ENHANCEMENT OF EEG SIGNAL

A thesis submitted in partial fulfillment of the requirement for the degree of

Master of Technology

In

Electronics and Communication Engineering

Specialization: Electronics and Instrumentation

By

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National Institute of Technology Rourkela

Rourkela, Odisha, 769008, India

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Under the guidance of

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May 2015

DEPT. OF ELECRTONICS AND COMMUNICATION ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY,

ROURKELA, ODISHA -769008.

CERTIFICATE

This is to certify that the work done in the thesis entitled "**ENHANCEMENT OF EEG SIGNAL"** by **Nitesh Ranjan** is a record of an original research work carried out by him in National Institute of Technology, Rourkela under my supervision and guidance during 2014-2015 in partial fulfillment for the award of the degree in Master of Technology in Electronics and Communication Engineering (Electronics and Instrumentation), National Institute of Technology, Rourkela.

Place: NIT Rourkela

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DECLARATION

I certify that

a. The work presented in this thesis is an original content of the research done by myself under the general supervision of my supervisor.

b. The project work or any part of it has not been submitted to any other institute for any degree or diploma.

c. I have followed the guidelines prescribed by the Institute in writing my thesis.

d. I have given due credit to the materials (data, theoretical analysis and text) used by me from other sources by citing them wherever I used them and given their details in the references.

Nitesh Ranjan

213EC3226

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ABSTRACT

This project is concerned with the rectification of EEG recording. EEG signal is often gets distorted due to the presence of various signals which are known as artifacts. Eye blinking is one of the major artifacts causing EEG to distort. Eye blinking distorts the EEG signal by varying the electric potential present over the scalp. To remove the artifacts, signal separation techniques are widely used in modern days. There are various methods used for removing different types of artifacts present in EEG recording and one of the techniques is Blind Source Separation which is used for separation of source signal from artifacts. This thesis also demonstrates the use of Second Order Blind Identification with Robust Orthogonalization (known as SOBI-RO) algorithm to remove the ocular artifacts and reconstruct the original EEG signal. Finally, the original signal and estimated signal is compared.

To illustrate the algorithm a raw EEG data has been taken from the database. The data has been processed on MATLAB platform using the SOBI-RO algorithm. In the end it was found that the ocular artifacts are successfully removed from the raw EEG data. The performance is evaluated using signal to distortion ratio.

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INTRODUCTION

CHAPTER 1: INTRODUCTION

Introduction

Electroencephalogram (EEG) records the potential generated by the brain. The EEG plays an important role for many applications. A current research involving EEG data is the development of brain machine interface (BCI) [9], [10]. A brain machine interface [11], [12] works as a communication system between brain and machine. EEG is frequently used because it is non-invasive and is capable of detecting rapid changes in electrical activity. Analysis of these recordings has been a major resource to gain some insight about the onset and activity associated with the development of seizure activity. Unfortunately, EEG data is commonly contaminated by ocular artefacts which make the analysis of real EEG data very difficult. The focus of this thesis is to detect and remove eye blink artifacts in order to facilitate analysis of EEG recordings.

One of BCI application is allowing disable people to communicate with machine such as robot and wheelchair [13], [14]. The block diagram of BCI scheme is shown in the fig.1.1.

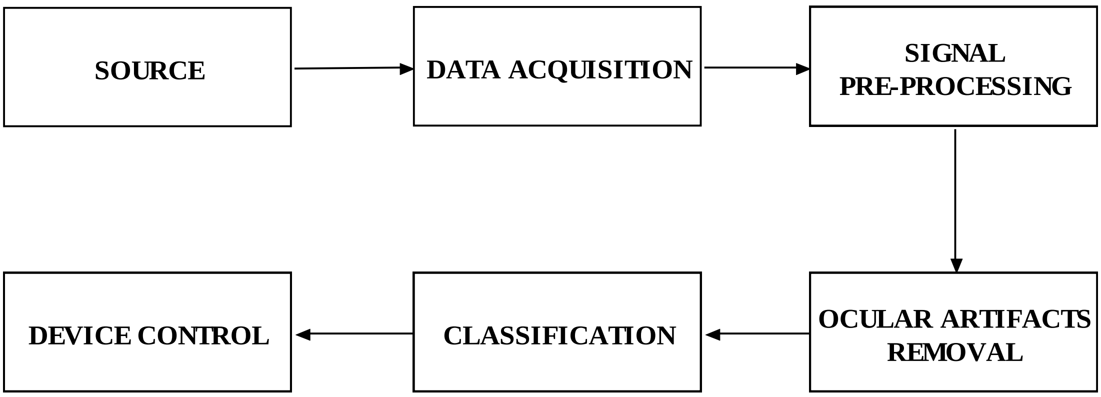

Fig.1. 1 BCI Block Diagram

One of the major applications of the separation of noise signal from EEG signal is in the field of medical research and in the brain machine interface. The effectiveness of brain machine interface is achieved by increasing the signal strength and decreasing the noise strength in the EEG signal and thus minimizing the error. By improving SNR value, we control the device in efficient way. In the brain machine interface system, the signal potential is generated by the activity of brain while noise is produced by unwanted sources. This unwanted source may be line noise, eye blinking, ocular movement, muscle contraction and others. One of the major sources of noise is blinking of the eye, which produced spikes of higher amplitude during the recording process [15], [16], [17]. The average range of amplitude of EEG signal is -50 to 50 microvolt's but the blinking creates spike of more than 100 microvolt's, which creates significant amount of noise.

1.1 Need of Physiological Measurement

The field of biomedical measurement has seen drastic changes in 19^{th} and 20^{th} centuries. During the world war 2^{nd}, a lot of work had been done on Electrocardiogram and Electroencephalogram. In the late of 20^{th} century, various instruments and apparatus have been developed to record the bioelectric potentials present in human body. For example, Pacemakers, Defibrillators were developed during this span.

1.2 Human Body: A Physiological Overview

Human body is a physiological system comprising various subsystems such as, the biochemical system, the cardiovascular system, respiratory system and the nervous system. These subsystems interact with each other causing it difficult to measure bioelectric potentials present in the human body. Problems don't end here; as these subsystems also interact with the environment as a whole producing various artifacts during the measurement.

The description of various physiological systems is given below.

1. Biochemical system: It produces energy for carrying out the activities of human body, various abstracts for the growth of body and repair of tissues. This subsystem is more like a self-contained chemical factory.

2. Cardiovascular System: It is one of the most complicated and distributed physiological system of the body. It contains a four chamber heart, blood carrying arteries and veins. The heart acts like a pump which circulates the blood in whole body.
3. Respiratory System: It is the only pneumatic system of the body consisting of an elastic bag, known as Lung and a passage, which constitutes pharynx, larynx, trachea and bronchi.
4. Nervous System: It is the most complicated system of the body having a self-adapting processor in its center known as Brain. Brain is responsible for decision making, solving complex problems, creating art, music and in feeling emotions. Billions of communication lines known as neurons act as bridge between brain and human body.

1.3 Bioelectric Potentials

The potentials generated by various systems of the body as a result of functions performed by them are known as bioelectric potentials. These potentials contains valuable information which build the base of the measurement.

Various bioelectric potentials generated by human body are listed below:

1. **Electrocardiogram:** Bioelectric Potentials generated by heart is known as Electrocardiogram (ECG). ECG originates at a point near the right atrium known as pacemaker or sinoatrial node. P wave is due to atrial depolarization, QRS complex is due to atrial repolarization and ventricle depolarization and T wave is due to ventricle repolarization.

2. **Electromyogram:** The bioelectric potential generated by the muscles of the human body are known as Electromyogram. The EMG response is always obtained for a group of muscles rather than an individual muscle. They look like the waveform of random noise.
3. **Electroretinogram:** Bioelectric potentials generated by the retina due to a visual stimulus is known as Electroretinogram.
4. **Electrooculogram:** Bioelectric potentials generated due to movement of eye ball is known as Electrooculogram. This causes significant amount of disturbance in the EEG waveform..
5. **Electrogastrogram:** Bioelectric potential generated by gastro intestinal tract of the digestion system is known as Electrogastrogram.

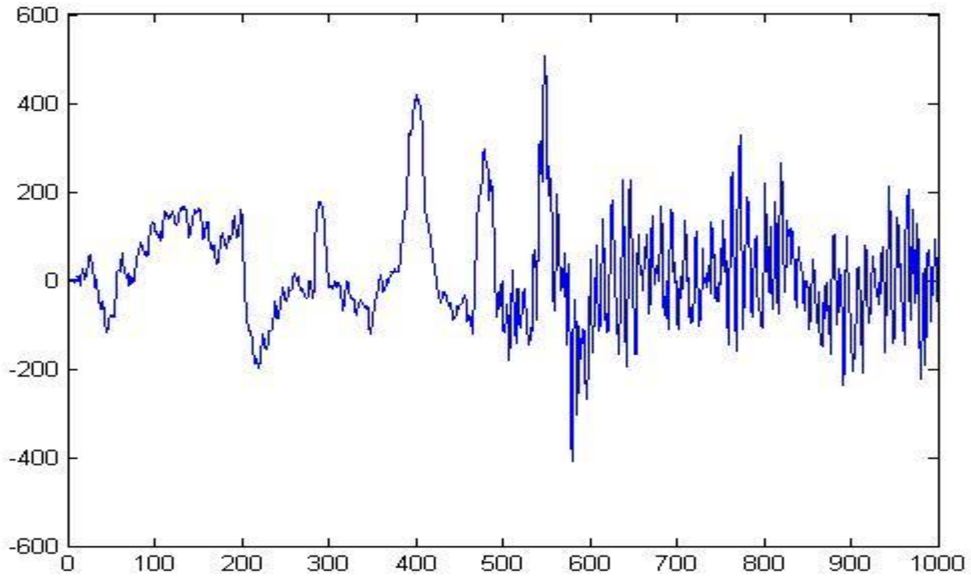

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Fig.1. 2 Typical EEG Waveform

Electroencephalogram: The bioelectric potentials generated by the brain is known as electroencephalogram. EEG has the most complicated waveform as compare to all other bioelectric potentials listed above. The typical EEG wave form is shown in figure 1.2.

It is evident from the above figure that EEG largely depends on the placement of electrodes. It means EEG waveform obtained for two different locations of electrode will be entirely different from each other. This is not the case in ECG waveform. Waveform recorded by electrodes represents the combined bioelectric potential of a fairly wide region of brain.

EEG records the potential generated by the brain which is a non-invasive technique. The EEG plays an important role for many applications such as in medical research and device control. A current research involving EEG waveform is the development of brain machine interface (BCI). A brain-machine interface works as a communication system between brain and machine. EEG is frequently used because it is non-invasive and is capable of detecting rapid changes in electrical activity. Analysis of these recordings has been a major resource to gain some insight about the onset and activity associated with the development of seizure activity. Unfortunately, EEG data is commonly contaminated by ocular artifacts which make the analysis of real EEG data very difficult. The focus of this thesis is to detect and remove eye blink artifacts in order to facilitate analysis of EEG recordings.

1.4 EEG data Acquisition

EEG data is recorded by placing electrodes on the scalp. It is done using internationally accepted 10-20 system. In this electrodes are placed in a cap according to standard 10-20 system and each electrode is defined alphabetically. There are four types of electrodes which is designated according to their placements like frontal lobe as F, temporal lobe as T, occipital lobe as O and parietal lobe as P.

The human brain is divided into four sections such as right hemisphere, left hemisphere, font and back part. The two hemispheres is divided by mid line. This is the most general method and internationally accepted method. The name of this system is based on the placement of electrodes which is placed on the interval of 10% & 20%. From ten percent above the nasion and inion, other electrodes are placed maintaining an interval of twenty percent. A circle is drawn ten percent above the nasion and twenty percent above the circle is Fz, twenty percent above the Fz is Cz and further twenty percent Pz is positioned. The other electrodes are placed with equal distance to circle drawn and vertical line.

1.5 Scalp EEG Database of CHB-MIT

We have obtained this raw data from database of MIT, which is recorded at Children's Hospital Boston namely CHB-MIT Scalp EEG Database. This data is a collection of EEG recording of patients suffering from seizure. The patients were monitored for several days. A total of 22 patients including 5 males of age group 3-22 and 17 females with age group 1.5-19 were chosen in order to record the data. The sampling frequency of these signals is 256 Hz having resolution of 16 bit. The signals were grouped in file and each file contain 23 EEG signal. The international 10-20 system has been taken as a reference for the placement of the electrodes.

1.6 EEG frequency bands

EEG frequency pattern depends on the mental activity of a subject. It is difficult to establish relationship due to wide variations of pattern from person to person and less chance of repeatability. The waveform pattern is different in different stages. The waveform in awake state and state of sleep are different. In alert stage or awaken stage high frequency waveform are generated. But there are certain patterns which show the common characteristics of disease like seizure. In the beginning of sleep the amplitude and frequency start decreasing but in the sound sleep the amplitude becomes large and low-frequency pattern is obtained.

The frequency band of EEG is classified in four ranges namely delta, theta, alpha and beta. Generally EEG pattern developed in the alpha band range when the subject is in relaxed condition. The amplitude of the EEG wave ranges from -50 to 50 μV (peak to peak) which is approximately 100 times less than the amplitude of ECG signal. The below figure shows the frequency pattern of EEG wave:

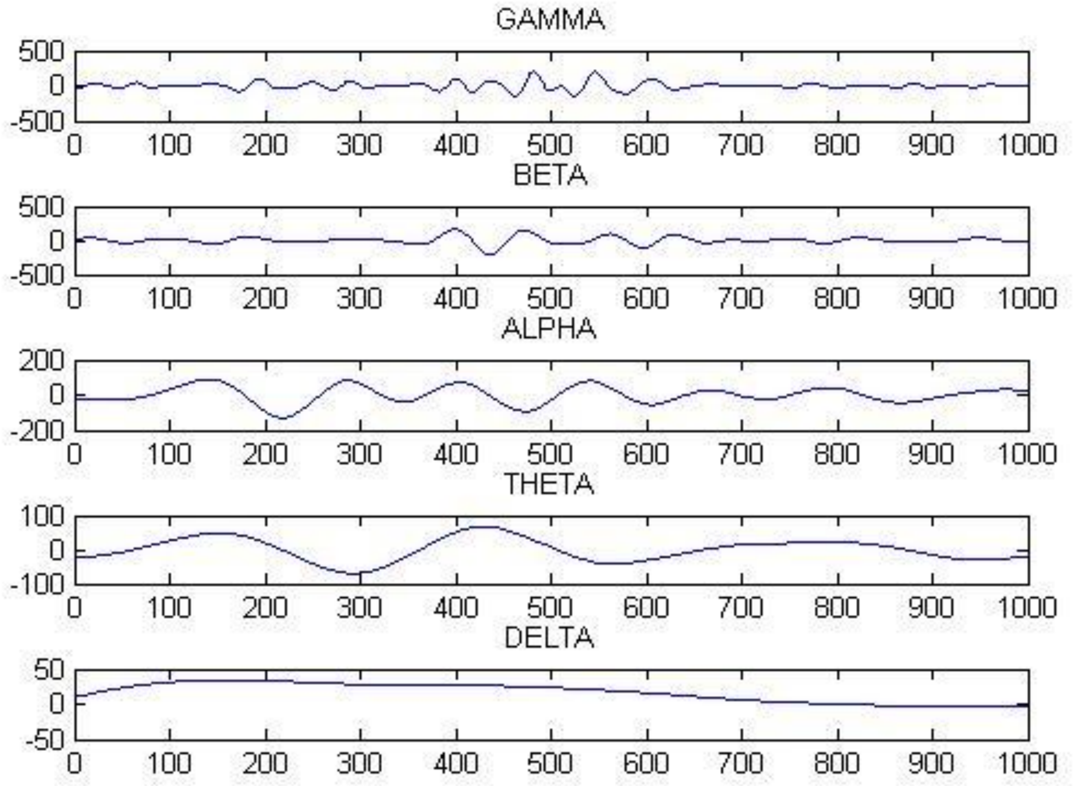

Fig.1. 3 EEG frequency pattern

Table1.1 Frequency Range of EEG signal

Frequency Range (Hz)	EEG Waves
0.5 – 4	δ
4 -8	θ
8 -13	α
> 13	β

1.7 Artifacts

The acquired EEG data can get corrupted at various points from recording to processing. The main reason for artifacts is external environment around the brain. These artifacts must be removed after the recording process. Various types of artifacts are listed below:

1.7.1 Eye Blink

The artifact due to eye blinking is one of the significant noise in acquiring of EEG data. It can be clearly seen that the low amplitude EEG waveform is corrupted by a high amplitude ocular artifact. Because of its high amplitude it can be clearly differentiated from other artifacts. Eye artifacts are generally measured while recording electrooculargram (EOG), a pair of electrodes is used above and around the eyes. The contaminated signal is much difficult to be separated to get the original EEG.

1.7.2 Eye Movement

It is due to the reorientation of the retinocorneal dipole. The diffusion across the scalp is stronger due to this artifact than that of the eye blink artefact. This artifact also has a higher amplitude than that of normal EEG potential. Eye blinks and eye movement often producing the effect simultaneously which makes it more difficult to remove them.

1.7.3 Line noise

The power supply used around the EEG machine can deteriorate the acquired data while transforming it from scalp electrodes to the EEG recorders. Notch filter is utilized for removal of Line noise. But use of notch filter is not recommended in case of lower frequency line noise and harmonics. If the frequency spectrum of Line noise matches with the frequency spectrum of EEG, interference occurs. If we use notch filter in that range, it can remove useful information. It can corrupt data of all the electrodes depending on how much powerful AC supply is. The frequency of noise depends on the frequency of power line (50Hz or 60Hz).

1.7.4 Muscle Activity

Muscle activities also create artifacts. Muscles responsible for this belong to neck and face. The signals generated by these muscles have various frequencies and these frequencies are delocalized across the entire set of electrodes which depends on the distance from the source muscles. For reduction of this artifact patient should be in stable state of mind.

1.7.5 Pulse

Artifacts due to pulse are generated due to placement of electrodes near the vessels which carrying blood for circulation. When vessel contracts or expands, change in voltage takes place. Pulse artifacts are of two types: normal pulse artifact and deformed pulse artifact. Pulse artifact can be removed by subtracting pulse artifact template from EEG signal.

1.7.6 Skin potential

There are two important artifacts that arise from skin changes. Perspiration artifact consists of slow waveform causes slow shift of the electrical baseline by slowly changing the electrical contact between the electrode and the skin. The second and less commonly recognized artifact produced by the galvanic skin response. It is produced by the swear gland and changes in skin conductance.

1.7.7 Baseline Noise

Due to poor contact of the electrodes and perspiration of the patient, the impedance of the electrode is changed and the baseline is shifted. It causes low frequency artifacts. Sometimes it may be due to variations in temperature as well as bias in the amplifier. This is undesired and should be removed before signal processing.

1.8 Objective

The objective of this thesis is to remove artifact from EEG recording. The focus is mainly on ocular artifact which is major source of error in EEG recording. The removal is done using SOBI-RO Algorithm of Independent Component Analysis technique.

1.9 Literature Survey

R. Romo Vazquez *et al*. [2] proposed a method of blind source separation and denoising [37], [38] for removing the EEG artifacts. A new method for artifact rejection and noise cancellation which is based on automation has been proposed in this paper.

Arjon Turnip *et al*. [1] proposed a method for removal of ocular artifact from EEG signal. The removal is done using SOBI-RO algorithm [39], [40] on Motor Imagery Experiment.

Y. Li *et al.* [6] proposed sparse representation for brain signal processing. It also includes application of sparse representation in component extraction, blind source separation and EEG inverse imaging, feature selection and classification.

Vaibhav Gandhi *et al*. [40] proposed filtering of EEG signal using Quantum Neural Network for Brain machine Interface. This paper shows use of RQNN filter model for signal filtering and feature extraction.

M. H. Soomro *et al*. [41] compared different methods of Blind source separation for removal of eye blink artifacts from EEG. It compares ICA, CCA and PCA to estimate the source signal.

Aapo Hyvarinen *et al.* [42] proposed Independent component analysis using FastICA algorithm and compares it with other existing ICA techniques, which shows the several advantage of FastICA over others.

1.10 Thesis Outline

This thesis is divided into four chapters. Chapter 1 gives the basics of physiological measurement such as EEG, ECG, EMG and EOG. It gives details about bioelectric potentials generated by human brain and their classification. It also deals with different types of artifacts in EEG recording. It includes eye-blinking, eye-movement, muscle contraction, line noise and base line noise. After the introduction in chapter 1, the remaining portion of thesis is organized as follows:

Chapter 2 ARTIFACT REMOVAL

Chapter 2 deals mainly with the removal of ocular artifact using different techniques. The Blind Source Separation (BSS) technique is compared with other techniques of ocular artifact removal. In this chapter the method of BSS is discussed and calculated the signal to noise ratio and mean square error of clean EEG signal.

Chapter 3 Ocular Artifact using ICA

Chapter 3 deals with the Independent Component Analysis [18], [19] which gives better source separation as compared to other techniques. In this chapter particularly SOBI-RO algorithm is used for removal of eye blinking artifacts. The motivation of using this method is to reject the high amplitude spike and retrieve the original EEG waveform.

Chapter 4 CONCLUSION AND FUTURE WORK

Chapter 4 gives the conclusion of the thesis and scope of future research.

CHAPTER 2

ARTIFACT REMOVAL

CHAPTER 2: ARTIFACT REMOVAL

Introduction

There are various methods to remove the eye blink artifacts. Different techniques have been proposed to remove the ocular artifacts by many researchers. Some of the common techniques are filtering, regression analysis, wavelet transform, principal component analysis and blind source separation. In this work, Blind Source Separation is applied for removal of ocular artifact.

2.1 Manual Method

The simplest way of removing this type of artifact is to prevent them from occurrence. It is uncomfortable for the subject to control the blinking or eye movement. It is almost impossible for a human being to control eye blinking and even if a person tries to do so, it will affect the overall EEG signal and may introduce various artifacts. This is inadequate to fix the eye because it doesn't eliminate eye movement and effectiveness degrades in case of children and patient who have disorder related to brain neurons [43], [44].

2.2 Linear Filtering

There is one solution when we faced the problem of artifact removal that by analysing the frequency characteristics of signal as well as artifact and using the appropriate filter the artifact is removed. Since due to spectral overlapping of EOG and EEG, it cannot be simply filtered out. Simply rejecting contaminated EEG epoch may cause considerable loss of collected information. The frequency of EEG signal generally ranges in between 0.5 Hz and

80 Hz, the normalized frequency spectrum of eye blink waveform is nearly DC up to 75 Hz. It clearly indicates that there is huge overlap in the spectrum.

2.3 Regression Analysis

This is a new method to remove the EOG signal from the EEG in frequency domain. It is based on complex regression analysis [45]. Eye movement activity is transferred to EEG can have frequency dependent phase and amplitude characteristics. This method is suitable for such transfer because the regression formulae are used in the frequency domain. A general procedure for regression analysis is described by Vigeon et al [46] in equations (1) through equation (4).

$$EEG_r(i) = EEG_o(i) + \gamma EOG(i), i = 1,2,3 \ldots . N \tag{1}$$

The correlation(R) at zero lag of EOG and EEG recorded is given by

$$R = \sum_{i=1}^{N} EEG_r(i) EOG(i) \tag{2}$$

Combining equations (1) and (2) results in an altered expression for the correlation

$$R = \sum_{i=1}^{N} EEG_o(i) EOG(i) + \gamma \sum_{i=1}^{N} EOG^2(i) \tag{3}$$

Equations (2) and (3) are equal to each other and thus attenuation factor is given by

$$\gamma = \frac{\sum_{i=1}^{N} EEG_r(i) EOG(i)}{\sum_{i=1}^{N} EOG^2(i)} \tag{4}$$

This is easy to implement but it is based on several assumptions which is not necessarily correct. One of assumption is that the EEG and EOG are not correlated to each-other and measured EEG comprises of EEG and ocular artifact.

2.4 Principal Component Analysis

This technique [9] transforms a multivariable data of n components into a set of uncorrelated component. Thus data set undergo reduction of dimension. It is very clear that transformation should have low variance. Here we assume that the components are orthogonal which is not true always. There is difficulty in this analysis is that ocular artifact generator could have correlation with EEG generator. It cannot remove ocular artifact from EEG when both have comparable amplitudes.

Table.2. 1 Comparison of EEG Artifact removal methods

Methods	Limitations
Manual Method	Controlling manually creates other artifacts and it is not realistic and nearly impossible to control
Linear Filtering	It may be chance of losing critical information which is not practical in clinical research.
Regression Analysis	It requires clean EOG channel and then it removes EOG from EEG
Principal Component Analysis	It cannot distinguish ocular artifact from EEG when both have almost same amplitudes

2.5 Blind Source Separation

It implies the separation of a source signal from a group of mixed signal, with the little information about the source signal. It is called blind source separation because we don't use any other information besides the mixtures. The observed brain signal is the linear mixture of the signal generated by brain [19]. Finding sources is the main concern of blind source separation. In fact, a number of brain sources are always larger than the mixtures that lead to a complex problem with infinite solution.

To understand this takes an example where number of source signal generates the signal and number of recorder records the signal. Then, each recorder records the mixture of individual source signal. It is difficult to distinguish them due to various reasons .Some of the difficulties are the different locations of source and recorder, varying distances to recorders, and so on. It is the function of source separation technique to separate the sources.

2.5.1 Methodological steps

R. Romo Vazquez *et al* [2] have describes below methodology in order to find the estimated signal. The function of source separation technique is to separate the sources. The noisy signal in this case is given as:

$$Y = Hs + N \tag{5}$$

Where, Y is noisy signals, H is unknown mixing matrix, s is the matrix of sources, and N is noise matrix which is added externally.

The aim is to separate the source signal by analysing the value of B. The estimated source signal M is given by

$$M = BHs + BN \tag{6}$$

Here, one of the assumptions is number of sources and number of electrodes are same. But this is not the practical situation; this is only for mathematical simplification. In reality number of electrodes is less than the sources. In this case, $H \in R^{Q \times Q}$ and the perfect separation is observed when

$$B = H^{-1} \tag{7}$$

2.5.2 Blind Source Separation evaluation

The blind source separation result is validated by separability index SI. Separable index is derived from the matrix G (=BA) which is termed as transfer matrix. It computes the index between original and estimated source. The absolute value of G is computed for separable index. The rows and column of matrix G (g_i , g_j) is normalized to $g_i^{'}$ and $g_j^{'}$ respectively:

$$g^{'} = \frac{g_i}{\max|g_i|} \tag{8}$$

$$g^{''} = \frac{g_j}{\max|g_j|} \tag{9}$$

The separable index values SI_1 and SI_2 are calculated as

$$SI_1 = \frac{\sum_{i=1}^{Q}\left(\sum_{j=1}^{Q}(G'(i,j) - 1)\right)}{Q(Q-1)} \tag{10}$$

$$SI_2 = \frac{\sum_{j=1}^{Q}\left(\sum_{i=1}^{Q}(G'(i,j) - 1)\right)}{Q(Q-1)} \tag{11}$$

The average of both is separable index SI which is written as

$$SI = \frac{SI_1 + SI_2}{2} \tag{12}$$

Separable Index value should be zero for perfect separation. Therefore SI gives measure of closeness of G to permutation matrix.

2.6 Result

The observed EEG signal is normalized by dividing the data with its length. The normalized data is then added with the noise for uniform distribution of noise throughout the signal. There are two types of noise, one is uniformly distributed noise and another one is normally distributed noise, which is added to the normalized signal. These noisy data is then filtered using butter worth filter as preprocessing. Blind source separation technique has been applied to this filtered signal. The estimated EEG signal is observed which is known as clean signal, shown in figure below.

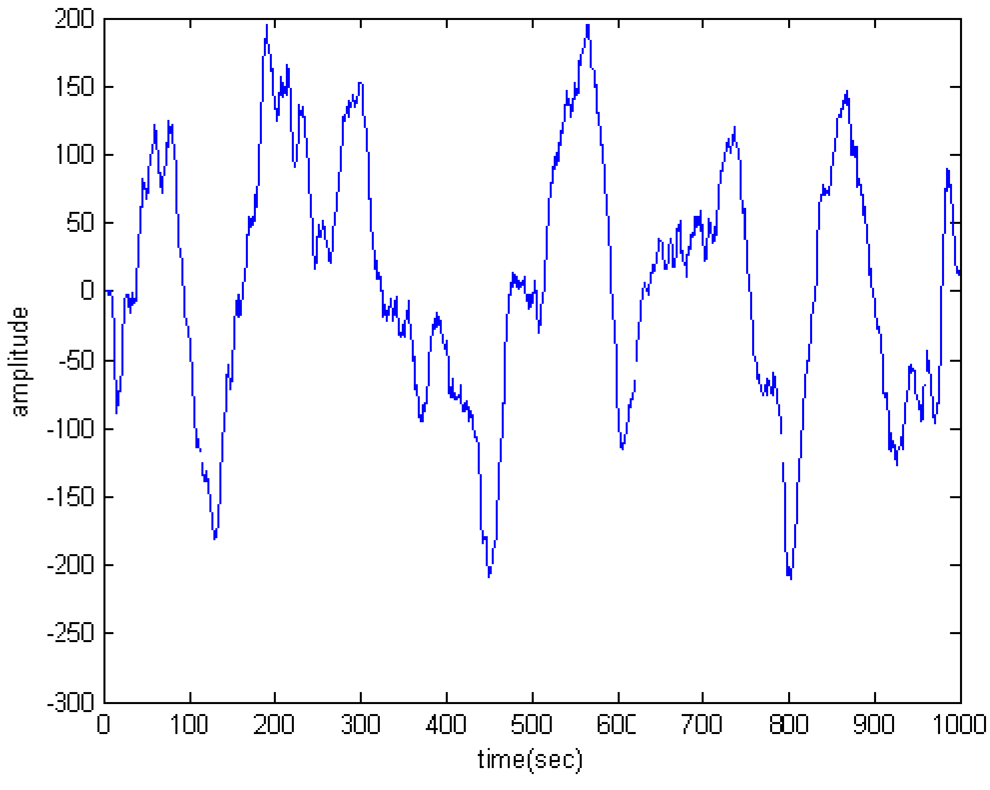

Fig.2. 1 Raw EEG Signal

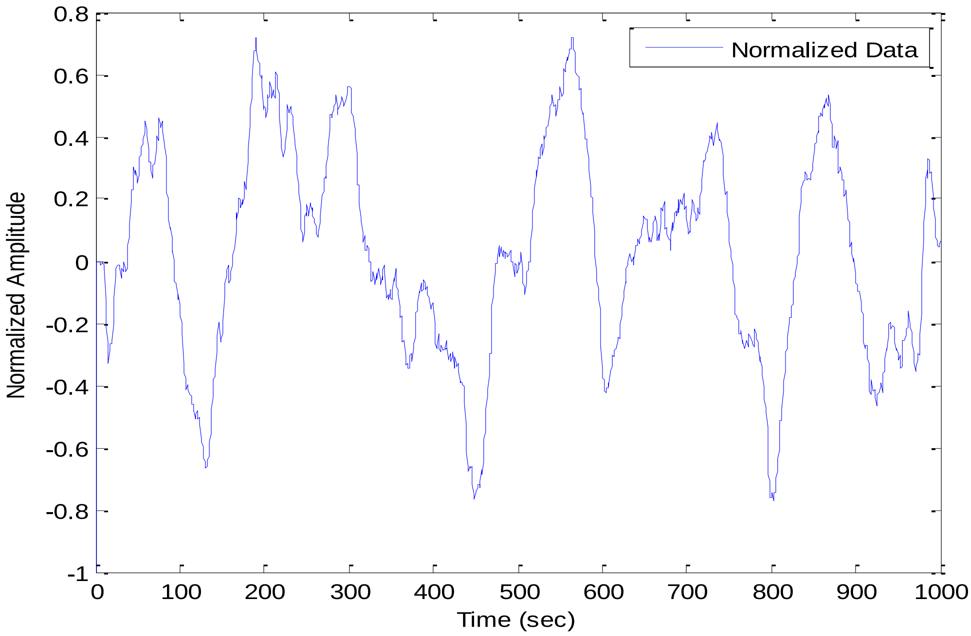

Fig.2. 2 Normalized EEG Signal

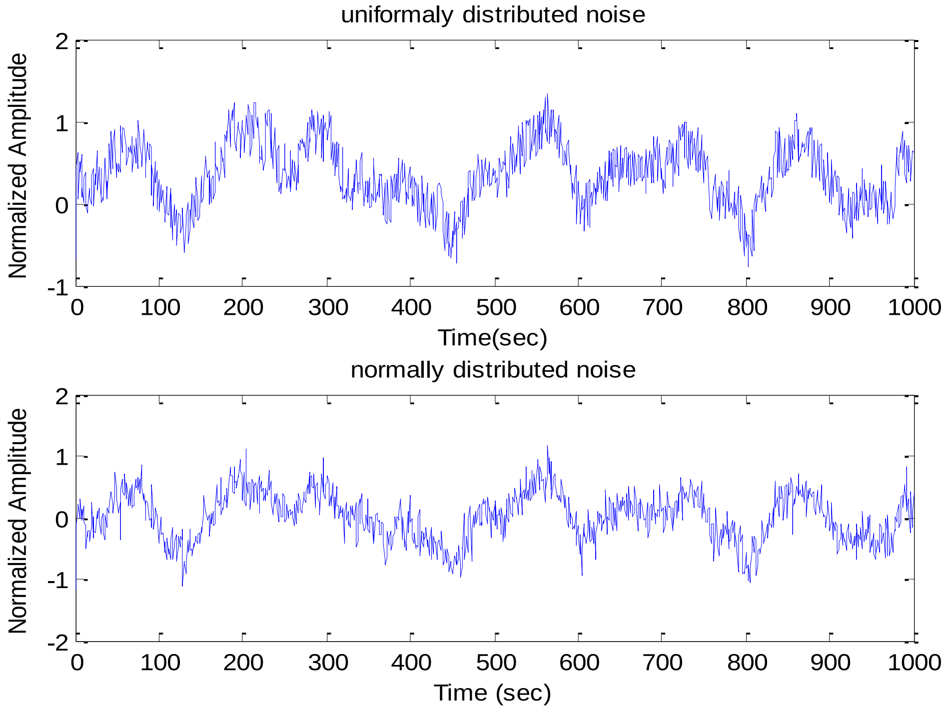

Fig.2. 3 Noisy Signal

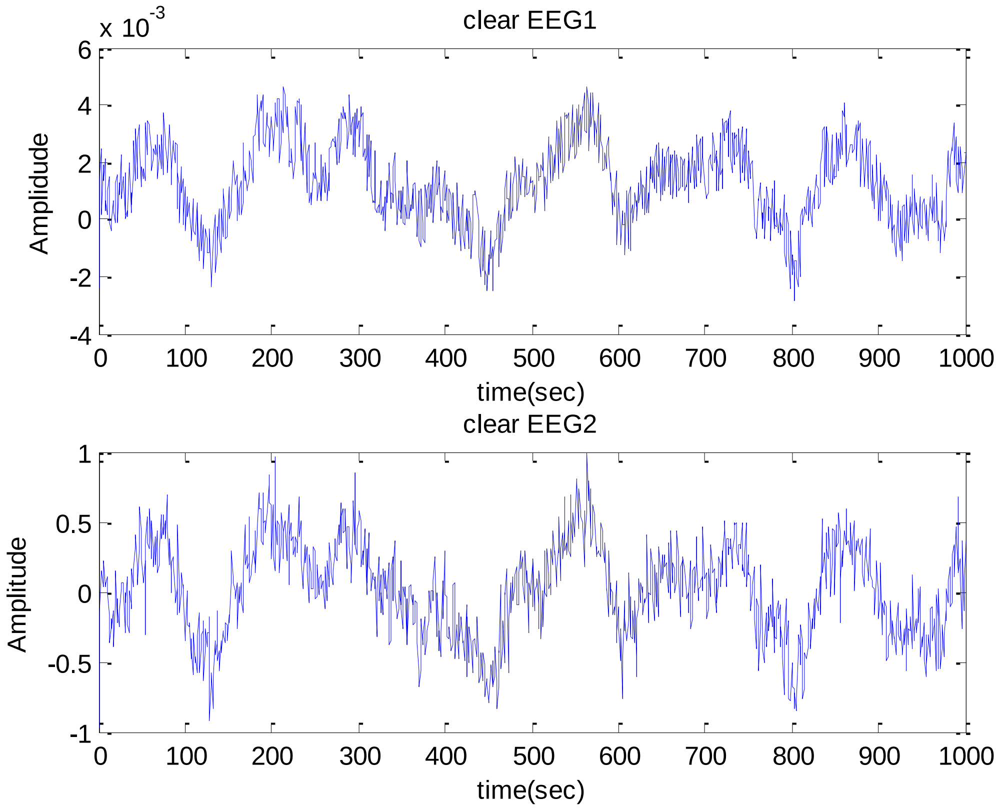

Fig.2. 4 Clean EEG Signal

When Blind Source Separation is applied to both contaminated data, it was observed that with increase in noise level, the SNR increases and at the same time MSE decreases. As the noise level increases, the signal strength is going to increase and the noise strength is going to decrease which is listed in the below table. The above result is observed when 5dB noise is added to the contaminated EEG signal. Similarly, other experimental results are tabulated in the Table 2.2 and Table 2.3.

Table.2. 2 SNR and MSE values under uniformly distributed noise

Noise in dB	SNR in dB	MSE
5	21.2207	0.0152
10	23.7335	0.0047
15	27.2942	0.0016
20	32.6641	0.0005
25	36.5484	0.0001

Table.2. 3 SNR and MSE values under normally distributed noise

Noise in dB	SNR in dB	MSE
5	23.7658	0.0671
10	25.2361	0.0210
15	26.1404	0.0068
20	33.5281	0.0022
25	34.3791	0.0006

Summary

This chapter describes the various methods used for removing different types of artifacts present in EEG recording and also justifies the use of Blind Source Separation for removal of artifacts from EEG signal. Initially raw EEG data has been taken and two types of noise have been added namely Normally Distributed Noise and Uniform Distributed Noise to generate two different sets of input. When Blind Source Separation is applied to both contaminated data, it was observed that with increase in noise level, the SNR increases and at the same time MSE decreases.

CHAPTER 3

ARTIFACT REMOVAL USING ICA

CHAPTER 3: ARTIFACT REMOVAL USING ICA

Introduction

Independent component analysis is generally used for feature extraction and source separation. It decomposes the mixed signals into independent one. This gives better separation based on two main assumptions: one of assumption is that the source signals are not dependent on others and second assume that each source signal is having non-Gaussian distribution. ICA concept is understood by an example of a cocktail party problem.

3.1 Cocktail Party Problem

Suppose there are three source of sound in a room at a time while three number of microphone is available in the room at different locations which recorded the signals. The signal is mixed with each other and recording is done as a weighted sum of individuals. The weight is determined according to the volume of speaker and the distance from the microphone. It is the duty of ICA to identify the individual speaker voice.

In the below figure, there are three source of signal and three recorder and the individual recording is the sum of linear mixture of all the sources. In this type of problem this ICA technique is applied to recover the individual signal. Here microphone gives three recorded time signals $x_1(t)$, $x_2(t)$ and $x_3(t)$, each having the weighted sum of speech signal which is denoted by $s_1(t)$, $s_2(t)$ and $s_3(t)$.This is represented by the linear combination as

$$x_1(t) = a_{11}.s_1 + a_{12}.s_2 + a_{13}.s_3 \tag{13}$$

$$x_2(t) = a_{21}.s_1 + a_{22}.s_2 + a_{23}.s_3 \tag{14}$$

Where coefficients $a_{11}, a_{12}, a_{13}, a_{21}, a_{22}$ and a_{23} value depends upon the microphone distance from source signal. This is known as the cocktail party problem.

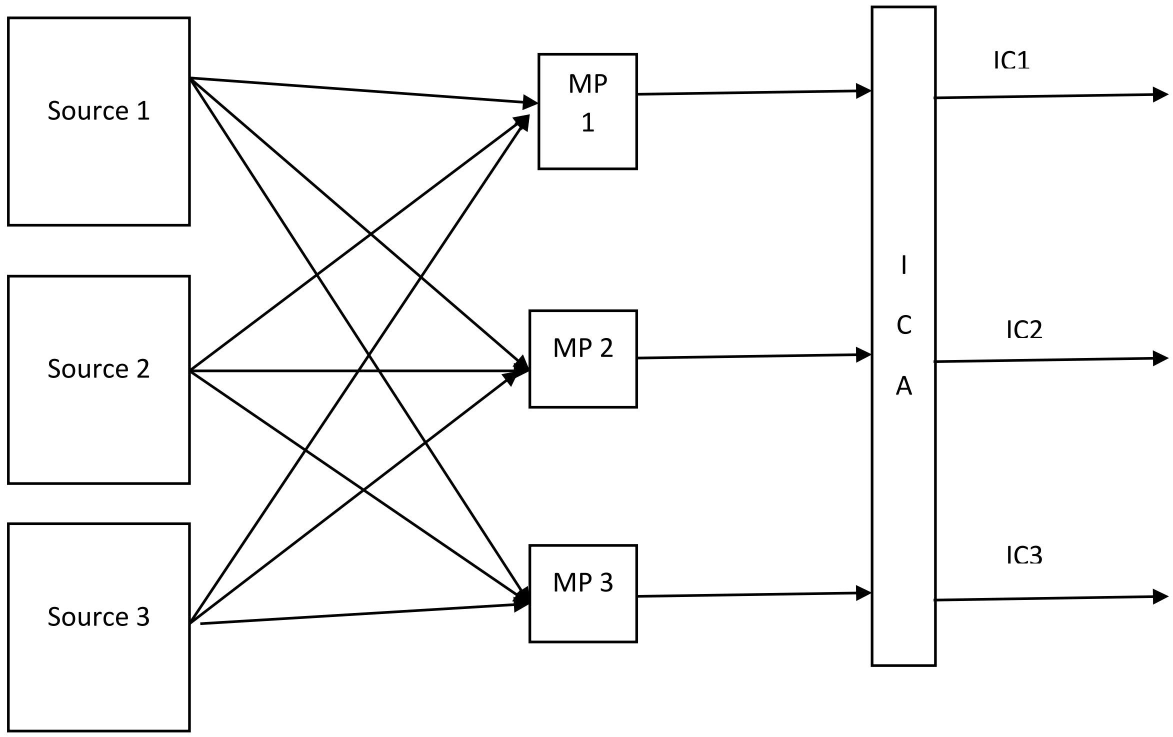

Fig. 3. 1 Cocktail Party Problem

3.2 Methodology

The methodology of implementing this algorithm is shown in the flowchart given below. All of five blocks are explained below in details starting from data acquisition to reconstruction of EEG signal.

3.2.1 Data Acquisition:

The EEG data is taken from the CHB-MIT Scalp EEG Database which is a standard data base. This data is taken using international 10-20 system of patient suffering from seizure. This database is collected from the Children's Hospital Boston which includes EEG recording of patient suffering from seizure. The patients were monitored for several days. A total of 22 patients including 5 males of age group 3-22 and 17 females with age group 1.5-19 were chosen in order to record the data.

3.2.2 Noisy Data:

This EEG signal contains ocular artifact particularly on the frontopolar channels and occipital channels. This artifact is a major source of distortion of useful data. In EEG waveform, this artifact is recognized as high amplitude peak. The blinking of eyes produce noise in the EEG waveform. It can be clearly seen that the low amplitude EEG waveform is corrupted by a high amplitude ocular artifact. Because of its high amplitude it can be clearly differentiated from other artifacts.

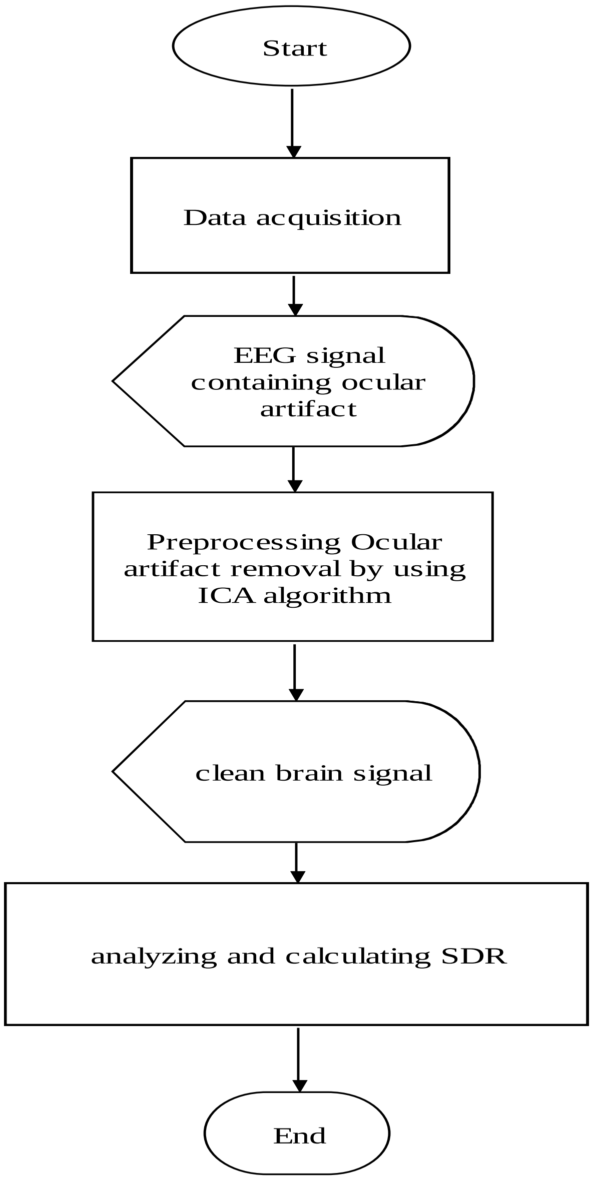

Fig. 3. 2 SOBI-RO Algorithm Flowchart

3.2.3 Preprocessing and Ocular artifact removal using ICA algorithm:

This EEG waveform is going to improve the signal to noise ratio using common average referencing or filtering. The type of filter used is very much depending on the goal of the application. The ICA technique [25], [26] is used to remove the ocular artifact. This model is also known as generative model because it is generated by mixing the source signal with unknown mixing matrix. Thus we observe the observed vector x and estimate the value of A and s using observed vector.In this project work SOBI-RO algorithm [1] is implemented for better artifact removal than others methods.

3.2.4 Clean Brain Signal and analysis:

At last the estimated EEG signal is retrieved using this technique. This method can be applied on any EEG signal including seizure. The clean EEG signal free from artifact is retrieved from the noisy EEG signal. The performance is evaluated using the Signal to Distortion Ratio (SDR) which gives better separation between clean EEG signal and noisy signal. The SOBI-RO algorithm [23], [24] gives a high value of SDR which indicates that the estimated signal is almost similar to the actual source signal.

3.3 Mathematical Model

Suppose there are n linear mixtures $x_1, x_2, \ldots\ldots, x_n$ of n independent components.

$$x_j = a_{j1}s_1 + a_{j2}s_2 + \ldots\ldots + a_{jn}s_n \text{ For all j} \tag{15}$$

We can represent the above model in vector-matrix form, which can be written as

$$x = As \tag{16}$$

Where A is the mixing matrix with element as a_{ij}.

This model can also be rewritten as

$$x = \sum_{i=1}^{n} a_i s_i \tag{17}$$

The above model is known as ICA model [25], [26], [27], [28]. This model is also known as generative model because it is generated by mixing the source signal with unknown mixing matrix. Thus we observe the observed vector x and estimate the value of A and s using observed vector. In starting we assume several assumptions to make the analysis simple.

One of the assumption is components s_i are statistically independent to each other. Another assumption is that components have nongaussian distribution. We also assume that the mixing matrix is square in nature.

After estimating the mixing matrix A, we easily calculate the inverse matrix of A, and using observed vector we get the components as

$$s = Wx \tag{18}$$

Where W is inverse of estimated matrix A.

3.4 ICA decomposition

The ICA decomposition [39], [8] can be easily understood by brain scalp model. In the EEG signal matrix representation, row represents EEG recording at different electrodes point while column represents EEG recording at different time slots. Here multichannel scalp data is multiplied with the W, commonly known as unmixing matrix. Again, this unmixing matrix along with scalp weight is mixed to get activation matrix which decomposes the mixed signal to independent components by multiplying with inverse of W.

3.5 Limitations of ICA

This ICA method is valid under certain conditions:

- The Source should be statistically independent.
- The distribution should not be Gaussian [29], [30].
- The number of electrodes must be at least equal to the number of sources.
- The independent sources should be combined linearly to give the mixture.
- The recording should be free from any type of delay or noise.
- The number of available mixture must be at least equal to number of independent components.

3.6 Removing Ocular Artifact of EEG signal using SOBI-RO

The contaminated EEG signal keeps both original source signal and noise signal which is artifacts. Ocular artifact which is on specific channels can be removed by this ICA technique. This is a second order statistics method [31], [32]. Independent component analysis works on the principle that signal is independent of each-other and thus source signal can be separated from the mixture signal [1], [33], [34], [35].

3.6.1 Methods

Arjon Turnip *et al* [1] have describes below methodology in order to find the estimated signal. The observed EEG signal is a mixture of source signal and weight matrix which is given as:

$$x(k) = Hs(k) \tag{19}$$

Where $x(k)$ is observed EEG signal.

Then calculated the autocovariances [20] of observed signal as:

$$C_{\mathrm{xx}} = \left(\frac{1}{N}\right)\sum_{k=1}^{N} \tilde{x}(k)\tilde{x}^{T}(k-p_i) = \mathrm{Q}C_{xx}Q^{T} \tag{20}$$

Where $\tilde{x}(k)$ is robust orthogonalization [21] of x (k) which is calculated as $\tilde{x}(k) = Qx(k)$.

Then, diagonal matrix is observed after performing joint approximation techniques of diagonalization as:

$$C_{xx} = \mathrm{Q}C_{xx}Q^{T} = \mathrm{U}D_{i}U^{T} \tag{21}$$

At the final stage the estimated source signal [22] is expressed as:

$$e(k) = U^{T}Qx(k) \tag{22}$$

The performance is evaluated using signal to distortion ratio which is calculated as

$$SDR = 10log_{10}\left(\frac{\sum_k s(k)^2}{\sum_k \left(s(k) - e(k)\right)^2}\right) \tag{23}$$

The EEG data which is obtained from standard database is the observed data vector, represented as x (k). This observed data is obtained from mixing the weight matrix with source signal. Here, H is weight matrix and s (k) is the original source signal. The weight value depends on various factors such as the distance from the source signal, strength of the signal, location of electrodes etc. Thus we can say that the EEG signal is a mixture of source signal with an unknown weight matrix.

The main artifact of the EEG waveform is ocular artifact. This causes major error in the analysis of EEG waveform. The ocular artifacts are identified by their high amplitude in comparison to normal EEG signal. The ocular artifact signals are mainly encountered at the frontopolar channel with occipital channel, as the electrodes for these channels are placed near eye. To counter this problem auto covariance technique has been used. In this technique the variance of the signal is calculated. Due to high amplitude, the time instant at which the ocular artifact occurs, the covariance is more compare to normal covariance.

The auto covariance matrix is now subjected to QR factorization using Gram-Schmidt, which includes three steps.

1. Orthogonal basis via Gram-Schmidt
2. Orthonormal (divide by length)
3. QR factorization

Our goal is to convert the original basis ($\vec{x}_1,....,\vec{x}_n$) for v to an orthogonal basis $\left(\vec{y}_1,.....,\vec{y}_n\right)$.

To achieve this a recursive idea is used as

$$\vec{y}_j = \text{ Part of } \vec{x}_j \text{ that is perpendicular to } \{\vec{y}_1,....,\vec{y}_{j-1}\}$$

$$\vec{y}_1 = \vec{x}_1,$$

$$\vec{y}_2 = \vec{x}_2 - P_{\vec{y}_1}^{\vec{x}_2} = \vec{x}_2 - \frac{\vec{y}_1.\vec{x}_2}{\vec{y}_1.\vec{y}_1}\langle\vec{y}_1\rangle,$$

$$\vec{y}_3 = \vec{x}_3 - P_{\vec{y}_1}^{\vec{x}_3} - P_{\vec{y}_2}^{\vec{x}_3} = \vec{x}_2 - \frac{\vec{y}_1.\vec{x}_3}{\vec{y}_1.\vec{y}_1}\langle\vec{y}_1\rangle - \frac{\vec{y}_2.\vec{x}_3}{\vec{y}_2.\vec{y}_2}\langle\vec{y}_2\rangle,$$

$$\overline{y}_k = \vec{x}_k - \sum_{j=1}^{k-1} P_{\vec{y}_j}^{\vec{x}_k} \tag{24}$$

The orthonormal basis is obtained by dividing the orthogonal basis with their length as given below:

$$\vec{z}_1 = \frac{\vec{y}_1}{|\vec{y}_1|}, \vec{z}_2 = \frac{\vec{y}_2}{|\vec{y}_2|}, \vec{z}_3 = \frac{\vec{y}_3}{|\vec{y}_3|} \tag{25}$$

The orthonormal vectors constitute to give Q matrix and the R matrix is calculated using the formula given below:

$$R = Q^T A \tag{26}$$

Where, A is original matrix

Q is an orthogonal matrix and

R is an upper triangular matrix.

The average amplitude of EEG waveform is -50 to 50 microvolts but due to ocular artifact or stimulus, amplitude becomes higher than normal which is shown in below figure 3.3.

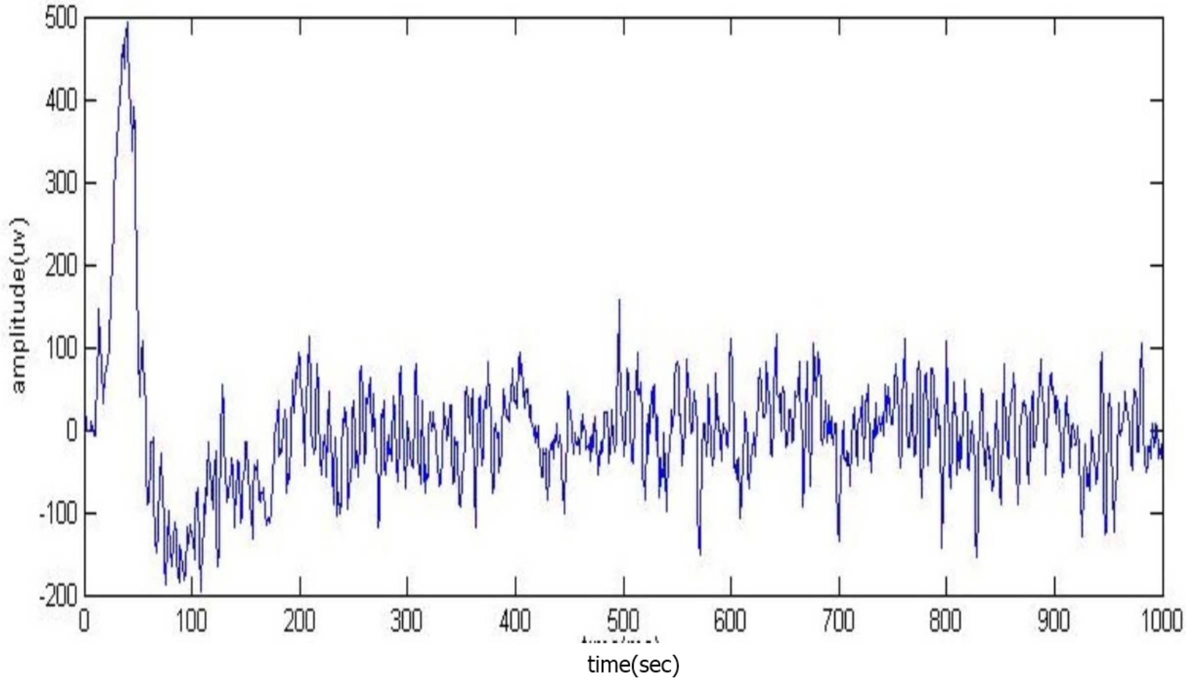

Fig. 3. 3 Raw EEG signal

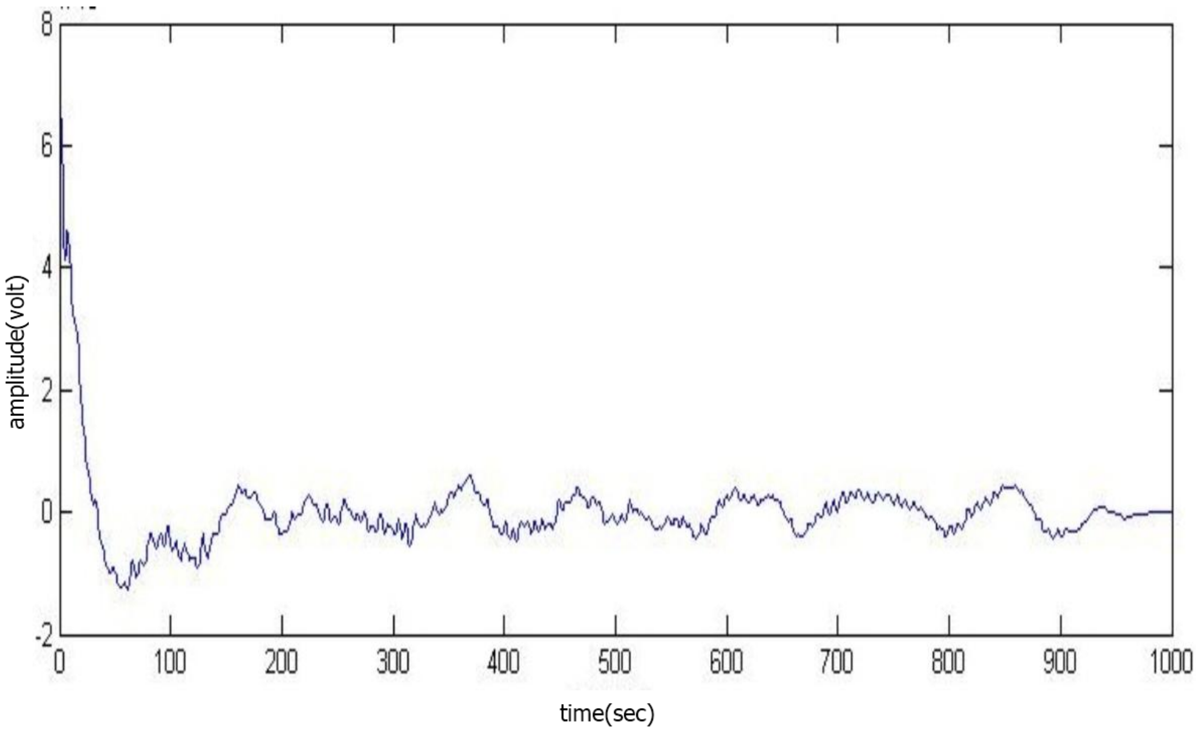

Fig. 3. 4 Auto covariance Signal

The auto-covariance waveform of contaminated EEG is shown in figure 3.4, which clearly indicates that the average variance is same except that where spike occurs. There are fixed pattern of ocular artifact at frontopolar and occipital channel.

Now, joint approximation Diagonalization (JAD) is applied to orthogonalized mixing matrix using UD factorization. The auto-covariance matrix which contains error value can be factorized using Cholesky factorization as given in Eq-21. Where, U and D are referred to as the U-D factors of C_{xx}. The value of U and D are unique provided Cxx is positive definite and factorization is done using the Cholesky algorithm.

At last the estimate of source signal is retrieved by the given formula as:

$$e(k) = U^T Q x(k) \tag{27}$$

Finally the signal to distortion ratio value is calculated to determine the effectiveness of the performed separation.

3.6.2 Result

The observed contaminated EEG signal shown in figure 3.5 is processed through the auto-covariance with different time delays. In this method, the main focus is to remove the ocular artefact. In SOBI-RO first of all auto covariance is calculated for contaminated EEG signal and the portions having higher variance are rejected. The clear EEG signal waveform is shown in the figure 3.6. The clear EEG waveform shows that the average amplitude of signal is in between -50 to 50 microvolt which indicates that the artifact is removed successfully

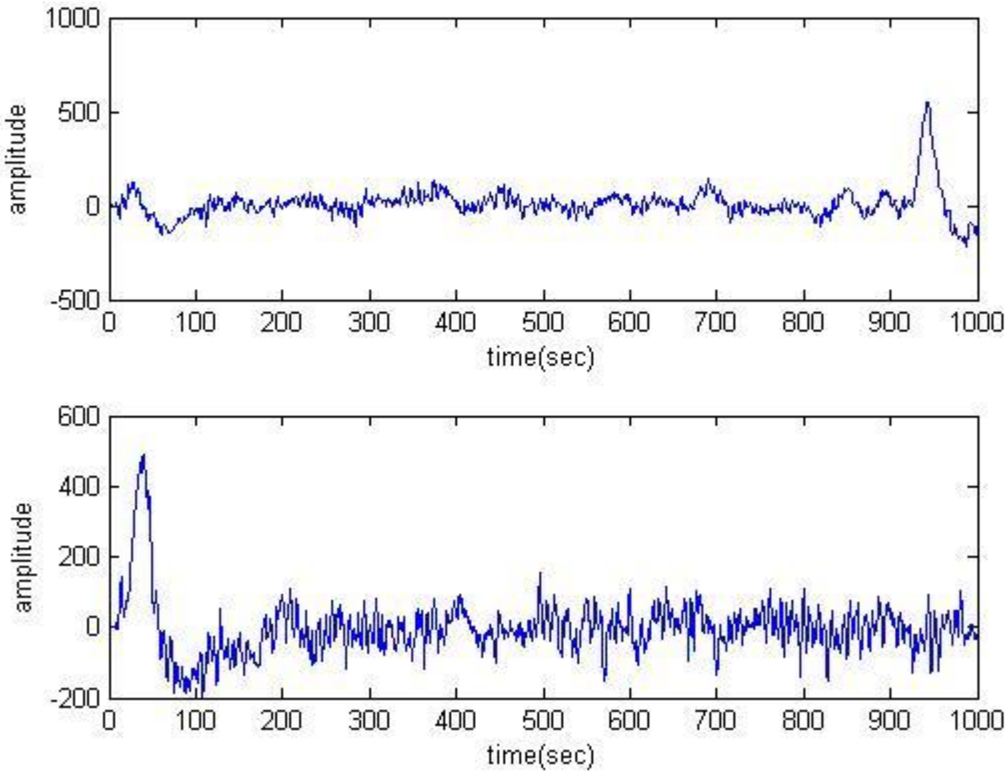

Fig. 3. 5 Raw EEG Waveform

After that Factorization along with Diagonalization is performed, orthogonal mixing matrix is calculated, to retrieve the estimated signal. To show the effectiveness of SOBI-RO, signal to distortion ratio (SDR) is calculated and it was observed that ocular artifact is removed. This result shows that SOBI-RO has better separation accuracy among all other methods.

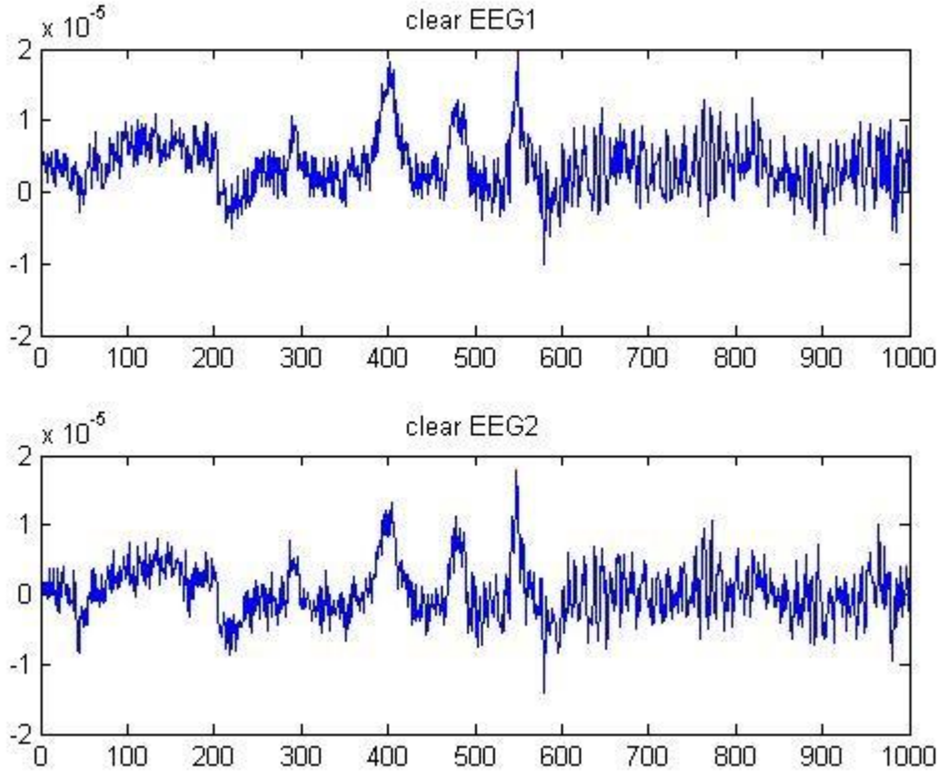

Fig. 3. 6 Clean EEG Signal

Summary

This chapter emphasizes on the ocular artifact and its removal to get clean EEG data. Out of various algorithms present in ICA techniques, SOBI-RO is used here because of its outstanding ability to remove noise from the contaminated EEG data. In SOBI-RO first of all auto covariance is calculated for contaminated EEG signal and the portions having higher variance are rejected. After that Factorization along with Diagonalization is performed to retrieve estimated signal. To show the effectiveness of SOBI-RO, signal to distortion ratio (SDR) is calculated and it was observed that ocular artifact is removed. This result shows that SOBI-RO has better separation accuracy among all other methods.

CHAPTER 4

CONCLUSIONS AND FUTURE WORKS

CHAPTER 4: Conclusions and Future Works

Conclusions

In this thesis, ICA technique is used to remove the ocular artifact from the EEG signal. The SOBI-RO algorithm is used because it is the most efficient algorithm for artifact removal. The data which is collected from CHB-MIT Scalp EEG Database is used for artifact removal. The clean EEG signal free from artifact is retrieved from the noisy EEG signal. The performance is evaluated using the Signal to Distortion Ratio (SDR) which gives better separation between clean EEG signal and noisy signal. The SOBI-RO algorithm gives a high value of SDR which indicates that the estimated signal is almost similar to the actual source signal.

Future Works

- The accurate EEG signal finds scope in various advanced areas of bio-medical like clinical research and brain-machine interface. To get the accurate EEG signal SOBI-RO is one of the finest methods. So if SOBI-RO is used in medical science, the cure of patient can be done effectively.
- Its use in device control like brain computer interface can change the life of patients suffering from severe neurological disorder like seizure.
- SOBI-RO method can be improved further by applying various other Linear Algebraic techniques of matrix operation.

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