite transform is utilized which computes shape basis function to identify and suppress the artifact. Nakamura et al. [19] also discussed about BCG artifact removal form EEG-fMRI data. In this work it is reported that previous works which are based on the average subtraction method suffers from the computation conditions and parameters i.e. according to average subtraction method it is assumed that recorded BCG waveforms are in periodic in nature which makes it more complex and unsuitable for various artifacts.

Non-linear unmixing is also discussed for BCG signal extractions which are recorded from most promising technique known as EEG-fMRI. In the first stage, with the help of EEG electrodes complete base is identified. Later non- Kirchhoffian variables are inferred using overcomplete basis function which are not consistent wit respect to electric field. This work shows that BCG artifacts not follow Kirchhoffian property whereas neural activities follow strongKirchhoffiannature which can be used for artifact removal.

In bio-medical signal processing, artifact removal or treating artifact in such a way that original signal should not get affected is achallenging task. Artifacts can be deal in following ways: (a) artifact avoidance (b) rejection of artifacts (c) artifact removal

a) Artifact avoidance: in bio-medical signal processing, avoiding the reoccurrences of signal can be utilized for artifact avoidance such artifacts are caused by eye blinking or body movement. This can be performed by instructing patient to avoid the body movement and eye blinking. But there are various disadvantages present of this approach. During signal acquisition, heart beat signals are always present in the brain signal which cannot be avoided. Muscle activity occurrencescannot be avoided during online monitoring system and collection of data which are not having any artifact is a crucial task due to neurological disability [21].
b) Artifact Rejection: it is a process to reject the signal acquisition or trials which are affected due to artifacts. It is known as simplest way to remove the artifacts present in the signal and provides better results when compared to artifact avoidance methods [22]. These artifacts can be rejected in two ways: manual rejection of artifacts and automatic rejection of artifacts but according to existing methods of measurement of neural activities, all artifact contaminated trails cannot be avoided. Generally, strong artifact containing trials only can be rejected which shows that artifacts are still present in the signal.
c) Artifact removal: it is a procedure to identify the artifact and remove it from original signal. According to today's technology advancements, a promising technology is required to remove the artifacts. Various schemes are presented in recent years for artifact removal which are: Linear filtering, Linear Combination and Regression, Blind Source Separation (BSS) [18], Principle Component Analysis (PCA) [23] etc.

Various techniques have been presented in the field of bio-medical signal processing. As discussed before that in this manuscript we aim on artifact removal from BCG signals. According to the literature study, still there is a need of new approach for artifact removal which can provide better clean output data which is not contaminated and can be used for further analysis.

3. Proposed Model

This section deals with proposed approach for artifact removal from BCG dataset. In this section detailed process of data acquisition, identification of artifact and removal is described.

For experimental analysis of proposed approach, datasets are obtained from Georgia Institute of Technology which contains male and female BCG signal data.Thisdataset contains total 17 healthy user's data which includes 10 male and 7 female users with the age of 23.6 ± 4.5 years, height variations are 172.8 ± 9.9cm and weight variation are taken as 70.7 ± 11.3 kg.

During signal acquisition, users were instructed to stand still for 60 s in an erect position on force plate measurement. Next, user performs stepping exercise for 60s durationand after that users were asked to stand on scale for 5 min to analyse full recovery of users. This dataset contains BCG, ECG and ICG measurements. BCG and ICG signals are provided a timing reference using ECG signal.Complete details about dataset for each user are presented in Table 1.

Table 1. Dataset Details

User ID	Gender	Weight (kg)	Height(cm)
1	Female	59	160
2	Female	68	168
3	Female	52	160
4	Female	49	152
5	Female	68	175
6	Female	75	163
7	Female	61	168
8	Male	75	175
9	Male	86	183
10	Male	74	175
11	Male	65	178
12	Male	88	178
13	Male	68	178
14	Male	88	190
15	Male	70	175
16	Male	76	185
17	Male	79	175

Figure 1 shows the complete system architecture of proposed model. In this approach, initially input data is taken and preprocessing steps are applied which includes high pass and low pass filtering using FIR filters. In the next stage, peak detection method is applied which results in peak detection. Pre-processed data is given to the independent component analysis (ICA) which gives weight and sphere of the pre-processed data and provides decomposed component of signal. Later harmonics and ICA are applied which provides filtered output.

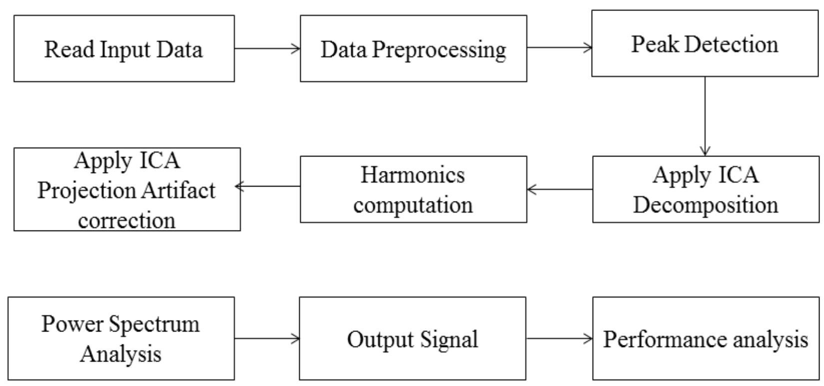

Figure 1. System Architecture

In this work, we apply ICA decomposition approach for pre-processed BCG data. By applying ICA decomposition, input data $P \times Q$ is decomposed into $L \times Q$ independent components where $P, Q\ and\ L$ representation of number of channels presents in data, number of ICA components and time-samples respectively. For each input signal based on the number of channels, independent components are extracted. This relation between input signal and independent components can be given as

$$C_{P\times Q} = M_{[P\times P]}.B_{[P\times Q]} \tag{1}$$

Where C denotes independent components, M is un-mixing matrix which contains linear combination coefficients computed between BCG data and independent components and B denotes BCG signal. By solving above given equation we obtain

$$B_{P\times Q} = M^{-1}_{[P\times P]}.C_{[P\times Q]} \Leftrightarrow B_{P\times Q} = X_{[P\times P]}.C_{[P\times Q]} \tag{2}$$

Mixing matrix is denoted as X, each column of this matrix presents the spatial map of the data corresponding to time samples.

As discussed before, according to independent component analysis (ICA), a matrix M is returned which denotes the unmixing data matrix. This is obtained when it is applied for BCG signal traces. Similarly average IED (Inter-ictal epileptiform discharges) matrix of M can be obtained by applying ICA to outer traces of BCG signal.Computations of IEDs become challenging and time consuming procedure for inspection of BCG data, so the computation is discarded here. Assumptions are made that if observed epileptic activity and independent components are corresponding to each other, in this scenario projection of average IEDs over given independent components can provide higher power spectrum efficiency when compared to the independent components which are not related to IED.

In order to address this, P projection computation can be performed as follows:

$$\mathcal{A} = M \times Q \tag{3}$$

$\mathcal{A}$ Denotes total number of projections

According to the proposed approach, projected power efficiency for given independent components is considered as a selection criteria for independent components. In proposed approach, selection of a priori average using IED is avoided which helps to represent the epilepti form activity. In the proposed approach, power of all projection is computed by taking square of each instant of time.These projections are used as discriminative feature which are used in k-means clustering approach. K means clustering is applied to achieve all higher power efficiency components clusters. Selection of optimal number of cluster is another challenging task which is also addressed here in this work. In this work, by considering BCG data, numbers of optimal clusters are always taken as 2 with the help of average silhouette. Silhouette computation shows the accuracy of measurement which is given as

$$d(i) = \frac{y(i) - x(i)}{\max\{x(i), y(i)\}} \tag{4}$$

$x(i)$ Denotes the average number of observation dispersion within the selected cluster, $y(i)$ is the representation of lowest observation dispersion to the neighbouring cluster.

From here it can be estimated that if $x(i) < y(i)$, then $d(i) < 0$ which can be said that it varies from -1 to 1and if this condition is achieved then it can be stated that observation is located efficiently in the neighbouring cluster. Later mean of silhouette is computed where number of clusters can be chosen based on the condition

$$x = \underset{k}{\arg max}\{\overline{d(k)}\} \tag{5}$$

4. Results and Discussion

In this section we provide detailed experimental study and analysis of outcome for BCG monitoring system. Proposed experiment is carried out by using MATLAB tool using windows platform. Dataset details are presented in Table 1 for both female and male healthy users. Initially healthy subject female's BCG data is taken for processing whose parameters are 168 cm height and 68 kg is weight during acquisition of BCG signal. For analysis of BCG we have considered simulation parameters which are given in Table 2. First parameter shows the total number of detection of beats in a trial of signal acquisition, threshold of peak detection is set to 0.6 which is detected based on the amplitude of the signal. For further analysis, we perform BCG segmentation, as we have discussed earlier that dataset contains EEG signal also. For BCG data segmentation left window threshold is set to 0 to obtain each time sample and right side window is set to 700. in order to perform sampling on the data, sampling frequency is set to 1000 which is followed by stop band frequency and pass band frequency as 0.2 and 1 respectively.

Table 2. Simulation Parameters

Parameter Name	Parameter Value
No. of Beats	5
Peak Detection Threshold	0.6
Left Side Window BCG segmentation	0
Right Side Window BCG segmentation	700
Sampling Frequency	1000
Stop Band Freq. 1	0.2
Pass band freq. 1	1

Table 3 shows the statistical parameter analysis for a raw data of female subject. For this analysis we compute mean, standard deviation of the signal.

Table 3. Statistical Parameter of female raw BCG signal

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

This raw data is given for preprocessing stage as depicted in Figure 1 which results in pre-processed output signal. In Table 4 we show statistical parameter of pre-processed BCG data 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 by normalizing the data.

Table 4. Pre-processed BCG data

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

Above mentioned figure shows the artifact removal stages for BCG signal data. Figure 2 shows raw BCG signal, in Figure 3 pre-processing stage output is depicted, later in Figure 4 we show the peak detection and finally Figure 5 shows the comparative analysis of proposed model with existing approach. These figures represent the measurement of BCG signal by considering time and amplitude of the signal. Finally in Table 5 we show the statistical performance of the proposed scheme and compared it to existing approach.

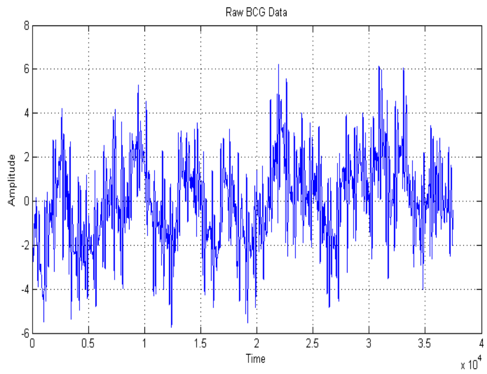

Figure 2. Input Raw BCG Signal

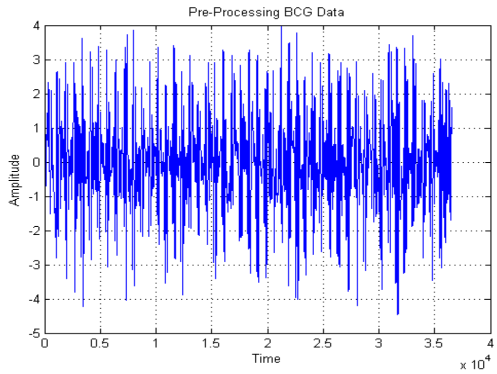

Figure 3. Pre-processed BCG Data

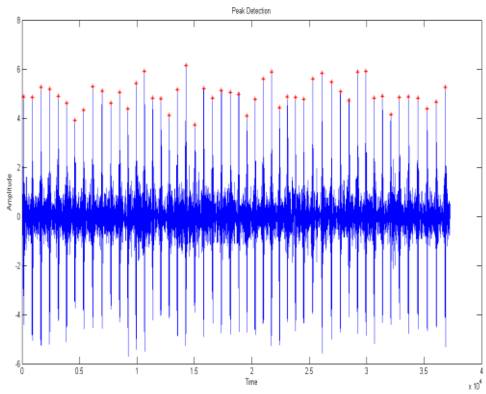

Figure 4. Peak Detection

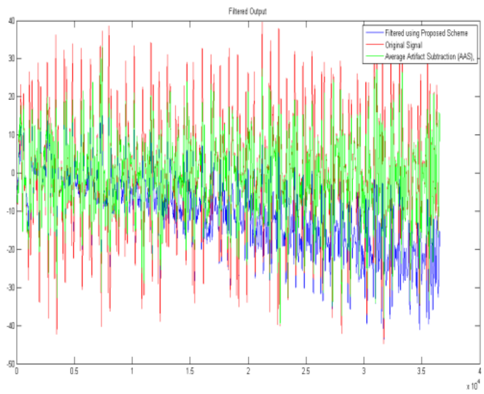

Figure 5. Filtered output comparison

Table 5. 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, we compute the performance of proposed model by considering Male BCG signal data. Here also we follow the same process and raw BCG data is given to preprocessing approach. For raw data and pre-processed datastastical analysis is presented in Table 6 and 7. Finally in Table 8, performance of artifact removed signal is given.

Table 6. Raw Male BCG data

User 1	Mean	Standard Deviation
Male subject (178 cm height and 65 kg)	0.2871	1.2466

Table 7. Pre-processed data

User 1	Mean	Standard Deviation
Male subject (178 cm height and 65 kg)	0.0284	0.8311

Table 8. Artifact Removed Signal

Female subject (168 cm height and 68 kg)	Mean	Standard Deviation
Existing System	-0.0142	0.6488
Proposed System	-0.6346	0.5649

According to the simulation study and analyses, it can be concluded that proposed model is capable remove artifact present in the BCG signals. In this paper, experimental analysis of artifact removal is presented for two users male and female. Artifact removal approach is compared with existing method which shows the better performance.

5. Conclusion

In this work, a novel approach is presented for artifact detection and removal for BCG signal processing systems. For bio-medical application, we have considered BCG signal and addressed the issue of artifact removal. Independent component analysis method is applied here for signal decomposition and later harmonics analysis and independent components are applied to obtain the filtered BCG signal. In this work, k-means clustering is applied for independent component extraction and artifacts are classified based on the power frequency of the clustered dataset.

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