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Independnt Component Analysis for Separation and Artifact Removal of Ballistocardiogram Signal

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Abstract— The fundamental problem in neural network research, as well as in many other disciplines, is finding a suitable representation of multivariate data, i.e. random vectors. For reasons of computational and conceptual simplicity, the representation is often sought as a linear transformation of the original data. In other words, each component of the representation is a linear combination of the original variables. Well-known linear transformation methods include principal component analysis, factor analysis, and projection pursuit. Independent component analysis (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. Such a representation seems to capture the essential structure of the data in many applications, including feature extraction and signal separation.In this paper, the author present the basic theory and applications of ICA, and our recent work focuses on separation of source signal and artefact removal using Independent Component Analysis.

Keywords— Ballistocardiogram ,Component, ICA,mixing,unmixing matrix

I. INTRODUCTION

Ballistocardiogram is a (BCG) is a Plot of repetitive motion of human body arising from the ejection of blood into the blood vessel .This plot is similar to ECG signal to measure the cardiac parameters. The Ballistocardiogram (BCG) signal filtering using adaptive filter [1-3] is designed to minimize the noise acquired during data acquisition. There may be a presence of artifacts due to vibration, head movement, muscle movement, motion artifacts and eye blinking during extraction of the signal. It is necessary to separate the ECG and BCG signal from the output of an Adaptive filter and minimize the artifacts of BCG signal. The artifacts can be minimized using Independent Component Analysis (ICA).The advantages of ICA are to remove noise and artifacts. These artifacts are not related to specific frequencies. The aim of the technique is to extract, estimation of sources from the mixtures. Digital filters are able to eliminate the frequencies in the selected range. Better results can be obtained using ICA algorithm to minimize the artifacts and to separate the source signal such as BCG and ECG signal. Because while extracting the BCG signal ECG signal appears as artifact.

II. RELATED WORK

Kavya et al.[4] proposed the comparison of Heart Rate Variability (HRV) indices of ECG and BCG Signals. After observing the HRV indices of ECG and BCG of around 20 subjects it has been concluded that there is a high correlation between them. It was also found that BCG can be more comfortable to the subject than ECG during data acquisition. BCG uses only sensors that can be laid under the bed for collecting data whereas ECG uses electrodes that has to be attached to the body of the subject. Both BCG and ECG are a non-invasive cardiac data acquisition technique which disturbs the subject’s freedom. For long term monitoring cases, it is quite imperative that BCG acquisition is less restrictive. The HRV Indices of ECG and BCG are almost the same, while long term monitoring is possible with BCG and also ensures good quality performance. Hence BCG signals are considered to monitor the heart continuously. The BCG signal can be extracted using EMFi sensors, accelerometer, chair or bed based systems.

The study of removal of artifact has reached the consistent conclusion that it successfully removes BCG artifacts from EEG data. Srivastava et al.[5] 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. They extracted EEG data from 2-s intervals between MR scanning and they did not use reference signals such as ECG or pulses. These conditions make the average subtraction method unsuccessful. Therefore, detailed evaluation of the relative effectiveness of ICA in removing BCG is still necessary. Furthermore no comparison of the various ICA algorithms has been made so far.

W.Nakamura et al[6] tested several different ICA algorithms for removing BCG from EEG data, and evaluated their results with objective indices. To obtain better performance many filtering techniques are developed to eliminate noise in BCG and ECG signal. Among all these ICA is one of the fast growing techniques to get noise free signal. To analyze the EEG events it is required to have knowledge on simultaneous recording of EEG and functional magnetic resonance imaging (fMRI). EEG data is recorded in the magnetic resonance (MR) scanner with MR Imaging. There are two specific artifacts are recorded EEG signal, namely imaging artifact and BCG. Here the author used average subtraction method and ICA method to eliminate the artifacts. Power spectral density analysis of the two approaches shows with ICA, distortion of recovered EEG data is small as that associated with the average subtraction approach. The authors also propose a hypothesis for how head movement causes BCG and shows how ICA can remove BCG artifacts arising from this source. Here BCG signal acts as an artifact, which has to be removed from the original EEG data. To obtain better filtering and to eliminate artifacts from BCG signal, Artifacts can be eliminated by using PCA (Principal Component Analysis) and ICA (Independent Component Analysis) approaches. These two techniques are well-known computational and transformation methods for separating a multivariate signal into additive subcomponents. ICA is used for large sets of data and PCA is used for small sets of data. Finding the linear representation of non-Gaussian data to obtain the independence is one of the goal of ICA.ICA is suitable approach to eliminate the artifacts present in the original data and also to get back the BCG signal from output of an Adaptive filter which contained both ECG and BCG together.

The artifacts include both internal and external artifacts. Internal artifacts are the observed variables from muscles and may be produced due to movement of the different parts of the body. External artifacts[7] present mainly because of baseline and power line noise. External sources of artifacts are categorized in two main noise groups, namely: (1) baseline (2) power line.

III. METHODOLOGY

Independent Component Analysis (ICA) is one of the statistical approach used to eliminate artifacts and to separate BCG signal from source data. ICA is invented by 'Jutten and Hérault'. This approach has m mixures (signals mixed with additive noise or artifacts such as eye blinking, body movement and muscle noises) in a linear form which considers m independent components and is given as

$$F_j = a_{j1}s_1 + a_{j2}s_2 + \ldots a_{jm}s_m \quad \text{for all j} \qquad (1)$$

Here't' is the time index and it is dropped in ICA model, because the assumption here is that each mixture and individual components are random variables and $F_j(t)$ has observed values. The example can be microphone signal problem of cocktail party [8].Here the assumption is both 'Independent components 'and mixtures have zero mean.

The equation for three sensors can be written as

$$F_1(n) = a_{11}s_1(n) + a_{12}s_2(n) + a_{13}s_3(n) \qquad (2)$$

$$F_2(n) = a_{21}s_1(n) + a_{22}s_2(n) + a_{23}s_3(n) \qquad (3)$$

$$F_3(n) = a_{31}s_1(n) + a_{32}s_2(n) + a_{33}s_3(n) \qquad (4)$$

The above equation can be expressed using vector-matrix notation,

$$F = As \qquad (5)$$

$$\text{Where } F = \begin{vmatrix} F1 \\ F2 \\ Fn \end{vmatrix} \qquad s = \begin{vmatrix} s1 \\ s2 \\ sn \end{vmatrix}$$

$$A = \begin{bmatrix} a11 & \cdots & a1n \\ \vdots & \ddots & \vdots \\ an1 & \cdots & ann \end{bmatrix} \qquad (6)$$

F: Random vector of mixture

s: Random vector of sources $s1. \ldots, sn$

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

$$F = \sum_{i=1}^{n} a_i s_i \qquad (7)$$

The research work considers three sources for experiment.ICA is similar to Blind Source Separation (BSS) problem. The aim is to find the unknown matrix W and original source signal. The un-mixing matrix W with coefficient W_{ij}, with this it is possible to separate the source signals can be separated. Applications of ICA include Brain imaging and speech processing and also in audio processing. After estimating the matrix A, inverse matrix W can be obtained.

$$z_1(t) = w_{11}F_1(t) + w_{12}F_2(t) + w_{13}F_3(t) \qquad (8)$$

$$z_2(t) = w_{21}F_1(t) + w_{22}F_2(t) + w_{23}F_3(t) \qquad (9)$$

$$z_3(t) = w_{31}F_1(t) + w_{32}F_2(t) + w_{33}F_3(t) \qquad (10)$$

$$s = A^{-1} F \qquad (11)$$

s = W F and it can be written as

$z = WF$ (12)

F : Random vector of mixtures $F1.\,.\,.\,., Fn$
s: Random vector of sources $s1.\,.\,.\,., sn$
A: mixing matrix with elements a_{ij}.
W is un-mixing matrix.

The ICA method is called 'Blind Source Separation' or BSS method, because here "source" is nothing but an original signal, i.e. independent component and it is just like speaker problem in a cocktail party. The meaning of "Blind" knows very little information and little assumptions on source signals. ICA approach is one of the most widely used, algorithms to identify blind sources.

Here ICA block is used to eliminate the artifacts if in the data and also to separate the source signal. Each of these sources has two main components BCG and ECG. The ICA block separates the two components and eliminates the artifacts present in the data. Block diagram of ICA is in figure 1.

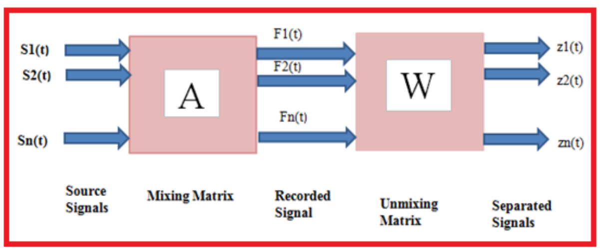

Figure 1: ICA block representation for n number of sources

Where
s(t) :Output of an adaptive filter,
F(t) : Recorded signal
z(t) : Estimation of sources,
A: Mixing matrix,
W : Un-mixing matrix

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 initial value of mixing matrix A is considered as

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

The un-mixing matrix W is obtained by inversing the matrix A.The value of W is $W=\begin{bmatrix} 12.8522 & -2.3792 \\ -5.1441 & 2.4126 \end{bmatrix}$= Output z is the separated estimation of the input.Mixing and un-mixing matrix is updated continuously up to 100 iterations. Here input data 's' is nx1 matrix , 'A' is 2x2 matrix, 'F(t)' is nx2 matrix, un-mixing matrix 'W' is 2x2 and it gives two separated outputs z_1(t) and z_2(t) of order nx2 of z(t). Both of these can be extracted separately. The result obtained is an estimation of source signal. Mean and standard deviation is calculated for this extracted signal. Results shows better improvement in signal quality compared to adaptive filter.

ICA Gradient Ascent

The un-mixing matrix W which extracts n components from the set of observed mixtures F The entropy of the components U=g(z) will be by definition:

$$H(Z) = H(F) + E\{\textstyle\sum_{i=1}^{n} \ln p(z_i)\} + \ln|W| \quad (13)$$

Where $z_i = w_i^{T} F$ is the i[th] component which is extracted by i[th] raw of un-mixing matrix W. This value is calculated using m samples of the mixture F.Using definition the pdf p is given by cdf g.

$$p(z_i) = \frac{d}{dz}\, g(z_i) \quad (14)$$

Where the derivative is denoted by $g(z_i) = p(z_i)$ so that it can be written as

$$H(Z) = H(F) + E\{\textstyle\sum_{i=1}^{n} \ln g'(z_i)\} + \ln|W| \quad (15)$$

The un-mixing matrix W is used to maximizes the entropy of Z.The entropy $H(F)$ of mixture $F$is unaffected by using W, Here $H(Z)$ is constant, and can be ignored.Thus it is possible to find W which maximizes the function $h(Z)$

$$h(Z) = E\{\textstyle\sum_{i=1}^{n} \ln g'(z_i)\} + \ln|W| \quad (16)$$

It can be done using gradient ascent on h by adjusting W.The main goal is to maximize the function h.The initial stage of the research work considers random value of mixing marix A and un-mixing matrix W.It can be updated by using the formula

$$W_{new} = W_{old} + \alpha(W^{-T} - \frac{2}{N} \textstyle\sum_{k=1}^{N} tanh(z^k)[F^k]^T \quad (17)$$

α: Small constant, k=1.2……..N
W_{new}: updated value of un-mixing matrix
W_{old}:Old value of un-mixing matrix

IV. Results and Discussion

The result of final correlation matrix indicates that the original source signals are extracted successfully. These extracted signals are shown in figure 2.

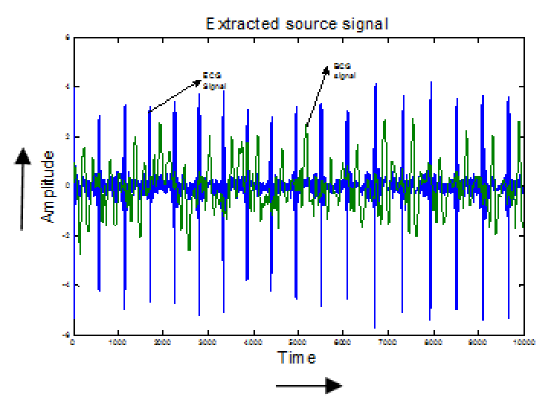

Figure 2: Both ECG and BCG signal

It is a combination of both ECG and BCG signal.

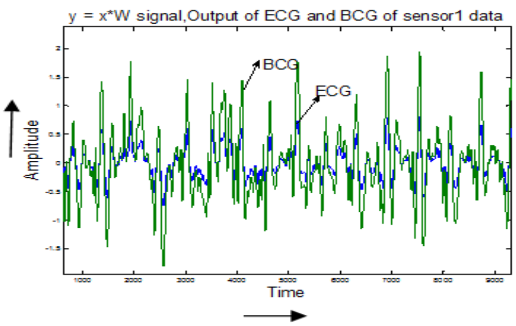

Figure 3 : ICA output for Sensor 1

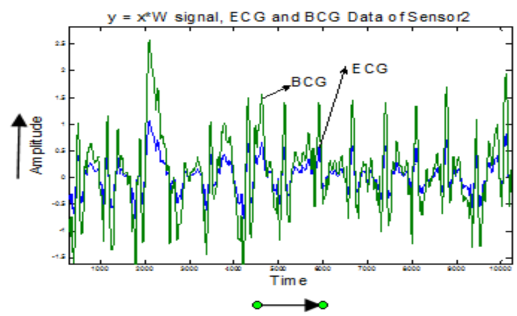

Figure 4: ICA output of Sensor 2

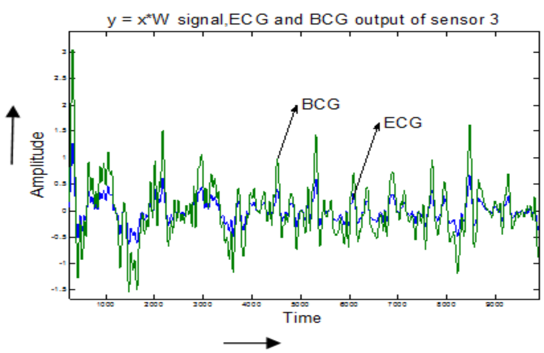

Figure 5: ICA output of Sensor 3

The waveforms obtained from three different sensors are presented.The extracted BCG signal from the sensor has both ECG and BCG data.The output shows the separation of these two signals using ICA algorithm.The results obtained is better compare to filtering algorithm and using these results it is possble to analyse the person's health condition.

V. EXPERIMENTAL RESULTS

Minimum three sensors are required to extract the data. For experimental purpose 17 recorded datasets are used. Frequency for sampling, cut-off frequency and other parameters required for simulation are presented in table 1.

Table 1: Experimental Parameters

Parameter	Value
Frequency for Sampling	1000 Hz
Nyquist Frequency	Sampling Frequency/2
No. of Beats	5
Threshold of Peak Detection	0.6
Frequency for Sampling	1000

The three heart data signals are used for simulation. (heartdata_1393269865",heartdata_1393269866",heartdata_1393269867"). The experiment is carried out by using MATLAB tool.

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.

Table 1 gives information on the parameters and its value for designing. Table 2 shows the statistical parameter analysis for an observed data of female subject. Mean and standard deviation are calculated for these signals and it is presented in table 2 and 3

Table 2: Statistical Parameter of female observed BCG signal

User 1	Mean	S.D
Female subject (168 cm height and 68 kg)	0.0072	2.0165

Comparing these results the author concludes that the deviation in the data is reduced which shows the stability in the signal and removal of unwanted signal.

Table 3: Pre-processed BCG data

User 1	Mean	S D
Female subject (168 cm height and 68 kg)	0.0020	1.4378

Simulation Results

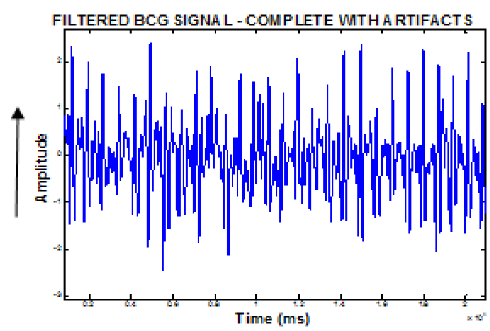

Figure 6: Filtered signal with Artifact

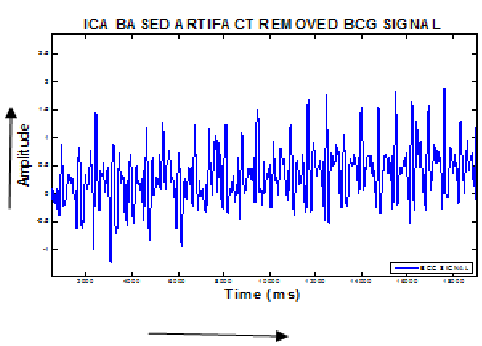

Figure 7: ICA based artefact removed signal

Table shows statistical performance of proposed scheme and its comparison approach.

Table 4: 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.

Table 5: Pre-processed data

User 1	Mean	S. D
Male subject (178 cm height and 65 kg)	0.0284	0.8311

Table 6: Performance of artifacts removed signal

Female subject (168 cm height and 68 kg)	Mean	S.D
Existing System	-0.0142	0.6488
Proposed System	-0.53	0.5649

According to simulation study and analysis, the author concludes that proposed model is capable of removing artifact present in the BCG signals. In this thesis, experimental analysis of artifact removal is presented for two users male and female. Artifact removal method is compared with presently existing approach which shows better performance.

A simulation result shows the designed system is capable of removing artifact present in the BCG signals fully. The correlation is also calculated between these two signals. Results obtained concludes it effectively eliminate the artifacts.

VI.CONCLUSION AND FUTURE SCOPE

BCG is one of the upcoming technology to measure the cardiac parameters. Artifacts present in the data can be eliminated by designing an ICA algorithm.ICA algorithm is used to separate BCG and ECG signal present in the dataset. For biomedical application, author has considered BCG signal and addressed the issue of artifact removal. Independent component analysis method is applied here for signal decomposition to obtain the filtered BCG signal. Magnitude of entropy gradient and function Value-Entropy is calculated for the BCG data. Result shows that around 100 iterations, the magnitude of entropy almost reaches to zero. The correlation matrix obtained for BCG data 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.

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