EEG SIGNALS SEPARATION USING BSS TECHNIQUES

A THESIS

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BY

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We certify that this thesis titled**"EEG Signals Separation Using BSS Techniques"** which is being submitted by **Safaa Mahmood** was prepared under our supervision at the Communication Techniques Engineering Department, Engineering Technical College-Najaf, AL-Furat Al-Awsat Technical University, as a partial fulfillment of the requirements for the degree of Master of Technical in Communication Engineering.

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Abstract

There is a growing interest in research on how to analyze brain signals, as there are electrical activities between neurons in the brain related to all activities in the body. Those activities can be seen using a non-surgical technique called Electroence-phalography (EEG).Analysis of such signals in medicine is an important issue. There are many challenges in analyzing brain signals that have not yet had a basic solution, such as having an artifact during the recording process, which makes analyzing brain signals very difficult.

In analyzing neurophysiological signals, Noise rejection and artifacts are an important area of research. Signal separation techniques such as Blind Source Separation (BSS) are used to overcome the artifact problem by separating artifacts and noise from the EEG signal as separate components. BSS is a method for separating primary sources from their mixtures with little or no information from the original sources and the proposed mixing separation process for a complete artifact rejection system based on modified blind source separation algorithms. The proposed system could remove artifacts such as [Electrooculogram (EOG), electrocardiogram (ECG) and power line noise interference (LN)] from the EEG mixture.

In this thesis, four Blind Source Separation BSS algorithms [STONE, Efficient Fast-Independent Component Analysis (EFICA),Block Expectation Fast Independment Component Analysis (BEFICA),and Fast Independent Component Analysis (FICA)]are used. Thise worke taken in two stages.The first stage in which the algorithms are processed with two

types of data (real and simulated) where the quality of the class for each is tested and compared to the these choose the best one.

The second stage optimized by Antlion algorithm which improved one of algorithms used in case simulation data is Block Expectation Fast Indepandment Component Analysis (BEFICA) which has the best response for optimization by the proven standards of (SNR,ISR) where the signal to noise ratio (SNR) is (26.46) and the intereferance to signal ratio(-26.46) after compared with all the algorithms .

While in case real data the Efficient Fast-Independent Component Analysis (EFICA) is more responce to the operation of optimization by used Power Spactral Density (PSD)is equal (0.0051)after compared with all the algorithms used .

Dedication

To **Moulay Imam**, the owner of the times and times.

To **Moulay Al-Hijjah Al-Mahdi**,

may God Almighty hasten his relief

For **my Parents** my God have mercy on them

.

For **my brother**, my God have mercy on him.

For **my sisters, my husband**, and **my friends** ...

To everyone who encouraged and helped me achieve my success

✍ **November/2021** **Safaa Mahmood**

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I would like to appreciate the extraordinary efforts and tips of **Prof. Ali Abdullah Al-Bakri** and **Asst. Prof. Dr. Ahmed Karim. Al-Bakri** who had a significant and effective role in achieving the requirements of the current study.

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✍**November/2021** **Safaa mahmood**

DECLARATION

I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged.

✍ **November/2021** **Safaa Mahmood**

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Abbreviations

Symbol	Description
ALO	Ant Lion Optimizer
BEFICA	Block Expectation Fast - ICA
BSS	Blind Source Separation
EEG	Electroencephalography
EOG	Electrooculogram
ECG	Electrocardiogram
EMG	Electromyogram
EFICA	Efficient Fast-Independent Component Analysis
FICA	Fast Independent Component Analysis
ICA	Independent Component Analysis
ISR	Interference Signal Ratio
NSGS	non-stationary and non-Gaussian scenario
PLN	Power line noise
PSD	Power Spectral Density
Pdf	probability density function
SNR	Signal to Noise Ratio

List of Symbles

Symbo	Definition	Unit
A	Mixing matrix	---
CRLB	Cramer-Rao Lower bound	---
$C(W_K)$	Contrast function	---
EY	Temporal predictability of y(k)	---
F(K)	Scaling factor	---
G	Gain matrix	---
G(X)	Covariance matrix	---
r(t)	random walk	---
S(t)	Source vector	---
S_D	Determined Sources	---
W	Separation Matrix	---
XL	Filter Response	---
X(t)	Observed signal	---
Y(L)	Long-term	---
Y(S)	Short-term	---
Z	Observed matrix	---

CHAPTER 1

Introduction and Literature Review

1.1 Introduction

As information technology is rapidly developed, The Electroencephalography (EEG) became an increasingly popular way to analyze hospital brain signals. EEG signals contribute greatly to Brain-Computer Interface (BCI)[1]. It is one of the devices translating the signals of the brain into output signals related to computer systems. Majorly, the output of BCI is utilized for restoring many functionalities with regard to motor disabled individuals, for instance, for communication or prosthesis control [2]. Moreover, the non-invasive nature regarding the EEG signal acquisition makes it very attractive to analyze EEG signals[3] .These signals are complex random signals that result from hundreds of millions of neurons in brain EEG mixtures containing many data on brain activity that reflect the brain state's electrical activity. Through it, many diseases can be diagnose by tracking EEG signals. Now, the most important problem in EEG signal analysis in neuroscience research has become especially for the clinical diagnosis of brain diseases.An important part of BCI systems is feature extraction algorithms. A key step in pre-processing for cleaning brain signals from artifacts is the artifact removal techniques and making the EEG signal more relevant and clearer in the case of analysis. Since the artifacts have a great influence on diagnosis; thus, such unwanted signals should be eliminated prior to the final decision[4]. The system is subject to one or more extraction procedures, such as capacitance and spectral or spatial measurements[٥].Blind Source Separation (BSS) Algorithm is a known technique for separating such signals. There are various applications covered via BSS, the most important of them is communication, speech signal, neurophysiological signal, image processing, and medical signal processing, which utilized to separate or extract primary sources from received signals; there were many approaches suggested for cleaning the brain signal. Each technology has its pros and cons, each according to its own working method.

1.2 Literature Review

There are many researchers who have expressed their interest in the BCI because of the significance of the system which lies in a wide range of the applications. Like the medical applications specially to help people who have disabilities such as helping them to deal with computers and communicating with the outside world, educational applications, security applications, etc. Will address a review of the literature on Blind Sources Separation techniques that consider a tool to clean up brain EEG data of various kinds for artifacts. This review represents the various aspects of artefactual EEG rejection methods. Includes review papers on developing techniques to reject EEG artifacts.

• **Croft, R.J. and R.J. Barry**, **2000 [6].** discuss a number of methods used to discard in-kind artifacts and manipulate features of the EOG repair procedure, frequency and time domain methods, and number of EOG channels. repair procedure, to obtain a suitable statistic for estimating and evaluating the correction factor for various eye movements in addition to performing the calibration and then introducing the EOG repair algorithm. to determine the factors of scaling between the EOG channels and all of the EEG channels.

- **Gu, X., et al., 2001 [7]**with others minimize the impact of the eye contamination in the EEG signals, visual inspections of the artifacts and methods of data augmentation have been utilized for removing the contamination of the eye. Artifact subspace reconstruction (ASR) can be defined one of the automatic component-based mechanisms as a step of preprocessing that could effectively eliminate the large-amplitude or transient artifacts contaminating the EEG data.

- **He, P., G. Wilson, and C. Russell**, **2004 [8].**Was given, a modification in filtering method of EOG ,where the signal is started with one indication signal. Amodification according to the separating between horizontal and vertical channels of the EOG is demonstrated and take them as a 2 different indication inputs. LMS (i.e. the Least Mean Square) represents a populations approach which is utilized in the daptive filtering and Recursive Least Square (RLS) approach is utilized for the reduction of the expectancy errors.

- **Krishnaveni, V., et al., 2005 [9].**Different types of ICA algorithms (JADE, RADICAL, Kernel-ICA) were compared to reject EOG and it was concluded that RADICAL algorithm has been the optimal algorithm that separates the EEG mixtures. ICA is a non-parametric algorithm that contains the advantage of PCA, and because PCA completely separates the movement of the brain, heart and eye as an independent component.

- **Xue, Z., et al2006 [10].** Two ICA algorithms, Extended-InfoMax (EI-ICA) and InfoMax (I-ICA) have been used to Extraction of 50 Hz power line noise and eye movements from mixture EEG), as EI-ICA has been shown to be The best way to isolate both super-meta-artifacts (eye flash) and sub-intrusive artifacts (streak Noise), while the (I-ICA) approach removes ultra-intrusive artifacts (eye flash).
- **Vijila, C.K.S., et al. 2007[11].** And others use an algorithm whose performance is related to a scrambling computing algorithm called Adaptive. Ambiguous Neural Inference System (ANFIS) to remove traces of EEG. And to demonstrate the ANFIS algorithm in action a comparison between the neural network and the adaptive filter using the least square average.
- **Tichavsky, P., et al. 2008 [12].** Their performance assessed using images and simulated signals The first algorithm, which has been abbreviated as EFICA algorithm can be defined as a sophisticated type of the common Independent Component Analysis (ICA) approach Fast-ICA. EFICA depends on making the statistical dependencies is minimizing between the instantaneous (secondary) estimated source signal distributions, which is why, neglectany possible source time structure. The second approach, which is the WASOBI, can be defined as a weight-adjusted type of the SOBI, a popular BSS approach which only utilizes the source signals' time structure for achieving separation. EFICA and WASOBI

  separation accuracy may be evaluated with the use of the estimated source signals only, thereby, permitting the selection of the most appropriate one of the two in each script.
- **Suresh, H. and C. Puttamadappa, 2008 [13].** Used an algorithm whose performance is related to a complex real-time neural network algorithm called Real

Time Recurrent Learning (RTRL) for the purpose of removing noise and enhancing the signal. Whereas, the neural network converges faster with a lower average and to remove artifacts without clipping the EEG data, the RTRL algorithm used a combination of signal enhancer and adaptive noise cancellation.

- **Kabardian, 2010 [14].**The mixtures were separated and the bypass problem of the acoustic signals was solved by time domain, using space-independent partial analysis (ISA) or independent component analysis (ICA) methods and compared them together. The test is based on assessing the separation of the pseudo-coiled mixture from the independent signal limiter. The mixture consists of real-world twisted features and simultaneous mixtures, taking into account that the compatibility of the algorithms is based on the characteristics of discrete signals.

- **Babu, P.A. and K. Prasad 2011 [15]**.They used an adaptive filter with a fast and wavelength RLS algorithm to eliminate EEG effects. So the algorithm is also used to increase the ratio of peak signal to noise and reduce elapsed time.

- **Hofmanis, J., et al. 2012 [16].**They provide a review of the physiological signals that are usually recorded in the home, detailing the always-occurring artifacts that cause great corruption. Artifact removal techniques are analyzed in detail, their advantages and disadvantages are covered, and then applied in the personal healthcare field.

- **Hofmanis, J., et al 2013 [17]**.The researchers set algorithm to get rid of the effects of epilepsy patients by deep brain stimulation (DBS) and the use of multiple contact electrodes [Stereotactic EEG (SEEG)]. It is used to eliminate target noise reduction signals and DBS-SEEG to restore the mask. The main sources and filtering methods are reviewed. It consists of a combination of filtration plus a generalized eigenvalue (GEVD). The study concluded with real SEEG simulations that the approach could separate sources of deep brain stimulation from brain activity.

- **Zeng, H. and A. Song, 2014 [18].**They have obtained an effective methodology that addresses the in-kind instrument problem that appears through The EEG recording is based on the fixed subspace analysis algorithm, by which the artifacts are made in Fewer components than blind source separation methods and then manual tool To be subtracted from the EEG signals by dropping the components again to obtain clean EEG signals.

- **Mousa, F.A., R.A. El-Khoribi, et al. 2015 [19].**Researchers have developed a new method for analysing EEG signal. Use a high pass. An artifact removal filter and also feature DWT algorithms extract the mean absolute value, mean root

- square, and simple integration square. The feature vectors are grouped using the Nearest Neighbour algorithm and then use the neural network algorithm to arrive at the correct nomenclature of the EEG signal class after clustering. The results of this method are better than other methods mentioned in the literature.

- **Zhang, C.Z., A.Kareem Abdullah,et al.2016[20].** They have demonstrated a beneficial method for extracting EOG and LN from brain mixtures when compared to a variety of the BSS technologies (Stone's BSS, EFICA, FICA, SOBI, and JADE). Two real EEG data types have been taken (first dataset and dataset second), in the first dataset, the signals were combined by an eye flash artefact with an LN 50Hz, and in the second dataset, the signals were mixed by the eye muscle, the eye blink artefact. With LN.

- **Patel, R.,et al. 2016 [21].**Researchers presented a novel approach to active suppression and for the efficient detection of those artefacts with the use of the single-channel EEG data through the combination of the Ensemble. Experimental mode analysis (EEMD) with some PCA. Provide a method for suppressing in-kind defects, through carrying out an EEMD on a contaminated segment of the EEG data to obtain basic mode functions (IMFs) and then eliminating artefacts through the automatic selection of some of the key components that are characteristic.

- **Zhang, C. and A. Albakri 2017 [22].**Many methods have been proposed to remove these artifacts from EEG recordings , modified blind source separation techniques (ESBSS and EMBSS) Blind source separation techniques, two algorithms ESBSS and EMBSS are applied to the multi-channel EEG recordings for the removal of various artefacts from the records of the EEG through the elimination of contributions of the artefactual sources onto scalp sensors . ESBSS and EMBSS algorithms have been proven to be influential techniques for the automatic extraction of the both and sub-gaussian as well as super-gaussian signal from the brain mixtures. fast genetic algorithm is used to overcome these problems. The initial candidate solutions in GA is increased by hybridization process.

- **Wu, D., et al 2017 [23].** Because EEG signals have been used often in BCIs, and are contaminated easily with the artefacts and noise, so the researchers performed pre-processing before introducing them into a machine learning algorithm. Then large-scale spatial filters were utilized for increasing the signal-to-signal ratio. Noise in the BCI and EEG problems, however, its applications in the regression problems of the BCI were quite limited.

- **Buvaneash, D. and M.S. John 2018 [24]**.The study discusses the recorded EEG signals from the scalp of the subjects via non-invasive electrodes. Time-Frequency (TF) analysis approaches have been utilized for the purpose of (signals analysis) extracting the features from EEG signals. ANN machine learning algorithm to learn the EEG signal features for the sufficient output classification. Their research presents performance analysis of the system's accuracy for the proposed TF analysis and an NN algorithm combination respectively for the feature extraction of the EEG.

- **Abdullah, A.K., A.G. Wadday, and A.A. Abdullah. 2019 [25].** They used a new method to extract the pure ECG signal from the raw ECG based on extracting the source of the blind stone, the main benefit of the new method in comparison to the classical approach is separating all beneficial information without eliminating the appropriate data from the signal The original. The efficiency of the suggested method is measured using MSE and SNR. And to demonstrate that this technology is the best compared to traditional methods. It was concluded that Stone BSS technology is the most effective power line noise removal.

- **Ahmed,M.A.,Q.Deyu,and.E.N.Alshemmary, 2020 [26].** The extraction of the EEG has been commonly utilized with the Stone's BSS approach. Which suggests a Stone's BSS hybridization with the PSO for boosting the process of the separation. An improved Stone's BSS (ISBSS) approach is utilized for the rejection of the eye blinking from EEG mix. The approach of the generalized eigen value decomposition (GEVD) has been implemented for the extraction of the EEG signals for obtaining a clean EEG signal. The clinical EEG data-base has been utilized for testing the enhanced and other approach. GEVD approach performs the estimation of the performance of the measurement of the suggested algorithm with the use of an integral square error and carrier-to-interference ratio and compares the suggested approach with the traditional Stone's BSS, Fast-ICA, EFICA, and JADE approaches for checking its effectiveness.Results have shown that the proposed hybrid approach has a more sufficient performance and reducing the elapsed time compared to the traditional Stone's BSS and other approaches.

In fact, the work submitted by Muhammad Ali Ahmed, under title “Rejecting the blink of an EEG.”Improvement based on the Hybrid Stone Blind Separation of origin and swarm of particles Optimization method, "in which he deals with Stone’s BS) Algorithms a with the PSO for the enhancement of the process of separation.While the current work used Antlion algorithm for optimization . An ISBSS approach has been utilized for the to rejection of the eye blinking from the electroencephalogram then, it is incorporated in PSO, the GEVD approach has been implemented for the extraction of the EEG singles for obtaining a clean EEG signal. Used the same dataset (a clinical EEG data-base) for testing the enhanced as well as the other approaches. And performs a comparison

of the suggested algorithm with the traditional Stone’s BSS, Fast-ICA, the evolutionary fast ICA (EFICA), and the JADE algorithms for checking its efficiency. Results have shown that the proposed hybrid approach has a more sufficient performance and reduced elapsed time compared to the traditional Stone’s BSS and other methods.

1.3 Motivation and challenges

Brain activity-based communication systems are of high importance and providing a new form related to communication and control Brain Computer Interface (BCI) either for increasing the integration into society or providing the persons with disabilities for various reasons such as cerebral palsy or muscular dystrophy to become an interaction's instrument with their environment with no assistance,or control of brain signals such as EEG[21].Therefore, EEG is

commonly used to evaluate brain activity due to its excellent accuracy. EEG signals are very complex, contaminated with different types of artifacts. Because EEG data is usually mixed with common tools such as Electrooculogram (EOG)[٢٠] . Electrocardiogram (ECG) [27]. power line noise interference analyzing brain data is very difficult since these artifacts EOG can distort brain data especially in epilepsy patient and make analysis difficult almost impossible[28]. So it is necessary to remove or separate physical artifacts from the required signal. BSS technologies obtained an amazing result in different applications, which led to the interest of researchers in this field to analyze the physiological signals in these technologies and the most

important applications for cleaning and removing signals, rejecting artifacts, and extracting the required signal in the analysis of EEG signals[29]. There are many researchers trying to remove artifacts and noise from EEG data, EEG data is strongly affected during the registration process by various types of artifacts that are created either

inside the brain or outside the scalp[30]. In addition, bad EEG signals are weak and of poor quality. The BSS is the most appropriate option for analyzing multiple data from brain signals.

1.4 Problem Statement

EEG recording signals are affected by cardiac interference signal, eye blinks, eye movement, ocular activity, non-biological sources (such as power-line noise) or involuntary muscle could obscure actual EEG signal, blocking the measurement of features utilized for controlling the system, therefore, needs a high-precision algorithm for separation.

1.5 Thesis Aims

Two main goals are suggested for this work :

(1) Useing different types of the BSS Blind Source Separation techniques to choose the best in the separation process by using Signal to Noise Ratio (SNR), Interferance to Signal Ratio (ISR) and Power Spectral Density (PSD) Critiria.

(2) Response enhancement of BCI system by removing the noise and artifacts based on modified blind source separation techniques . The evaluation is mainly performed using simulated and real EEG data .

1.6 Thesis Contributions

- Four algorithms BSS (STONE, FICA, BEFICA, EFICA) are used for the first time to process and extract artificial signals.
- A new approach on the basis of Ant Lion Optimization (ALO) technology has been implemented with four BSS algorithms (STONE, FICA, BEFICA, EFICA).To

obtain the best artifact rejection system in the electroencephalogram (EEG)signals . In case real EEG data & simulation data.

1.7 Thesis Layout

Beside this chapter, the remaining parts of the presented study include these chapters:

Chapter Two: Includes concepts related to the structure of BCI systems, and an idea of BSS technologies' principles provided.Definition, applications, classification, and pre-processing. Next the EEG system and a detailed explanation of brain activity's rhythms and the electrodes system, Then demonstrated that the EEG brain mixture is a BSS problem solved by BSS technologies.

Chapter Three: General description of BSS technology, a review is provided on EEG - artifacts, as well as the removal approaches. An initial overview of common artifacts such as EOG and ECG and Power Line Noise Interference (LN) is provided mass and improvement in ant algorithm method and our contribution to the way it integrates with the BSS technologies used.

Chapter Four: Highlights the results achieved for different cases.

Chapter Five: A summary and suggestions for future works are presented in this chapter.

Chpter 2

2.1 Introduction

In this chapter,discussed the main ideas behind Brain Computer Interface BCI. Then identified the basic concepts of techniques for blind sources separation. Starting with a discussion of the history, applications and classification, types of EEG artifacts the effects and the causes leading to them.Then explaining the most important techniques of blind sources separation .Which include STONE, FICA, BEFICA,EFICA.Finally the optimization algorithm Antlion(ALO)with a detailed explanation of the optimization mechanism and a statement the most important parameters that help accomplish this process.

2.2 EEG artifacts

When measuring EEG, many of the potential changes observed in EEG can come from other sources[31]. The changes are referred to artifacts and may result from sources such as subject or equipment. The figure below shows waveforms of some of the most common artefacts in EEG. These include artifacts as shown Figure 2-1.

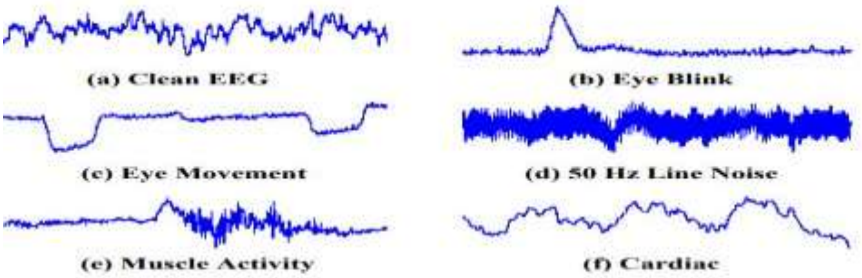


Figure 2 - 1 Artifact waveforms

2.3 Technical Artifacts

1. Noise interference to power lines: There are extremely strong signals created from AC power sources that pollute the EEG signals throughout the process of recording. However useful information which is EEG data is approximately 50/60 Hz. In addition, the line noise may interfere with all or part of electrodes that depend on the interference problem's source [32], as shown in Figure 2-1(d).

2. Sweating: This artifact type is the result of sweat that affects electrode resistance.

3. Electrophoresis: These artifacts are caused by different impedance to the electrode due to bad conditions or improper attachment.

2.4 Biological Artifacts

3. Muscle Activity artifact MEG: are the result of electrical activities that result from muscle cramps that occur when the patient chews, swallows, or speaks [33].These artifacts, which usually involve major disturbances in the brain signal as shown in Figure 2-1 (**e**).

4. ECG or heartbeat artifact: This artifact's type, which reflects the activity of the heart, gives a rhythmic signal of brain activity [34]. that occurs if the electrode is placed on or near any blood vessels [31], As shown in Figure 2-1 (f) .

2.5 BCI Concept

It is a rapidly growing emerging technology where a lot of studies are attempting to develop direct channels between computers and human brain. It can be defined as a collaboration where the brain is accepting and controlling the device's mechanic as anatural part related to its body representation [35]. Also, BCI might result in various applications particularly for disabled individuals. The majority of such applications are associated to disable individuals with the aim of helping them living their lives as normal individuals, one of the popular applications in such region is the wheelchair control. Simulating the human brain is the major aim of BCI researches. This is going to be significant in various areas such as computational intelligence and artificial intelligence [30] .

2.6 BCI System Structure

It is defined as system and communications device. It enables persons with disability to have some kind of interaction with their environment, without sharing muscles and peripheral nerves, as the system is assumed to reduce the costs of their care and enhance their quality of life. BCI can be defined as one of the AI systems with the capability of recognizing the brain signal patterns via 5 consecutive stages: 1-Signal acquisition, 2-Preprocessing and signal optimization, 3-Classification, 4-

Feature extraction, 5- Control interface[36]. In addition, the BCI system requires analysis, evaluation, monitoring the measurement in relation to the electrical activity related to the brain. Also, such basics are acquired via electrodes which are implanted inside the brain or electrodes placed on the scalp[37]. The major phases a system of BCI is (1- Signal acquisition , 2- Signal processing,3- Application interface) as displayed in Figure 2-2

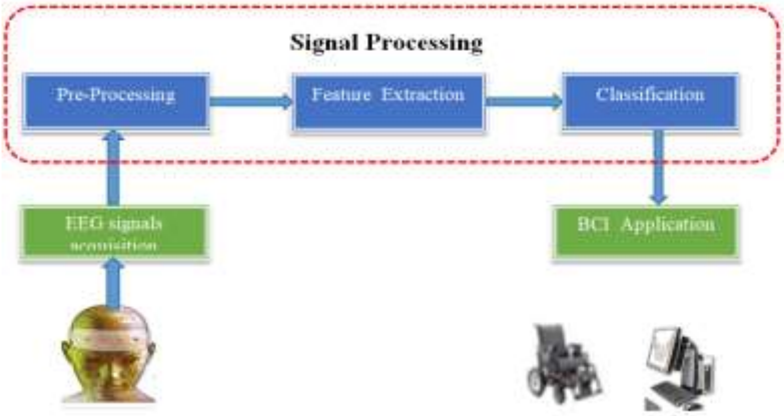


Figure 2-2 BCI system structure

2.7 EEG signals acquisition

For the purpose of capturing EEG signals the signals can be recorded using inexpensive equipment (such as amplifier and some electrodes). Based on (10-20) electrode system, the electrodes should be correctly positioned in a correct position. A voltage gain of 60-100 dB by amplifier will be used fpr amplifying the signal after it is captured. Because the capacity related to EEG signals is 100 µV, these big gains are of great importance [38] . And, through the acquisition equipment, the analog signal is captured and sampled to produce the digital signal[31] .

2.7.1 Processing Unit:

This unit uses the acquired signals to extract orders, and consists of : -

(A) Signal pre-processing unit: Before performing any additional analysis, once we get the signal, it is imperative that it is noise-free and free from any trace. Artifacts are known as recorded electrical potentials that have not been created in the brain [38]. Artifacts via EMG are used for the purpose of measuring the muscle stimulation signal. Retinal comfort is measured by EOG which may reduce EEG signals [31, 37, 39].

(B) Feature extraction: It indicates the extractions of certain signal features. There are undesirable signals in the EEG recordings, added to that is the brain's electrical signals. Such undesirable signals could bias EEG's analysis and might result in mistaken conclusions. Thus, feature extraction processes will be applied to the digitized signals[37].In the case when EEG signals were transmitted to computers, they will be converted to commands via the algorithms of signal processing, those commands will then be sent to the devices. The aim of feature extraction is obtaining the best features that indicate differences between a lot of classes of brain signals.

(C) Signal Classification: After the signals are cleaned, they will be classified for the purpose of determining the type of mental task the subject performs [31].

(3) Application interface: The output will be suitable for the purpose of the output device once the signals are rated. Other functions can be accomplished by controlling the speed associated with the mobile robot remotely by means of TCP / IP connection, also with respect to robot movement, an online screen is displayed for the IP camera, which displays user notes [37].

2.8 Types of BCI signal acquisition systems

Measurement of oscillations generated by the brain is a key component of BCI systems. It indicates the voluntary neurological procedures created by the user's current activity [37]. Depending on a few techniques the recording related to brain signals, such as non-invasive and invasive, can be classified, as shown in Figure 2-3

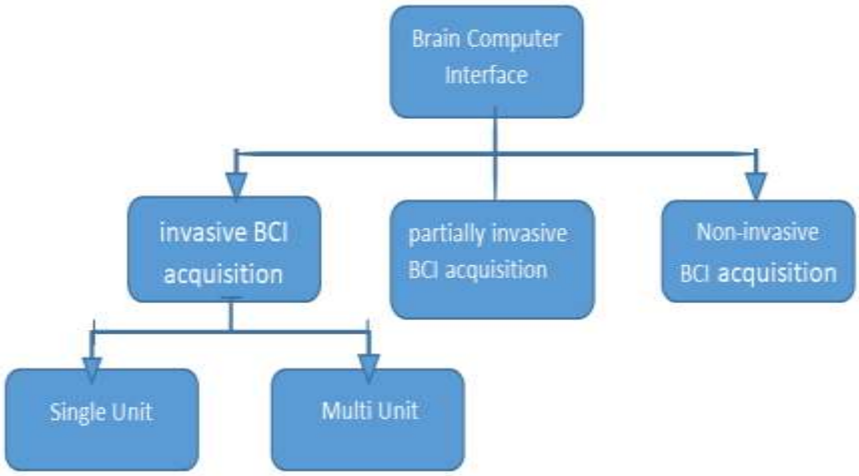


Figure 2-3 Types of BCI signal acquisition systems

2.8.1 Invasive BCI:

In this approach, the electrodes are implanted in neurosurgical manner inside the brain of a person or on the brain's surface [35]. One of the advantages of this approach is that the HF components can be estimated more accurately, so this approach is mainly used in experiments on Animals due to health risks to people [46].

2.8.2 Non-invasive BCI:

external sensors will be used to measure brain activities. Based on international standard 10-20, the electrodes will be placed outside the skull of the sick person. This approach is widely used in humans because it does not affect their health, and there is a drawback to this approach is that the measured signals will have a lot of noise [37].The invasive method relies on the use of ECoG from electrodes implanted in the skull and used by some epilepsy patients [47]. As well as monkeys [48]. Non invasive approaches were utilized on the basis of using EEG from electrodes which is placed on the scalp or imaging approaches, like functional magnetic resonance imaging (fMRI).

2.8.3 BCI partially invasive acquisition methods

These are devices with the ability of picking up brain signals, in which the sensors have been inserted into the skull at the brain’s top. Those devices are fairly weal compared to human brain signals, also they showed minimum risks for creating scars.

2.9 Rhythmic Brain Activity

The brain waves of normal individuals show various rhythmic activities. Various thoughts and actions impact these rhythms [40]. Thus, the rhythms could be characterized via their duration, frequency, amplitude, and areas of the brain areas where the rhythms are created[41]. There are 5 main types related to the continuous rhythmic EEG activities which are identified in recordings. They will be classified to different frequency bands as displayed in Figure 2-4.

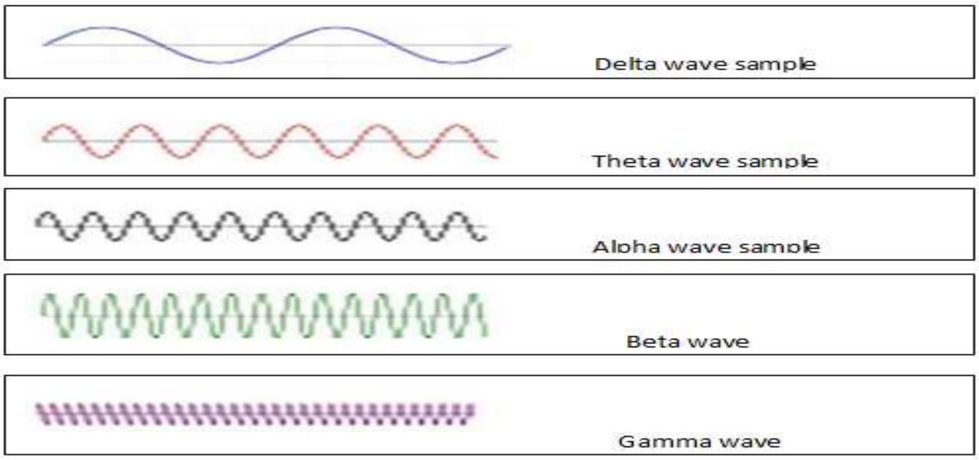


Figure 2-4 Rhythmic EEG activities

The waves of the brain that are recorded from scalp have small amplitude of about100μV. The frequency of such waves are between 0.5 to 100 Hz, and their properties are highly reliant on the degree of activity regarding cerebral cortex[42]. as displayed in the following in Figure 2-5

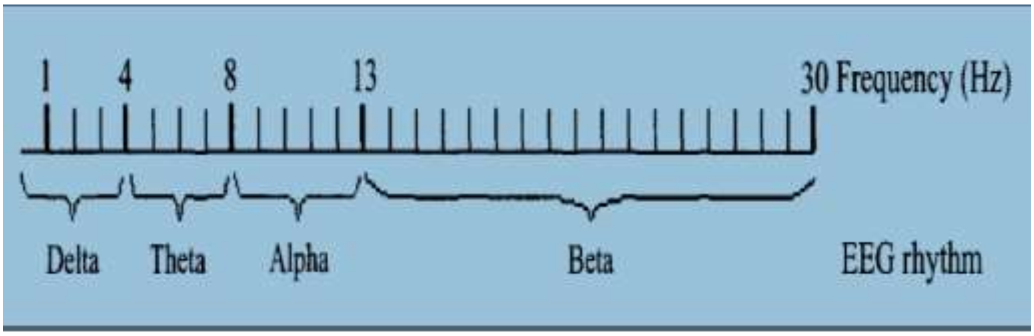


Figure 2-5 Frequency Bands of EEG signal

• **Delta Rhythm**: such rhythm is considered to be within frequency that ranged between 0.5Hz and 4Hz, and with variable amplitude. It is related to deep sleep shows a sample related to delta signals.

Theta Rhythm: Such rhythm is between 4-7 Hertz, with variable amplitude. Emotional stress is cause theta rhythm, also it is related with deep meditation and creative inspiration . Also, theta rhythm is related to young adulthood, childhood,

drowsiness, and adolescence. Also, they are identified through solving a problem, like the mathematical problems of subtracting and adding. It can be found in prefrontal part of cortex[43].

• **Alpha Rhythm:** the rhythm is at 8 to 13 Hertz and happen through sleeplessness over the head's posterior reas with variable amplitude yet is majorly not more than 50 μV in adults. It can be mainly perceived while closing the eyes and within certain conditions of relative mental inactivity and physical relaxation.

• **Beta Rhythm**: This type of Rhythm is considered to be 13-30 Hertz. Beta rhythm could be majorly identified over central and frontal reign. A central beta rhythm is associated to Mu Rhythm. Motor activities can block such rhythm, also it is related with solving concrete problems, active attention, active thinking, and focusing on outside world[44].

•. **Gamma Rhythms** : These rhythms have not been examined, due to the fact that old systems of EEG recordings cannot record signals over 25 Hertz. Such rhythms were not recognized until introducing digital recording systems. In 1964, one of the first articles described such rhythms. Gamma rhythms seems to be related to higher mental activities, such as consciousness, problem solving, perception, and fear[45].

2.10 Electroencephalography (EEG)

EEG signals are captured via Brain Computer Interface along with specific individual activity, after which various algorithms of signal processing are utilized for translating records into control commands with regard to various computer applications and devices. The fact that an individual's intentions can be represented (effectively) via signals which have been recorded from the activity of the brain [42]. EEG is a majorly utilized sign in bioinformatics because of its rich information on human activities. In addition, it is one of the significant clinical tools to assess the

activity of human brain [43]. There is a mixture of brain signals with other signals acquired from a limited group of the brain-related activities interfering in time and space, and can also be distorted by tools such as EOG, Power Line Noise Interference and EMG.

2.10.1 Electrocardiogram (ECG):

It records brain activity using electrodes placed directly on the exposed brain surface. Therefore, it requires surgery. It provides more ideal signal quality because the electric field is not wet through the scalp, SNR height [28],due to the wide range between 10-20 mV, and protected by external pollution.

2.11 Applications of EEG

Previously there was a useful EEG presentation in clinical neuroscience for the previously mentioned reasons. In particular, EEG is widely utilized because of its low costs. Consequently, many research centres and hospitals have their own EEG records system. Currently, EEG is used in various applications in clinical neuroscience. There are many of these applications:

- Identify brain areas affected by a specific accident or tumor. Diagnosis of insomnia, brain death and coma.
- Control the degree of anaesthesia in some cases. Nervous system testing and epilepsy diagnosis.
- Neural background applications.
- Determination of neurological effects of some drugs.Monitoring the development of the brain of humans and animals [41].

Various applications might be designed from the systems of BCI, like video game control and control machines, but other areas have benefited from the use of EEG. For example, an EEG in BCI was used to connect a human machine and brain. Although EEG was used mainly in clinical neuroscience.

2.12 Monitoring Brain Activity Using EEG

Many approaches are utilized for monitoring the activities of the brain including MEG, EEG, FMRI, FNIRS, PET and SPECT. Also, each one of the approaches has its properties, also advantages and disadvantages. As mentioned previously the potential generator activity can be measured directly by measuring the overlap of the potentials developed in various cortex areas with the use of scalp electrodes as well as electrodes impacting the EEG signal amplitude as a frequency function.Thus, EEG locations should be selected in an approach that the cortex regions were covered. With regard to the majority of applications, the 10-20 system has been internationally accepted standard in terms of the electrode positions. In addition, the electrodes are located at distances of 10 or 20% regarding the length of various connections between certain reference points provided via EEG International in the 1957 Federation [49]. Also, the electrodes have been placed on the basis of 10-20 system. The anatomical reference points should be identified prior to the system's electrode 10-20. Figure2-6 shows electrode positions of 10-20 system in the projection.

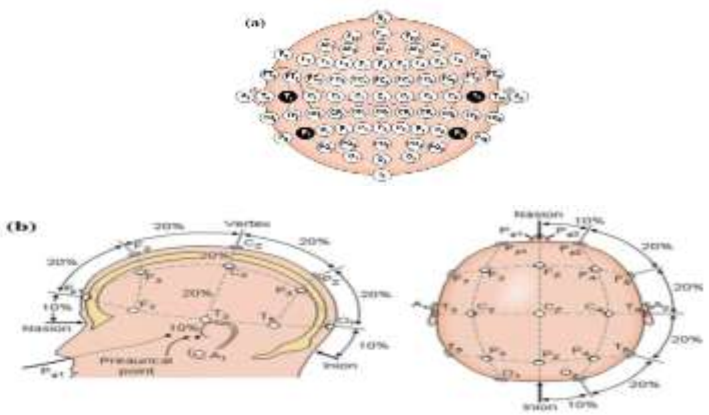


Figure 2-6 Electrode position. (a**)** Brain electrode (b) top view of the brain and electrodes positions

On the crust, the name of the position reflects a particular anatomical electrode the crust area above it. (Fp) means front, (F) means Frontal, (T) denotes temporalis, (C) denotes central, (P) refers to parietal, (O) represents occipital and (A) represents auricular, whereas (G) represents the Earth electrode, even numbers are referring to the head's right part, while the left part is represented via odd numbers [50].

In general, there were 2 artifacts' categories which might be differentiated in EEG, technical and biological measurements. Biological artifacts were resulting from recorded material, while the artwork is resulting from EEG recording device. Furthermore, the sources of various biological artefacts were dipoles for example of muscle activities that were considerably more powerful compared to EEG[51].

2.13 Blind source separation BSS:

The signal separation stage should be presented as a primary objective. Since BCI systems for human and machine interface in real time need to be fast and accurate, so academia and industry are constantly looking for new ways to reach these aims. BSS technology principles are used to process signals [52],[53]. BSS is an approach for the separation primary source signals from the observations (for instance, mixed signals) which are groups of original sources, with little or no information about sources to deal with confusion.

It addresses a problem recovering the original sources from the receiving mixture without previous information regarding the original sources or the mixing process. There isn't an idea related to the mixing procedures and the sources which occur in the head. Thus, brain signal analyses might be specified as one of the problems in BSS. In addition, the EEG data is a projection of a signal group that combines artifacts and brain signals of sensor locations (i.e., electrodes). BSS reduces the mixing of neural and non-neuronal variables with independent elements of one another. There are a variety of methods for measuring independence that give a variety of methods to BSS [54]. EEG signals are multi-channel data, and for this reason, BSS curricula are very suitable for analysis [55] . There is a wide range of methods that have been suggested for cleaning the brain signals, yet no single approach is the optimal approach, with each approach having a range of benefits and drawbacks.

In general, BSS methods are aiming to separate artifacts from EEG mixture. Recently, there are many statistical and computational methods that have been developed to solve this problem[56] [57]. In general, BSS technologies will change one set of mixed signals to another, where the recovered sources are independent of each other. Several algorithms were created for solving the BSS problem like Singular Value Decomposition (SVD), Indpendment Compenent Anylisis (ICA) and percutaneous coronary intervention (PCI)[33].One of the most useful techniques is the ICA - algorithm that is of great interest in the field of BSS. Gradually the various ICA algorithms have been improved.

Figur Figure 2-7 indicates a schematic diagram related to BSS mixing as well as separation processe [25].

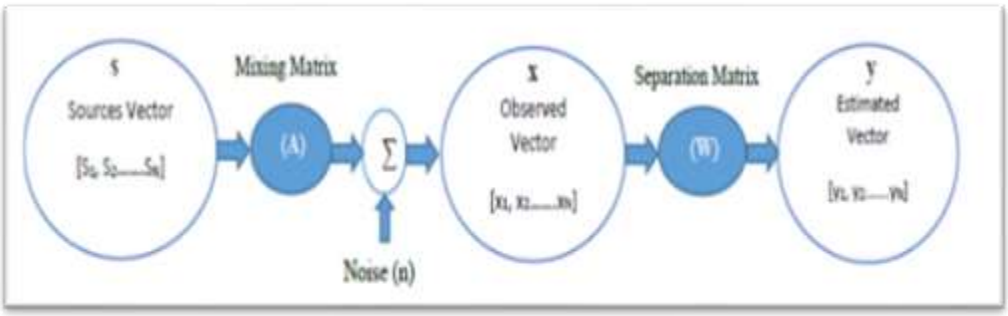


Figure 2-7 Blind source separation stages

The mixing equation is:

$$X(k) = AS(k) \qquad 2\text{-}1$$

Where:

$$X(k) = [X1(k), \ldots\ldots, X\,m(k)]^{t} \qquad 2\text{-}2$$

where, superscript t indicates the transpose operator; $A \in R_{m\times n}$ indicates the matrix of mixing. The symbol (k) represents the index of time or sample[58].The model of separating consider is the extracted equation as shown:

$$EY(k) = WX(k) \qquad 2\text{-}3$$

where, E denotes a matrix of scaling and permutation and the recovered source is:

$$Y(k) = [y1(k), \ldots\ldots, yn(k)]^{t} \qquad 2\text{-}4$$

The issue of BSS is estimating the optimal separating matrix W , which is optimally equal to A^{-1}.Approaching if BSS is successfully used in applied sciences and a wide range of engineering, then containing medicine and telecommunications, noise disposal, data processing and acoustic processing [59]. A wide range of strategies were used for BSS**.[٦٠],** which is designed on the basis of the central limit theory communicative Languch Teaching (CLT) .It seeks to find a weight vector in a way that the signal obtained from the mixture of signal mixes is non-Gaussian .The BSS approach such as Independent Component Analysis (ICA) tries to maximize its quantity from statistical independence between signals. Info-max-dependent ICA increases the entropy of the signal instead of its independence and achieves the same results. Rather than higher order statistics High Order Spectral (HOS), some methods use second order

statistics (SOS) for some .sources, such as Second-Order Blind Identification (SOBI), Stone BSS, and Algorithm for Multiple Unknown Signal Extraction

(AMUSE) [61]. Lately, Stone in [٦٢] presented an approach of BSS that it is a low complexity batch method, it drew the interest of many scholars [63]. with the use of short- and long-term predictors. It searches a weight vector providing an orthogonal mixture projection in a way that every obtained signal is as predictable as possible[51].

2.13.1 Stone's Temporal Predictability Measures:

It is One of the important technique This method took its same name from the scientist who has invented it [64] . This BSS approach utilizes the temporal predictability of mixed signals as can be seen from Figure 2-8.

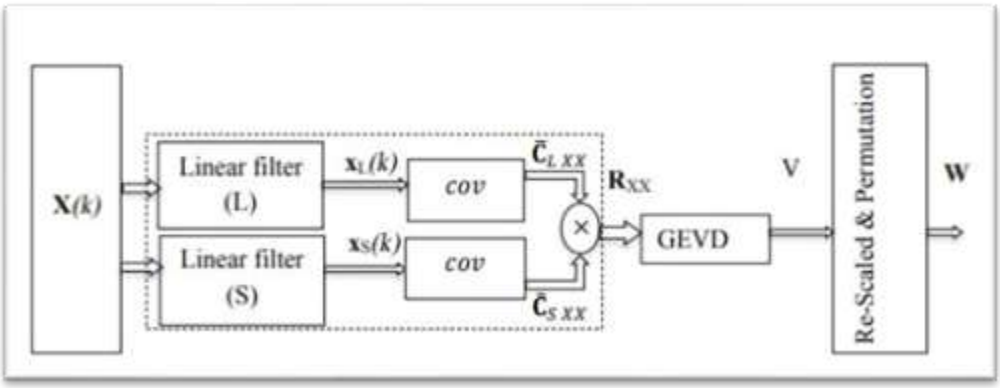


Figure 2-8 Schematic diagram of Stone BSS

In general there are 3 beneficial characteristics of signals:

1- Statistical independence degree.

2-Temporal predictability.

3- A probability density function of Gaussian, is based on the theorem of central limit.

Properties (1 and 3) have been utilized earlier as a separation base but in stone's BSS only the 2nd feature is utilized for separation. Stone has expectations for this approach, which could be beneficial for analyzing in medical areas [25]. The mixing system without noise is:

$$X(k) = AS(k) \qquad 2\text{-}5$$

Where

$X(k) = [X_1, \ldots, X_n]^t$ is the mixture vector (known),

$S(k) = [S_1, \ldots, S_d]^t$ is the source vector (unknown), and t superscript refers transpose operator. Which is represent mixing system without noise.Finding the recovered signals are calculated by the separating model which is value of XL (k) = Filter Response (L) ,As follow :

$$Y(k) = W \quad X(k) \qquad 2\text{-}6$$

Compute the short-term covariance matrix which is calculated as follow:

$$ci,j^{(\text{short})} = \sum_t \left(x_i(t) - x_i\ (t)^{(short)}\right)\left(x_i(t) - x_i\ (t)^{(short)}\right)^T \qquad 2\text{-}7$$

Compute the Long-term covariance matrix which is calculated as follow:

$$ci,j^{(\text{long})} = \sum_t \left(x_i(t) - x_i\ (t)^{(long)}\right)\left(x_i(t) - x_i\ (t)^{(long)}\right)^T \qquad 2\text{-}8$$

Finding the eigenvectors $(W1, W2, W3, \ldots, WM)$ of matrix as follow:

$$W_i\, c^{\text{short}}\, w_j\ (\text{short}) = \sum_t \left(x_i(t) - x_i\ (t)^{(short)}\right)\left(x_i(t) x_i\ (t)^{(short)}\right)^T \qquad 2\text{-}9$$

$$W_i\, c^{\text{long}}\, w_j\ (\text{long}) = \sum_t \left(x_i(t) - x_i\ (t)^{(\text{long})}\right)\left(x_i(t) -\ (t)^{(\text{long})}\right)^T \qquad 2\text{-}1$$

Finally [51] the separating matrix W calculated by MATLAB eigenvalue function as:

$$W = \text{eig}\ (ci,j^{(\text{long})} ci,j^{(\text{short})}) \qquad 0\text{-}2$$

2.13.2 Independent Component Analysis (ICA):

It is a very modern approach to BSS that performs better than conventional PCA (principle component analysis) in particular, in a variety of applications. It is applied to extract ophthalmic artifacts from EEG, but conventional PCA is unable

to separate eye artifacts from brain signals, especially when they have mathematical amplitude [65]

$$X = AS \qquad 2\text{-}12$$

here A is referred to as the matrix of mixing. BSS aims at generating a matrix of de-mixing W in a way that.

$$\hat{S} = WX \qquad 2\text{-}13$$

Where $\hat{S}$ refers to estimated sources, W is the inverse of A. In the case where the

$$〚X〛_{clean} = 〚AS〛_{clean} \qquad 2\text{-}14$$

BSS is implemented in EEG, artifacts' removal is carried out via setting sources that are characterized as artifacts to 0 in the following manner:

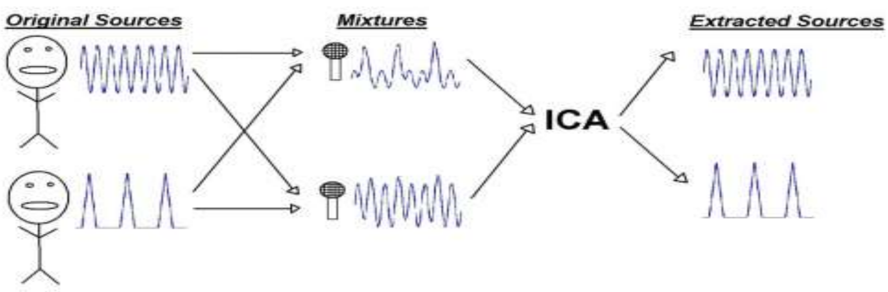


Figure 2-9 ICA in context of "cocktail party effect"

Before applying an ICA algorithm on the data,it is necessary to dosome preprocessing techniques, such as whitening and centering the data that makes the problem of ICA estimation simpler and better conditioned[66].

(A): Centering: It is the average of the observed variables by the subtraction of the average of the sample [80]. as in the equation below:

$$\mathbf{x} = \mathbf{x}' - E(\mathbf{x}') \quad 2\text{-}15$$

$$E(s') = \mathbf{A}^{-1}E(\mathbf{x}) \quad 2\text{-}16$$

Where x is the centered signal,x' is the observed signal, and E(x') is the expectation of x'. Center the independent components (made zero-mean), that is:

The subtracted mean can be simply reconstructed by adding $A^{-1}E(\mathbf{x}')$ to the zero-mean independent components.

(**B): Whitening**: is the transformation of the observed vector x into another vector y, such that its components are unrelated and their variance equal to unity.

2.13.3 Fast Independent Component Analysis FICA

Fast-ICA is an efficient implementation of ICA technique and a technique of popularly utilized BSS approach [67].It additionally has the benefit of multi-component extracting, and the performance of the system does not degrade .

It has computational efficiency and needs a smaller amount of memory compared to other algorithms due to the fact that it is capable of estimating independent components one after the other[68].

$$Z = A_m S_D \quad 2\text{-}17$$

Here, Z indicates the observed matrix, Am represents the separating matrix, and S_D represents determined sources. ICA is mainly utilized for the identification of separating matrix X for the sake of attaining the independent components in independent criteria pre-requisites.

$$S_D^* = X.Z \qquad 2\text{-}18$$

2.13.4 FAST-ICA and EFICA algorithms

$$C(W_K) = E[C(W_K^T Z)] \qquad 2\text{-}19$$

The Fast-ICA algorithm is based on improvment of a contrast function where W_K^T represents a k^{th} row of de-mixing $\hat{w}$ matrix to be evaluated, and z represents a vector derived via transforming signals x; thus, the elements of z aren't correlated, also they have unit variance. $C(W_K)$ improvment proceeds through iteration.

$$W_K^+ \leftarrow E\left[Zg\left(W_K^T Z\right)\right] - W_K E\left[g'\left(W_K^T Z\right)\right] \qquad 2\text{-}20$$

In which the theoretical expectations have been replaced via the respective sample means. Whereas the one-unit Fast-ICA is completing each one of the iterations via normalizing the vector W_K^+ . Also symmetric Fast-ICA is computing d iterations in parallel and conduct symmetric orthogonalization of $[W_1^+, \ldots, W_d^+]^T$ for estimating all the rows related to demixing matrix Wc.

It is pre-estimating all original signals using symmetric Fast-ICA, with regard to each k = 1, . . . , d, adaptively choosing non-linearity $g \stackrel{\text{def}}{=} gk$ to approximate the score function related to k-th signal, and do a fine tuning (further one unit Fast-ICA iterations utilizing the non-linearities,and refinement utilizing. The signals' samples must not be distributed (identically), particularly, assumes that there were M blocks regarding the same integer length N/M in which the signa's distribution is unchanging. In such situation, , the model in 2-2) holds in every one of the blocks, for instance:

$$x^{(I)} = AS^{I}, \qquad I = 1, \dots, M. \tag{2-21}$$

The theoretical performance analysis regarding algorithm as well as various derive selections of its parameters. This analysis is assuming a constant (unit) variance regarding the original signals in each one of the blocks.The performance of one-unit FastICA must be analyzed with the use of contrast function . That was vital in the fine tuning in step EEF-2.

The final performance related to Extended EFICA is provided following examining the impact of refinement step EEF-3.

2.13.5 EFICA Algorithm:

EFICA is an ICA algorithm designed to separate non-Gaussian $\mathrm{i.i.d.}$ signals. The underlying assumption is that each source signal S_k, $\mathrm{k} = 1, \dots, \mathrm{d}$ consists of N independent realizations of a random variable ξ_k having a non-Gaussian distribution functionF_k $(\mathrm{x}) = \mathrm{P}(\xi_k \leq \mathrm{x})$.

The algorithm EFICA is a version of the Fast ICA algorithm that features adaptive choice of the Fast ICA non-linearity. Letg_k $(\cdot)$ be the nonlinear function chosen for $\mathrm{k}-\mathrm{th}$ signal, $k = 1, \ldots, d$ and let $\grave{g_k}\mathrm{k}(\cdot)$ be its derivative. Finally, let "E" stand for the expectation operator, which can be realized by the sample mean.

In the best possible case, i.e., when g_k equals the score function ψ_k of the corresponding distribution.F_k (if it exists) for all $\mathrm{k} = 1, \ldots, \mathrm{d}$, is equal to the corresponding Cramer-Rao Lower Bound (CRLB) , which is:

$$\mathrm{CRLBk}` = 1K_k`\kappa K_k` - 1 \qquad \text{0-3}$$

where $K_k = \mathrm{E}[\psi 2\mathrm{k}(S_k)]$

The theoretical ISR was shown to approximate the empirical ISR very well provided that the independent components are $\mathrm{i.i.d.}$, that means that they have no time structure. If the components are strongly autocorrelated, the theoretical ISR appears to be biased, in particular, [70].

2.13.6 EFICA Algorithm

This is considered as an extension of the EFICA algorithm with regard to piecewise stationary as well as non Gaussian signals, the approach has the ability to take advantage of various original signals' distributions and from their different variances,

that is shown via simulations with signals of the real world. In the case of different constant signals, the excellent precisions that the approach might reach corresponding Cramer-Rao bound, in the case when all blocks score functions related to the original signals were identified.

This algorithm is on the basis of piecewise stationary model. It is indicated that its performance might be optimum, for instance, might be achieving Cramer Rao bound associated to the model with constant variance signals, also it is yielding considerable enhancement to separate real world signals. In addition, the concept work in such algorithm includes the next 3 steps comparable to the original EFICA which is described previously. The underlying model is specified in ICA is [35].

$$X = AS \quad 0\text{-}4$$

where $S = [S_1, \ldots, S_d]^t$ is considered as a vector related to independent random variables (RVs), with each one representing an unknown original signal, the goal is estimating the de mixing transform A^{-1}up to indeterminable order, signs, and scales of its rows. A few recent algorithms [66].have been created for achieving accuracy which approaches respective Cramer-Rao Bound CRLB [71]. where $G = \widehat{W}A$ is referred to as gain matrix, that must be close to identity, also $\mathcal{K}_k = E[\psi_k^2(\mathcal{X})]$, in which $\psi_k = -f_k'(\chi) / f_k(\chi)$ represents the score function related to

$$\mathrm{CRLB}[G_{K\ell}] = \frac{1}{N}\frac{\kappa_\ell}{\kappa_\kappa \kappa_\ell - 1}, k \neq \ell \quad 0\text{-}5$$

probability density function (pdf) $f_k(\chi)$ of $\kappa - \mathrm{th}$ RV s_k .In addition, the knowledge regarding the score functions or their adequate estimation is vital to algorithms for achieving the bound. Furthermore, another algorithm suggested for non Gaussian and non stationary scenario is **NSGS** by Pham [69].

The concept work of **BEFICA algorithm** consists of three steps similar to the original EFICA previously described.

- **Separation of EEF1** by FastICA homologous for achieving pre-estimate of W-degradation matrix.

- **EEF3 - Refinement** for the major accurate and definitive estimate related to the entire de blending matrix.Steps two and three worked to improve accuracy, which could be done with only nonlinear $g_k^{(I)}$functions correctly. It can be done adaptively by using the signals separated from it by the first step. Specifically, the function of each degree can be evaluated as optimal choice for nonlinear lines.

The moments were utilized in more computations, that is yielding computational savings. The implementation suggested in this work indicated two (K = 2) basis functions: h_1 (x) $= x^3$, which is excellent for sub Gaussian sources, and h_2 (x) $= x/(1 + 6|x|)^2$ working excellently with super-Gaussian sources.That was tailored for such distributions.Because of the various performances regarding the fine tuning approach in EEF-2. The parameters that control in process of optimization .

1. 1-stop epsilon 0.0001 stop algorithm
2. fien epsilon stop standard 1e-7 for smooth smoothing.
3. Fintuning is a standard limit for maximum replication of the homologous portion in an EEF2 block.
4. Maxi = 100.
5. Maxi test after saddle 30% The maximum number of iterations after saddle point determination.
6. Fine Tuning - Maxi-Et 50 The maximum percentage of fine iterations (smoothing) of the identical fraction in the EEF3 block.
7. minutes correlation 0.75 minutes. Wrapping

EEF3 - Refine to obtain the most accurate and definitive estimate of the full formulation matrix.

The third and sixth steps contribute greatly to improving accuracy, which can be done by properly using nonlinear functions. in Separation of EEF1

2.14 The Ant Lion Optimizer (ALO)

This is one of the novel algorithms inspired via nature, it is simulating the approach of hunting Ant Lion. There are 5 main prey hunting stages in this algorithm, which are, ants' random walking, building traps, trapping ants in traps, hunting prey, and rebuilding traps. ALO is finding excellent designs for the majority of conventional geometry problems, indicating that it solves constrained problems with the use of varied search.The next conditions are utilized throughout optimization:

- Ants are moving around the search space with the use of various random walks .
- Random walks were utilized to all ants' dimensions.
- Random walks were impacted via antlions' traps.
- Antlions might develop pits which are proportional to their fitness (high fitness cause large pit).
- Antlions with large pits have high probability for catching ants.
- Each one of the ants might be caught via an antlion in each one of the iterations and the elite (fittest antlion).
- The random walk range is adaptively reduced for simulating sliding ants towards antlions.
- In the case when an ant become fitter compared to antlion, this indicates that it was caught as well as pulled under the sand via antlion.

- The antlion will reposition itself to latest caught prey and build a pit for improving its change of catching another prey after every one of the hunts.

2.14.1Operation of the ALO algorithm

ALO has been characterized as a 3-tuple function which can approximate global optimum for the problems of optimization based on the equation below:

$$\mathrm{ALO}(\mathrm{A}, \mathrm{B}, \mathrm{C}) \qquad 0\text{-}6$$

where A represents a function generating random initial solutions, B performs the manipulation of initial population that has been given by function A, and C will return true in the case where the end criterion has satisfied functions A, B, and C have been defined as:

$$\emptyset \rightarrow [\mathrm{M}_{\mathrm{Ant}}, \mathrm{M}_{\mathrm{OA}}, \mathrm{M}_{\mathrm{Antlion}}, \mathrm{M}_{\mathrm{OAL}}] \qquad 0\text{-}7$$

$$[\mathrm{M}_{\mathrm{Ant}}, \mathrm{M}_{\mathrm{Antlion}}\} \xrightarrow{\mathrm{B}} \{\mathrm{M}_{\mathrm{Ant}}, \mathrm{M}_{\mathrm{Antlion}}] \qquad 0\text{-}8$$

$$[\mathrm{M}_{\mathrm{Ant}}, \mathrm{M}_{\mathrm{Antlion}}\} \xrightarrow{\mathrm{C}} \{\mathrm{true}, \mathrm{false}] \qquad 0\text{-}9$$

where MAnt represents the matrix of the ants' position, MAntlion includes the location of the ant-lions, MOA includes the corresponding ants' fitness, and MOAL has the fitness [72].The improvement process may be summarized in the points below:

- The ants are moving around search space utilizing a variety of the arbitrary walks
- Those arbitrary walks are implemented on all ants' dimension.
- The arbitrary walks are influenced with the antlion traps.

- The ant-lions have the ability of building the pits that are proportionate to the fitness (increased fitness means larger pit).
- Ant-lions with larger pits are of higher likelihood of catching the ants.
- Every one of the ants may be caught with an ant-lion in every one of the iterations and elite (i.e. the fittest ant-lion).
- The random walk range is adaptively reduced for the simulation of the sliding ants toward the ant-lions.
- In the case where one of the ants has become fitter compared to an ant-lion, It indicates the fact that it has been caught then pulled under sand by ant-lion.
- The ant-lion will re-position itself to the prey that has been caught latest and will build a pit for improving its chances to catch another prey following every one of the hunts.

Chapter 3

Proposed Work

3.1 Introduction

In this chapter, the implementation of the proposed system is presented in details to demonstrate the main steps in this system for implementing the BCI system, and it consists of a schematic description of the presented system in addition to the implementation details for each stage associated with the proposed system, and data extraction. The proposed system contains some important and potential stages like pre-processing signal, Signal analysis stage is cleared of noise, artefacts and lastly the optimization stage.

3.2 The Proposed System

The proposed system used to filter the brain signals that exported from the brain to predict of the people actions in order to implement such system . Number of data are needed to test such system and train it .Generally, the proposed system includes some basic stages to perform all relevant and verification tasks. There are two main phases the first phase called the EEG signal acquisition stage and the second is called EEG signals processing stage. Each phase has many stages or (sub-stages) such as pre-processing, and BSS algorithms stage to separation the signals . finally, the signal optimization stage (Antlion Optimizer) ALO able to remove noise and artifact. as shown in Figure 3-1.

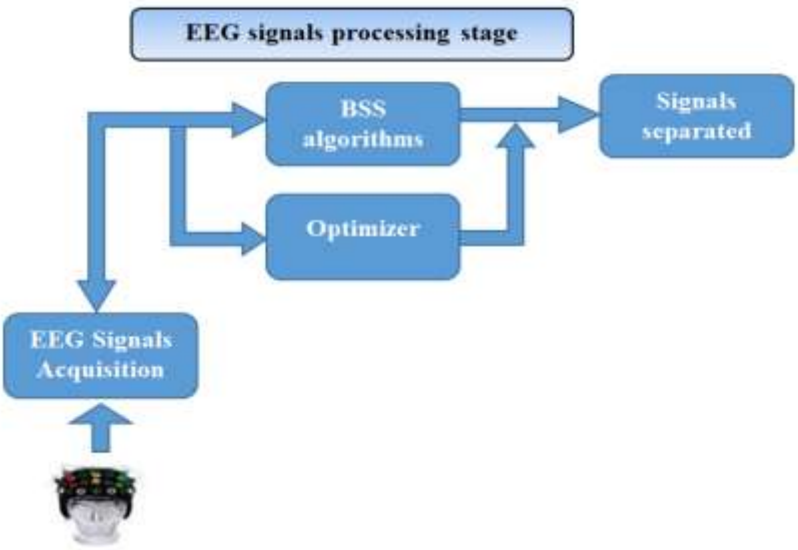


Figure 3-1 Block diagram of proposed system

3.2.1 Dataset Collection:

In this stage, brain signals are collected by invasive or non invasive acquisition and prepared for processing. This step involves collecting the information collected from the EEG device, its filtering, for further processing.In this system used two types of data;

1- Real data: The Real data were collected and taken from the site (Meag Mohit / EEG data set) [73] . This dataset generated using computerized EEG device, those signal are saved to data base and export as excel sheet for further processing and then analyzed. Three EEG recordings are included, where each capture a separate artifact.

The data was recorded from 8 electrodes for 30 seconds and sampled at 256Hz. The labels for the recorded electrodes are provided in each .mat file. The ground electrode was placed at position Cz, according to the 10-20 system.The electrode positions used were [Fp1, Fp2, C3, C4, O1, O2, vEOG, hEOG].And correspond respectively to the columns of the data matrix. For instance data(:,1) gives the recording corresponding to Fp1.The facial activity in each recording is as follows:

- Eye blinks
- Rolling the eyes
- Raising the eyebrows

The Table 3- shows the main specification for this data.In addition, a 50Hz line noise is present.

Table 3- 1 Data set specification

Gender	**age**	**position**	**motion**	**Kind of movements**	**Medical condition**	**situation**
Female	24	2m from computer monitor	Static	Eye blinks Rolling the eyes Raising the eyebrows	healthy	Sit on chair

2- Simulation Data :

It is a standard, dataset consisting of 7 channels ICALAB [82] . As following : (A) Channel -1 (EMG Signal), (B) Channel -2 (Eyelash Signal), (C) Channel -3 (Gaussian noise), (D) Channel -4 (ECG Signal), (E) Channel -5 (Power line noise),

(F) Channel -6 (EOG1 Signal), (G) Channel -7 (EOG2 Signal). Each channel contains one signal with a sampling rate of 250Hz. It also contains zero mean, unit variance, and 500 samples. Figure 3-2 Figure shows the Abio -7 Database signal.

Electrooculogram EOG Very common for this type of artifacts. As the analysis of the EEG signal, resulting from eye movements or eye blinking, is performed generating a signal with high amplitude and much larger than an EEG signal. It is so to interfere with all electrodes, even the ones that is at the back of head, especially the resulting effect artefacts of the eye which are going to be predominant in all anterior and anterior polar channels such as FP1, FP2[10, 63]. The ocular artefacts may be measured through pairs of labeled electrodes, EOG electrodes are also located over and around the eyes. Then the eye movement artefact results from the Retinal bipolar redirection [64] ,And it has a great impact and of ten Occur as the eyes blink. An EOG interference issue also arises with brain signals [65].

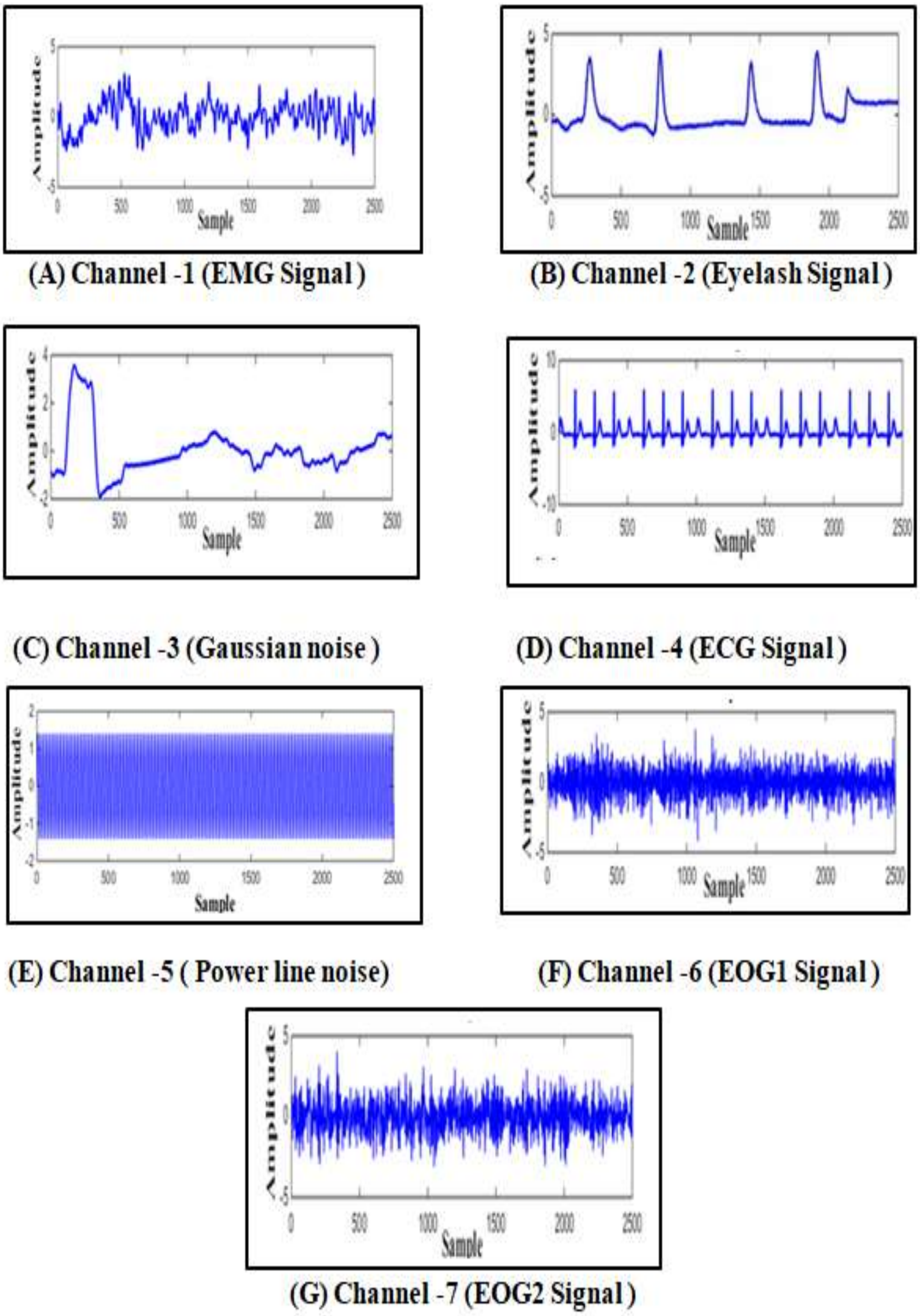


Figure 3-2 Abio-7 Database signal

The general algorithm steps of the suggested system has been shown in the **Algorithm 3.1** to show the main steps.

Algorithm 3.1 proposed system general algorithm steps
Input: Analysed data / real & simulation **Output**: The separated data
Start **Step1**: Read the data set **Step2:**Whitening process **Step3:** Apply blind sources separation BSS **Step4**: Apply optimization algorithm End

3.2.2 EEG Signals analysis stage:

The processing of brain signals allows understanding, interpreting, and decoding the signals of the brain. Before the analyzing brain signals, they must be processed suitably, such as removing the artifacts. The band of the specific frequency is obtained as well via signal processing. The suitable study of brain functionalities for different purposes have been based on signals which have been well processed. In the presented study brain signals have been processed with the use of three phases.

3.2.3 MULTI BSS:

The problem of separating the signals that represent the source signals from mixture signals with no obtaining information on signal sources, is called the blind source separation, BSS. In this proposed system, four blind source separation algorithms were used (STONE,FICA,BEFICA,EFICA),will be explain in detail.

1- Stone Algorithm

Statistical algorithm used uncomplicated batch algorithm which results in better signal separation. Where Stone BSS has been based upon separating original sources from their mixes on the Time Predictability Scale (TP) and the stone's guess are used: The Time Predictability of any mixed signal is the fact that of any one of its elements, such estimation has been utilized for finding the vector of weight that gives orthogonal mix projections.The main steps of the stone algorithm are shown in **algorithm 3.4**

Algorithm 3.4 Stone Algorithm
Input: Signals after whiting operations **Output:** The separated signals
Start **Step1**: Find the Mixture observation signals. according to equation **Error! Reference source not found.**. **Step2**: Finding the recovered signals that have been computed through the separation model. According to equation **Error! Reference source not found.**. **Step3**: Measure of temporal predictability of signal. According to equation 2-7. **Step4**: Compute the short-term covariance matrix. According to equation **Error! Reference source not found.**. **Step5**: Compute the long-term covariance matrix. According to equation **Error! Reference source not found.**. **Step6**: Finding the eigenvectors. According to equation 0-2and equation

Error! Reference source not found..
Step7: De mixing the matrixes . According to equation **Error! Reference source not found.**.
End

2- FICA Algorithm :

The FICA will mainly removing the vectors rows mean of the X matrix and then it is using the proper procedure (whiting procedure) for transformation to result the identity matrix .then the algorithm will search the matrix to find the mutually independent as components possible, then the matrix X is simply modified to S by using the separation matrix and the resulted S will be two dimension matrixes. Finally, the new EEG signal that contains only task related components can be reconstructed [74]. The main steps of the FICA Algorithm shown in algorithm 3.5.

Algorithm 3.5 FICA Algorithm
Input: Signals after whiting operations **Output**: The separated signals
Start **Step1:** Find the Mixture observation signals. according to equation**Error! Reference source not found.**. **Step2**: Use a whitening process for transforming covariance matrix of zero-mean to a matrix of identity. **Step3**: Search for matrix which transforms the whitened data to a collection of the elements that are maximally mutually exclusive. **Step4**: Matrix X has been transformed into matrix S through a matrix of

separation W where the matrix rows S are mutually independent. Where S is an m*n matrix
that includes independent components, W represents matrix of separation,

and X is an m*n input signal matrix.

Step5: Each mixing matrix column A that is a W^{-1}, denotes a spatial map

that

describes the relative weight of projection of corresponding components at

every one of the electrodes of EEG. Which is why, based on spatial maps,

components which exhibit a large projection have been classified as components

which are task-related and the remaining components have been classified as task-

unrelated components

Step6: The new EEG signal that contains only task related components can

be reconstructed by zeroing mixing matrix A columns. Corresponding to task

unrelated components .

End

3-BEFICA Algorithm :

This method is able to take advantage of the variable distribution of the original signals in addition to its differential contrast, which appears through simulations with real world signals. This method's precision can achieve corresponding limits of Cramer - Rao in the case of static contrast signals, if the resulting original signals' functions are known in every block.The main steps of the BEFICA Algorithm shown in **algorithm 3.6.**

Algorithm 3.6 BEFICA Algorithm
Input: Signals after whiting operations **Output**: The separated signals
Start **Step 1**: Find the Mixture observation signals depend on equation **Error! Reference source not found.**. **Step 2**: Use a whitening process for transforming covariance matrix of zero-mean to a matrix of identity **Step 3:** Use rate Contrast function for the symmetric part of Block EFICA (EEF1). **Step 4:** One-unit Fast-ICA completes every one of the iterations through the normalization of vector w k , the symmetrical Fast-ICA performs the calculation of the d iterations in a parallel manner and does a symmetrical orthogonal as equation **Error! Reference source not found.**. **Step 5:** : pre-estimates every original signal through symmetrical Fast-ICA. **Step 6:** Separations through symmetrical Fast-ICA for getting a pre-estimate of de-mixing matrix W. **Step 7:** Fine-tune (further iterations of 1-unit Fast-ICA utilizing non-linearities that have been found in step2 **Step 8**: refinement to get the most precise and final estimation of the entire de-mixing matrix. End

4-EFICA Algorithm:

EFICA is an ICA algorithm designed to separate non-Gaussian identifier signals. The underlying assumption is that each source signal S_kk $= 1, \ldots, \mathrm{d}$ consists of N independent realizations of a random variableξ_k having a non-Gaussian distribution function $\mathrm{F(X)} = \mathrm{P}(\xi_k \le \mathrm{X})$.The algorithm EFICA is a version of the Fast-ICA[75] . algorithm that features adaptive choice of the Fast-ICA non-linearity. Let $\mathrm{g}_k(\cdot)$ be the nonlinear function chosen for $\mathrm{k-th}$ signal. The main steps of the EFICA Algorithm shown in **algorithm 3.7**

Algorithm 3.7 EFICA Algorithm
Input: Signals after whiting operations **Output**: The separated signals
Start **Step 1:** construct matrix. According to equation **Error! Reference source not found.**. **Step 2:** Use a whitening process for transforming covariance matrix of zero-mean to a matrix of identity. **Step 3**: The elements of the ISR matrix includes samples of the original source signals. is an unknown regular mixing matrix. **Step 4:** When g_k = score function ψ_k of corresponding distribution F_k (if it exists) for all $\mathrm{k} = 1, ., \mathrm{d}$, then it's equal to the corresponding Cramer-Rao Lower Bound (CRLB) **Step 5:** Constructed matrix which transforms whitened data to a collection of components which are maximally exclusive. **Step 6:** The theoretical ISR be biased, in case The theoretical ISR was shown to approximate the empirical ISR very well provided that the independent

components.

Step 7: The mixing matrix A can be constructed by zeroing columns will be new EEG signal that contains only task related components.

End

3.2.4 Data Analysis:

The analysis stage aims at recovering this signal of the original source from mix signals with no noise, such as power line, eye, skew signals, etc.

3.2.5 The optimization stage of signals:

The output from the second stage will be the input to improve EEG signals. Then the analysed data is processed using an optimizer (Antlion's algorithm) for all the algorithms used in this work. The main steps of (ALO) Algorithm are shown in **algorithm 3.8.**

Algorithm 3.8 ALO Algorithm
Input: signals after whiting operations **Output**: Analyzed signals
Start **Stepe1:** Signal loading, initialization, the search parameters, which are four [**dim, n, lb, ub**].saving the location of every one of the ants, in an ant matrix (i.e. dimension), n represents the amount of the ants, and d represents the amount of the variables. The equivalent objective value for every one of the ant-lions is computed then stored in matrix as shown in Equation **Error! Reference source not found.**. **Step2:** Replace (lb, ub) with the parameters of the algorithm to be Improved and saving the fitness of every one of the ants in the matrix. **Step3:**Each ant has several variables represented by the fitness function, so will

create a fitness function for each ant lion and prey ant, and it is sorted according to the lower .

Step 4: Ant lions also hide some where in search space. For the purpose of saving their fitness values and positions, in the matrices are used as shown in.

Step 5 : The random walk x(t)is used for updating the ants' position where is minimal value of the random walk of lb different, is the maximal value of the random walk in the ub variable, update the position of ants is used in .

Step 6: The first stage of hunting begins with the search for the least value of fitness, and the second stage is the selection of a roulette site that is chosen randomly whose boundaries are located within the area of the action fitness and combine with the previous elite .

Step7: In case Building trapThe ALO approach is utilized as an operator of the roulette wheel to select the ant-lions according to their fitness values throughout the optimizations. Such approach can give higher possibility to fitter ant-lions to catch the ants.

Step8 : Ant-lions have the ability for building traps that are proportionate to their fitness values and the ants are needed to be moving in a random manner. None-the-less, the ant-lions will shoot sand outward the pit centre as soon as they understand that there is an ant is in a trap. For the mathematical modelling of such behavior, the ants' random walk hyper-sphere's radius will be adaptively reduced.

Step9 : The location of the target represented by a = rand is formed and the slip rate I (ratio) is calculated in terms of the lowest and highest dimension to determine the diameter of the new trap.

End

3.2.6 Advantages of the ALO algorithm

In theory, ALO is capable of Round the global limit for outstanding optimization issues for the reasons that have been outlined below:

- Exploring search space is ensured with random selections of the ant-lions as well as the random walks of ants around those ant-lions.
- There are high probabilities to resolve the stagnation of the local optima as a result of using roulette wheel and random walks.
- Exploiting the search space is ensured through ant-lions' traps' adaptive shrinking boundaries.
- Ants' movement's intensities cane be reduced adaptively through the iterations' course, guaranteeing ALO algorithm's convergence.
- This algorithm is population-based, which is why the avoidance of the local optima is essentially high.
- Ant-lions re-locate to best ants' position throughout the optimization, which is why, promising search space areas will be saved.
- Calculation of the random walks for each one of the ants and each one of the dimensions results in the promotion of population diversity.
- Ant-lions guide ants toward the promising search space regions.
- This algorithm has quite few parameters that require adjustment.
- The optimal ant-lion in every one of the iterations will be saved then compared with the best ant-lion that has been obtained yet (i.e. elite).
- This algorithm is gradient-free and considers the problem as black box.

3.2.7 Diagram of optimizer operations.

The schematic diagram of the optimization process as shown in Figure 3-3 , appeared how the optimizer controls the input of the data set in different BSS algorithms that are optimized and extracting the fitness function for each case and selecting the best.

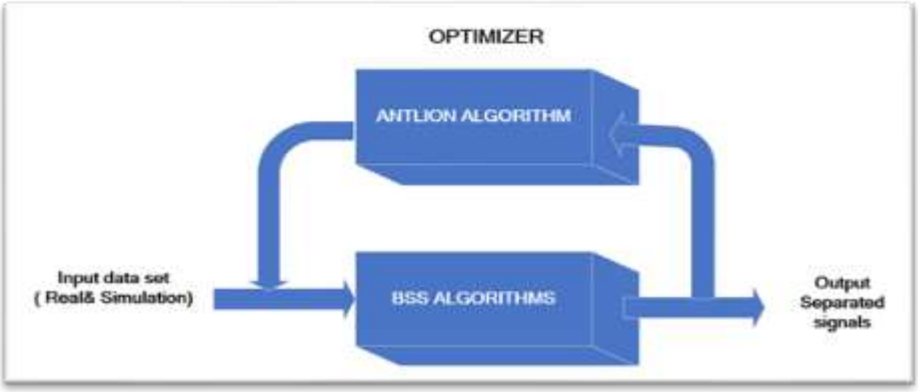


Figure 3-3 diagram of optimization operation

The fitness function is defined to ensure the independency between sources. The fitness function is designed depending on the cumsum of calculating the cumulative summation, as shown in equation **Error! Reference source not found.** and **Error! Reference source not found.** .

$$X(t)=[0,Cumsum(2r(t_1)-1),Cumsum(2r(t_2)-1)...Cumsum(2r(t_n)-1) \qquad 3\text{-}1$$

where n represents the maximal number of iterations, t represents the step of random walk (iteration), also r(t) represents the stochastic function.

$$F_1(Y) = \sum_{i=1}^{n} \sum_{j=1,j\neq i}^{n} y_i\, y_j^T \qquad 3\text{-}2$$

$$F_2(Y) = \sum_{i=1}^{n} \sum_{j=1,j\neq i}^{n} y_i^{\cdot} y_j^{\cdot T} \qquad 3\text{-}3$$

F1 and F2 depend on the cumsum calculates the cumulative sum of each element in a single row of the matrix as shown in equations where n represents the number of sources. The fitness function F should be minimized to ensure the independency between different sources [5].Then the fitness function would be.

$$F(Y) = (1 - \alpha_1).F_1(Y) + (1 - \alpha_2).F_2(Y) \qquad 03\text{-}4$$

Where α_1 and α_2 are two weight parameters.

In this fitness function the objective is to find matrix elements that minimize the fitness function. So ALO algorithm continue to search until a lower value of fitness function is reached as shown in equation (0).The best value for the designed fitness function is that occurs in the case where the ant becomes fitter compared to the corresponding ant-lion.Which shows the independency between sources. As defined ALO preview in a 3-tuple function which can approximate global optimum for the tasks of the optimization based on the equations 0-7 , 0-8 and 0-9 .It will be a summary of the processing operations to obtain the fitness function. The ALO parameters would be.

1. N = 10 (Number of ants)
2. Max iter = 100 (Number of Iterations)
3. Dim = 5 (numbers of parameters determined kind of algorithm used)
4. Lb = [0.0001 1 1 90 0.0001] lower boundary
   U b = [0.0009 5 5 110 0.0050] upper boundary
   parameters of algorithm

3.2.8 Flow chart Antlion algorithm

This flowchart illustrates the optimization process for the ant lion algorithm with the same prey hunting mechanism, which consists of five steps as mentioned previously. First, the target search process begins with random walking, then the fitness function for every one of the ant lions is calculated based on the parameters that came out from the algorithms of the blind source. Then the elites were identified for them and for the purpose of determining the exact location of a target by random walking, the roulette wheel is calculated for each one of them. And collect it with the elite, and then the ant sites (prey) are updated by calculating the equation of the fitness function for each ant based on parameters of the blind source algorithms used and the last step will be an ant lion updating its location, i.e. making a pit in a location close to the prey, according to the location of the highly fit ant, and then it is hunted the prey, and if the condition or required is not met, it returns and returns its calculations to equate the fitness function again to reach the goal of improvement as in the Figure 3-4

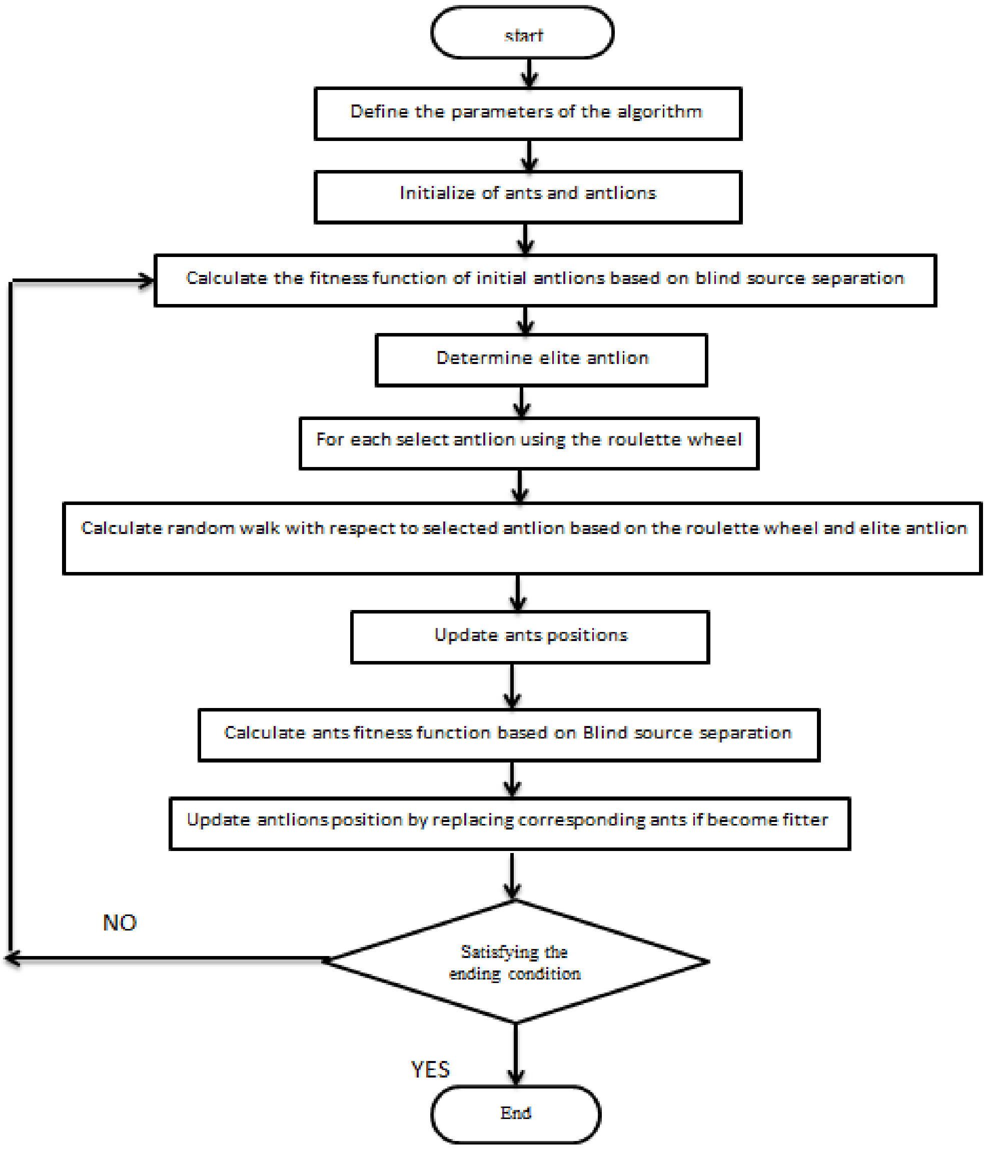


Figure 3-4 Flow chart Antlion algorithm

Chapter 4

Results and Discussion

Introduction

The experimental results are came after applying the algorithms in the proposed system, and the diagrams related to this implementation are shown in figures and tables in this chapter. The results in two parts. Part 1 shows the results calculated using BSS only while Part 2 shows the results calculated using the ant lion optimization algorithm. Acomparison of different types will be performed of BSS technology to verify the reliability of the best performing algorithms. In this work two cases will be discussed. Two types of data are used in this system. The first type is a set of simulated data taken from the position A Bio 7 Database, the second type a set of real data taken from EEG signals in the position database (Meag Mohit / EEG dataset) ,then passes theas data through a set of blind sources separation such as STONE , EFICA , BEFICA and FICA algorithms. Each individually optimized by the ant lion algorithm.To choose the best performs by using Signal to Noise Ratio (SNR), Interferance to Signal Ratio (ISR), and Power Spectral Density (PSD) standards.

4.2 Part 1- Blind Sources Separation Techneques before optimization

In this case, two types of signals are used The first signals is a simulated dataset, and the second signals is a real dataset . Then chosen the best algorithm to know the quality of the separation process of the algorithms in the two cases.

4.2.1 First Signals: Simulation dataset

The simulation data-set has been utilized for testing the performance of the four selected algorithms (STONE, EFICA, BEFICA & FICA). All the signals in the simulation dataset are mixed randomly together to produce the new input for the algorithms as shown in Figure Figure4-1.

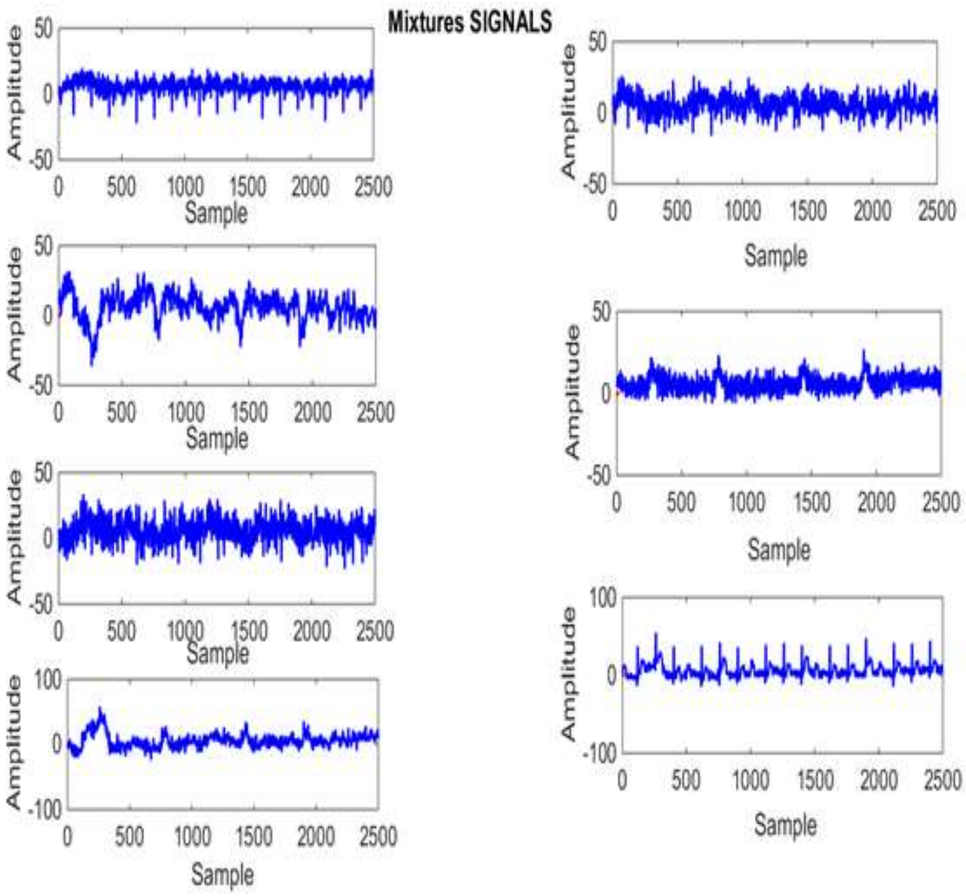


Figure 4-1 Mixture of simulation data

After all the signals are mixed, the mixture matrix is the inputs of the four algorithms (STONE, EFICA, BLOCK & FICA) to obtain the final restored signals. Figure 4-2 show the signals that has been recovered after using four BSS algorithms to recover all signal sources.

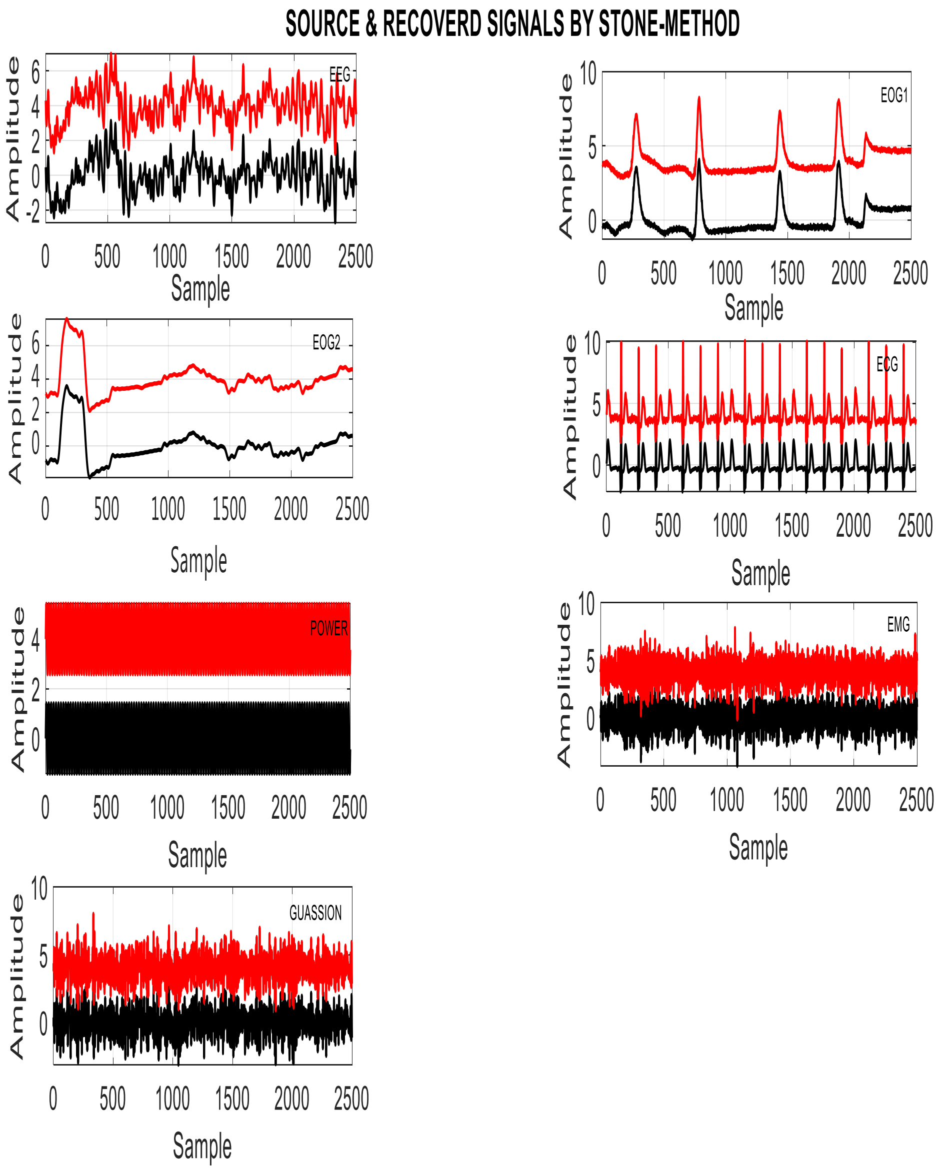


Figure 4-2 Source and restored signals by Stone algorithm

The red signal represents the recovered signal after using BSS technique while the black signal is the original signal. Where the first signal from the left represent (EEG signal) and the next (EOG1signal), sequancely (EOG2signal), (ECG signal), (Power line noise signal), (EMG signal), finally (Gaussian signals).

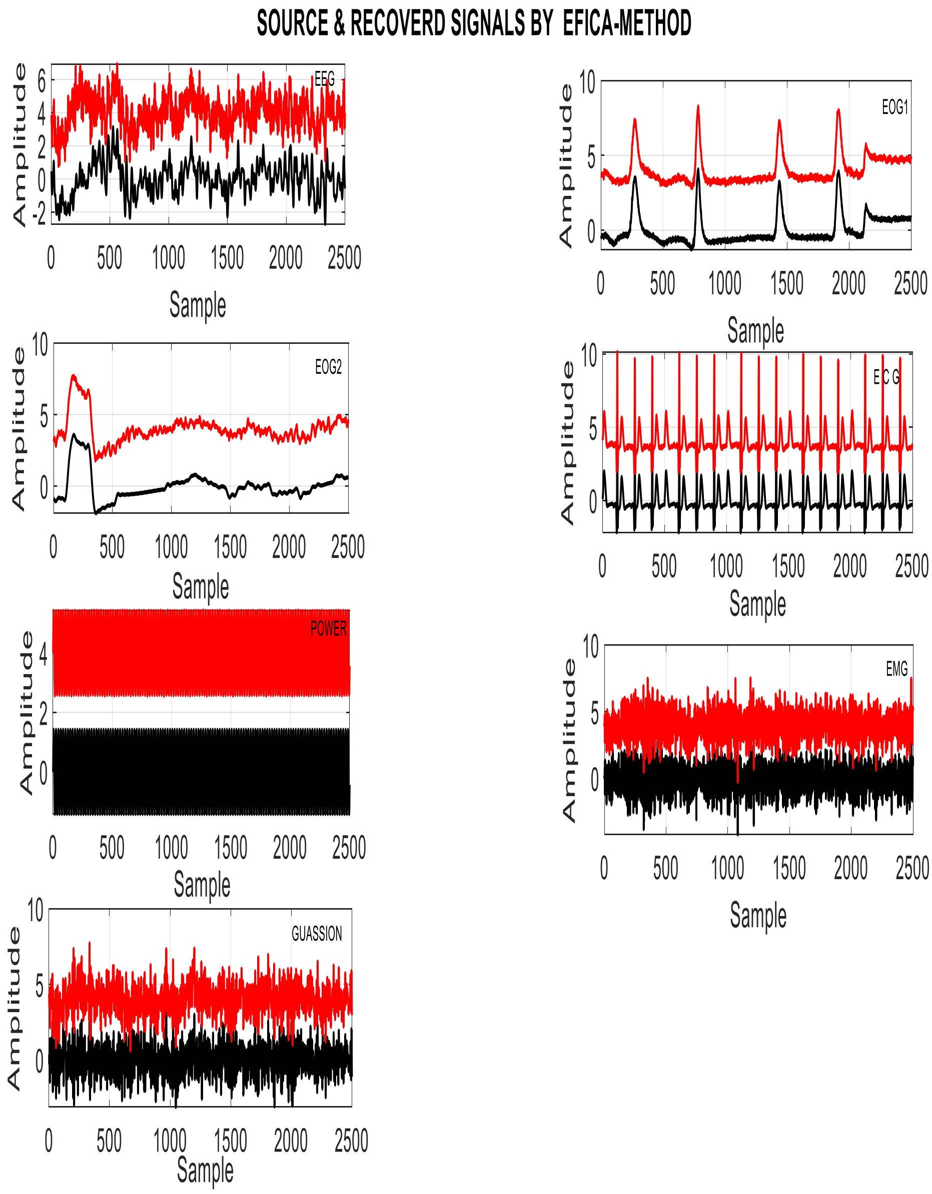


Figure 4-3 Source and restored signals by EFICA algorithm

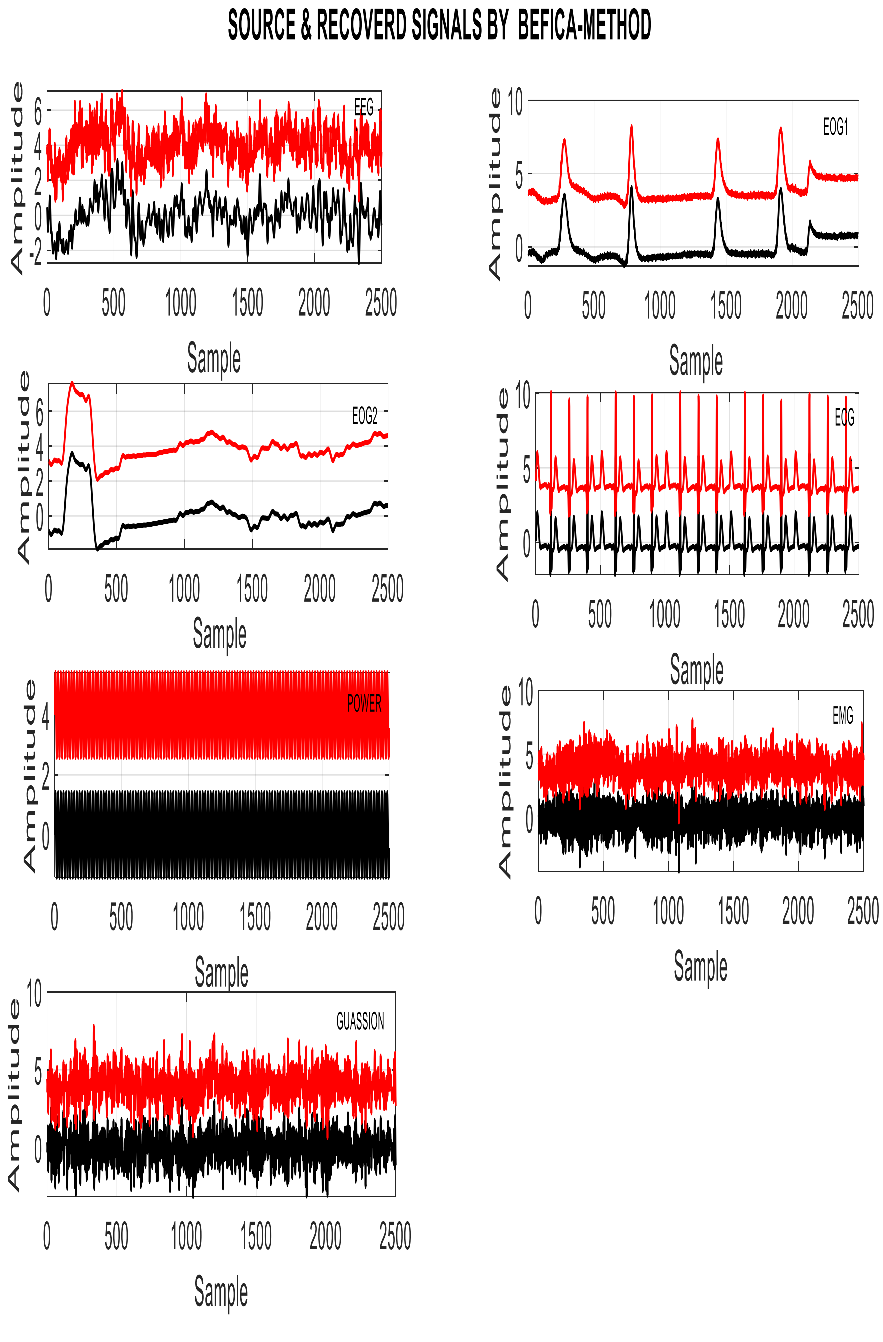


Figure 4-4 Source and restored signals by BEFICA algorithm

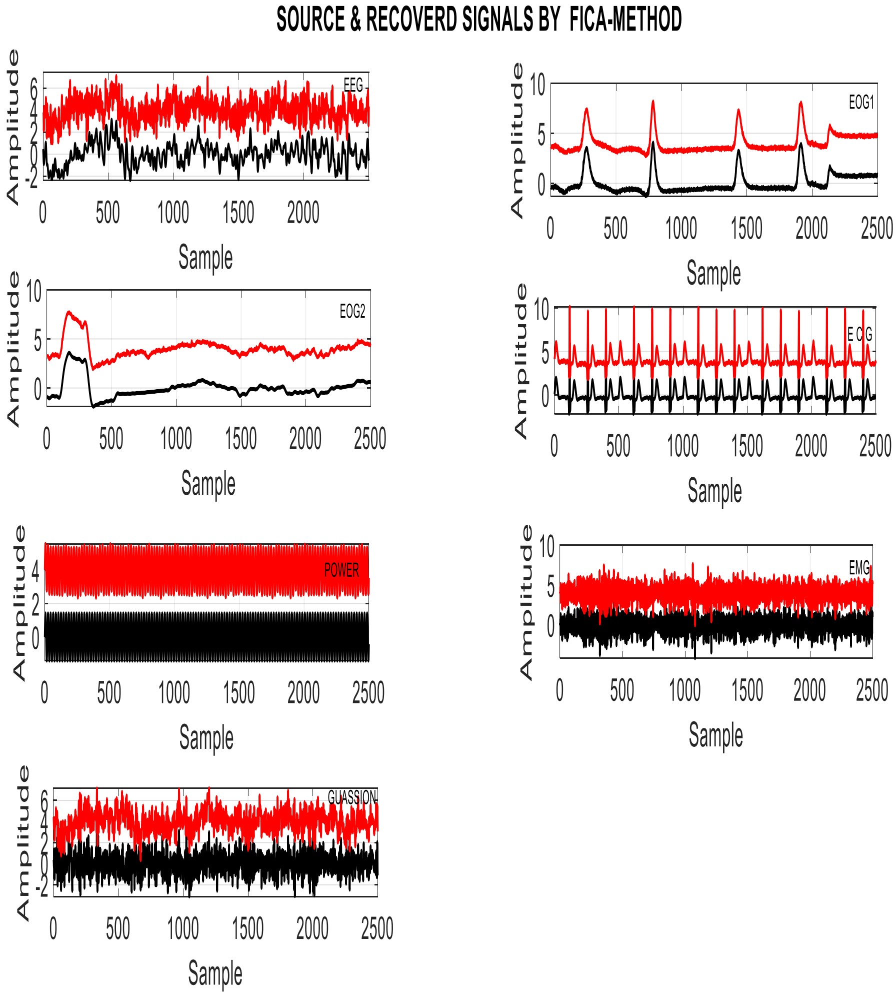


Figure 4-5 Source and restored signals through the FICA algorithm

The above figures do not give an idea about the best BSS algorithm in the extraction of signals where as all algorithms restore the signals perfectly. To verify which algorithm has the best performance need to compare them depending on the achieved SNR. Where SNR calculated by dividing the total power of the signal over the total power of the noise signal **Error! Reference source not found.**Table 4-1 represents a comparison between all algorithms according to the obtained average signal to noise ratio (SNR) for every method.

Table 4-1 The recorded average SNR in dB for each single algorithm

BSS Algorithms	STONE	FICA	EFICA	BEFICA
Signal to Noise Ratio (SNR)	21.2800	13.7899	16.1518	22.5233

Error! Reference source not found. From Table 4-1 BEFICA algorithm records highest calculated SNR value (22.52) while FICA (13.78) scores lowest SNR values from EFICA (26.15)and STONE (21.28) . Therefore, we can conclude that of all the algorithms used, the BEFICA algorithm has the best performs . As shown in the Figure 4-6.

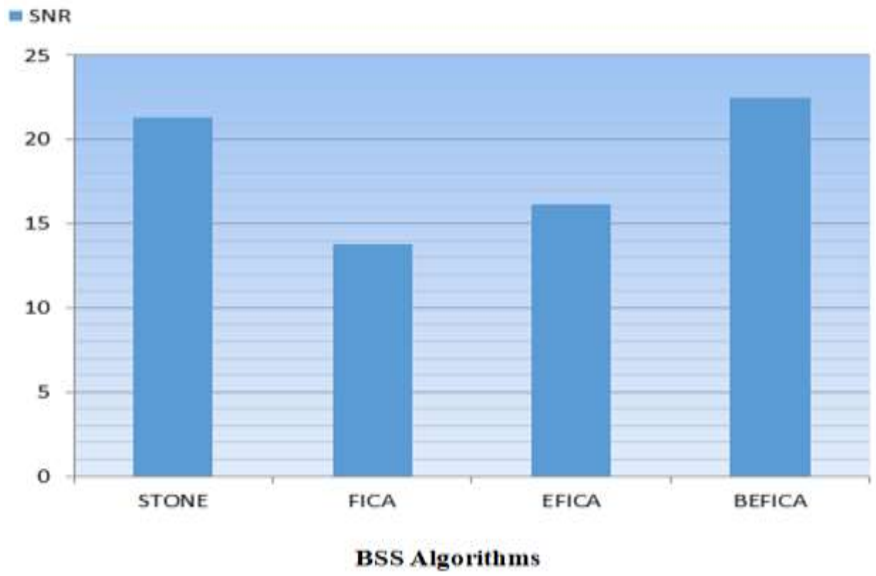


Figure 4-6 Values of SNR with BSS Algorithms

For more clarification the down Table 4-2 shows compare all restored signal (EEG,EOG,ECG,Power line, EMG,Gaussian) depending on the calculated the SNR and Interference to Signal Ratio (ISR) for each extracted signal. after being passed on the four separation techniques BSS.

Table 4-2 SNR and ISR in dB for each extracted signals

Method	Criteria	Signals						
		EEG	EOG1	EOG2	GAUSSION	ECG	P.LIONE	EMG
STONE	SNR	10.040	6.464	5.879	7.529	8.333	10.02	8.385
	ISR	-10.040	-6.464	-5.879	-7.529	-8.333	-10.02	-8.385
FICA	SNR	4.479	17.96	38.07	21.224	59.91	6.261	9.740
	ISR	-4.479	-17.96	-38.07	-21.224	-59.91	-6.261	-9.740
EFICA	SNR	10.82	17.22	20.13	20.414	19.43	8.005	8.1001
	ISR	-10.82	-17.22	-20.13	-20.414	-19.43	-8.005	-8.1001
BEFICA	SNR	212.6	21.16	16.25	20.044	19.33	14.860	2,747
	ISR	-212.6	-21.16	-16.25	-20.044	-19.33	-14.860	-2.747

Through the Table 4-1 and Table 4-2 can proves that BEFICA BSS algorithm record the highest value of SNR comparing to the other BSS algorithms.

4.2.2 – Second Signals: The Real data

In this part, Discussed the extraction of EEG signals based on the output of the four algorithms will be discussed. The eight channels of EEG dataset are shown in Figure 4-7 are the inputs for each BSS algorithm (STONE, EFICA, BEFICA and FICA). The brain signals are entered into the system and mixed done after taking the average of the zero and the contrast of the unit to be purified and filtered from impurities). for data as matrice size (8 x 2560).

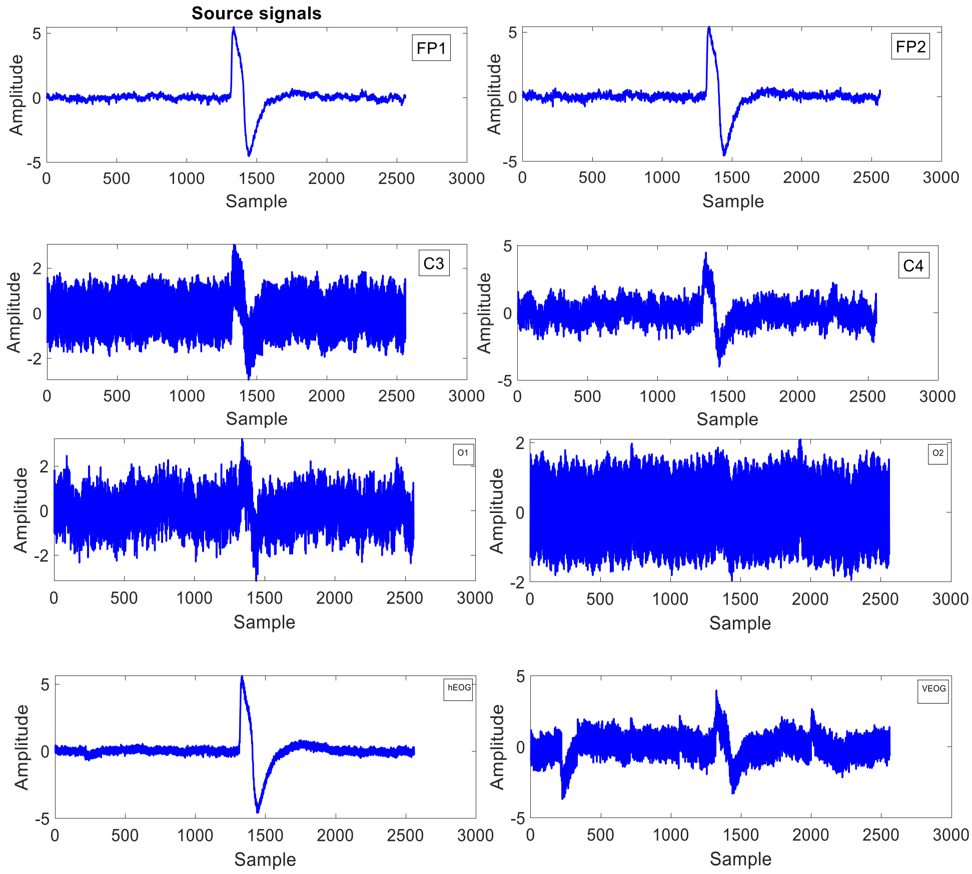


Figure 4-7 Source signals of real data set

These signals are a blink of the eye signal taken from eight electrodes placed on the scalp to represent EEG signals. The first signal from the left (FP1), followed by the second signal (FP2), the third signal (C3), the fourth signal (C4), the fifth signal (O1),sixth signal(O2), the seventh signal (hEOG) and the eighth signal (vEOG).

4.2.3Results After Using Blind Source Separation (BSS)

Signals are passed through the four blind separation sources, The eye blink and LN (50Hz) are mixed with others signals to produce EEG signals, the affected of blinking on Fp1, Fp2. so all channels are mixed with disparate contaminations. LN has been candid on C3 & C4 as well as on O1 & O2 [25]. As shown in Figure 4-7.

4.2.4 Results After Using STONE

The Results output signal for 8 channels after signal analysis by stone blind source separation are shown in Figure 4-8.

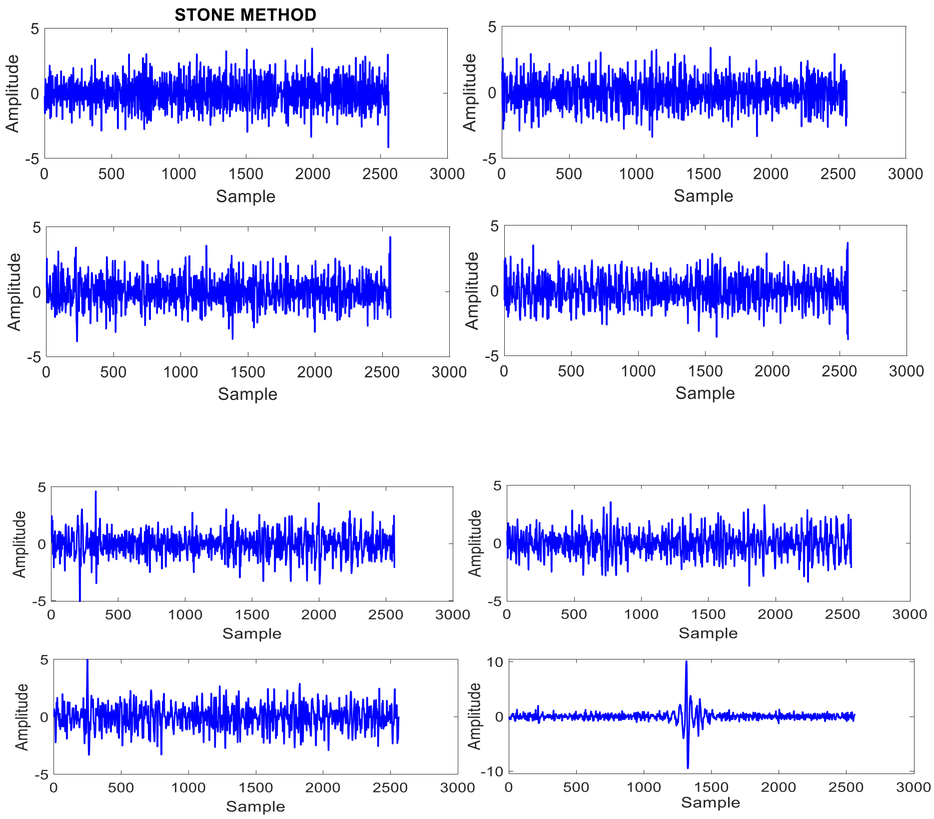


Figure 4-8 Recover Sources by STONE

This signals consisting of the same signals previous which appeared in Figure 2-7.

4.2.5 Results After Using EFICA

The Results output signal for 8 channels after signal analysis by blind source separation EFICA are shown in Figure 4-9.

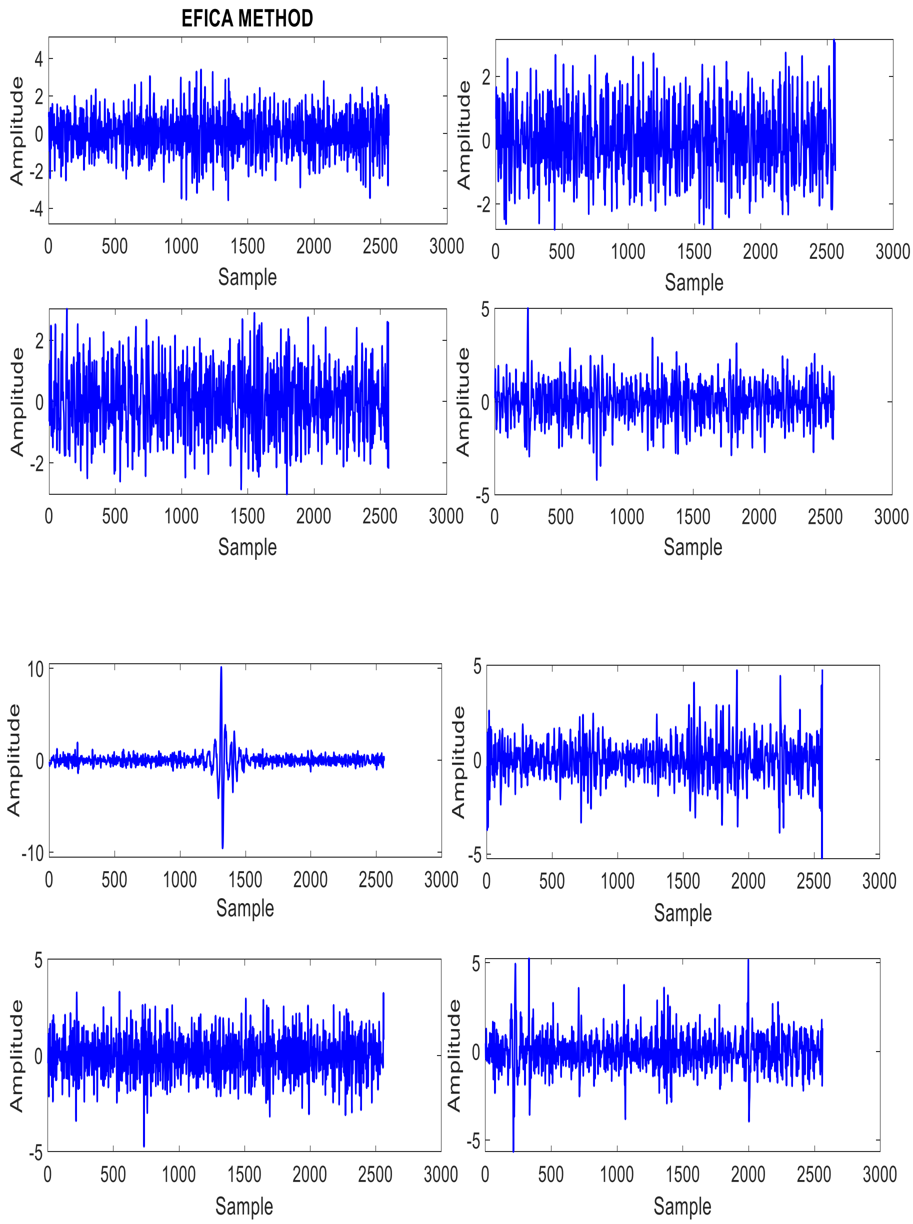


Figure 4-9 Recover sources by EFICA

4.2.6 Results After Using BEFICA

The Results output signal for 8 channels after signal analysis eby blind source separation **BEFICA** as shown in

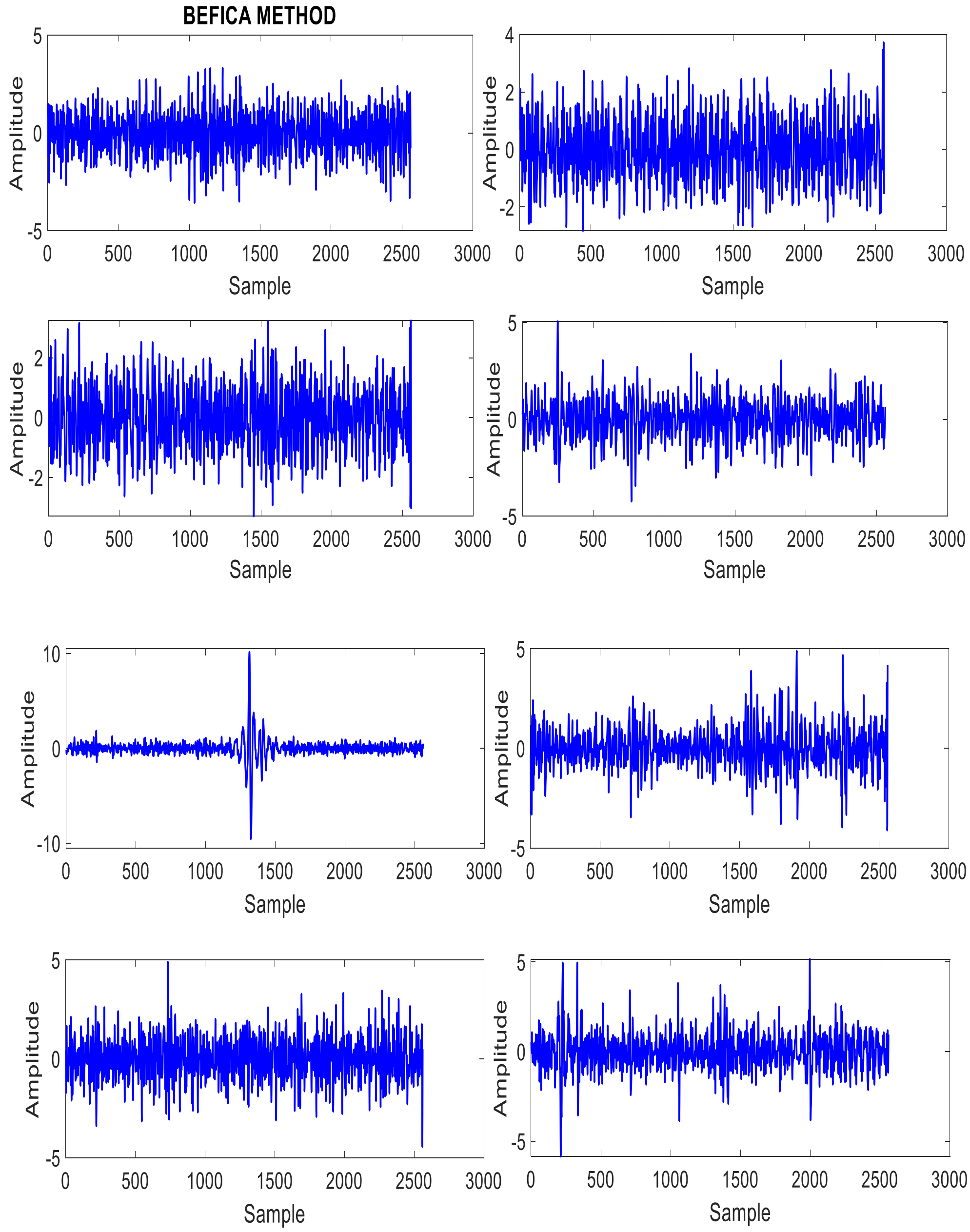


Figure 4-10 Recover Sources by BEFICA

4.2.7 Results After Using FICA

The Results output signal for 8 channels after signal analysis by blind source separation **FICA** as shown in

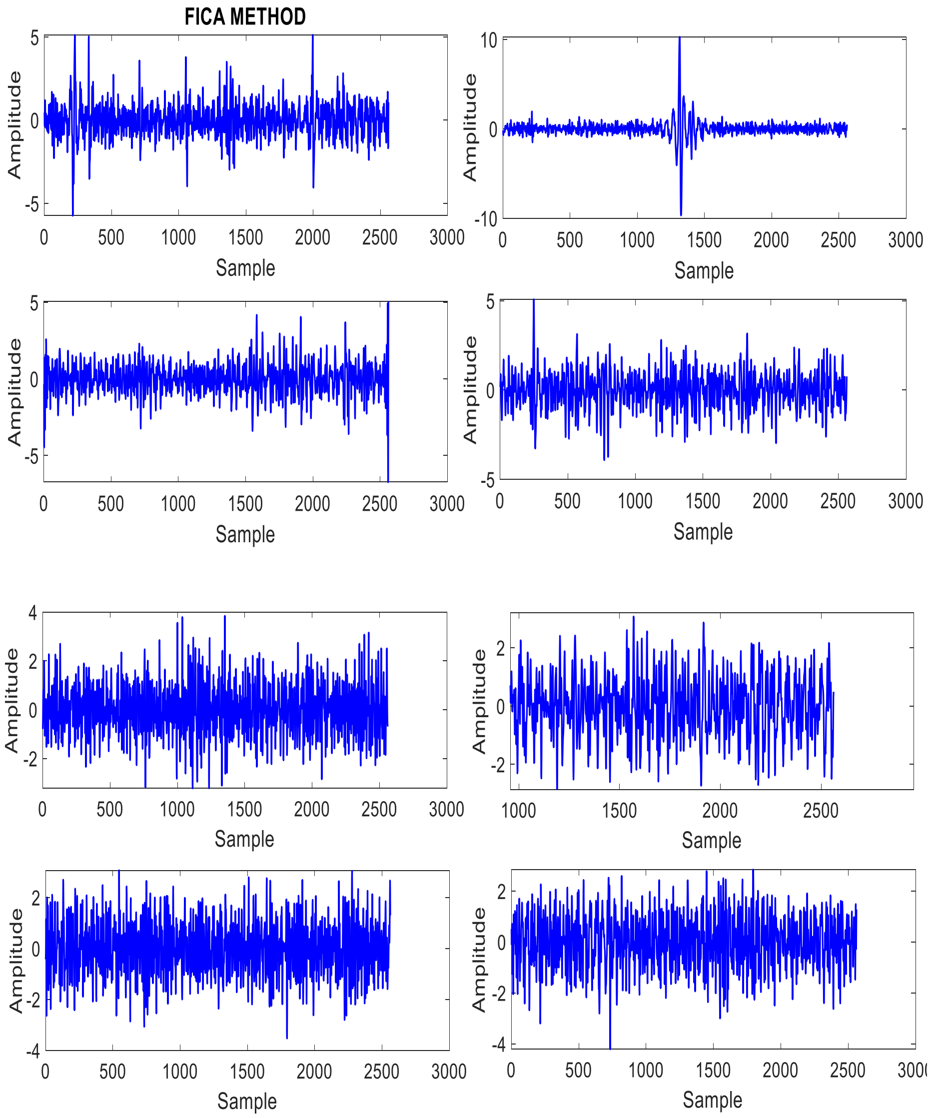


Figure 4-11 Recover Sources by FICA

After separating these mixed data using several source-blind separation algorithms, it was demonstrated that all algorithms recovered all signals. To choose the best-performing algorithm.Compared all the recovered signals based on the calculated power spectral density (PSD) As shown in the Table 4-3.

Table 4-3 power spectral density PSD for each algorithm

Total Power Real Signal	Total Power after STONE	Total Power after FICA	Total Power after BEFICA	Total Power after EFICA
8.0028	0.8573	1.399	0.7678	0.7552

4.3 Power spectral density (PSD)

Power spectral density function (PSD) shows the strength of the variations(energy) as a function of frequency. In other words, it shows at which frequencies variations are strong and at which frequencies variations are weak. The unit of PSD is energy per frequency. We also can obtain energy within a specific frequency range by integrating PSD within that frequency range. Computation of PSD is done directly by the method called FFT or computing autocorrelation function and then transforming it. The power spectral density formula, is asignal consisting of many similar subcarriers will have a constant power spectral density (PSD) over its bandwidth and the total signal power can then be found as P = PSD · BW.

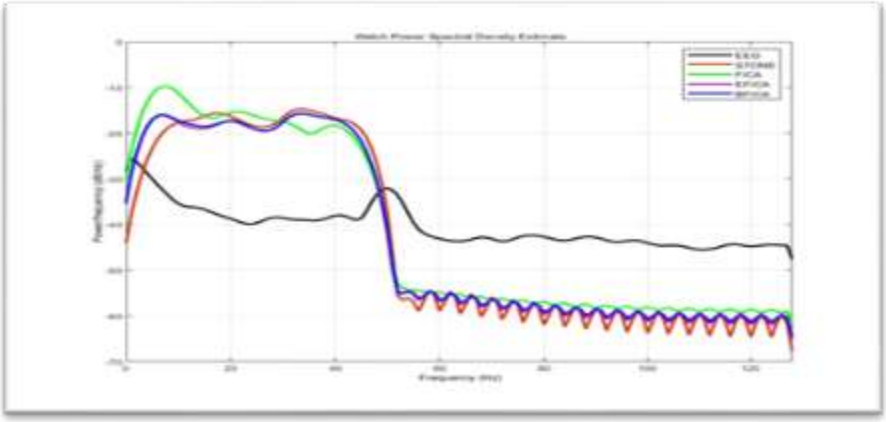


Figure 4-12 PSD of the first channel (FP1) of each algorithm

For more clarification the Figure 4-12 demonstrate the obtained PSD for the first channel FP1 for each algorithms. There is a discrepancy in the signal output according to the type of algorithms, where the signal output of the EFICA algorithm has the least discrepancy from the others of algorithms. This is evident through the SPD standard. The value was (0.7552) while the value of SPD to FICA algorithm (1.3599) therefor is the best.

4.4 Part 2 Optimization stage

The obtained results in this part are calculated depending on the optimization which has been demonstrated in Chapter Three.

4.4.1 First case: Simulation data set

The EEG signals coming out of the aforementioned group of blind separation sources that are performed by the optimization process by the ant-lion algorithm mentioned in detail in Chapter Three. Table 4-4 shows the results before and after optimization . Although the BEFICA algorithm is the best, its execution takes longer than the rest of the algorithms. The speed was about (147.799638 seconds).

Table 4-4 The Results after optimization

BSS Algorithms	STONE	FICA	EFICA	BEFICA
Average SNR Before Optimization	21.2800	13.7899	16.1518	22.5233
Average SNR After Optimization	25.64969	16.2422	17.0255	26.4969
Elapsed time seconds	0.443526	0.696886	13.873441	147.799638

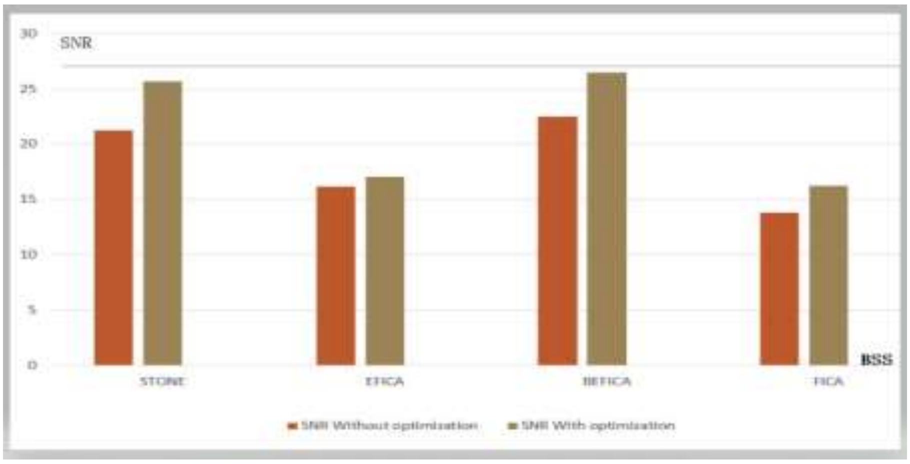


Figure 4-13 The relationship BSS to the SNR after optimization

It is noticed from the Figure 4-13 that the BSS graph with SNR after optimizing the results of the BEFICA algorithm has the best level after parameter tuning, as shown in the third chapter (algorithm 3.6). Therefore, when comparing the values of their results for SNR, there is a significant difference between the two cases, before optimization (22.52) dB and after optimization (26.49 dB), indicating the percentage of improvement obtained on the signals. Then comes STONE BSS and EFECA algorithm respectively wile FICA is lower quality (13.78 dB) before optimization , then becames (16.24 dB). These values confirm our previous conclusion that BEFICA BSS has better performance in retrieval and problem solving than other BSS algorithms.

4.4.2 Second case: Real data

In the case of real signals, the same previous steps are taken in terms of optimizing each algorithm used from blind separation sources by controlling the output data , and then comparing them to extract the best quality to the separation process.

4.4.2.1 Stone method with optimizer

The output signal results for 8 channels are shown after analysing the signal by separating the blind source of the BSS stone and after performing the optimization process on the algorithm for a single blinking eye movement experiment as in Figure 4-14

Figure

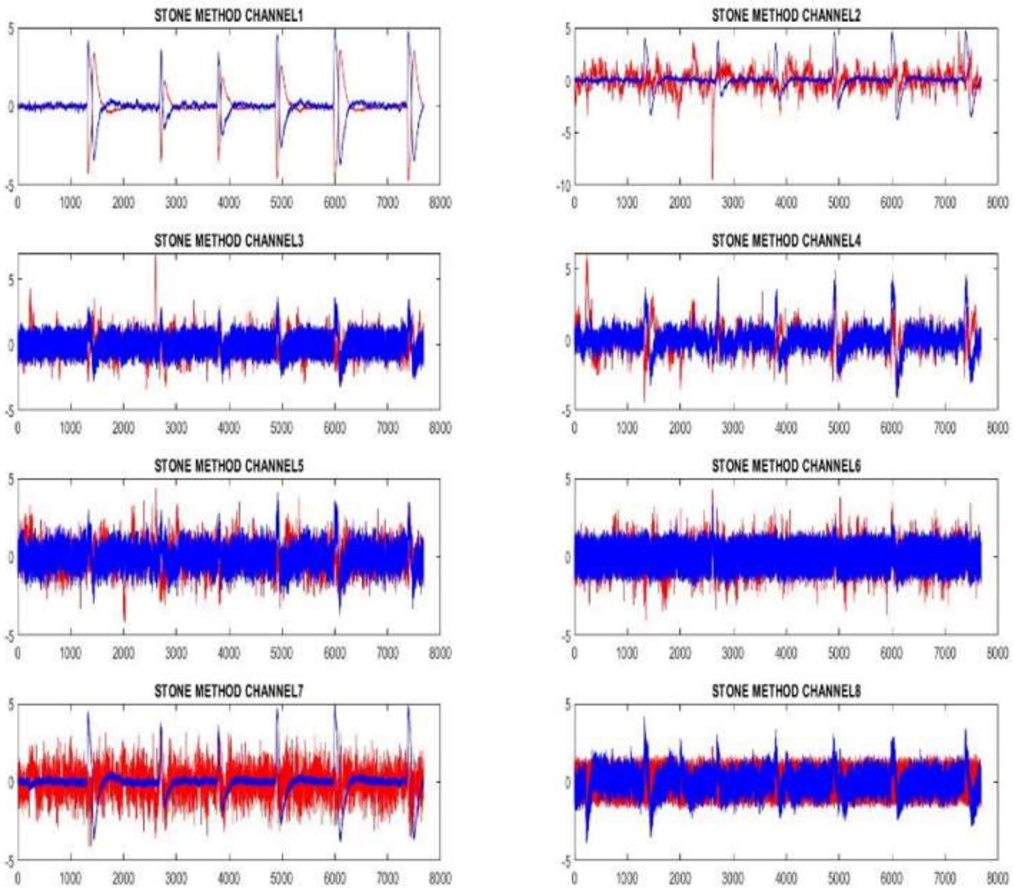


Figure 4-14 Recover sources by stone after optimization

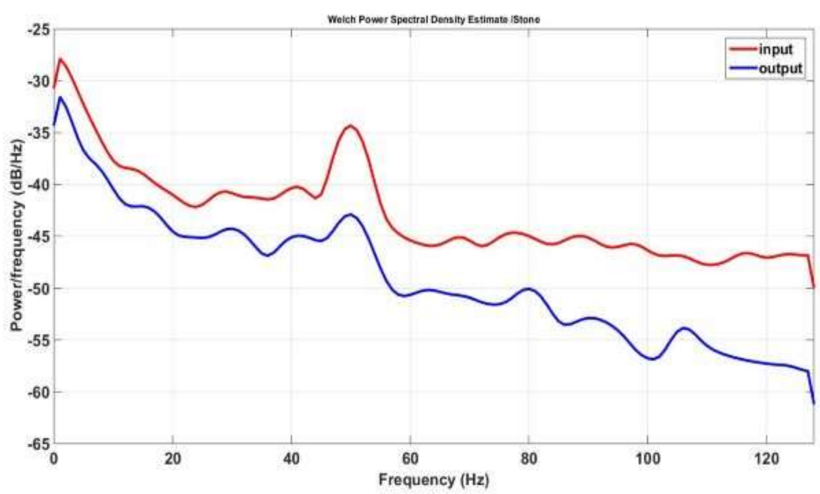


Figure 4-15 PSD for signals input and output after STONE

4.4.2.2 EFICA method with optimizer

The results of the output signal for 8 channels are shown after analysing the signal by separating the blind source of the BSS EFICA a single experiment of blinking eye movement and after performing the optimization process on the algorithm as in Figure 4-16 The Figure 4-17 shows the power spectrol density (PSD) for input and output signal after EFICA.

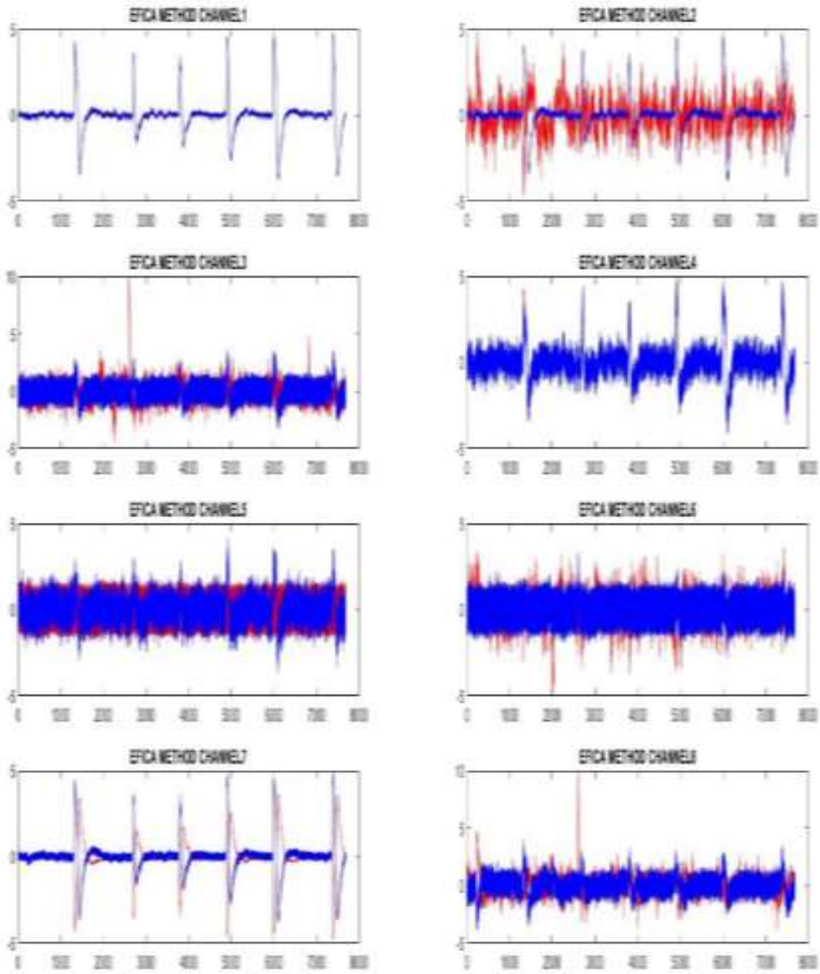


Figure 4-16 Recover Sources by EFICA after optimization

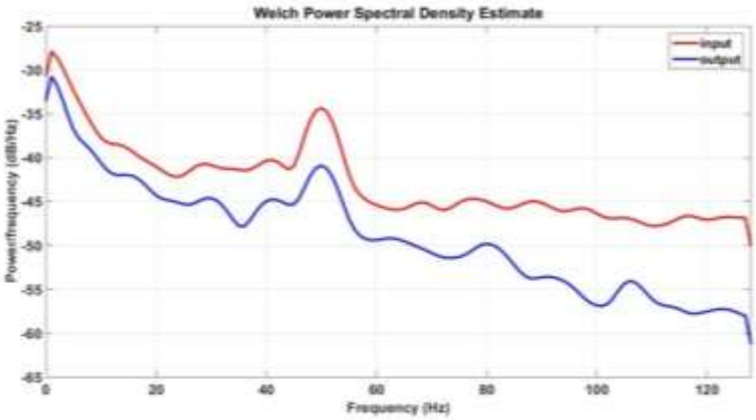


Figure 4-17 PSD for signals input and output after EFICA

4.4.2.3 BEFICA method with optimizer

The results of the output signal for 8 channels are shown after analysing the signal by separating the blind source of the BEFICA BSS, a single experiment of blinking eye movement and after performing the optimization process on the algorithm as in Figure 4-18 The.

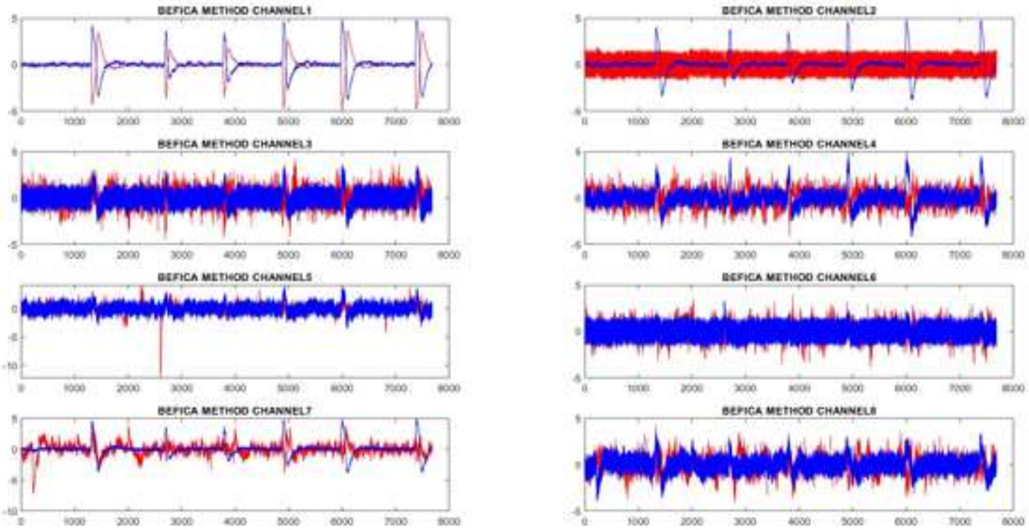


Figure 4-18 Recover Sources by BEFICA after Optimization

Figure 4-19 shows the power spectrol density (PSD) for input and output signal after BEFICA.

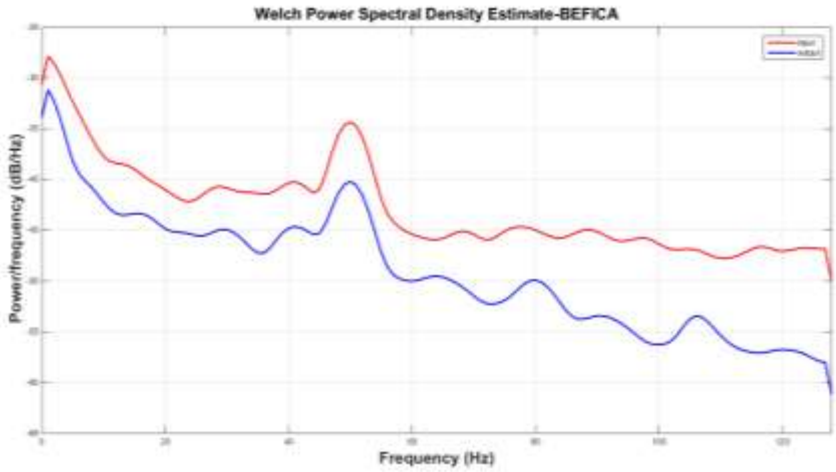
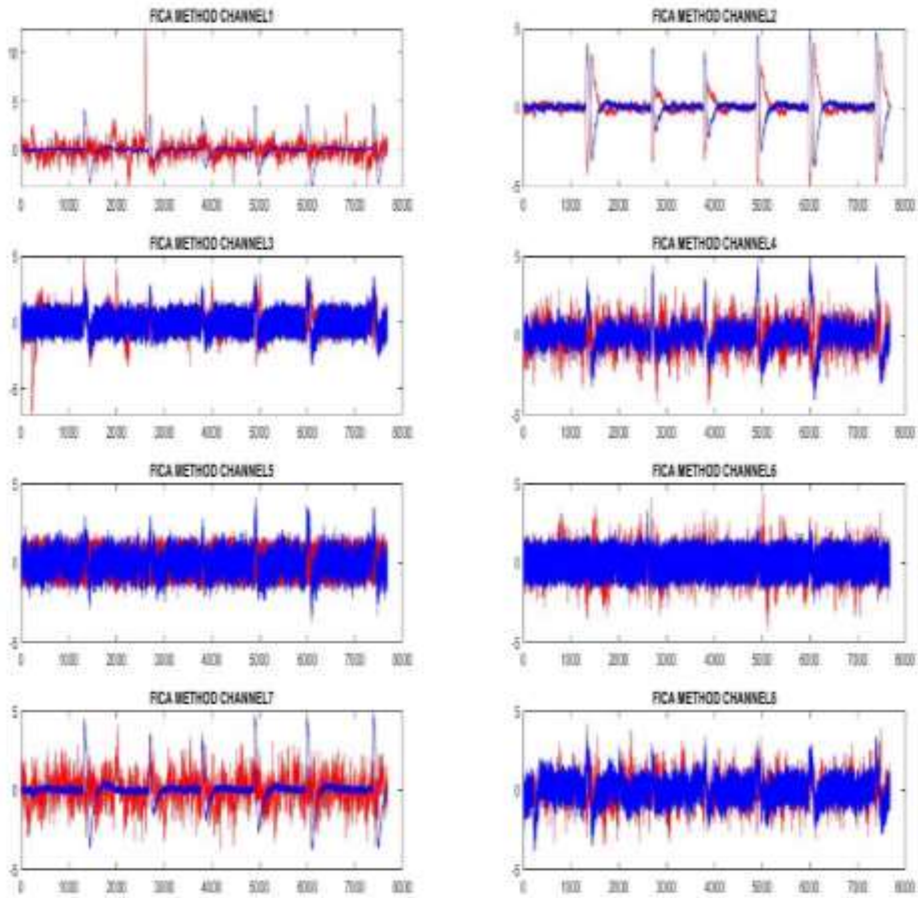


Figure 4-19 PSD for signals input and output after BEFICA

4.4.2.4 FICA method with optimizer

The results of the output signal for 8 channels are shown after analyzing the signal by separating the blind source of the BSS FICA, a single experiment of blinking eye movement and after performing the optimization process on the algorithm as in Figure 4-20. Shows the power spectrol density (PSD) for input and output signal after EFICA.



Figur 4-20 Recover Sources by FICA after Optimization

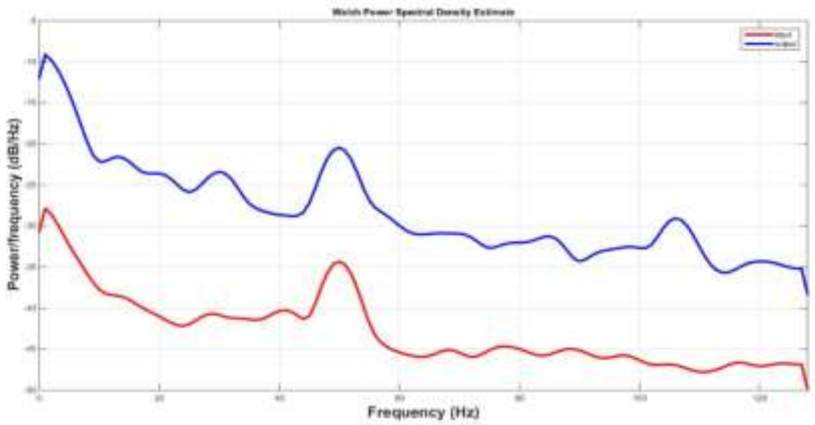


Figure 4-21 PSD for signals input and output after FICA

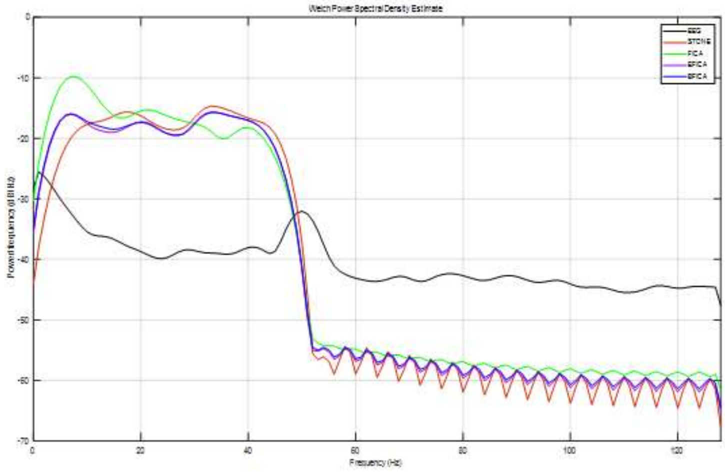


Figure 4-22 PSD for each algorithms after optimization

Table 4-5 PSD for each algorithm after optimization

Data set (8) electrodes	BSS Algorithms	Optimization Algorithm	Total power
Fb1 Fb2 C3 C4 O1 O2 VEOG HEOG	STONE	Ant lion Algorithm	0.0053
	FICA		0.0058
	BEFICA		0.7628
	EFICA		0.0051

Through the drawings Figure 4-22 and results presented in the Table 4-5, which obtained after performing the optimization process using the Antlion algorithm, as its effect was clear on the EFICA algorithm, by fine-tuning its parameters, as shown in the third chapter (algorithm 3.7). So when compared to other algorithms, the value of the spectral density of the energy became (0.0051) after optimization. It was high value before improvement and the lowest quality comes after it STONE(0.0053), FICA(0.0058) , BEFICA (0.7628). Therefore, it can be concluded that in the case of real data the EFICA algorithm was the best of them performance after the improvement phase.

4.5 Comparison of Results

This work consists of two stages, the first stage is just separation of operations by BSS algorithms without optimization, the second stage is optimization of operation to the BSS algorithms previous.

1- Results are taken from four different technologies (STONE, EFICA, BEFICA, and FICA). The brain signals are analyzed and the noise was separated from them. Two types of simulated and real data were used to separate the blind sources, and there are three main criteria (SNR, ISR, PSD) to indicate the quality of each algorithm, in the case of simulation, the SNR was measured. The higher value to the better separation of the algorithm, conversely the lower the ISR value of the signal indicated the quality of separating the noise from original signal, whereas in the case of real data, use power spectrum density (PSD) to find the variance in frequencies, i.e. when the contrast is Strong and weak, so lower PSD is better.

2- Represent the results obtained and a comparison is done between the proposed methods before the improvement operations. Table 4-6 shows that BEFICA algorithm has higher performance (22.523) than STONE algorithm (21.280), EFICA algorithm (16.151), FICA algorithm (13.789), this is in the case of simulated data, whereas when using real data, EFICA algorithm proved high performance (0.7552))

Where was the value of (PSD) while the value of STONE algorithm was equal to (0.8573), BEFICA, and FICA algorithm were (0.7678, 1.3599) respectively.

Table 4-6 comparison of results for first case (before optimization)

<table>
<tr><th>BSS Algorithms</th><th>Simulation data</th><th>SNR criteria</th><th>ISR criteria</th><th>Real data</th><th>PSD criteria</th></tr>
<tr><td>STONE</td><td rowspan="4">7 Signals
1-EEG
2- EOG1
3- ECG
4-EOG2
5-Gaussian noise
6-Power line noise
7-EMG signal</td><td>21.280</td><td>-21.2800</td><td rowspan="4">8 Electrodes
1- FP1
2- FP2
3- C3
4- C4
5- O1
6- O2
7- VEOG
8- HEOG</td><td>0.8573</td></tr>
<tr><td>EFICA</td><td>16.151</td><td>-16.1518</td><td>0.7552</td></tr>
<tr><td>BEFICA</td><td>22.523</td><td>-22.5233</td><td>0.7678</td></tr>
<tr><td>FICA</td><td>13.789</td><td>-13.7899</td><td>1.3599</td></tr>
</table>

Table 4-7 comparison of results for second case (after optimization)

BSSAlgorithms	Optimi-zationAlgorithm	Simulation data	SNR criteria	ISRcriteria	Rea ldata	PSD criteria
STONE		**7 Signals** **1-EEG**	**25.696**	**-25.696**	**8 Electrodes** **1- FP1** **2- FP2**	**0.0053**
EFICA	**Antlion**	**2- EOG1** **3- ECG** **4-EOG2**	**17.025**	**-17.025**	**3- C3** **4- C4**	**0.0051**
BEFICA		**5-Gaussian noise** **6-Power line noise**	**26.496**	**-26.496**	**5- O1** **6- O2** **7- VEOG**	**0.7628**
FICA		**7-EMG signals**	**16.242**	**-16.242**	**8- HEOG**	**0.0058**

3- For the optimization stage, used the Antlion algorithm, which is characterized by high performance optimization. The same previous data (simulated and real) was used and passed through algorithms (STONE, EFICA, BEFICA and FICA). After comparing the results as shown in Table 4-7, there are two types of algorithms that responded to the optimization process. In the simulated data, the BEFICA algorithm scored a higher SNR value (26.496) before optimization (22.523) and higher than the rest of the other algorithms where the values of STONE (25.696), EFICA (17.025) and FICA (16.242) were also in the real data case. The EFICA algorithm was stronger than the other algorithms, so the standard power spectral density (PSD) (0.0051) was much lower than it was before optimization (0.7552) and even lower than the other algorithms, so the value of the STONE algorithm (0.0053), the FICA algorithm (0.0058), and the algorithm BEFICA (0.7628), this indicates how the ant lion algorithm performs very well, since it has very few parameters for tuning, and the ALO algorithm also used random tracks with the roulette wheel, to get the better value of function fitness,thus reach the best improvement.

Chapter 5

Conclusions and Suggestions for Future Works

5.1 Conclusion

The purpose of this thesis is to be a resource for all researchers at BCI. The EEG was measured as a basic knowledge of brain waves. Then focus on specific algorithms that can separate EEG signals so that they are able to isolate and remove the artifcat (noise) like EOG, EMG, ECG and power lines (LN) into individual components. EEG patterns are effectively improved. Then it takes the task-related signals generated by the separation algorithms and refines them using an optimizer (ant lion) and then compares the proposed system algorithm with other systems that use other algorithms to separate blind sources such as (STONE, EFICA, BEFICA, FICA). By designing and carrying out this work, various conclusions are drawn from the results of the tests obtained:

- Since the EEG signal is a mixture of many brain-generated signal sources and damaged by different artifacts, the BEFICA and EFICA algorithms are sufficient to separate the EEG signal to its sources (recovered components).Function-related components are reconstructed to obtain a pure EEG signal that does not contain trace elements and non-task-related components. The BEFICA and EFICA algorithms have been discovered as suitable tools for brain signal feature extraction.

- Optimization of the brain computer interface based on four BSS algorithms (STONE, EFICA, BEFICA and FICA) to separate and isolate brain signals into individual components.

- High optimization accuracy is obtained using ANTLION algorithm with BEFICA algorithm compared to other BSS algorithm as in Table 4-6, which is obtained with a larger SNR value (26.49) than the case without SNR optimization (22.52).

- EFICA algorithm, showing higher performance as in Table 4-7.

Obtained on PSD (0.0051) after optimization by comparing the value of PSD without optimization (0.7552).

- As you know, one algorithm may not be enough to solve one set of problems but at the same time it is effective on another set of problems. It is the basis of many algorithms in this field.

5.2 Suggestions for the future works

The possible future researches for BCI take many aspects and provide possible methods to achieve them observement for mental conditions across the internet. For these reasons the importance of monitoring their progress in engineering and neurological applications are reflected with regard to the suggested future work.

In the first part of proposed system when used Simulation data the obtained results by BEFICA BSS with ALO optimizer are very motive to design and implement hardware equipment in future. It is very good way to separate the artifacts like EOG, Gaussian noise, ECG signal, Power line noise and EMG signal. Therefore it can be developed by insetting some of constraint signals to enhance more the separated wanted artifacts.

In the second part of proposed system when used Real data, EFICA BSS algorithm achieved best results with optimization technique which is very good way to detect the occurrence of ocular artifacts to separate the artifacts to obtain on pure signals which can be used in several applications in BCI systems.

The technique ALO optimization can be replaced to make modifications on BEFICA BSS & EFICA BSS algorithms by using several developed optimization techniques like Optimization chicken's algorithm, bat algorithms Optimization, Grey Wolf Optimizer (GWO)…etc.

So can conclusion the suggetions in three points :

1-Motive to implementation the hardware design.

2-Using huge data system for Brain tumor and anotheres cases .

3-The output should be used in classifier processing.

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Publications

- Safaa Mahmood Hamad, Ali A. Al-Bakri, Ahmed Kareem Abdullah

‘‘PURIFICATION OF BRAIN SIGNALS USING VARIOUS BLIND SOURCE SEPARATION TECHNIQUES”

manuscript has been accepted for publication in “Al-Furat Journal of Innovations in Electronics and Computer Engineering FJIECE”, in the next Issue, Vol. 1, Issue 4. Paper Id;110096

- “Enhancement of Brain Computer Interface System Based on Artificial Intelligent Technique Using Antlion optimization”.

manuscript has been accepted for publication in “Al-Furat Journal of Innovations in Electronics and Computer Engineering FJIECE. Paper Id: 210164 .

فصل اشارات الدماغ بواسطة تقنيات مصادر الفصل العمياء

الخلاصة

هناك اهتمام متزايد بالبحث حول كيفية تحليل إشارات الدماغ ، حيث توجد أنشطة كهربائية بين الخلايا العصبية في الدماغ مرتبطة بجميع الأنشطة في الجسم. يمكن رؤية هذه الأنشطة باستخدام تقنية غير جراحية تسمى-Electroence.

phalography (EEG) يعد تحليل مثل هذه الإشارات في الطب مسألة مهمة. هناك العديد من التحديات في تحليل إشارات الدماغ التي لم يكن لديها حل أساسي بعد ، مثل وجود قطعة أثرية أثناء عملية التسجيل ، مما يجعل تحليل إشارات الدماغ أمرًا صعبًا للغاية.

في تحليل الإشارات العصبية الفسيولوجية ، يعتبر رفض الضوضاء والتحف مجالًا مهمًا للبحث. تُستخدم تقنيات فصل الإشارات مثل فصل المصدر الأعمى (BSS) للتغلب على مشكلة القطع الأثرية عن طريق فصل القطع الأثرية والضوضاء عن إشارة EEG كمكونات منفصلة BSS .هي طريقة لفصل المصادر الأولية عن مخاليطها بمعلومات قليلة أو معدومة من المصادر الأصلية وعملية فصل الخلط المقترحة لنظام رفض كامل يعتمد على خوارزميات فصل المصدر الأعمى المعدلة. يمكن للنظام المقترح إزالة القطع الأثرية مثل [مخطط كهربية القلب (EOG) ، مخطط كهربية وتداخل ضوضاء خط الطاقة من خليط مخطط كهربائية الدماغ في هذه الاطروحه يتم استخدام اربعة خوارزميات BSS لفصل المصادر العمياء

STONE ، وتحليل مكونات الاستقلالية السريعة لتوقع الكتلة ة(BEFICA) ، وتحليل المكونات المستقلة السريعة الفعالة EFICA ، والتحليل السريع للمكونات المستقلة (FICA) إجراء هذا العمل على مرحلتين ، المرحلة الأولى التي يتم فيها معالجة الخوارزميات بنوعين من البيانات (حقيقية ومحاكاة) حيث يتم اختبار جودة فئة كل منهما ومقارنتها مع تلك التي يتم اختيار أفضلها.

المرحلة الثانية التي تم تحسينها بواسطة خوارزمية Antlion التي حسنت إحدى الخوارزميات المستخدمة في بيانات محاكاة الحالة هي Block Expectation Fast Independandment Component Analysis (BEFICA) والتي تتمتع بأفضل استجابة للتحسين وفقًا للمعايير المثبتة (SNR) ، (ISR) حيث نسبة الإشارة إلى الضوضاء (SNR) هو (٢٦.٤٦) ونسبة التداخل إلى الإشارة (-٢٦.٤٦) بعد المقارنة مع جميع الخوارزميات. بينما في حالة البيانات الحقيقية ، يكون تحليل المكون الفعال السريع المستقل (EFICA)أكثر استجابة لعملية التحسين بواسطة كثافة الطيف الطيفي (PSD) والتي تساوي (٠.٠٠٥١) بعد مقارنتها بجميع الخوارزميات المستخدمة.

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رسالة مقدمة إلى قسم هندسة الاتصالات

كجزء من متطلبات نيل درجة الماجستير التقني في هندسة الاتصالات

تقدم بها

صفاء محمود حمد

بكالوريوس في هندسة الاتصالات

إشراف

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