STUDY OF OCULAR ARTRIFACT REMOVAL METHODS FROM EEG

A DISSERTATION
SUBMITTED IN THE FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE
OF

MASTER OF TECHNOLOGY
IN
MICROWAVE AND OPTICAL COMMUNICATION

Submitted By:
ANCHAL YADAV

University Roll No. 2K16/MOC/01

Under the supervision of

Dr. M. S. Choudhary
Associate Professor

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
BAWANA ROAD DELHI-110042, INDIA

MAY, 2018

DECLARATION

I, Anchal Yadav, Roll No. 2K16/MOC/01 student of M.TECH, hereby declare that the project dissertation titled **"STUDY OF OCULAR ARTIFACT REMOVAL METHODS FROM EEG"** being submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Masters of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

Place: Delhi **ANCHAL YADAV**

Date: **(2K16/MOC/01)**

CERTIFICATE

I hereby certify that the Project Dissertation titled "**STUDY OF OCULAR ARTIFACT REMOVAL METHODS FROM EEG**" which is submitted by **ANCHAL YADAV, Roll No. 2K16/MOC/01,** Department of Electronics and Communication,Delhi Technological University, Delhiin partial fulfilment of the requirementsfor the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledgethis work has not been submitted in part or full for any Degree or Diploma to this university or elsewhere.

Place: Delhi
Date:

Dr. S. INDU
HEAD OF DEPARTMENT
DELHI TECHNOLOGICAL UNIVERSITY

Dr. M. S. CHOUDHARY
SUPERVISOR
ASSOCIATE PROFFESSOR
DELHI TECHNOLOGICAL UNIVERSITY

ACKNOWLEDGEMENT

I take great pride in expressing my unfeigned appreciation and gratitude to my learned mentor **Dr. M. S. Choudhary, Associate Professor** Department of Electronics and Communication Engineering, DTU for this invaluable inspiration, guidance and continuous encouragement throughout this project work..

I am also grateful to Prof. S. Indu, HOD, Department of Electronics and Communication Engineering, DTU for her immense support. I would also acknowledge DTU for providing the right academic resources and environment for this work to be carried out.

Finally, I extend my deep appreciation to my family and friends, for all that they meant to me during the crucial times of the completion of my project.

ANCHAL YADAV

(2K16/MOC/01)

(MICROWAVE AND OPTICAL COMMUNICATION)

ABSTRACT

Electroencephalography (EEG) signal is the recording of spontaneous electrical activity of the brain over a small period of time. Electroencephalography (EEG) signals are widely used in early diagnosis of brain diseases. During the data acquisition and transmission of EEG signal, signal gets corrupted by various types of noises e.g. electrode contact noise, ocular noise, electromyography noise etc. This work focuses on the removal of ocular artifact that strongly appears in frontal electrode. In this project the ocular artifact is removed from EEG signal using Ensemble Empirical Mode Decomposition(EEMD) and Spatial Constraint Independent Component Analysis (SCICA). Here, EEMD is used to disintegrate the artifactual EEG signal to find Implicit Mode Functions (IMFs). The artifactual IMFs are take out from the IMFs by separating the electrooculogram (EOG) related IMF signals. Now, the artifactual IMFs considered as the source to independent Component Analysis (ICA) as a result Independent Components (ICs) and mixing matrix are obtained. The artifactual ICs are separated using kurtosis and modified Mean Sample Entropy (mMSE). The mixing matrix is modified using spatial constraints. The restored IMFs are obtained by using inverse of modified mixing matrix and ICs. Finally, the artifact-free EEG signal is reconstructed by summing up artifact-free IMFs and restored IMFs. The proposed method is compared with other advanced methods in terms of mutual information, correlation, and coherence. The results show that the proposed method has better performance as compared other latest methods of ocular artifact removal from EEG.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

EEG: Electroencephalography

EOG: Electrooculogram

EMD: Empirical Mode Decomposition

EEMD: Ensemble Empirical Mode Decomposition

ICA: Independent Component Analysis

ICs: Independent Components

IMFs: Implicit Mode Functions

mMSE: modified Mean Sample Entropy

MI: Mutual Information

SCICA: Spatially Constrained Independent Component Analysis

CHAPTER 1

INTRODUCTION

Brain is one of most complicated and important organ which controls the co-ordination of nerves and human muscles. Electroencephalography (EEG) is an electrophysiological method which is used to record the electrical activity of the human brain. The test or the record which measures brain activity is known as electroencephalogram. EEG is a noninvasive method of measurement where electrodes are placed along the scalp and the electric potential of the brain is measured. In the humans, the neural activity of the brain starts only in the 17^{th} to 23^{rd} week of antenatal developmental stage. Since then, the brain signals are generated throughout life even when sleeping or in coma. The brain signals stop only when a person dies. The EEG signals do not only represent the signal related to brain activity but also the signals related to activity of the rest of the body. The words enkephalo (brain), graphein (to write) which are Greek together derive the word electroencephalogram which is the test or record to measure the voltage fluctuations of neurons of the brain. EEG signal is mainly used by doctors, scientists, or physicians to study the brain functions and also to diagnose neurological disorders like Alzheimer, seizure, etc. Moreover, EEG signal forms one of the means to interface brain and computer hence it helps in brain computer interface. These electrical signals of the brain are generated by the bombardment of the neurons within the brain. The neurons process the information by changing electrical current's flows across membranes. These currents produced by electro-magnetic fields are recorded by placing electrodes on surface of human's scalp. Then the potentials across different electrodes are amplified and recorded as Electroencephalogram (EEG). EEG is also an important tool for diagnosing sleep disorders, brain death, coma, epilepsy, dementia, encephalopathies and head injury. EEG is a first-line way of diagnosing strokes, tumors and focal brain disorders. Moreover, EEG is very helpful in treatment of abnormalities, attention disorders, learning problems, behavioral disorders like autism and language delay.

1.1 Historical background of EEG

The first scientist to ever observe EEG signal is Richard Caton. In 1800s, Richard Caton at Royal Infirmary had recorded the electrical activity from brains of monkeys and rabbits using mirror galvanometer. Caton's entire research was focused on animals. He not only recorded the signal but also analyzed the variations related to sleep, anesthesia, wakefulness and death. He observed the responses to stimulation of skin. These observations are regarded as earliest records of oscillating EEG and also of DC potentials, of motor-related and sensory evoked potentials.

Then came Adolph Beck (1863-1939), a polish scientist, who published the reports of steady potentials recorded from medulla and spine of frog and investigated the cord damage effects and removal of cerebrum hemispheres. He also studied the cerebrocerebellar relationships and recorded the physiological potentials without distortion.

Another scientist Fleischl von Marxow (1846-1891) recorded the observations of electrical activity from visual cortices of various animals, resulting from the illumination of retina. He also showed that responses were abolished by cooling and chloroform.

Later came Hans Berger (1873-1941) who was the first scientist to successfully record EEG signal from surface of human scalp on photographic paper. This was achieved in 1924. Berger used non-polarizable clay cylinder electrodes to record the electrical activity but later he abandoned non-polarizable electrodes because of high impedances which are near completely destroying the signal itself. Hans Berger also coined the terms "alpha'' and "beta" and in honor of Dr. Berger, 10Hz alpha waves are also called Berger waves. Later around 1935, instruments were made for recording EEG commercially and by 1940s, scientists were using EEGs to study about criminal behavior and some mental illness. By 1960s, EEGs have been used in sleep research, brain death etc. During 20th century EEGs demonstrated the absence of brain activity.

1.2 Activity of the neurons

There are more than a billion neurons present in the human brain, these neurons are also called nerve cells, these neurons have ability to influence majority of other neurons. Neuronsare electrically excitable cell and maintain the brain's electrical charges. Since neurons have electrochemical character so they can transmit electrical signals and share the messages with each other.

The central nervous system which includes brain, spinal cord, and peripheral nervous system has neuron as it's primary component. Depending on the specialization there are many types of neurons. Sensory neurons work for sensory organs, they sense stimulus such touch, sound, light, etc. The neurons convert these stimuli into electrical signal via transduction, which is then send to brain or spinal cord. There are motor neurons which receive signals from brain or spinal cord to control muscles. Interneurons are also present; these neurons connect two neurons and helps in flow of current within same region of brain or spinal cord. Neurons are present in many different shapes and sizes but basic structure of neuron is same which can be divided into three categories: cell body (soma) which is used for processing and integrating information, axons which is the middle part and conducts signals to other brain parts and dendrites which receives the information. The diagram of neuron is shown in Fig.1.1. The cell body contain cytoplasm and cell organelles and certain granular bodies which are called Nissl's granules. Dendrites are short fibers which branch repeatedly and transmit impulses to the cell body. They also contain Nissl's granules.The axon is a long fiber, the end of this fiber is branched. The termination of each branch is a bulb-like structure which is called synaptic knob. This knob contains synaptic vesicles which contains a chemical known as neurotransmitters. The main job of the axon is to transmit electric impulse away from cell body to a synapse or to a neuro-muscular junction. The neuron can be divided on the basis of number of axons and dendrites as multipolar, bipolar, and unipolar. Multipolar neurons have single axon and two or more dendrites and found in cerebral cortex. Bipolar neurons have single axon and single is dendrite and are found in the retina in eye. Unipolar neurons have one axon and no dendrite and are found in embryonic stage. The axon can be of two types myelinated and non-myelinated.

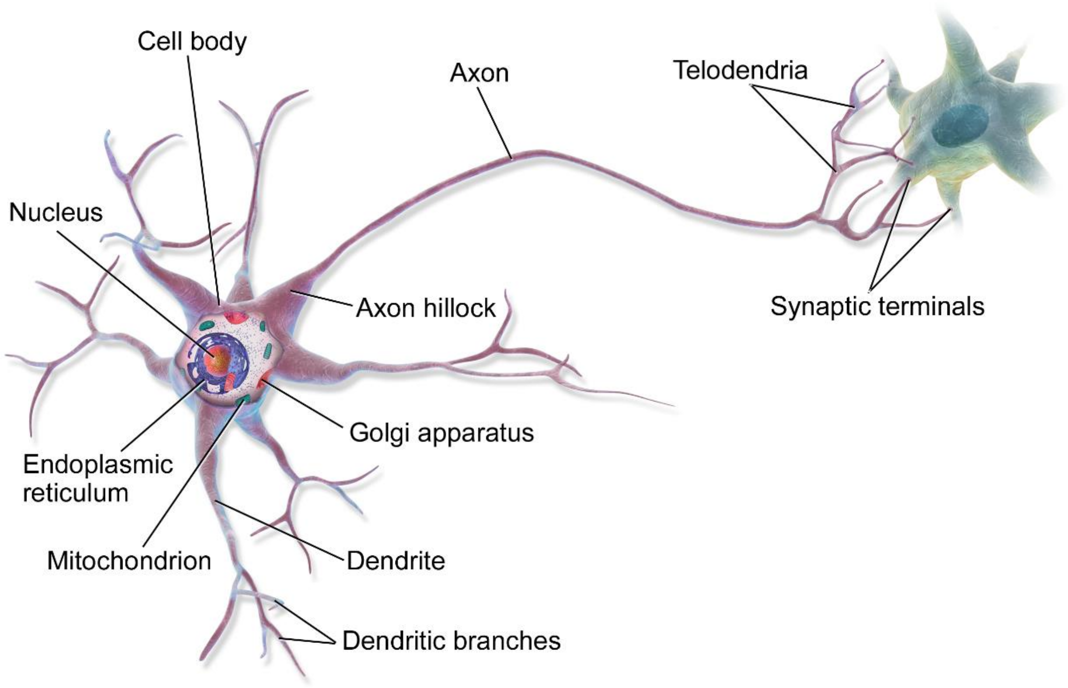

Fig.1.1: Structure of a neuron

Action potential is a way in which electric impulse travels from one neuron to another. When the neuron is at rest the resting potential is formed, this resting potential of the membrane has -70 mV potential difference with inside of membrane having less potassium ions and outside of membrane having more sodium ions. So, inside of cell is at 70 mV lower potential than outside. Ion needs a protein to facilitate their movement across the membrane. Ion channels are present through which the ions can cross the membrane. Some channels are always open but some require trigger to open them. There is different channel for each ion. When a stimulus is triggered sodium, channel opens up and sodium ion move inside the membrane and hence increasing the potential. Potassium ions flow out and net amount of flow decides the potential value. Once lot of sodium flow inside the membrane the potential may rise up to 30 mV as shown in Fig1.2. When the channel is closed sodium ions are blocked. When the potassium channels are open then the potassium ions move out of membrane and the potential becomes negative and finally reaches the resting potential. This positive and negative potential flows across the axon and the electric potential flows.

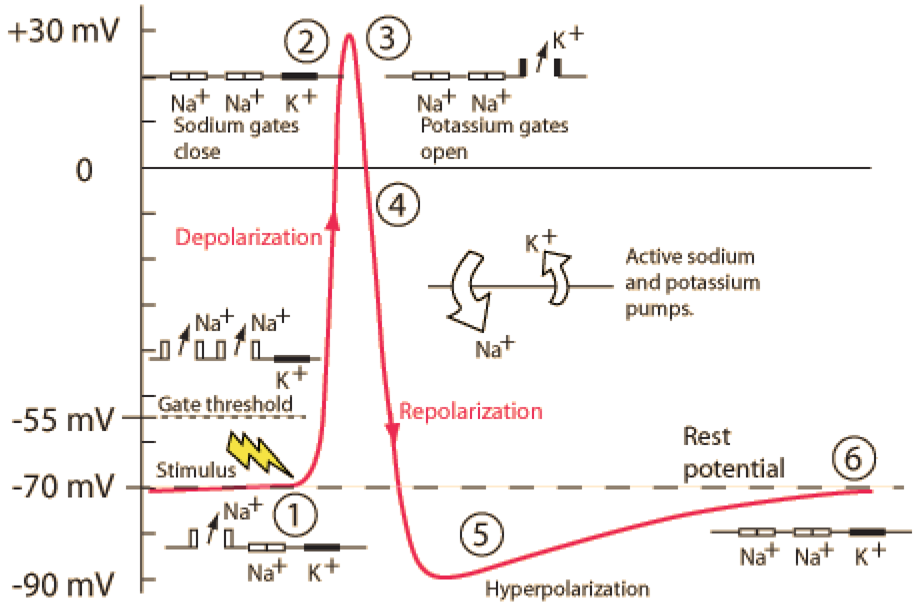

Figure 1.2: Potential developed in the axon of neuron

1.3 Human Brain

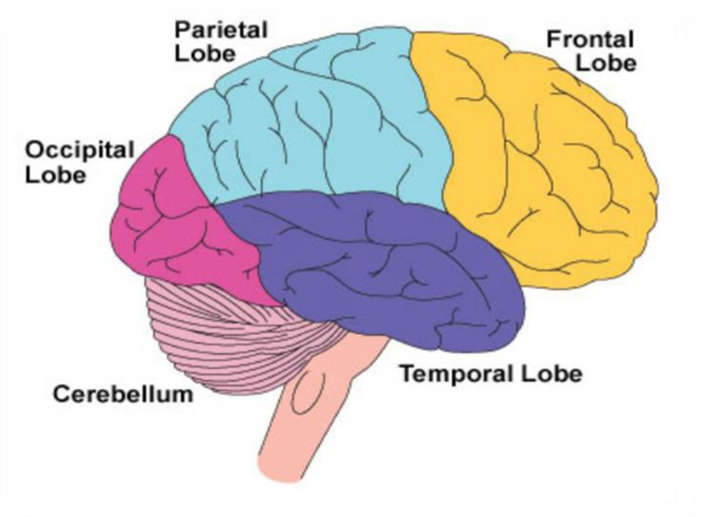

Fig.1.3 Human Brain

Brain is the central information processing unit of human body, Fig.1.3 shows the diagram of human brain. It acts as ‘command and control’ system of the body. Brain controls all voluntary and involuntary movements of the body. These involuntary movements include functioning of lungs, heart, kidneys, etc. activities of endocrine glands. Voluntary movements include balance of body. Moreover, brain acts as a site for processing of vision, speech, memory, etc. The brain is protected by the skull. The brain is mainly divided into forebrain, midbrain and hindbrain. The forebrain comprises of cerebrum, thalamus and hypothalamus.

Forebrain: It is the largest and uppermost part of brain. It is responsible for making human beings unique. All high order functions like high thoughts, language, and human conscience as well speech, learning, vision and hearing and fine control of movement are controlled by Cerebrum part of forebrain. The cerebrum is divided into two hemispheres which are connected by bunch of fibers called corpus callosum. Cerebral cortex is the grey color neuron tissue which is the outermost layer of cerebrum. Due to this grey color, it is also called grey matter. To understand the functioning of the cerebral cortex’s functioning, the hemisphere can be divided into four lobes: frontal, parietal, occipital and temporal lobes. These lobes are responsible for functioning of many variety of bodily matters.

The frontal lobe is mainly responsible for initiating and coordinating motor movements and also for higher cognitive skills such as thinking, organizing, problem solving, and planning.

The parietal lobe is mainly responsible for sensory processes, orientation, attention, movement and language. Moreover, this lobe helps in navigating spaces or ability to understand written or spoken language respectively.

The occipital lobe mainly responsible in facilitating visual information, including recognition of shapes and colors.

The temporal lobe supports the processing of auditory information and integrate information from all other senses.

Temporal lobe is important for short-term memory through its hippocampal formation and in learned emotional responses through its amygdala.

Midbrain: It mainly comprises of thalamus/hypothalamus of forebrain and pons of hindbrain. Midbrain and hindbrain together form brain stem. It controls the basic survival functions of the brain like breathing, movements of eyes, mouth and consciousness. Brainstem mainly comprises of three regions, these are medulla oblongata, the pons and the midbrain i.e. it comprises of mid-brain and hind-brain. The grey and white matter present in the brainstem is called reticular formation and it helps in managing muscle tone in body and behaves as switch in between the sleep and consciousness of body. Moreover, brainstem also acts as relay center connecting cerebrum and cerebellum to the spinal cord. The medulla oblongata is a cylindrical mass of nervous tissues that bridges to spinal cord on its low-level boundary and to the pons on its high-level boundary. The medulla comprises most of the white matter that takes nerve signals into the brain and spinal cord. In this, there are numbers of regions of grey matter which processes involuntary body functions. Blood pressure and oxygen levels are monitored by cardiovascular center of medulla and it also helps in regulating heart rate to provide sufficient oxygen supplies to body tissues. The rhythmicity center of it manages rate of breathing to provide oxygen to body. The pons region is superior to medulla oblongata, inferior to midbrain and anterior to cerebellum. It acts as bridge for nerve signals passing to and from cerebellum and carries signals between superior regions of brain and medulla and the spinal cord.

Hindbrain: It mainly comprises of pons, cerebellum and, medulla. The cerebellum is lined hemispherical region of brain located at lower back of head. It also can be divided into two hemispheres. These hemispheres enable control movement and cognitive proc - esses which needs careful timing. Moreover, it is 2nd largest part of brain after Cerebrum. Cerebellar cortex is the outermost layer of cerebellum which is made up of tightly folded grey matter that generates cerebellum’s processing power. Arbor vitae is a tree-shaped layer of white matter, which lies deep to cerebellar cortex and bridges the cerebellar cortex’s processing regions to the rest of brain and body. The main purpose of cerebellum is to synchronize in controlling motor functions like posture, balance and also helps in synchronization of complex muscle activities. Moreover, cerebellum receives sensory inputs from muscles and joints of the body which are used to keep the body balanced. It also manages timing and fitness of complex motor actions such as writing and walking.

1.4 Detecting EEG

EEG signal is detected from the brain by using 10-20 system or international10-20 system. This is shown in Fig.1.4. In this internationally recognised method, there is description about how the electrodes should be placed on the scalp in order to detect EEG signal. This method was developed in order to create a standardise testing methods in order to collect the results of subject's study. The study is used to analyse and compare the recorded data of the subjects using scientific methods. The base of the system is the relationship between the position of electrode and the cerebral cortex i.e. the underlying area of the brain. The brain produces many different electrical patterns whether a person is sleeping or awake. These signals are detected by electrodes placed on the scalp of the subject. In 10-20 system of measuring EEG signal, '10' and '20' corresponds to the distances between adjacent electrodes which is either 10% or 20% of the total front-back distance of the skull.

1.4.1 Measurement

For measurement of EEG signal, it is required to place the electrodes on special specific landmarks. The measurement can be done from various points as given below:

- Nasion-Inion: Nasion is the area between eyes and at the starting of nose bridge and inion is the bump present at the back of the skull. The Z electrodes are placed at 10%, 20%, 20%, 20%, 20% and 10%between the nasion and inion.
- Tragus to tragus: tragus is also called preauricular, it refers to the point in front of each ear. This is measured by placing the electrodes in the intervals of 10%, 20%, 20%, 20%, 20% and 10% for T3, C3, Cz, C4, and T4 respectively, measured across the head.
- Along skull circumference which is measured above the ears (T3 and T4), at the top of nose bridge (Fpz), and at the top of occipital point (Oz). By placing

electrode at 10%, 20%, 20%, 20%, 20% and 10% between above the ear and from front (Fpz) to back (Oz), Fp2, F8, T4, T6, and O2 are measured respectively.

- Others have different pattern of measurement like C3 and C4 are measured by placing electrodes diagonally from Nasion to Inion, and so on.

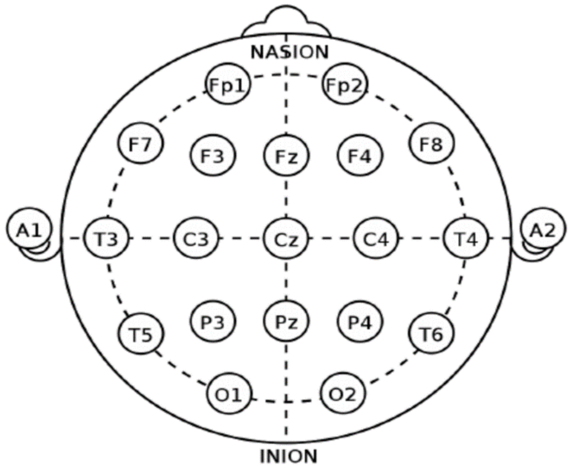

Fig.1.4. 10-20 international system for measuring EEG

1.5 EEG waves:

Brain can be considered as an electrochemical organ. According to the scientists a fully working brain can produce up to 10 watts of power. Though the power is very small, the ways of its occurrence are very specific which characterize the human brain. The electrical signals which brain emits are called brain waves. These brain waves can be classified on the basis of the frequency present in them, shown in Fig.1.5. So, the brain waves are classified from maximum activity to least activity as delta waves with frequency component of 0.5Hz to 4Hz, theta waves with frequency component of 4Hz to 8Hz, alpha waves with frequency component of 8Hz to 12Hz, beta waves with frequency component of 12Hz to 30Hz, and gamma waves with frequency component of 30Hz to 100Hz. These different waves are discussed below:

Delta Waves (0.1 to 4 Hz): In these brainwaves the amplitude is maximum but the frequency is minimum i.e. these are slowest brainwaves with maximum of 4 cycles per second. These waves can go down to 2 or 3 cycles per second in deep dreamless sleep.

But it can never reach zero cycles per second as that would mean a dead brain. Since, these waves have large amplitude they ay be confused with jaw muscle artifact.

Theta Waves (4 to 7 Hz): These brainwaves have amplitude lower than delta waves and frequency higher than delta waves. The speed of the wave is between 4 to 7 cycles per second. These waves occur when a person is daydreaming. For eg. taking a break from work to sit idle and day dream, when a person doesn’t really use brain and drives on a freely on a freeway, etc. It can also occur during sleep. Theta waves are characterized by saw-tooth shape of the wave. It acts as opening to learning and remembrance. In this, senses are focused only on signals originating within. These waves are generally seen in young children and adults who are drowsy.

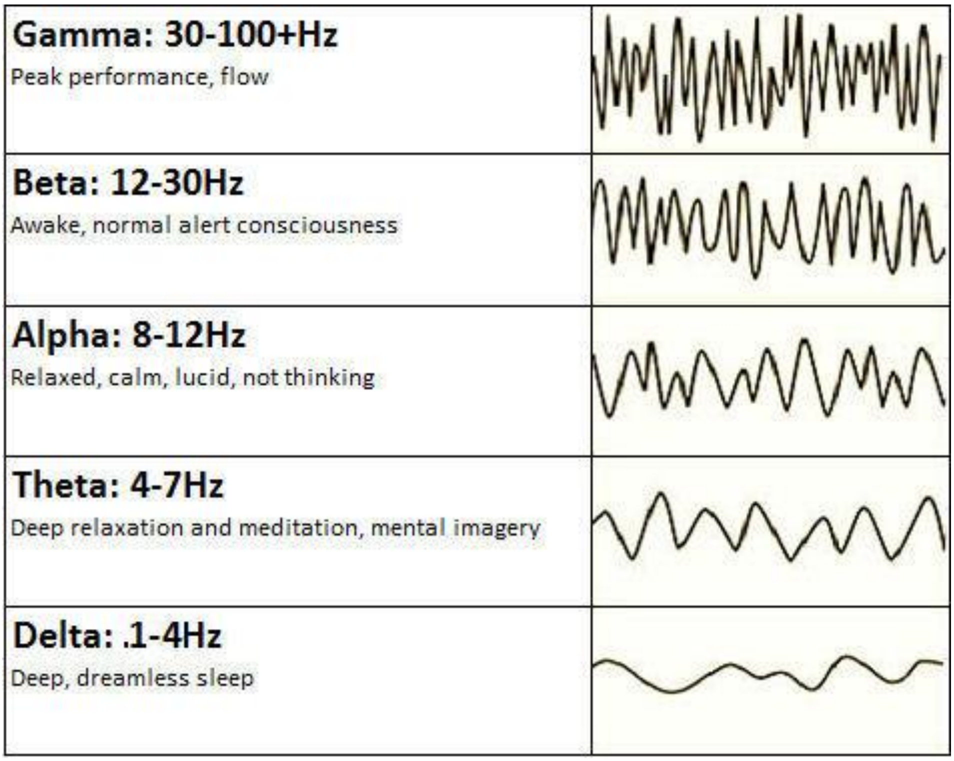

Figure 1.5: Different Brain Waves

Alpha Waves (8 to 12 Hz): These waves have amplitude lower than theta waves and speed or frequency higher than theta waves i.e about 8-12 cycles per second. These waves come into existence when a person sits and relax after performing a task, is in meditating state, takes break from a conference to walk in a garden, etc. These were the first waves observed by Hens Berger.

Beta Waves (12 to 30 Hz): The amplitude of these waves is lower than that of alpha waves and frequency can reach upto 30 cycles per second. So, these are fastest of other three waves. These waves arose from brain of people who are fully engrossed in their work i.e. the brain is working at its highest rate. In this state a person is alert, active, and engaged.

Gamma Waves (30 to 100 Hz): These waves have lowest amplitude but the speed or frequency is maximum which can reach up to 100 cycles per second. These waves are very rare and occur in case of any brain relate disease. Gamma Brainwaves are fastest brainwaves which are related to simultaneous processing of information from different brain areas. These waves may be drawn in creating unity of conscious perception.

1.6 Artifacts in EEG:

The EEG signal is measured by placing electrodes over scalp of a person. The electrodes not only measure the cerebral activity of the brain but also measure the potential from different sources like, eye blink, muscle movements, line interference, etc. These sources damage the cerebral activity output and hence the result contains other undesired noises which are termed as ‘artifacts’. These artifacts can be divided as physiological and extra physiological artifacts. These are described below:

1.6.1 Physiological Artifacts:

These artifacts occur because of interference of cerebral activity and electrical activity from other part of the body leading to noise in the cerebral activity. These can be of different types as discussed below:

- Ocular artifacts:

This artifact arises due to movement of the eyes and eyeballs which leads to a variation of potential in the electrodes placed close to the eyes at Fp1-Fp2 (Fronto Parietal). This artifact arises in the frequency range of 0-16 Hz[2]. Ocular artifact also occurs due to eye movement. Here, Electroretinogram [ERG] is defined as the potential difference between retina and cornea of the eye and with incident light which gets changed and cause ocular artifact in EEG signals. Eye blink can also cause ocular artifact eye blinks which leads to production of large amplitude signals that can be numerous times greater than the amplitude of EEG signals of interest as shown in Fig.1.6. Moreover, blinking repetitively or flattering of eyes leads to formation of slow wave, which seem like delta waves as shown in Fig.1.7.

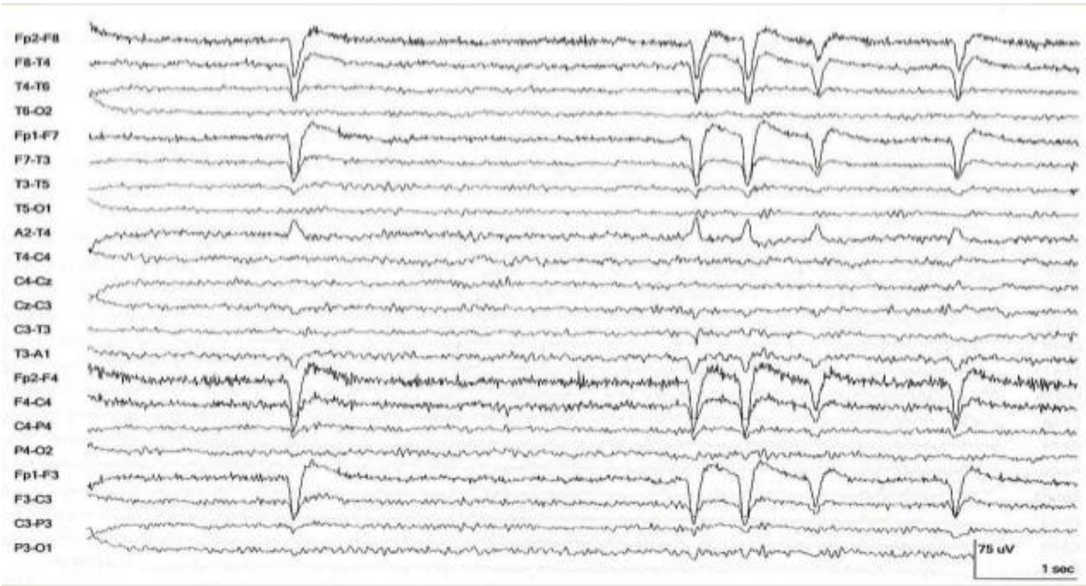

Fig.1.6. Eye blink artifact

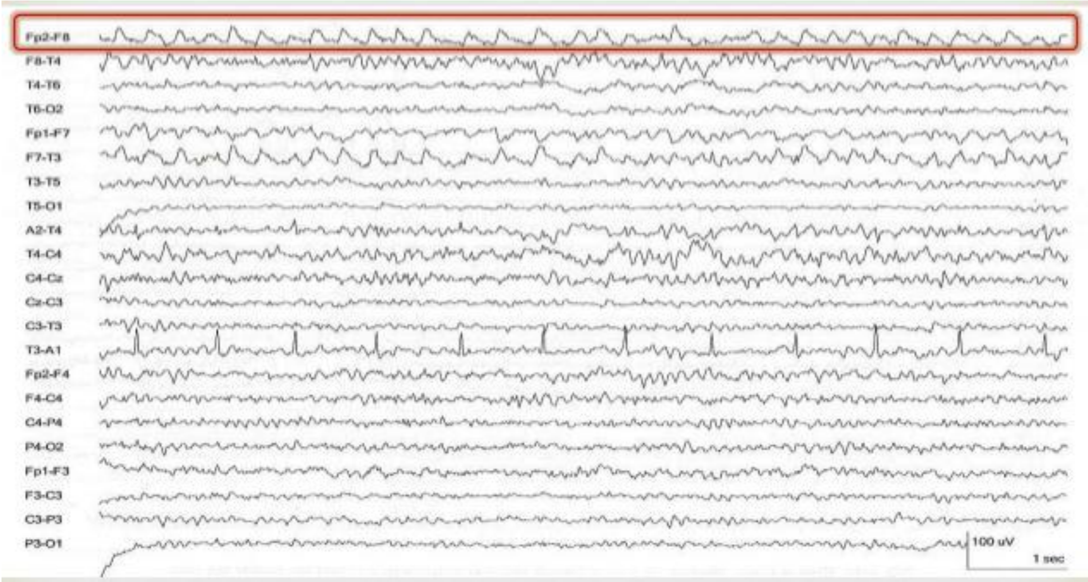

Fig.1.7. Flattering of eye artifact

- Muscle artifacts

These occur when the cerebral activity gets damaged because of electrical activity arising due to muscle movement like tongue movement, swallowing, grimacing, chewing, etc. It can be classified into glossokenetic (chew/swallow), surface electrode myography, photogenic. The shape of the signal depends on the degree of muscle contraction: weak contraction gives a low-amplitude spike train. Occurs less in sleep overlap with beta band (15-30Hz) as shown in Fig.1.8. Most commonly appears in the frontal and temporal electrode.

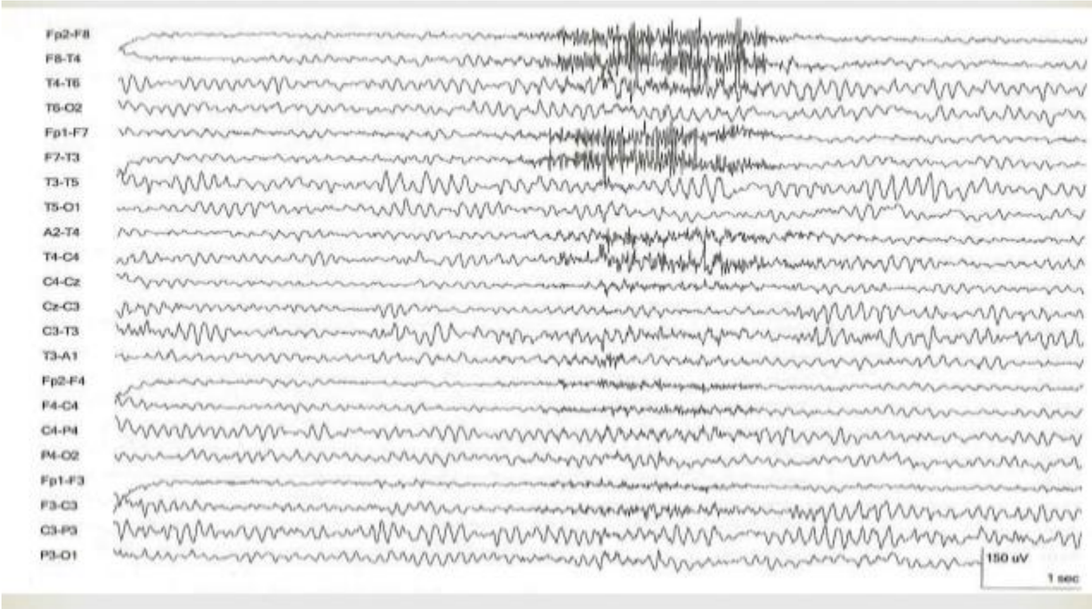

Fig.1.8. Muscle artifact

- Cardiac artifact

This includes artifacts produced by heart. It can be of two types: mechanical electrical artifacts which appear as ECG signal near temporal left region and are most commonly seen in short neck subjects. This electrical artifact appears as ECG waveform recorded from scalp and forms the QRS complex. Most of the cardiac artifact frequencies are near 1Hz and amplitude is in several millivolt as shown in Fig.1.9.

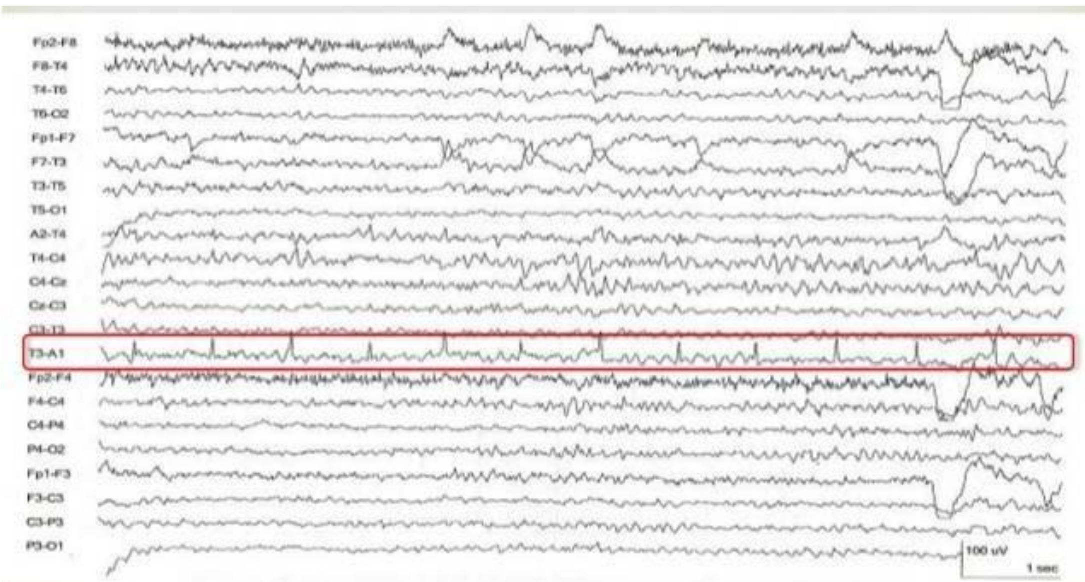

Fig.1.9. Cardiac artifacts

1.6.2 Extra physiological artifacts:

These artifacts are mainly due to external factors which damage the cerebral activity. The sources of these artifacts are electronic gadgets, transmission lines, environment lines etc. These are described as below:

- Transmission- line artifact:

  As the information of EEG signal is mainly present in frequency range of 0.5Hz-60Hz and the frequency of transmission lines is 50 Hz, so the signal easily combines with beta band of EEG signal. This artifact mainly affects all channels with poor impedance matching. The removal of the artifact is easy it can be removed by applying a notch filter of frequency range 50 Hz. This will filter out the transmission-line artifact.

- Phone artifact:

  This artifact is because of the interference of cerebral activity with mobile phone signals. In this a high frequency signal appears as a forged signal on the EEG signals. This artifact can be overcome by avoiding a mobile phone while EEG signal recording is going.

- Electrode artifact:

  There are low frequency artifact components which arise due to poor electrode contact. These are short-lived transients that are limited to one-electrode and coordinate with respiration due to the motion of the electrode.

- Electrode pop Artefact:

  These artifacts appear as sharply contoured transients that damage the background activity which may be confused as tumor.

- Lead movement artifact:

  Due to lead movement there can be variations in the cerebral activity which are jumbled morphology that does not appear like EEG activity in any form and often contains double phase reversal, that is, phase reversals without the evenness in polarity that indicates a cerebrally generated electrical field.

- Perspiration artifact:

  This artifact is exhibited as low amplitude and swelling waves that characteristically have periods larger than 2 sec. Thus, they are beyond the frequency range of cerebrally generated EEG.

- Physical movement artifact:

  This artifact occurs due to lose contact of electrode due to sudden physical movement of the subjects under observation. It is very different from actual EEG signal and hence can damage it.

CHAPTER 2

LITERATURE SURVEY

Ocular artifact is the main artifact which damages the EEG signal. Other artifacts are little easier to remove as compared to ocular artifact. There are many ways which have been used to remove ocular artifact from EEG signal. But yet no method is so satisfactory that it removes ocular artifact from EEG signal without causing loss of EEG signal. In this thesis, a new method is proposed to obtain an ocular artifact free EEG signal. In this method, Ensemble Empirical Mode Decomposition (EEMD) and Spatially Constraint Independent Component Analysis (SCICA) are used to obtain an ocular artifact free EEG signal.

Basic Independent Component Analysis (ICA) is one of the best technique which is used to remove ocular artifact from EEG signal. In this technique, the artifactual signal is divided into independent Component (ICs). The result is better if the number of observed signal in which ICA is applied is larger than the number of Independent Components (ICs). This condition of ICA can be fulfilled by using Empirical Mode Decomposition (EMD) along with ICA. In EMD, the signal is decomposed into various Implicit Mode Functions (IMFs), these IMFs can be treated as many inputs which are given to ICA, hence the result will improve. But, EMD gets affected by many noises such as modal noise, aliasing problem, etc. These can be overcome by using improved version of EMD which is EEMD. This EEMD is robust to noise and hence gives improved result with ICA as compared to EMD and ICA. ICA has some drawbacks like zeroing of artifacts leads to loss of EEG signal so, SCICA can be used in place of ICA to overcome this limitation. Moreover, the permutation problem of ICA can be solved by SCICA, though not fully but for constrained columns. So, EEMD and SCICA will give better results as compared to other state-of-the-art methods. The above discussed methods are studied in detail.

2.1 Independent Component Analysis (ICA)

The basic concept of ICA is to separate the signals which are statistically independent into their actual independent sources. In this method, statistical and computational techniques are used to separate mixture of signals into Independent Components (ICs). The only information available is the mixture of several independent sources at several recording channels and this information is used to find the mixing matrix and ICs.

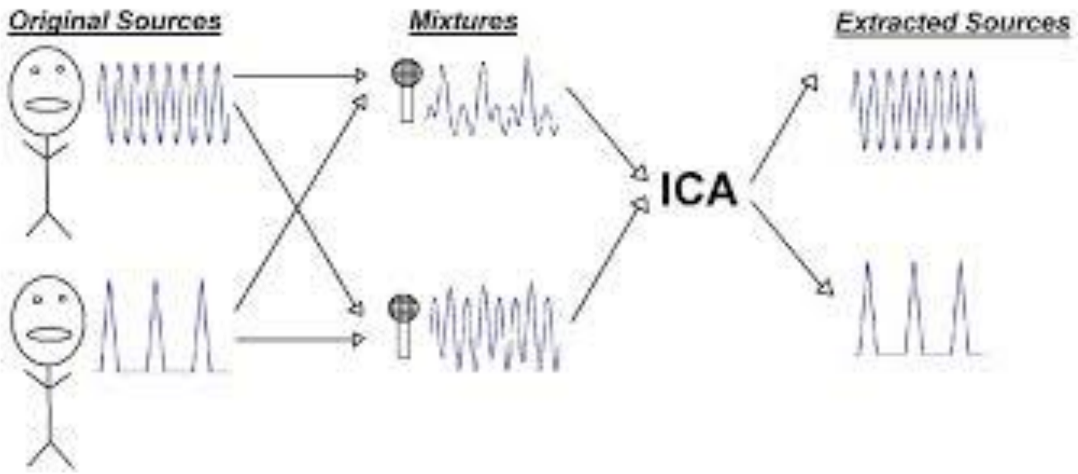

Figure 2.1: ICA concept; mixing and separation of signal

There are some assumptions which are made or considered before applying ICA method:

- The neural signal and artifact signal are combined linearly and are mutually statistically independent.
- For a better result of ICA number of observed sources must be greater or equal to number of independent sources.

- The delay generated because of propagation through mixing medium are considered to be insignificant.

Mathematical description of ICA is discussed below:

ICA is a tool which is used to separate independent signals from mixed recordings of various observed signals. Let us study an array of channels which provides N observed signals

$$x(k) = [x_1(k), x_2(k), \ldots\ldots, x_N(k)]^T \tag{1}$$

and actual sources are

$$s(k) = [s_1(k), s_2(k), \ldots\ldots, s_M(k)]^T \tag{2}$$

Here, the above assumptions are considered so the sources are non-gaussian in nature and they are mutually statistically independent. The main aim of ICA is to obtain the value of W which is the mixing matrix and also$x$ which are ICs.

$$s = W * x \tag{3}$$

Many algorithms are present to perform ICA and the one we have chosen in the paper is Infomax ICA. According to Bell et al [4], it is an unsupervised technique which uses information maximization in a single layer neural network and gives non-linear output. There is need to do pre-processing of the data before ICA is applied. This process includes centering and whitening of data.

- Centering:

  It is one of the most important steps as it is required to center$x$, this is done by subtracting mean vector of$x$and hence making x a zero-mean variable. Mean vector m=E(x).

- Whitening:

  It is required to make x white, that is its components are uncorrelated and variance is equal to unity. This implies covariance vector of x is equal to the identity matrix. E$\{xx^T\}$=I

  The most common method of whitening is eigenvalue decomposition (EVD) of the covariance matrix.

$$E\{ xx^T \}=EDE^T \tag{4}$$

where E is an orthogonal vector of eigenvalues of E{xx^T} and D is the diagonal matrix of eigenvalues of E{xx^T}.

$$D=diag(d1, d2,\ldots,dN) \tag{5}$$

Whitening can be done by using following formula:

$$x = ED^{-1/2}E^T x \tag{6}$$

After pre-processing the main algorithm of ICA is followed and W and ICs are calculated, the algorithm is shown below:

1. It is used to find the maximum of the non-gaussianity of $W^T x$
2. First, choose an initial weight vector
3. Let $W^+ = E\{xg(W^T x)\} - E\{g'(W^T x)\}$
4. Let W= W^+/|| W^+||
5. If the result is not converged go back to 3

2.1.1 Algorithm for using ICA to remove Ocular artifact:

- First, ICA is used to find various ICs.
- The kurtosis and mMSE for every IC is calculated and compared with the threshold levels of kurtosis and mMSE.
- The artifactual ICs are made zero.
- Inverse of mixing matrix is obtained and the original signal is obtained.

The algorithm of zeroing-ICA is shown in Fig.2.2.

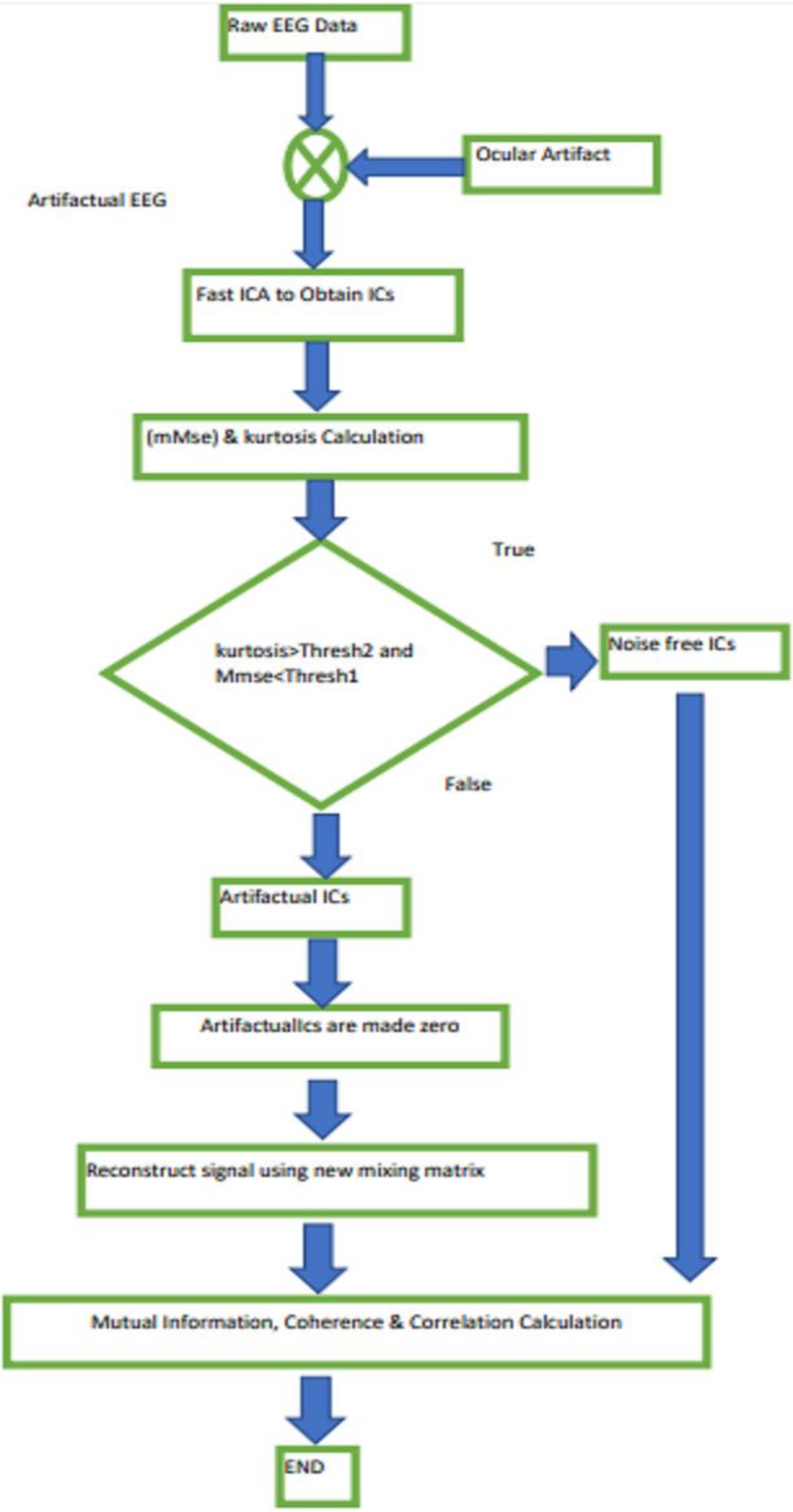

Fig.2.2. Algorithm for zeroing-ICA

2.2 Empirical Mode Decomposition (EMD)

It is a technique in which the signal is decomposed into various Implicit Mode Functions (IMFs). It gives best results for signals which are non-stationary, non-linear and random processes like cerebral activities. The IMFs are present in decreasing order of frequency component of signal. The first IMF has highest frequency component while the last IMF will have lowest Frequency component. The algorithm of EMD is described below:

Conditions to identify IMF:

- First is that number of extremas and zero crossings must differ at most by one.
- Second is that mean value of envelope defined by the local maxima and the envelope defined by local minima is zero or can say they should be symmetric with respect to zero.

To obtain IMFs of a signal a process called sifting is used. Steps involved in sifting process are debated in detail below [13]:

- Identifying extremas :

  In this step all the extremas i.e. identify all maxima and minima of given signal as Xmax(n) and Xmin(n).

- Interpolating the extremas:

  Connect all the maxima and minima of the signal and interpolate them to obtain interpolation of maxima i.e.Xmax(n) and interpolate between minima to get Xmin(n).

- Finding average envelope:

  The average is obtained by using interpolated extremas and this average is separated from the original signal, the newly obtained signal is considered to be $d_1(n)$.

- Extraction of IMFs:

  Considering $h_1(n) = x_1(n) - d_1(n)$. Here, $h_1(n)$ is checked whether it is an IMF or not. The above steps are repeated until the requirements of the IMF are fulfilled by the resulting signal. Now $c_1(n) = h_1(n)$. Here $c_1(n)$is the 1st IMF which contains the highest frequency component of the signal. The residual signal is given by $r_1(n) = x(n) - c_1(n)$.

- Criteria for halting:

  Consider $r_1(n)$as new data and repeat all previous steps until all the IMFs are extracted. The sifting procedure is halted [13]-[14] when them_{th}residue $r_m(n)$becomes less than a predetermined small number or becomes monotonic.

Below is the mathematical formula to obtain the signal from various IMFs:

$$x(n) = \sum_{k=1}^{n} c_k(n) + r \tag{7}$$

Since, EMD decomposes a signal into various IMFs so these IMFs can be used as inputs to ICA and the result of ICA can be improved.

2.2.1 Algorithm for ocular artifact removal using EMD and ICA:

- IMFs are obtained using EMD.
- Artifactual IMFs are extracted from the IMFs.
- These IMFs are treated as signals and given to ICA to obtain ICs.
- The artifactual ICs are obtained and made zero.
- The signal is reconstructed with artifact-free ICs and inverse of mixing matrix.

2.3 Ensemble Empirical Mode Decomposition (EEMD)

There are limitations of EMD that it is affected by modal noises, aliasing problem, etc. These drawbacks of EMD can be overcome by using EEMD. In EEMD the white noise of different amplitude is added to the original signal and then different IMFs are obtained using EMD algorithm. The final IMFs are obtained by taking average of IMFs obtained by adding different amplitude of white noise.

2.3.1 Algorithm for EEMD:

- Here, white Gaussian noise $w^i(n)$ (i =1, ……, L) of different amplitude is added to the original signal$x^i(n) = x(n) + \sigma w^i(n)$where σ is the standard deviation.

- For each value of $x^i(n)$ (i=1,……,L) various IMFs are calculated using EMD algorithm to obtain $IMF_k^i(n)$ for different values of weighted white noise.

- Finally, $IMF_k(n)$for EEMD is calculated as:

$$IMF_k(n) = \frac{1}{L}\sum_{i=1}^{L} IMF_k^i\,(n) \tag{8}$$

So, to obtain a better result EEMD and ICA is used as compared to EMD and ICA due to better results of EEMD as compared to EMD. The results can further be improved by using SCICA instead of ICA.

2.4 Spatially Constraint Independent Component Analysis (SCICA)

ICA has basic limitation that the cerebral information is lost when artifactual ICs are removed so to overcome this problem SCICA is used. In SCICA prior knowledge is incorporated to obtain reference topologies, which are used to obtain improved results of artifact removal. The permutation problem of the ICA can be overcome by SCICA for constraint columns.

SCICA is modified version of ICA [8]. Let us consider, the mixing matrix Awhich is obtained using ICA. Now, this mixing matrix is modified by applying Spatial Constraints to the artifactual columns of mixing matrix using prior knowledge

$$\hat{A} = [\hat{A}_C A_U] \quad (9)$$

about signal. Consider modified mixing matrix as Â which contains two parts as

where $\hat{A}_C$is the spatially constrained columns and A_U are unconstrained columns

Here, spatially constrained columns are obtained by using $A_C$which are predefined constraints. The spatially constrained columns $\hat{A}_C$ can be obtained by applying constraints in three ways:

- Hard constraints:

  For applying hard constraints, the reference constraints are considered to be quite accurate and $\hat{A}_C$= A_C is considered, where A_C represents the predefined constraint sensor projections treated as reference, which are in accordance with the constraints considered in [9].

- Soft constraints:

  Though it is simple to apply the hard constraints but it limits the accuracy of SCICA.So soft constraints are preferred over hard constraints [7].

The soft constraints are used by limiting the deviation between the constrained column $\hat{A}_C$ and their corresponding reference topographies A_C by a threshold value α. This can be done by considering,$a_c$and $\hat{a}_c$, where $a_c$and $\hat{a}_c$ represents unit norm column vector correspond to associated columns of A_C and $\hat{A}_C$ respectively.The main process to implement soft constraints, is to ensure that $\hat{a}_c$ and a_c subtend an absolute angle not greater than angular threshold α(0 < α $< \pi/2$) [7]. It can be explained in following steps: -

1. If $|a\cos({a_c}^T\hat{a}_c)|$< α then $\hat{a}_c$is not changed
2. Otherwise $\hat{a}_c$ is projected towards a_c to make $|a\cos({a_c}^T\hat{a}_c)|$ = α. This projection involves forming new normal vector $y = pa_c + (1-p)\hat{a}_c$so that cos(α) =$\frac{|{\hat{a}_c}^T|}{||y||}$.
3. The appropriate root for quadratic equation $c_1p^2 + c_2p + c_3$= 0 where

$$c_1 = 1 + 2{a_c}^T\hat{a}_c+({a_c}^T\hat{a}_c)^2\text{-}((2\text{-}2{a_c}^T\hat{a}_c)cos^2(\alpha)) \tag{10}$$

$$c_2 = (2{a_c}^T\hat{a}_c+2({a_c}^T\hat{a}_c)^2)\text{-}((2{a_c}^T\hat{a}_c - 2)cos^2(\alpha)) \tag{11}$$

$$c_3 = ({a_c}^T\hat{a}_c)^2\text{-}cos^2(\alpha) \tag{12}$$

The standard formula is used select p < 1 and substitute into the expression for y and set $\hat{a}_c$=$\frac{y}{||y||}$ [7].

- Weak constraints:

  In this the constraints are used to only provide an idea but are not considered to be absolutely true.

CHAPTER 3

PROPOSED METHOD

In this thesis a new approach to remove ocular artifact from EEG signal which used EEMD and SCICA. These techniques have been studied in the literature survey. This approach is better than previous methods like zeroing-ICA, EMD-ICA, and EEMD-SCICA. The results are compared by observing the waveforms and by comparing on the basis three parameters mutual information, correlation coefficient, and coherence.

3.1 Algorithm of the proposed method:

- The Real-time EEG signal is downloaded from physionet.com.
- The ocular artifact is added to the real-time signal to obtain an artifactual signal.
- This artifactual signal is decomposed into various IMFs
- The artifactual IMFs are selected on the basis of the correlation factor between (Electrooculogram) EOG signal and IMFs.
- The artifactual IMFs are given as sources to ICA and artifactual ICs are obtained.
- The artifactual ICs are extracted from ICs obtained by comparing the kurtosis and mMSE of each IC and comparing these values with the thresholds.

- The artifactual columns are modified using spatial constraints and restored IMFs are obtained by using inverse of modified mixing matrix
- The artifact-free signal is obtained by adding noise-free IMFs and restored IMFs.

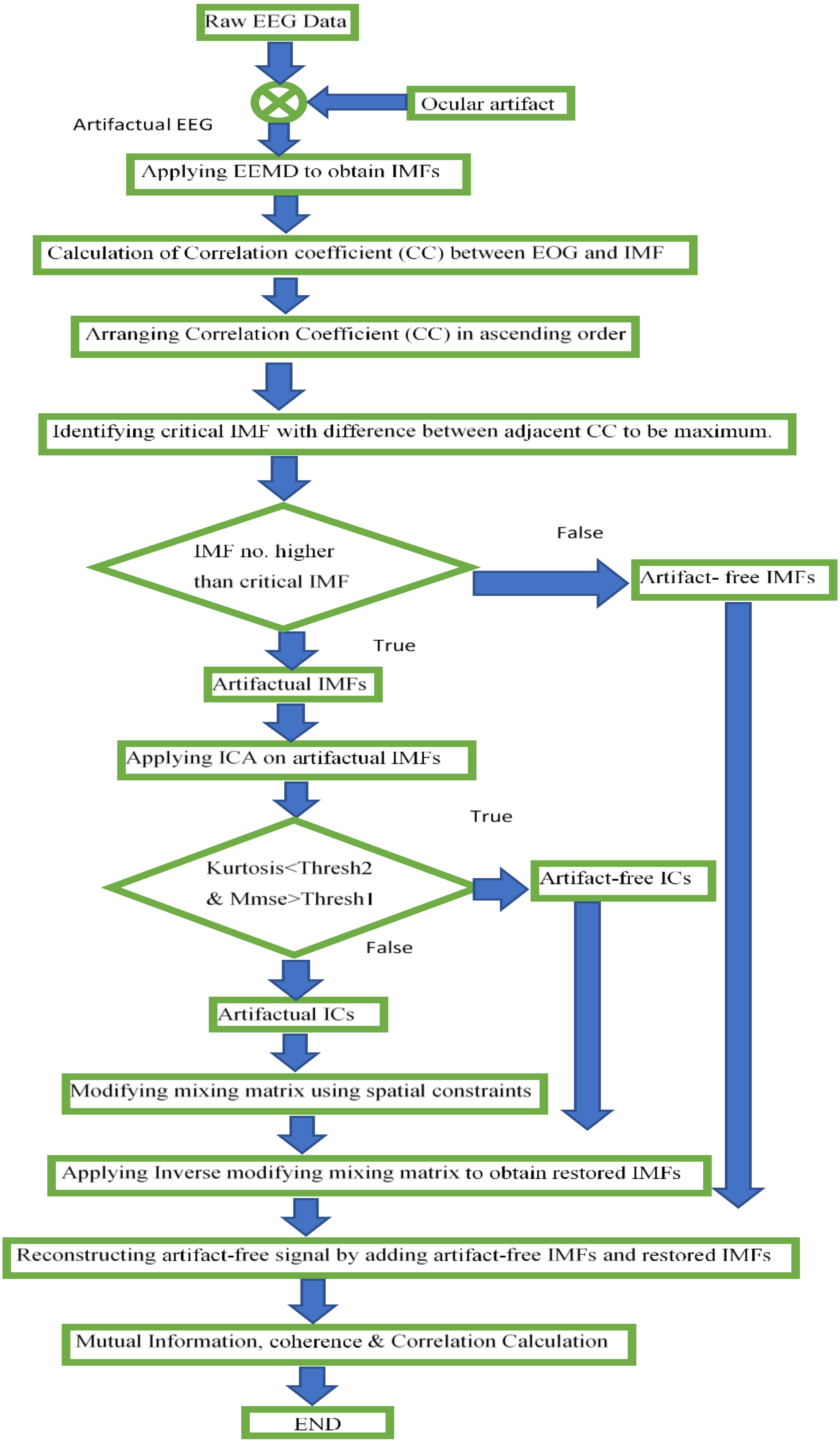

Fig.3.1. Block diagram of the method proposed

The block diagram Fig.3.1 can be explained in the following main steps:

1. Decomposition of the artifactual signal using EEMD.
2. Detection of artifactual IMFs.
3. Application of SCICA on artifactual IMFs.
4. Reconstruction of artifact-free signal.

3.1.1 Decomposition of the artifactual signal

In this EEMD is applied to decompose the artifactual signal into various IMFs. The algorithm used is described in the literature survey. These IMFs are obtained in the decreasing order of frequency component with highest frequency component present in the first IMF and lowest frequency component in the last IMF.

3.1.2 Detection of artifactual IMFs

The IMFs which are calculated using EEMD should now be divided into artifactual and artifact-free IMFs. The basis of this separation is the relation between Time Frequency Representation (TFR) of EOG and TFR of each IMF.

- The TFR of EOG and IMF signals are calculated using wavelet transform.
- The correlation coefficient is calculated between TFR of EOG and TFR of IMFs.
- The correlation coefficient is arranged in ascending order.
- The adjacent difference between correlation coefficient is calculated and the maximum difference is observed.
- The IMF corresponding to maximum difference is the critical IMF. All the IMFs above the critical IMF is considered to be artifactual in nature.

- The artifactual IMFs are recognized and separated from other IMFs. Hence, IMFs are classified as artifact-free IMFs and artifactual IMFs.

3.1.3 Application of SCICA on artifactual IMFs

The artifactual IMFs obtained in the are now used as the source and provided to the ICA to obtain ICs. The ICs obtained are now classified as artifactual and artifact-free ICs. For detection of ICs kurtosis and mMSE are used which are described below:

- Kurtosis:

  Kurtosis is calculated to check for Gaussianity between independent components (ICs). Kurtosis is the fourth-order cumulant to measure the peaked distributions of the random variables and is mathematically computed using the

$$K = m_4 - 3m_2^2 \quad (13)$$

$$m_4 = E\{(x - m_1)^2\} \quad (14)$$

  following equations:

  where m_n, m_1 and E are the nth order central moment of the variable, mean and the expectation function respectively.

  The cerebral activity or neural activity generally have lower kurtosis value than the eyeblink signals. So, eyeblink signals have peak distributions which leads to large values of kurtosis. So, if the value of kurtosis reaches above the value of upper threshold the IC is considered to be artifactual in nature.

- Modified Mean Sample Entropy(mMSE):

  As Entropy is used to measure the randomness in a signal. There are many entropy's like wavelet entropy,Shannon's entropy, Renyi's entropy, and sample entropy. As per Bos et al. [15] modified Mean Sample Entropy (mMSE) gives more information about regularities of EEG time series in comparison to other single-scale entropies.

For ocular artifact the value of mMSE will be low and for cerebral activity the value will be comparatively high. This is so because ocular artifact's pattern is more predictable as compared to the pattern of artifact-free EEG signal. The process of the method is first, coarse-grinding of every sample is done for many scales and then Sample Entropy is found for every scale. The coarse-grinding is calculated by taking the average of successive data points of series in the nonoverlapping window as:

$$x_j{}^{\tau} = \frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau} v_i \, ; 1 \le j \le \frac{K}{\tau} \tag{15}$$

The above represents coarse-grained series τ is scaling factor, v is independent component time series, K is total data points in original series, $\frac{K}{\tau}$ is the limitation on each coarse-grained series. Now, Multiscale Sample Entropy for each coarse-grained series is calculated as

$$\text{mMSE (n, s)} = \log \left(\frac{P_s{}^n}{Q_s{}^n}\right) \tag{16}$$

For maximum length of epochs for matching templates, the value of n =2 and value of tolerance, s = 0.2 × SD; where SD is the standard deviation of the data vectors P and Q are the counters to track the n and (n+1) template matches within the tolerance value s respectively.

- Thresholding:

If in any method, the number of the ICs which are dealt with is less then two-sided t-distribution (with 95% CI) can be used in place of Z-distribution to detect the artifactual ICs [11]. As it is a known fact that the value of mMSE for the artifactual IC is less than that for cerebral activity related IC so, the proposed method uses the lower limit of the 95% CI of the mean for thresholding the IC on the basis of mMSE [11].

So, all the ICs having mMSE value below the threshold value are considered to be artifactual ICs and are corrected using spatial constraints. The lower limit of 95% CI of the mean is calculated as

$$\text{Lower limit} = \bar{x} - \frac{\sigma}{\sqrt{N}} * T_{N-1} \tag{17}$$

where $\bar{x}$is the sample mean, σ is the sample standard deviation, and (N-1) is the degrees of freedom. At 95% significance level, T_{N-1} = 2.201 for two-tailed test [11].

To increase the efficiency of the procedure, kurtosis is also used to find ocular artifact in the IC signal. As it was discussed in the previous section that kurtosis is zero for Gaussian distribution, positive for the peaked activities (which correspond to ocular artifact) and negative for the smooth distributions. So, for the value of upper limit, the upper bound of the 95% CI of the mean is considered as the threshold.

$$\text{Upper limit} = \bar{x} + \frac{\sigma}{\sqrt{N}} * T_{N-1} \tag{18}$$

Here, threshold2 is considered as upper limit and threshold1 as lower limit.

Once the artifactual ICs are detected the columns corresponding to these ICs is considered for applying spatial constraints. These columns are changed according to soft constraints and modified mixing matrix is obtained. The modified inverse mixing matrix is calculated and the restored IMFs are found by taking inverse ICA.

3.1.4 Reconstruction of artifact-free signal

The restored IMFs obtained using SCICA are added to the artifact-free IMFs to obtain the artifact-free signal.

CHAPTER 4

OBSERVATIONS AND RESULTS

A real-time signal is obtained from physio.net and is made ocular artifact affected by adding ocular artifact. Fig.4.1 shows the real-time signal and the ocular artifact added artifactual signal. It can be clearly seen from the figure that the artifact is added between 3rd and 4th second and also in 7th and 8th second.

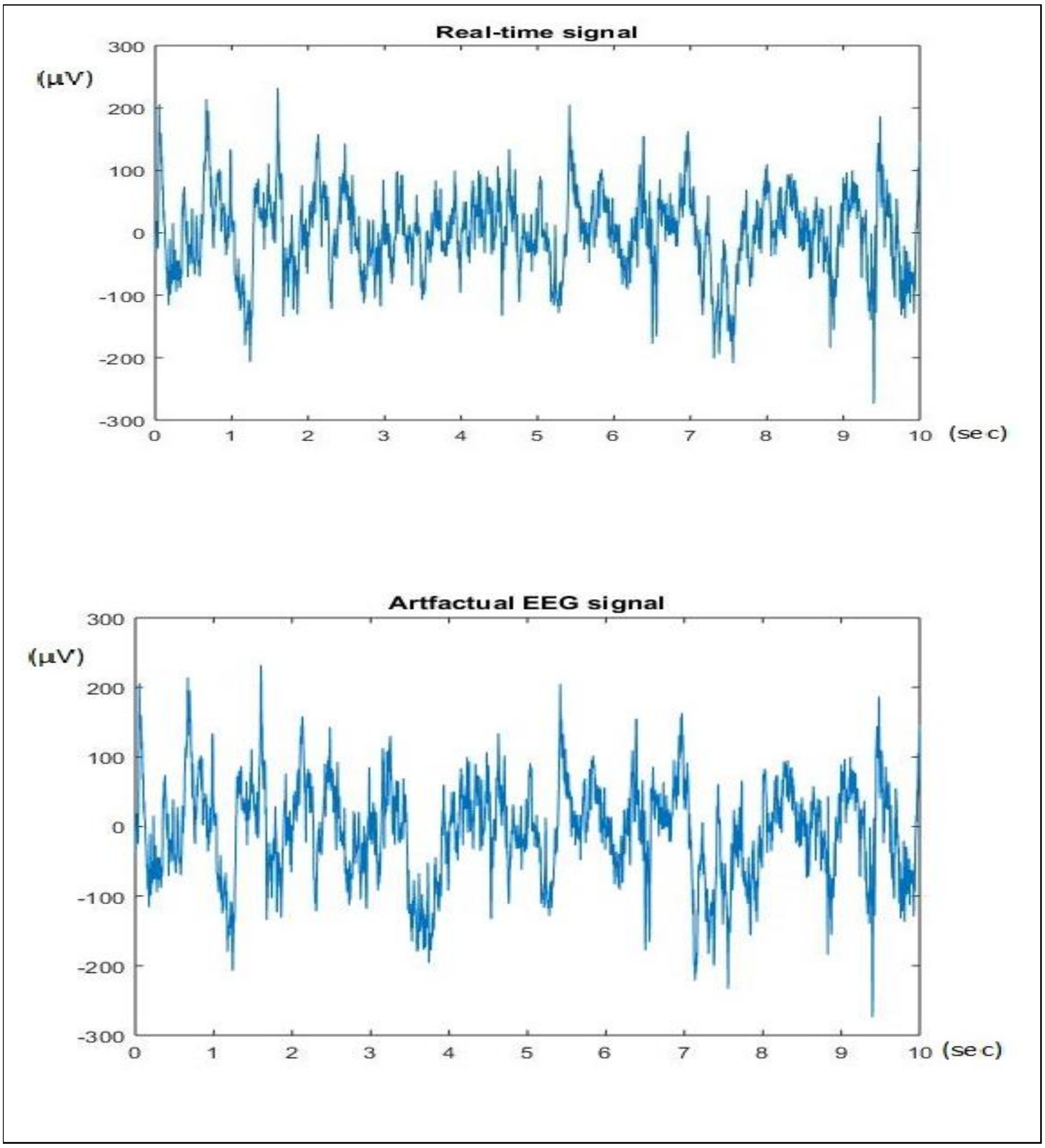

Fig.4.1. Real-time signal and artifactual signal

Now, the artifactual signal is decomposed into various IMFs by applying EEMD algorithm as discussed in literature survey. Fig.4.2 shows the various IMFs obtained.

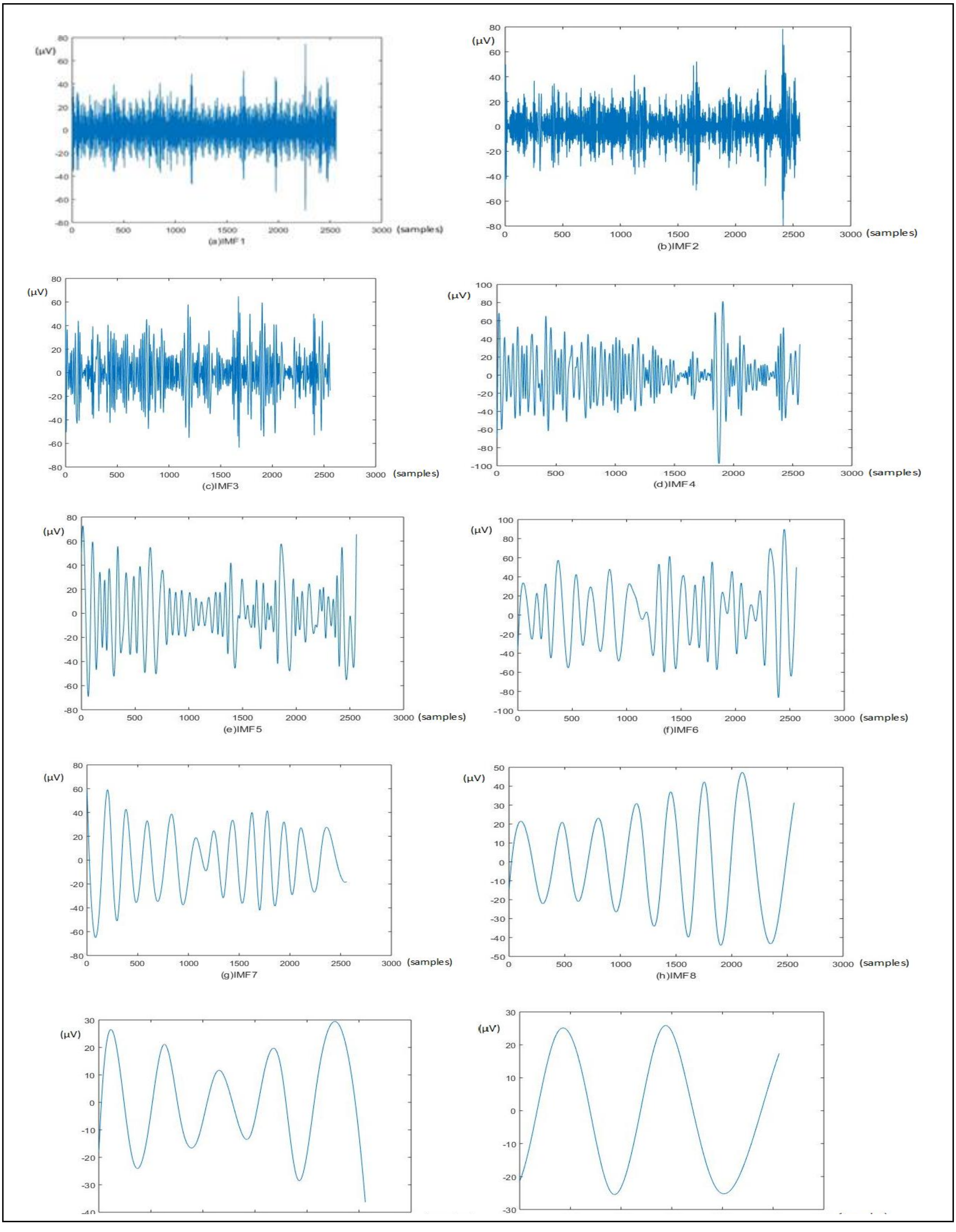

Fig.4.2. IMFs obtained using EEMD

So, using EEMD on artifactual signal shown in Fig.4.1, 10 IMFs are obtained.

Now, for these IMFs TFR is calculated by wavelet transform and TFR is also calculated for EOG signal. The correlation coefficient is calculated between TFR of IMFs and TFR of EOG signals. The correlation coefficients are arranged in ascending order and the adjacent difference between the correlation coefficient is calculated. The maximum difference is used to detect the critical IMF.

The correlation coefficients are 0.0117, 0.1117, 0.2546, 0.3189, 0.3348, 0.4179, 0.4644, 0.4852, 0.7189, 0.8240. So, it can be seen that 6^{th} IMF has maximum difference hence it is the critical difference. All the IMFs higher than critical IMF are considered to be artifactual.

The artifactual IMFs are treated as sources and provided to ICA to find ICs. Five ICs are obtained using ICA which are shown in Fig.4.3.

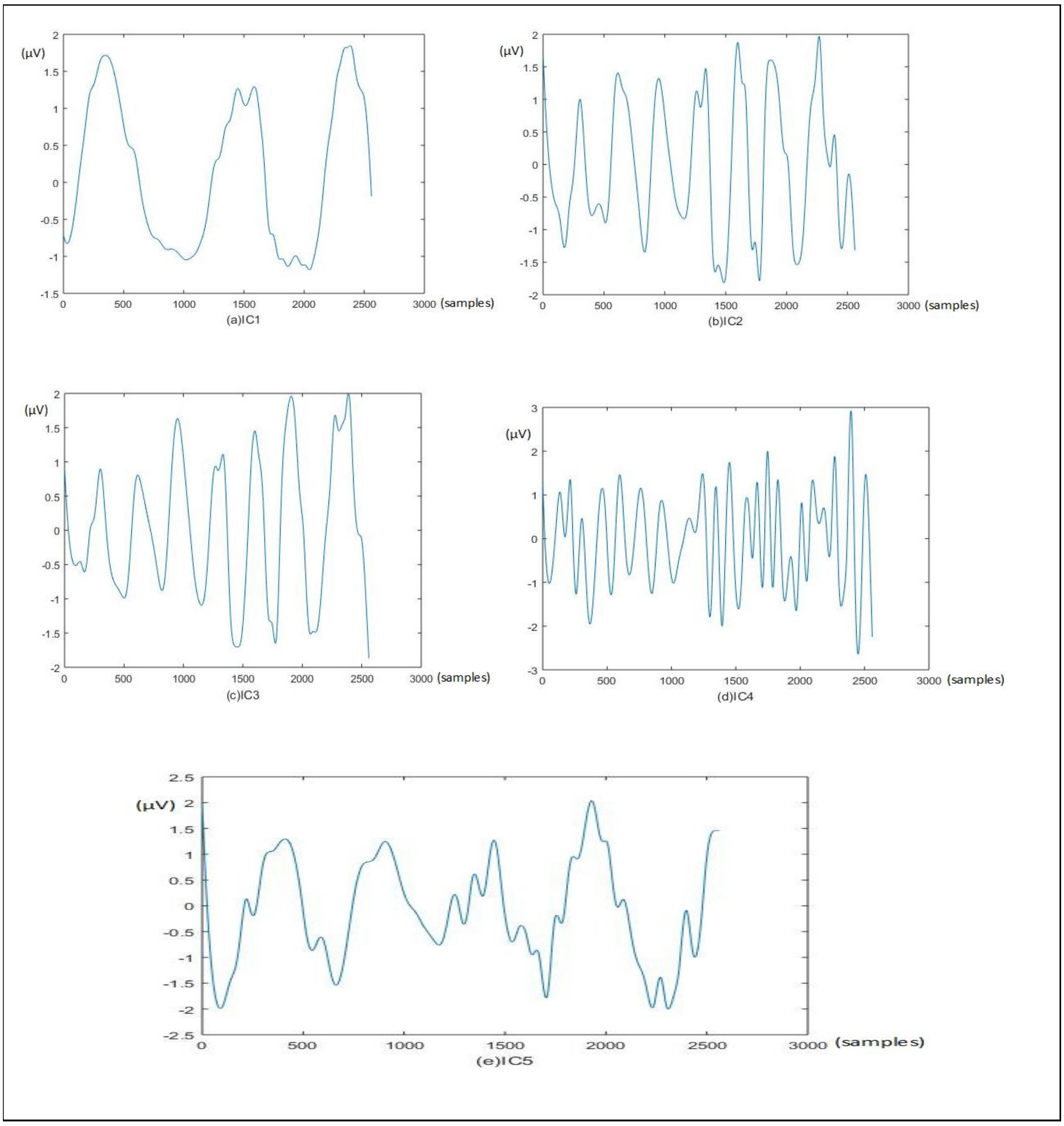

Fig.4.3 ICs obtained using ICA

Now, kurtosis and mMSE are calculated for each and every IC and the threshold levels are calculated. This threshold is calculated using the formulas discussed and in the previous section. The comparison of kurtosis and mMSE is done with the threshold levels. Fig.4.4 shows various values of kurtosis and the threshold level comparison.

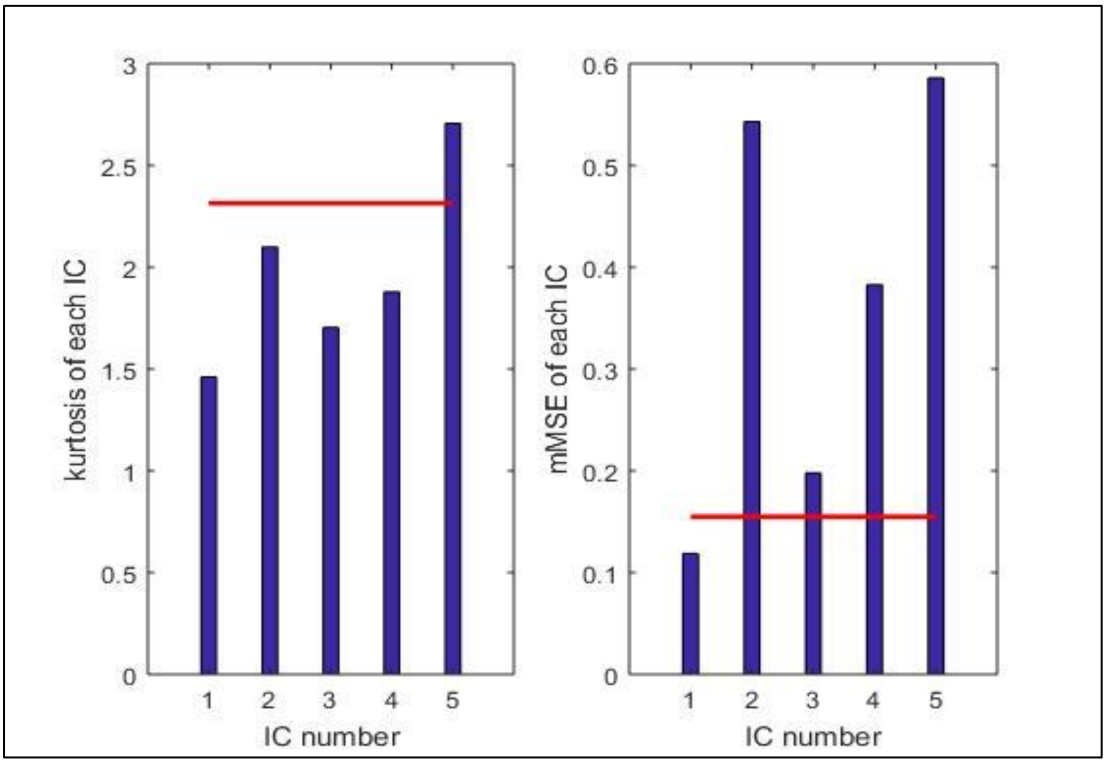

Fig.4.4 Kurtosis and mMSE of ICs and thresholds

In Fig.4.4. the thresholds are shown with red line and on comparison it can be seen that ICs 1st and 5th are found to be artifactual. For 1st IC the mMSE value comes out to be lower than threshold value and for 5th IC the kurtosis value is above the threshold hence, it is also considered to be artifactual.

These artifactual ICs corresponds to artifactual columns so the 1st and 5th columns are considered to be artifactual. These columns are modified using spatial constraints.

The mixing matrix obtained using ICA is given below:

$$A = \begin{bmatrix} -4.2394 & 0.7226 & -24.6049 & -20.8140 & -2.8446 \\ -23.9179 & 5.9560 & 1.5303 & -3.8094 & -5.7146 \\ 0.0485 & -3.6108 & -7.8763 & 14.5854 & -19.3326 \\ -3.6939 & 0.3228 & -7.6902 & 7.1017 & 9.8159 \\ 4.9252 & 16.2922 & -0.0910 & 0.6771 & -1.2548 \end{bmatrix}$$

Now, the obtained mixing matrix is modified by applying spatial constraints and it is observed to be as given below:

$$\hat{A} = \begin{bmatrix} 3.5865 & 0.7226 & -24.6049 & -20.8140 & 10.1271 \\ 3.4166 & 5.9560 & 1.5303 & -3.8094 & 10.1168 \\ 3.6235 & -3.6108 & -7.8763 & 14.5854 & 10.0683 \\ 3.5912 & 0.3228 & -7.6902 & 7.1017 & 10.1722 \\ 3.6656 & 16.2922 & -0.0910 & 0.6771 & 10.1327 \end{bmatrix}$$

Now, the restored IMFs are obtained by taking inverse ICA using inverse of modified mixing matrix.These restored IMFs are shown in Fig.4.5.

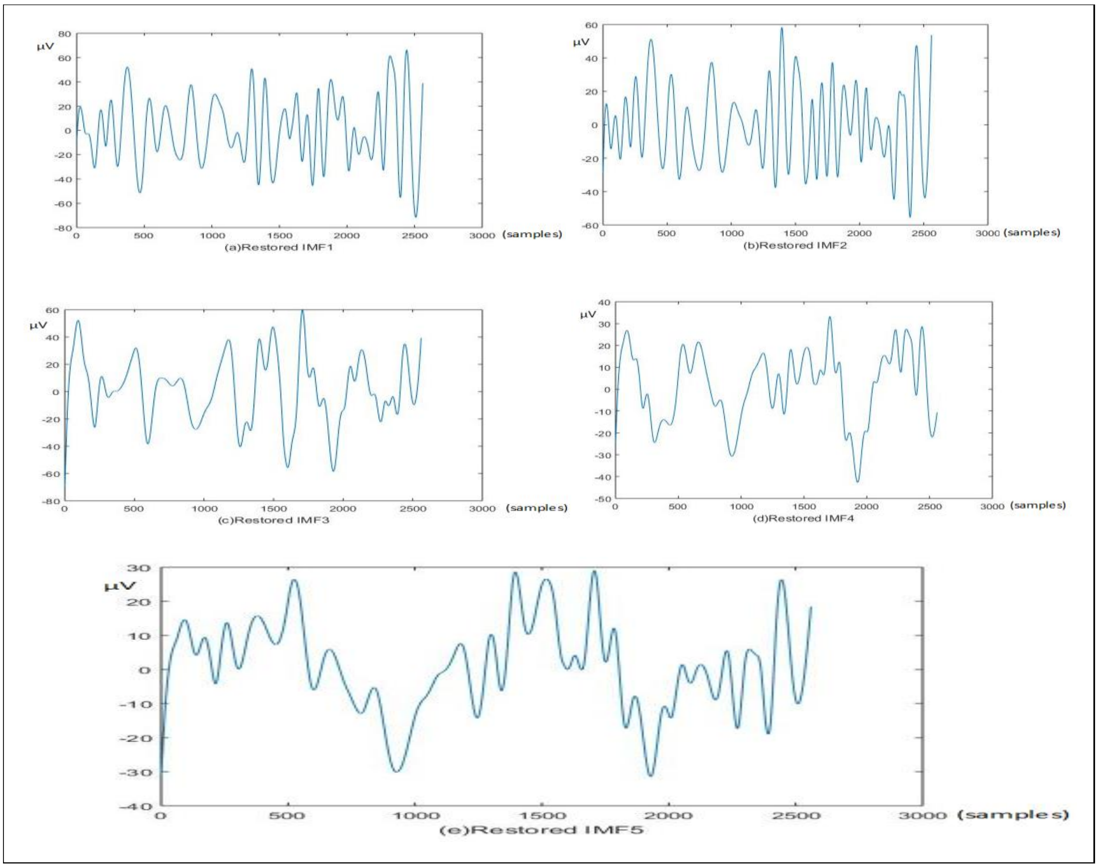

Fig.4.5 Restored IMFs

Now, the restored IMFs and artifact-free IMFs are added to obtain an artifact-free signal.

The artifactual signal is denoised using EMD-ICA, EEMD-ICA, and EEMD-SCICA and the result is observed as shown in Fig.4.6.

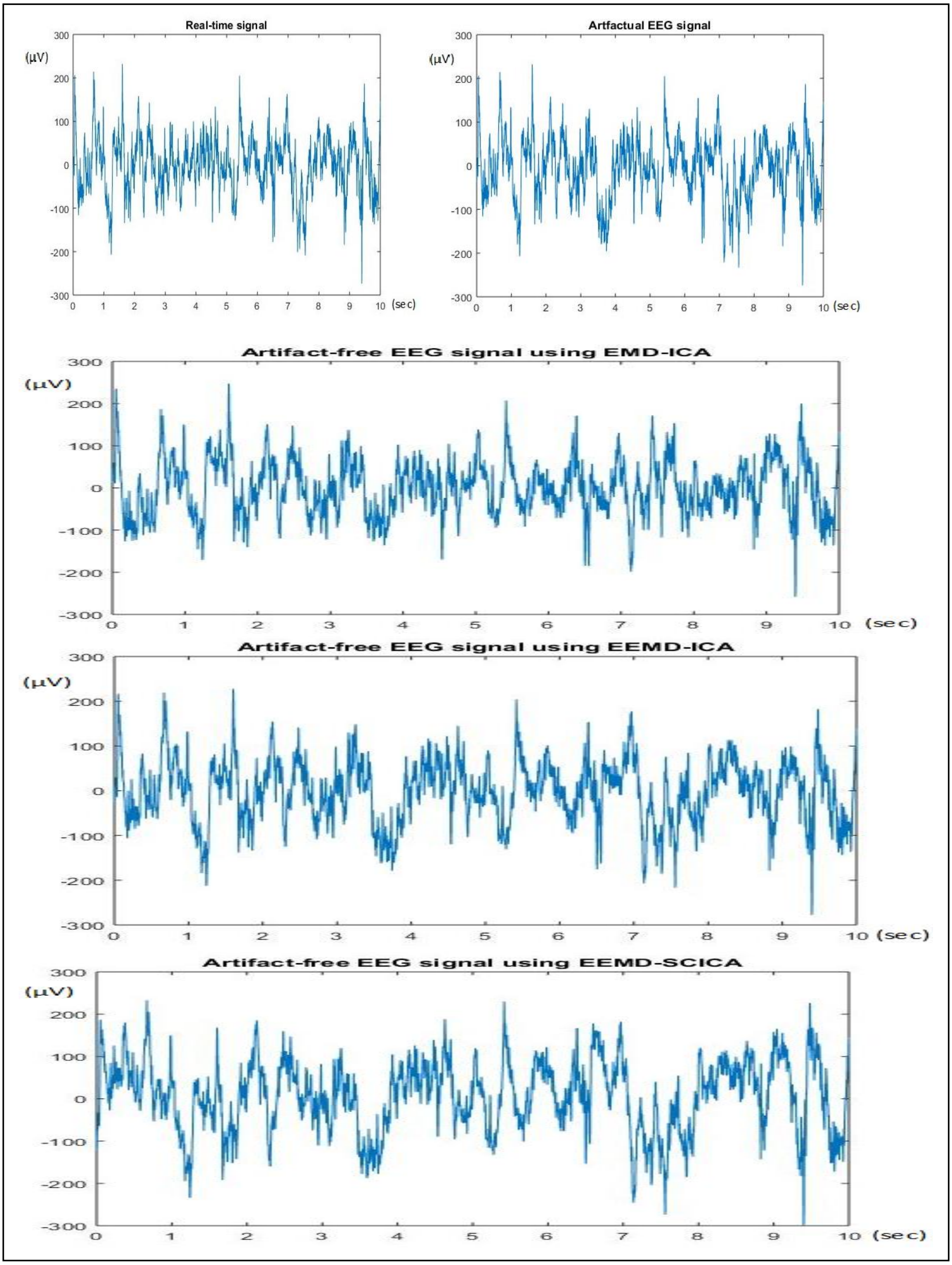

Fig.4.6 Denoised signal for EMD-ICA, EEMD-ICA, and EEMD-SCICA

To check the results the various parameters i.e. mutual information, correlation coefficient, and coherence are compared. These parameters are discussed below:

4.1 Mutual Information:

Mutual information (MI) is the quantity which deals with how much information one random variable gives about another random variable. Here, it is used between real-time signal and the artifact-free signal for EMD-ICA, EEMD-ICA, and EEMD-SCICA methods. The results are compared.According to Shannon information theory, MI can be calculated by Kullback- Leibler distance between the product of the marginal pdfs of random variable A and B and their joint pdf, which can be given as:

$$I(a,b) = \iint_{-\infty}^{\infty} f(a,b)\log(\frac{f(a,b)}{f(a)f(b)})dadb \tag{19}$$

where $f(a)$ and $f(b)$are individual marginal pdfs and $f(a,b)$ is the joint pdf. Mutual information is large if two random variables are closely related.

TABLE1:MUTUAL INFORMATION

S.No.	EMD-ICA	EEMD-ICA	EEMD-SCICA
1	0.4288	0.4601	0.4752
2	0.5094	0.5554	0.6573
3	0.8958	0.8094	0.9094
4	0.3812	0.7994	0.8691
5	0.3857	0.3759	0.5492

4.2 Coherence:

It is used to analyze information in the frequency domain. It is calculated in magnitude square term as:

$$C_{ab}(f) = \frac{|G_{ab}(f)|^2}{G_{aa}(f)G_{bb}(f)} \tag{20}$$

where $G_{ab}(f)$ is cross spectral density, $G_{aa}(f)$ is the auto spectral density of random variable A and $G_{bb}(f)$ is the auto spectral density of random variable B. The coherence of three methods is shown in Fig.4.6.

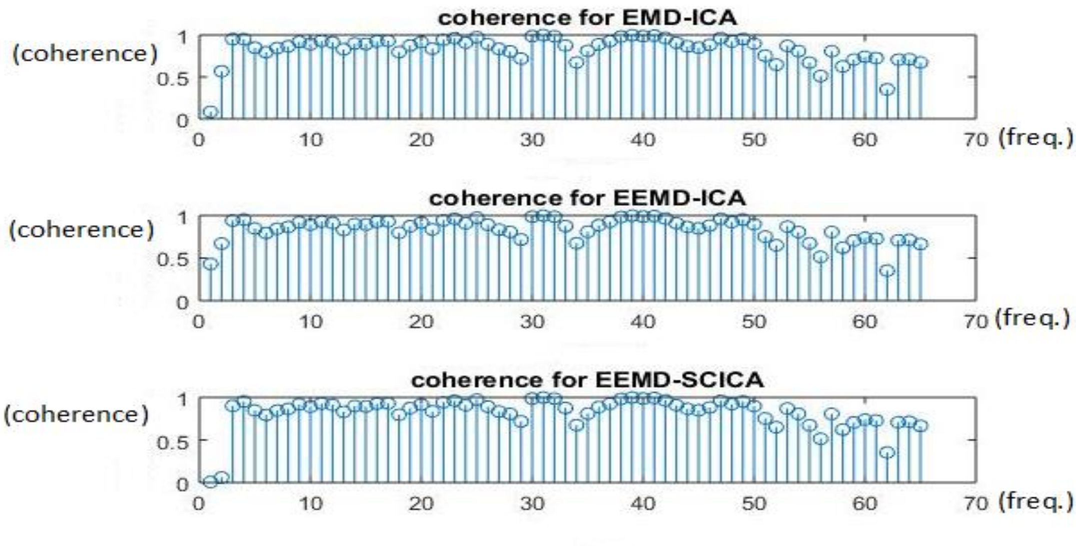

Fig. 4.7 The Coherence of EMD-ICA, EEMD-ICA and EEMD-SCICA

4.3 Correlation Coefficient:

It is used to measure linear relationship between two random variables. It uses second order statistics to measure similarity between random variables. It can have 1 as maximum value. It is mathematically given by:

$$r_{ab} = \frac{cov(a,b)}{\sigma_a \sigma_b} \tag{21}$$

Here A is pure EEG signal, B is denoised EEG signal, cov is covariance, σ is the standard deviation.

TABLE2:CORRELATION COEFFICIENT

S.No.	EMD-ICA	EEMD-ICA	EEMD-SCICA
1	0.7701	0.7766	0.7770
2	0.8535	0.8492	0.8935
3	0.8847	0.8996	0.9973
4	0.8032	0.8743	0.8897
5	0.7928	0.8301	0.8894

CHAPTER 5

CONCLUSION

The new approach discussed contains denoising of artifactual EEG signal using EEMD with SCICA to obtain an ocular artifact-free signal. The artifactual signal is disintegrated into several IMFs using EEMD technique as described in the literature survey. The artifactual IMFs from the set of IMFs on the basis of their relation with EOG signals. The artifactual IMFs are then disintegrated into ICs. The columns of corresponding to artifactual ICs are modified using spatial constraints to obtain modified mixing matrix. The restored IMFs are obtained using modified inverse mixing matrix and then adding artifact-free IMFs to restored IMFs to obtain artifact-free signal.

The ICA efficiency is increased if the number of observed sources are equal to or greater than the independent sources, this is achieved by applying EEMD on the artifactual EEG signal. As EEMD decomposes a signal into many IMFs and these IMFs are provided as input to the ICA and hence increasing the number of observed signals. Moreover, EEMD also overcomes the drawbacks of EMD like modal mixing problem and aliasing problem. The use of SCICA also improves the results as instead of zeroing all the artifactual ICs, the ICs are improved using spatial constraints.

The output obtained is compared with the outputs of EEMD-ICA and EMD-ICA methods. It is observed the result is better for proposed method than other methods from the waveform results. Moreover, on the basis of the values of correlation, mutual information, and coherence the proposed method is better.
For the future scope the EEMD problems like amplitude reduction can be removed by replacing it with CEEMD.

CHAPTER 6

REFERENCES

[1] http://emedicine.medscaple.com/article/1140247-overview.

[2] D. Hagemann and E. Naumann, "The effects of ocular artifacts on (lateralized) broadband power in the EEG," Clin. Neurophysiol., vol. 112, no. 2, pp. 215–231, 2001.

[3] Ke Zeng, Dan Chen, Gaoxiang Ouyang, Lizhe Wang, Xianzeng Liu, and XiaoliLi."An EEMD-ICA Approach to Enhancing Artifact Rejection for Noisy Multivariate Neural Data". IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 24, no. 6, June 2016.

[4] T. P. Jung, C. Humphries, T. W. Lee, S. Makeig, M. J. McKeown, V. Iragui, and J. Sejnowski," Ext. ICA Removes Artifacts from EEG Recordings", Advances in Neural Info. Processing Systems, vol.10, pp.894-900, 1998.

[5] S. Makeig, A. J. Bell, T. P. Jung, and T. J. Sejnowski, "ICA of Electroencephalographic Data, Advances in Neural Info. Processing Systems", vol.8, pp.145-151, 1996.

[6] 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.S.

[7] Christian W. Hesse, and Christopher J. James, Senior Member, IEEE "The FastICA Algorithm With Spatial Constraints" IEEE Signal Processing Letters, VOL. 12, NO. 11, 2005.

[8] C. J. James and C. W. Hesse, "On Semi-Blind Source Separation Using Spatial Constraints With Applications in EEG Analysis", IEEE Trans. On Biomed. Eng., vol.53, no. 12, Dec 2006.

[9] N. Ille, “Artifact correction in continuous recordings of the electro- and magnetoencephalogram by spatial filtering,” Ph.D. dissertation, Univ. Mannheim, Mannheim, Germany, 2001.

[10] BrahmantyaAji Pramudita, YabesDwi Nugroho1, Igi Ardiyanto1, Mohd.Ibrahim Shapiai2, Noor Akhmad Setiawan1.” Removing Ocular Artefacts in EEG Signal by Using Combination of Complete EEMD (CEEMD)- Independent Component Analysis (ICA) Based Outlier Data”,IEEE.

[11] Ruhi Mahajan and Bashir I. Morshed “ Unsupervised Eye Blink Artifact Den – oising of EEG Data with Modified Multiscale Sample Entropy, Kurtosis, and Wavelet-ICA”. IEEE Journal of Biomedical and Health informatics, vol. 19, no. 1, January 2015.

[12] M. K. Islam, A. Rastegarnia, and Z. Yang, “Methods for artifact detection and removal from scalp EEG: A review,” Neurophysiol. Clin.Neurophysiol., vol. 46, no. 4–5, pp. 287–305, 2016.

[13] N. Huang et al., “The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis,” Proc. R.Soc. A Math. Phys. Eng. Sci., vol. 454, no. 1971, pp. 995, 903, 1998.

[14] G. Rilling, P. Flandrin, and P. Es, “On Empirical Mode Decomposition and Its Algorithms,” IEEE-EURASIP Work. nonlinear signal image Process., vol. 3, pp. 8–11, 2003.

[15] W. Bosl, A. Tierney, H. T. Flusberg, and C. Nelson, “EEG complexity as a biomarker for autismspectrum disorder risk,” BMC Med., vol. 9, no. 1, pp. 1–16, 2011.

[16] Gang Wang, Chaolin Teng, Kuo Li, Zhonglin Zhang, and Xiangguo Yan” The Removal of EOG Artifacts From EEG Signals Using Independent Component Analysis and Multivariate Empirical Mode Decomposition”, IEEE Jrnl of Biomed. And Health Inf., vol.20, no. 5, Sept. 2016.