Republic of Iraq
Ministry of Higher Education
and Scientific Research
University of Diyala
College of Science

Enhancement of Brain Computer Interface System Based on A classified Blind Sources Separation

A Research
Submitted to the Department of Computer Science\ College of Sciences\ University of Diyala in a Partial Fulfillment of the Requirements for the Degree of Master in Computer Science

By

Zainab kadham Abees

Supervised By

Dr .Taha M. Hassan
Assistant Professor

Dr. Ahmed K. A. AL-Bakri
Assistant Professor

2020 A.D **1441A.H**

بِسۡمِ ٱللَّهِ ٱلرَّحۡمَٰنِ ٱلرَّحِيمِ

﴿قُلْ هُوَ الَّذِي أَنشَأَكُمْ وَجَعَلَ لَكُمُ السَّمْعَ
وَالْأَبْصَارَ وَالْأَفْئِدَةَ قَلِيلاً مَا تَشْكُرُونَ ٢٣
قُلْ هُوَ الَّذِي ذَرَأَكُمْ فِي الْأَرْضِ
وَإِلَيْهِ تُحْشَرُونَ ٢٤﴾

صَدَقَ ٱللَّهُ العَظِيم

سورة الملك

آيات (٢٣-٢٤)

Dedication

To...

My dear parents

My dear brothers and sisters

All our distinguished teachers those who paved the way for our science and knowledge

Zainab kadham Abees

Acknowledgment

First of all, praise is to GOD, the lord of the whole creation, on all the blessing was the help in achieving this research to its end.

I wish to express my thanks to my supervisors, ***Assist. Prof Dr. Taha Mohammad Hassan*** *and* ***Assist. Prof Dr.Ahmed Kareem Abdullah*** *for supervising this research and for the generosity, patience and continuous guidance throughout the work. It has been my good fortune to have the advice and guidance from them. My thanks to the academic and administrative staff at the Department of the computer sciences.*

I would like to express my gratitude to my father, my mother, my sisters and my brothers who were unlimited support and patience.

Finally, there are no words enough to thank my friends for being supportive and believing in me all the time and encouragement during the period of my study. Praise be to God Who helped me and gave me the ability and power to perform and complete my thesis.

Zainab Kadham Abees

Supervisor's Certification

*We certify that this thesis entitled "**Enhancement of Brain Computer Interface System Based on A classified Blind Sources Separation**" was prepared under my supervision at Department of Computer Science\ College of Sciences\ University of Diyala in a partial fulfillment of the requirements for the degree of **Master of Science in Computer Science.***

Signature:

Name: Asst. Prof. Dr. Taha Mohammad Hassan

Date: / /2020

Signature:

Name: Asst. Prof. Dr. Ahmed Kareem Abdullah AL-Bakry

Date: / / 2020

Approved by the Department of Computer Science at University of Diyala

Signature:

Name: Asst. Prof. Dr. Taha Mohammad Hassan

Date: / / 2020

(Head of Computer Science Department)

Linguistic Certification

I certify that this thesis entitled **"*Enhancement of Brain Computer Interface System Based on A classified Blind Sources Separation*"** *was prepared by* ***Zainab Kadham Abees*** *And was reviewed linguistically. Its language was amended to meet the style of English language.*

Signature :

Name: Dr. Ghazwan Muhammad Jaafar

Date : / /2020

Examination Committee Certification

We certify that we have read the thesis entitled ***"Enhancement of Brain Computer Interface System Based on A classified Blind Sources Separation"*** *and as examination committee, examined the student* ***"Zainab Kadham Abees"*** *in the thesis content and that in our opinion, it is adequate as fulfill the requirement for the Degree of Master in Computer Science at the Computer Science Department, University of Diyala.*

(*Chairman*)

Signature:

Name: Prof. Dr. Ziyad Tariq Mustafa

Date: / /2020

(*Member*)

Signature:

Name:Asst. Prof.Dr. Ali .A. A. Al-Bakry

Date: / /2020

(*Member*)

Signature:

Name: Asst. Prof. Dr. Hadi .A. Hamed

Date: / /2020

(Member\ Supervisor)

Signature:

Name:Asst. Prof. Dr. *Taha .M. Hassan*

Date: / /2020

(Member\ Supervisor)

Signature:

Name :Asst. Prof. *Dr.Ahmed. K .Abdullah*

Date: / /2020

Approved by the Dean of College of Science Computer , University of Diyala

(The Dean)

Signature:

Name: Prof. Dr. Tahseen Hussein Mubarak

Date: / /2020

(Head of Computer Science Department)

Abstract

In the past ten years, there was a considerable advancement in researches that concern with brain-computer interfaces (BCI) system for providing new quality to interactions between humans and machines. BCI as a communication system that is developed for allowing individuals experiencing complete paralysis sending commands or messages with no need to send them via normal output pathways of brain. The presented study has the aim of being a reference in the field of BCI by presenting the fundamental knowledge concerning the waves of the brain and their measuring, and also emphasize on chosen algorithms which are capable of separating and classifying task-related Electro-encephalography signal (EEG).The task is the motions of the index finger of right or left. The separation process based on hybridization between the classical method represented by the filtering process and modern method represented by Stone's blind source separation technique (SBSS) .The proposed method is able to separate artifacts as Electrocardiography(ECG),electromyography (EMG), electrooculography (EOG) and power line (LN) into individual components. This separating would effectively speed up classification patterns of EEG. Task-related signals of the EEG were taken resulting from separation algorithms and classified using two classifiers (Naïve Bayes and Hoeffding Tree) and compare proposed system with other systems used other blind source separation algorithms such as Fast Independent Component Analysis (FICA), Joint Approximation Diagonalization of Eigenmatrices (JADE). The proposed algorithm is tested and trained with the use of real recorded signals of EEG measured according to the International system which has been termed as the ten-twenty and has been obtained from computerized systems of EEG. The results obtained indicate

that ;the proposed system has high average precision rate compared to other existing methods. Where it (82%) average precision rate using stone with Naïve Bayes, and average precision rate using stone with Hoeffding Tree is (82%).

Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviations	Meaning
AC	alternating current
BCI	Brain Computer Interface
BPF	Band-pass filtering
BSS	blind source separation
CA	Classification accuracy
CLT	central limit theorem
CVFDT	Concept-Adapting Very Fast Decision Tree
DC	direct current
DOC	disorders of consciousness
ECG	Electrocardiography
ECoG	Electrocorticography
EEG	Electroencephalogram
EMG	electromyography
EOG	electrooculography
F, T, C, P, O	frontal, temporal, central, parietal and occipital
FICA	Fast Independent Component Analysis
FIR	finite impulse response
fMRI	Functional Magnetic Resonance Imaging
FN	False negative
FP	False positive
HOS	higher-order statistics
HT	Hoeffding Tree
ICA	independent component analysis
JADE	Joint Approximation Diagonalization of Eigenmatrices
LN	power line
MEG	Magnetoencephalography
MRI	Magnetic resonance imaging
NB	NaiveBayes
NIRS	Near Infrared Spectroscopy
NN	Neural Network
PCA	Principal component analysis
PET	positron emission tomography
SBSS	stone blind source separation
SNR	Signal-to-noise ratio
SOS	second-order statistics
TCP/IP	Transmission Control Protocol and the Internet Protocol
TN	True negative
TNR	True negative rate
TP	True positive
TPR	True positive rate

Symbols Table

Symbol	Meaning
δ	Delta rhythm
θ	Theta rhythm
α	Alpha rhythm
β	Beta rhythm
γ	Gamma rhythm
μV	microvolt
mV	millivolt
$\hat{S}$	estimated sources

List Algorithms

Chapter One

Introduction

Chapter One
Introduction

1.1 Over View

Brain Computer Interface (BCI) is defined as a software and hardware system of communication. BCI enables the individuals to have some sort of interaction with their environments, with no participation of the muscles and peripheral nerves, novel non-muscular channel is used via the BCI for relaying the intentions of individuals to external devices like neural prostheses, speech synthesizers, computers, and assistive appliance. Persons with extreme motor disability are the major target of such system, since the system is assumed to decrease the costs of their care and enhance their life quality. BCI is considered as an AI system which have the ability of recognizing a specific sequence of patterns in the signals of the brain following 5 successive phases: signal acquisition, pre-processing or signal improvement, feature extraction, classification, and control interface [1].

The disabled patients are majorly assisted via using this system. The system of BCI require analyzing, assessment, observing and measurement regarding the electrical activity of the brain. These necessities will be obtained via electrodes which are implanted in the brain or electrodes that have been set on the scalp. One type of the signals of the brain is EEG signals. The classification regarding EGG is achieved according to the frequency which 5 major types: (Delta rhythm δ that is between the frequency range 0.5-4 Hz, Theta rhythm θ that is between (4-7) Hz, Alpha rhythm α that is between (8Hz-13Hz), Beta rhythm β that is between (13Hz -30Hz), Gamma rhythm γ that is over 25 Hz) [2] [3] [4].

The EEG signals are captured via Brain Computer Interface along with certain activity of the individual, after that it utilizes various algorithms of signal processing for the purpose of translating the records to control commands for various machine and computer applications. It is a fact that the intentions of the individual can be effectively represented via signals which have been recorded from the brain activity [5] . EEG signal is one of the most widely used signals in the bioinformatics area because of its rich information about human activity. The Electroencephalogram (EEG) has been an important clinical tool to assess human brain activity [6].

There is some sort of mixing between the signals of the brain with other signals which are obtained from finite set of activities related to the brain which overlap in space and time. Furthermore, the signals are not typically stationary, also they could be distorted via artefacts like electrooculography (EOG) and electromyography (EMG). The dimension of the feature vector should be low, for reducing the complexity of feature extraction, yet with no significant loss of information. The classification stage signals taking into account the feature vector. Thus, choosing optimum discriminating features very important for achieving efficient pattern recognition, for the purpose of deciphering the intentions of the users. Lastly, the phase of control interface operate by translating classified signals to important commands for the connected devices, like computer or wheel chair [7].

In the year 1999, BCI had been introduced in the first international conference which had been dedicated to BCI studies held in Rensselaerville Institute near Albany, New York, it has been identified in the following way: ("A BCI is a communication system that does not depend on the brains normal output pathways of peripheral nerves and muscles"[8].

1.2 Related Works

Several researchers have shown their interest in BCI since the importance of the system lies in many applications, such as medical applications especially to assist people with disabilities as their assistance Dealing with computers or helping people with Syndrome In-Locked communicate with the External world , and advertising applications, educational applications and security applications; The following are some of the published works that are related our:

- ***Salim 2007***[8]: that researcher Used the algorithms to separate and classify the EEG signals related to the movement of the left index finger or the right finger index finger.For the separation process they used the independent component analysis algorithm .This separation increases the speed of classification of electrical brain electrical signals, and the signal is classified by using the adaptive pattern class consisting of combing Kohonen map Self-Organizing (SOM) with Quantitative Learning (LVQ),The recognition rate was 75% and 53% .
- ***Mousa, El-Khoribi, and Shoman 2015*** [2]: The researchers developed a novel EEG signal analysis method. They used a high pass; filter to remove artifacts and also DWT algorithms for the feature Extract like Mean Absolute Value, Root Mean Square and Simple Square Integral. Clustering the feature vectors by using KNearest Neighbor algorithm and then use the neural network algorithm to find the correct label for the EEG signal class after clustering. The results of this proposed method outperform better than the methods mentioned in the literature. a FKNN classifiern gave a poor accuracy comparing to the results when we used a proposed method that gives us 81.8% accuracy than FKNN that gives us 61.1% accuracy.

- ***Pan, Li, and Wang 2016.*** [9] ***:***They suggested EEG-based BCI system that was used to identify emotions to detect two emotional states of happiness and sadness. The selection of frequency bands played a vital role in the differentiation of emotion-related brain patterns. They discovered a new way of identifying appropriate frequency bands for the subject rather than using fixed frequency bands to identify emotions. Where a common spatial pattern and vector support were used to classify two affective states. They began two experiments involving six topics to verify method as well as the BCI system. The average accuracy of the Internet achieved 74.17% for two categories. The results of the data analysis indicated that the suggested method based on the specific frequency bands of the subject gave higher results than the method based on fixed frequency bands.
- ***Anh et al. 2016***[10]***:*** The researchers had recorded the EEG signals from 4 individuals as they were going through various mental states. Their study was introduced ANN-based method to classify EEG signals into various mental states that were considered to be corresponding to various control commands for the implementation of Brain Computer Interface. The inputs for ANN are the spectral features which are dimensionally decreased through PCA. The experimental results have outperformed the other classifiers (K-NN, Naïve Bayesian, SVMs, and LDA) in the data set of EEG with highest classification results on dual and triple mental state problems of 95.36% and 76.84%, respectively.
- ***Bhaduri et al. 2016*** [11]***:*** The researches had used feature extraction approach and classifier. Pre-processing regarding EEG signals are implemented and the related features will be extracted. After that, the extracted features will be utilized for classifying right and left imagery movements via Naïve-Bayes and K-NN. The optimum accuracy for

classification was recorded via K-NN for the power spectral density feature set necessitating a time of 0.0531 seconds.

- ***Abiyev et al. 2016*** [12]***:*** this study talk about BCI for Control of Wheelchair Using Fuzzy Neural Networks .They used a Fast Fourier Transform(FFT) to extract important features from the EEG signal. Then the extracted features are input signals of the FNN based classifier, they found that using FFN is very effective in the classification of EEG signals. accuracy of FNN classification model is 100%.
- ***Kucukyildiz et al. 2017***[13]***:*** Researchers had suggested designing and implementing multi-sensor-based BCI. The created system consisted of EMG and EEG sensors, Kinect camera, wheel chair, computer, and motor controller card of high-power. Initially, ANNs, SVMs, and random forest methods are utilized to classify the EMG data. There are 3 cognitive tasks: relaxing, math problem solving, text reading which are specified for the system's EEG based control. The subjects have been required to carry out certain cognitive tasks for the purpose of controlling the wheel chair. The average specificities of ANN, SVM, RF and the proposed classifiers were 0.767, 0.899, 0.828 and 0.904, respectively. Besides having the highest sensitivity, the proposed scheme also had the highest specificity
- ***Azhar et al., 2017***[14]***:***Non-invasive EEG data from a healthy subject of right-hand movement were processed by using two feature extraction algorithms on the basis of independent component analysis (ICA) using coefficient of determination. Results by using the proposed ICA algorithm showed compatibility with the results obtained based on Independent Component Analysis (ICA) method written in MATLAB platform. by "EEGLAB".

- ***Kim, Kwak, and Lee 2018***[15]***:*** researchers utilized conventional electrodes which were attached around the ear in a distance of 1.5 cm from the ear. The researchers had classified 2-class MI tasks through the use of ear-around EEG. Furthermore, They had suggested common spatial pattern (CSP)-based frequency-band optimization algorithm and put it to comparison with 3 present approaches. The optimum results of classificants for 2 data sets were 71.8 percent and 68.07 percent, respectively.
- ***Wu et al. 2018*** [16]***:*** The researchers performed preprocessing of EEG signals in the computer brain interfaces (BCI) which have been simply contaminated via noise and artifacts by using mysterious groups which collected 143 session related to the important motor vigilance data from seventeen subjects in 5 months, prior being presented to the algorithm of machine learning for regression or classification. Using spatial filters for increasing the SNR of the EEG, the researchers suggested candidates for CSP regarding the EEG-based regression problems in BCI, that is extending from CSP filter to classification. The results have indicated that the quality of EEG signals could be increased via the suggested spatial filters. When utilized in LASSO and assessed k gradient(KNN) for estimating the speed of the user's response. the spatial filters can reduce the root mean square estimation error by $10.02 - 19.77\%$, and at the same time increase the correlation to the true response speed by $19.39 - 86.47\%$.
- ***Taran et al. 2018***[17]**:** The researchers proposed analytic intrinsic mode functions (AIMFs) to classify the EEG signals that are related to various MI tasks. The following features: raw moment related to the first derivative of the instantaneous frequency, area, spectral moment that is related to the power spectral density, and PSD's peak

value are estimated from AIMFs. For reducing the classifier's biased nature, the features will be normalized. The normalized features have be utilized as inputs for the least squares support vector machine (LS-SVM). The system presented by this study has better performance than state-of-the-art approaches. The radial basis kernel function for IMF1 provides better MI task classification accuracy 97.56%, sensitivity 96.45%, specificity 98.96%, positive predicted value 99.2%, negative predictive value 95.2%, and minimum error rate detection 4.28%.

- ***Gonzalez et al. 2018***[18]***:*** They presented a system which has 3 major phases: organizing the EEG signals, feature extraction, and executing the classification algorithms. There are 4 motor actions represented via the utilized EEG signals: Right Hand, Left Hand, Foot, and Tongue movements, in the context of Motor Imagery Paradigm. The phase of feature extraction has been implemented through utilizing the CSP algorithm as well as a statistical approach which is referred to as Root Mean Square (RMS). The utilized classification algorithms are: K-NNs, SVMs, Multi-layer Perceptron (MLP), and Dendrite Morphological Neural Networks (DMNN). The algorithm has been utilized in the recognition between 4 classes of MI tasks. Subject 1 - 93.9 percent and Subject 2 - 68.7 percent.
- ***Buvaneash and John 2018***[19]: The study discuss the recorded EEG signals from the scalp of the subjects via noninvasive electrodes. Time-Frequency (TF) analysis approaches have been utilized for the purpose of extracting the features from EEG signals. ANN machine learning algorithm has been utilized as a classifier for learning EEG signals features for efficient classification of the output. They study presented performance analysis regarding the system's precision for

the suggested combination of TF analysis and an NN algorithm respectively for the EEG feature extraction and classifier.

- ***Braga, Lopes, and Becker 2019***[20]: The researchers presented an EEG processing method in Brain-Computer Interfaces (BCIs), it have the ability to detect certain patterns in the motor imagery of the subject, through splitting patterns in right hand or left hand imagery. They utilized Round Cosine Transform (RCT) and ANN module that identify the patterns. The approach is analyzed in real-time (RT) continuous EEG processing experiment simulation, controlling mouse arrow horizontally on screen based on the imagery motor activity of the user. The performance regarding this approach is estimated with regard to mutual (information (MI), the time for classification and rate of misclassification (%)). The obtained results have been 0.49 bits, 5.25 sand 15.6%, respectively.
- ***Corsi et al. 2019***[21]***:***A combination approach was adopted the features of EEG and magnetic brain signals (MEG) to improve the performance of classification in image-based computer brain interfaces (BCIs). The methodology applied to a group of fifteen healthy people found a considerable improvement in the performance of the classification in comparison to standard mono-beta approach in the alpha and beta domains. Combined, the results indicated that the BCI performance will be improved via integrating information from simultaneous EEG and MEG signals.
- ***Zheng et al. 2019***[22]***:*** They presented efficient system for ECG signals for MI classification. Initially, the TF features will be extracted through the use of modified S-transform (MST) algorithm, after that, SVM will be used to train the classifier. Furthermore, for the purpose of reducing the complexity related to MI-based BCI system, a channel selection will be implemented. The approach has been tested on BCI.

MST together with SVM has the ability of obtaining acceptable classification.

- ***Isa et al. 2019*** [23]: Researchers focus on the classification of MI in BCI through the use of classifiers from ML approach. The features of Fast Fourier Transform (FFT) has been extracted from EEG signals for transforming signals to frequency domain.Linear Discriminant Analysis (LDA) was utilized for minimizing the number of dimensions. There are 5 classifiers which are utilized in this study: SVMs, K-NNs, Naïve Bayes, Logistic Regression, and Decision Trees. Thus, SVMs, Naïve Bayes, and Logistic Regression reached the optimum accuracy.

In fact ,thesis submitted by ***Salim 2007***[8] under title " Design and Implementation of AI Controller Based on Brain Computer Interface " is the closest research with this study. used the same dataset(19 Channel)of signal EEG for brain computer interface to perform a task movement of right or left index finger , and test the performance of the Classification of brain signals.Used BSS algorithem to improve system performance.The researcher depended on FICABSS method while used stone BSS method. The signal was classified by using of adaptive pattern classifier that consists of a combination of the Kohonen Self-Organizing Map(SOM) and LVQ.We used two classifiers (NaiveBayes and Hoeffding Tree) , the results are better.

1.3 Problem Statement

The important problem in EEG recording is the large number of features. It does come from the fact that:

1. The EEG signals are nonstationary, therefore the features should be assessed in time-varying approach and could be distorted via artefacts

like EOG and EMG. And other artifacts ;This affects the performance of the system.

2. There is a large number of EEG channels. Furthermore, it is not easy to identify the mental state of the subject via EEG signals, the signals might be of high dimensionality, nonstationary, noisy, and complex.

1.4 Aim of The Thesis

The major aim of our work is analyzing EEG data of normal, voluntary and imagination of hand movements. Also, an algorithm that process EEG signals to extracts features that lead to a kind of mental tasks (whether it is left or right finger movement). Thereby determining whether humans can control machines by using their thoughts in EEG based Brain-Computer Interface. Also, aimed in this work is used classification and signal analyses algorithms. These algorithms will improve the speed and accuracy of EEG based BCIs by delete the artifacts that affect the accuracy of the system rating, also implement classification to discriminate between classes. and compare features extraction techniques.

1.5 Contributions

In short can summarize our contributions as follows:

- Design and implementation Automated, complete artifact rejection system in the electroencephalogram (EEG) signals.
- Using Algorithm to extract independent components in specific band by blind source separation.
- Using a stone algorithm with two classifier (Hoeffding Tree, Naïve Bayes) as first for Motor Imagery tasks classification.

1.6 Thesis Organization

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

Chapter Two: ***Theoretical Background***

This chapter includes concepts related to the structure of BCI systems as well A brief description is given of the basic functions of extracting signals from the brain and processing them.

Chapter Three: ***Implementation of the Proposed System***

This chapter present the implementation and analysis of the algorithm steps of the system.

Chapter Four: ***Experimental Results***

This chapter presents the obtained results and discussion for the evaluation of the performance of the established system.

Chapter Five: ***Conclusions and Suggestions for Future Work***

This chapter contains some derived conclusions and a list of suggestions for future work.

Chapter Two

Theoretical Background

Chapter Two
Theoretical Background

2.1 Introduction

In this chapter discuss the main ideas behind the BCI and blind source separation approaches that used for signal separation and We use of classifier to classify brain signals (Naïve Bayes and Heoffing tree). Also there is a brief introduction about the digital filters that used for filtering and smoothing the EEG signals.

2.2 BCI Concepts

Brain-Computer Interface (BCI) can be defined as a communication system which is developed for allowing individuals experiencing complete paralysis sending commands or messages without the need to send them via the normal output pathway of the brain. By using of control signals which are created from EEG activity[24]. The technology of BCI has been initially created for providing simply communications with no movement. Through identifying certain patterns related to the brain activity, BCI have the ability of getting an overview regarding the commands or messages the person that need to send. As an example for that, suppose a movement of the left-hand for the purpose of moving a cursor, wheel chair, or humanoid robots to left. BCI have the ability of detecting the activity of the brain via some sensors outside the head, like the electrode caps which identify EEG or sensors in the head, like the electrocorticography (ECoG) activity which is spotted throughout neurosurgeries. Initially, BCI have been presented for the purpose of helping individuals with severe motor disabilities, who else cannot have any sort of communications. Recently, there is a change in novel

applications and groups of patients, like providing help to the neurosurgeon to map the brain with extra accuracy for performing a surgery quickly and with more safety, as well as help the patients experiencing strokes to regain their movement, also involving BCI for helping new groups of patients like individuals with severe brain damage and cerebral palsy [25].

2.3 History of BCI

The creating of BCI systems goes back to the 70's as the Department of Defense in the United States had the aim to create systems which provide assistance for the pilot to interact with his aircraft. Regrettably, such aim was not possible in that time, since the computers which had been used in that time were extremely slow .Also there was no development for suitable approaches to handle huge data streams [26]. Since 1990, the studies on BCI field had initiated with much efficiency. since novel possibilities had provided via using optimum EEG devices and faster computers. Thus, there were more than twenty BCIs research groups, they have utilized various methods for addressing this subject, online BCIs have been built by not more than half of BCIs research groups [27].

2.4 BCI system structure

The major phases a system of BCI are (signal acquisition , signal processing, Application interface) as displayed in Figure (2.1).

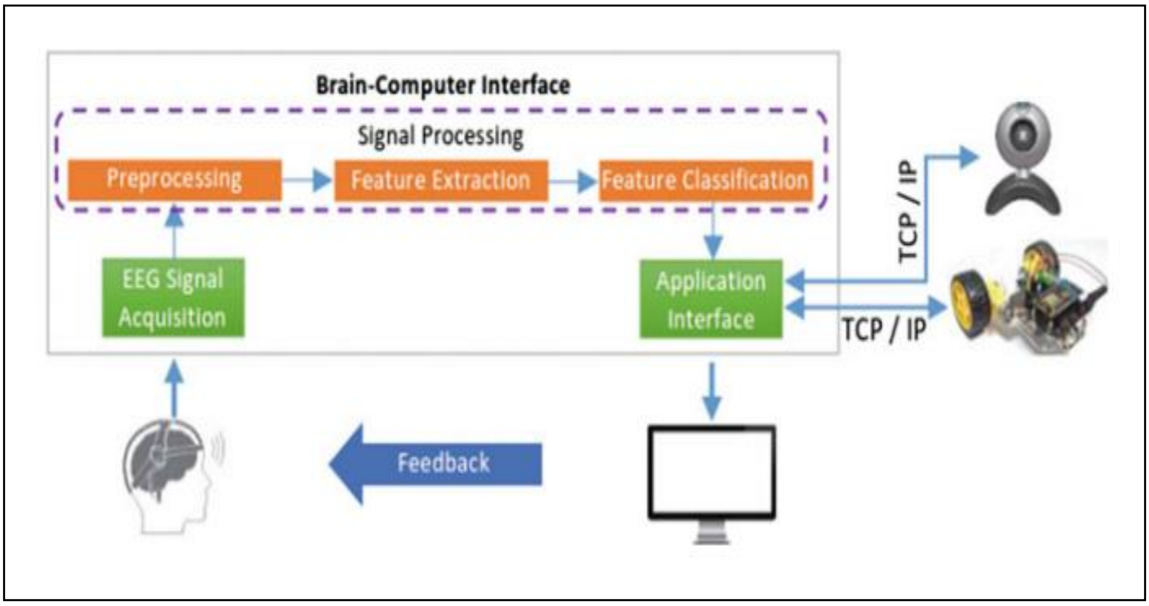


Figure (2.1): The components regarding the BCI-Based system[29].

(A):EEG signals acquisition unit: EEG signals might be simply recorded with the use of low-cost equipment (particularly, an amplifier and few electrodes). For the purpose of capturing the EEG signals, the electrodes must be correctly placed on the right position based on 10-20 System of Electrodes Placement. In the case of capturing the signal, 60-100 dB voltage gain will be used by the amplifier to amplify the signal. Due to the fact that the amplitude related to the EEG signals is approximately 100 µV, these large gains are of high importance [30]. With regard to such procedure, the analogue signal which have been captured that will be sampled for producing digital signal through acquisition equipment[31].

(B): Processing unit: This unit processes the acquired signals to extract the commands, and it includes:-

• **Signal preprocessing unit**: Prior to additional analysis, as soon as acquiring the signal, they must be noise-free and artifacts-free. Artifacts are defined as the electrical potentials which have been recorded and are

not created in the brain[32]. It has been indicated that the artifacts via EMG are used for the purpose of measuring the muscle's activation signal. EOG is measuring the retina's resting potential which might decrease EEG signals [8], [31].

• **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 [28]. 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.

• **Signal classification**: As soon as cleaning the signals, they must be classified for the purpose of identifying what type of mental task is performed by the subject [8].

(C) Application interface: As soon as classifying the signals, the output will be fit for the purpose of the output device. Additional functions could be accomplished, like speed control that is related to remote mobile robot through the use of TCP/IP connection, and displaying online screen of IP camera, that display feedback for the user with regard to the robot's movement [29].

2.5 Types of BCI signal acquisition systems

One of the major components of BCI systems is to measure the brain generated oscillations. It indicates the voluntary neural actions created via the current activity of the user [6]. Egistration regarding the signals of

the brain could be classified depending on few approaches, like noninvasive and invasive [29],as displayed in Figure (2.2).

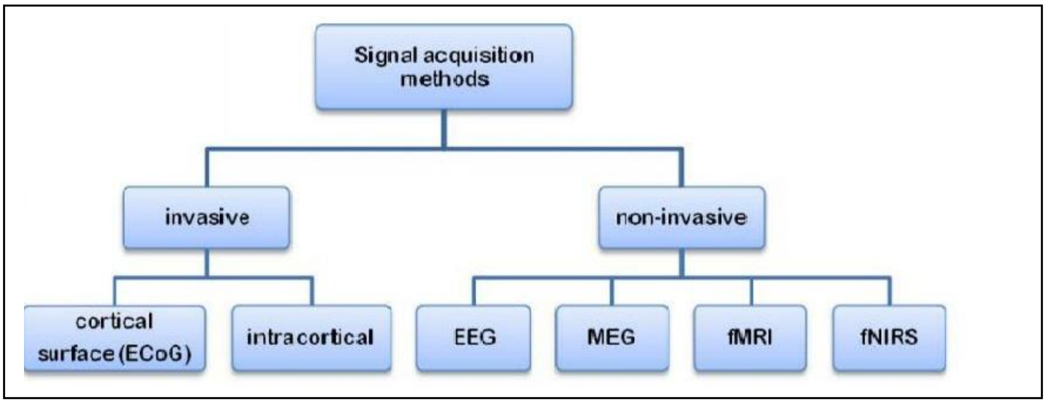


Figure (2.2): Signal acquisition methods[29].

2.5.1 Invasive BCI: In this approach, the electrodes will be implanted in neurosurgical way over the brain's surface or inside the brain of the subject. The advantages of such approach is that high-frequency components could be estimated with more accuracy, yet such approach is utilized mainly in animal experiments because of certain ethical aspects and risks related to the health of subjects [33]**.**

2.5.2 Noninvasive BCI: with regard to this approach, external sensors will be utilized for measuring the brain activities. Based on the international 10-20 standard, the electrodes will be fixed outside he skull. Such approach are utilized widely on humans since it does not affect their health, yet the drawback of this approach is that the measured signals have a lot of noise [29]. Invasive method depends on utilizing ECoG from the electrodes which have been implanted in the skull and it was used on certain epilepsy patients [34], as well as monkeys [35]. Noninvasive methods are utilized based on the use of EEG from the electrodes placed on the scalp or imaging approaches, like the functional Magnetic Resonance Imaging (fMRI)[36].

2.6 Neuroimaging

Recording the activity of the brain could be achieved via direct measurement regarding electrophysiological signals resulted from the action potentials, or via observing the changes flow of blood. The majorly utilized are the EEG, fMRI, near-infrared spectroscopy (NIRS), and magnetoencephalography (MEG). In the following sections, brief view regarding their applications will be presented:

2.6.1 Magnetoencephalography (MEG): record the magnetic field which are generated via the brain's electrical activity. It holds high spatial and temporal resolution, yet it is of high sensitivity to external magnetic fields. As an example, the natural magnetic field of the earth is quite a few magnitudes stronger than the MEG. Also, the MEG are big and costly devices, and that make them not fitting for BCI[38],as shown in Figure (2.3).

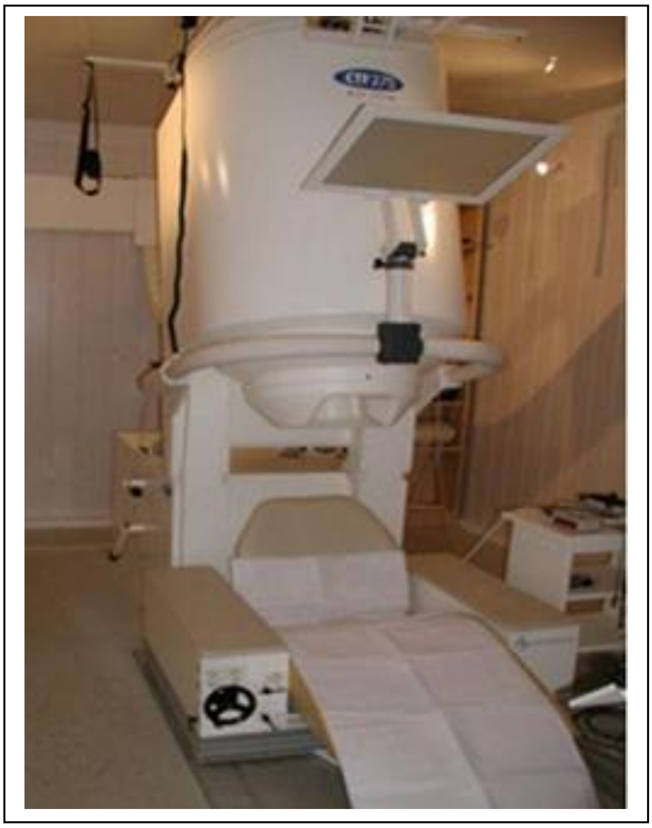


Figure (2.3): MEG acquisition[39].

2.6.2 Electrocorticography (ECoG): They record the cerebral activity via using electrodes positioned directly on the brain's exposed surface. Thus, this needs an invasive process. As the electric field is not damped via the scalp, it offers significant more optimum signal quality, with amplitudes in range between 10-20 mV, and protected through external contamination that lead to higher SNR[38],as displayed in the next Figure (2.4)**.**

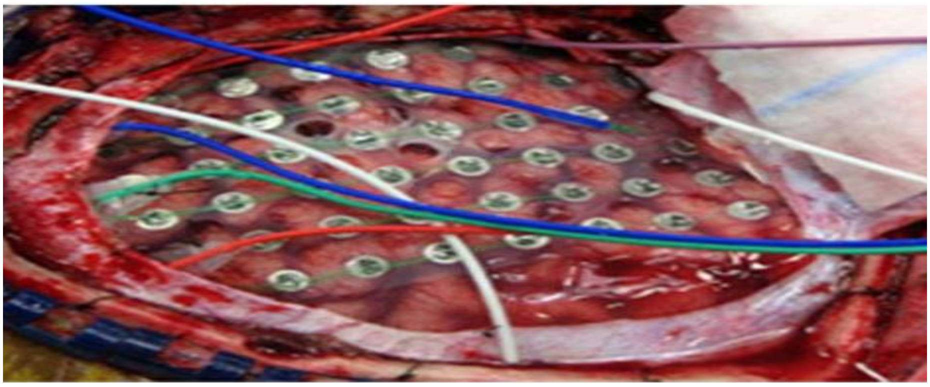


Figure (2.4): ECoG acquisition [39].

2.6.3 Functional Magnetic Resonance Imaging (fMRI) : As shown in the following Figure (2.5). One of the major neuroimaging methods is the fMRI, this method detects changes in oxygenation levels, cerebral blood flow, and local cerebral blood volume throughout the neural activation via using electromagnetic fields. The FMRI is majorly implemented through the use of MRI scanners that utilize electromagnetic fields of strength. High-space resolution is the major benefit of utilizing fMRI. Therefore, fMRI were utilized to localize the active regions in brain [40]. Nevertheless, there is low-temporal resolution of approximately one or two seconds with regard to fMRI. Furthermore, a physiological delay from three to six seconds is introduced via

hemodynamic response [41].FMRI is very susceptible to head motion artifacts inappropriate to be used for BCI rapid communication.

Figure (2.5): fMRI acquisition[39].

2.6.4 Near Infrared Spectroscopy (NIRS): As shown in the following Figure (2.6). NIRS can be defined as optical spectroscopy approach which uses infrared light for characterizing non-invasively obtained fluctuations in the cerebral metabolism through neural activity. The infra-red light penetrate the skull to a depth of about one to three centimeters below the skull's surface, as the intensity regarding the attenuated light allow alterations in deoxyhemoglobin and oxyhemoglobin concentrations to be estimated. Since only shallow light can penetrate the brain, such optical neuroimaging approach is used only on outer cortical layer. In comparable approach to the fMRI, a major drawback of NIRS can be defined as the nature regarding hemodynamic response, since the vascular changes happen some minutes following its related neural activity [42]. There is low spatial resolution in NIRS, in order of one centimeter [43]. However, NIRS provides inexpensive, elevated portability, as well as suitable temporal resolution in order of one-hundred milliseconds [44].

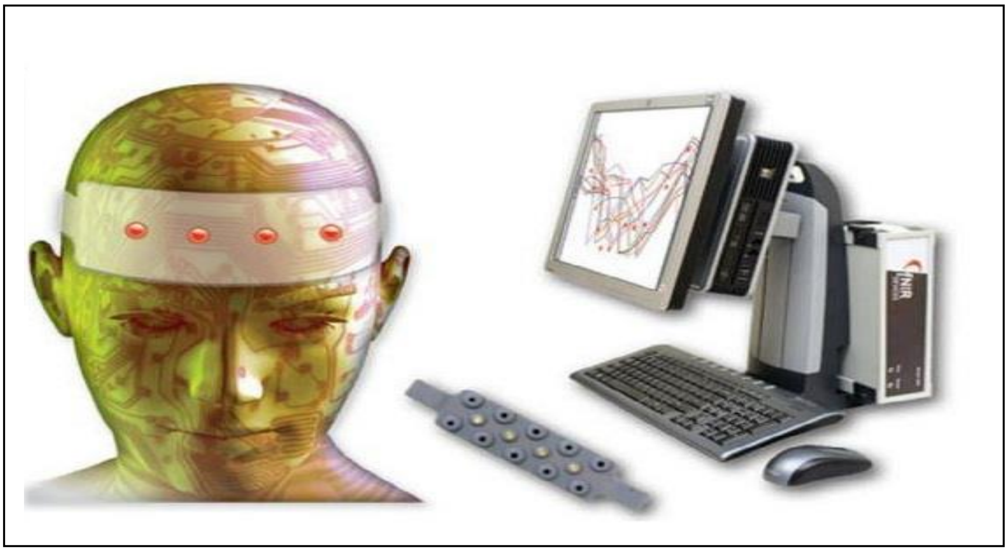


Figure (2.6):NIRS acquisition[39].

2.6.5 Intracortical Neuron Recording: It can be defined as neuroimaging approach which operate by measuring the electrical activities in the brain's gray matter. It can be defined as invasive recording modality which requires implanting micro-electrode arrays in cortex for capturing local field potentials and spike signals from the neurons. The temporal and spatial resolution provided by intracortical neuron recording is higher than that provided via EEG recording. Thus, intracortical signals are used with more simplicity than the EEG signals. Yet, the quality of the signals could be impacted via the reaction of the cerebral tissues to the implanted recording micro-electrode and via modifications in the micro-electrode's sensitivity, that could be increasingly impaired throughout days and year [45].

2.6.6. Electroencephalography:EEG can be defined as noninvasive medical approach which is utilized for measuring the electrical activity of the brain, that is generated from the joint activities regarding millions of cortical neurons. Electrodes placed on the scalp of humans are used to measure such activities [46]. The amplitude regarding the EEGs signal is considered to be in the order of microvolt[26]. In 1924, H. Berger Was

first Whose measured EEG signals in humans. In the year 1929, he presented the initial study for explaining the approach to record the brain's electrical activities from the scalp [27]. EEG signals are complicated spatio-temporal signals, they are also based on the subject's state and on certain external aspects, even in the case when the behavioral state of the subject is just about constant. The duration that is related to epochs which hold the same statistical features (in other words, which are stationary) that is considered to be limited. EEG signals temporal resolution is optimum in milliseconds or even better. Whereas the spatial resolution is insignificant, it is on the basis of the number of electrodes about in centimeter range [3], as displayed in Figure (2.7).

Figure (2.7): EEG acquisition[39].

At first, researches utilizing EEG extracted conclusions through manual measurements and visual interpretations regarding EEG traces. Thus, results have been inaccurate. Because of the advances in computerized data processing, it was feasible for the EEG signals to be analyzed digitally with non-parametric and parametric approaches. The advances in electrical engineering field with the brain of humans were the main focus of studies from various fields for the purpose of investigating the recordings of EEG. Today, there is at minimum 3 reasons explaining which such approach is utilized extensively [47] [4].These reasons are :

i. High-temporal resolution is provided via EEG that cannot be implemented via other approaches of neuroimaging. A resolution of several milliseconds is provided via EEG, while fMRI and PET are limited to a several seconds.

ii. Information regarding the approach which generate spontaneous EEG activity has elevated.

iii. The systems of EEG recordings takes less money than the PET and fMRI scans taking multi millions. Recently, novel approaches for EEG analysis have been developed, like the Blind Source Separation (BSS), or time-frequency analysis like wavelet analysis.

In The past EEG was introduced as beneficial took in clinical neuroscience for the above-mentioned reasons. Particularly, the EEG system was utilized extensively due to its low costs. Thus, a lot of hospitals and research centers presently have their own system of EEG recordings. Today, EEG is utilized in various applications in clinical neuroscience. Several of these applications are:

- Diagnosis of insomnia, brain death and coma.
- Identify areas of the brain affected by a particular accident or tumor.
- Neural tract test.
- Background neurological applications.
- Control the degree of anesthesia in some cases.
- Diagnosis of epilepsy.
- Monitor the development of the brain in humans and animals.
- Determination of neural effects of certain drugs.

For more information ,see [48] [4].Although that EEG was mainly utilized in clinical neuroscience, other fields have taken advantage of

using EEG. For instance, EEG was utilized in BCI for the purpose of communicating a machine and the brain of humans. Various applications could be generated from the systems of BCI, like controlling machines and controlling video games.

2.7 Rhythmic Brain Activity

Depending on the consciousness level, the brain waves of normal individuals show various rhythmic activities. Various thoughts and actions impact these rhythms [39]. Thus, the rhythms could be characterized via their duration, frequency, amplitude, and areas of the brain areas where the rhythms are created [49]. 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 (2.8).

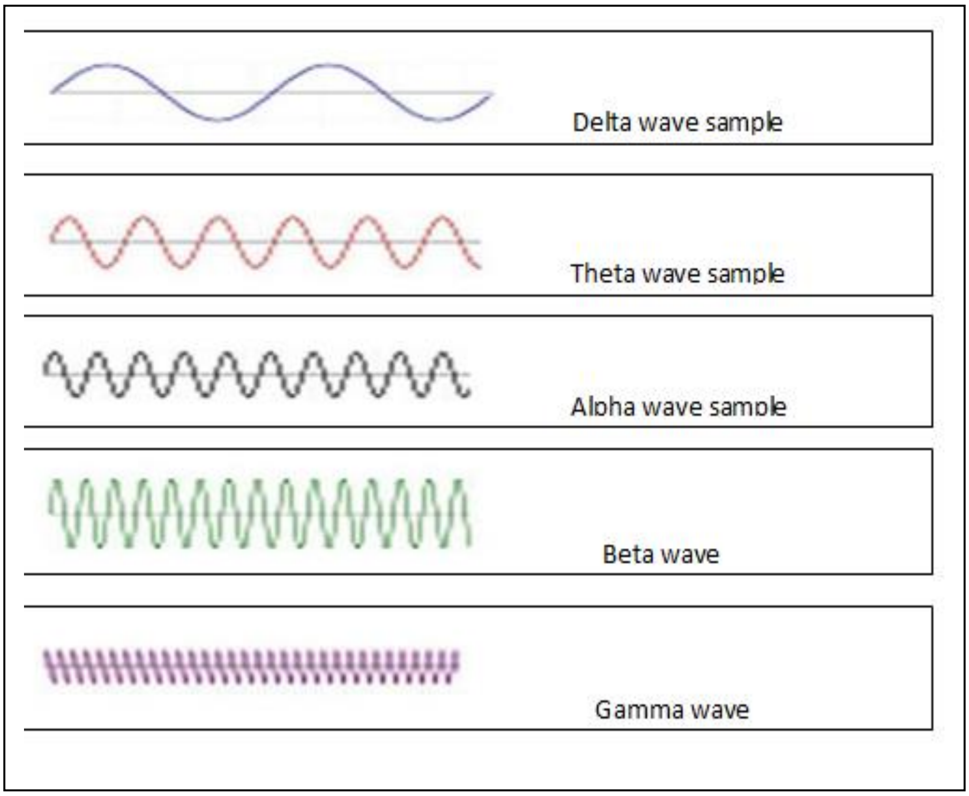


Figure (2.8): EEG waves[28].

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 [6]. as displayed in the following Figure (2.9).

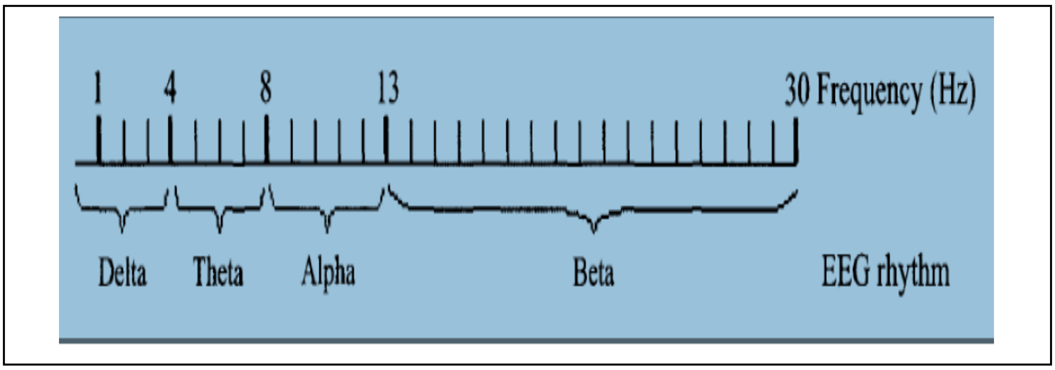


Figure (2.9): Frequency Bands of EEG signal[6].

1. 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[3].

2. 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 [27]. 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[47].

3. 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.

• **Mu Rhythm**: Mu Rhythm is considered to be 8-12 Hertz, with amplitude not more than 50 μV, and it is related with motor activities .It excellently recorded over motor cortex. The movement will block this rhythm. The block will appear prior to the actual movement of the muscles, thus it is associated to the movement's conceptual planning [3].

4 .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 [3].

5. 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 [4].

2.8 EEG Electrodes System

The first standardized system was presented at the 2nd International Congress of IFSECN in Paris in 1949 and published by Jasper in the year of 1958, International Federation in Electro-encephalography and Clinical Neuro-physiology have adopted standardizing for the placement of electrodes which was referred to as the 10- 20 electrode placement system[8].The "10-20" system is an internationally recognized approach that describes scalp electrode locations for an EEG test, as shown in Figure(2.10).This system has been modeled on the basis of the correlation between the electrode's location and the underlying cerebral cortex area. The numeric term "10" and "20" means the distances between

neighboring electrodes are either 10% or 20% of the skull's total right - left or front - back distance. Every site is labelled with a letter identifying the lobe and a number for identifying the location of the hemisphere. The letters F, T, C, P and O respectively indicate the frontal, temporal, central, parietal and occipital. A line joining nasion and inion divides scalp into two hemispheres (i.e. left and right) [50].

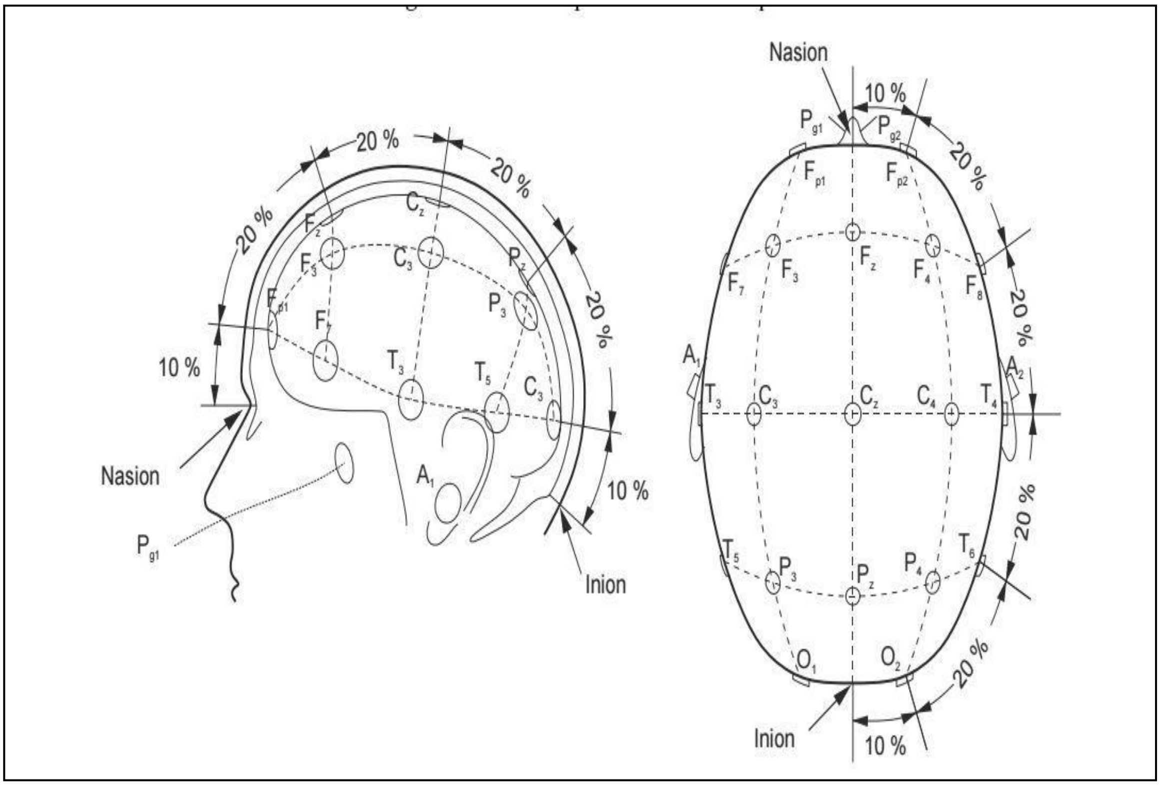


Figure (2.10): Electrode placement over scalp[1] .

2.9 EEG Recording System

The brain signal is usually taken by several different pairs of electrodes to obtain several different signals from the brain signals, thus obtaining a general idea of the entire brain signal rather than the one region .There are two most common modes used in EEG recording system, are :

2.9.1 Bipolar mode

In this mode differential measures are carried out between consecutive electrode pairs. This mode became void with inventing computerized EEG, Pairs of surface electrodes reach the entrances of the amplifiers in a symmetrical order. Typically, half of these inputs reach the electrodes from one side of the head, so we can compare the electrical efficiency of the corresponding regions of the brain by comparing the signal of each electrode with another electrode[8]. as illustrated in Fig. (2.11).

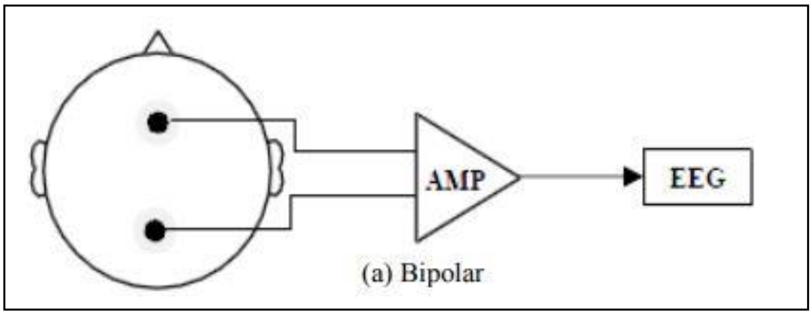


Figure (2.11): EEG placement electrode method (Bipolar mode).

2.9.2 Monopolar mode

A reference electrode that chosen in monopolar mode is a reference channel which is used to all channels, and ideally this reference is electrically inactive, but in practice case it has electrical activity. There are many positions on the head used as a reference electrode: Forehead, Cz electrode, linked ears, contralateral ear, linked mastoids, and ipsilateral ear. The choice of reference is very important to obtain useful information from brain, and could generate topographic distortions in the case where rather electrically neutral region isn't used. Monopolar mode is used widely because it is easy to localize the event of interest [46]. Whereas the reference of Cz is beneficial when located in the middle amongst active electrodes, nonetheless for adjacent points it gives bad resolution [8]. as depicted in Fig. (2.12).

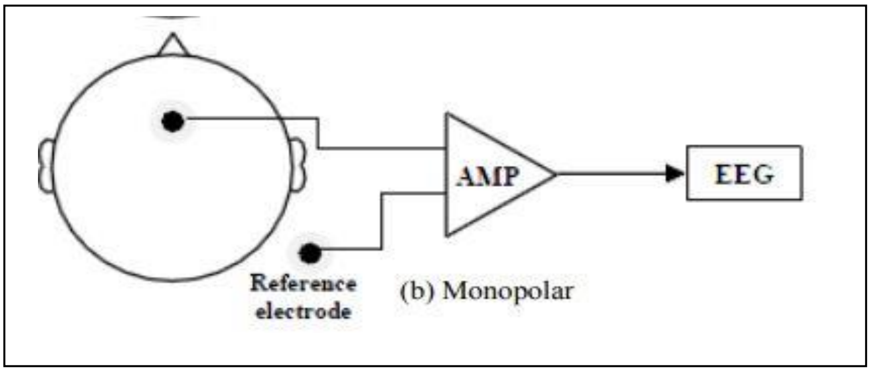


Figure (2.12):EEG placement electrode method (Monopolar mode).

The difference between bipolar and monopolar recordings is their placement Both electrodes are putted on the interest area in bipolar mode, but one of the electrodes is placedon the scalp, and the other one is putted away from the interest area in the monopolar mode.

2.10 EEG Artifacts

When EEG is measured, each signal does not come from the brain's electrical activity. Numerous possible changes that are observed in EEG could come from other sources. Those changes are referred to artifacts and they might result from sources such as the subject or the equipment . Fig (2.13) illustrates wave-forms of some of the most common artifacts of EEG. Those artifacts include [27].

2.10.1 Technical Artifacts

1. **Noise interference of the power lines**: Highly strong signals that are produced from AC power supplies contaminating the signals of EEG throughout the process of recording. The Notch filter is utilized for removing this artifact that is of lower frequency and harmonics. However, notch filter is well eliminated useful information which is the EEG data about 50/60 Hz. Line noise might interfere with part of the electrodes that

are based on the interference issue source or all of them [51], as shown in Figure (2.13, d)**.**

2. **Sweating:** This artifact type is a result of sweat that affects electrode impedance.
3. **Electrode artifacts**: Those artifacts are a result of varying electrode impedance because of improper attachment or poor conditions**.**

2.10.2 Biological Artifacts

1. Eye Blinking Artifact: This is one of the common artifacts in the data of EEG, it results in a signal of high amplitude which may be several times stronger compared to the relevant EEG signals. Due to its high amplitude, a blink of the eye might damage the data on every electrode, even the electrodes that are located at the back of the head. Eye artifacts are usually measured in a more direct way in electroocculargram (EOG), electrode pairs that are placed around and above the eyes. Unluckily, those measures are contaminated with the signals of EEG [52]. Eye blinks are shaped like spikes [51] , as shown in Figure (2.13, b).

2. Eye Movement Artifact: Those artifacts result from the movements of the eye, because of a frictive mechanism which is similar to the one underlying artifacts of eye blinks but involve cornea and retina instead of cornea only. The artifact of eye movement impacts the frontal electrodes positioned near the temporal region, for example F7 and F8. This impact on the electrodes may be asymmetrical or symmetrical, based on whether the motion is horizontal or vertical, respectively[4]. Movements of the eye are shaped like squares [51], as depicted in Fig. (2.13, c). The impact of the artifacts of eye movement is very similar to impact of the artifacts of blinking, except for the fact that the content of their frequency is even lower, and the amplitudes are usually larger [4].

3. Muscle Activity artifact MEG: Those artifacts, usually implying considerable brain signal disturbances, are a result of the electrical

activities which are result from the contractions of muscles that happen when the patient is chewing, swallowing, or talking, [1], as shown in Figure (2.13, e).

4. Electrocardiogram ECG or heartbeat artifact: It is occurring in the case where the electrode is placed on or near any blood vessels [8]. This type of artifact, reflecting the activity of the heart, give a rhythmic signal to the activity of the brain [53], as shown in Fig. (2.13, f).

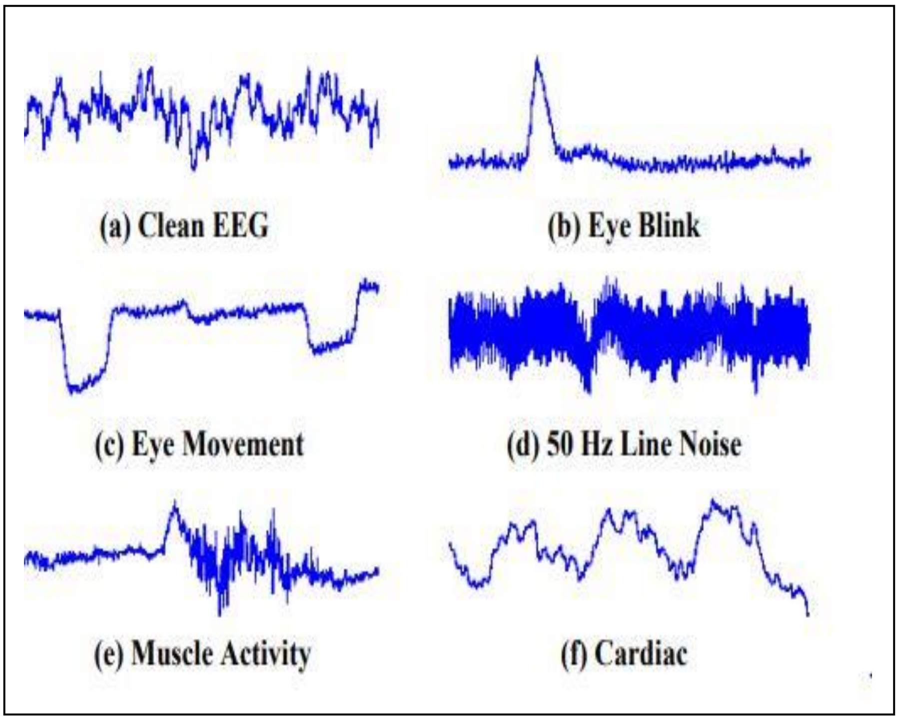


Figure (2.13): Artifact waveforms[8].

2.11 Applications of Brain Computer Interface

BCI is an area of interest to the experts, due to the fact that it may be helpful in solving numerous issues that are seemingly impossible. The key objective of the BCI applications is converting the thoughts or intent of the user into an action in an external computer or device and control those devices. Numerous BCI applications are focused on the patients suffering from disorders of consciousness (DOC).Those patients are not capable of communicating with the surrounding world [54]. With the use

of the BCI, those patients become capable of controlling some devices for performing important and basic jobs that they need with no help, such as getting something to eat or drink, or moving with wheelchair with the use of robotic arms or legs that are controlled with the brain. Technologies of BCI are utilized for restoring vision to the blind via connecting an external camera to the brain [55]**.** Device control applications don't only include patients, but healthy users as well, such as the ones who need to get many jobs done simultaneously like astronauts and drivers where they keep their hands on swimming, operate equipment and the steering wheel[56]. Some research also show the applications of the brain computer interface in below:

1. **Understand the work of the brain:** BCI was used to understand the functioning of the nervous system as in research[57]. It was known that the skilled movements are generated in the brain and movement rhythmic as the pathway is generated in the spinal cord. But after getting the MEG signals from 6 people in several movements and processing it, shows that the spinal cord also contributes to the generation of skilled movements, not just the brain.

2. **Sure to save information**: Researchers in [58],investigated whether it was possible to predict the proper conservation of words previously learned through brain activity only. Participants were asked to memorize two pairs of words in German and Korean. Their memorization was examined on the same day and the next day after learning. To find out if Recorded brain activity using multi-channel EEG was able to predict formation in memory. Where they used statistical methods and then classified to indicate by using linear discriminator linea analysis .Then The were using convolutional neural network where they were able to predict the words to be saved by of brain activity in the methods used.

3. Helping spinal cord patients to move: Spinal cord injury disrupts the transmission of signals between the brain and the rest of the body, preventing mobility and causing paralysis. Robotic machines and prostheses can help patients to move independently as they are controlled by the interface between the machine and the brain to transform brain signals into commands[59].

4. Wheelchair Control: BCI is used to control the wheelchair by using EEG signals for people with total and non-paralysis able to control the chair[12].

5. Balance game (Mid Balance) : It is a game that uses the BCI to interact with the virtual world. This game includes a 3D animated character in a virtual environment and the goal is to maintain the balance of this character as it moves on a rope in one direction by using the EEG for the player[60].

2.12 Signal preprocessing

An important problem in the automated analysis of EEG is detecting the various types of artifacts (i.e. wave-forms of interference) which is added to the signal of EEG throughout the sessions of recording [61]. Detecting and eliminating artifacts from EEG is a complex task, nonetheless it is of great importance to develop practical systems. Artifacts are the undesirable signals that exist in the EEG. They are of different origins, including the frequency of utility (which is 60Hz in the U.S.A or 50Hz in Europe), blinks, or movements of the body and the eyes, the frequency artifacts of the utility have been already eliminated from data with the use of the notch filter. Which is why, there is a need for removing eye artifacts, for which there are 3 main methods: removal avoidance, and rejection [53].

In the avoidance of artifacts, the user is simply does not to be executing motions resulting in artifacts of EEG. This may decrease the number of artifacts, however, as it is obvious, blinks and eye movements can never be completely avoided, which is why, those artifacts happen from time to time. What is more, continuously avoiding blinking is tiring for the user.

One more method is rejecting each trial, which is contaminated with artifacts. This may be accomplished automatically or manually. In the manual process of artifact rejection, the expert decides the trials that are contaminated via visual examining. In automatic process of artifact rejection the algorithm is done that is capable of determining whether or not a trial is contaminated with an artifact. One of the simple versions of this algorithm could be operating via checking whether the electrooculogram (EOG, an approach for the recording of the movements of the eyes) channel amplitude is greater than a predetermined threshold. Then it should be considered a trial to be contaminated. The key issue with the rejection of artifacts is that it decreases the training set size, and it may affect the accuracy of classification.

In the last method, removal of artifacts, some approaches are utilized to remove any components that are related to artifacts from the signal of EEG, but preferably maintain the integrity of the desired brain-originated signal. The sufficient artifact removal approach is signal high-pass filter. The artifacts of the eye happen in 0Hz–4Hz frequency range, therefore, via filtering out those components, EOG artifacts may be reduced. Filters are vitally important in the pre-processing step for removing certain frequencies from a received signal and reduce the amount of artifacts.

2.12.1 Band-pass filtering(BPF)

Band-pass filter is utilized to remove some artifacts distributed in some frequency range, and to get useful information about physiological phenomena. For example, the frequency of EOG is usually less than 4 Hz. Band-pass filtering may be employed to remove this artifact before extracting ERD feature associated with mu and beta rhythms. Before spatial filtering, band-pass filtering is usually employed[62]. Band-pass filtering can be easily implemented by infinite impulse response filter, such as Butterworth filter. In MI-BCI system, the frequency band including mu and beta rhythms is determined. The maximum frequency of EOG is 4 Hz, and minimum frequency of EMG is 30 Hz. The low-pass filter and the high-pass filter are adopted to remove them respectively. Frequency filtering is simple and common. The disadvantage is the amount of information that is limited and it is unable to handle time-varying signals [8].

A high-pass filter allows to pass frequencies which are the frequency of the cut-off and it eliminates any or slow fluctuations or any component of steady direct current (DC) from the signal. For the sake of stabilizing a signal’s baseline, those filters have to be utilized, in other words, minimizing the baseline drift in the signal of ECG [2].

2.12.2 Notch filtering

Notch filtering is usually implemented by the filter in hardware amplifier, to suppress 50/60 Hz power line noise. In most countries, 50 Hz power frequency voltage is employed[62].

2.13 Blind Source Separation(BSS):

As real time human-machine interfaces based on BCI systems require being fast and accurate, the signal separation stage must present these attributes in its implementation, as a primary objective, too. Therefore, both the academia and the industry are continuously researching on new ways to reach this goal. There are two popular approaches which can accomplish the goal, which are: beamforming and blind source separation (BSS) [63].

Blind source separation(BSS), which is referred to as blind signal separation as well, is an approach for the separation of underlying source signals from observations (i.e. the mixed signals) that are combinations of the original sources, with no or very little information concerning the original mixing process sources. In a non-invasive approach (EEG), the sensors (i.e. the electrodes) are located around or at the surface of the head (i.e. the scalp) at quite close distances. For any human action, many source numbers (i.e. neurons) are active (i.e. stimulus). Every one of the sensors (i.e. electrodes) measures a mix of those stimuli from sources and every one of the sensors is measuring a different mix based on the distance between them and the sources[64], as depicted in Figure (2.14).

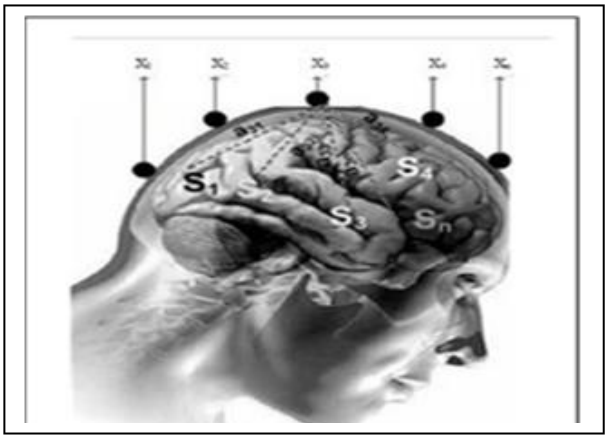


Figure (2.14):Brain signal analysis: BSS problem [64].

Due to the fact that those are non-invasive approaches, there is no idea of the sources and the procedure of mixing which took place in the head. Which is why, the analysis of cerebral signal may be viewed as an issue of BSS. The data of EEG represents a projection of a signal set that are mixing artifact and cerebral signals, onto the sites of sensors (i.e. electrodes). BSS decreases the mixes of the neural and the non-neural variables to the independent elements of one another. A variety of approaches of the measure of independence give a variety of BSS approach [65]. Signals of EEG are multi-channel data, which is why, approaches of BSS are very suitable for analyzing them[64]. There is a wide range of approaches that have been suggested for cleaning brain signals, nonetheless there isn't one single approach that is considered as the optimal one, where each approach has its own set of benefits and drawbacks. In general, the approaches of BSS are the more judicious for separating the artifacts from mixes of EEG.

The diagram of the processes of mixing and separating in BSS has been illustrated in Figure (2.15). Astandard linear BSS mixing model with m observed mixes ($x_1(k)$, $x_1(k)$, ..., $x_m(k)$) of an independent component ($s_1(k)$, $s_2(k)$, ..., $s_n(k)$) [66].

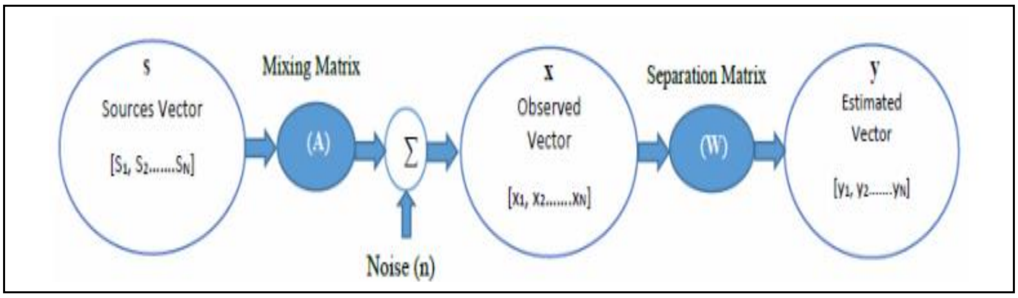


Figure (2.15): Blind source separation stages[67].

That may be expressed as:

$$X\ (k)=AS(K) \qquad (2.1)$$

where:

$$X(k) = [x_1(k),\ldots..,x_m(k)]^t \qquad (2.2)$$

$$S(k) = [s_1(k),s_n(k)]^t \qquad (2.3)$$

where, superscript t refers transpose operator; $A \in R^{m*n}$ indicates the matrix of mixing. The symbol (k) represents the index of time or sample. The model of separating can be expressed as:

$$EY(k) = WX(k) \qquad (2.4)$$

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

$$Y(k) = [y1(k),y_n(k)]^t \qquad (2.5)$$

The issue of BSS is estimating the optimal separating matrix W, which is optimally = A^{-1}.

Approaches if BSS have been utilized with success in a wide range of engineering and applied science areas, Then it include tele-communications, medicine, noise elimination, audio processing, and data processing [68]. A wide range of strategies were utilized for BSS. One of those strategies is the pursuit of projection [69],which has been modeled on the basis of the central limit theorem (CLT). It has the aim of finding a vector of weight in a way that the signal which has been obtained from a group of signal mixes is as non-gaussian as possible. An approach of BSS such as the ICA (independent component analysis) attempts to maximize the inter-signal statistical independence. ICA which is based on Info-max increases the signal distribution entropy rather than their independence and it accomplishes the same results. Rather than higher-order statistics (HOS), some approaches utilize the second-order statistics (SOS) of some

sources, such as SOBI, Stone BSS, and AMUSE [70]. Lately, Stone in [71] presented an approach of BSS 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. Due to the fact that it is a low complexity batch method, it drew the interest of many scholars [72].

2.13. 1 History:

Blind technique was found in the 1980s; the word "blind" is denoting the inversion or recording method which based on observation only [73].This technique was used firstly to design adaptive equalizer for digital communication system. In 1982; the formulation of source separation was prepared by Comon in [74]. The blind source separation problem was formulated around 1984 ,see [73].Using higher-order moments for matrix approximation and then other similar studies on this field was developed to describe theoretical fundamentals as in [75]. The fast BSS algorithm was developed for independent component analysis [76].

2.13.2. BSS Applications

The approaches of BSS have been utilized with success in a wide variety of engineering and applied science areas, which include medicine, audio processing, tele-communications, data processing, and noise reduction [68]. During the last decades, wide research area are opened when using BSS technique to analyze the medical signals, particularly in brain signal, whereby the BSS used as a signal processing tool to reject the artifacts and clean the brain data. [77].

2.13.3 Stone's Temporal Predictability Measures:

One of the important technique is the stone BSS technique, this method of BSS utilize the temporal predictability of the mixed signals as shown in Figure(2.16). This method took its same name from the scientist who invented it[78].

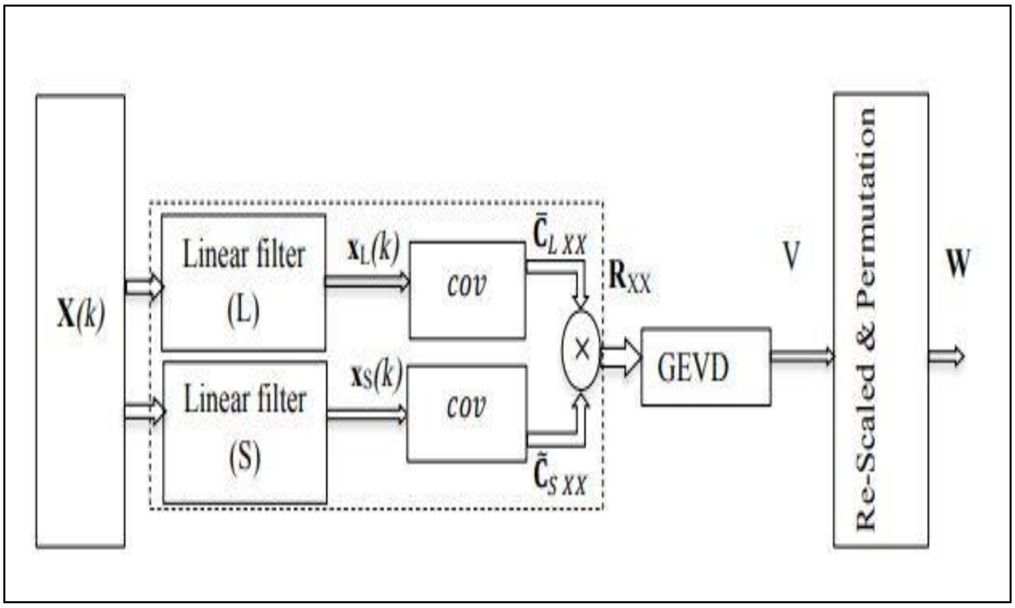


Figure (2.16). Schematic diagram of the Stone BSS[78].

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 2^{nd} feature is utilized for separation. Stone has expectations for this approach, which could be beneficial for analyzing in medical areas [66]. The mixing system without noise is:

$$X(k) = A\,S(k) \tag{2.6}$$

Where

$x(k)=[\, x_1, x_2 \ldots. X_n]^t$ is the mixture vector (known),

$S(k)=[\, s_1, s_2 \ldots. s_n]^t$ 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

$$Y(K)= W\, X(K) \qquad (2.7)$$

Where

y(k)=[y1, y2 …. yn]t, y is the permutation of s up to scaling factor. Stone's measurement of the temporal predictability of a signal y(k) has been characterized as

$$F(K) = LOG\,\frac{VY}{UY} \qquad (2.8)$$

Which is simplified to

$$F(K) = LOG\,\frac{\sum_{k=1}^{n}(\text{ylong(k)} - \text{y(k)}) * (\text{ylong(k)} - \text{y(k)})}{\sum_{k=1}^{n}(\text{yshort(k)} - \text{y(k)}) * (\text{yshort(k)} - \text{y(k)})} \qquad (2.9)$$

Where

Yshort(k)=βs yshort(k-1)+(1-βs) y (k-1),0<= βs<=1

Ylong(k)=βS ylong (k-1)+(1-βs) y (k-1), 0<= βs<=1

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

$$ci,j^{(\,short)} = \sum_t \left(x_{it} - x_{it}^{(short)}\right)\left(x_{it} - x_{it}^{(short)}\right) \qquad (2.10)$$

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

$$ci,j^{(\,long)} = \sum_t \left(x_{it} - x_{it}^{(long)}\right)\left(x_{it} - x_{it}^{(long)}\right) \qquad (2.11)$$

Finding the eigenvectors (W1,W2,W3,…..,WM) of matrix as follow

$$W_i\, c^{short}\, w_j \;\; (\,short) = \sum_t \left(y_{it} - y_{it}^{(short)}\right)\left(y_{it} - y_{it}^{(short)}\right) \qquad (2.12)$$

$$W_i c^{long} w_j \ \ (long) = \sum_t \left(y_{it} - y_{it}^{(long)}\right)\left(y_{it} - y_{it}^{(long)}\right) \qquad (2.13)$$

Finally the separating matrix w calculated by Matlab eigenvalue function as:

$$W = \mathrm{eig}(ci, j^{(long)} ci, j^{(short)} \qquad (2.14)$$

2.13.4 Independent Component Analysis(ICA):

ICA is quite a recent approach for BSS that appears to perform better than the traditional PCA(Principal component analysis) in a wide variety of applications. Particularly, it is implemented for extracting ocular artifacts from EEG, while conventional PCA was not capable of separating artifacts of the eyes from signals of the brain, particularly when they have mathematically similar amplitudes [80].

$$X = AS \qquad (2.15\ )$$

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

$$\widehat{\mathrm{S}} = \mathrm{WX} \qquad (\ 2.16\ \ )$$

Where, $\hat{S}$ refers to estimated sources, W is the inverse of A. in the case where the BSS is implemented in EEG, artifacts' removal is carried out via setting sources that are characterized as artifacts to 0 in the following manner:

$$X_{clean} = \ A\hat{S}_{clean} \qquad (\ 2.17\ )$$

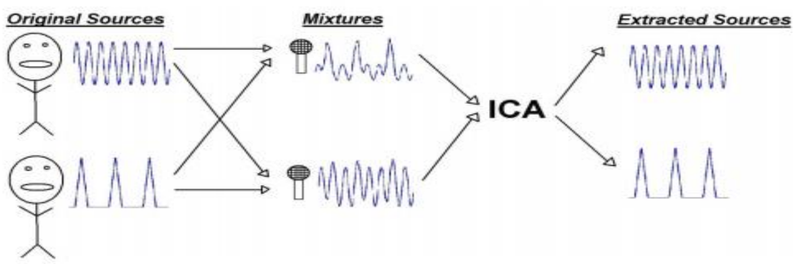


Figure (2.17):ICA in context of "cocktail party effect" [81].

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

(A): Centering: is to center the observed variables by subtracting their sample mean[80], as in the equation below:

$$\boldsymbol{x} = \boldsymbol{x'} - E(\boldsymbol{x'}) \quad (2.18)$$

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:

$$E(s') = \boldsymbol{A}^{-1}E(\boldsymbol{x}) \quad (2.19)$$

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

(B): Whitening: whitening is to transform the observed vector x to another vector y, so that its components are uncorrelated and their variance equal to unity ; That is the covariance matrix of y equal to identity matrix:

$$E(\boldsymbol{y}\,\boldsymbol{y}^T)=\boldsymbol{I} \quad (2.20)$$

The whitening is a linear transformation (transforms the observed vector x by linearly multiplying it with some matrix V) [81].

$$\boldsymbol{y}(k)=\boldsymbol{Vx}(k) \qquad (2.21)$$

Where y is the whitened vector, and V is the whitening matrix.

by using the Eigen- valued composition technique (EVD) of the covariance matrix the whitening matrix is obtained :

$$GX = E(xx^T) = EDET \qquad (2.22)$$

where Gx is the covariance matrix of x, E is the orthogonal matrix of eigenvectors of Gx, and D is the diagonal matrix of Eigen vales of Gx.

Thus the whitening matrix is[8]:

$$V=D^{-1/2}\, E^T \qquad (2.23)$$

2.13 .5 Fast Independent Component Analysis (FICA):

FastICA is an efficient implementation of ICA technique and a technique of popularly utilized BSS approach [83] . 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. It additionally has the benefit of multi-component extracting, and the performance of the system does not degrade [82].

$$Z = A_M . s_D \qquad (2.24)$$

Here, Z indicates the observed matrix, A_m 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.

$$s_D^* = X.Z \quad (2.25)$$

$$X = A_m^{-1} \quad (2.26)$$

The FastICA . unit vector w such that the projection $w^T x$ maximizes the nongaussianity. The nongaussianity is here measured by the approximation of negentropy. The basic form of FastICA for obtaining one independent component .

2.13.6 JADE - Joint Approximation Diagonalization of Eigenmatrices:

The JADE algorithm that is particularly a statistic based approach[84]. Besides the previous approaches of kurtosis and entropy, JADE[85], as SOBI does, uses JD and whitening. However, the main difference between both is the set of target matrices on which JD is done JADE performs it on $\frac{n}{2}(n+1)$ eigenmatrices that are computed by the fourth order cumulants of whitened signals:

[Qz(epeqH]ij) = Cum(zi, zj, zp, zq) (2.27)

the source components that is estimated and founded by using the rotation matrix O and processed matrix X.

$$Z = X * O^{-1} \quad (2.28)$$

2.14 Classification:

One of the most significant data mining methods is the classification of huge data sets, also it is utilized for solving ML algorithms and statistics for the aim of extracting patterns and rules from the data which are utilized for prediction[86].

There are various types of classification approaches such as NN method, rule-based classifier, nearest neighbor classifier, statistical approaches, and decision tree induction. The main aim of classification is building mapping function which assign class label for every new instance or verifying the suitability of class labels previously assigned[87].

Mathematically: the classification process can be specified in the following way: Assumed database $X = \{x_1, x_2, x_3, .., x_n\}$ of tuples (records and items) in addition to set of classes $Y = \{y_1, y_2, y_3, …., y_m\}$. The classification process is about learning a target function $f: X \rightarrow Y$ which map every attribute set x to one of pre-defined class labels y. Informally, the target function has been recognized as a model of classification and is shown in Figure (2.18). Therefore, classification is the process of mapping input attribute x into its class label y.

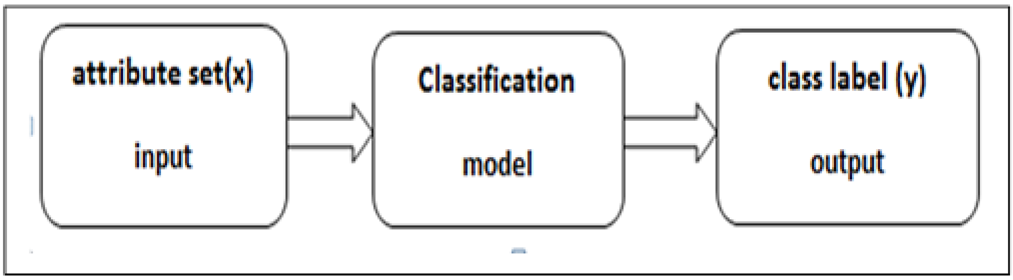


Figure (2.18):Classification problem as the task of mapping

The common method to solve classification problems Initially, training set which consist of records whose class labels are recognized should be presented .The training set will be utilized for building classification model, that will be utilized to the testing set that include records with unidentified class labels. There are various algorithms which are utilized for data stream classification .

2.14.1 Hoeffding Tree (HT)

HT are initially suggested in [88] by Kirkby. It can be defined as one of the major algorithms that is used for the classification of stream data. This algorithms is state-of-the-art approach. Utilizes Hoeffding bound (HB) to construct and analyze decision trees and utilized for deciding how many instances must be operating for the purpose of achieving particular confidence levels. HT have the ability of learning from huge streams of data with the suggestion that the distribution generating examples will be changed with time. Classification problem can be defined as collection of training samples of the formula (m, n), in which 'm' represents the vector of the n attributes and n can be defined as the discrete class label. The main aim is producing model n=f (m) for the purpose of providing and predicting classes n for the future examples m with elevated precision. With regard to classification, decision tree learning is considered to be of high importance because of its robustness. Decision tree learning node has check on the attributes and every branch offering output regarding the check [89]. It has been selected as the base approach on which to advance this study of data stream classification and experimental assessment. This algorithm was selected for the following aspects. Firstly, HT is considered as an optimum method to start with, since it is ground-breaking and efficient at data stream classification of high-speed, also it present possibilities for enhancement [90]. HT adopt the concept that small sample could be enough for choosing optimum splitting attribute[88]. Mathematically, it has been verified that Hoeffding bound is utilized by HT algorithm. For the purpose of understating the significance of Hoeffding bound, several statements have been made. Supposing 'N' is an independent observation regarding random variable 'r' that have the range 'R', in which 'r' represent the attribute selection

measure. With regard to Hoeffding trees, ‘r’ can be defined as the information gain, and in the case when we estimated the mean value that is related to r ‘rmean’ of this sample Hoeffding bound states which the true mean of ‘r’ is at least 1–δ where δ is user stated and Performance analysis of Hoeffding trees in data streams is:

$$\mathrm{HB} = \sqrt{\frac{\mathrm{R}^2 \ \ln {}^{1}/_{\delta}}{2\mathrm{N}}} \qquad (2.29)$$

The major benefits of HT are it is naturally incremental, it is achieving high-precision though the use of small samples, multiple scans on the same data are certainly not achieved. HT compares attribute more efficiently than the other algorithms. Furthermore, it takes less memory and provide improved application with data sampling. Yet; it take a lot of time to inspect if ties happening [87]. Yet; the major drawbacks of HT are: HT does not have the ability of handling the concept drift since as soon as the node is developed, it will never be changed again[91]. Described using classifiers to handle the concept drift. The algorithm spend a lot of time with attributes which have almost matching splitting quality. Furthermore, the utilizations of memory could be optimized even more.

2.14.2 Naïve Bayes classifier (NB):

NB is defined as a simple approach which has a classification node that is considered as a parent node for all the other nodes. There are no other connections are enabled in NB [92].

NB method has been utilized in the presented study, because of its easiness and transparency in ML modalities. NB method is basically

utilized according to Bayes theorem with suppositions of strong independence among features [93]. The classifier at all times aim for reaching optimum hypothesis H via certain training data set. Bayes theorem allow calculating posteriori probability (probability regarding hypothesis taken into account the value of the variable) depending on priori probability (frequency of every one of the hypotheses) of total data and the identified data [94]. Based on Equation (2.24), we have

$$P(v_j/A) = \frac{\mathrm{P}\ (\mathrm{A} \mid v_j)\ \mathrm{P}\ (v_j)}{\mathrm{P}\ (\mathrm{A})} \qquad (2.30)$$

In which $\mathrm{P}\left(\mathrm{v_j}\ \middle|\mathrm{A}\right)$ represent feature probability regarding class (target) of certain feature, P ($\mathrm{v_j}$) can be defined as the prior probability regarding the class, P (A | $\mathrm{v_j}$) represents the possibility that is the probability regarding feature given class, and P (A) is the prior probability related to the feature [93].

NP having very large amount of samples is very important. Furthermore, it is computationally expensive, because it is a requirement to estimate joint probabilities for all likely A. Considering that, this study recommended using NB classifier, that assume the independency of all attributes in A. There is a study examining that even in the case when those attributes are not completely independent, it is conceivable to acquire efficient classification performance. Furthermore, it has straightforward application [94]. Therefore, the joint probability will be specified via:

$$P(a_{1,}a_{1,}\ \dots .\ a_{n,}/v_j) = \prod_i \mathrm{P}\ (a_i \mid v_j) \qquad (2.31\ \ )$$

and the classifier output will be specified via:

$$v_{MAP} = argmax_{v_{j \in V}} \left\{ \mathrm{P}\left(v_j\right) \times \prod_i \mathrm{P}\left(a_i \mid v_j\right) \right\} \qquad (2.32)$$

Where V_{MAP} can be defined as maximal aposteriori probability estimated within the space of the hypothesis V. It is of high importance to calculate the probability distribution regarding every attribute for every one of the classes, it's not important to estimate P(A) in the case when the number of observations is the same for all classes.

2.15 Performance evaluation

2.15.1 k-fold cross-validation method

The present research utilizes the process of 13-fold cross-validation for assessing the efficiency of the presented method. In this cross-validation process, a dataset is divided to 13 distinctive sub-sets (i.e. folds) almost equally sized and this process is done over 13 times. At every time, one fold is utilized as a testing set and the other 9 are merged together in order to produce a training set [95].

2.15.2 Classification accuracy (CA)

The performance stability of the presented approach is evaluated according to various statistical measurements, like the true positive rate (sensitivity), true negative rate (specificity), and accuracy. The latter is a considerable concern in systems of BCI, the present research utilized accuracy of the classification as one of the main criteria for evaluating the efficiency of the suggested approach. The measurement system accuracy is the level of measurements closeness of a quantity to the actual (true) value, as described in equations (2.33), (2.34) (2.35),(2.36), and (2.37). Those statistical measurements are computed from every one of the 13

folds. The general efficiency of the suggested approach is calculating by the averaging of the values of accuracy through all trials [95], [96].

$$\text{True positive rate (TPR)} = \text{Sensitivity(Se)} = \frac{TP}{TP + FN} \qquad (2.33)$$

$$\text{True negative rate (TNR)} = \text{Specificity(SP)} = \frac{TN}{TN + FP} \qquad (2.24)$$

True positive (TP) $or\ Recall$:patterns correctly predicted as pertaining to the positive class. True negative (TN): patterns that have been predicted correctly as a member of the negative class.

False negative (FN): patterns that have been predicted as negative whose actual class is positive.

False positive (FP): patterns that have been predicted as positive that come from a negative class.

$$\text{Precision} = \frac{TP}{Actual\ Results} = \frac{TP}{TP + FP} \qquad (2.35)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} = \frac{TP + TN}{total} \qquad (2.36)$$

$$AC = \left(\frac{N_{cn}}{N_{tn}}\right) \times 100 \qquad (2.37)$$

Here, AC is the percentage of the accuracy of classification, N_{tn} is the entire count of samples, and N_{cn} is the count of samples that have been correctly classified.

Overall performance=$\frac{1}{13}\sum_{k=1}^{13}$ accuracy^{k},where accuracy K is the accuracy th fold (k=1,2,......13).

Chapter Three

Proposed System

Chapter Three

The Proposed System

3.1 Introduction

In this chapter the implementation of the proposed system is presented in details to show the main steps in this system to implement BCI system able to classify the left or right index finger movement, which generated from brain directly .It consists of the layout description of the suggested system as well as the implementation details of each stage that is related to the proposed system. The proposed system using machine learning and data mining approaches. However, the proposed system has some significant and potential stages such as preprocessing signal ,signal analysis stage (feature extraction) , and finally the classification stage.

3.2.The Proposed System

the proposed system is shown in figure (3.1) and used to classify the brain signals that exported from the brain to predict of the people actions in order to implement such system huge, 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 phase The first phases called the training model and the second is called the testing and verification model. Each phase has many stages or (sub-stages) such as pre-processing, and feature extraction stage and finally the classification stage. able to classify the left or right index finger movement.

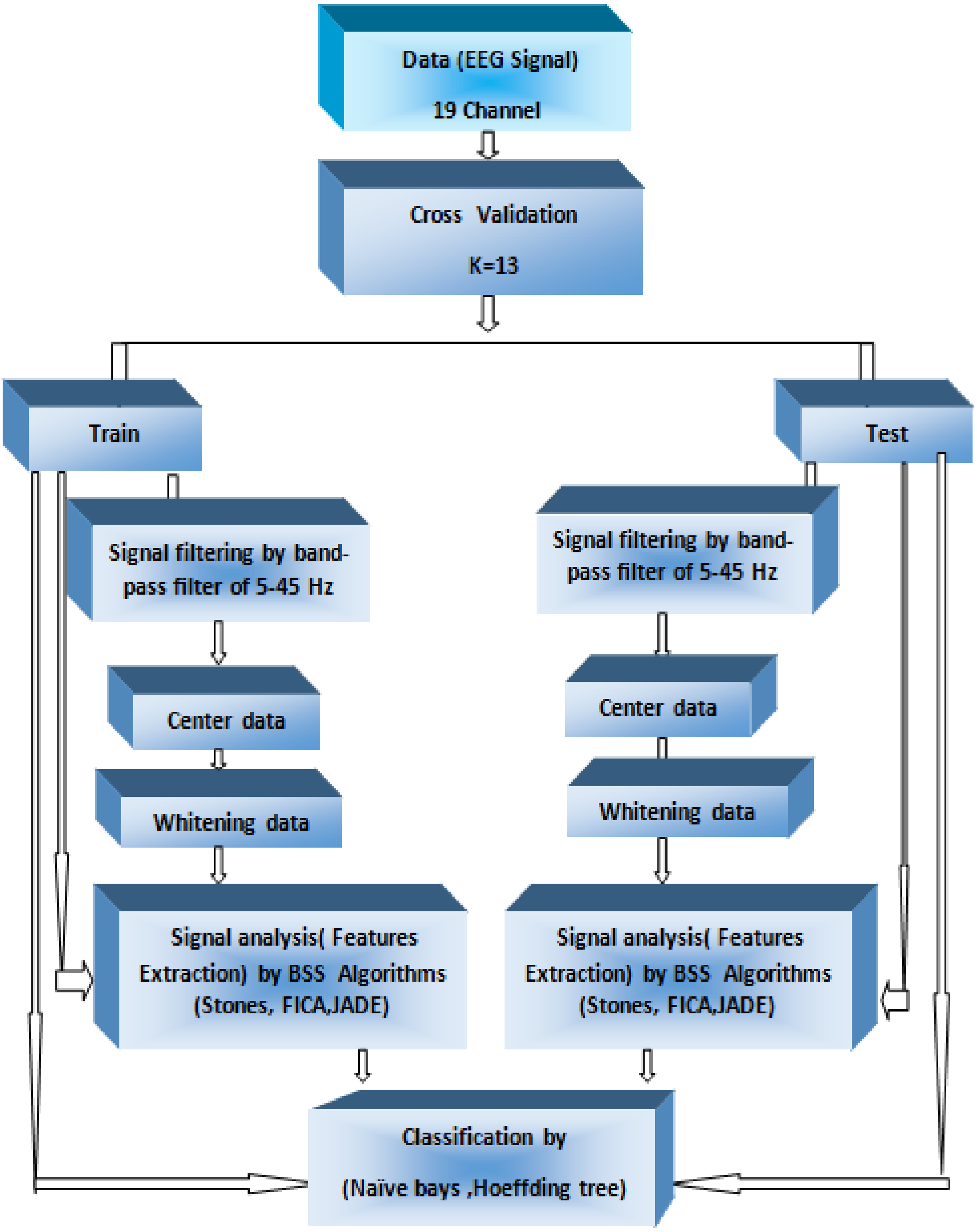


Figure (3.1) Block diagram of the proposed system

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

Algorithm 3.1 proposed system algorithm
Input: analyzed data **Output**: classified data
Start **Step1**: read the data set **Step2**: apply cross validation with K=13 **Step3**:apply band pass filter **Step4**:apply blind sources separation BSS **Step5**: apply classification algorithm end

Also for more explanation the outlines of the proposed system is explained in several stages:

3.2.1Data set: In this stage the signals of brain is collected and prepared for further processing.

A- Data set collection: This step include gathering the information collected from EEG device ,taken from [8] and form it as an excel sheet for further processing.

B- Cross validation: The dataset will split up to two main parts train and test where all the data will used for train or test and the mix of data guarantee that no data ignored during the processing of the date.

3.2.2 processing stage: The presented system consists of three phases :

A: preprocessing :First phase is starting using band pass filter that is used to preprocess the data which will lead to removing DC, eye artifacts, Drift, and power line noise of 50Hz.

B: Data analysis: The second phase is that takes the output from phase one as input to the analysis is done using blind sources separation BSS using (Stone, FICA or JADE) algorithms.

C. Classification: The output from phase two as input to Classifier to classify the EEG signal of Motor imagery .Classification of the analyzed data is done by using two algorithm(Naive Bayes , Hoeffding tree). Each stage will be explained in details:

3.3 Data set:

A -Collection

Real data are collected and taken from [8] , the data set is imported to the suggested system to execute and evaluate the system. 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 (see appendix A). A 24 year age healthy male participate in data set collected sitting on a comfortable chair without moving with 1 meter distance from the computer monitor. The data recording in two sessions one for left index finger and the other for right movements every session consist of many trails each trail is 10 sec period. Nineteen channels signals each signal consist of 256 samples in Hz. Table (3.1) shows the main specification for this data.

Table (3.1) Data set specification

Gender	age	position	motion	Medical condition	situation
Male	24	1m from computer monitor	static	healthy	Sit on chair

B-Cross Validation:

The critical data of the brain signals can be very useful for human and the results of such system need to be accurate as possible and the system is training and testing for kind of data that is not processed before each movement is different signal than the other For that reason a validation method is used to mix the data and provide each data in the system with a chance to be a train data and test data to ensure that the numerical relationship between data is kept.

Algorithm 3.2 shows the main steps of the used cross validation algorithm

Algorithm 3.2 Cross Validation Algorithm
Input: data set **Output**: train data , test data
start **step1**: set the k to 13 (try and test shows 13 is better than 5,7,9,10) **step2**: for i=1 to k Split the data to k folds where one fold is test and the remains fold is train. **Step3**: fitting the model using k-1 **Step4**: loop according to i. End

According to algorithm 3.2 the k value is choose k=13 which mean 13 times the data will split to train and test and the data spilt to train and test and the process is repeated until all the data is being train data and test data in the system.

3.4. Signal processing

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 3 phases:

3.4.1 Preprocessing:

Since the EEG signal generally is weak and can be affected by many types of noise which will need to be eliminated as possible for that reason the preprocessing phase is done in this work to reduce the noise affected to signal. There is a DC component that needs to be rejected. A pass band filter (5-45 Hz) is implemented with the use of Windowed-Sinc FIR filter with a 256 sample per second sampling rate, a 1024 Filter kernel length *M*. A Blackman window was utilized; which is why, the filter kernel of the low-pass filter has been computed.

Algorithm 3.3 shows the pass band filter algorithm adopted in this work

Algorithm 3.3 pass band filter algorithm
Input: train data , test data **Output**: preprocessed signals

Star t
Step1: Let M=1025, srate=256, fc1=5, fc2=45, f1= fc1/srate, f2= fc2/srate.
Step2: Calculate the kernel of the low-pass filter at f1 by:
for i=1 to M
if (i−(M+1)/2) =0 Then
hl[i] = 2×π×f_1
else
hl[i] = (sin(2×π×f_1×(1− (M+1)/2))/(1− (M+1)/2))×
(0.42−0.5×cos(2×π×i/M)+0.08×cos(4×π×i/M))
end if
end for
step3: Calculate the kernel of the low-pass filter at f2 by:
for i=1 to M
if (i−(M+1)/2) =0 Then
hh[i] = 2×π×f2
else
hh[i] = (sin(2×π×f2×(1− (M+1)/2))/(1− (M+1)/2))×
(0.42−0.5×cos(2×π×i/M)+0.08×cos(4×π×i/M))
EndIf
EndFor
step4: Normalizing the kernels of both filters
hl = hl/sum(hl)
hh = hh/sum(hh)

Continuous of Algorithm (3.3)

step5: Change the kernel of the low-pass filter of hh to high-pass filter with the use of the spectral inversion

hh= −1×hh

hh((M+1)/2) = hh((M+1)/2)+1

step6: Adding the kernel of the low-pass filter hl to the kernel of the high filter hh for the sake of obtaining a band-reject filter kernel

hb=hl+hh

step7: Changing the band-reject filter kernel to a band-pass filter with the use of the spectral inversion

hb = −1×hb

hb((M+1)/2) = hb((M+1)/2)+1

step8: output = convolution the input signal with the filter kernel

end

3.4.2 Data Analysis:

The problem of separation of the signals that are represent the source (source signals) from the mixtures signals without have information about the signals sources is called Source separation, BSS. The analysis phase is aimed to recover this original source signal from the mix signals, several solutions to this problem can be applied in this work three algorithms were used:

(A): Stone:

statistical algorithm (second order) used a batch algorithm with very low complexity which leads to produce better separation to the signals. Stone's BSS is based on the temporal predictability measure (TP) to separate the original sources from their mixture. The conjecture of Stone is: The TP of any signal mixture is ≤ that of any of its components, this conjecture is used to find the weight vector which gives an orthogonal projection of mixtures.

The main steps of the stone algorithm have been defined in algorithm 3.4

Algorithm 3.4 Stone Algorithm
Input: signals after BPF **Output:** Analyzed signals
Start **Step1**: find the Mixture observation signals. according to Eq(2.7). **Step2**: Finding the recovered signals are calculated by the separating model. According to Eq(2.8). **Step3**: measure of temporal predictability of signal. According to Eq(2.9). **Step4**: Compute the short-term covariance matrix. According Eq to (2.10). **Step5**: Compute the long-term covariance matrix. According to Eq(2.11). **Step6**: Finding the eigenvectors. According to Eq(2.12) and Eq(2.13). **Step7**: De mixing the matrixes . According to Eq(2.14). end

(B):FICA:

In this work the FICA will mainly removing the vectors rows mean of the X matrix and then it is using the proper procedure (whiting procedure in this work) 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.

Algorithm 3.5 shows the main steps of FICA

Algorithm 3.5 FICA Algorithm
Input: signals after BPF **Output**: Analyzed signals
Start **Step1**: Remove the row (every row vector) mean of X matrix. According to Eq (2.10). **Step2**: Use a whitening process for transforming covariance matrix of 0-mean to a matrix of identity. According to Eq (2.20),(2.23) **Step3**: Search for matrix which transforms whitened data to a collection of components which 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. According to Eq (2.15). where S is an m*n matrix that includes independent components, W represents the matrix of separation, and X is an m*n input signal matrix. **Step5**: Each column of mixing matrix 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 columns of the mixing matrix A. Corresponding to the task-unrelated components .According to Eq (2.16). End

- **JADE ((joint approximate diagonalization of eigenmatrices)**

This algorithm mainly used in this work to separate the mixed signals into latent source signals by calculating four moments (order moments), these four orders moments measures the non- Gaussianity which is defining the independent signals. The matrix X which is represent the input mix data that need to filter and analyze to obtain the original source and remove the noise from it with size M*N, this algorithm will be optimized by removing the mean of the row vector which is moved to identity matrix. The four cumulant is computed for the matrix X and the optimization rotation matrix O is founded by optimize the contrast function finally the source components that is estimated and founded by using the rotation matrix O and processed matrix X.

Algorithm 3.6 JADE algorithm
Input: signals after BPF **Output**: Analyzed signals
Start **Step1**: Let X be the matrix with m*n size which is denote an observed data matrix. According to Eq (2.15). **Step2**: Remove the row (every one of the row vectors) mean of the X matrix. According to Eq (2.18). **Step3**: Utilizing a process of whitening for transforming the matrix of covariance of 0-mean to a matrix of identity. According to Eq (2.20),(2.23). **Step4**: Computing fourth-order cumulant of X According to Eq to (2.27). **Step5**: Optimizing a contrast function to obtain a m* m rotation matrix O **Step6**: Estimate the source components given by the rows of the m* n dimensional matrix According to Eq (2.28). end

3.4.3 Classification phase:

Two algorithms where used in this system to apply the classification step :

3.4.3.1 Classification using Hoeffding tree

Decision tree which have the learning ability for the data streams enter the system (in our cases the input is the signals data sources without noise. This classification algorithm assume while working that distribution is not changing overtime, the strength of this algorithm that is it can work with small amount of data and it will be enough to choose the main split attribute.

Algorithm 3.7 Hoeffding tree
Input: Analyzed signals **Output:** classified signals
Start **Step 1**: Create tree data structure with a single root node. **Step 2**: Creating a decision tree learner via Filtering down every training data inclemently to a proper leaf. **Step 3**: Estimating the information gain when splitting any attribute: $Gain\ (A, S) = Entropy(S) - \sum_{v \in Value(A)} \frac{S_v}{S} Entropy(s_v)$ **Step 4**: Finding the optimal attribute at a node and performing a test according to the provided data for deciding if a specific attribute has given more sufficient result when compared to other attributes with the use of the Hoeffding bound. **Step 5**: Find the attribute that provides more sufficient result compared to all the other nodes, results in splitting the node for growth of tree. **end**

3.4.3.2 Classification using naïve bays

This algorithm use a probabilistic classifier which is offer fast and scoring abilities comparing to other classification algorithms and can be used for classify the binary and numeric data. This supervised algorithm assumed that the input data (source signals) are independent and not connected to each other.

Algorithm 3.8 naïve bays
Input: Analyzed signals **Output:** classified signals
Start **Step1**: for the calculation of posteriori probability (which is the probability of a hypothesis considering a value of the variable) according to the a priori probability (which is the frequency of every one of the hypotheses) of both the data found and the total data According to Eq (2.30). **Step2**: count the joint probability According to Eq (2.31). **Step3:** Count the V_{MAP} is the maximal a posteriori probability which has been computed within the hypotheses space According to Eq (2.32). end

The results obtained from classification using this algorithm is discussed in chapter four.

Chapter Four

The Experimental Results

Chapter Four

The Experimental Results

4.1 Introduction:

Experimental results have been obtained after applying the algorithm in proposed system and the charts related to this execution is shown in figures and tables in this chapter. Two classes are used in this system. Class one represent the brain signal of the right finger within the right hand. Class two represent the brain signal of the left finger within the left hand. The proposed system is implemented in two languages MATLAB R2015A to analyses signals and JAVA NetBeans IDE 8.0.2 to classify signal using lap top computer. The experiments were performed on an Intel (R) Core (TM) i5-3337U CPU @ 1.80 GHz , 64 bit Operating System and 4GB RAM.

4.2 Input signal of Brain

The brain signals are entered to the system and the mixture is done using the cross-validation algorithm to ensure that all data will be in the system as a training and test data. The input signal for 19 channel one trial of right index finger movement and input signal for 19 channel one trial of left index finger movement is shown in figure (4.1) and (4.2). size of data as matrices of (19×15360). Each channel contains a mixture of signals which includes(EEG,EOG,EMG,ECG,LN). According to the session, right or left index finger movement.

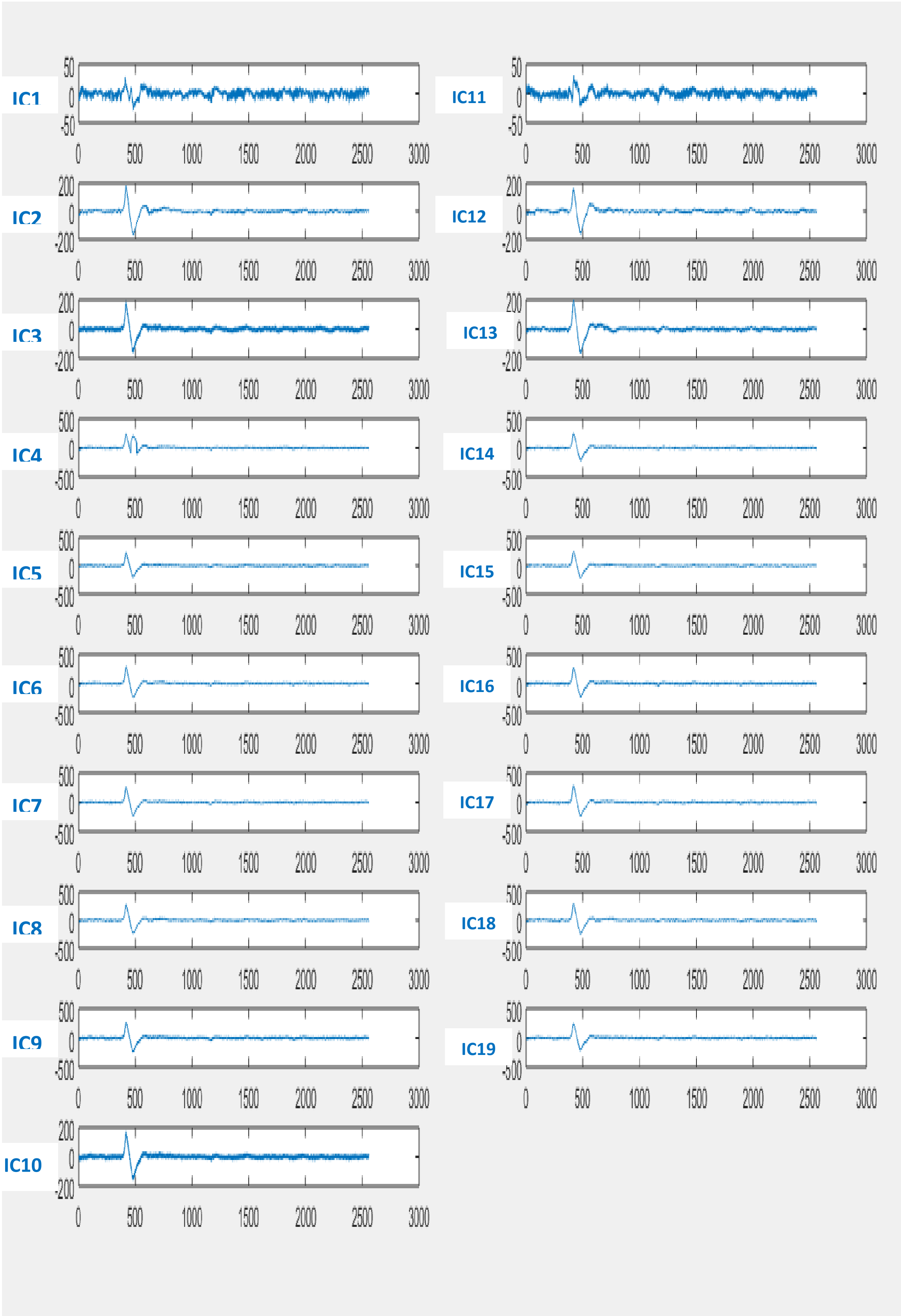


Figure (4.1) the input signal of right index finger movement

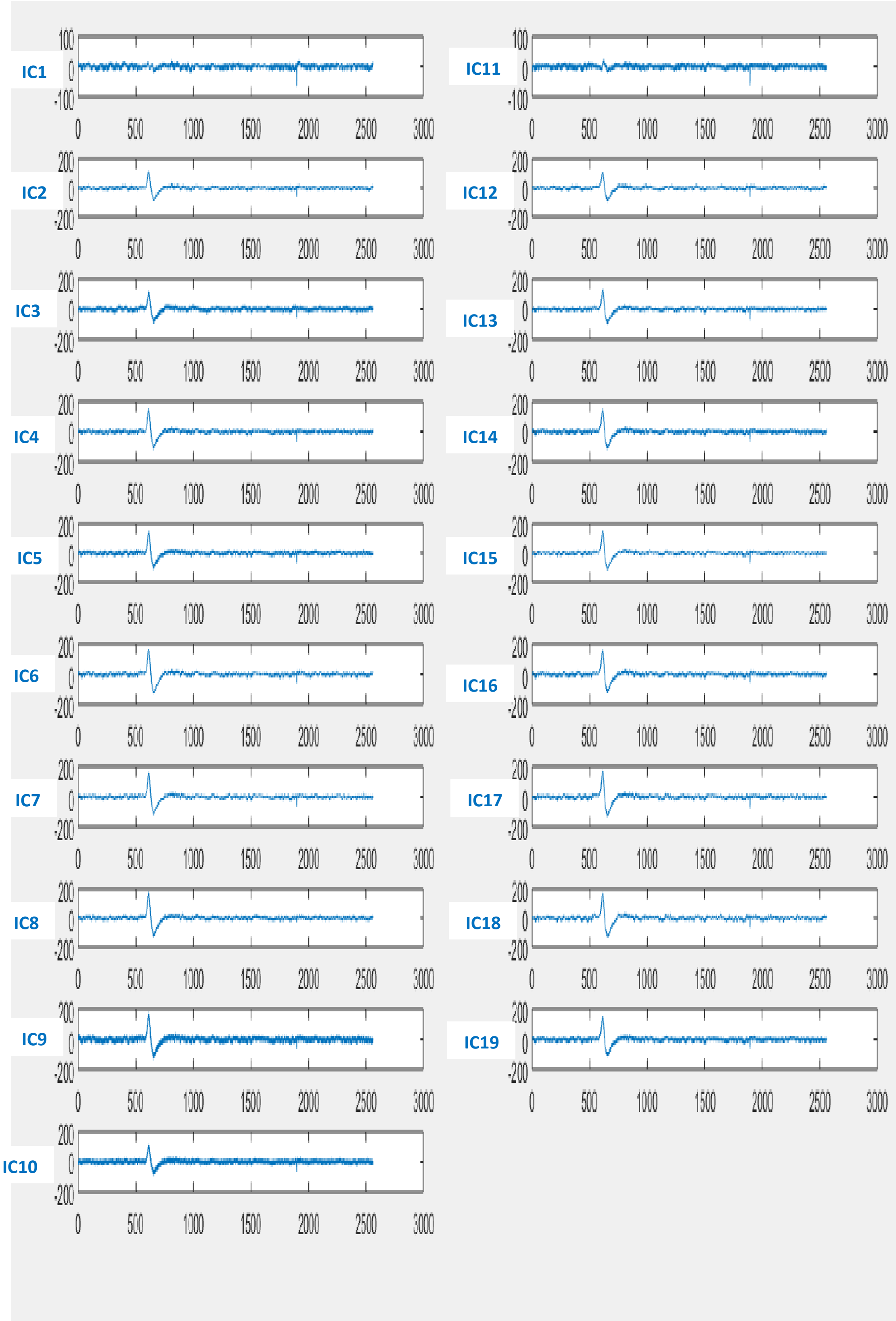


Figure (4.2) the input signal of left index finger movement

4.3 Results After Using Band Pass Filter(BPF)

The Results output signal for 19 channels after BPF one trial of right and left index finger movement is show in figure (4.3) and (4.4).

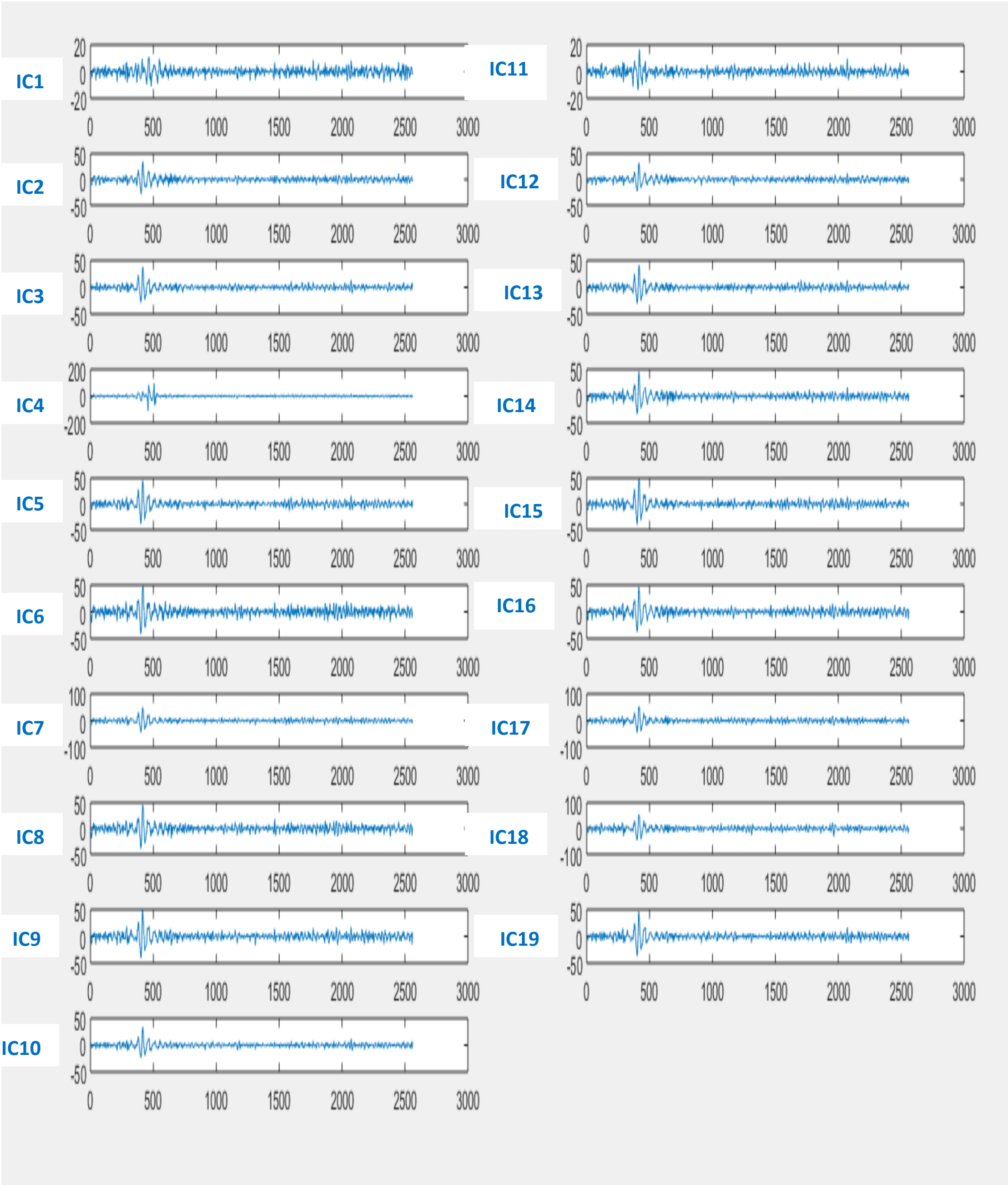


Figure (4.3) the out signal after BPF of right index finger movement

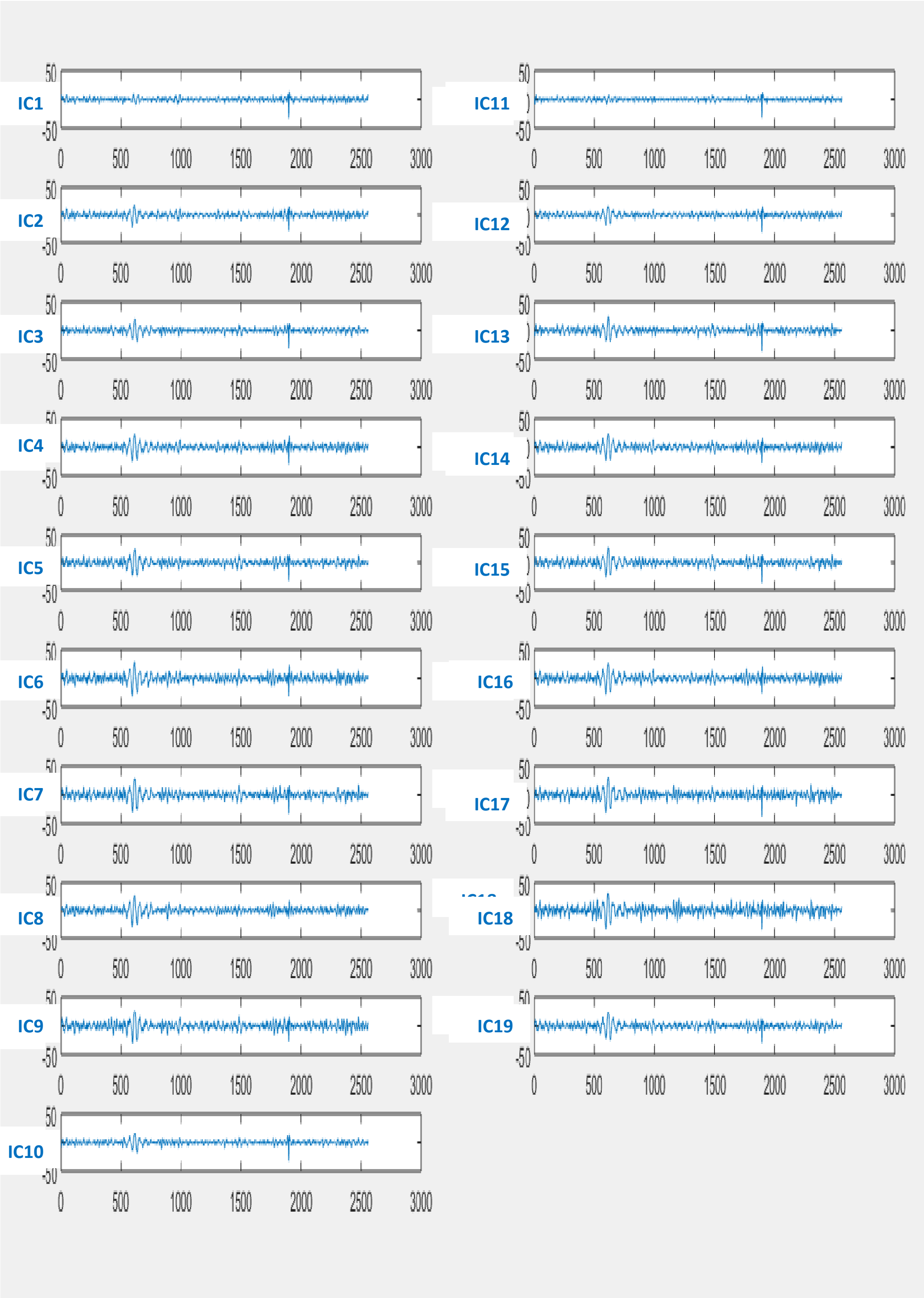


Figure (4.4) the out signal after BPF of left index finger movement

4.4 Results After Using Blind Source Separation (BSS)

A: Results After Using STON

The Results output signal for 19 channels after signal analysis by stone blind source separation SBSS one trial of right and left index finger movement is show in figure (4.5) and (4.6).

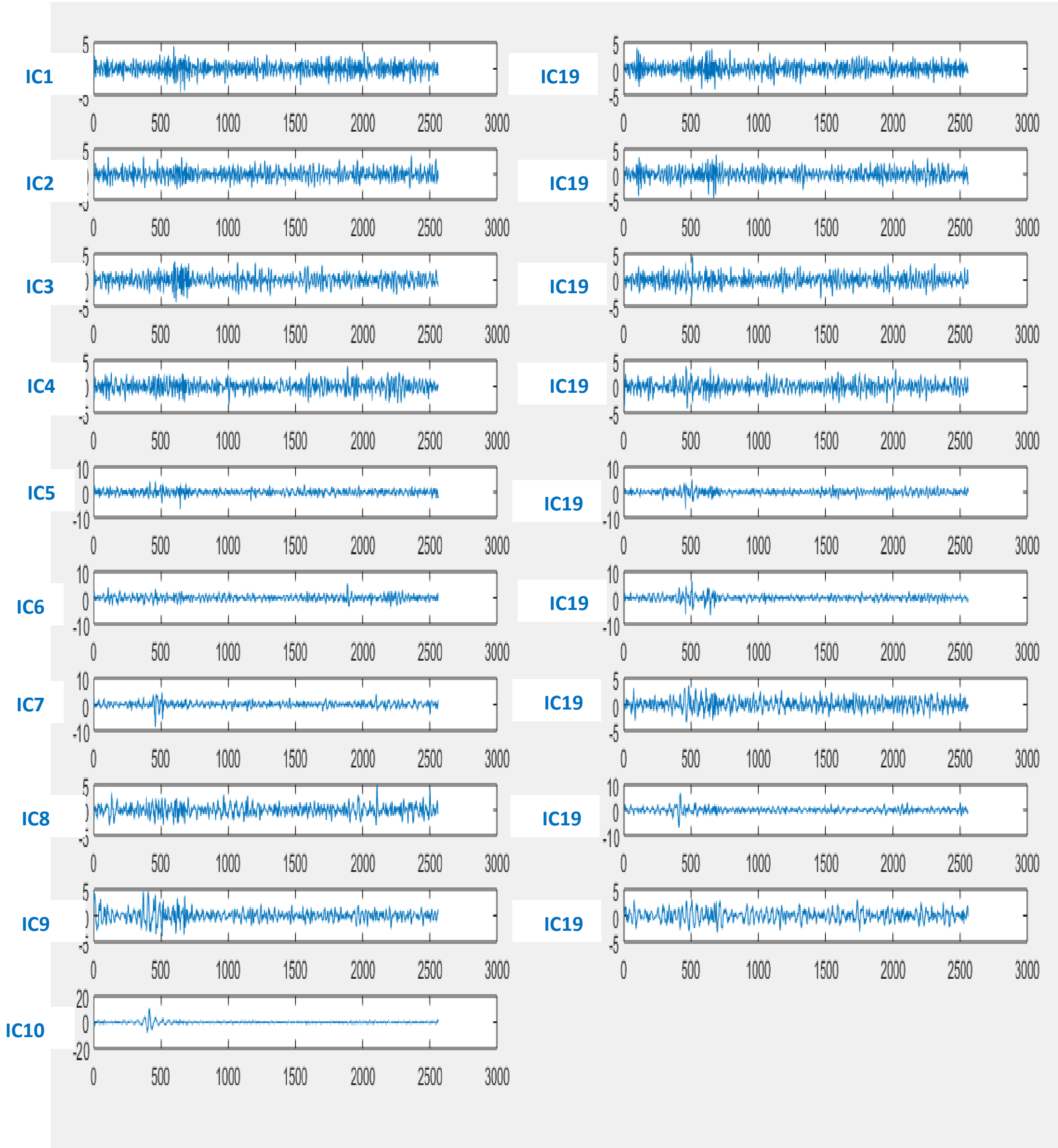


Figure (4.5): Recover Sources by STONE of right index finger movement

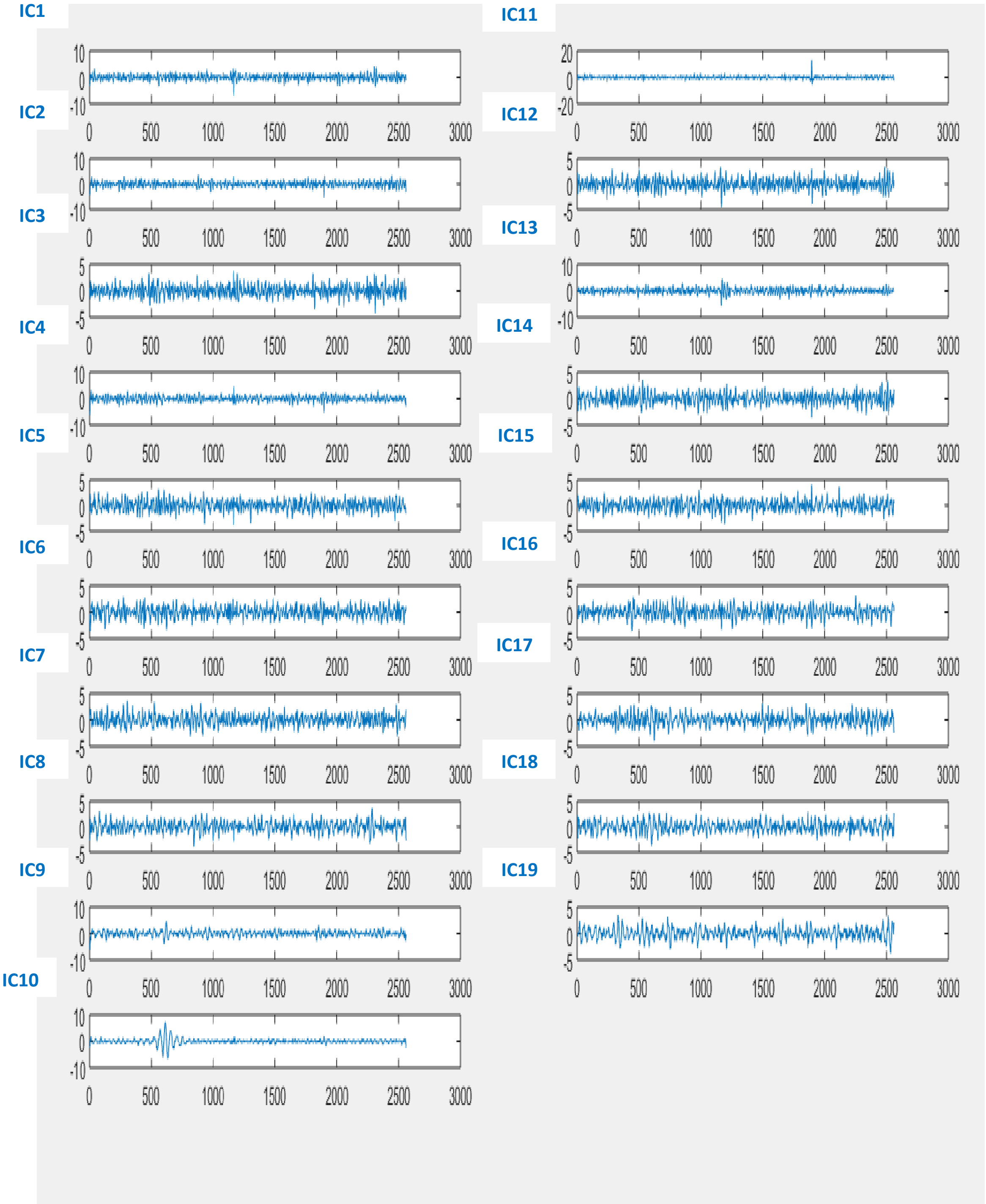


Figure (4.6): Recover Sources by STONE of left index finger movement

B: Results After Using FICA

The Results output signal for 19 channels after signal analysis by blind source separation FICA one trial of right and left index finger movement is show in figure (4.7) and (4.8).

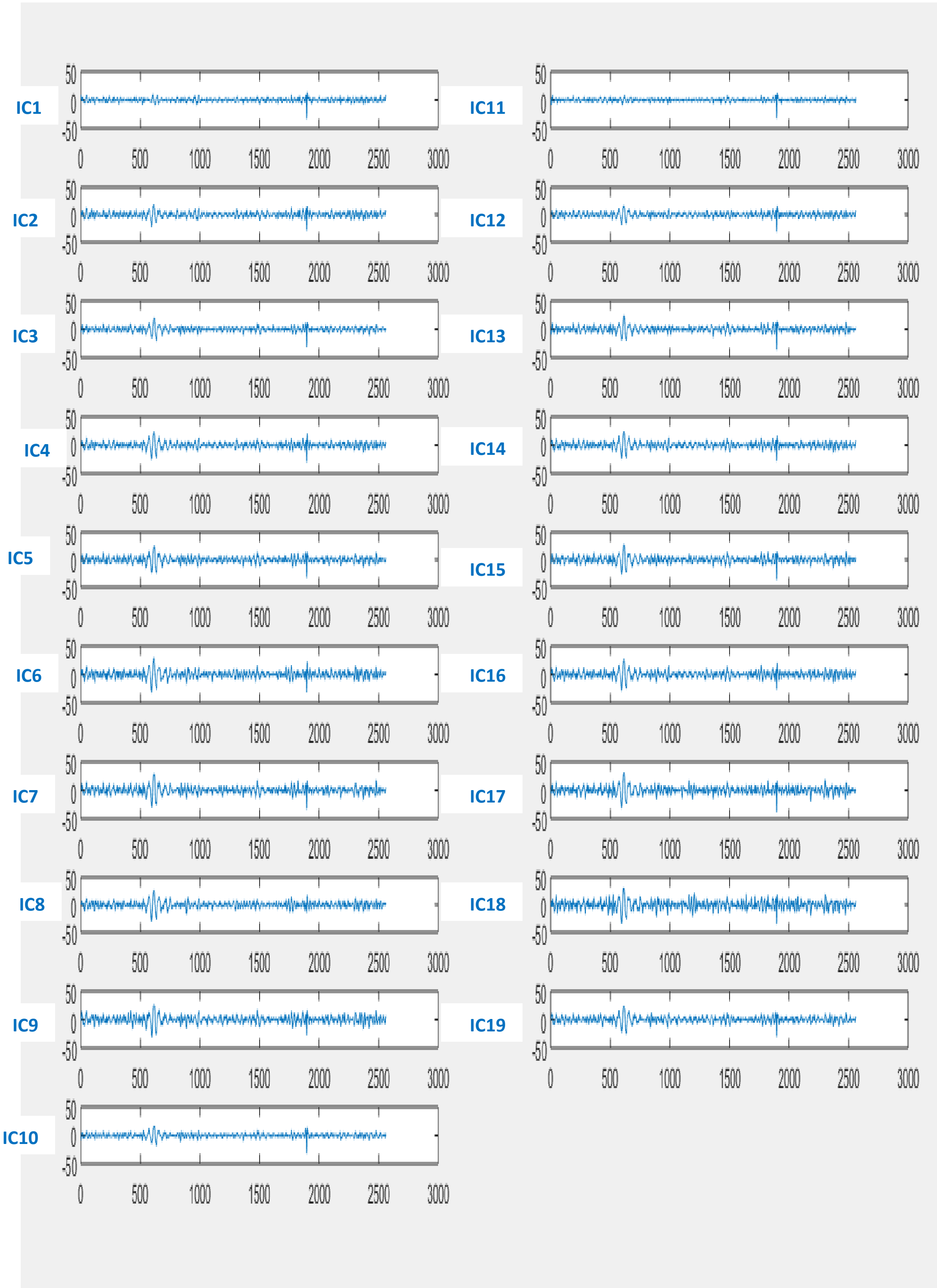


Figure (4.7) :Recover Sources by FICA of right index finger movement

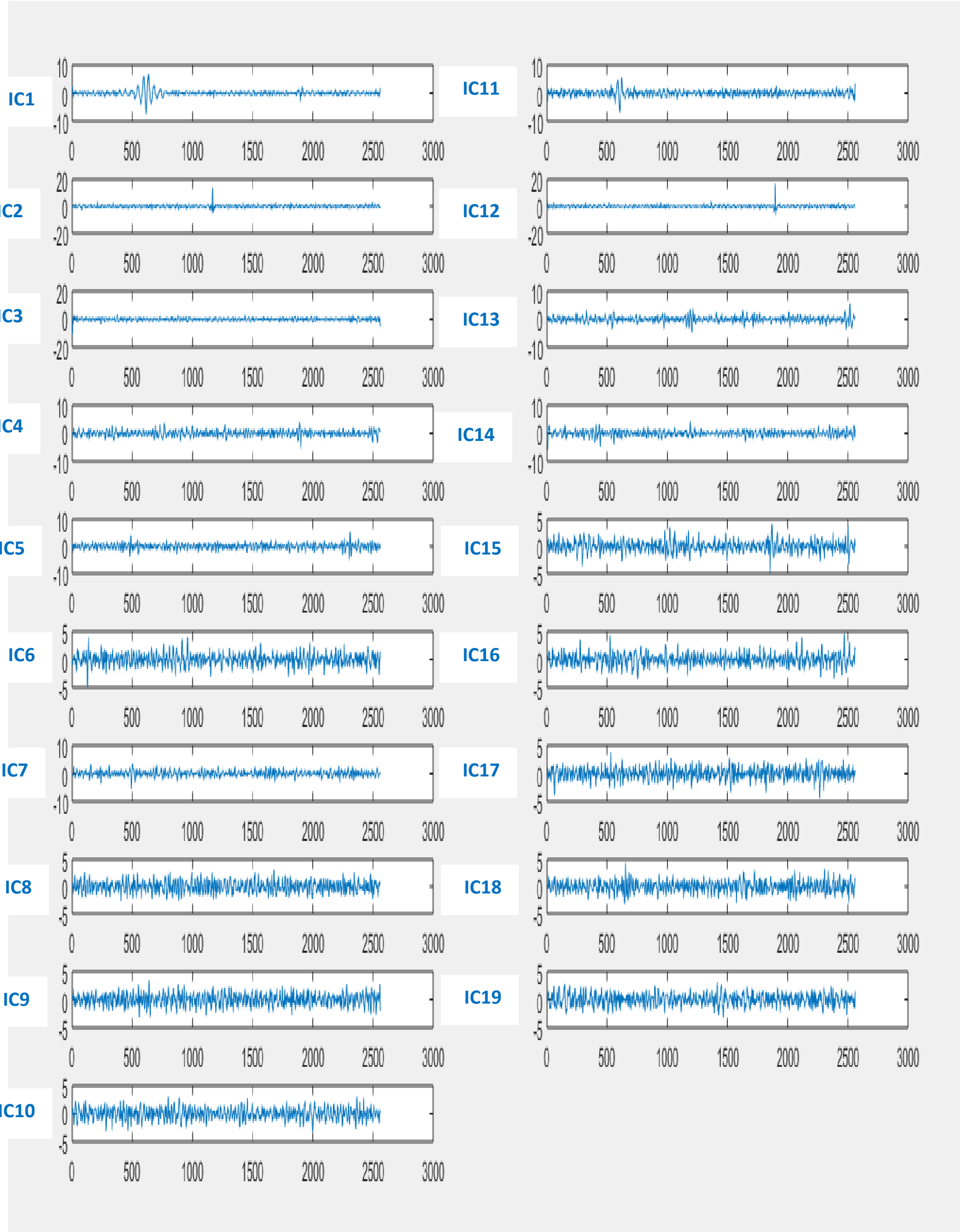


Figure (4.8) :Recover Sources by FICA of left index finger movement

C: Results After Using JADE

The Results output signal for 19 channels after signal analysis by blind source separation JADE one trial of right and left index finger movement is show in figure (4.9) and (4.10)

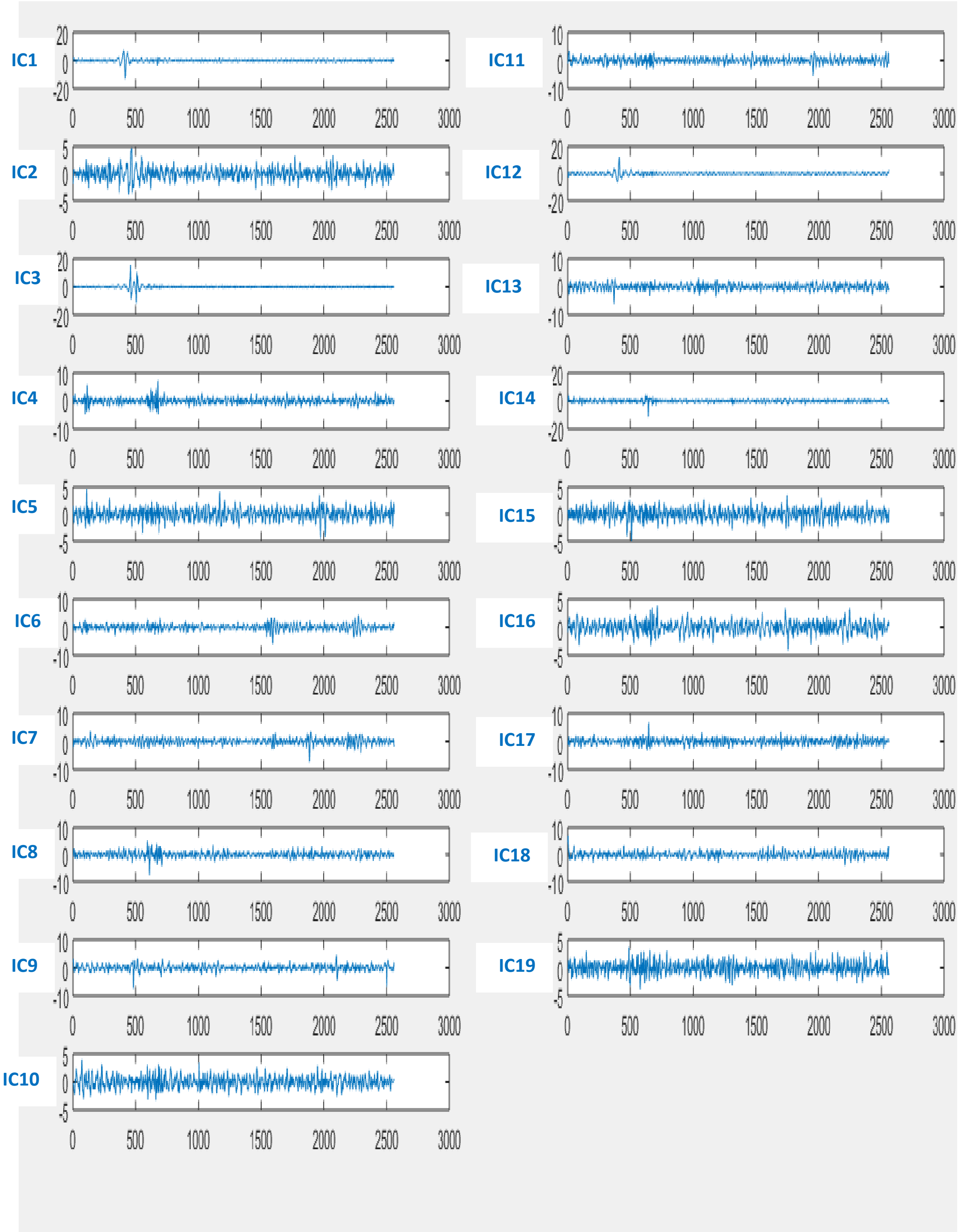


Figure (4.9) Recover Sources by JADE of right index finger movement

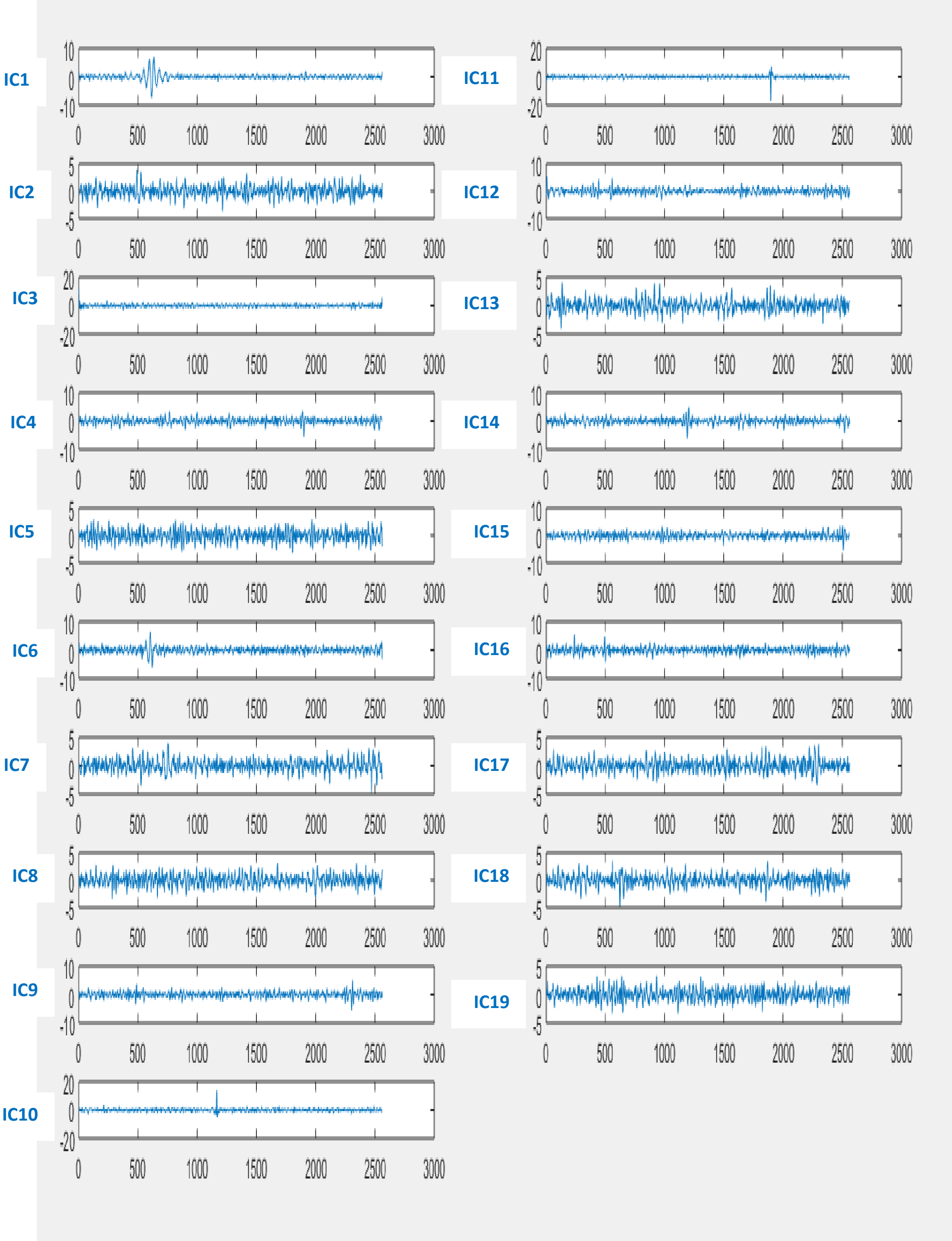


Figure (4.10) : Recover Sources by JADE of left index finger movement

4.5 Results After Classification

4.5.1 Results After Using Hoeffding Tree(HT) Classifier

- **Results of Classify data into Left and right without preprocessing or signal analysis**

The EEG signals which is entered to the system , split up to train and test using cross-validation and classified using the Hoeffding Tree classifier . Table 4.1 and Figure (4.11) show the results obtained after classifying it.

Table (4.1) Classification Using Hoeffding Classifier

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.669	0.602	0.526	0.669	0.589	0.069	0.548	0.537	L
0.398	0.331	0.546	0.398	0.46	0.069	0.548	0.549	R

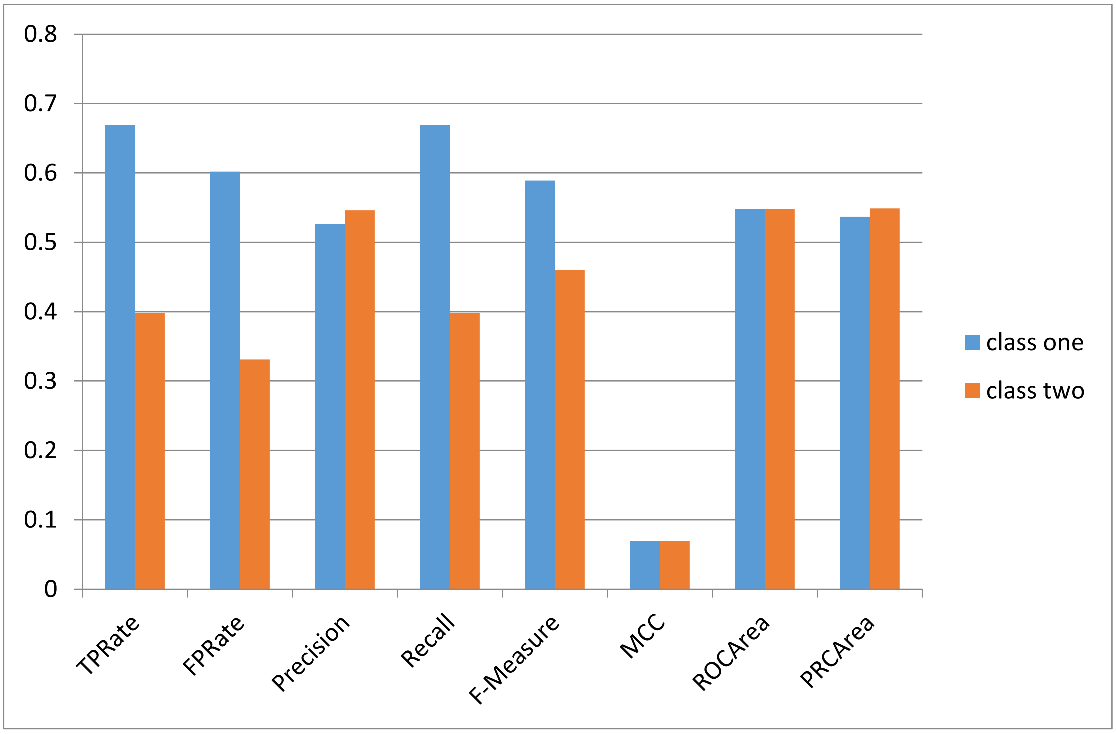


Figure (4.11) Results Obtained for Execute the System Using Hoeffding Tree

- **Results of Classify data into Left and right After (Stone)**

The EEG signals which is entered to the system , split up to train and test using cross-validation and then data is analyzed using stone method to return to the source object and classified using the Hoeffding Tree classifier. Table 4.2 and Figure (4.12) show the results obtained after classifying it.

Table (4.2) Classification Using Hoeffding Classifier and stone

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.947	0.474	0.667	0.947	0.783	0.522	0.762	0.686	L
0.526	0.053	0.909	0.526	0.667	0.522	0.777	0.79	R

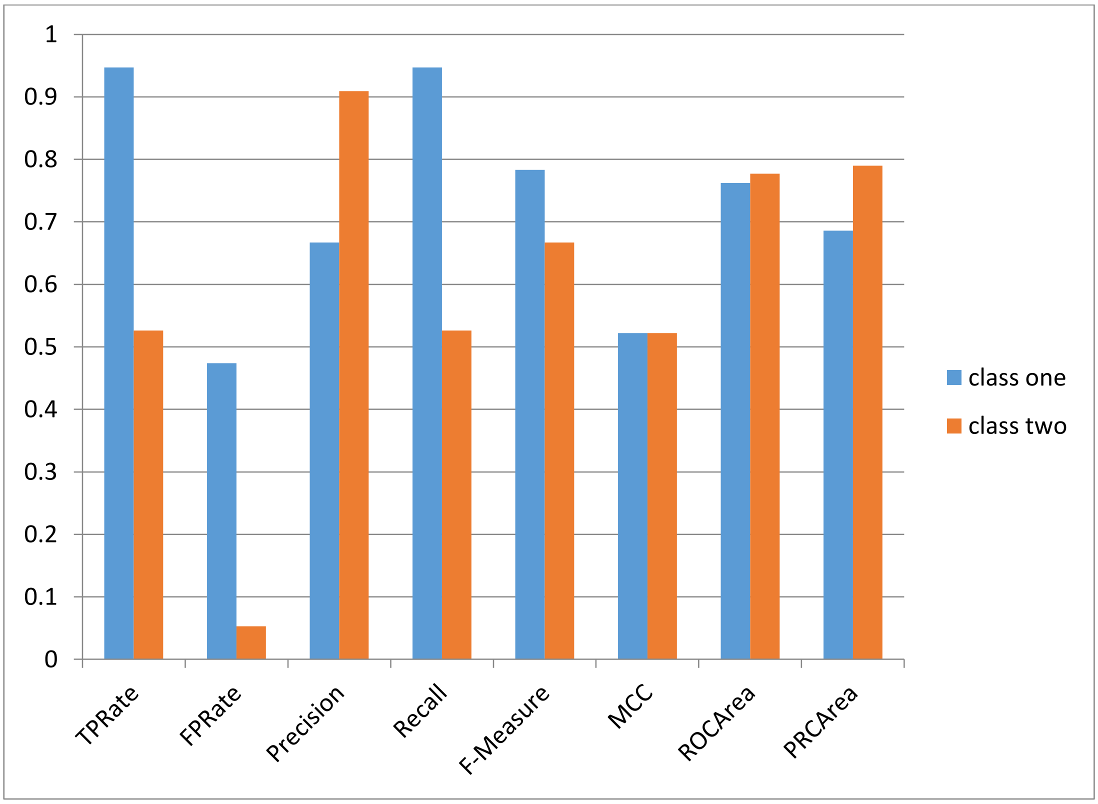


Figure (4.12) Results Obtained for Execute the System Using Stone and HT

- **Results of Classify data into Left and right After (FICA)**

The EEG signals which is entered to the system , split up to train and test using cross-validation and then data is analyzed using FICA method. to return to the source object and classified using the Hoeffding Tree classifier Table 4.3 and Figure (4.13) show the results obtained after classifying it.

Table (4.3) Classification Using Hoeffding Classifier and FICA

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.947	0.813	0.581	0.947	0.72	0.211	0.531	0.558	**L**
0.188	0.053	0.75	0.188	0.3	0.211	0.326	0.448	**R**

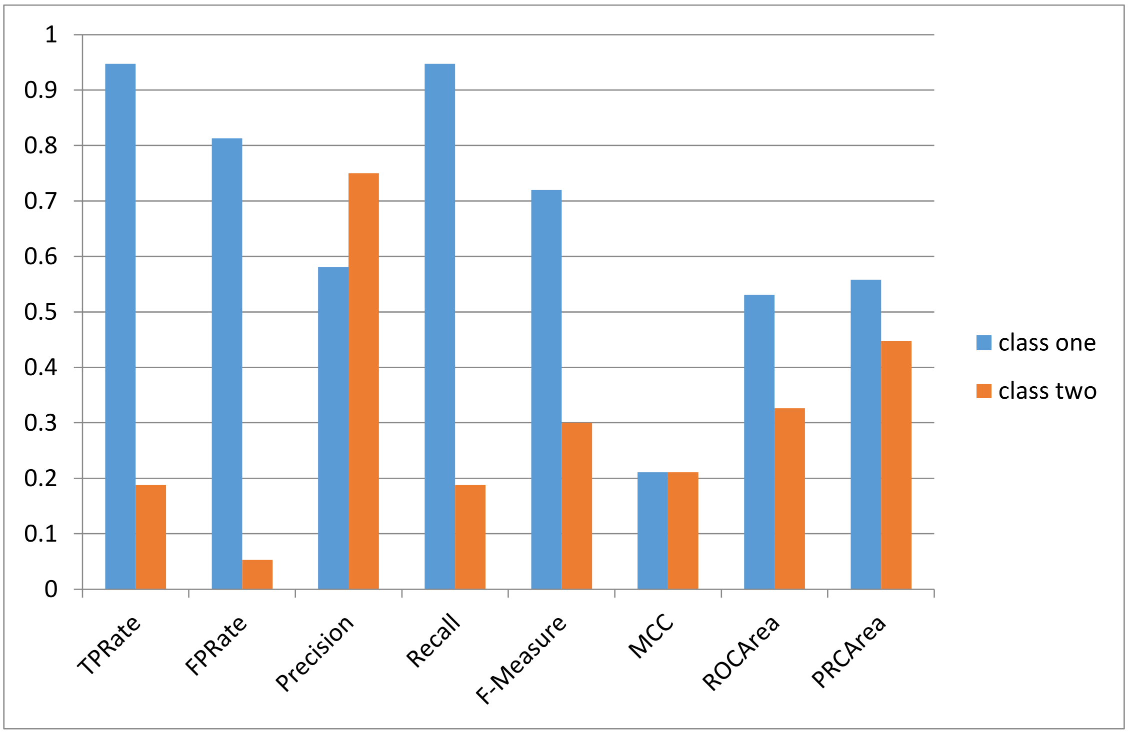


Figure (4.13) Results Obtained for Execute the System with Left and Right Data using FICA and Hoeffding Tree

- **Results of Classify data into Left and right After (JADE)**

The EEG signals which is entered to the system , split up to train and test using cross-validation and then data is analyzed using JADE method .to return to the source object classified using the Hoeffding Tree. classifier Table 4.4 and Figure (4.14) show the results obtained after classifying it.

Table (4.4) Classification using Hoeffding Classifier and jade

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.316	0.632	0.333	0.316	0.324	-0.316	0.352	0.420	L
0.368	0.684	0.350	0.368	0.359	-0.316	0.283	0.413	R

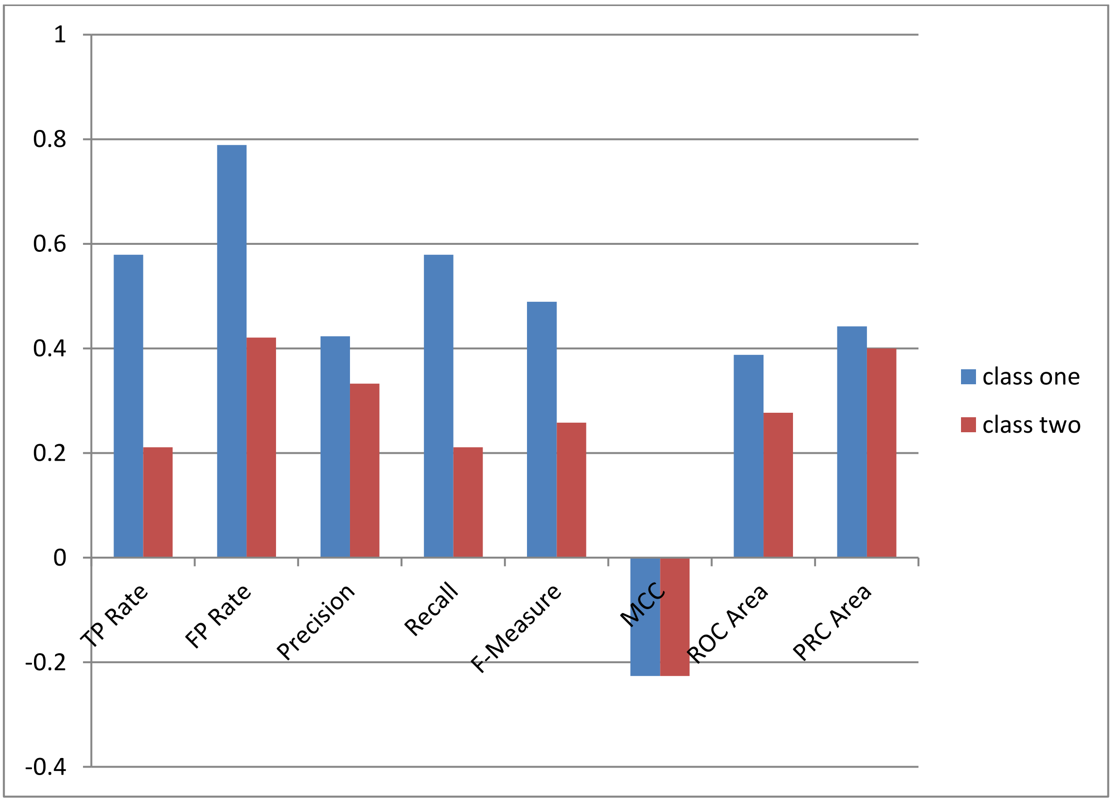


Figure (4.14) Results Obtained for Execute the System with Left and Right Data using JADE and Hoeffding Tree

•Results of Classify data into Left and right After (BPF) and (Stone)

The EEG signals which is entered to the system and split up to train and test using cross-validation and then data filtering by band pass to remove noise and analyzed using stone method to return to the source object .classified using the Hoeffding Tree classifier Table 4.5 and Figure (4.15) show the results obtained after classifying it.

Table (4.5) classification using Hoeffding classifier with (BPF) and (Stone)

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.895	0.263	0.773	0.895	0.829	0.64	0.852	0.816	L
0.737	0.105	0.875	0.737	0.8	0.64	0.909	0.888	R

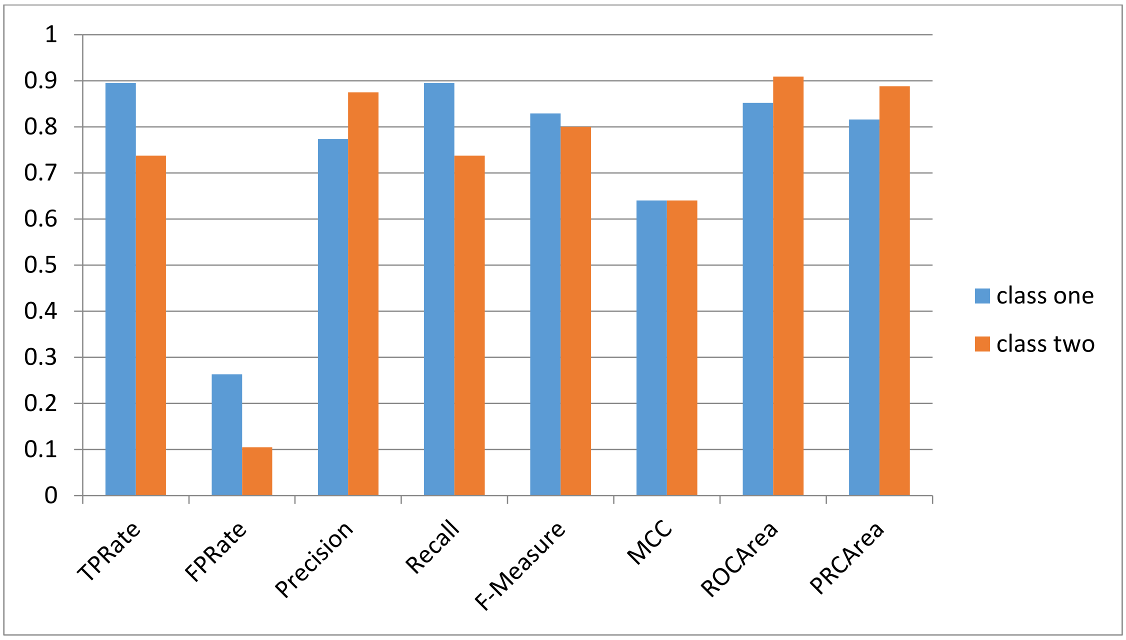


Figure (4.15) Results Obtained for the System Using BPF with STONE and HT

•Results of Classify data into Left and right After (BPF) and (FICA)

The EEG signals which is entered to the system and split up to train and test using cross-validation and then data filtering by band pass to remove noise , analyzed using FICA method to return to the source object classified using the Hoeffding Tree classifier. Table 4.6 and Figure (4.16) show the results obtained after classifying it.

Table (4.6) Classification Using Hoeffding Tree with (BPF) and (FICA)

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.895	0.824	0.548	0.895	0.68	0.103	0.531	0.542	L
0.176	0.105	0.6	0.176	0.273	0.103	0.525	0.554	R

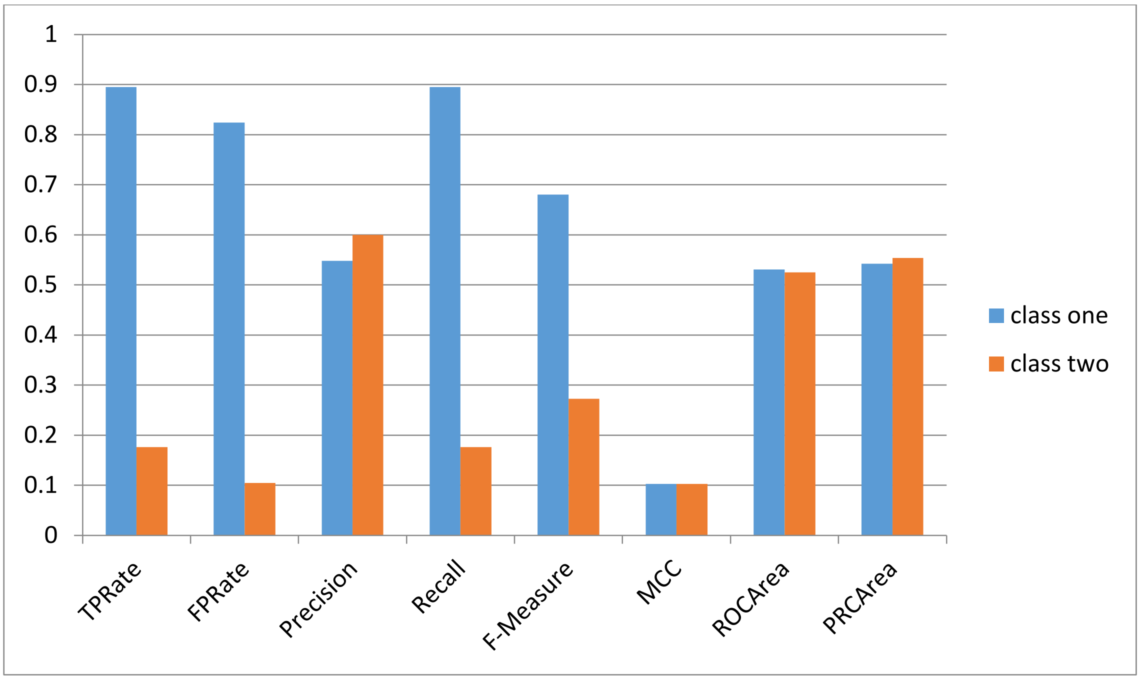


Figure (4.16) Results Obtained for Execute the System with Left and Right Data Using BPF with FICA and Hoeffding Tree

- **Results of Classify data into Left and right After (BPF) and (JADE)**

The EEG signals which is entered to the system and split up to train and test using cross-validation and then data filtering by band pass to remove noise , analyzed using JADE method to return to the source object and classified using the Hoeffding Tree classifier Table 4.7 and Figure (4.17) show the results obtained after classifying it.

Table (4.7) Classification Using Hoeffding Tree with (BPF) and (JADE)

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.474	0.842	0.360	0.474	0.409	-0.388	0.274	0.391	L
0.158	0.526	0.231	0.158	0.187	-0.388	0.256	0.382	R

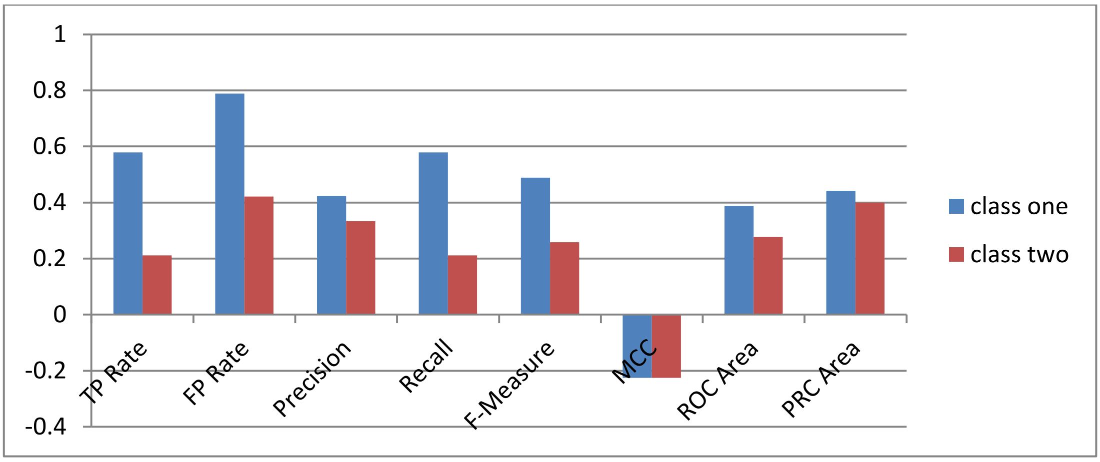


Figure (4.17) Results Obtained for Execute the System with Left and Right Data using BPF with JADE and Hoeffding Tree

Table 4.8 and Figure (4.18) show the results obtained after Analysis of brain signals by blind source separation algorithms. For the brain computer interface system (BCI) and then classifying it by Hoeffding Tree classifier.

Table (4.8) Results of Detailed Accuracy by Hoeffding Tree Classifier of BCI System

	TP Rate	**FP Rate**	**Precision**	**Recall**	**F-Measure**	**MCC**	**ROC Area**	**PRC Area**
without filtering	0.533	0.467	0.536	0.533	0.525	0.069	0.548	0.543
JADE	0.342	0.658	0.342	0.342	0.342	-0.316	0.317	0.416
BPF with JADE	0.316	0.684	0.295	0.316	0.298	-0.388	0.265	0.386
FICA	0.60	0.465	0.658	0.6	0.528	0.211	0.437	0.508
BPF with FICA	0.556	0.484	0.573	0.556	0.488	0.103	0.528	0.548
SBSS	0.737	0.263	0.788	0.737	0.725	0.522	0.769	0.738
BPF with SBSS	**0.816**	**0.184**	**0.824**	**0.816**	**0.815**	**0.64**	**0.88**	**0.852**

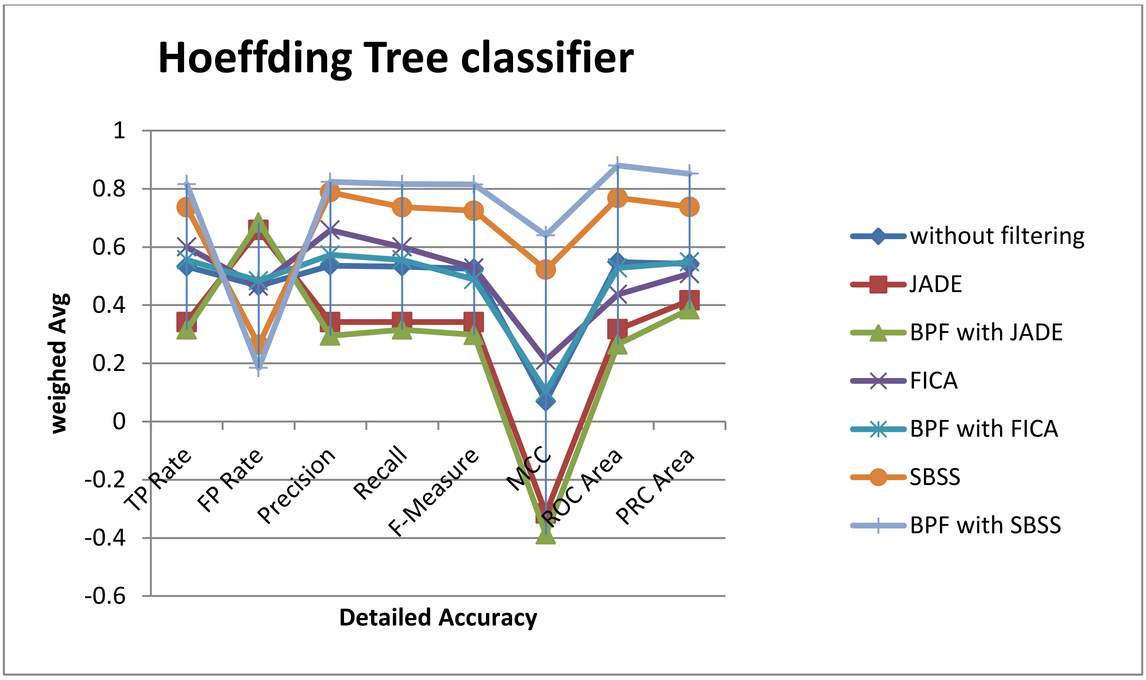


Figure (4.18) Results Obtained Detailed Accuracy by Hoeffding Tree

The most important criterion for knowing the performance of the brain and computer interface system is Precision. it is clear in Table (4.2). where proportion of instances that are truly of a class divided by the total instances classified in data raw is small because of the bad or inaccurate measurements of EEG signal that makes the detecting of ERS impossible . precision was 53%. After analyzed data by JADE , it precision is smaller than of raw data without filtering was because analyzing data Badly ,JADE is algorithm very old and not suitable for analyzing signals EEG Where it became precision 43% . After being passed it to band pass filter led to a decrease in classification precision in to 29%.analyzed data by FICA algorithm led the system performance has been improved relatively .Accuracy of classification reached 65%.While Whereas when using the filter with an FICA algorithm. It also led to a decrease in accuracy as it reached 57%. This means the filter negatively affects the blind source separation algorithms(JADE, FICA).When using the blind source separation algorithm (stone) .It greatly improved the system as shown in the table, where the reached precision 78 % . When using the filter with

the stone algorithm, it gave a high rating accuracy of up to 82 %. The filter has a good effect on the stone algorithm but is not suitable for algorithms(JADE, FICA).

4.5.2 Results After Using Naïve Bays(NB) classifier :

- **Results of Classify data into Left and right without preprocessing**

The EEG signals which is entered to the system and split up to train and test using cross-validation and classified direct using the naïve bays classifier. Table 4.9 and Figure (4.19) show the results obtained after classifying it.

Table (4.9) Classification using Naïve Bays Classifier

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.954	0.923	0.508	0.954	0.663	0.064	0.554	0.528	L
0.077	0.046	0.625	0.077	0.138	0.064	0.554	0.553	R

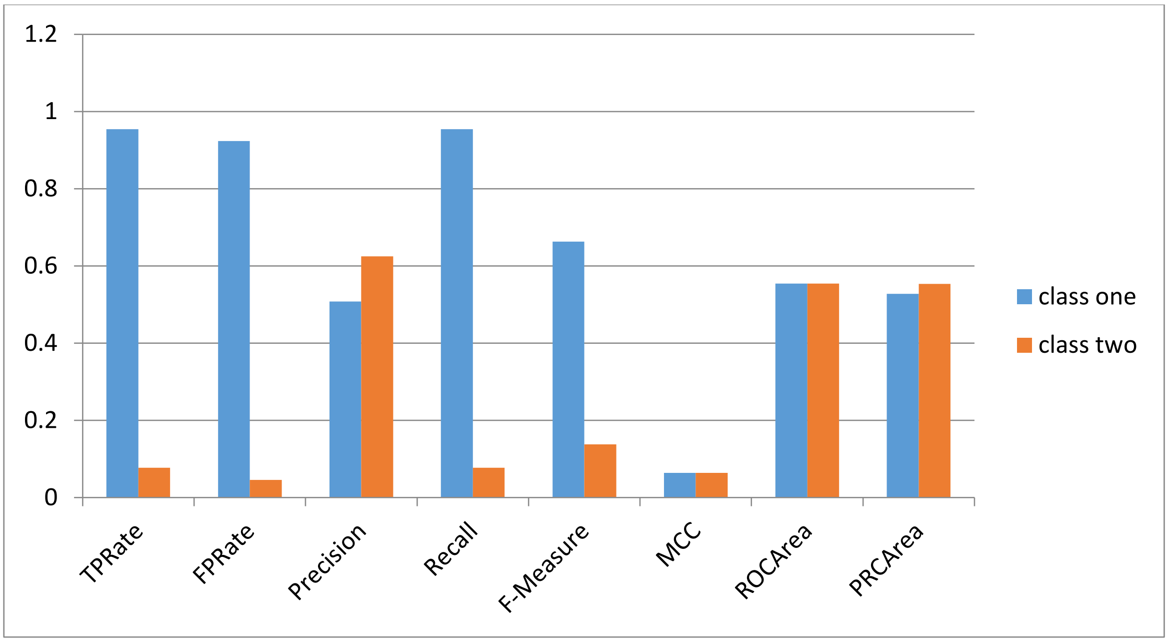


Figure (4.19) Results Obtained for Execute the System with Left and Right Data using Naïve Bays

•Results of Classify data into Left and right After (Stone)

The EEG signals which is entered to the system and split up to train and test using cross-validation and then data is analyzed using stone method to return to the source object classified using the naïve bays classifier Table 4.10 and Figure (4.20) show the results obtained after classifying it.

Table (4.10) Classification using Naive Bays Classifier and stone

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.947	0.474	0.667	0.947	0.783	0.522	0.762	0.686	L
0.526	0.053	0.909	0.526	0.667	0.522	0.78	0.791	R

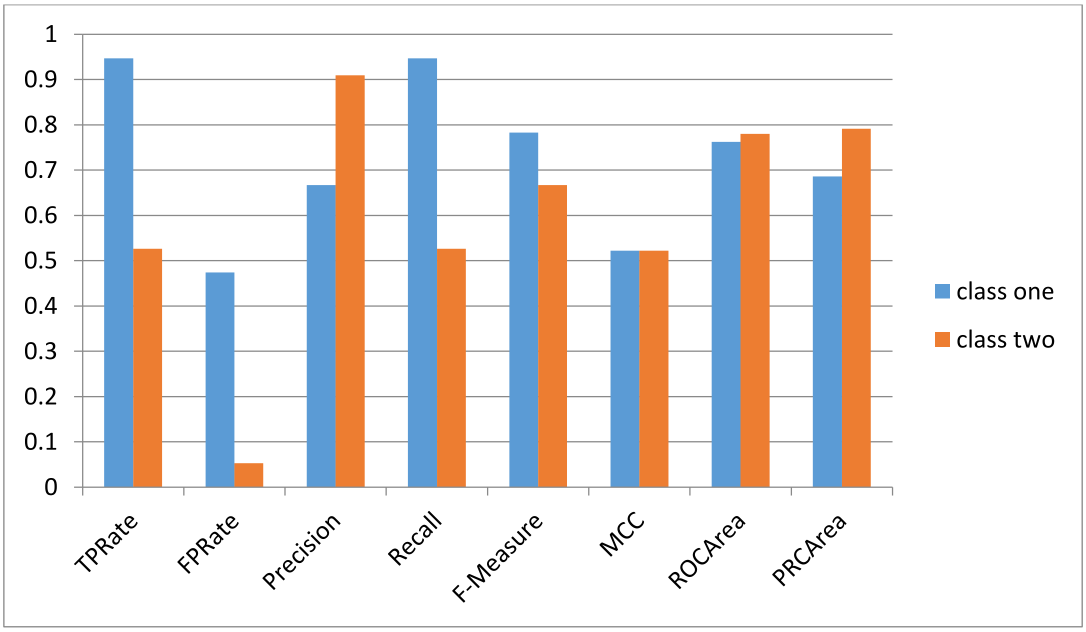


Figure (4.20) Results Obtained for Execute the System with Left and Right Data using Stone and Naive Bays

•Results of Classify data into Left and right After (FICA)

The EEG signals which is entered to the system and split up to train and test using cross-validation and then data is analyzed using FICA method to return to the source object classified using the naïve bays

classifier Table 4.11 and Figure (4.21) show the results obtained after classifying it.

Table (4.11) Classification using Naïve Bays Classifier and FICA

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.895	0.75	0.586	0.895	0.708	0.191	0.533	0.559	L
0.25	0.105	0.667	0.25	0.364	0.191	0.349	0.443	R

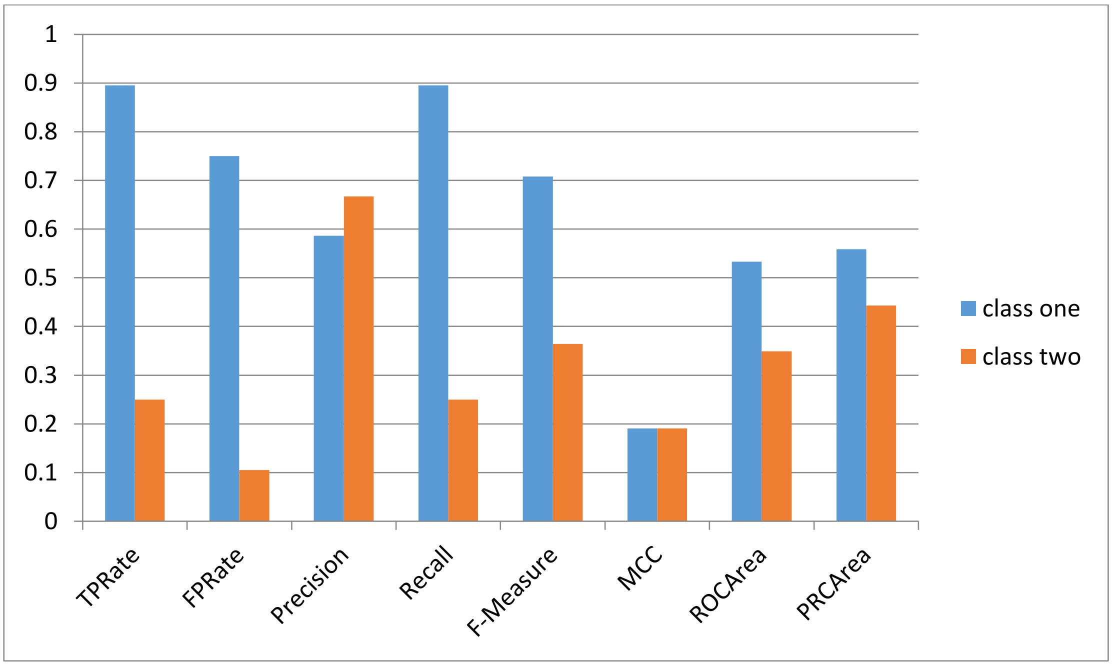


Figure (4.21) Results Obtained for Execute the System with Left and Right Data using FICA and Naïve Bays

- **Results of Classify data into Left and right After (JADE)**

The EEG signals which is entered to the system and split up to train and test using cross-validation and then data is analyzed using JADE method to return to the source object classified using the naïve bays classifier Table 4.12 and Figure (4.22) show the results obtained after classifying it.

Table (4.12) Classification using Naïve Bays Classifier and JADE

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.526	0.789	0.400	0.526	0.455	-0.277	0.349	0.415	L
0.211	0.474	0.308	0.211	0.250	-0.277	0.249	0.399	R

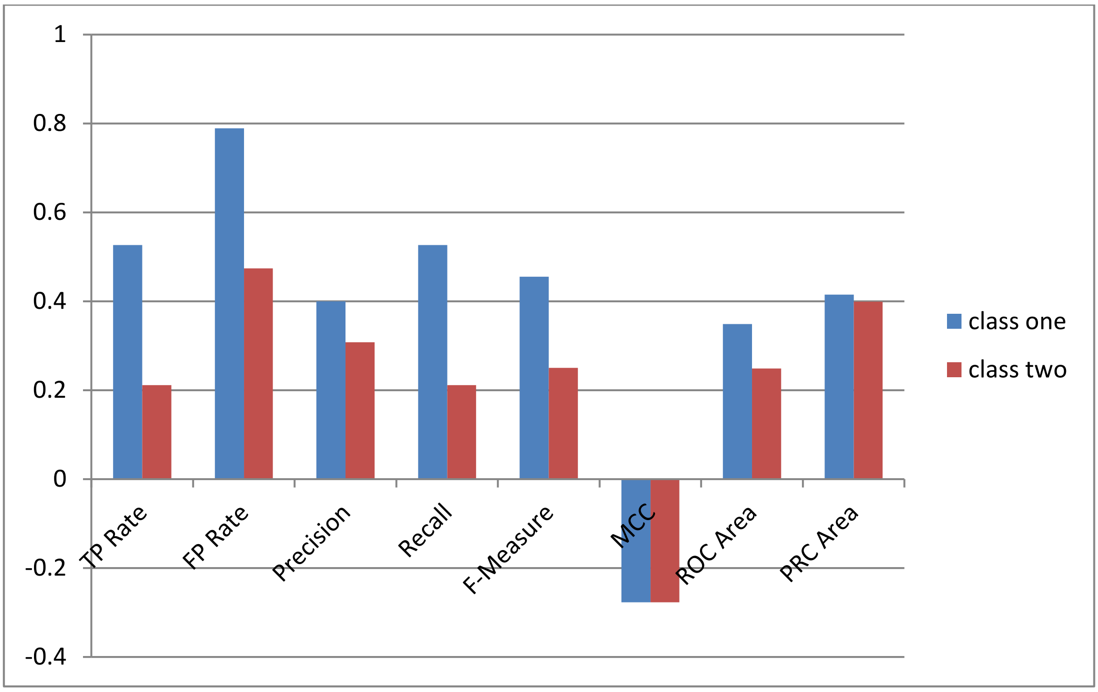


Figure (4.22) Results Obtained for Execute the System with Left and Right data using JADE and Naïve Bays

- **Results of Classify data into Left and right After (BPF) and (Stone)**

The EEG signals which is entered to the system and split up to train and test using cross-validation. then data filtering by band pass to remove noise and analyzed using stone method to return to the source object classified using the naïve bays classifier Table 4.13 and Figure (4.23) show the results obtained after classifying it.

Table (4.13) Classification using Naïve Bays Classifier with (BPF) and (Stone)

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.895	0.263	0.773	0.895	0.829	0.64	0.852	0.816	L
0.737	0.105	0.875	0.737	0.8	0.64	0.91	0.892	R

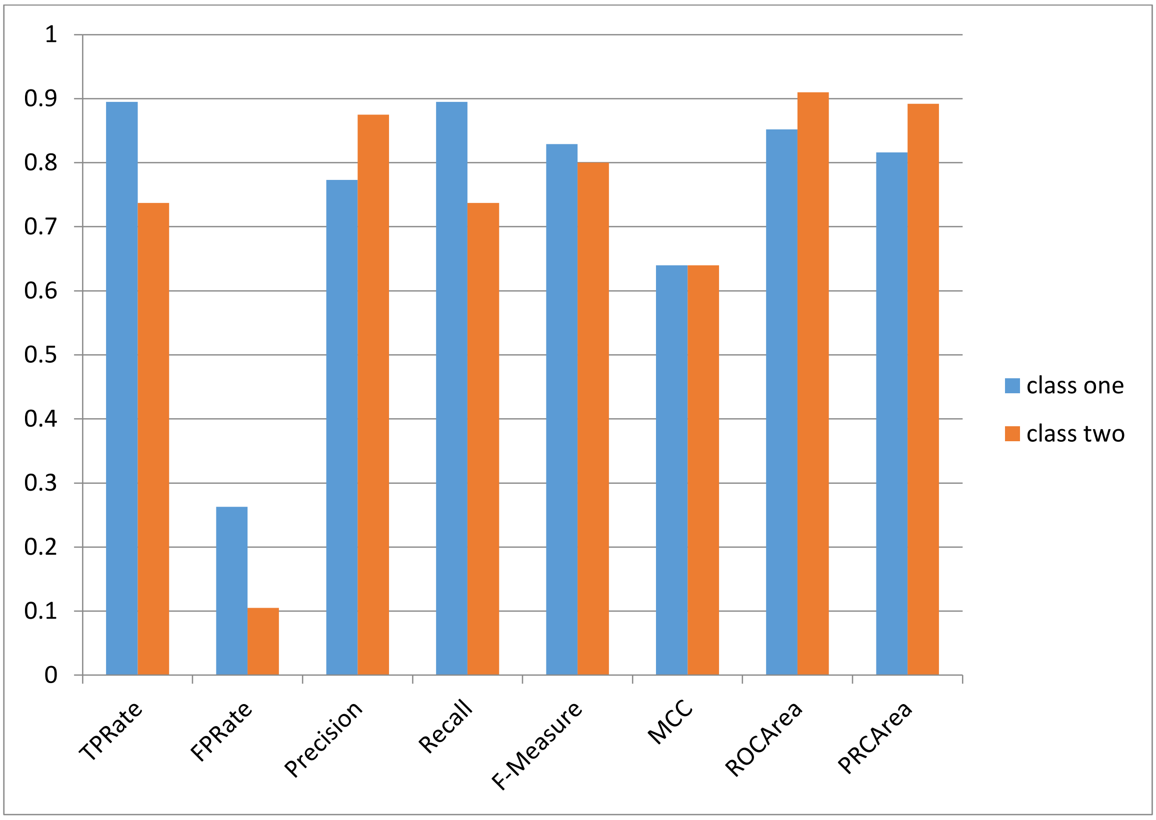


Figure (4.23) Results Obtained for Execute the system with Left and Right data using BPF with Stone and Naïve Bays

•Results of Classify data into Left and right After (BPF) and (FICA)

The EEG signals which is entered to the system and split up to train and test using cross-validation .then data filtering by band pass to remove noise and analyzed using FICA method to return to the source object classified using the naïve bays classifier Table 4.14 and Figure (4.24) show the results obtained after classifying it.

Table (4.14) Classification using Naïve Bays with (BPF) and (FICA)

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.895	0.765	0.567	0.895	0.694	0.174	0.548	0.553	L
0.235	0.105	0.667	0.235	0.348	0.174	0.526	0.579	R

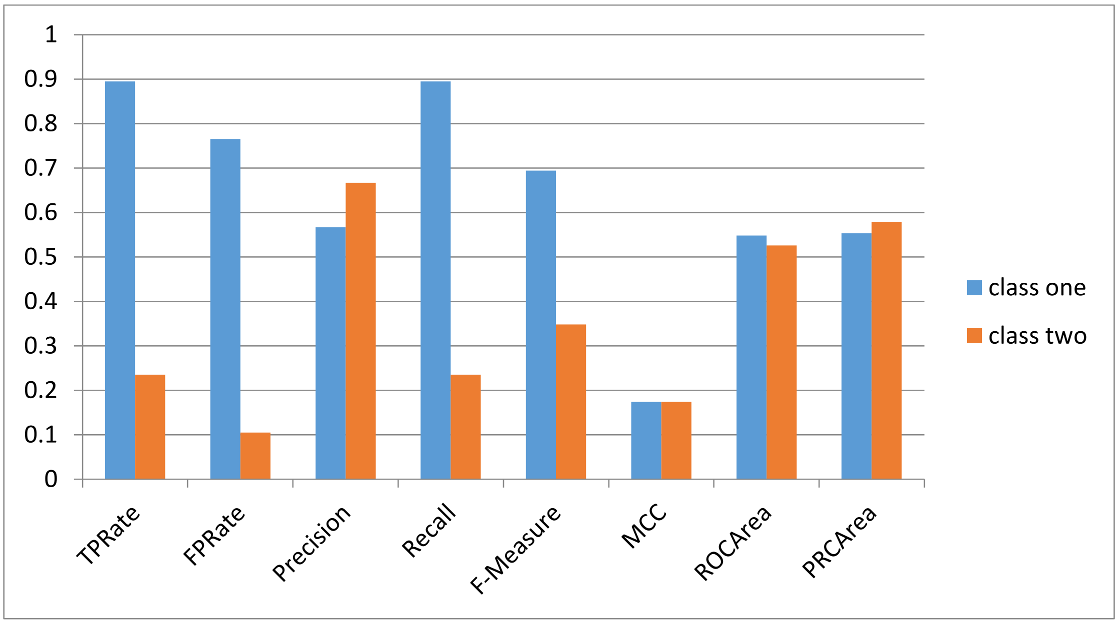


Figure (4.24) Results Obtained for Execute the System with Left and Right data using BPF with FICA and Naïve Bays

•Results of Classify data into Left and right After (BPF) and (JADE)

The EEG signals which is entered to the system and split up to train and test using cross-validation. Then data filtering by band pass to remove noise and analyzed using JADE method to return to the source object classified using the naïve bays classifier Table 4.15 and Figure (4.25) show the results obtained after classifying it.

Table (4.15) Classification using Naïve Bays Classifier with (BPF) and (JADE)

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.579	0.789	0.423	0.579	0.489	-0.226	0.388	0.442	L
0.211	0.421	0.333	0.211	0.258	-0.226	0.277	0.400	R

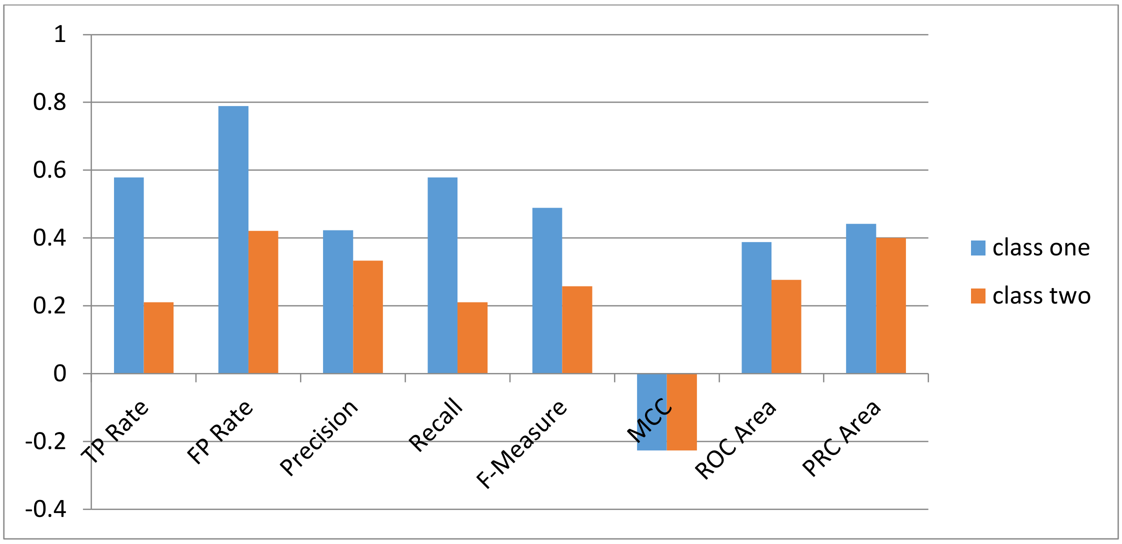


Figure (4. 25) Results Obtained for Execute the system with Left and Right data using BPF with JADE and Naïve Bays

Then Table 4.16 and Figure (4.26) show the results obtained after analysis of brain signals by blind source separation algorithms for the brain computer interface system (BCI) and classify it by Naive Bayes classifier.

Table (4.16) Results of Detailed Accuracy by Naïve Bayes Classifier of the BCI

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
without filtering	0.515	0.485	0.566	0.515	0.400	0.064	0.554	0.541
JADE	0.368	0.632	0.354	0.368	0.352	-0.277	0.299	0.407
BPF with JADE	0.395	0.605	0.378	0.395	0.373	-0.226	0.332	0.421
FICA	0.600	0.455	0.623	0.600	0.551	0.191	0.449	0.506
BPF with FICA	0.583	0.453	0.614	0.583	0.53	0.174	0.538	0.565
SBSS	0.737	0.263	0.788	0.737	0.725	0.522	0.771	0.739
BPF with SBSS	**0.816**	**0.184**	**0.824**	**0.816**	**0.815**	**0.64**	**0.881**	**0.854**

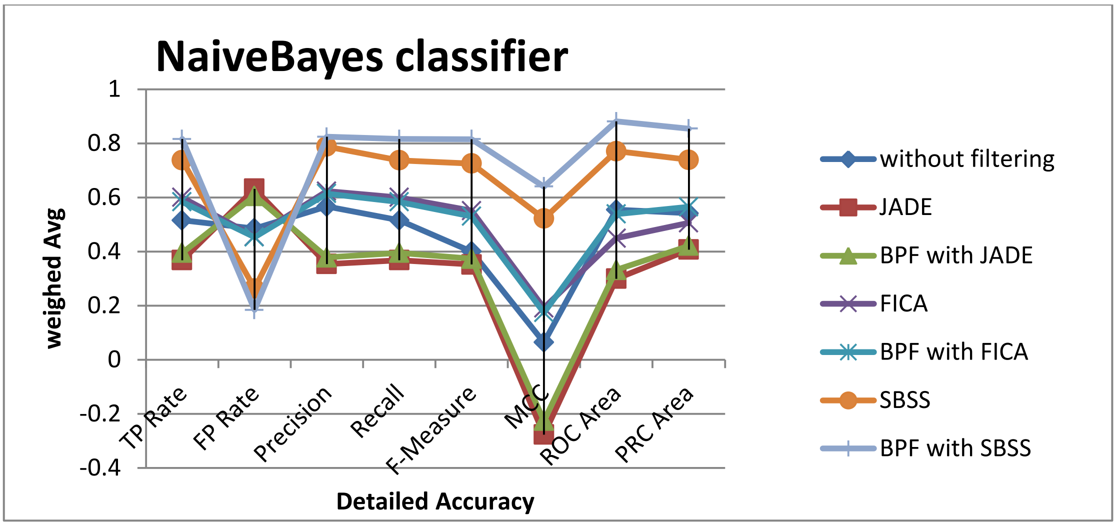


Figure (4.26) Results Obtained Detailed Accuracy by Naïve Bayes

The most important criterion for knowing the performance of the brain and computer interface system is Precision. it is clear in Table (4.16). where proportion of instances that are truly of a class divided by the total instances classified in data raw is small because of the bad or inaccurate measurements of EEG signal that makes the detecting of ERS impossible . precision was 56%. After analyzed data by JADE , it precision is smaller than of raw data without filtering was because analyzing data Badly ,JADE is algorithm very old and not suitable for analyzing signals EEG Where it became precision 35% . After being passed it to band pass filter led to a increase in classification precision in to 37%. Naïve Bayes has an effect on an algorithm JADE. analyzed data by FICA algorithm led the system performance has been improved relatively .Accuracy of classification reached 62%.While Whereas when using the filter with an FICA algorithm. It also led to a decrease in accuracy as it reached 61%. This means the filter negatively affects the blind source separation algorithms(JADE, FICA).When using the blind source separation algorithm (stone) .It greatly improved the system as shown in the table, where the reached precision 78 % . When using the filter with the stone algorithm, it gave a high rating accuracy of up to 82 %. The filter has a

good effect on the stone algorithm but is not suitable for algorithms(JADE, FICA).

4.7 Comparison of Results

The results drawn from three different techniques(stone , FICA,JADE) algorithm) with preprocessing by band pass filter adopted in this research . Brain signals have been decomposed and features have been extracted by blind sources separation and classification by (naïve bays and Hoeffding Tree) . Tables (4.17) and (4.18) represent the results obtained and comparison between Proposed Techniques, where show Table numbers showed that the SBSS has higher performance and higher classification accuracy than FICA algorithm and JADE algorithm and we focus on three basic criteria(precision, Recall, F-Measure).

Table (4.17) Results of classification precision using Naïve Bayes classifier

EEG	Preprocessing	Classification	precision	Recall	F-Measure
Raw Data	Without filtering	Naïve Bayes	56.6%	51.5	40
	JADE		35.3%	36.8	35.2
	BPF with JADE		37.8%	39.4	37.3
	FICA		62.2%	60	55
	BPF with FICA		61.3%	58.3	53
	STONE		78.7%	73.6	72.4
	BPF with STONE		**82.3%**	**81.5**	**81.4**

Table (4.18) Results of classification precision using Hoeffding Tree classifier

EEG	Preprocessing	Classification	precision	Recall	F-Measure
Raw Data	without filtering	Hoeffding Tree	53.6%	53.3	52.4
	JADE		34.1%	34.2	34.2
	BPF with JADE		29.5%	31.5	29.8
	FICA		65.8%	60	52.8
	BPF with FICA		57.2%	55.5	48.7
	STONE		78.7%	73.6	72.4
	BPF with STONE		**82.3%**	**81.5**	**81.4**

it is clear in the Table (4.17) and (4.18). High results were obtained when hybridizing the filter with a stone algorithm and classifying by(Hoeffding Tree and Naïve Bayes) Where was the precision 82.3%, Recall is 81.5% and F-Measure is 81.4% .Compared to other blind source separation algorithms . Results with both classifiers are stable and fixed with the stone algorithm but different with algorithms(FICA,JADE).

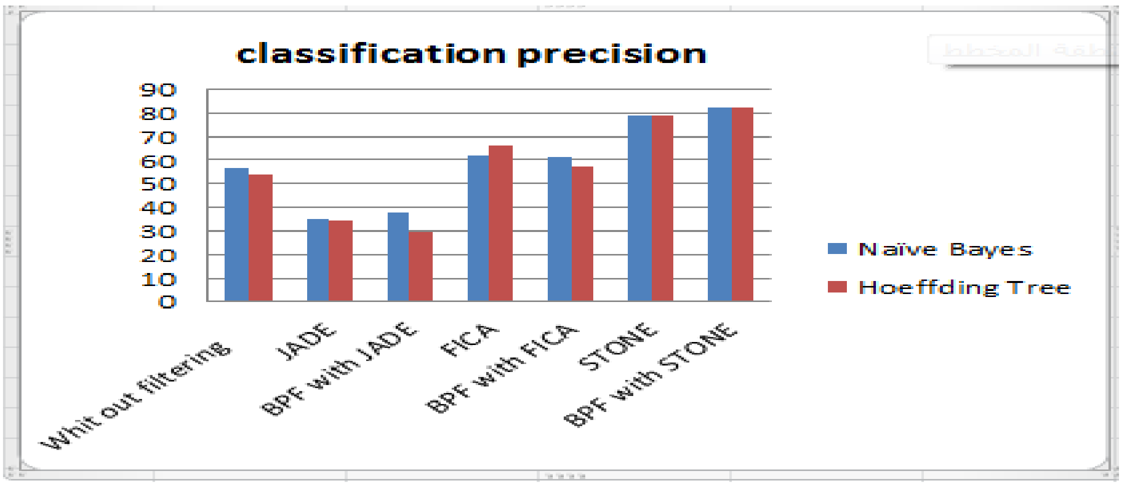


Figure (4.27) Results Obtained for Execute Two System with Classification precision by Naïve Bayes & Hoeffding Tree

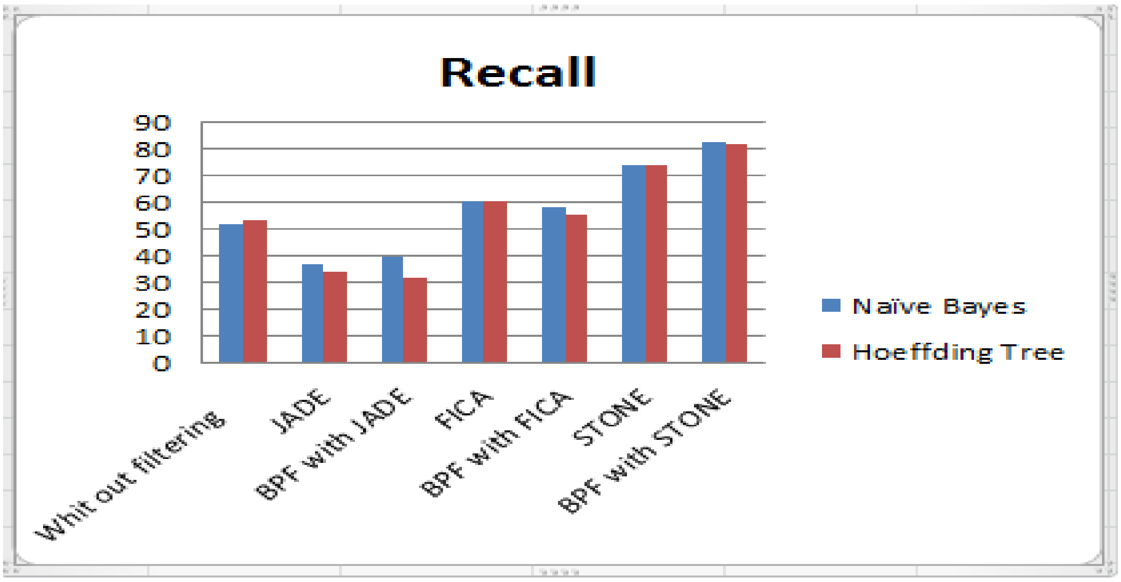


Figure (4.28) Results Obtained for Execute Two System with Recall by Naïve Bayes & Hoeffding Tree

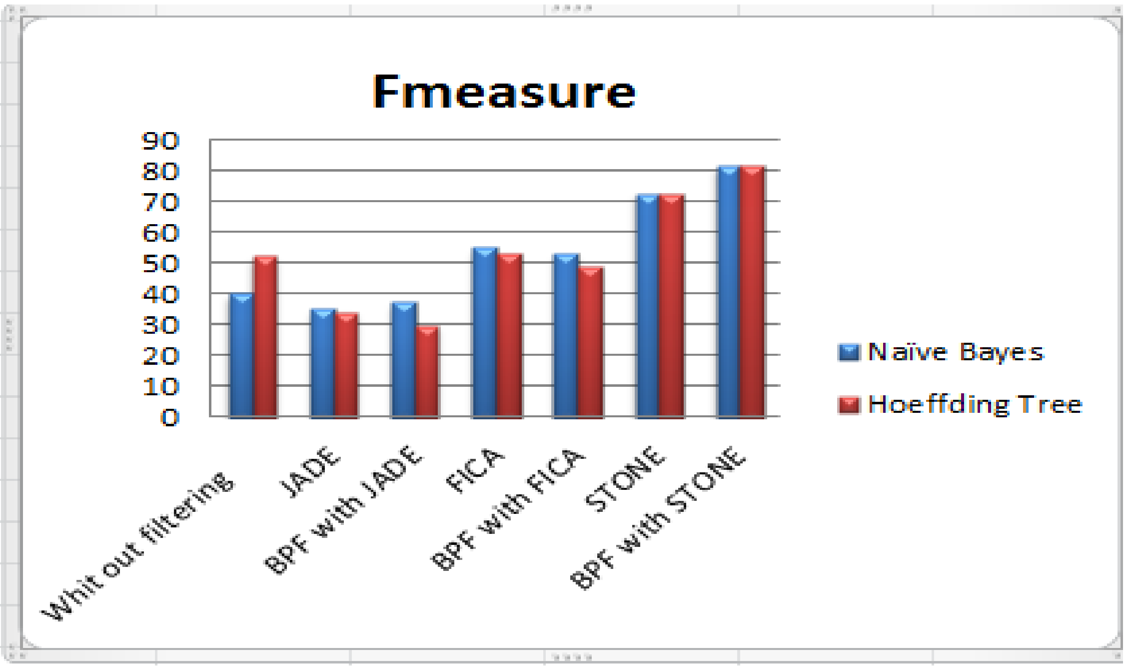


Figure (4.29) Results Obtained for Execute Two System with F-Measure by Naïve Bayes & Hoeffding Tree

Chapter Five

Conclusions and Suggestions for Future Works

Chapter Five

Conclusions and Suggestions for Future Work

5.1 Conclusions

During designing and implementing this work, several conclusions have been deduced from the obtained test results:

- One of the main problems which need to be taken under consideration in designing a BCI system is the scalp's spatial resolution and the small number of electrodes which have been used in measuring EEG gives imprecise brain source localization at the scalp.
- Since EEG signal is a mixing of many signal sources generated by the brain and corrupted by different artifacts, the stones algorithm is a sufficient algorithm for separating EEG signal into its sources (components). The task-related components are reconstructed to produce a pure EEG signal that does not contain artifacts and task-unrelated components. The stone algorithm has been discovered as a sufficient brain signal feature extraction tool.
- Improving of brain computer interface which are based on Three algorithms of blind source separation(STONE, FICA, JADE) to separate and isolate brain signals into individual components And classification by Naïve Bayes (NB) led to perfect precision rate (62 %) for (FICA), while (79. %) for Stone.
- Obtained high classification accuracy used Hoeffding Tree (HT) classifier with stone algorithm compared with another BSS .As in Table (4.8).

- The Naïve Bayes (NB) & Hoeffding Tree (HT) algorithm, shows high performance. As in Table (4.8), .(4.16) .
- The hybridization process between band pass filter and the stone algorithm led to high precision rate. As in Table (4.8), .(4.16) .

5.2 Suggestions for Future Works

The possible future works for BCI take several directions and offer quite potential ways of achieving on-line objective monitoring of the mental states of the operators and the users. Which is why, there is an importance in pursuing their progress for neuro-ergonomics implementations. Thus the following points are suggested including:

- Developing a method which is capable of distinguishing the 2 MI task categories and providing important data from the patients that suffer from severe movement disabilities.
- The Focus on having strong learning algorithms in addition to trying and developing systems which are capable of actually working on-line, and in addition adapting each level of signal processing and interface.
- inecreasing the number of electrodes which are utilized for measuring the signal of EEG.
- Developing an algorithm to determine the reactive frequency of beta band and to select it automatically.
- extended the proposed algorithm for multiclass MI classification purpose and increasing the number of mental activities such as foot and tongue movements.

References

References

[1] L. F. GomeNicolas-Alonso and J. Z-Gil, "Brain computer interfaces, a review," *sensors*, vol. 12, no. 2, pp. 1211–1279, 2012.

[2] F. A, R. A. El-KhoriMousabi, and M. E. Shoman, "An integrated classification method for brain computer interface system," in *2015 Fifth International Conference on Digital Information Processing and Communications (ICDIPC)*, 2015, pp. 141–146.

[3] S. Kalagi, J. Machado, V. Carvalho, F. Soares, and D. Matos, "Brain computer interface systems using non-invasive electroencephalogram signal: A literature review," in *2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, 2017, pp. 1578–1583.

[4] E. Gallego Jutglà, "New signal processing and machine learning methods for EEG data analysis of patients with Alzheimer's disease." Universitat de Vic-Universitat Central de Catalunya, 2015.

[5] M. H. Alomari, E. A. Awada, A. Samaha, and K. Alkamha, "Wavelet-based feature extraction for the analysis of EEG signals associated with imagined fists and feet movements," *Comput. Inf. Sci.*, vol. 7, no. 2, p. 17, 2014.

[6] S. Garg and R. Narvey, "Denoising & feature extraction of EEG signal using wavelet transform," *Int. J. Eng. Sci. Technol.*, vol. 5, no. 6, p. 1249, 2013.

[7] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, 2002.

[8] M. H. Salim, "Design and implementation of AI controller based on brain computer interface." MS Thesis, Nahrain University, 2007.

[9] J. Pan, Y. Li, and J. Wang, "An EEG-based brain-computer interface for emotion recognition," in *2016 International Joint Conference on Neural Networks (IJCNN)*, 2016, pp. 2063–2067.

[10] N. T. H. Anh, T. H. Hoang, V. T. Thang, and T. T. Q. Bui, "An artificial neural network approach for electroencephalographic signal classification towards brain-computer interface implementation," in *2016 IEEE RIVF International Conference on Computing & Communication Technologies, Research, Innovation, and Vision for*

the Future (RIVF), 2016, pp. 205–210.

[11] S. Bhaduri, A. Khasnobish, R. Bose, and D. N. Tibarewala, "Classification of lower limb motor imagery using K Nearest Neighbor and Naïve-Bayesian classifier," in *2016 3rd International Conference on Recent Advances in Information Technology (RAIT)*, 2016, pp. 499–504.

[12] R. H. Abiyev, N. Akkaya, E. Aytac, I. Günsel, and A. Çağman, "Brain-computer interface for control of wheelchair using fuzzy neural networks," *Biomed Res. Int.*, vol. 2016, 2016.

[13] G. Kucukyildiz, H. Ocak, S. Karakaya, and O. Sayli, "Design and implementation of a multi sensor based brain computer interface for a robotic wheelchair," *J. Intell. Robot. Syst.*, vol. 87, no. 2, pp. 247–263, 2017.

[14] M. Azhar, I. Ahmed, S. T. Iqbal, M. Jahangir, N. A. Shah, and I. Siddiqui, "Feature Extraction Using Independent Component Analysis Method from Non-Invasive Recordings of Electroencephalography (EEG) Brain Signals," *J. Basic Appl. Sci.*, vol. 13, pp. 259–267, 2017.

[15] Y.-J. Kim, N.-S. Kwak, and S.-W. Lee, "Classification of motor imagery for Ear-EEG based brain-computer interface," in *2018 6th International Conference on Brain-Computer Interface (BCI)*, 2018, pp. 1–2.

[16] D. Wu, J.-T. King, C.-H. Chuang, C.-T. Lin, and T.-P. Jung, "Spatial filtering for EEG-based regression problems in brain–computer interface (BCI)," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 2, pp. 771–781, 2018.

[17] S. Taran, V. Bajaj, D. Sharma, S. Siuly, and A. Sengur, "Features based on analytic IMF for classifying motor imagery EEG signals in BCI applications," *Measurement*, vol. 116, pp. 68–76, 2018.

[18] C. D. V. Gonzalez, J. H. S. Azuela, E. R. Espino, and V. H. P. Ponce, "Classification of Motor Imagery EEG Signals with CSP Filtering Through Neural Networks Models," in *Mexican International Conference on Artificial Intelligence*, 2018, pp. 123–135.

[19] D. Buvaneash and M. R. S. John, "Brain robot interface using artificial neural network," in *IOP Conference Series: Materials Science and Engineering*, 2018, vol. 402, no. 1, p. 12017.

[20] R. B. Braga, C. D. Lopes, and T. Becker, "Round Cosine Transform

Based Feature Extraction of Motor Imagery EEG Signals," in *World Congress on Medical Physics and Biomedical Engineering 2018*, 2019, pp. 511–515.

[21] M.-C. Corsi *et al.*, "Integrating eeg and meg signals to improve motor imagery classification in brain–computer interface," *Int. J. Neural Syst.*, vol. 29, no. 1, p. 1850014, 2019.

[22] W. Zheng *et al.*, "Classification of Motor Imagery Electrocorticogram Signals for Brain-Computer Interface," in *2019 9th International IEEE/EMBS Conference on Neural Engineering (NER)*, 2019, pp. 530–533.

[23] N. E. M. Isa, A. Amir, M. Z. Ilyas, and M. S. Razalli, "Motor imagery classification in Brain computer interface (BCI) based on EEG signal by using machine learning technique," *Bull. Electr. Eng. Informatics*, vol. 8, no. 1, pp. 269–275, 2019.

[24] Y. Li, J. Pan, F. Wang, and Z. Yu, "A hybrid BCI system combining P300 and SSVEP and its application to wheelchair control," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 11, pp. 3156–3166, 2013.

[25] C. Guger, B. Allison, and J. Ushiba, "Brain-Computer Interface Research: A State-of-the-Art Summary 5," 2017, pp. 1–6.

[26] M. D. Mileros, "A real-time classification approach of a human brain-computer interface based on movement related electroencephalogram." Institutionen för konstruktions-och produktionsteknik, 2004.

[27] J. Lehtonen, "EEG-based brain computer interfaces," *Trab. grado Maest. Dep. Electr. Commun. Eng. Helsinki Univ. Technol. Espoo, Finl.*, 2002.

[28] R. A. Ramadan, S. Refat, M. A. Elshahed, and R. A. Ali, "Basics of brain computer interface," in *Brain-Computer Interfaces*, Springer, 2015, pp. 31–50.

[29] J. Katona, T. Ujbanyi, G. Sziladi, and A. Kovari, "Electroencephalogram-based brain-computer interface for internet of robotic things," in *Cognitive Infocommunications, Theory and Applications*, Springer, 2019, pp. 253–275.

[30] P. Malmivuo, J. Malmivuo, and R. Plonsey, *Bioelectromagnetism: principles and applications of bioelectric and biomagnetic fields*. Oxford University Press, USA, 1995.

[31] R. Yang, “Signal processing for a brain computer interface.” 2010.

[32] A. Srinivasulu and M. S. Reddy, “Artifacts removing from EEG signals by ICA algorithms,” *IOSR J Electr Electron Eng*, vol. 2, pp. 11–16, 2012.

[33] C. Yeon, D. Kim, K. Kim, and E. Chung, “Sensory-evoked potential using a non-invasive flexible multi-channel dry EEG electrode with vibration motor stimulation,” in *SENSORS, 2014 IEEE*, 2014, pp. 519–522.

[34] E. C. Leuthardt, K. J. Miller, G. Schalk, R. P. N. Rao, and J. G. Ojemann, “Electrocorticography-based brain computer interface-the Seattle experience,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 194–198, 2006.

[35] M. D. Serruya, N. G. Hatsopoulos, L. Paninski, M. R. Fellows, and J. P. Donoghue, “Brain-machine interface: Instant neural control of a movement signal,” *Nature*, vol. 416, no. 6877, p. 141, 2002.

[36] T. Hinterberger, N. Weiskopf, R. Veit, B. Wilhelm, E. Betta, and N. Birbaumer, “An EEG-driven brain-computer interface combined with functional magnetic resonance imaging (fMRI),” *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 971–974, 2004.

[37] M. Soukup, “Brain-Computer Interface In Control Systems.” Institutt for teknisk kybernetikk, 2014.

[38] S. N. Abdulkader, A. Atia, and M.-S. M. Mostafa, “Brain computer interfacing: Applications and challenges,” *Egypt. Informatics J.*, vol. 16, no. 2, pp. 213–230, 2015.

[39] R. Christopher deCharms, K. Christoff, G. H. Glover, J. M. Pauly, S. Whitfield, and J. D. E. Gabrieli, “Learned regulation of spatially localized brain activation using real-time fMRI,” *Neuroimage*, vol. 21, no. 1, pp. 436–443, 2004.

[40] N. Weiskopf *et al.*, “Principles of a brain-computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI),” *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 966–970, 2004.

[41] S. M. Coyle, T. E. Ward, and C. M. Markham, “Brain–computer interface using a simplified functional near-infrared spectroscopy system,” *J. Neural Eng.*, vol. 4, no. 3, p. 219, 2007.

[42] G. Taga, F. Homae, and H. Watanabe, “Effects of source-detector distance of near infrared spectroscopy on the measurement of the

cortical hemodynamic response in infants,” *Neuroimage*, vol. 38, no. 3, pp. 452–460, 2007.

[43] R. P. Kennan, S. G. Horovitz, A. Maki, Y. Yamashita, H. Koizumi, and J. C. Gore, “Simultaneous recording of event-related auditory oddball response using transcranial near infrared optical topography and surface EEG,” *Neuroimage*, vol. 16, no. 3, pp. 587–592, 2002.

[44] L. F. Nicolas-Alonso and J. Gomez-Gil, “Brain computer interfaces, a review,” *sensors*, vol. 12, no. 2, pp. 1211–1279, 2012.

[45] M. Teplan, “Fundamentals of EEG measurement,” *Meas. Sci. Rev.*, vol. 2, no. 2, pp. 1–11, 2002.

[46] J. D. Kropotov, “Quantitative EEG, Event-Related Potentials And Neurotherapy. 525 B Street, Suite 1900, San Diego, CA 92101-4495.” USA: Elsevier Inc, 2009.

[47] M. Elgendi *et al.*, “From auditory and visual to immersive neurofeedback: application to diagnosis of Alzheimer’s disease,” in *Neural Computation, Neural Devices, and Neural Prosthesis*, Springer, 2014, pp. 63–97.

[48] J. A. Urigüen and B. Garcia-Zapirain, “EEG artifact removal—state-of-the-art and guidelines,” *J. Neural Eng.*, vol. 12, no. 3, p. 31001, 2015.

[49] O. Mecarelli, “Electrode Placement Systems and Montages,” in *Clinical Electroencephalography*, Springer, 2019, pp. 35–52.

[50] C. Z. Zhang, A. Kareem Abdullah, and A. Abdullabs Abdullah, “Electroencephalogram-Artifact Extraction Enhancement Based on Artificial Intelligence Technique,” in *Journal of Biomimetics, Biomaterials and Biomedical Engineering*, 2016, vol. 27, pp. 77–91.

[51] R. Dhiman, J. S. Saini, and A. M. Priyanka, “Artifactre moval from eeg recordings – Anoverview," *Proc. NCCI*, pp. 1–6, 2010.

[52] M. Fatourechi, A. Bashashati, R. K. Ward, and G. E. Birch, “EMG and EOG artifacts in brain computer interface systems: A survey,” *Clin. Neurophysiol.*, vol. 118, no. 3, pp. 480–494, 2007.

[53] C. Chatelle, S. Chennu, Q. Noirhomme, D. Cruse, A. M. Owen, and S. Laureys, “Brain–computer interfacing in disorders of consciousness,” *Brain Inj.*, vol. 26, no. 12, pp. 1510–1522, 2012.

[54] H. S. Anupama, N. K. Cauvery, and G. M. Lingaraju, “Brain

computer interface and its types-a study," *Int. J. Adv. Eng. Technol.*, vol. 3, no. 2, p. 739, 2012.

[55] J. Van Erp, F. Lotte, and M. Tangermann, "Brain-computer interfaces: beyond medical applications," *Computer (Long. Beach. Calif).*, vol. 45, no. 4, pp. 26–34, 2012.

[56] H. G. Yeom, J. S. Kim, and C. K. Chung, "Common neural mechanism for reaching movements," in *2016 4th International Winter Conference on Brain-Computer Interface (BCI)*, 2016, pp. 1–3.

[57] T. Kang, Y. Chen, S. Fazli, and C. Wallraven, "Decoding of human memory formation with EEG signals using convolutional networks," in *2018 6th International Conference on Brain-Computer Interface (BCI)*, 2018, pp. 1–5.

[58] G. R. Müller-Putz *et al.*, "Towards non-invasive brain-computer interface for hand/arm control in users with spinal cord injury," in *2018 6th International Conference on Brain-Computer Interface (BCI)*, 2018, pp. 1–4.

[59] A. Lécuyer, F. Lotte, R. B. Reilly, R. Leeb, M. Hirose, and M. Slater, "Brain-computer interfaces, virtual reality, and videogames," *Computer (Long. Beach. Calif).*, vol. 41, no. 10, pp. 66–72, 2008.

[60] J. Sleight, P. Pillai, and S. Mohan, "Classification of executed and imagined motor movement EEG signals," *Ann Arbor Univ. Michigan*, pp. 1–10, 2009.

[61] J. Hong, X. Qin, J. Li, J. Niu, and W. Wang, "Signal processing algorithms for motor imagery brain-computer interface: State of the art," *J. Intell. Fuzzy Syst.*, no. Preprint, pp. 1–15, 2018.

[62] L. Wang, H. Ding, and F. Yin, "Speech separation and extraction by combining superdirective beamforming and blind source separation," in *Blind Source Separation*, Springer, 2014, pp. 323–348.

[63] T. Rasheed, "Constrained blind source separation of human brain signals." PhD Thesis, Department of Computer Engineering, Kyung Hee University, Seoul , 2010.

[64] C. A. Joyce, I. F. Gorodnitsky, and M. Kutas, "Automatic removal of eye movement and blink artifacts from EEG data using blind component separation," *Psychophysiology*, vol. 41, no. 2, pp. 313–325, 2004.

[65] A. K. Abdullah, Z. C. Zhu, L. Siyao, and S. M. Hussein, “Blind source separation techniques based eye blinks rejection in EEG signals,” *Inf. Technol. J.*, vol. 13, no. 3, pp. 401–413, 2014.

[66] A. K. Abdullah, A. G. Wadday, and A. A. Abdullah, “Separation Enhancement of Power Line Noise from Human ECG Signal Based on Stone Technique,” in *Journal of Biomimetics, Biomaterials and Biomedical Engineering*, 2019, vol. 40, pp. 71–78.

[67] L. Huang *et al.*, “Electrical signal measurement in plants using blind source separation with independent component analysis,” *Comput. Electron. Agric.*, vol. 71, pp. S54–S59, 2010.

[68] W. Liu, D. P. Mandic, and A. Cichocki, “Blind second-order source extraction of instantaneous noisy mixtures,” *IEEE Trans. Circuits Syst. II Express Briefs*, vol. 53, no. 9, pp. 931–935, 2006.

[69] M. Khosravy, M. R. Asharif, and K. Yamashita, “A theoretical discussion on the foundation of Stone’s blind source separation,” *Signal, Image Video Process.*, vol. 5, no. 3, pp. 379–388, 2011.

[70] J. V Stone, *Independent component analysis: a tutorial introduction*. MIT press, 2004.

[71] S. Jia and Y. Qian, “Improved stone’s complexity pursuit for hyperspectral imagery unmixing,” in *18th International Conference on Pattern Recognition (ICPR’06)*, 2006, vol. 4, pp. 817–820.

[72] P. Comon and C. Jutten, *Handbook of Blind Source Separation: Independent component analysis and applications*. Academic press, 2010.

[73] B. Ans, “Adaptive neural architectures,” *Detect. primitives. Proc. Cogn.*, pp. 593–597, 1985.

[74] P. Comon, “Independent component analysis, a new concept?,” *Signal Processing*, vol. 36, no. 3, pp. 287–314, 1994.

[75] A. Hyvärinen, J. Karhunen, and E. Oja, *Independent component analysis*, vol. 46. John Wiley & Sons, 2004.

[76] A. A. A. Al-Bakry, A. G. Wadday, N. M. Yasin, and A. J. Sultan, “A novel Technique for Electrical Power System Harmonics Identification Based on Blind Source Extraction (BSE),” *Int. J. Appl. Eng. Res.*, vol. 13, no. 8, pp. 6004–6008, 2018.

[77] A. K. Abdullah and Z. C. Zhu, “Enhancement of Source Separation

Based on Efficient Stone's BSS Algorithm," *Int. J. Signal Process. Image Process. Pattern Recognit.*, vol. 7, no. 2, pp. 431–442, 2014.

[78] J. Cheng *et al.*, "Remove Diverse Artifacts Simultaneously From a Single-Channel EEG Based on SSA and ICA: A Semi-Simulated Study," *IEEE Access*, vol. 7, pp. 60276–60289, 2019.

[79] D. Langlois, S. Chartier, and D. Gosselin, "An introduction to independent component analysis: InfoMax and FastICA algorithms," *Tutor. Quant. Methods Psychol.*, vol. 6, no. 1, pp. 31–38, 2010.

[80] A. Mishra, V. Bhateja, A. Gupta, and A. Mishra, "Noise Removal in EEG Signals Using SWT–ICA Combinational Approach," in *Smart Intelligent Computing and Applications*, Springer, 2019, pp. 217–224.

[81] H. Ngarianto, A. A. S. Gunawan, and W. Budiharto, "Separating Multi Speeches in Intelligent Humanoid Robot using FastICA," *IPTEK J. Technol. Sci.*, vol. 29, no. 1, 2018.

[82] J.-F. Cardoso, "High-order contrasts for independent component analysis," *Neural Comput.*, vol. 11, no. 1, pp. 157–192, 1999.

[83] G. SAHONERO-ALVAREZ, B. La Paz, H. CALDERON, and B. La Paz, "A Comparison of SOBI, FastICA, JADE and Infomax Algorithms."

[84] J. Han, J. Pei, and M. Kamber, *Data mining: concepts and techniques*. Elsevier, 2011.

[85] P. K. Srimani and M. M. Patil, "Performance analysis of Hoeffding trees in data streams by using massive online analysis framework," *Int. J. Data Mining, Model. Manag.*, vol. 7, no. 4, pp. 293–313, 2015.

[86] G. Hulten, L. Spencer, and P. Domingos, "Mining time-changing data streams," in *Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining*, 2001, pp. 97–106.

[87] A. Kumar, P. Kaur, and P. Sharma, "A Survey on Hoeffding Tree Stream Data Classification Algorithms," *CPUH-Research J.*, vol. 1, no. 2, 2015.

[88] R. B. Kirkby, "Improving hoeffding trees." The University of Waikato, 2007.

[89] H. Wang, W. Fan, P. S. Yu, and J. Han, "Mining concept-drifting data streams using ensemble classifiers," in *Proceedings of the ninth*

ACM SIGKDD international conference on Knowledge discovery and data mining, 2003, pp. 226–235.

[90] W. Ding, S. Yu, Q. Wang, J. Yu, and Q. Guo, “A novel naive bayesian text classifier,” in *2008 International Symposiums on Information Processing*, 2008, pp. 78–82.

[91] N. Naseer, N. K. Qureshi, F. M. Noori, and K.-S. Hong, “Analysis of different classification techniques for two-class functional near-infrared spectroscopy-based brain-computer interface,” *Comput. Intell. Neurosci.*, vol. 2016.

[92] J. Machado and A. Balbinot, “Executed movement using EEG signals through a Naive Bayes classifier,” *Micromachines*, vol. 5, no. 4, pp. 1082–1105, 2014.

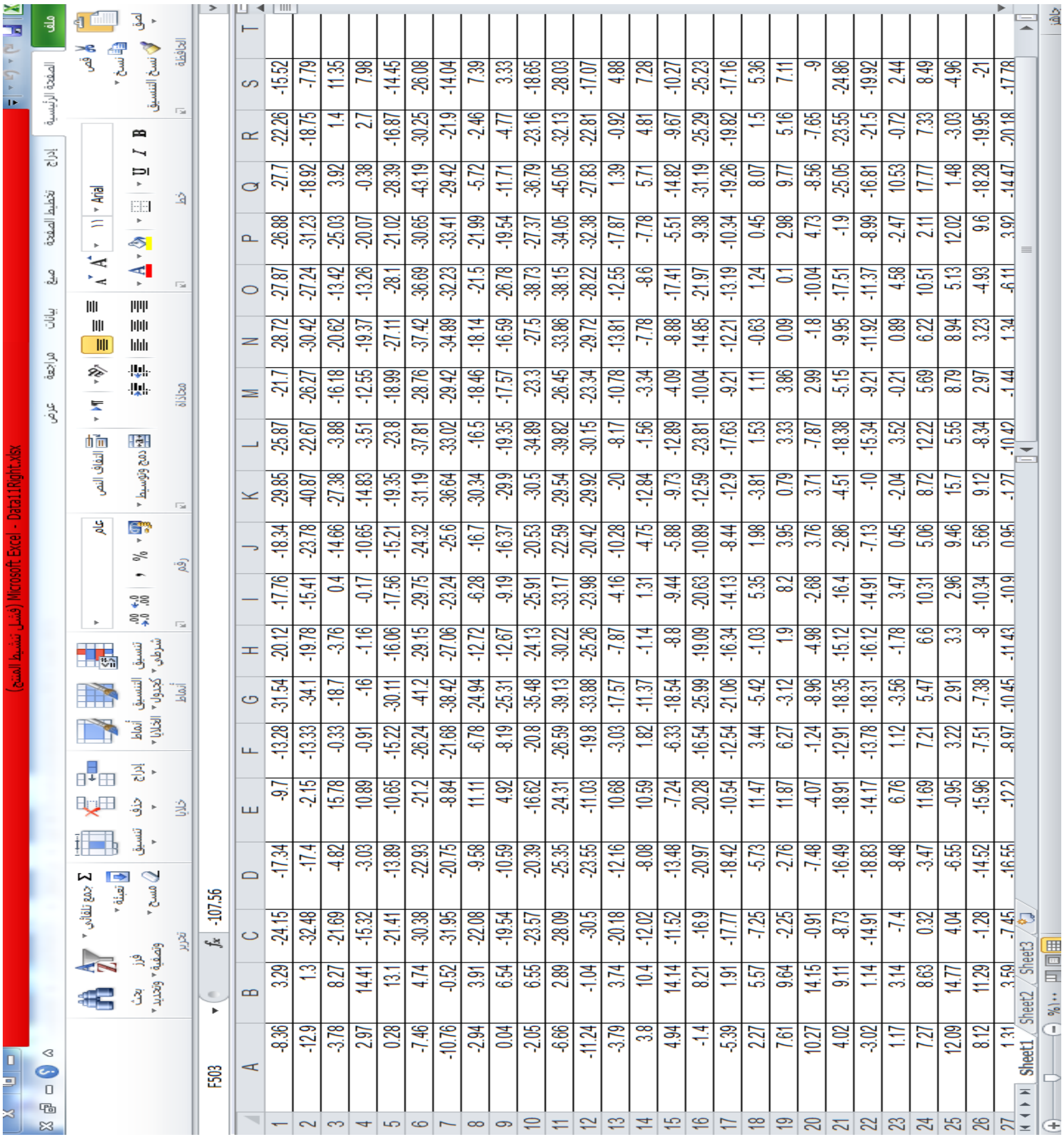
[93] Y. Li and P. Wen, “Identification of motor imagery tasks through CC-LR algorithm in brain computer interface,” *Int. J. Bioinform. Res. Appl.*, vol. 9, no. 2, pp. 156–172, 2013.

[94] H. Wang and Y. Zhang, “Detection of motor imagery EEG signals employing Naïve Bayes based learning process,” *Measurement*, vol. 86, pp. 148–158, 2016.

Appendix A

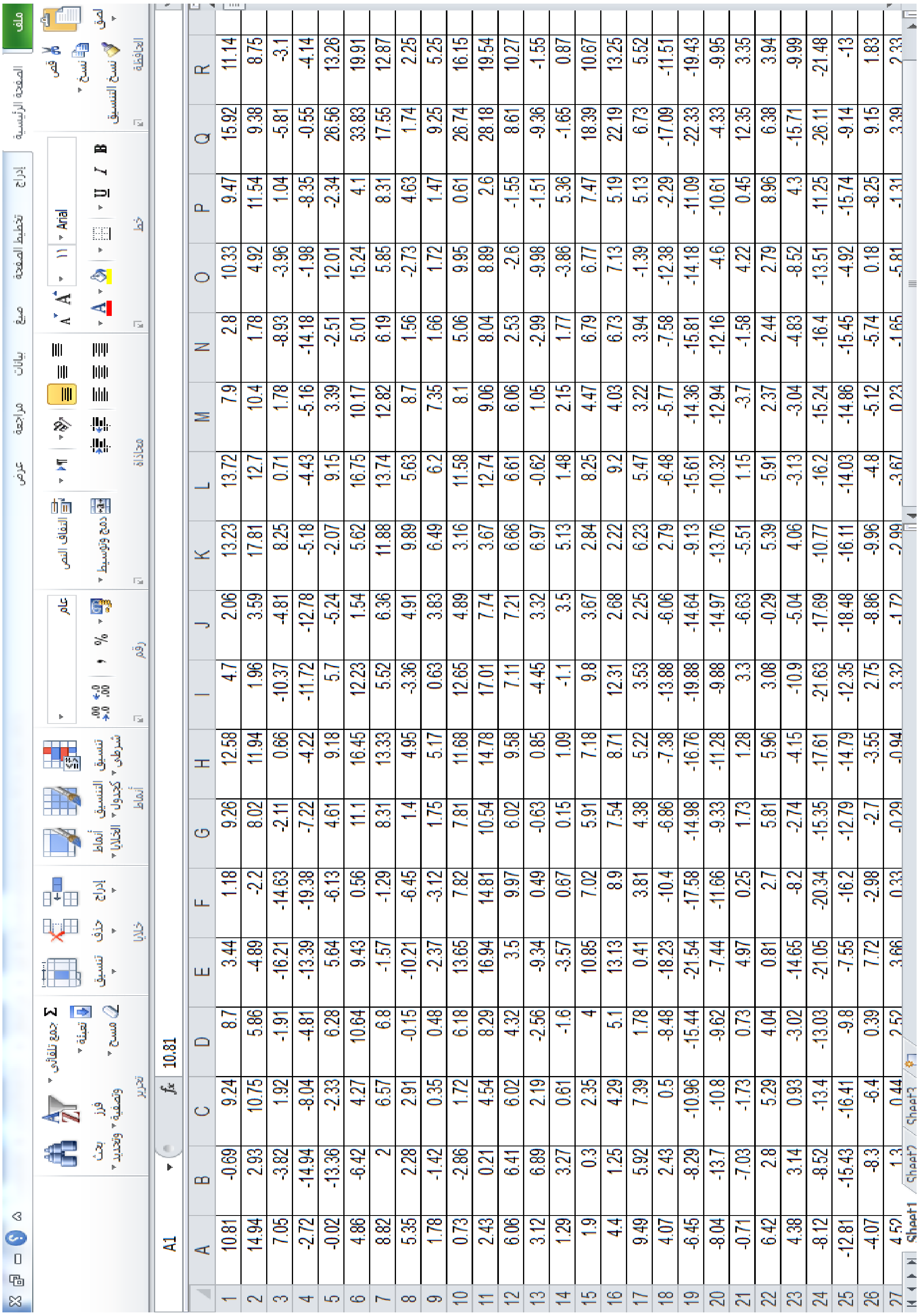
Data set:

this dataset generated using computerized EEG device, those signal are saved to data base and export as excel sheet for further processing



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	-8.36	3.29	-24.15	-17.34	-9.7	-13.28	-31.54	-20.12	-17.76	-18.34	-29.85	-25.87	-21.7	-28.72	-27.87	-26.88	-27.7	-22.26	-15.52	
2	-12.9	1.3	-32.48	-17.4	-2.15	-13.33	-34.1	-19.78	-15.41	-23.78	-40.87	-22.67	-26.27	-30.42	-27.24	-31.23	-18.92	-18.75	-7.79	
3	-3.78	8.27	-21.69	-4.82	15.78	-0.33	-18.7	-3.76	0.4	-14.66	-27.38	-3.88	-16.18	-20.62	-13.42	-25.03	3.92	1.4	11.35	
4	2.97	14.41	-15.32	-3.03	10.89	-0.91	-16	-1.16	-0.17	-10.65	-14.83	-3.51	-12.55	-19.37	-13.26	-20.07	-0.38	2.7	7.98	
5	0.28	13.1	-21.41	-13.89	-10.65	-15.22	-30.11	-16.06	-17.56	-15.21	-19.35	-23.8	-18.99	-27.11	-28.1	-21.02	-28.39	-16.87	-14.45	
6	-7.46	4.74	-30.38	-22.93	-21.2	-26.24	-41.2	-29.15	-29.75	-24.32	-31.19	-37.81	-28.76	-37.42	-36.69	-30.65	-43.19	-30.25	-26.08	
7	-10.76	-0.52	-31.95	-20.75	-8.84	-21.68	-38.42	-27.06	-23.24	-25.6	-36.64	-33.02	-29.42	-34.89	-32.23	-33.41	-29.42	-21.9	-14.04	
8	-2.94	3.91	-22.08	-9.58	11.11	-6.78	-24.94	-12.72	-6.28	-16.7	-30.34	-16.5	-18.46	-18.14	-21.5	-21.99	-5.72	-2.46	7.39	
9	0.04	6.54	-19.54	-10.59	4.92	-8.19	-25.31	-12.67	-9.19	-16.37	-29.9	-19.35	-17.57	-16.59	-26.78	-19.54	-11.71	-4.77	3.33	
10	-2.05	6.55	-23.57	-20.39	-16.62	-20.8	-35.48	-24.13	-25.91	-20.53	-30.5	-34.89	-23.3	-27.5	-38.73	-27.37	-36.79	-23.16	-18.65	
11	-6.66	2.89	-28.09	-25.35	-24.31	-26.59	-39.13	-30.22	-33.17	-22.59	-29.54	-39.82	-26.45	-33.86	-38.15	-34.05	-45.05	-32.13	-28.03	
12	-11.24	-1.04	-30.5	-23.55	-11.03	-19.8	-33.88	-25.26	-23.98	-20.42	-29.92	-30.15	-23.34	-29.72	-28.22	-32.38	-27.83	-22.81	-17.07	
13	-3.79	3.74	-20.18	-12.16	10.68	-3.03	-17.57	-7.87	-4.16	-10.28	-20	-8.17	-10.78	-13.81	-12.55	-17.87	1.39	-0.92	4.88	
14	3.8	10.4	-12.02	-8.08	10.59	1.82	-11.37	-1.14	1.31	-4.75	-12.84	-1.56	-3.34	-7.78	-8.6	-7.78	5.71	4.81	7.28	
15	4.94	14.14	-11.52	-13.48	-7.24	-6.33	-18.54	-8.8	-9.44	-5.88	-9.73	-12.89	-4.09	-8.88	-17.41	-5.51	-14.82	-9.67	-10.27	
16	-1.4	8.21	-16.9	-20.97	-20.28	-16.54	-25.99	-19.09	-20.63	-10.89	-12.59	-23.81	-10.04	-14.85	-21.97	-9.38	-31.19	-25.29	-25.23	
17	-5.39	1.91	-17.77	-18.42	-10.54	-12.54	-21.06	-16.34	-14.13	-8.44	-12.9	-17.63	-9.21	-12.21	-13.19	-10.34	-19.26	-19.82	-17.16	
18	2.27	5.57	-7.25	-5.73	11.47	3.44	-5.42	-1.03	5.35	1.98	-3.81	1.53	1.11	-0.63	1.24	0.45	8.07	1.5	5.36	
19	7.61	9.64	-2.25	-2.76	11.87	6.27	-3.12	1.9	8.2	3.95	0.79	3.33	3.86	0.09	0.1	2.98	9.77	5.16	7.11	
20	10.27	14.15	-0.91	-7.48	-4.07	-1.24	-8.96	-4.98	-2.68	3.76	3.71	-7.87	2.99	-1.8	-10.04	4.73	-8.56	-7.65	-9	
21	4.02	9.11	-8.73	-16.49	-18.91	-12.91	-18.35	-15.12	-16.4	-2.86	-4.51	-18.38	-5.15	-9.95	-17.51	-1.9	-25.05	-23.55	-24.86	
22	-3.02	1.14	-14.91	-18.83	-14.17	-13.78	-18.31	-16.12	-14.91	-7.13	-10	-15.34	-9.21	-11.92	-11.37	-8.99	-16.81	-21.5	-19.92	
23	1.17	3.14	-7.4	-8.48	6.76	1.12	-3.56	-1.78	3.47	0.45	-2.04	3.52	-0.21	0.89	4.58	-2.47	10.53	-0.72	2.44	
24	7.27	8.63	0.32	-3.47	11.69	7.21	5.47	6.6	10.31	5.06	8.72	12.22	5.69	6.22	10.51	2.11	17.77	7.33	8.49	
25	12.09	14.77	4.04	-6.55	-0.95	3.22	2.91	3.3	2.96	9.46	15.7	5.55	8.79	8.94	5.13	12.02	1.48	-3.03	-4.96	
26	8.12	11.29	-1.28	-14.52	-15.96	-7.51	-7.38	-8	-10.34	5.66	9.12	-8.34	2.97	3.23	-4.93	9.6	-18.28	-19.95	-21	
27	1.31	3.59	-7.45	-16.55	-12.2	-8.97	-10.45	-11.43	-10.9	0.95	-1.27	-10.42	-1.44	1.34	-6.11	3.92	-14.47	-20.18	-17.78	

Fig. (A.1) The Excel window to input signal of right index finger movemen



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	10.81	-0.69	9.24	8.7	3.44	1.18	9.26	12.58	4.7	2.06	13.23	13.72	7.9	2.8	10.33	9.47	15.92	11.14
2	14.94	2.93	10.75	5.86	-4.89	-2.2	8.02	11.94	1.96	3.59	17.81	12.7	10.4	1.78	4.92	11.54	9.38	8.75
3	7.05	-3.82	1.92	-1.91	-16.21	-14.63	-2.11	0.66	-10.37	-4.81	8.25	0.71	1.78	-8.93	-3.96	1.04	-5.81	-3.1
4	-2.72	-14.94	-8.04	-4.81	-13.39	-19.38	-7.22	-4.22	-11.72	-12.78	-5.18	-4.43	-5.16	-14.18	-1.98	-8.35	-0.55	-4.14
5	-0.02	-13.36	-2.33	6.28	5.64	-6.13	4.61	9.18	5.7	-5.24	-2.07	9.15	3.39	-2.51	12.01	-2.34	26.56	13.26
6	4.86	-6.42	4.27	10.64	9.43	0.56	11.1	16.45	12.23	1.54	5.62	16.75	10.17	5.01	15.24	4.1	33.83	19.91
7	8.82	2	6.57	6.8	-1.57	-1.29	8.31	13.33	5.52	6.36	11.88	13.74	12.82	6.19	5.85	8.31	17.55	12.87
8	5.35	2.28	2.91	-0.15	-10.21	-6.45	1.4	4.95	-3.36	4.91	9.89	5.63	8.7	1.56	-2.73	4.63	1.74	2.25
9	1.78	-1.42	0.35	0.48	-2.37	-3.12	1.75	5.17	0.63	3.83	6.49	6.2	7.35	1.66	1.72	1.47	9.25	5.25
10	0.73	-2.86	1.72	6.18	13.65	7.82	7.81	11.68	12.65	4.89	3.16	11.58	8.1	5.06	9.95	0.61	26.74	16.15
11	2.43	0.21	4.54	8.29	16.94	14.81	10.54	14.78	17.01	7.74	3.67	12.74	9.06	8.04	8.89	2.6	28.18	19.54
12	6.06	6.41	6.02	4.32	3.5	9.97	6.02	9.58	7.11	7.21	6.66	6.61	6.06	2.53	-2.6	-1.55	8.61	10.27
13	3.12	6.89	2.19	-2.56	-9.34	0.49	-0.63	0.85	-4.45	3.32	6.97	-0.62	1.05	-2.99	-9.98	-1.51	-9.36	-1.55
14	1.29	3.27	0.61	-1.6	-3.57	0.67	0.15	1.09	-1.1	3.5	5.13	1.48	2.15	1.77	-3.86	5.36	-1.65	0.87
15	1.9	0.3	2.35	4	10.85	7.02	5.91	7.18	9.8	3.67	2.84	8.25	4.47	6.79	6.77	7.47	18.39	10.67
16	4.4	1.25	4.29	5.1	13.13	8.9	7.54	8.71	12.31	2.68	2.22	9.2	4.03	6.73	7.13	5.19	22.19	13.25
17	9.49	5.92	7.39	1.78	0.41	3.81	4.38	5.22	3.53	2.25	6.23	5.47	3.22	3.94	-1.39	5.13	6.73	5.52
18	4.07	2.43	0.5	-8.48	-18.23	-10.4	-6.86	-7.38	-13.88	-6.06	2.79	-6.48	-5.77	-7.58	-12.38	-2.29	-17.09	-11.51
19	-6.45	-8.29	-10.96	-15.44	-21.54	-17.58	-14.98	-16.76	-19.88	-14.64	-9.13	-15.61	-14.36	-15.81	-14.18	-11.09	-22.33	-19.43
20	-8.04	-13.7	-10.8	-9.62	-7.44	-11.66	-9.33	-11.28	-9.88	-14.97	-13.76	-10.32	-12.94	-12.16	-4.6	-10.61	-4.33	-9.95
21	-0.71	-7.03	-1.73	0.73	4.97	0.25	1.73	1.28	3.3	-6.63	-5.51	1.15	-3.7	-1.58	4.22	0.45	12.35	3.35
22	6.42	2.8	5.29	4.04	0.81	2.7	5.81	5.96	3.08	-0.29	5.39	5.91	2.37	2.44	2.79	8.96	6.38	3.94
23	4.38	3.14	0.93	-3.02	-14.65	-8.2	-2.74	-4.15	-10.9	-5.04	4.06	-3.13	-3.04	-4.83	-8.52	4.3	-15.71	-9.99
24	-8.12	-8.52	-13.4	-13.03	-21.05	-20.34	-15.35	-17.61	-21.63	-17.69	-10.77	-16.2	-15.24	-16.4	-13.51	-11.25	-26.11	-21.48
25	-12.81	-15.43	-16.41	-9.8	-7.55	-16.2	-12.79	-14.79	-12.35	-18.48	-16.11	-14.03	-14.86	-15.45	-4.92	-15.74	-9.14	-13
26	-4.07	-8.3	-6.4	0.39	7.72	-2.98	-2.7	-3.55	2.75	-8.86	-9.96	-4.8	-5.12	-5.74	0.18	-8.25	9.15	1.83
27	4.52	1.3	0.44	2.52	3.66	0.33	-0.29	-0.94	3.32	-1.72	-2.99	-3.67	0.23	-1.65	-5.81	-1.31	3.39	2.33

Fig. (A.2) The Excel window to input signal of left index finger movement

the worksheets are copied and pasted into an m-files of the MATLAB program (each worksheet pasted in a separated m-file), that save these data as matrices of (19 $\times$ 15360) as shown in Fig. (A.3) and Fig(A.4) for left index finger and right index finger.

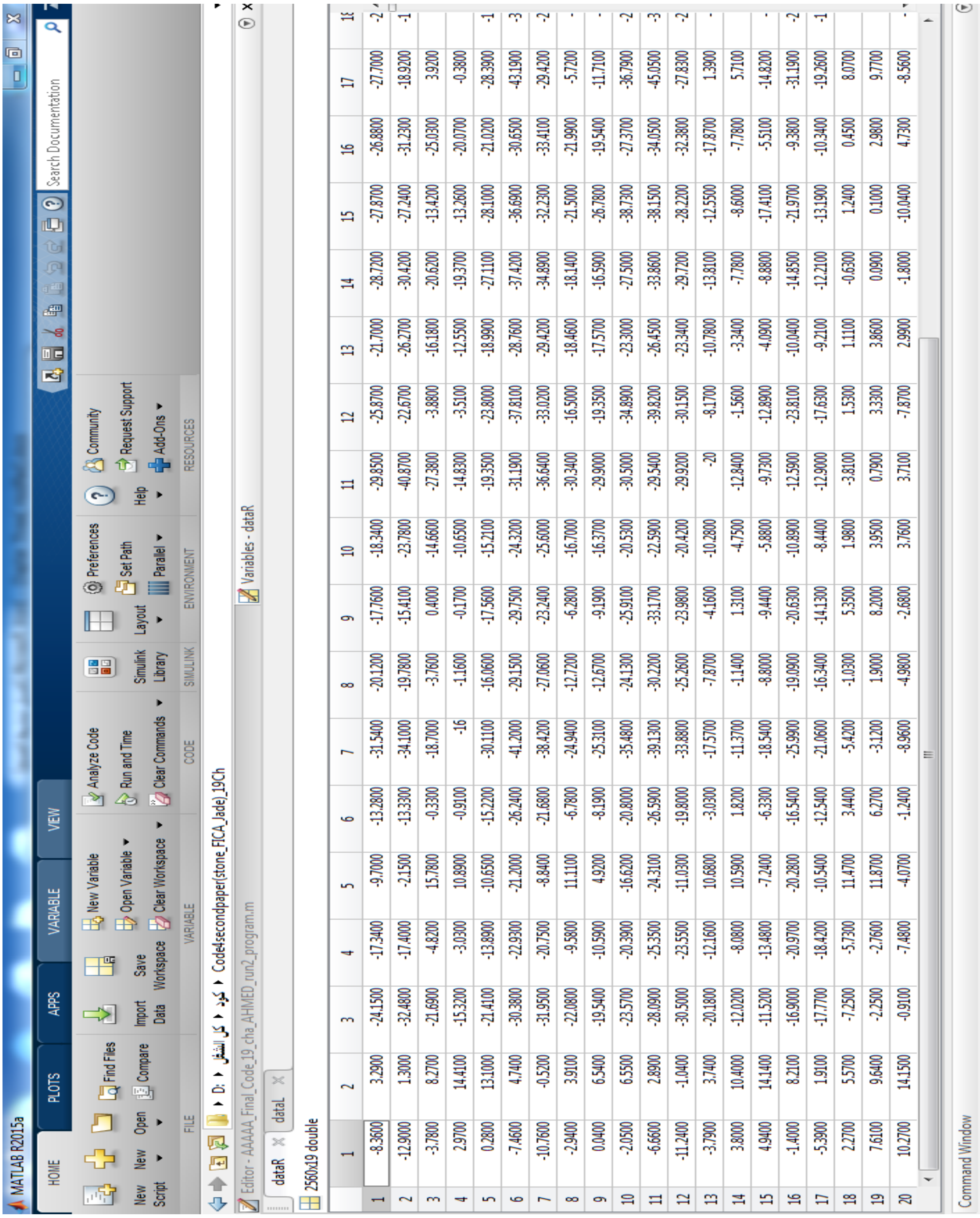


Fig. (A.3) The copy of data from the Excel program to the MATLAB program of right index finger movement.

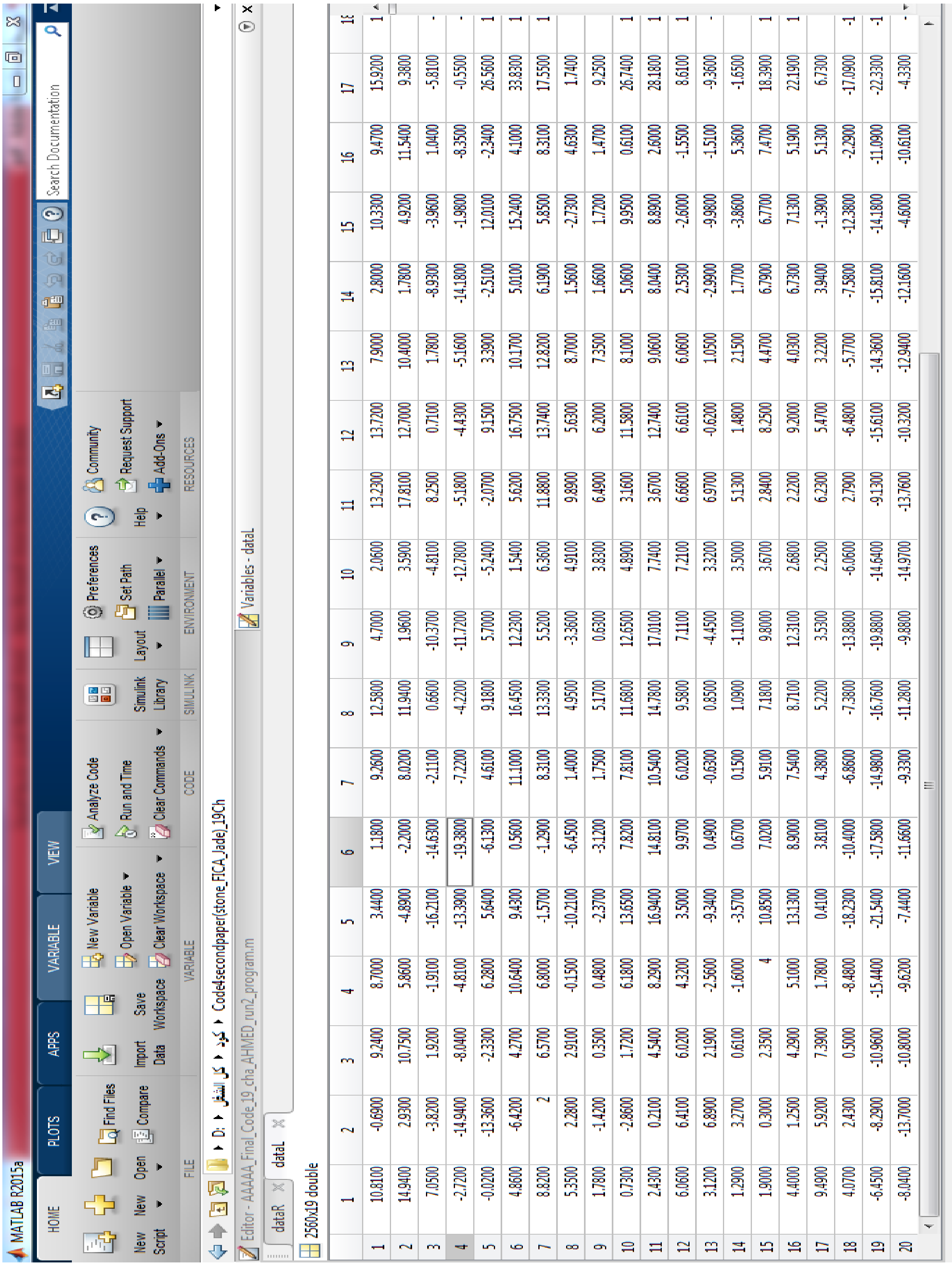


Fig. (A.4) The copy of data from the Excel program to the MATLAB program of left index finger movement.

الخلاصـــــة

شهد القرن الماضي ، تقدماً كبير في مجال البحوث المتعلقة بواجهات الدماغ و الحاسوب ، والتي لديها القدرة على توفير قناة للتفاعل بين الإنسان والآلة. يمكن تعريف واجهة الدماغ والحاسوب كنظام اتصال تم تطويره للسماح للأفراد الذين يعانون من شلل تام بإرسال أوامر أو رسائل دون إرسالها عبر مسار الإخراج الطبيعي للدماغ. هدف هذه الرسالة أن تكون مرجعًا في مجال BCI. حيث نقدم المعرفة الأساسية حول موجات الدماغ وقياسها في شكل EEG. ثم نركز على خوارزميات محددة يمكنها فصل وتصنيف إشارة كهربية الدماغ (EEG) المتعلقة بالمهمة من إشارات EEG المستمرة. المهمة هي حركة الابهام الايمن أو الايسر. تم الفصل بواسطة التهجين بين الطريقة الكلاسيكية التي تمثلها عملية الترشيح والطريقة الحديثة التي تمثلها تقنية ستون BSS. تكون قادرة على عزل وحذف الاثار الجانبية (الضوضاء) التي تتمثل بالتخطيط الكهربائي العضلي (EMG) و تصوير العين الكهربائية (EOG) وتخطيط كهربائية الدماغ (ECG) وخطوط الطاقة (LN) إلى مكونات فردية والتي تعتبر ضوضاء. هذا الفصل من شأنه أن يسرع بشكل فعال تصنيف أنماط EEG. ومن ثم أخذ الاشارات المتعلقة بالمهمة الناتجة من خوارزميات الفصل وتصنيفها باستخدام مصنفين (Naïve Bayes & Hoeffding Tree) ومن ثم مقارنة خوارزمية النظام المقترح مع انظمة اخرى تستخدم خوارزميات فصل المصدر الأعمى الأخرى مثل (JADA ،FICA).دربت الخوارزمية وتم اختبارها باستخدام إشارات حقيقيه من (EEG) الذي تم الحصول عليها وفقًا لقياس النظام الدولي (١٠-٢٠) باستخدام نظام EEG المحوسب ، وتشير النتائج إلى أن النظام المقترح لديه معدل دقة مرتفع مقارنة بالطرق الأخرى الحالية اذ بلغ متوسط معدل الدقة (٨٢٪) باستخدام (stone مع (Naïve Bayes (NB)) و(٨٢%) متوسط معدل الدقة باستخدام (stone with Hoeffding Tree)

جمهورية العراق

وزارة التعليم العالي والبحث العلمي

جامعة ديالى

كليــة العلوم

تحسين نظام واجهة الدماغ و الحاسوب بالاعتماد على فصل المصادر العمياء المصنفة

رســالة

مقدمة الى قسم علوم الحاسوب / كلية العلوم / جامعة ديالى وهي جزء من متطلبات نيل درجة الماجستير في علوم الحاسوب

من قبل

زينب كاظم عبيس

باشراف

أ.م.د طــه محمد حسـن

أ.م.د أحمد كريم عبد الله البكري

١٣٤١هـ ٢٠٢٠م