Sudan University of Science and Technology

College of Engineering

Biomedical Engineering Department

Features Extraction Techniques of EEG Signals for Brain Computer Interface Applications

تقنيات استخلاص الميزات من اشارات تخطيط الدماغ لتطبيقات الربط الدماغي الحاسوبي

A Research Submitted In Partial fulfillment for the Requirements of the Degree of B.Sc.(Honors) in Biomedical Engineering

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استهلال

قال تعالى:

(ولقد كرمنا بني آدم و حملناهم في البر والبحر ورزقناهم من الطيبات وفضلناهم

على كثير ممن خلقنا تفضيلا)

سورة الاسراء الآية رقم(70)

Dedication

I dedicate this humble work to my father, who never wasted any thing one me, And to my mother , who gave me affection and love , I said to them : you gave me life and hope and the emergence of a passion for knowledge .And to my brothers and sisters and all my family , and to every one who taught me a character that has become a shining light to illuminate the road in front me.

ACKNOWLEDGEMENT

After a journey of research , effort and diligence culminated in the completion of this project , we thank God for the blessings that he gave to us and he is the Almighty. And we cannot but to acknowledge the highest words of thanks and appreciation ***Dr. fregon*** *for the effort and advice and knowledge that he gave to us throughout the completion of this project. And we give a special thanks to the* ***Engineer Rania*** *who provided us with her advice and give us her valuable time and her rich knowledge and generous generosity , we ask Allah to bless her in her time and age and reward her with his greatness and kindness. Also we extend our thanks , appreciation and respect to* ***Engineer Montasir*** *for his advice and guidance .*

Abstract

Electroencephalography (EEG) signals were analyzed in many research applications as a channel of communication between humans and computers. EEG signals associated with imagined fists and feet movements were filtered and processed using wavelet transform analysis for feature extraction. The proposed work used Neural Networks (NNs) as a classifier that enables the classification of imagined movements into one of the four classes (left hand , right hand , foot and tongue).Daubechies wavelet mother function(db8) was used analyze the extracted events and then different feature extraction measures were calculated for three detail levels of the wavelet coefficients .Intensive NN training and testing experiments were carried out, The result of classification performance is 86.7% was achieved with a NN classifier of 17 hidden layers while using the Integral EEG (IEEG) of the wavelet Daubechies coefficients as inputs to FNN**.**

المستخلص

اشارات الدماغ (EEG) تم تحليلها للعديد من التطبيقات البحثية كقناة اتصال بين الانسان والكمبيوتر . اشارات تخطيط الدماغ التي لها علاقة بالحركات (اليد اليمنى , اليد اليسرى , القدم واللسان) تمت تشخيصها و معالجتها بأستخدام تحليل تحويل المويجات من اجل استخلاص الميزات . العمل المخترح استخدم الشبكات العصبية (NNs) كمصنف له القدرة علي تصنيف الحركات المتخيلة (اليد اليمنى , اليد اليسرى , القدم واللسان) استخدمت الدالة الأم Db8 من عائلة الديباتشي لتحليل واستخلاص الميزات من ثلاثة مستويات من التفاصيل (الفا , بيتا , دالتا) لمعاملات الدالة الأم . تم القيام بالعديد من عمليات التدريب والأختبار علي الشبكة العصبية. كان الاداء لعملية التصنيف هو 86.7% وتم الحصول عليه بأستخدام شبكة عصبية مكونه من 20 طبقة خفية عند أستخدام (IEEG) تخطيط أشارات الدماغ المتكامل كدخل للشبكة العصبية ذات التغذية العكسية الامامية.

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CHAPTER ONE

INTRODUCTION

1.1 General review

There are a significant number of people suffering from severe motor disabilities due to various causes, high cervical injuries, cerebral palsy, multiple sclerosis or muscular dystrophy. In these cases the communication systems based on brain activity play an important role and provide a new form of communication and control, either to increase the integration into the society or to provide to these people a tools for interaction with their environment without a continued assistance. There are various techniques and paradigms in the implementation of brain-computer interfaces (BCI). A brain-computer interface is a communication system for generating a control signal from brain signals such as EEG and evoked potentials. The Communication between the two essential parts of BCI (brain and computer), is governed by the fact that the brain generates the command and the computer must to interpret.

To measure and study the brain activity signals, there are different methods such as: magnetic resonance imaging (MRI), computed tomography (CT), the ECOG scale, single photon emission computed tomography (SPECT), CT positron emission tomography (PET), magnetoencephalography (MEG), functional MRI (fMRI), but these signals are not practical to implement a human-machine interface, because some are only anatomical information, other techniques are very invasive, others are a lot of exposure to radiation and another are very expensive . To work with electroencephalographic (EEG) is the most convenient and therefore the BCI is based on detecting the EEG signals associated with certain mental states.

1.2 Problem Statement

The important problem in EEG recording is the huge number of features. It comes from the fact that

(*i*) EEG signals are non-stationary, thus features must be computed in a time-varying manner and

(*ii*) the number of EEG channels is large .

Also identifying the user's mental state from EEG signals is no easy task, such signals being noisy, non-stationary, complex and of high dimensionality

1.3Objectives

The objectives of this research as show below:

1.3.1 General Objective

To design program to analyze the electrical activity of human brain.

To extract features of EEG signal for BCI application

1.3.2 Specific Objectives

- To analyze EEG into:-Delta, Theta, Alpha, Beta, Gamma.

-To analyze the variations of EEG signal in front of the different tasks under study and implementation of an algorithm of extraction of characteristics

-To implement classification system to discriminate between classes.

-To compare between features extraction techniques

1.4 Methodology:

EEG signal was taken from database and filtered by band pass filter in the preprocessing phase, and then the signal was converted from time domain to frequency domain in the feature extraction. In the classification phase the converted signal was sub divided to sub division (Delta, Theta, Beta, Alpha, and Gamma) by wavelet transform.

1.5 Layout of research:

The remainder of this report is structured as follows. Chapter 2 describes previous work in the area of EEG features extraction and classification. Chapter3 the presentation of the theoretical background. Chapter 4 goes into the theoretical details of methods to be used. Chapter 5 presents empirical results on real EEG data, followed by detailed discussion of said results. Concluding remarks can be found .

CHAPTER TWO

LITERATUR REVIEWS

Chapter Tow: Literature reviews

-In 2013 Sachin Garg 1, Rakesh Narvey., The research about denoising and features extraction of eeg signals using wavelet transform and proposes a technique of detecting epilepsy disorder using discrete wavelet transform using MATLAB. The contribution presents the use of wavelet transform for a given signal. EEG data were used as input to the wavelet transform offers a perfect success in the rejecting undesired frequencies and permits the DWT levels to discriminate the EEG waves only. Once the delta wave is identified and measured, the features like Mean, Max, Min and median was calculated and then ANN is used for the classification. This method offers more efficiency, which it can be easily distinguished between normal and epileptic. EEG data were used as input to the wavelet transform offers a perfect success in the rejecting undesired frequencies and permits the DWT levels to discriminate the EEG waves only. Once the delta wave is identified and measured, the features like Mean, Max, Min and median was calculated and then ANN is used for the classification. This method offers more efficiency, which it can be easily distinguished between normal and epileptic.

-In 2016, Rahib H. Abiyev, NurullahAkkaya, ErsinAytac, IrfanGünsel, and AhmetÇaLman talk about Brain-Computer Interface for Control of Wheelchair Using Fuzzy Neural Networks.They used Fast Fourier Transform(fft) to extract important features form the EEG signal. Then the extracted features are input signals of the FNN based classifier ,they found that the use of FFN is very effective in the classification of EEG signals.

-In 2014, Mohammad H. Alomari, Emad A. Awada, Aya Samahaand Khaled Alkamha talk about Wavelet-Based Feature Extraction for the Analysis of EEG Signals Associated with Imagined Fists and Feet Movements.They used wavelet transform for features extraction and neural network for the classification,Symlets, Daubechies, Coiflets wavelet families were compared for their abilities to decompose EEG signals and extract features that can be used as inputs to neural networks,they found that The optimum classification performance was achieved with a NN classifier of 20 hidden layers while using the mean absolute value of the Coiflets wavelet coefficients as inputs to NN. Their work describes a classification system that can classify imagined EEG signals into fists and feet movements. Symlets, Daubechies, Coiflets wavelet families were compared for their abilities to decompose EEG signals and extract features that can be used as inputs to neural networks. Extensive experiments were carried out and the neural networks were optimized. The optimum classification performance of 89.11% was achieved with a NN classifier of 20 hidden layers while using the mean absolute value of the Coiflets wavelet coefficients as inputs to NN. It is believed that this work is one of the best to achieve such classification performance while working on imagined fists and feet activities. Real-time applications of this work can be implemented in the near future.

-In 2011, Marcin Kołodziej, Andrzej Majkowski, and Remigiusz J. Rak talk about, A new method of feature extraction and selection of EEG signal for brain-computer interface design is presented. method of feature extraction using HOS and DWT gives more accurate results then the algorithm based on discrete Fourier transform (DFT).

-In 2012, California Polytechnic State University San Luis Obispo , Team Members Christopher Nguyen (Advisor Tina Smilkstein) ,Fan Wai Lu ME Senior StudMarino , Joseph MariSmet , Adrian Smet , Dr. Tina Smilkstein and Dr. Dennis Derickson , talk about Brian Computer Interface for EEG/EMG Signal Correlation CPConnect Grant Proposal .

Brain Computer Interface (BCI) systems are designed to directly communicate a pathway between the brain and an external device.They found that EEG data were used as input to the wavelet transform offers a perfect success in the rejecting undesired frequencies and permits the DWT levels to discriminate the EEG waves only. Once the delta wave is identified and measured, the features like Mean, Max, Min and median was calculated and then ANN is used for the classification. This method offers more efficiency, which it can be easily distinguished between normal and epileptic. They found that the goal for the BCI correlation project is to provide a system that can gather knowledge in the field of neuroscience. This knowledge will reduce the training time required for patients to command prosthetics by eliminating the dependency for the patients to develop certain new thoughts to command. Further implementation of this project will allow opportunities for students in fields of engineering and sciences. Once the project is completed we will submit a publication with findings and conclusions to the Engineering in Medicine and Biology Society (EMBS) IEEE. Instead of contracting muscles or activating nerves to control prosthetics, patients will be able to simply think a command that causes a prosthetic to follow through with a natural thought based motor function. This system allows the learning curve of the prosthetic to be designed into the technology, and not the patient.

-In 2015 Rabie A. Ramadan, S. Refat, Marwa A. Elshahed and Rasha A. Ali, *they talk about* Brain-Computer Interface (BCI) that is a fast growing emergent technology in which researchers aim to build a direct channel between the human brain and the computer. It is a collaboration in which a brain accepts and controls a mechanical device as a natural part of its representation of the body. The BCI can lead to many applications especially for disabled persons. Most of these applications are related to disable persons in which they can help them in living as normal people. Wheelchair control is one of the famous applications in this field. In addition, the BCI research aims to emulate the human brain. This would be beneficial in many fields including the Artificial Intelligence and Computational Intelligence. Throughout this chapter, an introduction to the main concepts behind the BCI is given, the concepts of the brain anatomy is explained, and the BCI different signals are stated. In addition, the used hardware and software for the BCI are elaborated.

-In 2013 Ales Prochazka and Jaromir Kukal.Oldrich Vysata,they talk about Wavelet Transform Use for Feature Extraction and EEG Signal Segments Classification. Segmentation, feature extraction and classification of signal components belong to very common problems in various engineering, economical and biomedical applications. The paper is devoted to the use of discrete wavelet transform (DWT) both for signal preprocessing and signal segments feature extraction as an alternative to the commonly used discrete Fourier transform (DFT). Feature vectors belonging to separate signal segments are then classified by a competitive neural network as one of methods of cluster analysis and processing. The paper provides a comparison of classification results using different methods of feature extraction most appropriate for EEG signal components detection. Problems of multichannel segmentation are mentioned in this connection as well.

-In 2012 Anupama. H. S, Cauvery. N. K, G. M. LINGARAJU,they talk about Brain computer interface and its types, they study about Brain Computer Interface (BCI) provides a communication path between human brain and the computer system. With the advancement in the areas of information technology and neurosciences, there has been a surge of interest in turning fiction into reality. The major goal of BCI research is to develop a system that allows disabled people to communicate with other persons and helps to interact with the external environments. This area includes components like, comparison of invasive and noninvasive technologies to measure brain activity, evaluation of control signals (i.e. patterns of brain activity that can be used for communication), development of algorithms for translation of brain signals into computer commands, and the development of new BCI applications. They found that use of EEG signals as a vector of communication between man and machines represents one of the current challenges in signal theory research. The principal element of such a communication system is known as "Brain Computer Interface". BCI is the interpretation of the EEG signals related to the characteristic parameters of brain electrical activity. EEG measures tiny voltage potentials where signal is weak and prone to interference. Signals have to be recorded from brain in a clinical condition where there are no external (noise free environment), users have to be trained to perform various tasks with full concentration and Handling high dimensional data.

CHAPTER THREE

THEORITICAL

BACKROUND

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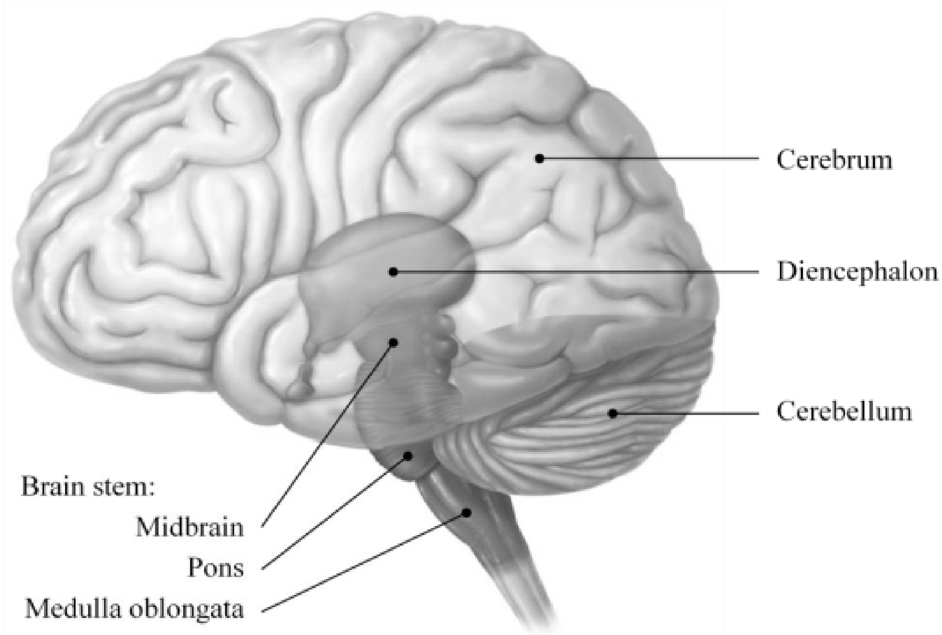
3.1 Anatomy of brain



Fig(3.1) General anatomy of the brain

3.1.1 Cerebrum

Divided into two hemispheres, the cerebrum is the largest region of the human brain – the two hemispheres together account for ~ 85% of total brain mass. The cerebrum forms the superior part of the brain, covering and obscuring the diencephalon and brain stem similar to the way a mushroom cap covers the top of its stalk. Elevated ridges of tissue, called gyri (singular: gyrus), separated by shallow groves called sulci (singular: sulcus) mark nearly the entire surface of the cerebral hemispheres.

Deeper groves, called fissures, separate large regions of the brain. Much of the cerebrum is involved in the processing of somatic sensory and motor information as well as all conscious thoughts and intellectual functions. The outer cortex of the cerebrum is composed of gray matter – billions of neuron cell bodies and unmyelinated axons arranged in six discrete layers. Although only 2 – 4 mm thick, this region accounts for ~ 40% of total brain mass. The inner region is composed of white matter – tracts of myelinated axons. Deep within the cerebral white matter is a third basic region of the cerebrum, a group of sub-cortical gray matter called basal nuclei. These nuclei, the caudate nucleus, putamen, and globus pallidus, .are important regulators of skeletal muscle movement.[1]

3.1.2 Diencephalon

Surrounded by the cerebral hemispheres, the diencephalon forms the central core of the brain. Consisting of largely of three paired structures, the thalamus, hypothalamus, and epithalamus, the diencephalon plays a vital role in integrating conscious and unconscious sensory information and motor commands.[1]

3.1.3 Brain stem

The brain stem begins inferior to the thalamus and runs approximately 7 cm before merging into the spinal cord. The brain stem centers produce the rigidly programmed, automatic behaviors necessary for survival. Positioned between the cerebrum and the spinal cord, the brain stem also provides a pathway for fiber tracts running between higher and lower brain centers.[1]

3.1.4 Cerebellum

Located on the lower dorsal aspect of the brain, the cerebellum accounts for ~ 11% of the total brain mass. Like the cerebrum, the cerebellum has two major hemispheres with an outer cortex made up of gray matter with an inner region of white matter. The cerebellum is located dorsal to the pons and medulla and it protrudes under the occipital lobes of the cerebral hemispheres, from which it is separated by the transverse fissure. By processing inputs received from the cerebral motor cortex, various brain stem nuclei, and sensory receptors, the cerebellum provides the precise timing and appropriate patterns of skeletal muscle contraction for smooth, coordinated movements and agility needing for our daily lives (e.g., driving). Cerebellar activity occurs subconsciously, we have no awareness of it.[1]

3.1.5 Ventiricels

Situated within the brain are central hollow civilities called ventricles. These ventricles are continuous with one another and with the central canal of the spinal cord. The hollow ventricular chambers are filled with cerebrospinal fluid, a fluid that forms a liquid cushion for the brain. In addition, the cerebrospinal fluid helps nourish the brain and there is some evidence that hormones circulate in the brain via this pathway.[1]

3.1.6 Meninges

The meninges are three connective tissue membranes that lie just external to the brain. The function of theses layers are to:

1) cover and protect the brain.

2) protect blood vessels and enclose venous sinuses.

3) contain cerebral spinal fluid.

4) form partitions within the skull.[1]

3.2 Electroencephalography(EEG)

Is a medical imaging technique that reads scalp electrical activity generated by brain structures. The electroencephalogram (EEG) is defined as electrical activity of an alternating type recorded from the scalp surface after being picked up by metal electrodes and conductive media[2] . The EEG measured directly from the cortical surface is calledelectrocortiogram while when using depth probes it is called electrogram. In this article, we will refer only to EEG measured from the head surface. Thus electroencephalographic reading is a completely non-invasive procedure that can be applied repeatedly to patients, normal adults, and children with virtually no risk or limitation. When brain cells (neurons) are activated, local current flows are produced. EEG measures mostly the currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. Differences of electrical potentials are caused by summed postsynaptic graded potentials from pyramidal cells that create electrical dipoles between soma (body of neuron) and apical dendrites (neural branches). Brain electrical current consists mostly of Na+, K+, Ca++, and Cl- ions that are pumped through channels in neuron membranes in the direction governed by membrane potential[3] . The detailed microscopic picture is more sophisticated, including different types of synapses involving variety of nurotransmitters. Only large populations of active neurons can generate electrical activity recordable on the head surface. Between electrode and neuronal layers current penetrates through skin, skull and several other layers. Weak electrical signals detected by the scalp electrodes are massively amplified, and then displayed on paper or stored to computer memory[4] . Due to capability to reflect both the normal and abnormal electrical activity of the brain, EEG has been found to be a very powerful tool in the field of neurology and clinical neurophysiology. The human brain electric activity starts around the 17-23 week of prenatal development. It is assumed that at birth the full number of neural cells is already developed, roughly 1011 neurons[5] . This makes an average density of 104 neurons per cubic mm. Neurons are mutually connected into neural nets through synapses. Adults have about 500 trillion (5.1014) synapses. The number of synapses per one neuron with age increases, however the number of neurons with age decreases, thus the total number of synapses decreases with age too. From the anatomical point of view, the brain can be divided into three sections: cerebrum, cerebellum, and brain stem. The cerebrum consists of left and right hemisphere with highly convoluted surface layer called cerebral cortex. The cortex is adominant part of the central nervous system. The cerebrum obtains centres for movement initiation, conscious awareness of sensation, complex analysis, and expression of emotions and behaviour. The cerebellum coordinates voluntary movements of muscles and balance maintaining. The brain stem controls respiration, heart regulation, biorythms, neurohormone and hormone secretion, etc[6]. The highest influence to EEG comes from electric activity of cerebral cortex due to its surface position. There are some theoretical and practical differences between EEG and MEG. Although the MEG is produced by the same electrical currents, it can provide complementary information to EEG.[7]

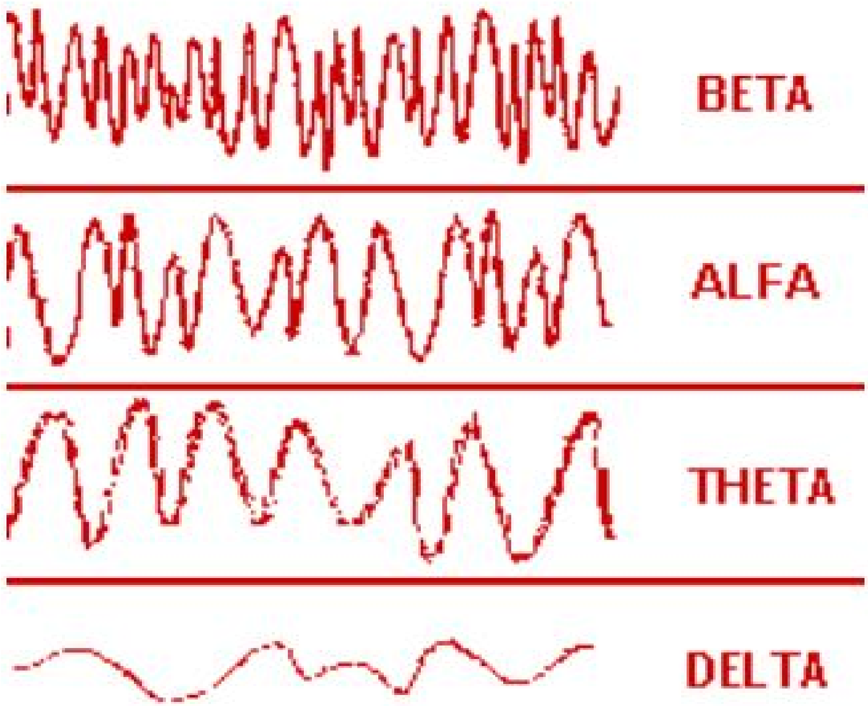
3.3 History

During more than 100 years of its history, encephalography has undergone massive progress. The existence of electrical currents in the brain was discovered in 1875 by an English physician Richard Caton.

Caton observed the EEG from the exposed brains of rabbits and monkeys. In 1924 Hans Berger, a German neurologist, used his ordinary radio equipment to amplify the brain's electrical activity measured on the human scalp. He announced that weak electric currents generated in the brain can be recorded without opening the skull, and depicted graphically on a strip of paper. The activity that he observed changed according to the functional status of the brain, such as in sleep, anaesthesia, lack of oxygen and in certain neural diseases, such as in epilepsy. Berger laid the foundations for many of the present applications of electroencephalography. He also used the word electroencephalogram as the first for describing brain electric potentials in humans. He was right with his suggestion, that brain activity changes in a consistent and recognizable way when the general status of the subject changes, as from relaxation to alertness[8] . Later in 1934 Adrian and Matthews published the paper verifying concept of “human brain waves” and identified regular oscillations around 10 to 12 Hz which they termed “alpha rhythm”.[8]

3.4 Brain waves classification

For obtaining basic brain patterns of individuals, subjects are instructed to close their eyes and relax. Brain patterns form wave shapes that are commonly sinusoidal. Usually, they are measured from peak to peak and normally range from 0.5 to 100 µV in amplitude, which is about 100 times lower than ECG signals. By means of Fourier transform power spectrum from the raw EEG signal is derived. In power spectrum contribution of sine waves with different frequencies are visible. Although the spectrum is continuous, ranging from 0 Hz up to one half of sampling frequency, the brain state of the individual may make certain frequencies more dominant. Brain waves have been categorized into four basic groups (Figure 1): - beta (>13 Hz), - alpha (8-13 Hz), - theta (4-8 Hz), - delta (0.5-4 Hz).



Fig(3.2). Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta band.

3.5 EEG recording techniques

Encephalographic measurements employ recording system consisting of

- electrodes with conductive media
- amplifiers with filters
- A/D converter
- recording device.

Electrodes read the signal from the head surface, amplifiers bring the microvolt signals into the range where they can be digitalized accurately, converter changes signals from analog to digital form, and personal computer (or other relevant device) stores and displays obtained data. A set of the equipment is shown in Fig(3.2). Scalp recordings of neuronal activity in the brain, identified as the EEG, allow measurement of potential changes over time in basic electric circuit conducting between signal (active) electrode and reference electrode [9]. Extra third electrode, called ground electrode, is needed for getting differential voltage by subtracting the same voltages showing at active and reference points. Minimal configuration for monochannel EEG measurement consists of one active electrode, one (or two specially linked together) reference and one ground electrode. The multi-channel configurations can comprise up to 128 or 256 active electrodes.

Fig(3.3). Equipment for EEG recording: amplifier unit, electrode cap, conductive jelly, injection, and aid for disinfection.

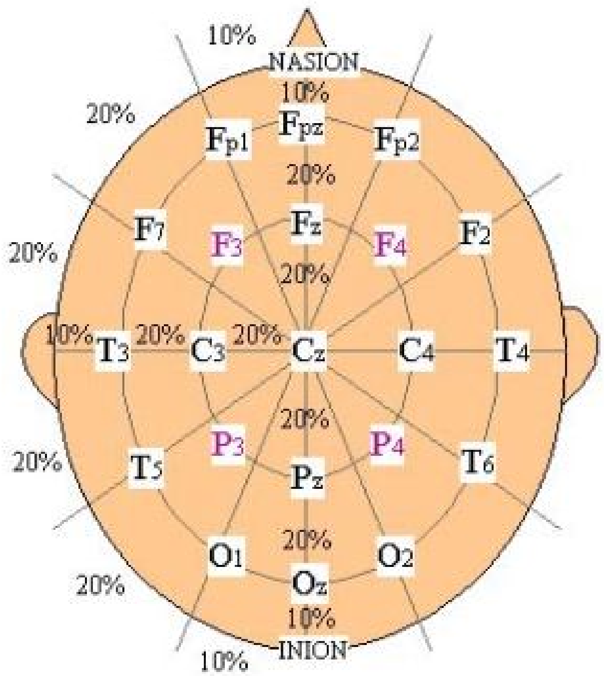
3.6. Recording electrodes

The EEG recording electrodes and their proper function are critical for acquiring appropriately high quality data for interpretation. Many types of electrodes exist, often with different characteristics. Basically there are following types of electrodes:

- disposable (gel-less, and pre-gelled types)
- reusable disc electrodes (gold, silver, stainless steel or tin)
- headbands and electrode caps
- saline-based electrodes
- needle electrodes

For multichannel montages, electrode caps are preferred, with number of electrodes installed on its surface (Figure3 .3). Commonly used scalp electrodes consist of Ag-AgCl disks, 1 to 3 mm in diameter, with long flexible leads that can be plugged into an amplifier [10]. AgCl electrodes can accurately record also very slow changes in potential [11]. Needle electrodes are used for long recordings and are invasively inserted under the scalp. Skin preparation differs, generally cleaning of the skin surface from oil and brushing from dried parts is recommended. With disposable and disc electrodes, abrasive paste is used for slight skin abrasion. With cap systems, abutting needle at the end of injection is used for skin scraping, which can cause irritation, pain and infection. Especially when person's EEG is measured repeatedly and cap is mounted for the same electrode points, there is a threat of certain pain and bleeding. That is why the right hygiene and safety protocol should be kept. Using the silver-silver chloride electrodes, the space between the electrode and skin should be filled with conductive paste also helping to stick. With the cap systems, there is a small hole to inject conductive jelly. Conductive paste and conductive jelly serve as media to ensure lowering of contact impedance at electrode-skin interface. In 1958, International Federation in Electroencephalography and Clinical Neurophysiology adopted standardisation for electrode placement called 10-20 electrode placement system [12]. This system standardized physical placement and designations of electrodes on the scalp. The head is divided into proportional distances from prominent skull landmarks (nasion, preauricular points, inion) to provide adequate coverage of all regions of the brain. Label 10-20 designates proportional distance in percents between ears and nose where points for electrodes are chosen. Electrode placements are labelled according adjacent brain areas: F (frontal), C (central), T (temporal), P (posterior), and O (occipital). The letters are accompanied by odd numbers at the left side of the head and with even numbers on the right side (Figure 3.4). Left and right side is considered by convention from point of view of a subject.

Fig(3.4). Electrode cap with electrodes placed after 10-20 electrode placement system.



Fig(3.5).labels for points according to 10-20 electrodes placement system

As it is known from tomography different brain areas may be related to different functions of the brain. Each scalp electrode is located near certain brain centres, e.g. F7 is located near centres for rational activities, Fz near intentional and motivational centres, F8 close to sources of emotional impulses. Cortex around C3, C4, and Cz locations deals with sensory and motor functions. Locations near P3, P4, and Pz contribute to activity of perception and differentiation. Near T3 and T4 emotional processors are located, while at T5, T6 certain memory functions stand. Primary visual areas can be found bellow points O1 and O2. However the scalp electrodes may not reflect the particular areas of cortex, as the exact location of the active sources is still open problem due to limitations caused by the non-homogeneous properties of the skull, different orientation of the cortex sources, coherences between the sources, etc. [13]. High impedance can lead to distortions which can be difficult to separate from actual signal. It may allow inducing outside electric frequencies on the wires used or on the body. Impedance monitors are built in some commercially available EEG devices. In order to prevent signal distortions impedances at each electrode contact with the scalp should all be bellow 5 K Ohms, and balanced within 1 K Ohm of each other. Similar standard is required for clinical use of the EEG and for publication in most reputable journals. Practically, impedance of the whole circuit comprising two electrodes is measured, but built in impedance checks usually display results already divided by two. Control of all impedances is desirable also after finishing every single measurement. Several different recording reference electrode placements are mentioned in the literature. Physical references can be chosen as vertex (Cz), linked-ears, linked-mastoids, ipsilateral-ear, contralateral-ear, C7 reference, bipolar references, and tip of the nose. Reference-free techniques are represented by common average reference, weighted average reference, and source derivation. Each technique has its own set of advantages and disadvantages. The choice of reference may produce topographic distortion if relatively electrically neutral area is not employed. Linking reference electrodes from two earlobes or mastoids reduces the likelihood of artificially inflating activity in one hemisphere. Nevertheless, the use of this method may drift away "effective" reference from the midline plane if the electrical resistance at each electrode differs [14]. Cz reference is advantageous when it is located in the middle among active electrodes, however for close points it makes poor resolution. Reference-free techniques do not suffer from problems associated with an actual physical reference. Referencing to linked ears and vertex (Cz) are predominant. With modern instrumentation, the choice of a ground electrode plays no significant role in the measurement [15]. Forehead (Fpz) or ear location is preferred [16], but sometimes wrist or leg is also used. The combination of all active electrodes with reference and ground electrode compose channels. The general configuration is called montage.

3. 7. Amplifiers and filters

The signals need to be amplified to make them compatible with devices such as displays, recorders, or A/D converters. Amplifiers adequate to measure these signals have to satisfy very specific requirements. They have to provide amplification selective to the physiological signal, reject superimposed noise and interference signals, and guarantee protection from damages through voltage and current surges for both patients and electronic equipment. The basic requirements that a biopotential amplifier has to satisfy are [17]:

- The physiological process to be monitored should not be influenced in any way by the amplifier.
- The measured signal should not be distorted.
- The amplifier should provide the best possible separation of signal and interferences.
- The amplifier has to offer protection of the patient from any hazard of electric shock.
- The amplifier itself has to be protected against damages that might result from high input voltages as
they occur during the application of defibrillators or electrosurgical instrumentation. The input signal to the amplifier consists of five components:

The desired biopotential, undesired biopotentials, a power line interference signal of 50/60 Hz and its harmonics, interference signals generated by the tissue/electrode interface, and noise. Proper design of the amplifier provides rejection of a large portion of the signal interferences. The desired biopotential appears as the differential signal between the two input terminals of the differential amplifier [17].

The amplifier gain is the ratio of the output signal to the input signal. In order to provide optimum signal quality and adequate voltage level for further signal processing, the amplifier has to provide a gain of 100-100,000 [17] (the highest need not to be the best, combination of more parameters is involved, e.g. the range of the A/D converter, sampling rate, noise of the used elements) and needs to maintain the best possible signal-to-noise ratio. In order to decrease an impact of electrically noisy environment differential amplifiers must have high common-mode rejection ratios (at least 100 dB) and high input impedance (at least 100 M Ohms). The common-mode rejection ratio is the ratio of the gain of differential mode (wanted signal) over the gain of the common mode (original input signal between the inputs and ground). Special electrically shielded rooms minimize the impact of urban electric background, in particular 50/60 Hz alternating current line noise. For usual medical purposes, shielded room is not necessary. For research purposes when maximal amount of information is desired, shielded room is used. Then amplifiers run on batteries and an optical cable leads to the PC standing outside from the shielded space. In addition to the optical cable, electrical/optical and optical/electrical converters are necessary. Usually information of interest lies bellow this line noise and we can use low-pass filters with cut-off bellow 50/60 Hz, or for keeping higher frequency bands a notch filter can be applied, that is able to reduce only a narrow band around 50/60 Hz (but distorts phases). When computers are used as recording devices, channels of analog signal are repeatedly sampled at a fixed time interval (sampling interval), and each sample is converted into a digital representation by an analog- to-digital (A/D) converter. The A/D converter is interfaced to a computer system so that each sample can be saved in the computer's memory. The resolution of the converter is determined by the smallest amplitude that can be sampled. This is obtained by dividing the voltage range of the A/D converter by 2 raised to the power of the number of bits of the A/D converter [7]. A/D converter usually uses minimally 12 bits (discerning 4,096 value levels). Ability to resolve 0.5 μV is recommended [18].

Sufficient sampling rate is required, at least double of the highest frequency component of our interest. Analog (hardware) filters have to be integrated in the amplification unit. A high-pass filter is needed for reducing low frequencies coming from bioelectric flowing potentials (breathing, etc.), that remain in the signal after subtracting voltages toward ground electrode. Its cut-off frequency usually lies in the range of 0.1-0.7 Hz. To ensure that the signal is band limited, a low-pass filter with a cut-off frequency equal to the highest frequency of our interest [7] is used (in the range from 40 Hz up to less than one half of the sampling rate). Analog low-pass filters prevent distortion of the signal by interference effects with sampling rate, called aliasing, which would occur if frequencies greater than one half of the sampling rate survive without diminishing. Once data are stored, digital filtering can be used. The strength of the analog filters is limited thus for displaying and processing of the signals further decreasing of DC components is usually needed. It is possible to choose from linear (FIR, IIR) filtering or novel non-linear filtering methods. The choice should be done according to the objectives put on the signal processing. Predominantly finite impulse response (FIR) filters are used which do not distort wave phases. The data points width typically range on the order of 1000 and one of the window function (Blackman, Hanning, Hamming, or rectangular) should be chosen. Filters should be designed in a way to influence useful signal properties minimally. Before performing the final measurements the whole EEG system should be tested. Inter-channel calibrations with known wave signal parameters should not display significant discrepancies. The output noise (referred to input) consists mainly from the noise caused by the analog amplifier circuitry and by A/D converter circuitry. Noise value should be consistent with manufacturer information, about 0.3-2 μV pp. (range from negative peak to positive peak) but this value depends on the way of noise estimation and on the system configuration (low-pass filter, sampling rate, choice of circuitry). The noise can be determined by connecting the inputs of the amplifier together, or abased them into a salty solution, or "short-circuiting" the inputs, and then measuring the output of the amplifier. The number of useful information bits can be counted as a power of two from the ratio of average EEG signal amplitude over the noise amplitude (e.g. 50μV/1μV results in over 5 bits). One of the limitations of recordings is due to storage requirements. For example, 1 hour of eight channels 14-bit signal sampled with 500 Hz occupies 200 MB of the memory. There exist portable recording systems used for longer monitoring of a subject without limiting movement of a person. Some of the commercial EEG recording systems comes from following suppliers: Lexicor, Electrical geodesics, Biosemi, NeuroScan, Sigma Medizin, Contact Precision Instruments, Stellate, Thought Technology, Xltek.

3.8 Artefacts

Among basic evaluation of the EEG traces belongs scanning for signal distortions called artefacts. Usually it is a sequence with higher amplitude and different shape in comparison to signal sequences that doesn’t suffer by any large contamination. The artefact in the recorded EEG may be either patient-related or technical. Patient-related artefacts are unwanted physiological signals that may significantly disturb the EEG. Technical artefacts, such as AC power line noise, can be decreased by decreasing electrode impedance and by shorter electrode wires. The most common EEG artefact sources can be classified in following way:

Patient related:

- any minor body movements
- EMG
- ECG (pulse, pace-maker)
- eye movements
- sweating

Technical:

- 50/60 Hz
- impedance fluctuation
- cable movements
- broken wire contacts
- too much electrode paste/jelly or dried pieces
- low battery

Excluding the artefact segments from the EEG traces can be managed by the trained experts or automatically. For better discrimination of different physiological artefacts, additional electrodes for monitoring eye movement, ECG, and muscle activity may be important.

3.9. BCI (Brain Computer Interface)

A Brain Computer Interface (BCI) provides a communication path between human brain and the computer system. With the advancement in the areas of information technology and neurosciences, there has been a surge of interest in turning fiction into reality. The major goal of BCI research is to develop a system that allows disabled people to communicate with other persons and helps to interact with the external environments. This area includes components like, comparison of invasive and noninvasive technologies to measure brain activity, evaluation of control signals (i.e. patterns of brain activity that can be used for communication), development of algorithms for translation of brain signals into computer commands, and the development of new BCI applications. This Paper provides an insight into the aspects of BCI, its applications, recent developments and open problems in this area of research. Brain–computer interface (BCIs) started with Hans Berger's inventing of electrical activity of the human brain and the development of electroencephalography (EEG). In 1924 Berger recorded an EEG signals from a human brain for the first time. By analyzing EEG signals Berger was able to identify oscillatory activity in the brain, such as the alpha wave (8–12 Hz), also known as Berger's wave. The first recording device used by Berger was very elementary, which was in the early stages of development, and was required to insert silver wires under the scalp of the patients. In later stages, those were replaced by silver foils that were attached to the patients head by rubber bandages later on Berger connected these sensors to a Lippmann capillary electrometer, with disappointing results. More sophisticated measuring devices such as the Siemens double-coil recording galvanometer, which displayed electric voltages as small as one ten thousandth of a volt, led to success. Berger analyzed the interrelation of alternations in his EEG wave diagrams with brain diseases. EEGs permitted completely new possibilities for the research of human brain activities.

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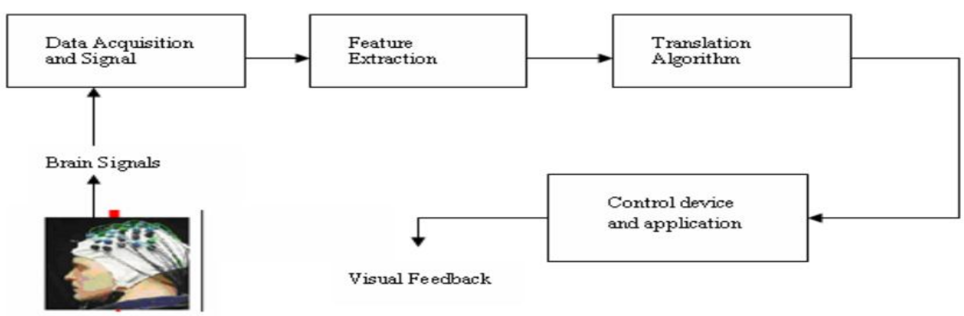
3.9.1 Overview of brain coputer interface (BCI)

A Brain–Computer Interface (BCI), often called a Mind-Machine Interface (MMI), or sometimes called a direct neural interface or a Brain–Machine Interface (BMI), is a direct communication channel between the brain and an external device. Brain-computer interface (BCI) is an upcoming technology which aims to convey people's intentions to the outside world directly from their thoughts, enhancing cognitive capabilities [19]. BCIs are often directed at assisting, augmenting, or repairing human cognitive or sensory-motor functions. The BCI can be used for people who are unable to express through speech. Normally these people are "locked in" meaning they can't move their face or any of their appendages. The field of BCI research and development has been focused on neuroprosthetics applications. This aims at restoring damaged hearing, sight and movement. BCI provides a new communication channel between the human brain and the computer. Mental activity leads to changes of electrophysiological signals like the EEG. The BCI system detects such changes and transforms it into a control signal which can be used in various applications like video game, motion of a wheel chair etc. One of the main goal is to enable completely paralyzed patient to communicate with their environment. The machine should be able to learn to discriminate between different patterns of brain activity as accurate as possible and the user of the BCI should learn to perform different mental tasks in order to produce distinct brain signals [20], [8], [9]. A BCI is a communication and control system that does not depend in any way on the brain’s normal neuromuscular output channels. The user’s intent is conveyed by brain signals (such as EEG) rather than by peripheral nerves and muscles, and these brain signals do not depend for their generation on neuromuscular activity. Furthermore, as a communication and control system, a BCI establishes a real-time interaction between the user and the outside world. The user receives feedback reflecting the outcome of the BCI's operation, and that feedback can affect the user's subsequent intent and its expression in brain signals as shown in fig(3.1)[1]. The first step in developing an effective BCI paradigm is to determine suitable control signals from the EEG. A suitable control signal has the following attributes: (i) it can be precisely characterized for every individual, (ii) it can be readily modulated or translated to express the intention, and (iii) it can be detected and tracked consistently and reliably[21]. The EEG eye blink signals have all the above three attributes and hence can be used as a control signal.



Fig(3.6) Representation of a BCI

3.9.2 Types of brain coputer interface

There are several types of brain-computer interfaces that are reported. The basic purpose of these devices or types is to intercept the electrical signals that pass between neurons in the brain and translate them to a signal that is sensed by external devices.

3.9.3 Invasive Brain Computer Interfaces

Invasive Brain Computer Interface devices are those implanted directly into the brain and have the highest quality signals. These devices are used to provide functionality to paralyzed people. Invasive BCIs are also used to restore vision by connecting the brain with external cameras and to restore the use of limbs by using brain controlled robotic arms and legs. As they rest in the grey matter, invasive devices produce the highest quality signals of BCI devices but are prone to scar-tissue build-up, causing the signal to become weaker or even lost as the body reacts to a foreign object in the brain. In vision science, direct brain implants have been used to treat non-congenital i.e. acquired blindness. One of the first scientists to come up with working brain interface to restore sight as private researcher, William Dobell. He implanted first prototype into Jerry, A man blinded in adulthood, in 1978. He inserted single array BCI containing 68 electrodes into Jerry's visual cortex and succeeded in producing the sensation of seeing light. In 2002, experiment was conducted on Jens Neumann where Dobell used more sophisticated implant enabling better mapping of phosphenes into coherent vision and after the experiment Neumann was interviewed on CBS's show as shown in fig(3 .2).BCIs focusing on motor Neuroprosthetics aim to either restore movement in paralyzed individuals or provide devices to assist them, such as interfaces with computers or robot arms. Researchers at Emory University in Atlanta led by Philip Kennedy and Roy Bakay were first to install a brain implant in a human that produced signals of high enough quality to stimulate movement.

3.9.4 Partially Invasive Brain Computer Interfaces

Partially invasive BCI devices are implanted inside the skull but rest outside the brain rather than within the grey matter. Signal strength using this type of BCI is bit weaker when it compares to Invasive BCI. They produce better resolution signals than non-invasive BCIs. Partially invasive BCIs have less risk of scar tissue formation when compared to Invasive BCI. Electrocorticography (ECoG) uses the same technology as non-invasive electroencephalography, but the electrodes are embedded in a thin plastic pad that is placed above the cortex, beneath the dura mater. ECoG technologies were first trade-in humans in 2004 by Eric Leuthardt and Daniel Moran from Washington University in St Louis. In a later trial, the researchers enabled a teenage boy to play Space Invaders using his ECoG implant. This research indicates that it is difficult to produce kinematics BCI devices with more than one dimension of control using ECoG. Light Reactive Imaging BCI devices are still in the realm of theory. These would involve implanting laser inside the skull. The laser would be trained on a single neuron and the neuron's reflectance measured by a separate sensor. When neuron fires, the laser light pattern and wavelengths it reflects would change slightly. This would allow researchers to monitor single neurons but require less contact with tissue and reduce the risk of scar-tissue build up.

3.9.5 Non Invasive Brain Computer Interfaces

Non invasive brain computer interface has the least signal clarity when it comes to communicating with the brain (skull distorts signal) but it is considered to be very safest when compared to other types. This type of device has been found to be successful in giving a patient the ability to move muscle implants and restore partial movement. Non-Invasive technique is one in which medical scanning devices or sensors are mounted on caps or headbands read brain signals. This approach is less intrusive but also read signals less effectively because electrodes cannot be placed directly on the desired part of the brain. One of the most popular devices under this category is the EEG or electroencephalography capable of providing a fine temporal resolution. It is easy to use, cheap and portable.

3.10 EEG Based BCI

Electroencephalography (EEG) is a type of non-invasive interface, which has high potential due to its fine temporal resolution, ease of use, portability and low set-up cost. A common method for designing BCI is to use EEG signals extracted during mental tasks [24], [25]. EEG is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp. The EEG is modified by motor imagery and can be used by patients with severe motor impairments (e.g., late stage of amyotrophic lateral sclerosis) to communicate with their environment and to assist them. Such a direct connection between the brain and the computer is known as an EEG-based BCI. EEG-based BCI have become a hot spot in the study of neural engineering, rehabilitation, and brain science [22]. The most commonly used signal that is identified and captured with EEG method is called the P300 wave. The P300 is an event related potential, a measurable electrical charge that is directly related with impulse. Therefore, by capturing the P300, a BCI can directly translate a persons' intent into electrical commands that control artificial devices [23]. A P300 speller is based on this principle, where the detection of P300 waves allows the user to write characters. The P300 speller is composed of two classification problems. The first classification is to detect the presence of a P300 in the electroencephalogram (EEG). The second one corresponds to the combination of differentP300 responses for determining the right character to spell. A new method for the detection of P300 waves is presented. This model is based on a convolution neural network (CNN) [26]. The applications of BCI have extensions into many different fields like Medicine, Military, Manufacturing, Gaming and Communications.

3.11. Applications of BCI

BCI is one of the exiting areas of research. This device has been developed to control the thoughts of the different users. Some of the applications of this technology may seem interesting such as the ability to control a video game by thought. If you think a remote control is convenient, channels could be controlled by our mind. This device would allow severely disabled people to work independently without anybodies support and also offers the paralyzed patients to improve the quality of life. BCI is well suited for patients who are paralyzed or locked-in and because of that they have very limited options of communication with other people, such as ALS (Amyotrophic Lateral Sclerosis) patients on a ventilator. BCIs are being developed for a variety of applications ranging from assistive technologies for patients with motor disabilities to entertainment devices . Possible applications of an EEG-based BCI are, e.g., to move a cursor by mental control, which allows the patient to select letters or words and to control a functional electrical stimulation device for patients with spinal cord lesions. These applications can be controlled by at least one binary output signal of the BCI, which is obtained, for example, by classification of EEG patterns during imagination of left and right hand movements . Several laboratories have managed to record signals from monkey and rat cerebral cortices in order to operate BCIs to carry out movement. Monkeys have navigated computer cursors on screen and commanded robotic arms to perform simple tasks simply by thinking about the task and without any motor output. Schmidt, Fetz and Baker in the 1970s established that monkeys could quickly learn to voluntarily control the firing rate of individual neurons in the primary motor cortex. In the 1980s, Apostolos Georgopoulos at Johns Hopkins University found a mathematical relationship between the electrical responses of single motor-cortex neurons in rhesus macaque monkeys and the direction that monkeys moved their arms(based on a cosine function).

3.12 Methods of EEG Signal Features Extraction

3.12.1 Fast Fourier Transform (FFT) Method

This method employs mathematical means or tools to EEG data analysis. Characteristics of the acquired EEG signal to be analyzed are computed by power spectral density (PSD) estimation in order to selectively represent the EEG samples signal. However, four frequency bands contain the major characteristic waveforms of EEG spectrum [27]. The PSD is calculated by Fourier transforming the estimated autocorrelation sequence which is found by nonparametric methods. One of these methods is Welch's method. The data sequence is applied to data windowing, producing modified periodograms [28]. The information sequence x (n) is expressed as

$$x_i(n) = x(n + iD), \quad n = 0, 1, 2, \ldots, M-1 \quad \text{while} \quad i = 0, 1, 2, \ldots, L-1; \tag{1}$$

take iD to be the point of start of the ith sequence. Then L of length $2M$ represents data segments that are formed. The resulting output periodograms give

$$\tilde{\tilde{P}}_{xx}^{(i)}(f) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)w(n)e^{-j2\pi fn}\right|^2 \quad (2)$$

Here, in the window function, U gives normalization factor of the power and is chosen such that

$$U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n), \quad (3)$$

where $w(n)$ is the window function. The average of these modified periodograms gives Welch's power spectrum as follows:

$$P_{xx}^{W} = \frac{1}{L}\sum_{i=0}^{L-1} \tilde{\tilde{P}}_{xx}^{(i)}(f). \quad (4)$$

3.12.2 Wavelet Transform (WT) Method

WT plays an important role in the recognition and diagnostic field: it compresses the time-varying biomedical signal, which comprises many data points, into a small few parameters that represents the signal [29]. As the EEG signal is nonstationary [30], the most suitable way for feature extraction from the raw data is the use of the time-frequency domain methods like wavelet transform (WT) which is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets . Since WT allows the use of variable sized windows, it gives a more flexible way of time-frequency representation of a signal. In order to get a finer low-frequency resolution, WT long time windows are used; in contrast in order to get high-frequency information, short time windows are used . Furthermore, WT only involves multiscale structure and not single scale. This method is just the continuation of the orthodox Fourier transform method . Moreover, it is meant to resolve issues of nonstationary signals such as EEG [29]. In the WT method, the original EEG signal is represented by secured and simple building blocks known as wavelets. The mother wavelet gives rise to these wavelets as part of derived functions through translation and dilation, that is, (shifting) and (compression and stretching) operations along the time axis, respectively . There are two categories for the WT; the first one is continuous while the other one is discrete [29].

3.12.2.1 Continuous Wavelet Transform (CWT) Method

This can be expressed as

$$\mathrm{CWT}(a,b) = \int_{-\infty}^{\infty} x(t)\,\psi_{a,b}^{*}(t)\,dt, \qquad (5)$$

$x(t)$ stands for the unprocessed EEG, where a stands for dilation, and b represents translation factor. The ψ (t) denotes the complex conjugate and can be calculated by

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right), \qquad (6)$$

where $\psi(t)$ means wavelet. However, its major weakness is that scaling parameter a and translation parameter b of CWT change continuously. Thus, the coefficients of the wavelet for all available scales after calculation will consume a lot of effort and yield a lot of unused information [29].

3.12.2.2 Discrete Wavelet Transform (DWT)

In order to address the weakness of the CWT, discrete wavelet transform (DWT) has been defined on the base of multi scale feature representation. Every scale under consideration represents a unique thickness of the EEG signal . The multi resolution decomposition of the raw EEG data $x(n)$ is shown in Figure 3. Each step contains two digital filters, $g(n)$ and $h(n)$, and two down samplers by 2. *The* discrete mother wavelet $g(n)$ is a high pass in nature, while its mirror image is $h(n)$ is a low-pass in nature

As shown in Figure 3, each stage output provides a detail of the signal *D* and an approximation of the signal *A*, where the latest becomes an input for the next step. The number of levels to which the wavelet decomposes is chosen depending on the component of the EEG data with dominant frequency [29]. The relationship between WTs and filter *h*, that is, low pass, can be represented as follows:

$$H(z)H(z^{-1}) + H(-z)H(-z^{-1}) = 1. \quad (7)$$

Here, $H(z)$ represents filter's h□□z-transform. The high-pass filter's complementary z-transform is expressed as

$$G(z) = zH(-z^{-1}). \quad (8)$$

By precisely describing the features of the signal segment within a specified frequency domain and localized time domain properties, there are a lot of advantages that overshadow the high computational and memory requirement of the conventional convolution based implementation of the DWT [29,32]

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3.12.3Eigenvectors

These methods are employed to calculate signals' frequency and power from artifact dominated measurements. The essence of these methods is the potential of the Eigen decomposition to correlate even artifact corrupted signal. There are a few available eigenvector methods, among them are Pisarenko's method, MUSIC method, and minimum-norm method [34, 35]

3.12.3.1 Pisarenko's Method

Pisarenko's method is among the available eigenvector approaches used to evaluate power spectral density (PSD). To calculate the PSD, the mathematical expression $A(f)$ is employed and given as [36, 37].

$$A(f) = \sum_{k=0}^{m} a_k e^{-j2\pi fk}. \quad (9)$$

In the equation above, a stands for coefficients of the defined equation and m defines eigenfilter's $A(f)$ order [34, 35]. Pisarenko method uses signal desired equation to estimate the signal's PSD from eigenvector equivalent to the minimum eigenvalue as follows:

$$P_{\text{PISARENKO}} = \frac{1}{|A(f)|^2}. \quad (10)$$

3.12.3.2 MUSIC Method

This method eradicates issues related to false zeros by the help of the spectra's average equivalent to artifact subspace of the whole eigenvectors [37]. Resulting power spectral density is therefore obtained as

$$P_{\mathrm{MUSIC}}(f) = \frac{1}{(1/K)\sum_{i=0}^{K-1}|A(f)|^2}. \quad (11)$$

3.12.3.3. Minimum Norm Method

This method makes false zeros in the unit circle to separate them from real zeros to be able to calculate a demanded noise subspace vector *a* from either the noise or signal subspace eigenvectors. However, while the Pisarenko technique form application of only the noise subspace eigenvector corresponding to the minimum eigenvalue, the minimum norm technique picks a linear combination of the whole of noise subspace eigenvectors [34, 36]. This technique is depicted by

$$P_{\mathrm{MIN}}(f, K) = \frac{1}{|A(f)|^2}. \quad (12)$$

All the aforementioned eigenvector methods can best address the signal that is composed of many distinctive sinusoids embedded in noise. Consequently, they are prone to yield false zeros and thus resulting in a relatively poor statistical accuracy [35].

3.12.3. Time-Frequency Distributions

These methods require noiseless signals to provide good performance.
Therefore, very restricted preprocessing stage is necessary to get rid of all

sorts of artifacts. Being time-frequency methods they deal with the stationary principle; windowing process is therefore required in the preprocessing module [38]. The definition of TFD for a signal $x(n)$ was generalized by Cohen as [39]

$$P(t,w) = \frac{1}{2\pi} \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} A(\theta,\tau)\,\Phi(\theta,\tau)\,e^{-j\theta t - jw\tau}\,d\theta\,d\tau, \tag{13}$$

Where

$$A(\theta,\tau) = \frac{1}{2\pi} \int_{-\infty}^{\infty} x\left(u+\frac{\tau}{2}\right) x^{*}\left(u-\frac{\tau}{2}\right) e^{j\theta u}\,du \tag{14}$$

$A(\theta, \tau)$ is popularly known as ambiguity Function, and $\Phi(\theta, \tau)$ refers to kernel of the distribution, while r and w are time and frequency dummy variables, respectively. Smooth pseudo-Wigner-Ville (SPWV) distribution is a variant method which incorporates smoothing by independent windows in time and frequency, namely, $W(\tau)$ and $W(t)$ [38]:

$$\mathbf{SPWV}(t,w) = \int_{-\infty}^{\infty} W_w(\tau) \left[\int_{-\infty}^{\infty} W_t(u-t)\, x\left(u+\frac{\tau}{2}\right) \times x^{*}\left(u-\frac{\tau}{2}\right) du\right] e^{-jw\tau}\,d\tau. \tag{15}$$

The feature extraction using this method is based on the energy, frequency, and the length of the principal track. Each segment gives the values E , F , and L . The EEG signal is firstly divided into k segments; then, the construction of a three-dimensional feature vector for each segment will take place. Energy of each segment k can be calculated as follows:

$$E_k = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \vartheta_k (t, f)\, dt\, df, \quad (16)$$

where (t, f) stands for the time-frequency representation of the segment. However, to calculate the frequency of each segment k, we make use of the marginal frequency as follows:

$$F_k = \int_{-\infty}^{\infty} \vartheta_k (t, f)\, dt. \quad (17)$$

Finally, for achieving good results, noiseless EEG signals or a well-denoised signal should be used for TFD [39].

3.12.4. Autoregressive Method

Autoregressive (AR) methods estimate the power spectrum density (PSD) of the EEG using a parametric approach. Therefore, AR methods do not have problem of spectral leakage and thus yield better frequency resolution unlike nonparametric approach. Estimation of PSD is achieved by calculating the coefficients, that is, the parameters of the linear system under consideration. Two methods used to estimate AR models are briefly described below [27, 28].

3.12.4.1. Yule-Walker Method

In this method, AR parameters or coefficients are estimated by exploiting the resulting biased approximate of the autocorrelation data function. This is done by subsequently finding the minimization of the least squares of the forward prediction error as given below [40]:

$$\begin{bmatrix} r(0)_{xx} & r(-1)_{xx} & \cdots & r(-p+1)_{xx} \\ r(1)_{xx} & r(0)_{xx} & \cdots & r(-p+2)_{xx} \\ \vdots & \vdots & \ddots & \vdots \\ r(p-1)_{xx} & r(p-2)_{xx} & \cdots & r(0)_{xx} \end{bmatrix} \times \begin{bmatrix} a(1) \\ a(1) \\ \vdots \\ a(p) \end{bmatrix}, \qquad (18)$$

where *r* can be defined by

$$r_{xx}(m) = \frac{1}{N}\sum_{N=0}^{N-m-1} x^*(n)\, x(n+m), \quad m \geq 0. \qquad (19)$$

Calculating the above set of (p + 1) linear equations, the AR coefficients can be obtained:

$$P_{xx}^{BU}(f) = \frac{\sigma_{wp}^2}{\left|1+\sum_{k=1}^{P} \widehat{a}_p(k) e^{-j2\pi fk}\right|^2}, \qquad (20)$$

Calculating the above set of (p + 1) linear equations, the AR coefficients can be obtained:

$$\sigma_{wp}^2 = E_p^f = r_{xx}(0)\prod_{k=1}^{p}\left[1-|a_k(k)|^2\right]. \qquad (21)$$

3.12.4.2. Burg's Method

It is an AR spectral estimation based on reducing the forward and backward prediction errors to satisfy Levinson-Durbin recursion [41]. Burg's method estimates the reflection coefficient directly without the need to calculate the autocorrelation function. This method has the following strength: Burg's method can estimate PSD's data records to look exactly like the original data value. It can yield intimately packed sinusoids in signals once it contains minimal level of noise. The difference between method of Yule-Walker and Burg's method is in the way of calculating the PSD. For Burg's method, the PSD is estimated as follows:

$$P_{xx}^{BU}(f) = \frac{\widehat{E}_p}{\left|1+\sum_{k=1}^{P} \widehat{a}_p(k) e^{-j2\pi fk}\right|^2} \quad (22)$$

Parametric methods like autoregressive one reduce the spectral leakage issues and yield better frequency resolution. However, selecting the proper model order is a very serious problem. Once the order is too high, the output will induce false peaks in the spectra. If the order is too low, the result will produce smooth spectra [42].

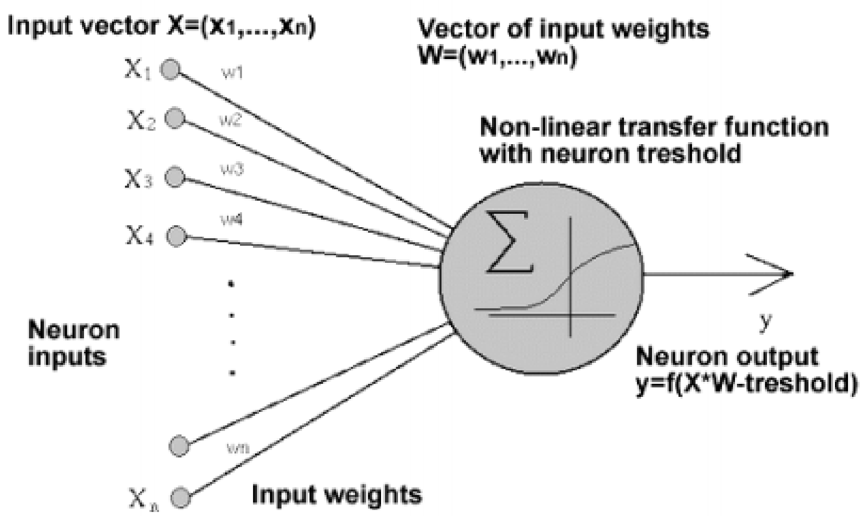
3.13. Performance of Methods

The general aim of this review is to shed light on EEG signal feature extraction and to show how fast themethod used for the signal extraction an d how reliable it will be the extracted EEG signal features. Moreover, how these extracted features would express the states of the brain for different mental tasks, and to be able to yield an exact classification and translation of mental tasks. The speed and accuracy of the feature extraction stage of EEG signal processing are therefore very crucial, in order not to lose vital information at a reasonable time. So far in the discussed literature, wavelet method is introduced as a solution for unstable signals; it includes the representation by wavelets which are a group of functions derived from the mother wavelet by dilation and translation processes. The window with varying size is the most significant specification of this method since it ensures the suitable time frequency resolution in all frequency range [35]. Autoregression analysis suffers from speed and is not always applicable in real-time analysis while FFT appears to be the least efficient of the discussed methods because of its inability to examine nonstationary signals.

It is highly recommend to use AR method in conjunction with more conservative methods, such as periodograms, to help to choose the correct model order and to avoid getting fooled by spurious spectral features [42]. The most important application for eigenvectors is to evaluate frequencies and powers of signals from noise corrupted signal; the principle of this method is the decomposition of the correlation matrix of the noise corrupted. Three methods for eigenvectors module were discussed: Pisarenko, multiple signal classification (MUSIC), and minimum norm [36]. The good thing about the eigenvector method is that it produces frequency spectra of high resolution even when the signal-to-noise ratio (SNR) is low. However, this method may produce spurious zeros leading to poor statistical accuracy [35]. The TFD method offers the possibility to analyze relatively long continuous segments of EEG data even when the dynamics of the signal are rapidly changing. At the same time a good resolution both in time and frequency is necessary, making this method not preferable to use in many cases [39].

3.14. Classification using Neural Network (NN)

A biological neural network is composed of a group or groups of physically connected or functionally associated neurons. A single neuron can be connected to many other neurons and the total number of neurons and connections in a network can be extremely large. Connections, called synapses, are usually formed from axons to dendrites, though dendrodentritic microcircuits and other connections are possible. Neural networks are extremely complex. Artificial intelligence and cognitive modeling try to simulate some properties of neural networks. An artificial neural network is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an artificial neural network is an adaptive system that changes its structure based on external or internal information that flows through the network.



Fig(3.7) Neuron model

Neural network have more good attributes. For example teach ability: the network changes its structure following information for better artificial neural network performance. According to propagation of signal, two main groups of neural networks are possible:

• Feed-forward – Data enters at the inputs and passes through the network, layer by layer, until it arrives at the outputs. During normal operation, that is when it acts as a classifier, there is no feedback between layers.[43]

• Recurrent - a network of neurons with feedback connections between layers. Learning classify into: learning with teacher and learning without teacher[43]. Learning is a systematic process, where knowledge's are saved into synaptic weights of neural network. In learning state:

$$\frac{\partial W}{\partial t} \neq 0 \qquad (1)$$

W is a matrix of all synaptic weights of neural network. After learning is the network learnt and then:

$$\frac{\partial W}{\partial t} = 0 \qquad (2)$$

3.15. Backpropagation algorithm

90% applications from neural networks are based on backpropagation algorithm. It is a basic algorithm for controlled teaching.Backpropagation is recursive gradient method for neural network weights adjusting with heed on learning error *J* minimalization.

$$J = \frac{1}{2}\sum_{i=1}^{N_0}(ev_i - x_i)^2 \qquad (3)$$

N0 is number of input neurons, ei is required activation value of i-neuron, xi is activation of ineuron and p index means that it belongs to ppattern. For each neuron hold:

$$x_i = f_i(i_i) \qquad i_i = \sum_{j=1}^{M} w_{ij} x_j + \theta_i \qquad (4)$$

ii is input of i-neuron, fi is activation function of ineuron, M is number of i-neuron inputs, wij is weight from z-neuron to i-neuron and i is threshold value of i-neuron. Backpropagation is gradient method and therefore for weight change wij hold:

$$\Delta w_{ij} = -\gamma \frac{\partial J}{\partial w_{ij}} = -\gamma \frac{\partial J}{\partial i_i} \frac{\partial i_i}{\partial w_{ij}} = \gamma \delta_i x_j \qquad (5)$$

Calculated synaptic weight change between neuron from hidden layer and output neuron is then increment with current weight value:

$$w_{ij} = w_{ij} + \Delta w_{ij} \qquad (6)$$

For learning rate (5) hold:

$$\delta_i = -\frac{\partial J}{\partial i_i} = -\frac{\partial J}{\partial x_i} \frac{\partial x_i}{i_i} = -\frac{\partial J}{\partial x_i} f'(i_i) \qquad (7)$$

If is i-neuron output neuron, then hold:

$$\delta_i = -\frac{\partial J}{\partial x_i} f'(i_i) = (ev_i - x_i) f'(i_i) \qquad (8)$$

If is it not output neuron:

$$\delta_i = -f\,'(i_i)\sum_{h=1}^{N_h}\frac{\partial J}{\partial i_h}\frac{\partial i_h}{\partial x_i} = -f\,'(i_i)\sum_{h=1}^{N_h}\frac{\partial J}{\partial i_h}\frac{\partial}{\partial x_i}\sum_{l=1}^{N_l} w_{hl}x_l =$$

$$= -f\,'(i_i)\sum_{h=1}^{N_h}\frac{\partial J}{\partial i_h}\,w_{hi} = f\,'(i_i)\sum_{h=1}^{N_h}\delta_h w_{hi} \tag{9}$$

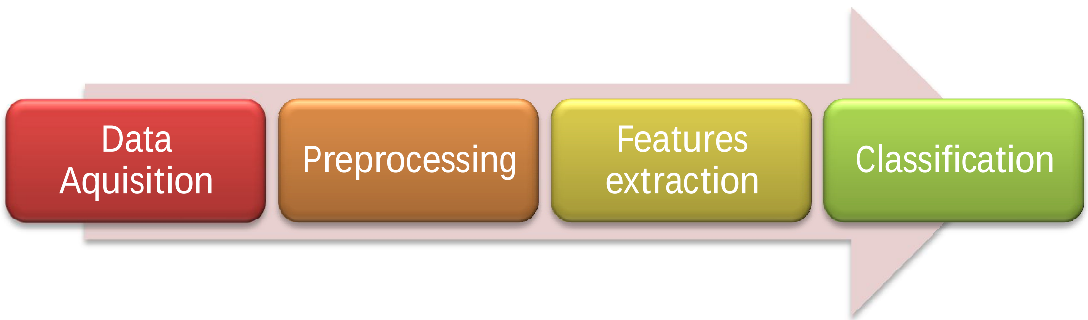
Formula 9 is main backpropagation relationship and shows recursive propagation of error signal from output neurons to network input.

CHAPTER FOUR

METHDOLOGY

Chapter Four: Methodology

4.1 Method:



Fig(4.1): Methodology flowchart

4.1.1.Data Acquisition:

Data was obtained from BCI Competitions(http://biosig.sourceforge.net/.) This data set consists of EEG data from 9 subjects. The cue-based BCIparadigm consisted of four different motor imagery tasks, namely the imagination of movement of the left hand (class 1), right hand (class 2), bothfeet (class 3), and tongue (class 4). Two sessions on different days wererecorded for each subject. Each session is comprised of 6 runs separated byshort breaks. One run consists of 48 trials (12 for each of the four possibleclasses), yielding a total of 288 trials per session.At the beginning of each session, a recording of approximately 5 minuteswas performed to estimate the EOG influence. The recording was dividedinto 3 blocks: (1) two minutes with eyes open (looking at a fixation crosson the screen), (2) one minute with eyes closed, and (3) one minute witheye movements. A04T and contains only the eye movement condition .The subjects were sitting in a comfortable armchair in front of a computer screen. At the beginning of a trial (t = 0 s), a fixation cross appearedon the black screen. In addition, a short acoustic warning tone was presented. After two seconds (t = 2 s), a cue in the form of an arrow pointingeither to the left, right, down or up (corresponding to one of the four classesleft hand, right hand, foot or tongue) appeared and stayed on the screen for1.25 s. This prompted the subjects to perform the desired motor imagerytask. No feedback was provided. The subjects were ask to carry out themotor imagery task until the fixation cross disappeared from the screen att = 6 s. A short break followed where the screen was black again.

1.1 Data recording:

Twenty-two Ag/AgCl electrodes (with inter-electrode distances of 3.5 cm)were used to record the EEG. Allsignals were recorded monopolarly with the left mastoid serving as referenceand the right mastoid as ground. The signals were sampled with 250 Hz andbandpass-filtered between 0.5 Hz and 100 Hz. The sensitivity of the amplifierwas set to 100 µV. An additional 50 Hz notch filter was enabled to suppressline noise.In addition to the 22 EEG channels, 3 monopolar EOG channels wererecorded and also sampled with 250 Hz. They werebandpass filtered between 0.5 Hz and 100 Hz (with the 50 Hz notch filterenabled), and the sensitivity of the amplifier was set to 1 mV. The EOGchannels are provided for the subsequent application of artifact processingmethods and must not be used for classification.

1.2 Data file description:

All data sets are stored in the General Data Format for biomedical signals(GDF), one file per subject and session.

Table 4.1:List of all files contain in the dataset

ID	Training	Evaluation
1	A01T.gdf	A01E.gdf
2	A02T.gdf	~~A02E.gdf~~
3	A03T.gdf	~~A03E.gdf~~
4	A04T.gdf	~~A04E.gdf~~
5	A05T.gdf	~~A05E.gdf~~
6	A06T.gdf	~~A06E.gdf~~
7	A07T.gdf	~~A07E.gdf~~
8	A08T.gdf	~~A08E.gdf~~
9	A09T.gdf	~~A09E.gdf~~

Table(4.2):List of event types (the first column contains decimal values and the second hexadecimal values).

Event type		Description
276	0x0114	Idling EEG (eyes open)
277	0x0115	Idling EEG (eyes closed)
768	0x0300	Start of a trial
769	0x0301	Cue onset left (class 1)
770	0x0302	Cue onset right (class 2)
771	0x0303	Cue onset foot (class 3)
772	0x0304	Cue onset tongue (class 4)
783	0x030F	Cue unknown
1023	0x03FF	Rejected trial
1072	0x0430	Eye movements
32766	0x7FFE	Start of a new run

4.2 Preprocessing:

4.2.1 **Channel selection**:

It was shown in the literature that the most of the EEG channels are representing redundant information. in addition ,it was concluded that the neural activity that is mostly correlated to the motor sensory signals is almost exclusively contained within the channels C3,C4 and Cz of the EEG channels .So, we assumed that there is no need to analyze all the available EEG channels and is more efficient to process C3,C4 and Cz channels of data.

4.2.2 **Filtering:**

EEGs are noisy and non-stationary signals that have to be filtered to get ride of the unnecessary content from the raw signals . So, we filtered the selected channels for the purpose of removing the DC shifts and minimizing the presence of filtering artifacts at epoch boundaries. This was accomplished by applying band pass filter from 0.5 Hz to 50 Hz from the forth order using Chebychev band pass filter.

4.3 Feature Extraction:

4.3.1 Wavelet Transform:

The wavelet transform analysis was used in a wide range of research topics within the field of signal processing .based on a multi-resolutions process, the wavelet properties of a scalable window allow pinpointing signal components .these properties of dilation and translation enable the extraction of all components for every position by creating different scales and shifted functions (in time domain) of a signal .As a result, wavelet finer and large scaling , permit all information of the signal , while small scales shows signal details by zooming into the signal complements.

For discrete data, such as the data set used in this work , the Discrete Wavelet Transform (DWT) is better fit for analysis . A suitable wavelet function must be used to optimize the analysis performance . A large selection of DWT mother wavelets is available to be used in our work .but the Daubechies (Db) wavelets were proved to be the most suitable families in similar applications . So , in this work we decided to calculate the Duabechies orthogonal wavelet Db8.

The main purpose of the DWT is to decompose the recorded EEG signal into multi-resolution subsets of coefficients a detailed coefficient subset (cDi) and an approximation coefficient subset (cAi) at the level i. So, at the first decomposition level we obtain cD1 and cA1 then the first approximation cA1 can be transformed into cD2 and cA2 all the second level , and so on.

4.3.2 Feature Vectors Construction:

The wavelet transform of any EEG recorded at eight levels result in eight details and one approximation .there are many electrophysiolgical features that are associated with the brain's normal motor output channels. Some of these important features are the mu (8-12Hz) and beta (13-30Hz)rhythms we conclude from table 1 that the details cD2,cD3 and cD4provide proper representation for the mu and beta rhythms and we decided to extract the vectors of features from these details only.

Phinyomark et al. (2013) provided the mathematical definitions of many amplitude estimators for neurological activities. If we assumed that the

Nth sample of a wavelet decomposed detail at level i is Di(n), then we can define the following features :

- Root Mean Square(RMS)

$$RMSi=\sqrt{}1/N\sum_{n=1}^{N} Di\hat{}2(n)$$

- Mean Absolute Value(MAV)

$$MAVi=1/N\sum_{n=1}^{N} |Di(n)|$$

- Integrated EEG(IEEG)

$$IEEGi=\sum_{n=1}^{N} |Di(n)|$$

- Variance of EEG(VAR)

$$VARI=1/N-1\sum_{n=1}^{N} Di\hat{}2(n)$$

The Daubechie was used to analyze the channels C3,C4 and Cz f each EEG record . then the features RMS , MAV , IEEG and VAR were calculated for the wavelet coefficient using previous equations . this process was repeated for each event in our dataset of features . at the end of these calculations , 9RMS features (3channels*3details) , 9MAV features, 9IEEG features , and 9 VAR features were generate to the wavelet. These features were numerically represented in format that is suitable for use with NN algorithms .

4.4 Classification:

Neural networks learning algorithms were used and provided good classification performance. The MATLAB NN toolbox was used for all the training and testing experiments. The training experiments were handled with the aid of the feed ward back learning algorithm .

Four networks were created with one output node representing the target function of the for classes:

- Network 1:9 input representing the VAR features.
- Network 2:9 input representing the RMS features.
- Network 3:9 input representing the IEEG features.
- Network 4:9 input representing the MAV features.

The number of hidden layers for these networks was varied from 1 to 20. At each specific number of hidden layers 70% of the samples were randomly selected and used for training and the remaining 30% for testing and validation .

A huge number of training and testing experiments were carried out for each of the four networks.

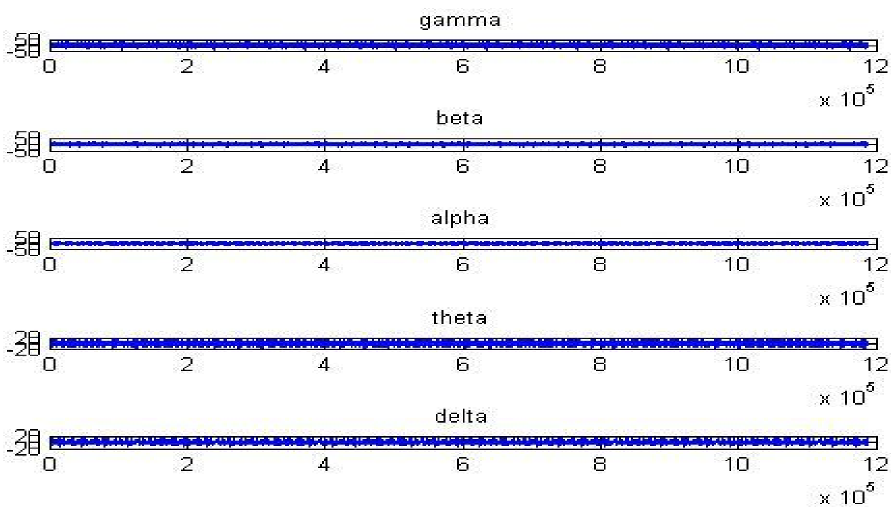
CHAPTER FIVE

RESULTS

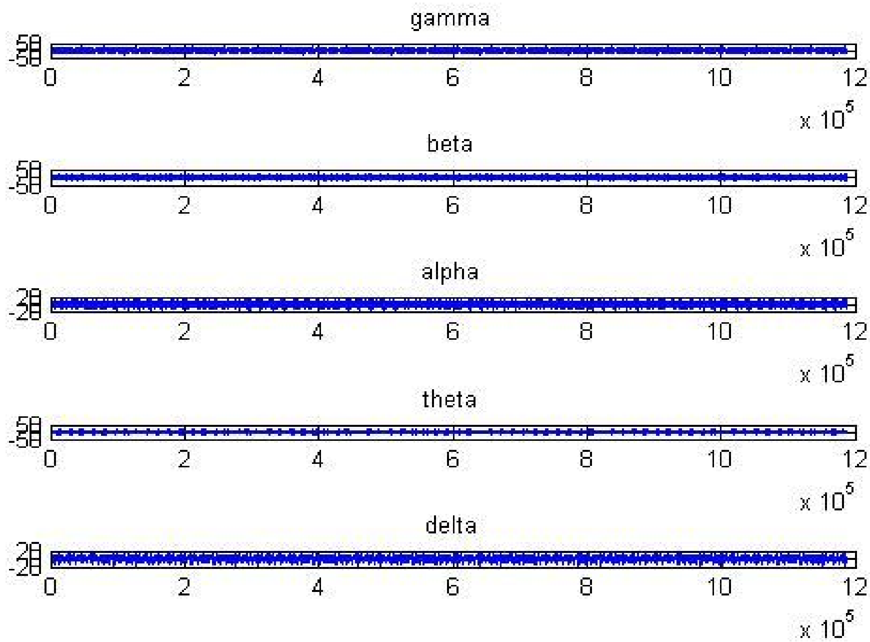
Chapter five: Results

5.1 Daubechies(db8) wavelet features:

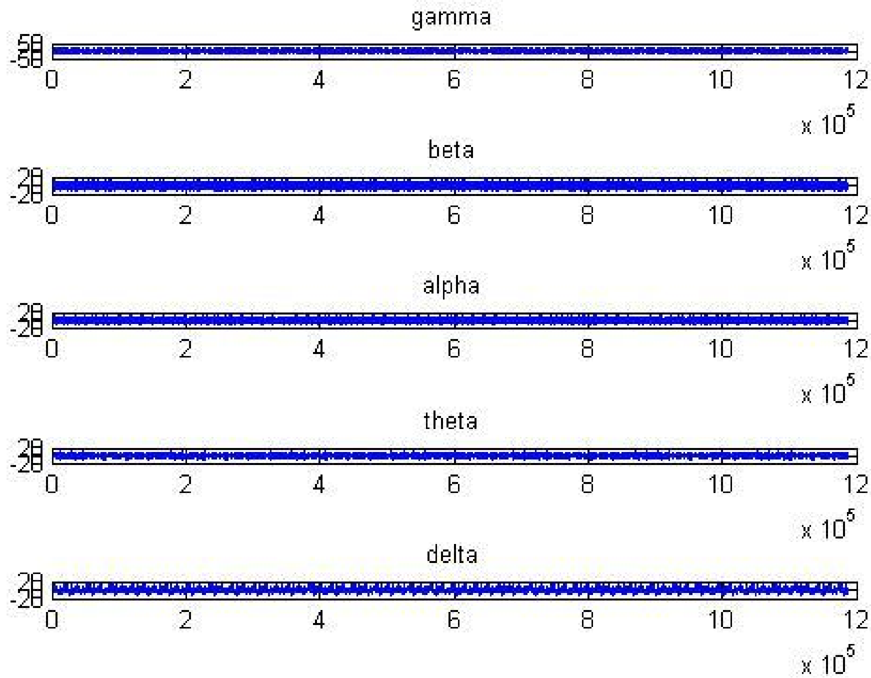
Plot diagram for A01(class1,class2,class3 , class4 respectively) :



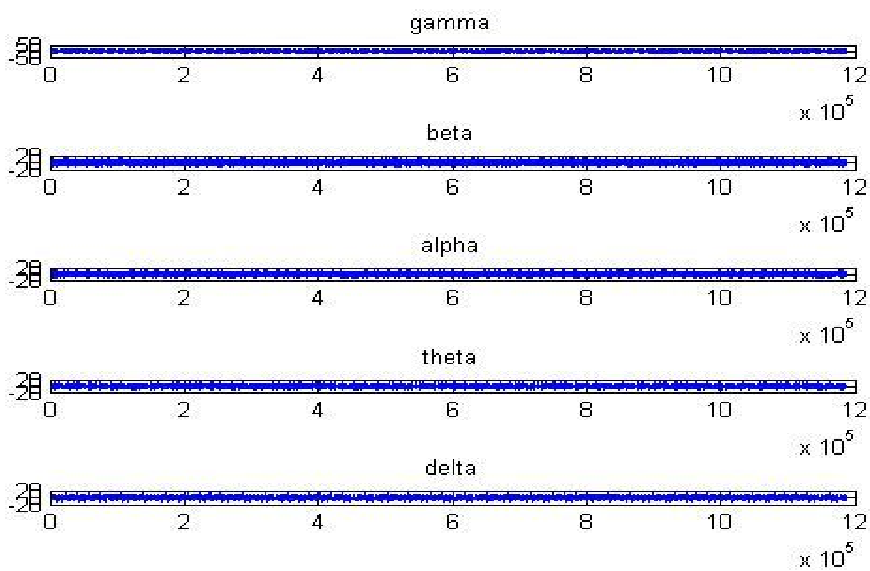
Fig(5.1):Plots of class1 decomposition



Fig(5.2):Plots of class2 decomposition

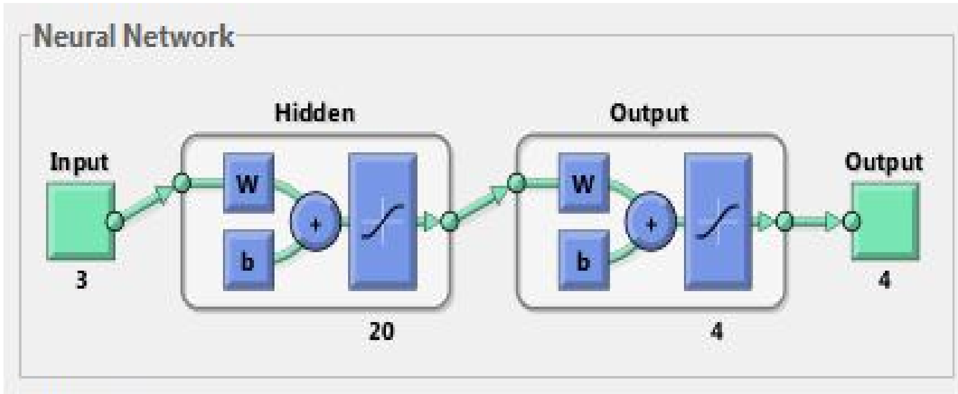


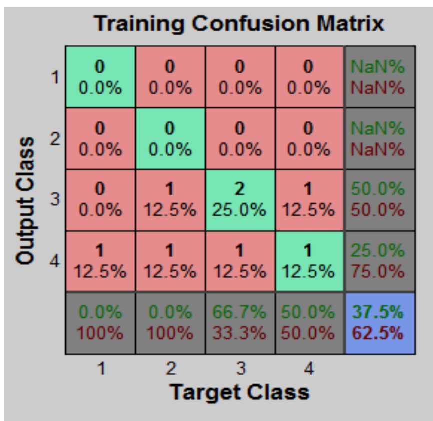
Fig(5.3):Plots of class3 decomposition

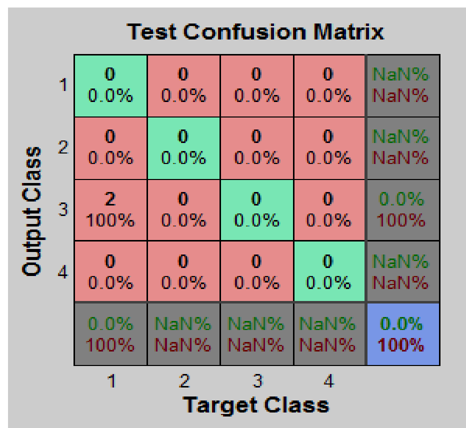


Fig(5.4):Plots of class4 decomposition

5.2Classification result:







Tabel(5.1):Average Accuracy(AvgAcc) results achieved using Daubechies (db8) with different features and a variable number of Hidden Layers (HL) for the NN classifier:

Features	VAR		RMS		IEEG		MAV	
Daubechies	HL	AvgAcc	HL	AvgAcc	HL	AvgAcc	HL	AvgAcc
Db8	20	0.7778	20	0.7855	17	0.8678	8	0.8310

By comparing the results, it was found that the optimum classification accuracy that can be achieved using our system is 86.7%. This performance was achieved by inputting the IEEG feature of a db8 wavelet into a neural network of 17 hidden layers

CHAPTER SIX

CONCLUSION & RECOOMMENDATIONS

Chapter six

6.1 Conclusion :

This work describes a classification system that can classify imagined EEG signals into four classes(left hand, righthand,foot and tongue) .Daubechie(db8) was used for it's ability to decompose EEG signals and extract features that can be used asinputs to neural networks.Extensive experiments were carried out and the neural networks were optimized .The optimum classification performance of 86.7%.was achieved with a NN classifier of 20 hidden layers while using the Integral EEG as inputs to NN.

6.2 Recommendations:

- More features can be extracted using different wavelet mother function and classified using different classification methods (Fuzzy Logic ,support vector machine….etc),
- Then compare the methods and apply the best result to the real time applications.

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