BRAIN COMPUTER INTERFACE BASED WHEEL CHAIR CONTROL USING NEURAL NETWORKS

Name of Student: **- Avinav Sharan(7102186)**

-Ankur Gupta (7102192)

Name of supervisor: - **Mr. Vijay Khare,** Senior Lecturer

Department of Electronics and Communications

JIITU, Noida.

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1.1 Motivation

Would it be much more than reality if the channels on your TV changed while you were just thinking about it, or the lights in your room were switched off when you felt drowsy, or a robot was controlled just by your thoughts, or even communicating telepathically(not in any language probably, but might through something like Morse code).
The answer would be no, the research on Brain Computer Interface (BCI) began in 1970s, which is a direct communication pathway between a brain and an external device. In May 2008 photographs that showed a monkey operating a robotic arm with its mind at the Pittsburgh University Medical Center were published in a number of well known science journals and magazines.

Life of people suffering from paralysis or physically challenged people could be made easy using BCI controlled Machines like wheel-chairs and robotic arms.

1.2 Objective

The objective of the project is to make BCI that controls a wheel-chair from EEG signals of the subject. The EEG signal is to be classified for five tasks for wheel-chair (or its prototype):

- Forward Movement
- Backward Movement
- Left Rotation
- Right Rotation
- Stop

The EEG data is first pre-processed, selecting the proper segment from data of 10 second sample. Then feature extraction is done using wavelet transform. The classification is applied using neural networks. The motors are controlled through serial communication between Matlab and micro-controller.

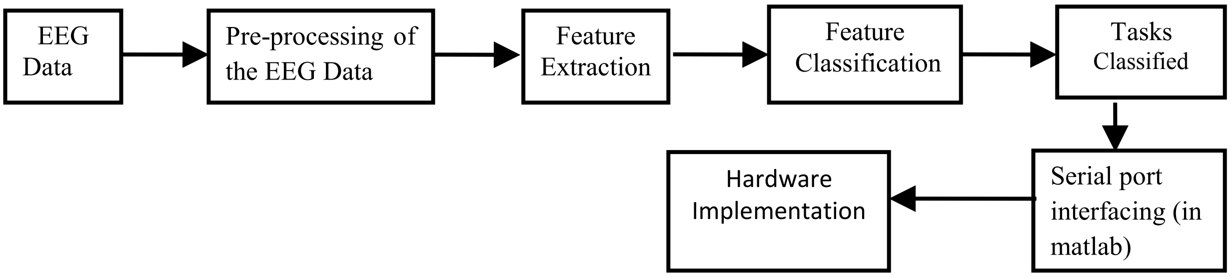


Figure 1.1: Flow Chart

1.3 Literary Survey

Our project includes the use of EEG signal and Artificial Neural Networks, therefore a prior knowledge of Brain Structure and Biological Neural Networks was required. Internet Pages [10], [11] and EEG Signal Processing by S. Sanei[8] and J.A. Chambers gave detailed explanation about brain structure and acquisition of EEG signal.

For feature extraction of EEG signal Short Time Fourier Transform and Wavelet Transform were studied from "The Wavelet Tutorial" by R. Polikar [3] and the paper on wavelet transform, "Wavelet Transform Use for Feature Extraction and EEG Signal Segments Classification", A. Proch´azka and J. Kukal [7], was very helpful in implementing the transform.

For understanding Neural Networks, Artificial Neural Network by B.Yegnanarayana [1] and Introduction to Artificial Neural Network Systems by J. M. Zurada [2] were very helpful. Multilayer perceptrons and backpropagation learning by S. Seung [5] and Using Time-Dependent Neural Networks for EEG Classification, by E. Haselsteiner and G. Pfurtscheller [4] were helpful in understanding and implementing Multilayer Perceptron Network.

Brain Computer Interface 2

2.1 Introduction

A brain computer interface (BCI) is an external devices that communicate directly to the brain of humans or animals through neuron silicon interfaces. These external devices can either transmit or receive signals to and from the brain which can then be used to restore function or movement to sensory organs or limbs. Furthermore, these external devices can range from simple circuits to advanced silicon chips. As of today, brain computer interface devices have been successful in restoring damaged sight, movement and hearing. The success of these devices stems from the fact that the brain is able to adapt to brain computer interfaces and treats implant-controlled prosthesis as natural limbs. With the new technologies, it is even possible to augment human capacity in the near future.A Brain-Computer Interface (BCI) is a system that acquires and analyzes neural signals with the goal of creating a communication channel directly between the brain and the computer. Such a channel potentially has multiple uses.

For example, Bioengineering applications, Human subject monitoring, Neuroscience research, Man – Machine Interaction. BCI have concentrated mainly in developing new communication and control technologies for people with severe neuromuscular disorders. The immediate goal is to provide communication capabilities so that any subject can control the external world without using the brain's normal output pathways of peripheral nerves and muscles. To achieve this goal, many aspects of BCI systems are currently being investigated. Research areas include evaluation 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.

Brain Computer interface (BCI) is a communication system that recognized user's command only from his or her brainwaves and reacts according to them. For this purpose PC and subject is trained.

2.2 System Overview

The BCI developed behave like any other communication or control system. It has an input (EEG signal from the user) and an output (an Action command), It has components that translate input into output. The architecture of the BCI system consists of the five main aspects.

The common structure of a Brain Computer Interface is the following:

1) **Signal Acquisition:** The EEG signals are obtained from the brain through invasive or non-invasive methods (for example, electrodes). After, the signal is amplified and sampled.

2) **Signal Pre-Processing:** Once the signals are acquired, it is necessary to clean them. It involves feature extraction with the help of wavelet transformation in order to choose the representative feature.

3) **Signal Classification: O**nce the signals are cleaned and the feature extraction is done, they will be processed and classified to find out which kind of mental task the subject is performing .The classification is done with help of neural networks.

4) **Computer Interaction and Hardware Control**: Once the signals are classified, they will be used by an appropriate algorithm for the development of a certain application. The action of the user is to drive the hardware, i.e. user can move a robot in this thesis Left, Right, forward, backward and stop. The hardware is interfaced with computer using Serial port.

2.3 Types of Brain Computer Interface

1) Invasive Brain Computer Interfaces

Invasive Brain Computer Interface Devices are those implanted directly into the brain and has the highest quality signals. These devices are used to provide functionality to paralyzed people. Invasive BCIs can also be 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.The problem with this type of device though, is that scar tissue forms over the device as a reaction to the foreign matter. This reduces its efficiency and increases the risk to the patient.

2) Partially Invasive Brain Computer Interfaces

Partially Invasive BCIs, on the other hand, are implanted inside the skull but outside the brain. Although signal strength using this type of BCI device is a bit weaker, partially invasive BCIs has less risk of scar tissue formation.

3) Non Invasive Brain Computer Interfaces

Non invasive brain computer interface, although it has the least signal clarity when it comes to communicating with the brain (skull distorts signal), is also the safest. This type of device has been found to be successful in giving a patient the ability to move muscle implants and restore partial movement. 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, relatively cheap and portable.

Introduction to EEG signals 3

3.1 Introduction

Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain.[2] In clinical contexts, 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..It is well known that the variation of the surface potential distribution on the scalp reflects functional activities emerging from the underlying brain. This surface potential variation can be recorded by affixing an array of electrodes to the scalp, and measuring the voltage between pairs of these electrodes, which are then filtered, amplified, and recorded. The resulting data is called the EEG .The first recordings were made by Hans Berger in 1929 although similar studies had been carried out in animals as early as 1870.

The waveforms recorded are thought to reflect the activity of the surface of the brain, the cortex. This activity is influenced by the electrical activity from the brain structures underneath the cortex. The nerve cells in the brain produce signals that are called action potentials. These action potentials move from one cell to another across a gap called the synapse. Special chemicals called neurotransmitters help the signals to move across the gap. There are two types of neurotransmitters; one will help the action potential to move to the next cell, the other will stop it moving to another nerve cell. The brain normally works hard to keep an equal amount of each of these neurotransmitters in the brain. EEG activity is quite small, measured in microvolt (µV) with the main frequencies of interest up to approximately 30 Hertz (Hz) .

3.2 Human Brain

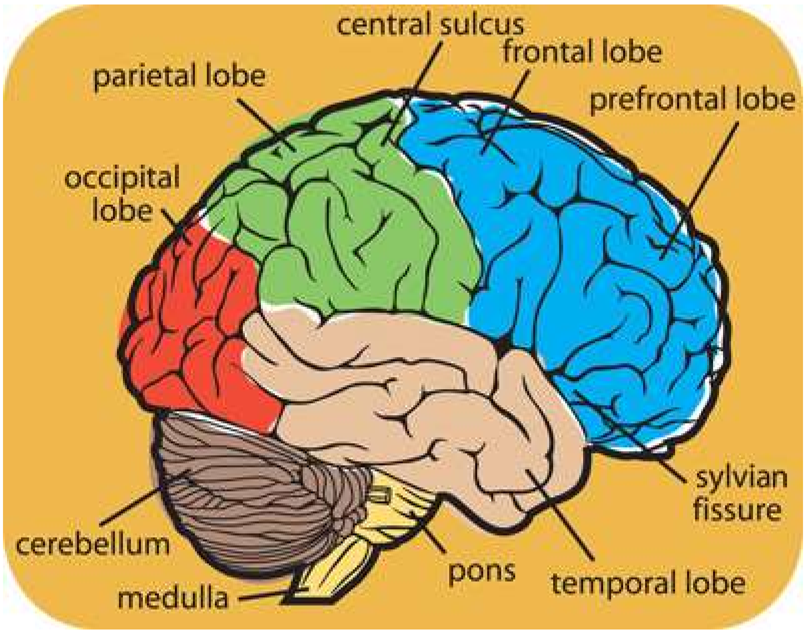


Figure 3.1: Different Parts of Human Brain [14]

The human brain is the center of the human nervous system. The brain is the control center of the central nervous system, responsible for behavior. In mammals, the brain is located in the head enclosed in the cranium, The brain monitors and regulates the body's actions and reactions. It continuously receives sensory information, and rapidly analyzes this data and then responds, controlling bodily actions and functions. The distinction between the mind and the brain is fundamental in philosophy of mind. The mind-body problem is one of the central problems in the history of philosophy. The brain is the physical and biological matter contained within the skull, responsible for electrochemical neuronal processes. The mind, in contrast, consists in mental attributes, such as beliefs, desires, perceptions, and so on.A cerebral hemisphere (hemispherium cerebrale) is defined as one of the two regions of the brain that are delineated by the body's median plane. The brain can thus be described as being divided into left and right cerebral hemispheres. Each of these hemispheres has an outer layer of grey matter called the cerebral cortex that is supported by an inner layer of white matter. The hemispheres are linked by the corpus callosum, a very large bundle of nerve fibers, and also by other smaller commissures, including the anterior commissure, posterior commissure, and hippocampal commissure. These commissures transfer information between the two hemispheres to coordinate localized functions. The architecture, types of cells, types of neurotransmitters and receptor subtypes are all distributed among the two hemispheres in a markedly asymmetric fashion. However, it must be noted that, while some of these hemispheric distribution differences are consistent across human beings, or even across some species, many observable distribution differences vary from individual to individual within a given species. The primary motor cortex (or M1) works in association with pre-motor areas to plan and execute movements. M1 contains large neurons known as Betz cells which send long axons down the spinal cord to synapse onto alpha motor neurons which connect to the muscles. Pre-motor areas are involved in planning actions (in concert with the basal ganglia) and refining movements based upon sensory input (this requires the cerebellum).

Brain Structure and their Functions

- **Central Nervous System**: The central nervous system (CNS) is the part of the nervous system that integrates the information that it receives from, and coordinates the activity of, all parts of the bodies of human beings.

- **Peripheral Nervous System**: The peripheral nervous system, or PNS, consists of the nerves and ganglia outside of the brain and the spinal cord. The main function of the PNS is to connect the central nervous system (CNS) to the limbs and organs**.**

- **Cerebrum:** In the cerebrum, there are fifty hundred to one hundred thousand neurons, the telegram of information is sent from place to place like a telegram. The cerebrum is divided in to two hemispheres, the right and left hemispheres. The dividing point is a deep grove called the longitudal cerebral fissure. The different sides of the cerebrum do different things for the opposite sides of the body. The right side of the cerebrum controls things such as imagination and 3-D forms. The other side of the brain, the left side, controls numbering skills, posture, and reasoning. The hemispheres also consist of many other parts such as the lobes. Each hemisphere is divided into four sections, the frontal, parietal, temporal, and the occipital lobes. The hemispheres also consist of a inner core called the white matter and the cortex, the wrinkly outer layer.

  - **Frontal Lobe**- associated with reasoning, planning, parts of speech, movement, emotions, and problem solving
  - **Parietal Lobe**- associated with movement, orientation, recognition, perception of stimuli
  - **Occipital Lobe**- associated with visual processing
  - **Temporal Lobe**- associated with perception and recognition of auditory stimuli, memory, and speech

3.3 Origin of EEG

The brain's electrical charge is maintained by billions of neurons. Neurons are electrically charged (or "polarized") by membrane that pump ions across their membranes. When a neuron receives a signal from its neighbor via an action potential, it responds by releasing ions into the space outside the cell. Ions of like charge repel each other, and when many ions are pushed out of many neurons at the same time, they can push their neighbors, who push their neighbors, and so on, in a wave. This process is known as volume conduction. When the wave of ions reaches the electrodes on the scalp, they can push or pull electrons on the metal on the electrodes. Since metal conducts the push and pull of electrons easily, the difference in push, or voltage, between any two electrodes can be measured by a voltmeter. Recording these voltages over time gives us the EEG.

3.4 EEG Signal Acquisition

In conventional scalp EEG, the recording is obtained by placing electrodes on the scalp with a conductive gel or paste, usually after preparing the scalp area by light abrasion to reduce impedance due to dead skin cells. Many systems typically use electrodes, each of which is attached to an individual wire. Some systems use caps or nets into which electrodes are embedded; this is particularly common when high-density arrays of electrodes are needed. Small metal discs called electrodes are placed on the scalp in special positions. These positions are identified by the recordist who measures the head using the International 10/20 System. This relies on taking measurements between certain fixed points on the head. The electrodes are then placed at points that are 10% and 20% of these distances. Each electrode site is labeled with a letter and a number. The letter refers to the area of brain underlying the electrode e.g. F - Frontal lobe and T - Temporal lobe. Even numbers denote the right side of the head and odd numbers the left side of the head. Figure 3 shows Electrode placement according to 10-20 system.

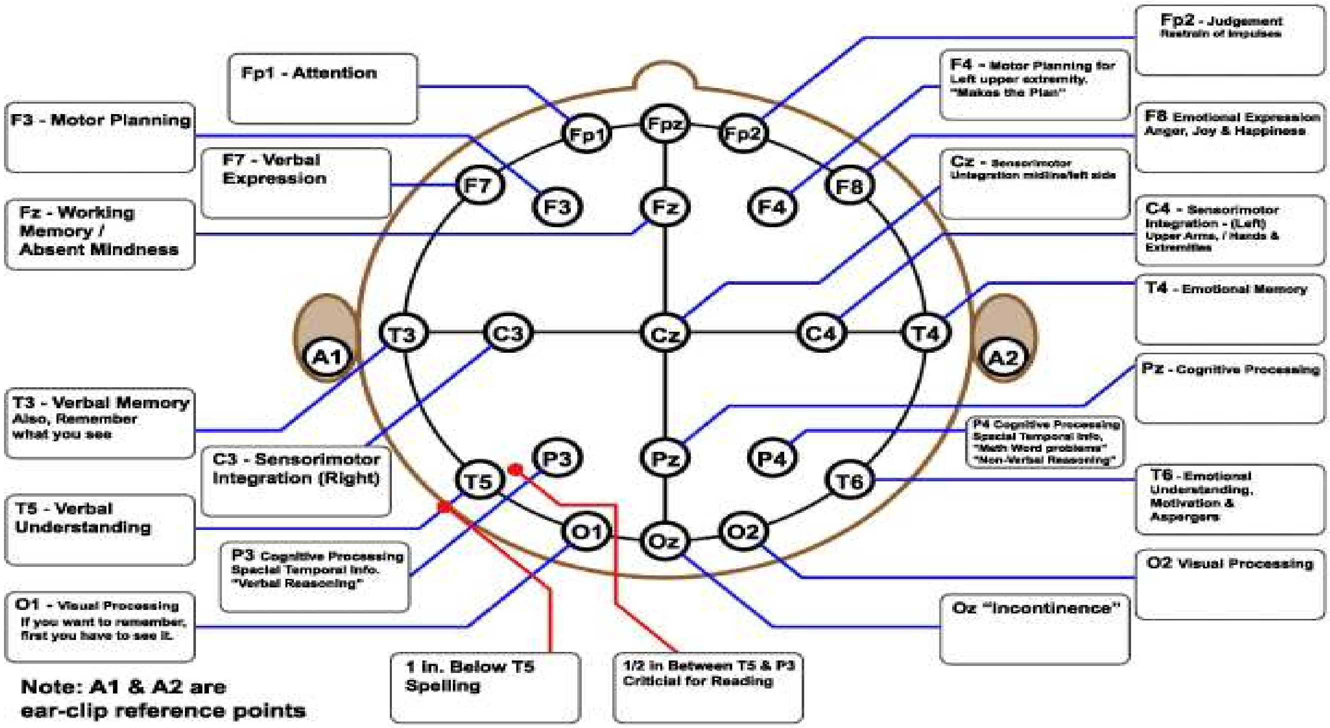


Figure 3.2 The 10-20 System of Electrode Placement [13]

Each site has a letter (to identify the lobe) and a number or another letter to identify the hemisphere location. The letters F, T, C, P, and O stand for Frontal, Temporal, Central, Parietal and Occipital. Even numbers (2, 4, 6, 8) refer to the right hemisphere and odd numbers (1, 3, 5, 7) refer to the left hemisphere. The z refers to an electrode placed on the midline.

Nasion: Point between the forehead and nose.

Inion: Bump at back of skull.

There is a great variety of electrodes that can be used. The majority is small discs of stainless steel, tin, gold or silver covered with a silver chloride coating. These normally have a lead attached. Alternative methods consist of a cap in which the electrodes are already embedded.

3.5 Montages

EEG machines use a differential amplifier to produce each channel or trace of activity. Each amplifier has two inputs. An electrode is connected to each of the inputs.

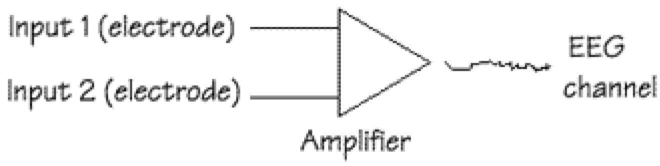


Figure 3.3: Differential amplifier [11]

Differential amplifiers measure the voltage difference between the two signals at each of its inputs. The resulting signal is amplified and then displayed as a channel of EEG activity.

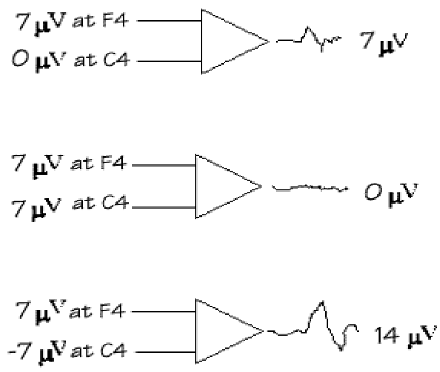


Figure 3.4: Amplifier principle [11]

The manner in which pairs of electrodes are connected to each amplifier of the EEG machine is called a montage. Each montage will use one of three standard recording derivations, common reference, average reference or bipolar.

Common reference derivation: Each amplifier records the difference between a scalp electrode and a reference electrode. The same reference electrode is used for all channels. Electrodes frequently used as the reference electrode are A1, A2, the ear electrodes, or A1 and A2 linked together.

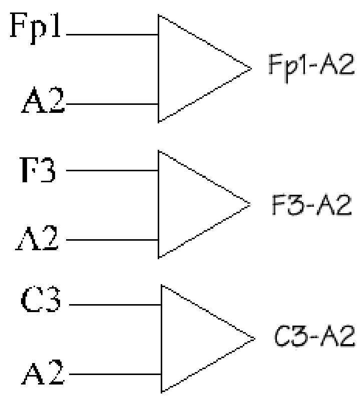


Figure 3.5: Common reference derivation[11]

Average reference derivation: Activity from all the electrodes are measured, summed together and averaged before being passed through a high value resistor. The resulting signal is then used as a reference electrode and connected to input 2 of each amplifier and is essentially inactive. All EEG systems will allow the user to choose which electrodes are to be included in this calculation.

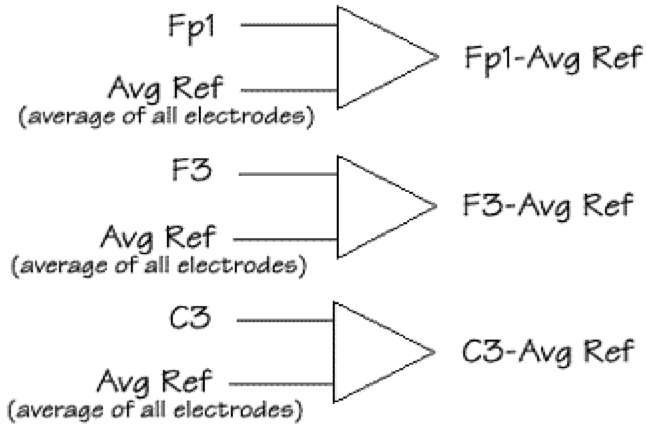


Figure 3.6 Average reference derivation [11]

Bipolar derivation: These sequentially link electrodes together usually in straight lines from the front to the back of the head or transversely across the head. For example the first amplifier may have electrodes FP1 and F3 connected to it and the second amplifier F3 and C3 connected to it.

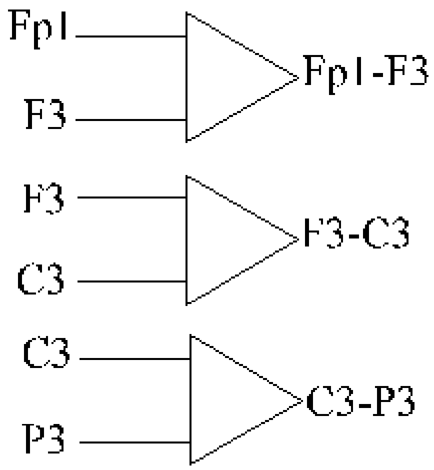


Figure 3.7: Bipolar derivation [11]

3.6 EEG Frequency Bands

EEG activity can be broken down into 4 distinct frequency bands:

Table 1 different EEG activities.

Band	Frequency [Hz]	Amplitude [μV]	Location
Alpha (α)	8-13	10-150	Occipital/Parietal regions
μ-rhythm	9-11	Varies	Precentral / Postcentral regions
Beta (β)	14-30	25	Typically frontal regions
Theta (θ)	4-7	Varies	Varies
Delta (δ)	<3	Varies	Varies

- **Beta Activity**

The rate of change lies between 13 and 30 Hz, and usually has a low voltage between 5-30μV (Fig 3.8).Beta is the brain wave usually associated with active thinking, active attention, focus on the outside world or solving concrete problems. It can reach frequencies near 50 hertz during intense mental activity.

- **Alpha Activity**

The rate of change lies between 8 and 13 Hz, with 30-50 μV amplitude. Alpha waves have been thought to indicate both a relaxed awareness and also inattention. They are strongest over the occipital (back of the head) cortex and also over frontal cortex. Alpha is the most prominent wave in the whole realm of brain activity and possibly covers a greater range than has been previously thought of. It is frequent to see a peak in the beta range as high as 20 Hz, which has the characteristics of an alpha state rather than a beta, and the setting in which such a response appears also leads to the same conclusion. Alpha alone seems to indicate an empty mind rather than a relaxed one, a mindless state rather than a passive one, and can be reduced or eliminated by opening the eyes, by hearing unfamiliar sounds, or by anxiety or mental concentration.

- **Theta Activity**

Theta waves lie within the range of 4 to 7 Hz, with an amplitude usually greater than 20 μ V. Theta arises from emotional stress, especially frustration or disappointment. Theta has been also associated with access to unconscious material, creative inspiration and deep meditation. The large dominant peak of the theta waves is around 7 Hz .

- **<u>Delta Activity</u>**

Delta waves lie within the range of 0.5 to 4 Hz, with variable amplitude. Delta waves are primarily associated with deep sleep, and in the waking state, were thought to indicate physical defects in the brain. It is very easy to confuse artifact signals caused by the large muscles of the neck and jaw with the genuine delta responses. This is because the muscles are near the surface of the skin and produce large signals whereas the signal which is of interest originates deep in the brain and is severely attenuated in passing through the skull. Nevertheless, with an instant analysis EEG, it is easy to see when the response is caused by excessive movement.

- **<u>Gamma Activity</u>**

Gamma waves lie within the range of 35Hz and up. It is thought that this band reflects the mechanism of consciousness - the binding together of distinct modular brain functions into coherent percepts capable of behaving in a re-entrant fashion (feeding back on themselves over time to create a sense of stream-of- consciousness).

- **<u>MU Activity</u>**

It is an 8-12 Hz spontaneous EEG wave associated with motor activities and maximally recorded over motor cortex. They diminish with movement or the intention to move. Mu wave is in the same frequency band as in the alpha wave, but this last one is recorded over occipital cortex. Most attempts to control a computer with continuous EEG measurements work by monitoring alpha or mu waves, because people can learn to change the amplitude of these two waves by making the appropriate mental effort. A person might accomplish this result, for instance, by recalling some strongly stimulating image or by raising his or her level of attention.

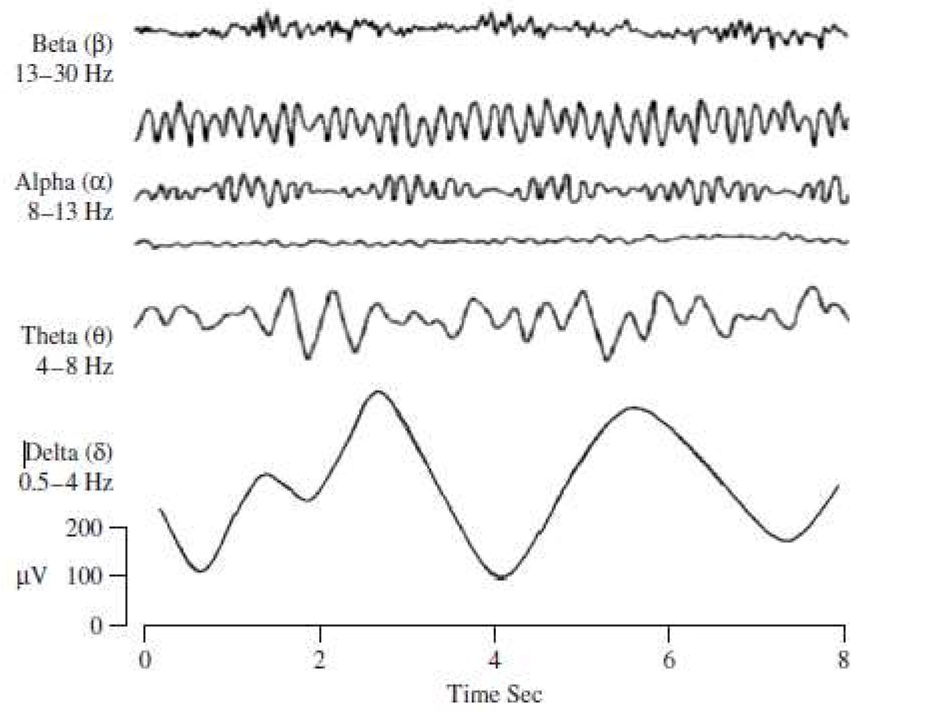


Figure 3.8: EEG activities [8]

3.7 EEG Signal Acquisition of Our Subject

The Subject's EEG Data was taken at Gangaram Hospital, New Delhi. The **Bipolar Derivation Montage and Common Reference Derivation Montage** was used. 16 electrodes were used using Fp1 and Fp2 as reference. The following arrangement was made:

Fp2-REF	F4-M2
Fp1-REF	C4-M2
F4-C4	P4-M2
C4-P4	O2-M2
P4-O2	F3-M1
F3-C3	C3-M1
C3-P3	P3-M1
P3-O1	O1-M1

The following mental tasks were done:

(All the tasks were performed with eyes closed)

- **Complex Arithmetic Calculation:** Multiplication of two digit numbers.
- **Simple Arithmetic Calculation:** Multiplication of single digit numbers.
- **Imagining Rotation:** A rotating object is first seen and the rotation is then imagined.
- **Imagining Right Hand Movement:** Right hand is imagined to move in right direction.
- **Relax:** Mind is relaxed.

Figure 3.9: EEG acquisition of Subject

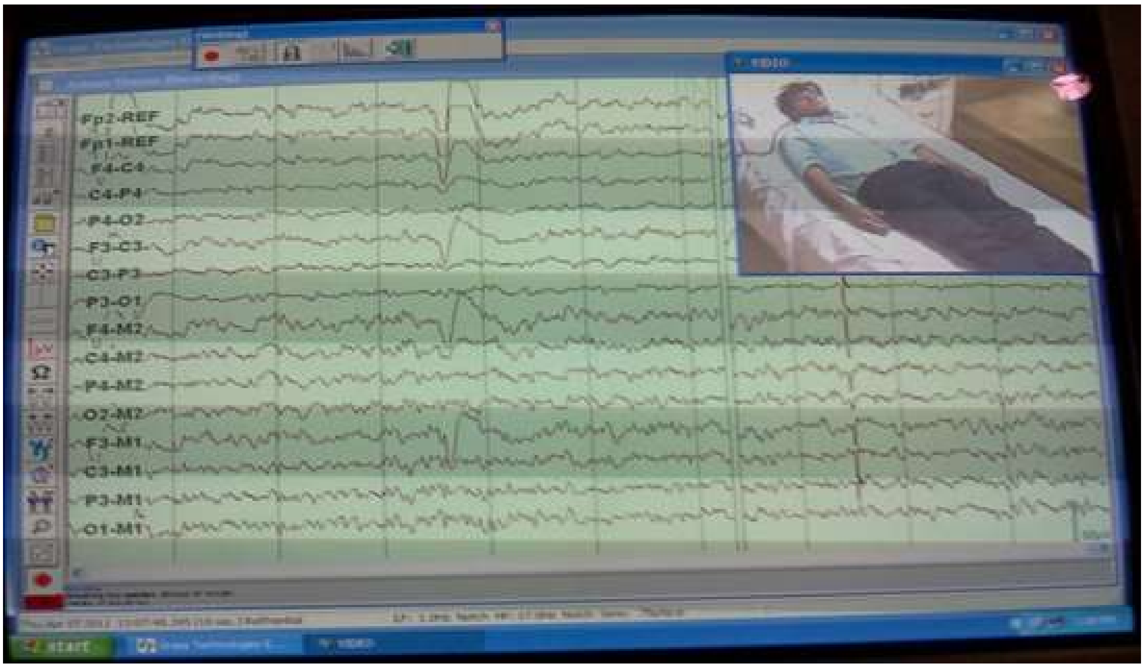


Figure 3.10: EEG acquisition Software

3.8 Frequency domain analysis of the data

All the tasks were assumed to affect the signal in alpha range (between 8 to13Hz) at each electrode. The following test is performed:

- To determine the frequency of the signal with maximum change and
- To determine which task affects which region of brain.

The input data set consists of data of **ten subjects**. Each subject had 5 mental tasks to perform (complex arithmetic calculations, simple arithmetic calculations, rotation, and right hand pseudo motion). Each task had 5 samples of ten seconds each.

3.8.1 Frequency component with Maximum Change

The EEG signal is transformed into frequency domain using Fourier Transform. The frequency with at which the maximum peak is observed is selected. This task is performed on each electrode of each sample.

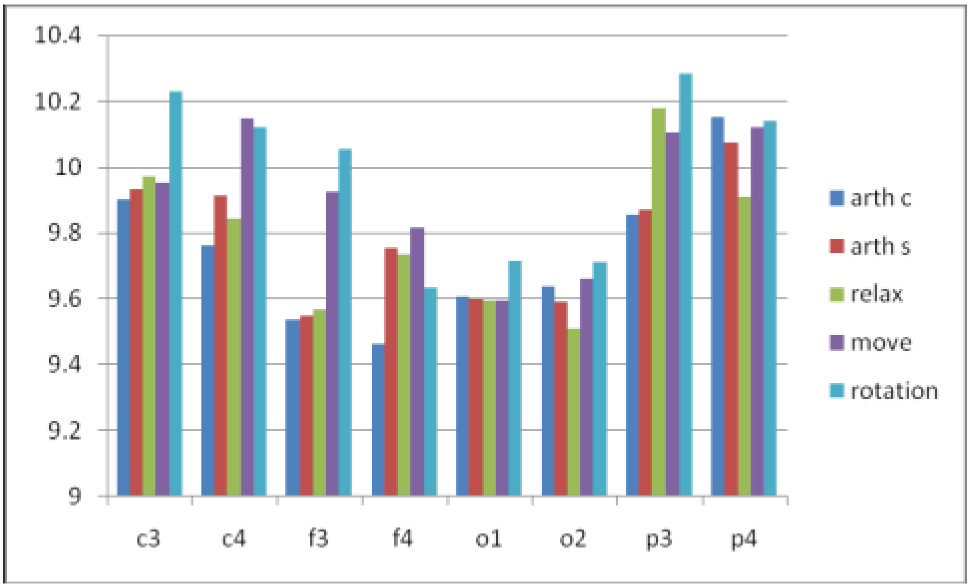


Figure 3.11 Average Frequency Components with maximum peaks for each task and electorde

From the above figure we can conclude that all the activity is from 9.4 to 10.3 Hz.

3.8.2 Determination of the region of Brain affected by Each Task

Maximum peaks of EEG signal are observed in frequency domain for each electrode.

Figure 3.12: Average of the amplitude of fourier transform in alpha range for each task

<u>We can conclude from the above figure that:</u>

(Figure 3.1 and 3.2 may be referred)

- Maximum EEG activity occurs at ‘p3’ electrode which is the left side of parital lobe.
- **Complex Arithmetic Calculations:** Found to be lowest at ‘p4’ electrode (right side of parital lobe) and maximum at ‘p3’ electrode.
- **Simple Arithmetic Calculation:** Found to be lowest at ‘f4’ electrode (right side of the frontal lobe) and maximum at ‘p3’ electrode.
- **Right Hand Pseudo-Movement:** Found to be lowest at ‘f4’ electrode (right side of the frontal lobe) and maximum at ‘p3’ electrode.
- **Rotation:** Found to be lowest at ‘f4’ electrode (right side of the frontal lobe) and maximum at ‘p3’ electrode.
- **Relaxed:** Found to be lowest at ‘f4’ electrode (right side of the frontal lobe) and maximum at ‘p3’ electrode.

Feature Extraction 4

4.1 Introduction

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called features extraction. Analysis with a large number of variables generally requires a large amount of memory and computational power or a classification algorithm which over fits the training sample and generally poorly to new sample. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

Mathematical transformations are applied to signals to obtain further information from that signal that is not readily available in the raw signal. Most of the signals in practice are time-domain signals in their raw format. In many cases, the most distinguished information is hidden in the frequency content of the signal. The frequency spectrum of a signal is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal.

There are many types of transformations namely Fourier Transform, short-time Fourier transform, Wigner distributions, the Radon Transform, the wavelet transform. Since almost all biological signals, for example, are non-stationary. Some of the most famous ones are ECG (electrical activity of the heart, electrocardiograph), EEG (electrical activity of the brain, electroencephalograph), and EMG (electrical activity of the muscles, electromyogram). For such signals the time localization of the spectral components are needed, a transform giving the Time-Frequency representation of the signal is needed. And for that the ultimate solution is Wavelet transform.

4.2.1 Fourier Transform

The Fourier transform is the operation that decomposes a signal into its constituent frequencies. FT gives the frequency information of the signal, which means that it tells us how much of each frequency exists in the signal. The Fourier transform tells whether a certain frequency component exists or not.

$$X(f) = \int_{-\infty}^{\infty} x(t) \bullet e^{-2j\pi ft} dt \ldots\ldots(1)$$

$$x(t) = \int_{-\infty}^{\infty} X(f) \bullet e^{2j\pi ft} df \ldots\ldots(2)$$

Robi Polikar, Ames IA. 1994

In the above equation, t stands for time, f stands for frequency, and x denotes the signal at hand. Note that x denotes the signal in time domain and the X denotes the signal in frequency domain. If the result of this integration (which is nothing but some sort of infinite summation) is a large value, then we say that: the signal x(t), has a dominant spectral component at frequency "f". This means that, a major portion of this signal is composed of frequency f. If the integration result is a small value, then this means that the signal does not have a major frequency component of f in it. If this integration result is zero, then the signal does not contain the frequency "f" at all. The information provided by the integral, corresponds to all time instances, since the integration is from minus infinity to plus infinity over time. It follows that no matter where in time the component with frequency "f" appears, it will affect the result of the integration equally as well. In other words, whether the frequency component "f" appears at time t1 or t2, it will have the same effect on the integration. This is why Fourier transform is not Suitable if the signal has time varying frequency, i.e., the signal is non-stationary. If only, the signal has the frequency component "f" at all times (for all "f" values), then the result obtained by the Fourier transform makes sense.

4.2.2 Limitations of Fourier Transform

1. Fourier transform is not suitable if the signal has time varying frequency, i.e., the signal is non-stationary (Signals whose frequency content change in time).

2. FT tells us how much of each frequency exists in the signal, but it does not tell us when in time these frequency components exist.

3. FT is not a suitable tool for analyzing non-stationary signals.

4. i.e., signals with time varying spectra

   x(t)=cos(2*pi*5*t)+cos(2*pi*10*t)+cos(2*pi*20*t)+cos(2*pi*50*t)

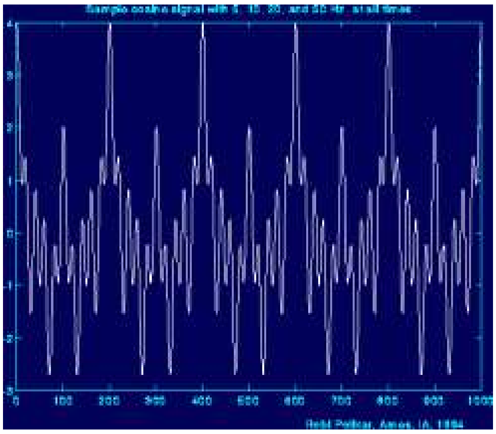


Fig 4.1(a): Stationary Signal X (t) [3]

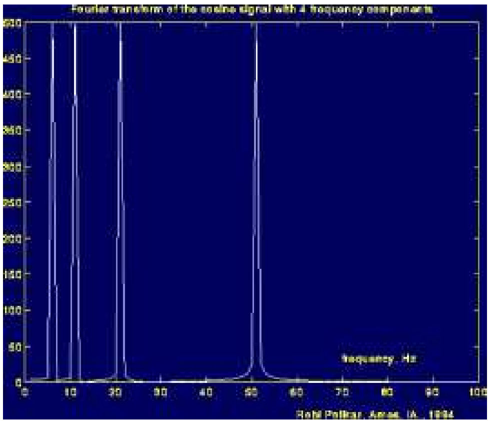


Fig 4.1(b): Fourier of X (t) [3]

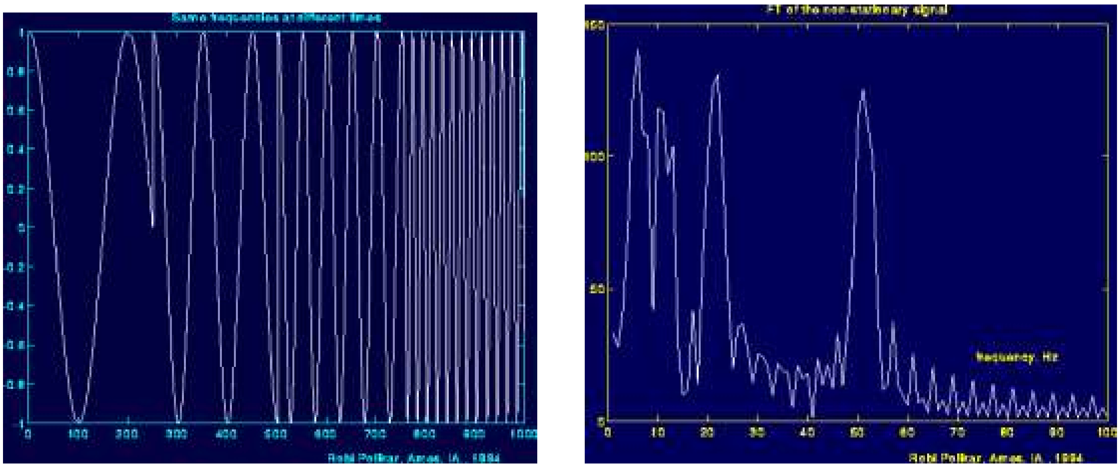


Fig 4.2: Fourier of Non-Stationary Signal [3]

Both Are Approximately Same

It can be easily observed from the figures below that the FT of those two signal is almost same. Note the major four peaks corresponding to 5, 10, 20, and 50 Hz. The reason of the noise like thing in between peaks shows that, those frequencies also exist in the signal. But the reason they have small amplitude, is because, they are not major spectral components of the given signal, and the reason we see those, is because of the sudden change between frequencies. Especially note how time domain signal changes at around time 250 (ms).

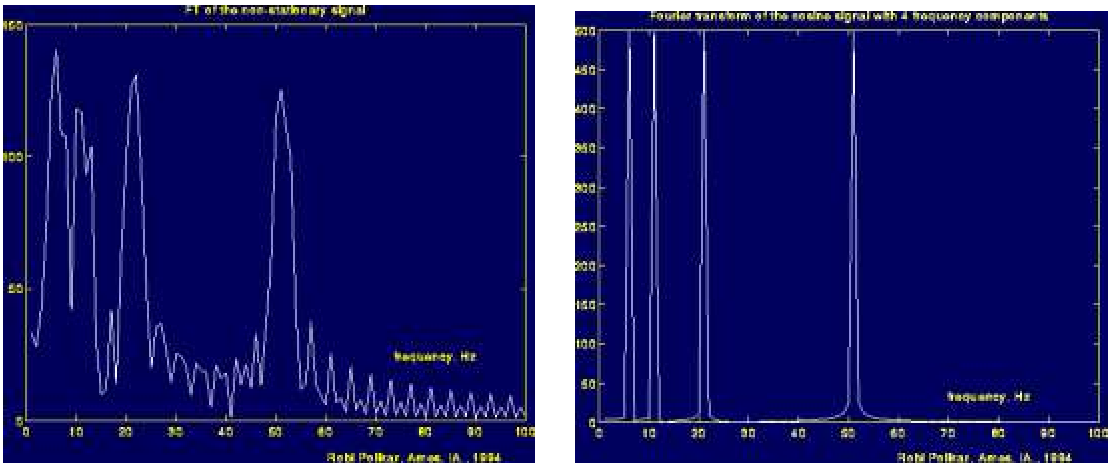


Fig 4.3: Comparison between Stationary and Non-Stationary FT [3]

4.3 Wavelet Transformation

4.3.1 Introduction

A wavelet is a kind of mathematical function use to divide a given function into different frequency component and study each component with the resolution that matches its scale. A wavelet transform is the representation of the function by wavelets. The wavelets are scaled and translated copies (known as “daughter wavelets”) of a finite-length or fast-decaying oscillating waveform (known as “mother waveforms”).

The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions. Because of this collection of representations we can speak of a multi resolution analysis. In the case of wavelets we normally do not speak about time-frequency representations but about time-scale representations, scale being in a way the opposite of frequency, because the term frequency is reserved for the Fourier transform.

In formal terms , this representation is a wavelet series representation of a square integrable function with respect to either a complete , orthonormal sets of basis function , or an over complete set of frame function for the Hilbert space of the square integrable function.

In EEGs, the latency of an event-related potential is of particular interest (Event-related potential is the response of the brain to a specific stimulus like flash-light, the latency of this response is the amount of time elapsed between the onset of the stimulus and the response).Wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal.

They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields of mathematics, quantum physics, electrical engineering, and seismic geology.

4.3.2 Wavelet Overview

The fundamental idea behind wavelets is to analyze according to scale. Indeed, some researchers in the wavelet field feel that, by using wavelets, one is adopting a whole new mindset or perspective in processing data. Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. Wavelet algorithms process data at different scales or resolutions.

Wavelets are functions that satisfy certain requirements. The very name wavelet comes from the requirement that they should integrate to zero, “waving” above and below the x-axis. The diminutive connotation of wavelet suggests the function has to be well localized. Other requirements are technical and needed mostly to insure quick and easy calculation of the direct and inverse wavelet transform.

4.3.3 Wavelet Analysis and Transform

Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low frequency information, and shorter regions where we want high-frequency information. Here’s what this looks like in contrast with the time-based, frequency-based, and STFT views of a signal:

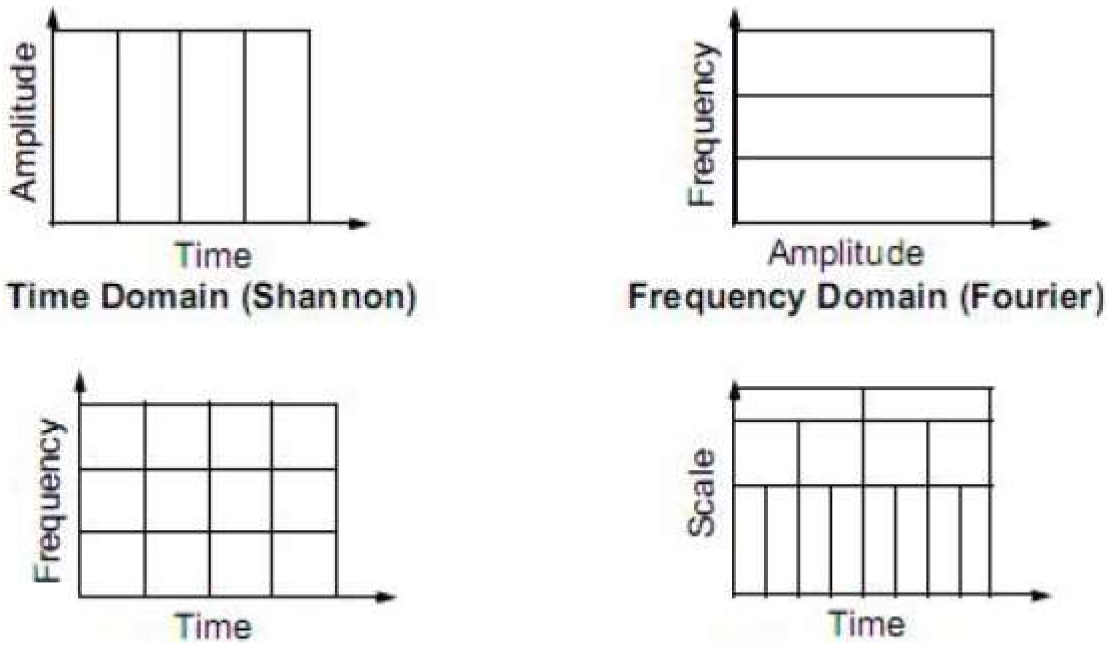


Fig 4.4: Time Domain, Frequency Domain, STFT and WT

Note that wavelet analysis does not use a time-frequency region, but rather a timescale region.

4.3.4 Continuous Wavelet Transform

The continuous wavelet transform (CWT) is defined as the sum over all time of the signal Multiplied by scaled, shifted versions of the wavelet function: ψ

$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)dt$$

The results of the CWT are many wavelet coefficients C, which are a function of scale and position .Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal.

- **Scaling**

  We've already alluded to the fact that wavelet analysis produces a time-scale view of a signal, and now we're talking about scaling and shifting wavelets. Scaling a wavelet simply means stretching (or compressing) it. To go beyond colloquial descriptions such as "stretching," we introduce the scale factor, often denoted by the letter 's', if we're talking about sinusoids, for example, the effect of the scale factor is very easy to see.

- **Shifting**

  Shifting a wavelet simply means delaying (or hastening) its onset. Mathematically, delaying a function f(t) by k is represented by f(t-k) :The continuous wavelet transform was developed as alternative approaches to the short time Fourier transform to overcome the resolution problem. The wavelet analysis is done in a similar way to the STFT analysis, in the sense that the signal is multiplied with a function, {\it the wavelet}, similar to the window function in the STFT, and the transform is computed separately for different segments of the time-domain signal.

- **Differences between the STFT and the CWT:**

  1. The Fourier transforms of the windowed signals are not taken, and therefore single peak will be seen corresponding to a sinusoid, i.e., negative frequencies are not computed.
  2. The width of the window is changed as the transform is computed for every single spectral component, which is probably the most significant characteristic of the wavelet transform. The continuous wavelet transform is defined as follows:

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^* \left(\frac{t-\tau}{s}\right) dt$$

The transformed signal is a function of two variables, tau and s, the translation and scale Parameters, respectively.

- ψ(t) is the transforming function, and it is called the mother wavelet .
- The term wavelet means a small wave.
- The term Translation is related to the position of window function.
- Where * denotes complex conjugation. This equation shows how a function $f(t)$ is Decomposed into a set of basic functions ψ (t) called the wavelets.

The wavelets are generated from a single basic wavelet ψ (t), the so-called mother wavelet, by scaling and translation :s is the scale factor, τ - is the translation factor and the factor s-1/2 is for energy normalization across the different scales. It is important to note that the wavelet basis functions are not specified. This is a difference between the wavelet transform and the Fourier transform, or other transforms. The theory of wavelet transforms deals with the general properties of the wavelets and wavelet transforms only. It defines a framework within one can design wavelets to taste and wishes.

4.3.5 Wavelet Families

There are a number of basic functions that can be used as the mother wavelet for Wavelet Transformation. Since the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting Wavelet Transform. Therefore, the details of the particular application should be taken into account and the appropriate mother wavelet should be chosen in order to use the Wavelet Transform effectively.

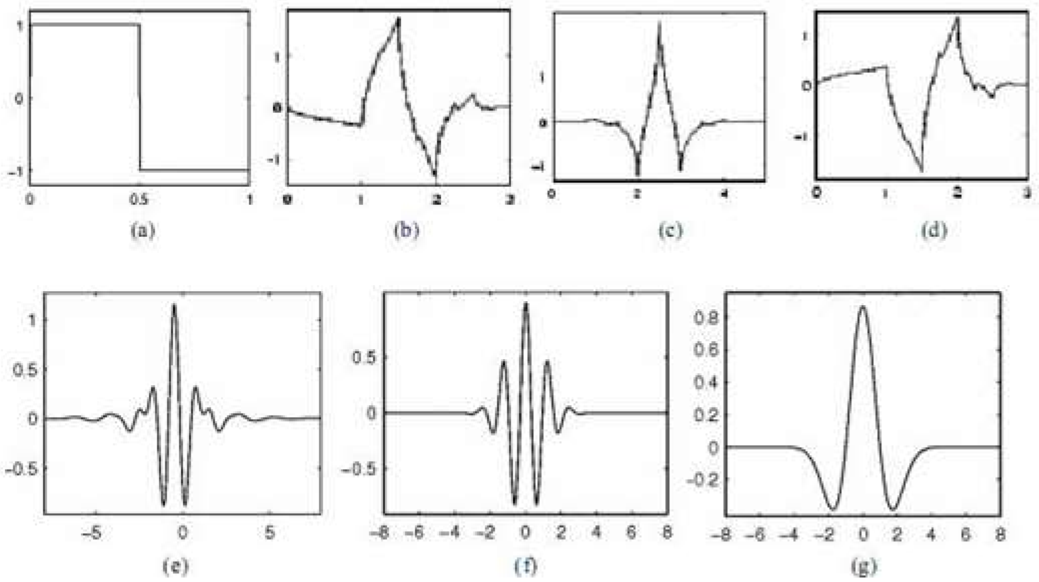


Fig 4.5:wavelet families (a)Haar (b) Daubechies4 (c) Coiflet1 (d) Symlet2 (e) Morlet (f) Mexican Hat

Figure 4.5 illustrates some of the commonly used wavelet functions. Haar wavelet is one of the oldest and simplest wavelet. Therefore, any discussion of wavelets starts with the Haar wavelet. Daubechies wavelets are the most popular wavelets. They represent the foundations of wavelet signal processing and are used in numerous applications. These are also called Maxflat wavelets as their frequency responses have maximum flatness at frequencies 0 and π. This is a very desirable property in some 13 applications. The Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets. These wavelets along with Meyer wavelets are capable of perfect reconstruction. The Meyer, Morlet and Mexican Hat wavelets are symmetric in shape. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application.

- **Haar wavelet**

  Any discussion of wavelets begins with Haar wavelet, the first and simplest. Haar wavelet is discontinuous, and resembles a step function. It represents the same wavelet as Daubechies db1.

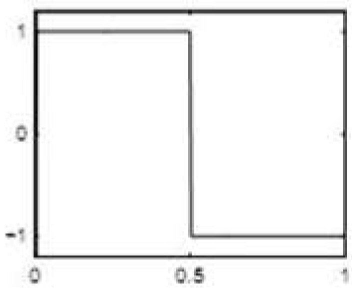


Fig 4.6:Wavelet function psi

- **Daubechies wavelets**

  Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets — thus making discrete wavelet analysis practicable. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet. Here are the wavelet functions psi's of the next nine members of the family:

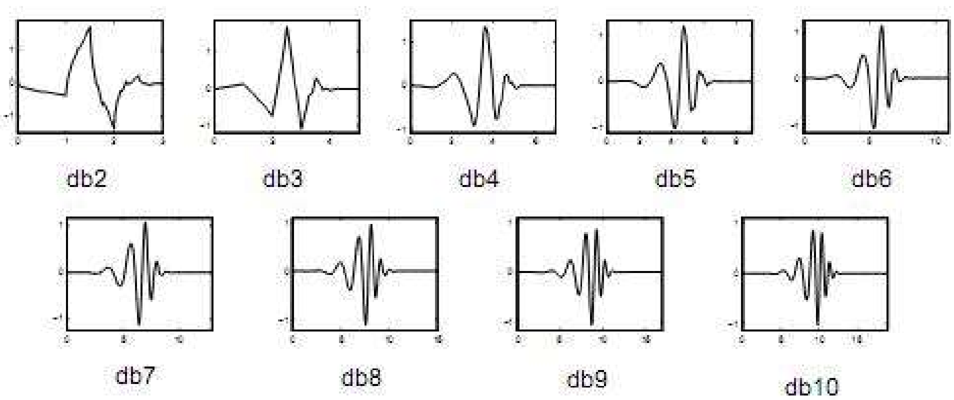


Fig 4.7: Daubechies Wavelets

4.3.6 Working of Wavelet Transform

We pass the time-domain signal from various high pass and low pass filters, which filters out either high frequency or low frequency portions of the signal. This procedure is repeated, every time some portion of the signal corresponding to some frequencies being removed from the signal. Here is how this works:

Suppose we have a signal which has frequencies up to 1000 Hz. In the first stage we split up the signal in to two parts by passing the signal from a high pass and a low pass filter (filters should satisfy some certain conditions, so-called admissibility condition) which results in two different versions of the same signal: portion of the signal corresponding to 0-500 Hz (low pass portion), and 500-1000 Hz (high pass portion). Then, we take either portion (usually low pass portion) or both, and do the same thing again. This operation is called decomposition. Assuming that we have taken the low pass portion, we now have 3 sets of data, each corresponding to the same signal at frequencies 0-250 Hz, 250-500 Hz, 500-1000 Hz. Then we take the low pass portion again and pass it through low and high pass filters; we now have 4 sets of signals corresponding to 0-125 Hz, 125-250 Hz,250-500 Hz, and 500-1000 Hz. We continue like this until we have decomposed the signal to a pre-defined certain level. Then we have a bunch of signals, which actually represent the same signal, but all corresponding to different frequency bands. We know which signal corresponds to which frequency band, and if we put all of them together and plot them on a 3-D graph, we will have time in one axis, frequency in the second and amplitude in the third axis.

We have used the wavelet packet analysis for determining the optimum node for the dataset of 400 samples. The optimum node is obtained by reconstructing the wave tree from different nodes. The aim is to obtain the original signal as close as possible to the reconstructed signal. The figure shows the 1-D wavelet packet analysis. The lower window has the reconstructed signal and the upper window has the original signal.

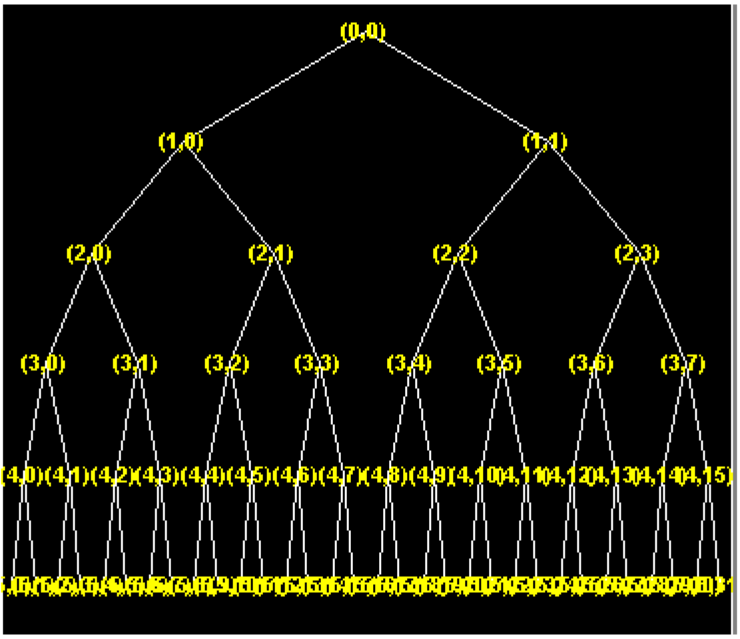


Figure 4.8: 1-D Wave-tree decomposition and reconstruction

4.3.7 Mother Wavelet Selection

If we assume that our input is of size ‘n’, then each input set can be defined as a point on the n-dimensional space. These points need to be classified into five different sections of space according to our given problem. The classification of these input sets will be easier in the case where the input set is most different from each other or in other words the correlation of the input set with each other is minimum.

The following figures show the average of the correlation of wavelet coefficients of all the tasks (complex arithmetic calculations, simple arithmetic calculations, rotation, and right hand pseudo motion). Each task had four samples.

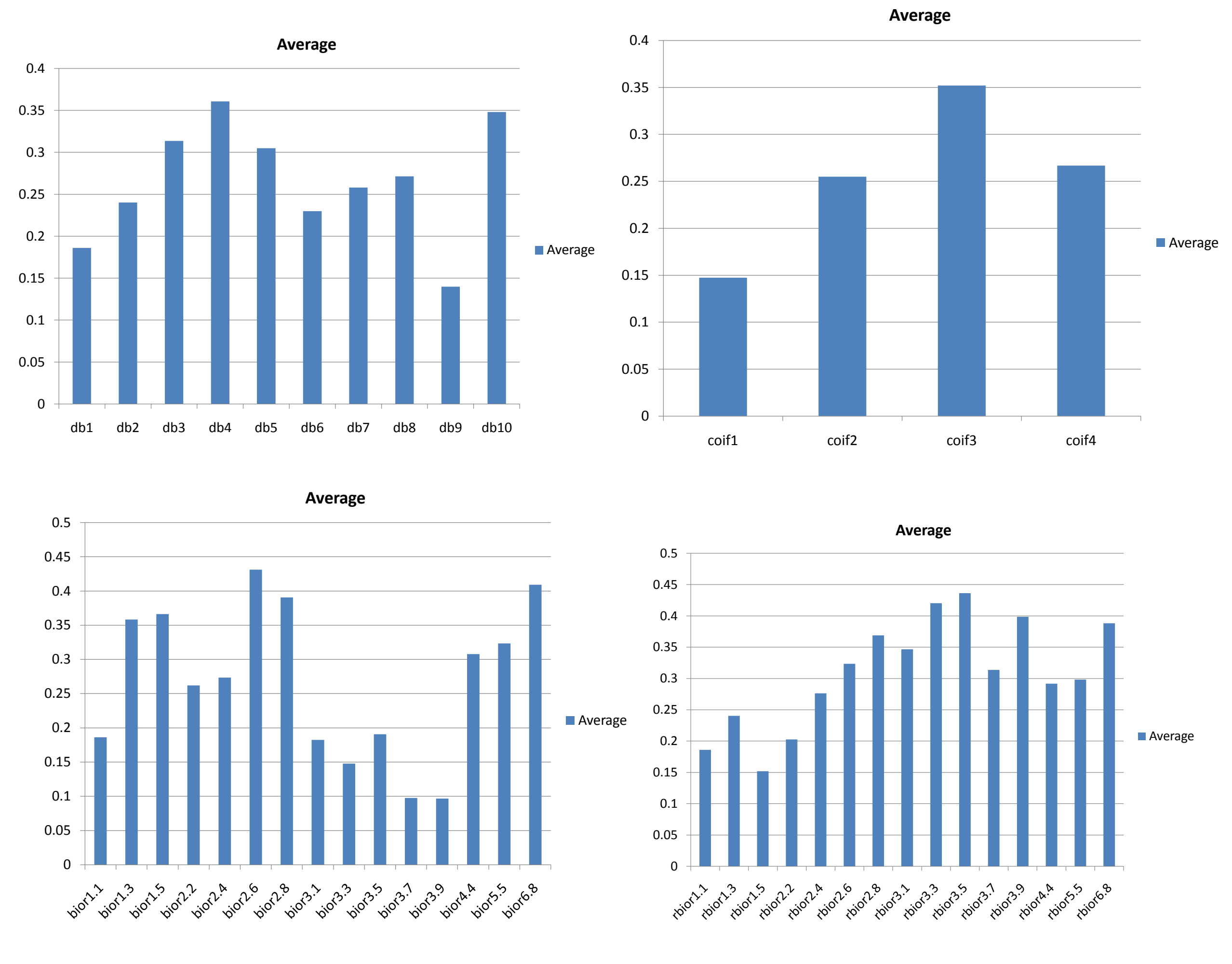


Fig 4.9 : Average of correlation of wavelet coefficients of tasks with each other.

From the above figures we conclude that wavelet ‘bior 3.7’ has the minimum correlation. Thus we select it for wavelet transformation for feature extraction.

Signal Classification

5

5.1 Biological Neural Networks

In neuroscience, a neural network describes a inter population of physically connected neurons or a group of disparate neurons whose inputs or signaling targets define a recognizable circuit. Communication between neurons often involves an electrochemical process. The interface through which they interact with surrounding neurons usually consists of several dendrites (input connections), which are connected via synapses to other neurons, and one axon (output connection). If the sum of the input signals surpasses a certain threshold, the neuron sends an action potential (AP) at the axon hillock and transmits this electrical signal along the axon.

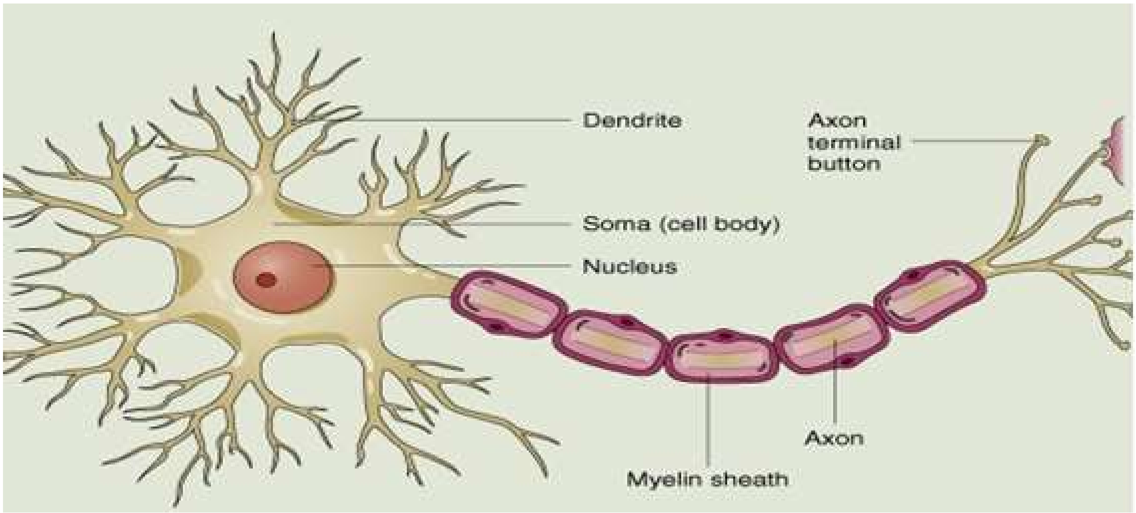


Fig 5.1: Biological Neural Network

http://www.thomasjwestmusic.com/graphics/neuron.JPG

Similarity of Biological Neural network and Artificial Neural Network:

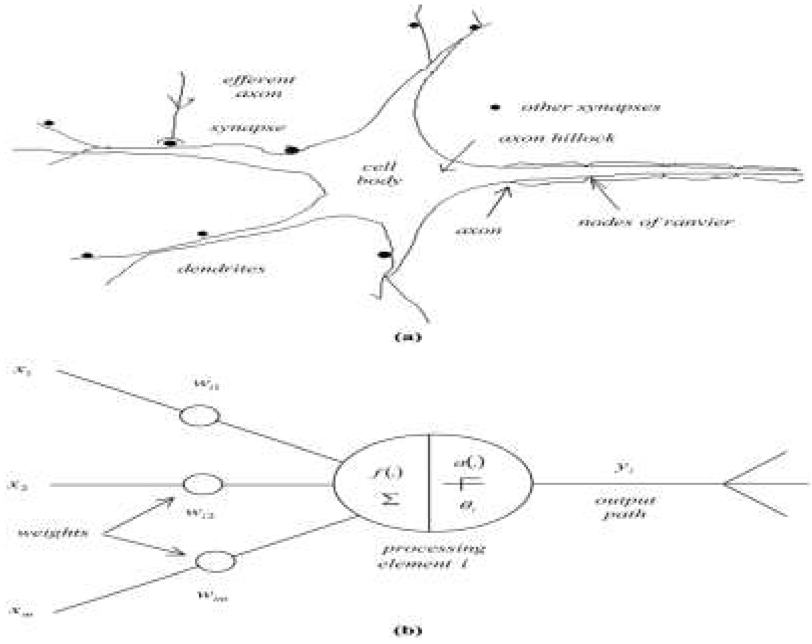


Fig 5.2: Similarity of Biological Neural network and Artificial Neural Network

We have used neural network for signal classification. Neural network (NN) [known as artificial neural network (ANN)] is an interconnected group of artificial neurons that uses a mathematical model or computational model for information processing based on a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network.

5.2 Artificial Neural Network: Overview

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. The most basic system has three layers. The first layer has input neurons which send data via synapses to the second layer of neurons and then via more synapses to the third layer of output neurons. More complex systems will have more layers of neurons with some having increased layers of input neurons and output neurons. The synapses store parameters called "weights" which are used to manipulate the data in the calculations.

5.2.3 Layers of Neurons

Neurons are usually grouped into layers. Layers are groups of neurons that perform similar functions. There are three types of layers. The input layer is the layer of neurons that receive input from the user program. The layer of neurons that send data to the user program is the output layer. Between the input layer and output layer can be zero or more hidden layers. Hidden layer neurons are connected only to other neurons and never directly interact with the user program.

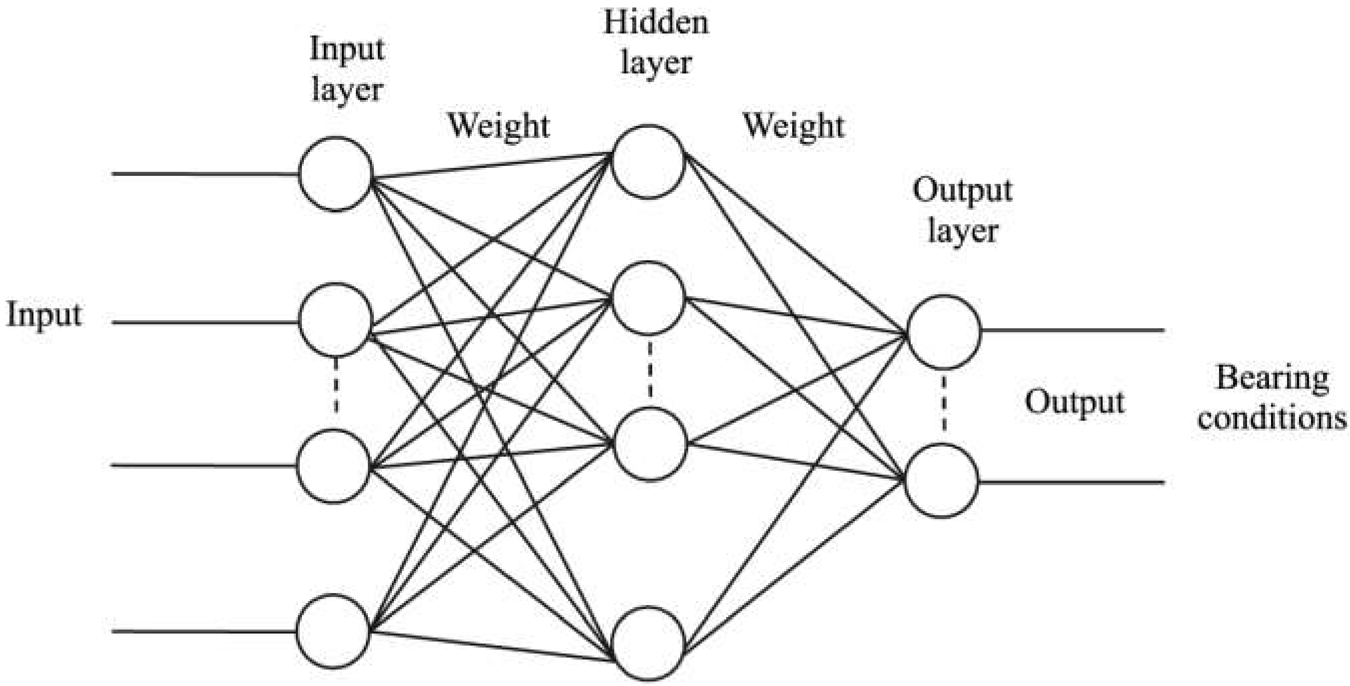


Fig 5.3: Architecture of Neural Network

Figure shows a neural network with five hidden layer. The input layer presents this pattern to the hidden layer. The hidden layer then presents information on to the output layer. Finally the user program collects the pattern generated by the output layer. Every neuron in a neural network has the opportunity to affect processing. Processing can occur at any layer in the neural network. Not every neural network has this many layers. The hidden layer is optional. The input and output layers are required, but it is possible to have one layer act as both an input and output layer.

5.2.4 Learning paradigms

There are three major learning paradigms, each corresponding to a particular abstract learning task. These are supervised learning, unsupervised learning and reinforcement learning. Usually any given type of network architecture can be employed in any of those tasks.

1. **Supervised learning**

In supervised learning, we are given a set of example pairs $(x,y), x \in X, y \in Y$ and the aim is to find a function $f: X \to Y$ in the allowed class of functions that matches the examples. In other words, we wish to infer the mapping implied by the data; the cost function is related to the mismatch between our mapping and the data and it implicitly contains prior knowledge about the problem domain.

A commonly used cost is the mean-squared error which tries to minimize the average squared error between the network's output, f(x), and the target value y over all the example pairs. When one tries to minimize this cost using gradient descent for the class of neural networks called Multi-Layer Perceptrons, one obtains the common and well-known back propagation algorithm for training neural networks. Tasks that fall within the paradigm of supervised learning are pattern recognition (also known as classification) and regression (also known as function approximation). The supervised learning paradigm is also applicable to sequential data (e.g., for speech and gesture recognition). This can be thought of as learning with a "teacher," in the form of a function that provides continuous feedback on the quality of solutions obtained thus far.

2. **Unsupervised learning**

In unsupervised learning we are given some data x and the cost function to be minimized, that can be any function of the data x and the network's output, f.The cost function is dependent on the task (what we are trying to model) and our a priori assumptions (the implicit properties of our model, its parameters and the observed variables).As a trivial example, consider the model $f(x)=a$, where a is a constant and the cost $C=E[(x-f(x))^2]$. Minimizing this cost will give us a value of a that is equal to the mean of the data. The cost function can be much more complicated. Its form depends on the application: for example, in compression it could be related to the mutual information between x and y, whereas in statistical modeling, it could be related to the posterior probability of the model given the data. (Note that in both of those examples those quantities would be maximized rather than minimized).Tasks that fall within the paradigm of unsupervised learning are in general estimation problems; the applications include clustering, the estimation of statistical distributions, compression and filtering.

3. **Reinforcement learning**

In reinforcement learning, data x are usually not given, but generated by an agent's interactions with the environment. At each point in time t, the agent performs an action y_t and the environment generates an observation x_t and an instantaneous cost c_t, according to some (usually unknown) dynamics. The aim is to discover a policy for selecting actions that minimizes some measure of a long-term cost; i.e., the expected cumulative cost. The environment's dynamics and the long-term cost for each policy are usually unknown, but can be estimated.

5.2.5 Classical Model of Artificial Neuron

1. The McCulloch-Pitts Model of Neuron

The early model of an artificial neuron is introduced by Warren McCulloch and Walter Pitts in 1943. The McCulloch-Pitts neural model is also known as linear threshold gate. It is a neuron of a set of inputs $I_1, I_2, I_3, ..., I_m$ and one output y. The linear threshold gate simply classifies the set of inputs into two different classes. Thus the output y is binary. Such a function can be described mathematically using these equations:

$$Sum = \sum_{i=1}^{N} I_i W_i, \qquad y = f(Sum).$$

W_1 , W_2 …. Wn are weight values normalized in the range of either (0,1) or (-1,1) and associated with each input line, sum is the weighted sum, and T is a threshold constant. The function f is a linear step function at threshold T as shown in fig 5.5.

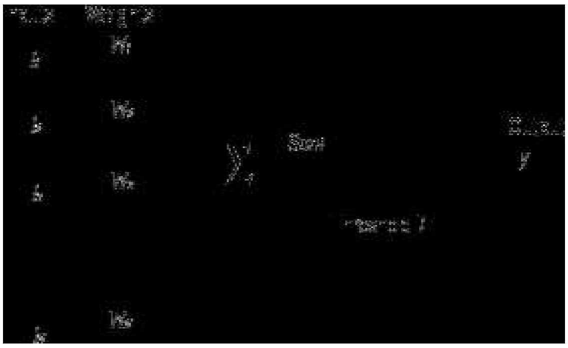


Fig 5.4 **:** Linear Threshold Function Gate

Fig 5.5 **:** Symbolic Illustration of Linear Threshold G

The McCulloch-Pitts model of a neuron is simple yet has substantial computing potential. It also has a precise mathematical definition. However, this model is so simplistic that it only generates a binary output and also the weight and threshold values are fixed..

2. Perceptron

The perceptron is a binary classifier which maps its input *x* (a real-valued vector) to an output value *f*(*x*) (a single binary value) across the matrix.

$$f(x) = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ 0 & \text{else} \end{cases}$$

where w is a vector of real-valued weights and w.x is the dot product (which computes a weighted sum). b is the 'bias', a constant term that does not depend on any input value.

The value of f(x) (0 or 1) is used to classify x as either a positive or a negative instance, in the case of a binary classification problem. If b is negative, then the weighted combination of inputs must produce a positive value greater than | b | in order to push the classifier neuron over the 0 threshold. Spatially, the bias alters the position (though not the orientation) of the decision boundary. The perceptron learning algorithm does not terminate if the learning set is notlinearly separable.The perceptron is considered the simplest kind of feed-forward neural network.

5.2.6 Multilayer Perceptron Neural Network Model

The following diagram illustrates a perceptron network with three layers:

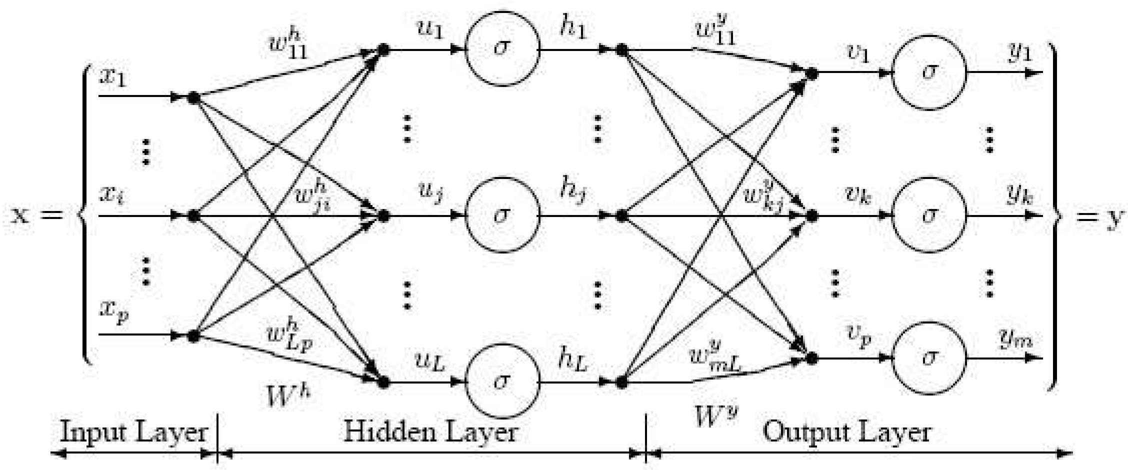


Fig 5.6: Perceptron with three layers

There is one neuron in the input layer for each predictor variable. In the case of categorical variables, N-1 neurons are used to represent the N categories of the variable.

- **Input Layer** — A vector of predictor variable values ($x_1 ... x_p$) is presented to the input layer. The input layer (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the bias that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron.
- **Hidden Layer** — arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (w_{ji}), and the resulting weighted values are added together producing a combined value u_j. The weighted sum (u_j) is fed into a transfer function, σ, which outputs a value h_j. The outputs from the hidden layer are distributed to the output layer.
- **Output Layer** — Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight (w_{kj}), and the resulting weighted values are added together producing a combined value v_j. The weighted sum (v_j) is fed into a transfer function, σ, which outputs a value y_k. The y values are the outputs of the network.

- **Training Multilayer Perceptron Networks**

The goal of the training process is to find the set of weight values that will cause the output from the neural network to match the actual target values as closely as possible. There are several issues involved in designing and training a multilayer perceptron network:

- Selecting how many hidden layers to use in the network.
- Deciding how many neurons to use in each hidden layer.
- Finding a globally optimal solution that avoids local minima.
- Converging to an optimal solution in a reasonable period of time.
- Validating the neural network to test for overfitting.

- **Selecting the Number of Hidden Layers**

For nearly all problems, one hidden layer is sufficient. Two hidden layers are required for modeling data with discontinuities such as a saw tooth wave pattern. Using two hidden layers rarely improves the model, and it may introduce a greater risk of converging to a local minima. There is no theoretical reason for using more than two hidden layers.

- **Deciding how many neurons to use in the hidden layers**

One of the most important characteristics of a perceptron network is the number of neurons in the hidden layer(s). If an inadequate number of neurons are used, the network will be unable to model complex data, and the resulting fit will be poor.If too many neurons are used, the training time may become excessively long, and, worse, the network may over fit the data. When over fitting occurs, the network will begin to model random noise in the data. The result is that the model fits the training data extremely well, but it generalizes poorly to new, unseen data.

The best number of hidden units depends in a complex way on:

- the numbers of input and output units
- the number of training cases
- the amount of noise in the targets
- the complexity of the function or classification to be learned
- the architecture
- the type of hidden unit activation function
- the training algorithm

How large should the hidden layer be? One rule of thumb is that it should never be more than twice as large as the input layer.

- **Finding a globally optimal solution**

A typical neural network might have a couple of hundred weighs whose values must be found to produce an optimal solution. If neural networks were linear models like linear regression, it would be a breeze to find the optimal set of weights. But the output of a neural network as a function of the inputs is often highly nonlinear; this makes the optimization process complex.

5.2.7 The Back Propagation Algorithm

Let's diagram the network as

$$x^0 \xrightarrow{W^1, b^1} x^1 \xrightarrow{W^2, b^2} \dots \xrightarrow{W^L, b^L} x^L \qquad (1)$$

where X^l belongs to R^{n_l} for all l = 0,…..,L and W_l is an n_l x n_{l-1} matrix for all l = 1,…,L. There are L+1 layers of neurons, and L layers of synaptic weights. We'd like to change the weights W and biases b so that the actual output x_L becomes closer to the desired output d.

The backprop algorithm consists of the following steps.

1. **Forward pass.** The input vector x^0 is transformed into the output vector x^L, by evaluating the equation:

$$x_i^l = f(u_i^l) = f\left(\sum_{j=1}^{n_{l-1}} W_{ij}^l x_j^{l-1} + b_i^l\right)$$

For l = 1to L

2. **Error computation.** The difference between the desired output d and actual output x^L is computed.

$$\delta_i^L = f'(u_i^L)(d_i - x_i^L) \qquad (2)$$

3. **Backward pass.** The error signal at the output units is propagated backwards through the entire network, by evaluating

$$\delta_j^{l-1} = f'(u_j^{l-1}) \sum_{i=1}^{n_l} \delta_i^l W_{ij}^l \qquad (3)$$

For l = L to 1

4. **Learning updates.** The synaptic weights and biases are updated using the results of the forward and backward passes,

$$\Delta W_{ij}^l = \eta \delta_i^l x_j^{l-1} \qquad (4)$$
$$\Delta b_i^l = \eta \delta_i^l \qquad (5)$$

These are evaluated for l = 1 to L. The order of evaluation doesn't matter.

5.3 Designed Neural Network in Matlab

Multi-layer Perceptron network is implemented.

The Network consists of the following:

- An input layer with the numbers of nodes equal to the number of wavelet coefficients of the input signal.

- Two hidden layer with the number of nodes equal to the number of nodes in input layer.
- An output layer with 5 nodes.
- Input Layer has a simple fan-out configuration.
- Hidden Layer Units have a Sigmoid Activation Function.
- Output Layer Units have Binary Activation Function.

Procedure for Signal Pre-Processing and Classification 6

6.1 Input Data Set

The input data set consist of 1 subject. Subject performs five mental tasks. Each task has five samples of 10 seconds each, three of which is used for training and two for testing. Therefore, we have15 training samples and 10 testing samples.

(All the tasks were performed with eyes closed)

- **Complex Arithmetic Calculation:** Multiplication of two digit numbers.
- **Simple Arithmetic Calculation:** Multiplication of single digit numbers.
- **Imagining Rotation:** A rotating object is first seen and the rotation is then imagined.
- **Imagining Right Hand Movement:** Right hand is imagined to move in right direction.
- **Relax:** Mind is relaxed.

6.2 Reducing Human Error

Each sample of 10 seconds is broken into 10segments of 1 second. The best segment is chosen. This is done to reduce human error, assuming that the mental task performed by the subject cannot be of 100% accuracy.

The segments are transformed into frequency domain using FFT. Please note all the analysis is done in the alpha range. Each segment of each task is compared with the corresponding segment of relaxed sample (as it is considered as the baseline). The maximum difference in the peak of each segment is noted for each electrode. The segment with maximum difference is forwarded for feature extraction.

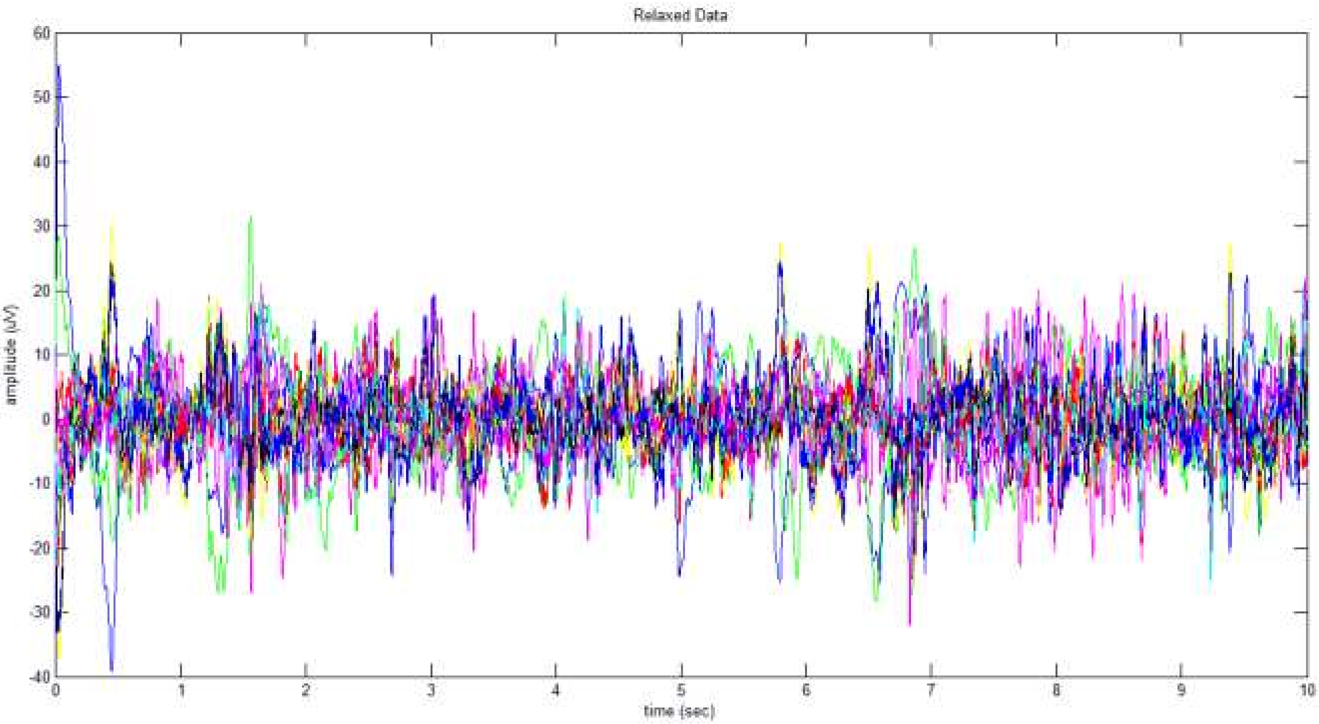


Fig 6.1: Relaxed Data in time domain (Each color represents each electrode)

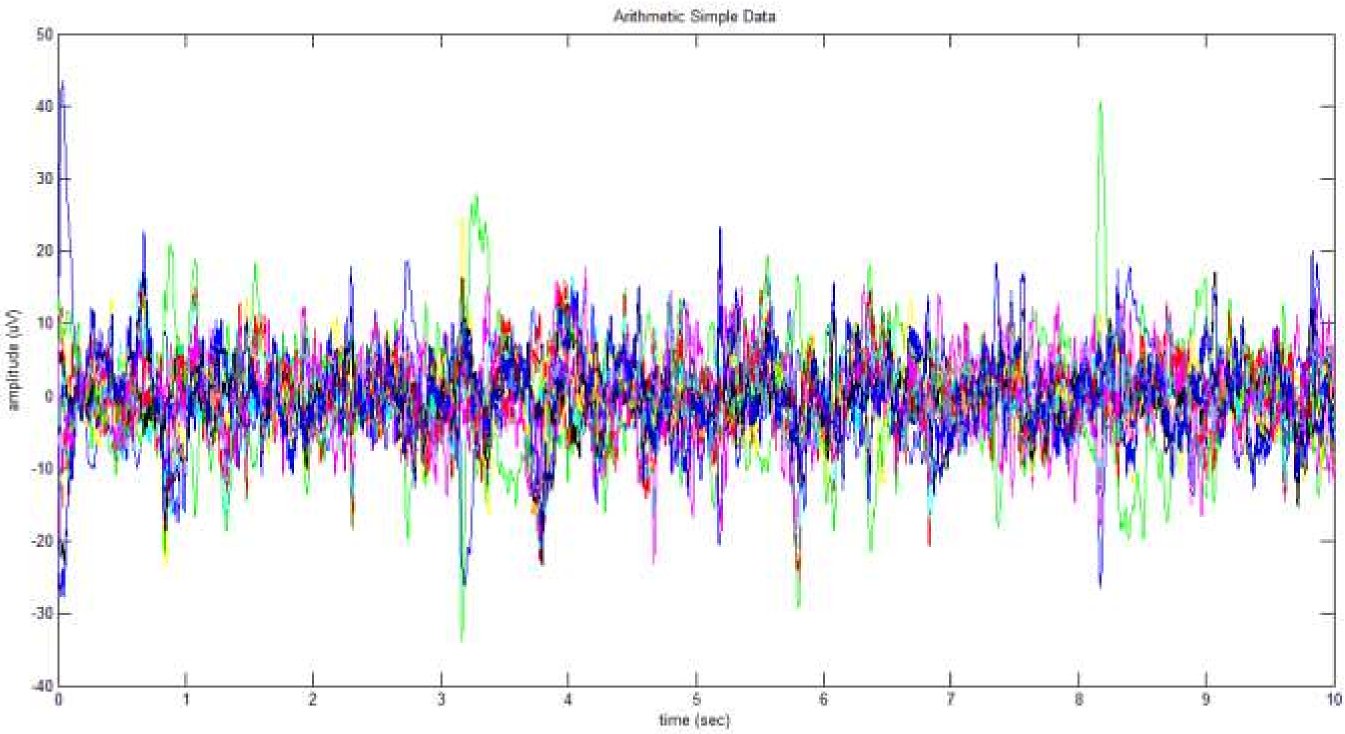


Fig 6.2: Arithmetic Simple Data in time domain (Each color represents each electrode)

Sampling Rate of input is 400 Hz; therefore the maximum frequency component present will be 200Hz which could be seen in Fourier Transform below. We can also see a peak at 50Hz, due to the fact that electricity is supplied at 50Hz in India, which interferes with the EEG signal.

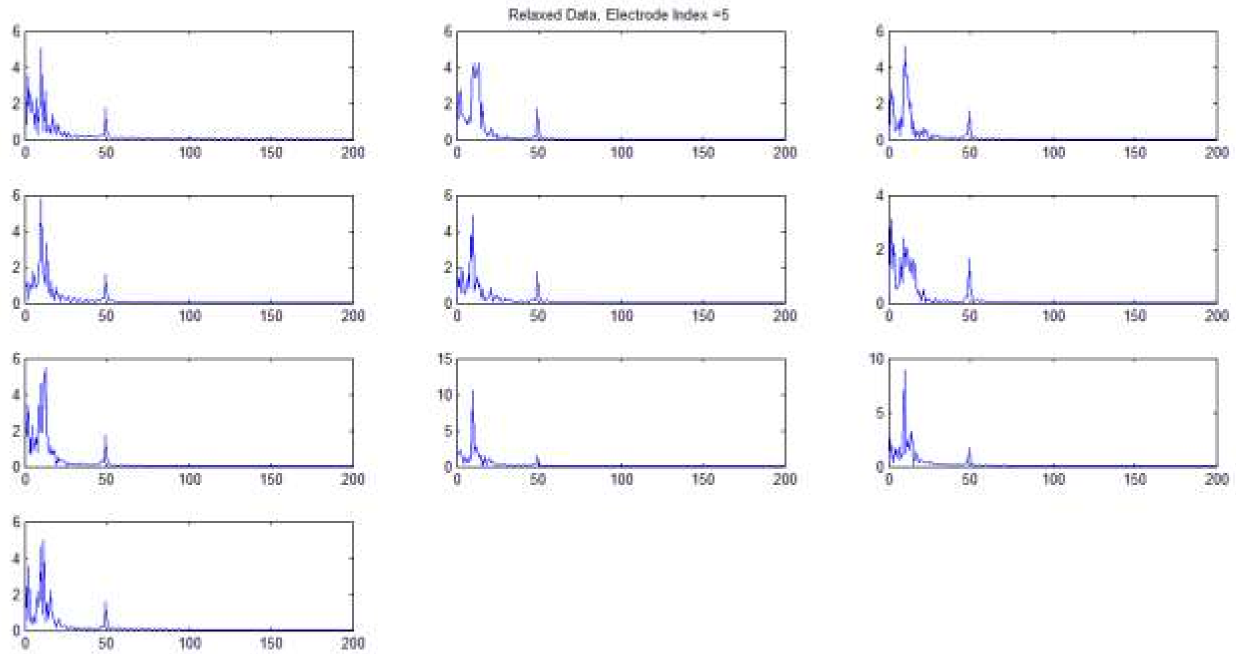


Fig 6.3: FFT of each of the 10 segments of selected electrode of Relaxed Data

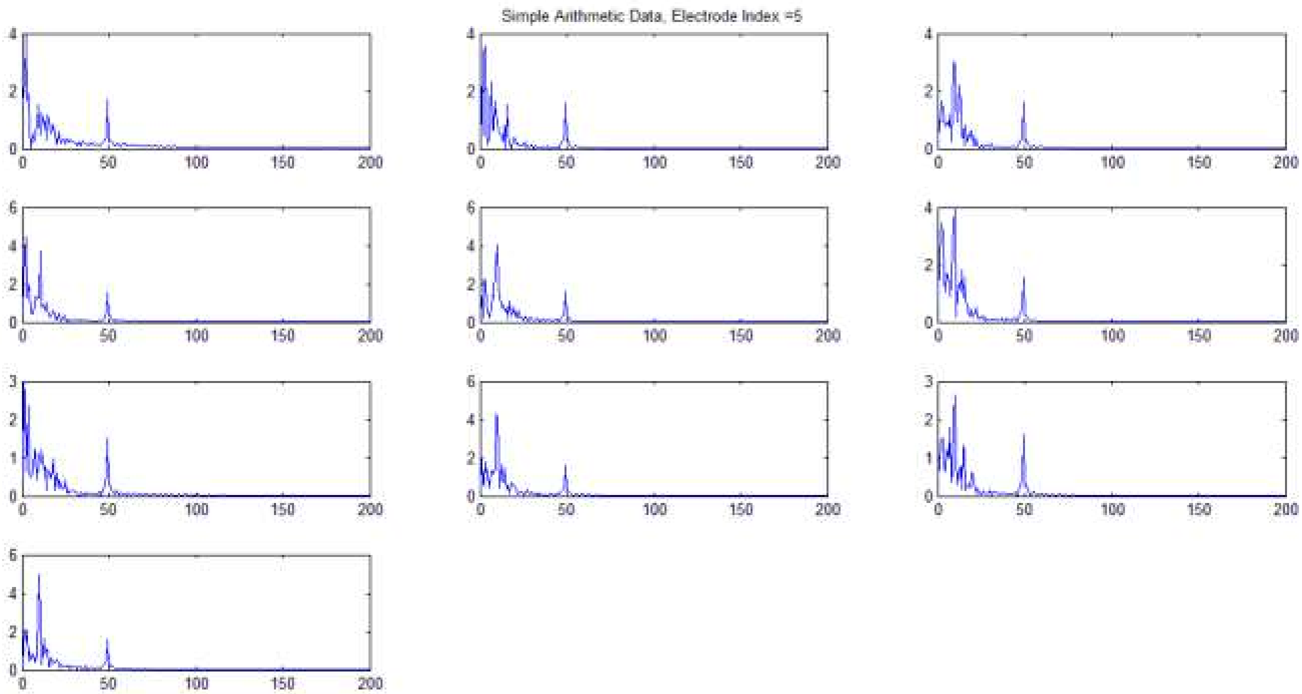


Fig 6.4: FFT of each of the 10 segments of selected electrode of Simple Arithmetic Data

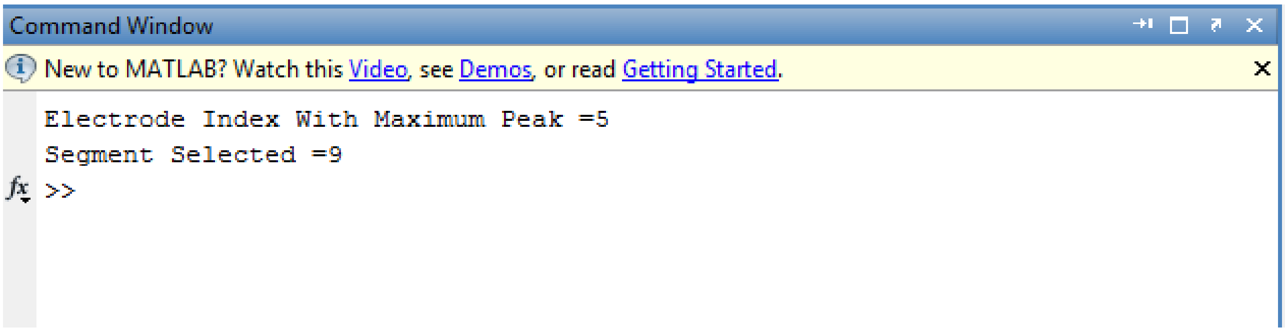


Fig 6.5: Selected Electrode Index and Segment

The selected segment and electrode is passed on for feature extraction.

6.3 Feature Extraction

The sample segment is transformed into wavelet coefficients using wavelet '**bior 3.7**'. The wavelet is selected as discussed in section 4.4.7.Maximum frequency component is 200Hz.

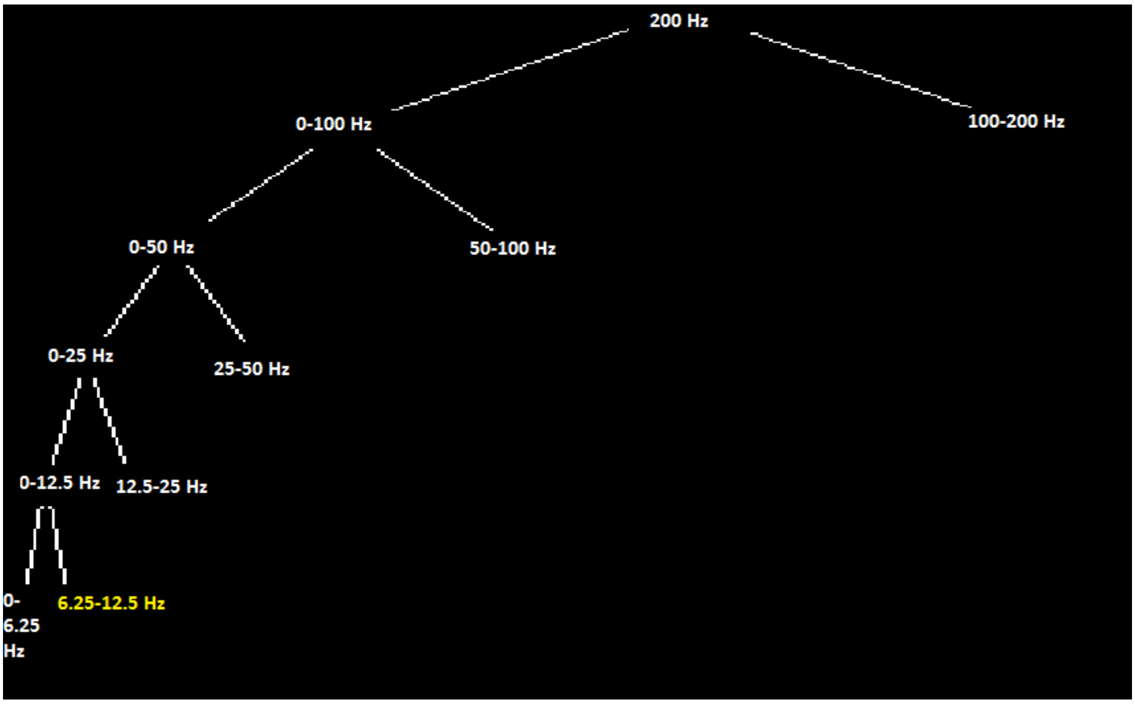


Fig 6.6: Wavelet Tree

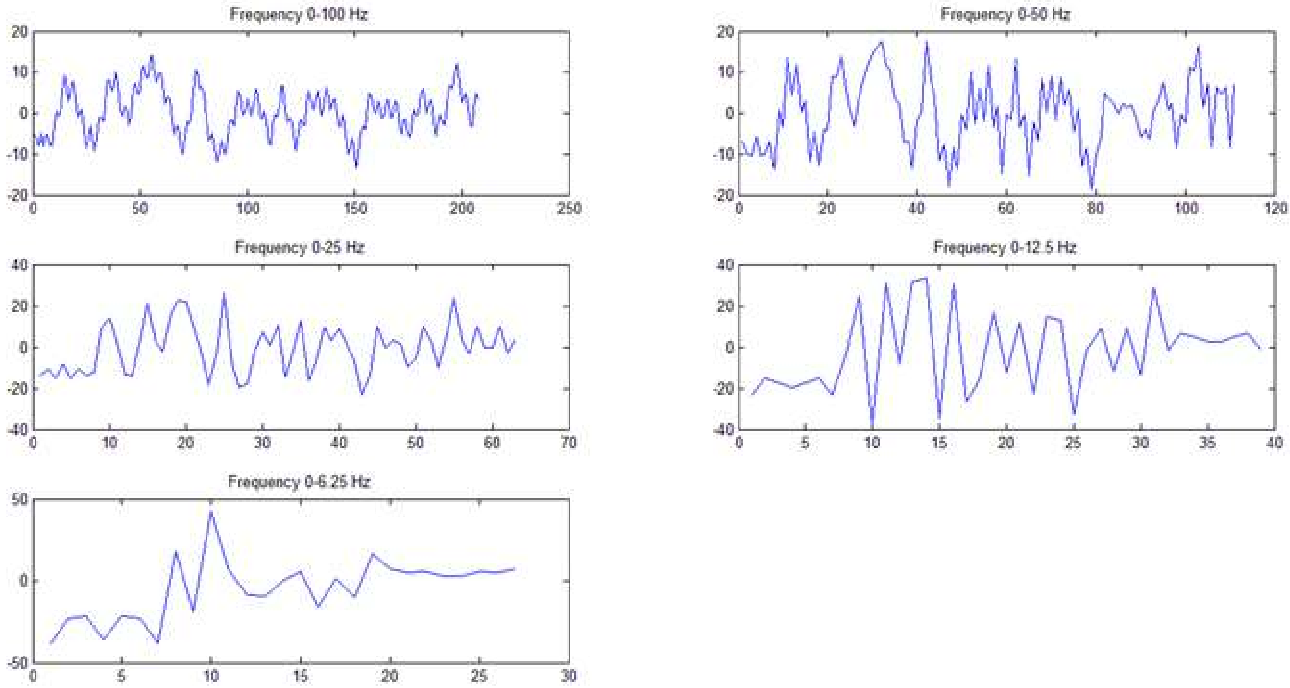


Fig 6.7: Approximate Wavelet Coefficients

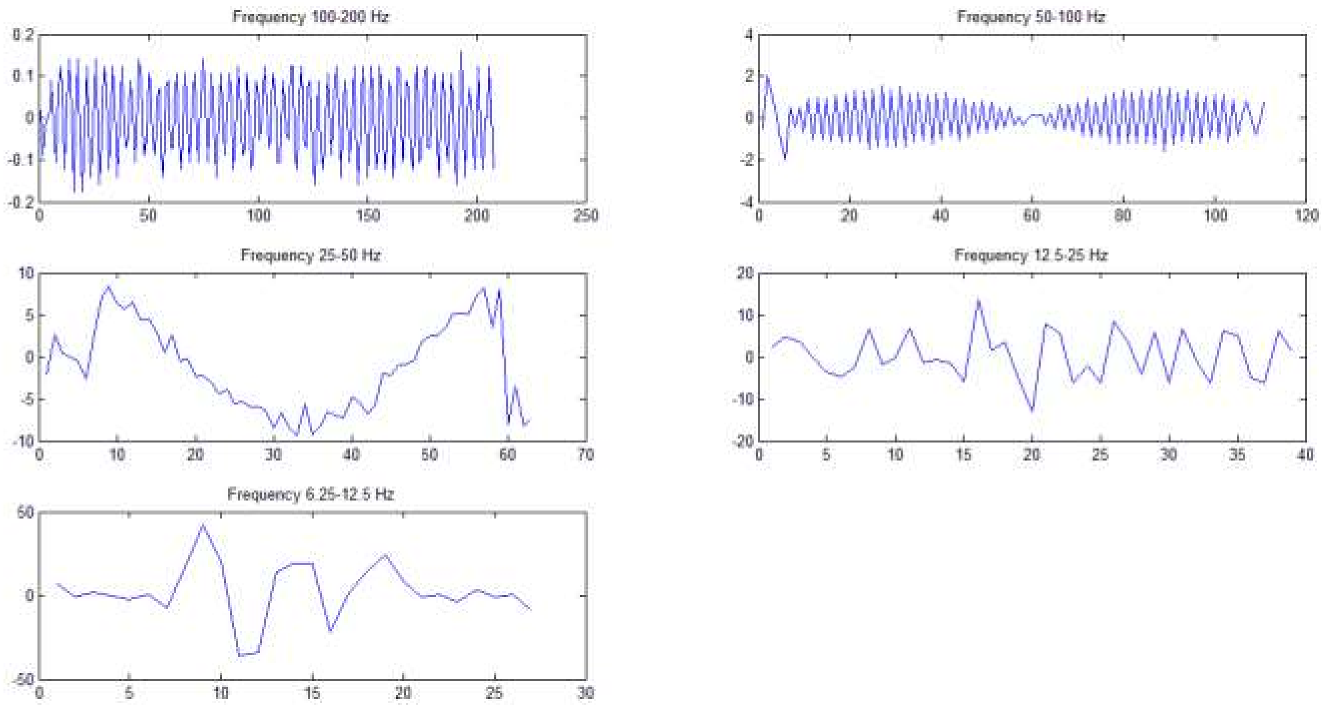


Fig 6.8: Detailed Wavelet Coefficients

We can see at the fifth level of transformation, frequency component range of detailed coefficients is 6.25 to 12.5 Hz, which is approximately the alpha range. These coefficients are passed on to neural network.

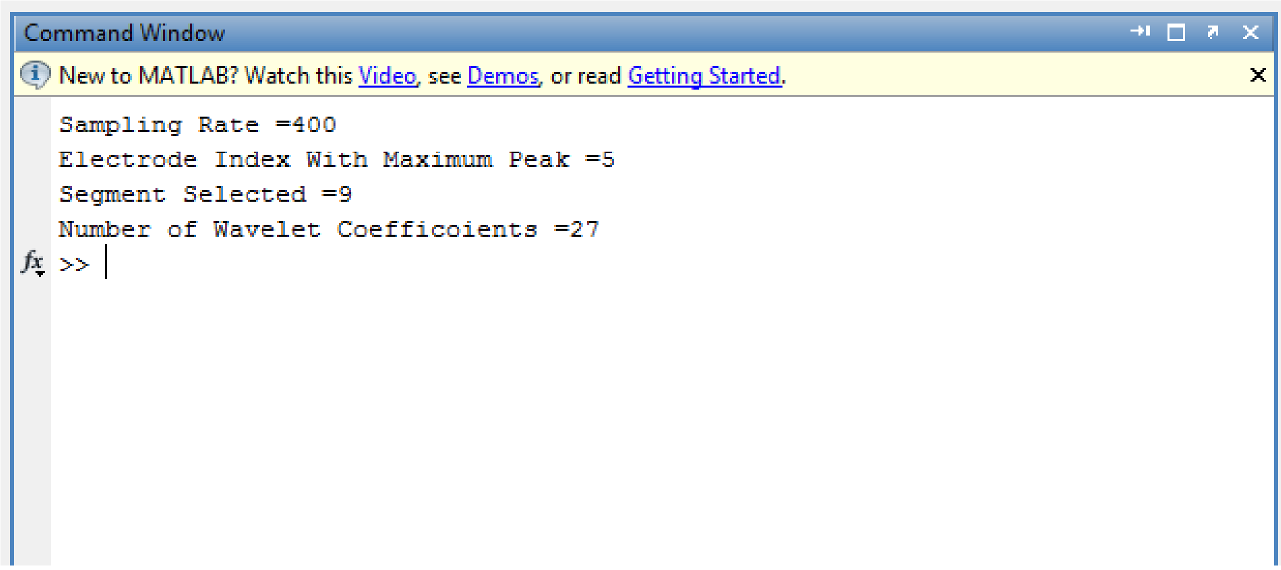


Fig 6.9: Showing number of wavelet coefficients

6.4 Signal Classification

The classifier used is Multi-Layer Neural Network with 2 hidden layers. Delta learning law and back-propagation algorithm is implemented.

During the training number of steps taken to bring the output equal to projected output is observed. And the 'weights' of the network is updated by sample input sample until the 'number of steps' becomes constant and does not reduce any further.

The 5 binary nodes in the output layer may result in one of the five outputs:

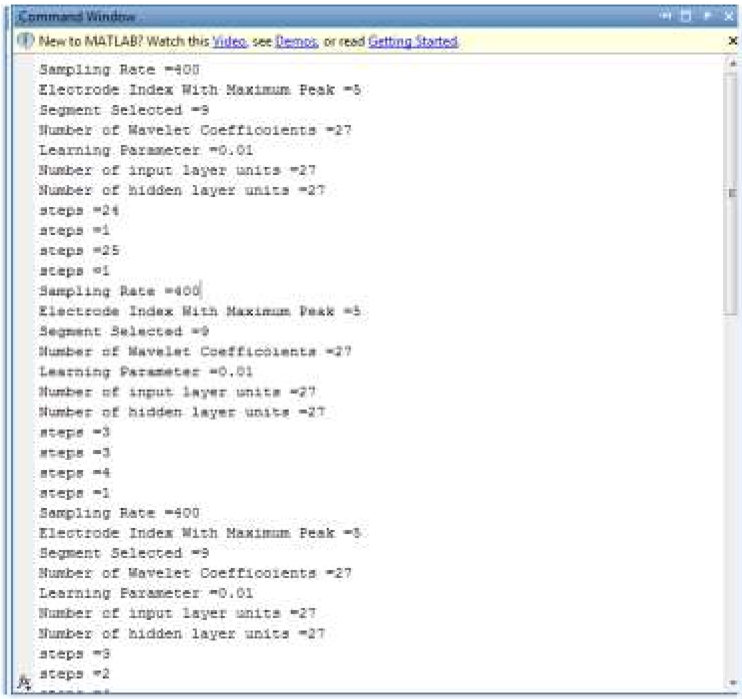
{**1**,-1,-1,-1,-1}: Complex Arithmetic Calculations

{-1, **1**,-1,-1,-1}: Simple Arithmetic Calculations

{-1,-1, **1**,-1,-1}: Relaxed State

{-1,-1,-1, **1**,-1}: Right Hand Pseudo-Motion

{-1,-1,-1,-1, **1**}: Rotation of an Object



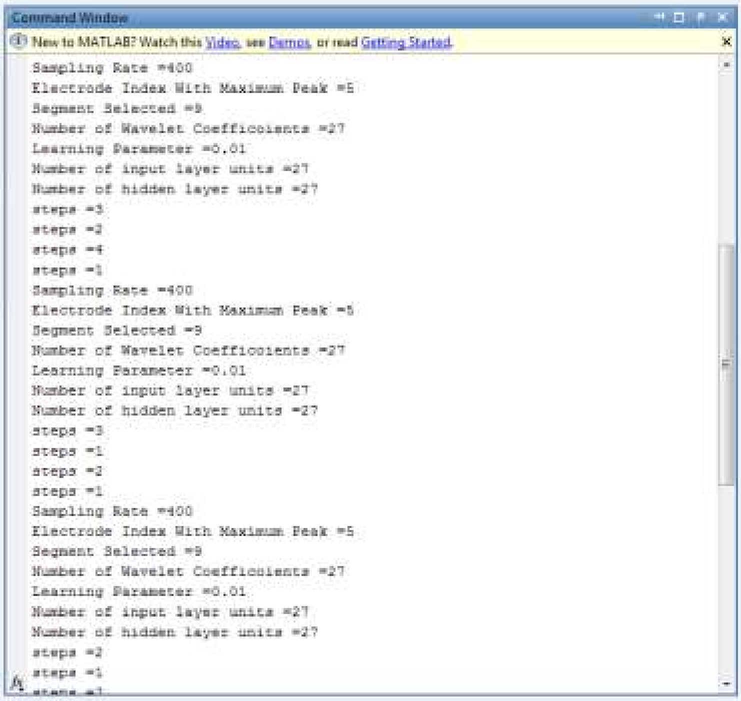


Fig 6.10 (a) Multiple Trainings with number of steps continuously decreasing.

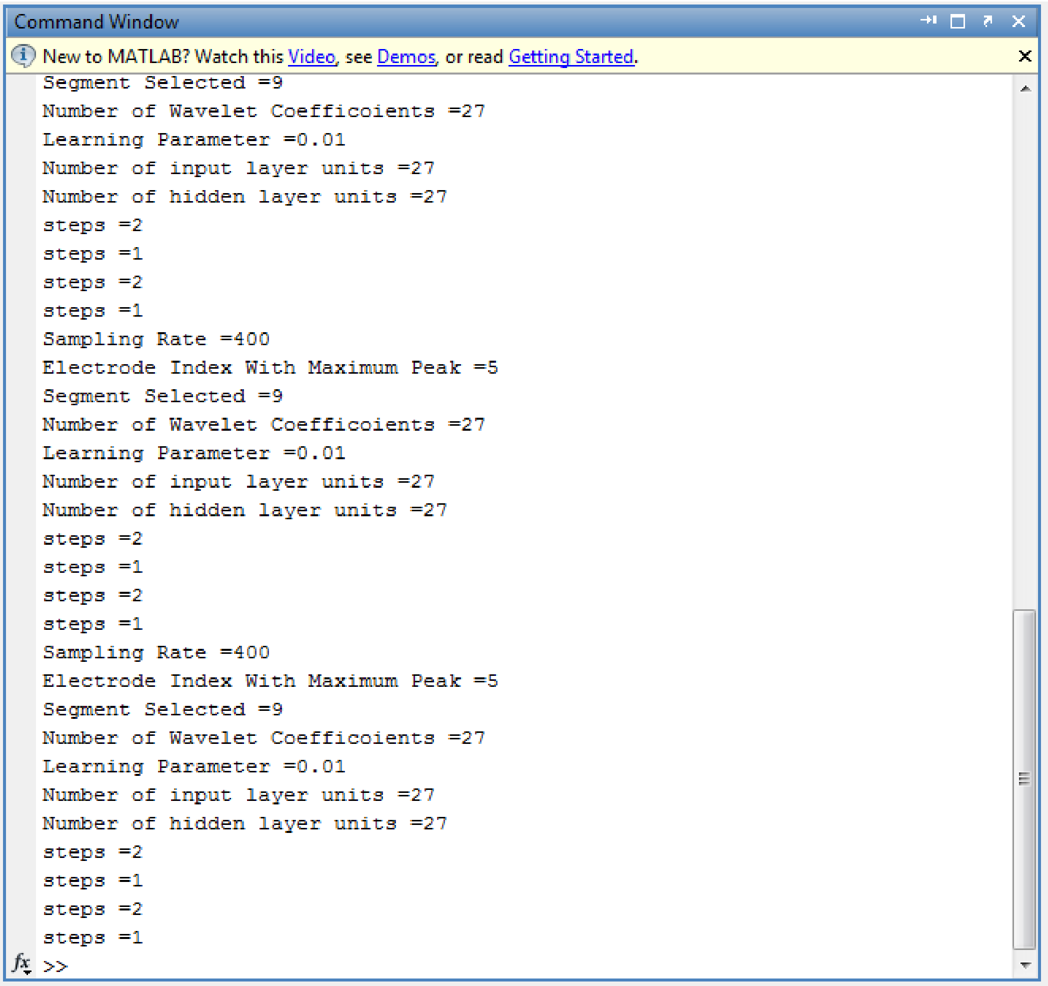
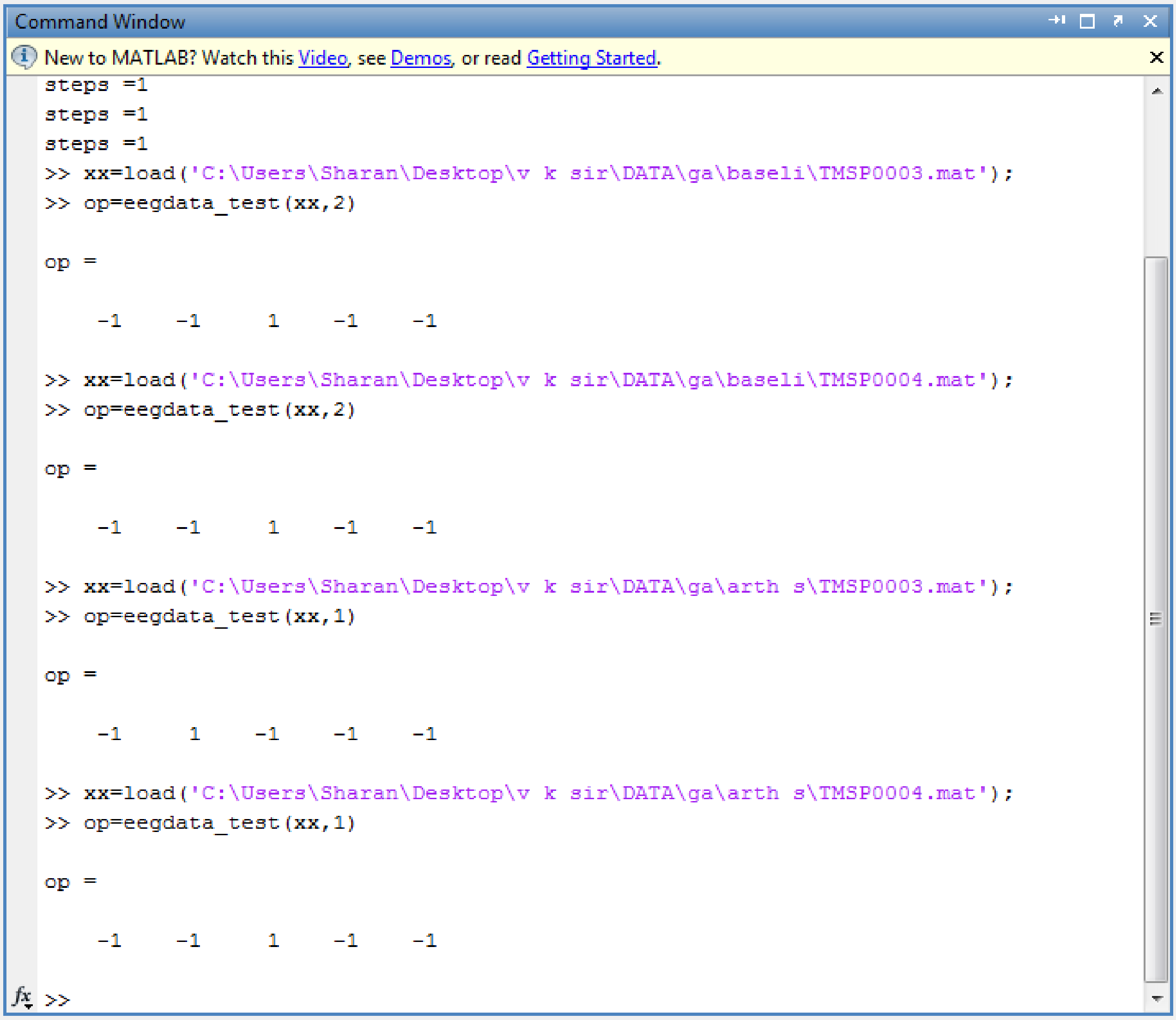


Fig 6.11: Number of steps becomes constant.

6.5 Testing

Three samples of each task is used for training, and two of these are used for testing. Figure below shows testing of Simple Arithmetic task with relaxed state. Simple arithmetic should give the output {-1, 1,-1,-1,-1}, and relaxed state should give {-1,-1, 1,-1,-1}. We can see three out of four inputs give the correct output.



```
Command Window
New to MATLAB? Watch this Video, see Demos, or read Getting Started.
steps =1
steps =1
steps =1
>> xx=load('C:\Users\Sharan\Desktop\v k sir\DATA\ga\baseli\TMSP0003.mat');
>> op=eegdata_test(xx,2)

op =

    -1    -1     1    -1    -1

>> xx=load('C:\Users\Sharan\Desktop\v k sir\DATA\ga\baseli\TMSP0004.mat');
>> op=eegdata_test(xx,2)

op =

    -1    -1     1    -1    -1

>> xx=load('C:\Users\Sharan\Desktop\v k sir\DATA\ga\arth s\TMSP0003.mat');
>> op=eegdata_test(xx,1)

op =

    -1     1    -1    -1    -1

>> xx=load('C:\Users\Sharan\Desktop\v k sir\DATA\ga\arth s\TMSP0004.mat');
>> op=eegdata_test(xx,1)

op =

    -1    -1     1    -1    -1

fx >>
```

Fig 6.12: Showing the testing

The Network is tested with accuracy of 68.75%. Reasons for low accuracy can be accounted to the fact that a temporal data is classified using static classifier. The Wavelet Transform although converts the temporal data into static data and it reduces about 800 sample points to 17-27 sample points but the reduction in input size and faster processing costs in the reduction in accuracy.

Hardware Implementation

7

7.1 Stepper Motor

A stepper motor is a brushless, synchronous electric motor that converts digital pulses into mechanical shaft rotation. Every revolution of the stepper motor is divided into a discrete number of steps. Step motors are used every day in both industrial and commercial applications because of their low cost, high reliability, high torque at low speeds and a simple, rugged construction that operates in almost any environment. Stepper motors are great to use in robotics. Stepper motors consist of a permanent magnet rotating shaft, called the rotor, and electromagnets on the stationary portion that surrounds the motor, called the stator. Figure illustrates one complete rotation of a stepper motor. At position 1, we can see that the rotor is beginning at the upper electromagnet, which is currently active (has voltage applied to it). To move the rotor clockwise (CW), the upper electromagnet is deactivated and the right electromagnet is activated, causing the rotor to move 90 degrees CW, aligning itself with the active magnet. This process is repeated in the same manner at the south and west electromagnets until we once again reach the starting position.

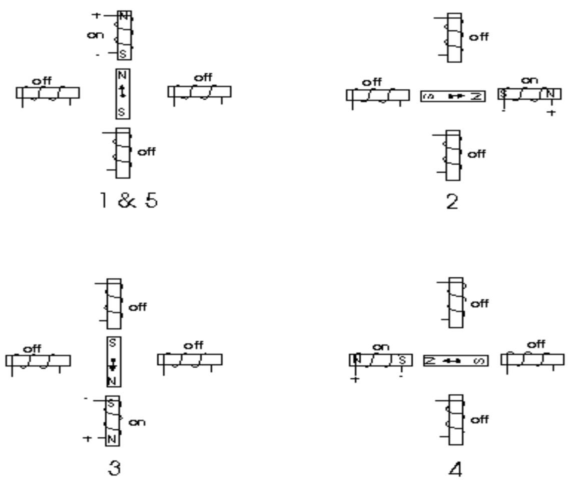


Fig 7.1(a): Working of Stepper motor

We may double the resolution of some motors by a process known as "half-stepping". Instead of switching the next electromagnet in the rotation on one at a time, with half stepping we turn on both electromagnets, causing an equal attraction between, thereby doubling the resolution. As illustrated in Figure, in the first position only the upper electromagnet is active, and the rotor is drawn completely to it. In position 2, both the top and right electromagnets are active, causing the rotor to position itself between the two active poles. Finally, in position 3, the top magnet is deactivated and the rotor is drawn all the way right. This process can then be repeated for the entire rotation.

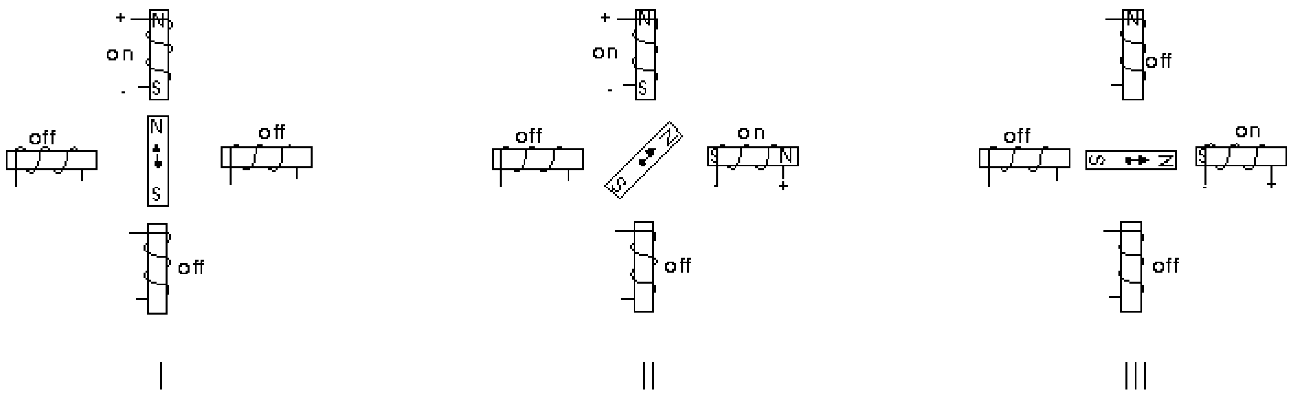


Fig 7.1(b): Working of Stepper motor

The **L293D** motor driver chip contains two H-bridges for driving small DC motors.

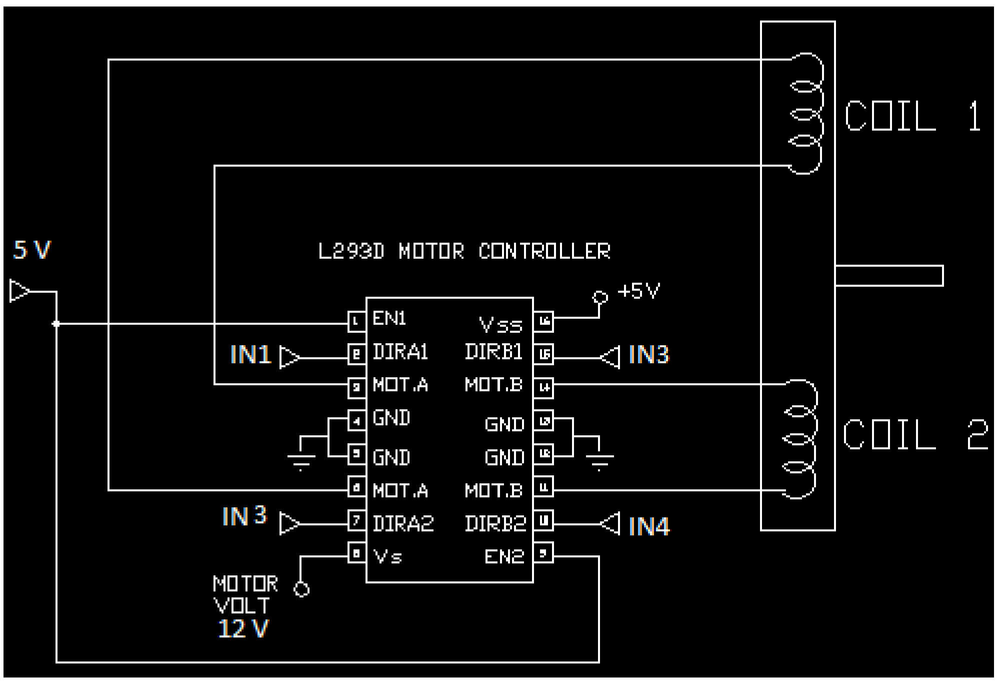


Fig 7.2: Circuit of L293D

Unipolar Stepper Motors

The unipolar stepper motor has five or six wires and four coils (actually two coils divided by center connections on each coil).Minimum Step angle is 1.8 degrees. The center connections of the coils are tied together and used as the power connection. They are called unipolar steppers because power always comes in on this one pole.

	Wire 1	Wire 2	Wire 3	Wire 4
STEP 1	High	Low	High	Low
STEP 2	Low	High	High	Low
STEP 3	Low	High	Low	High
STEP 4	High	Low	Low	High

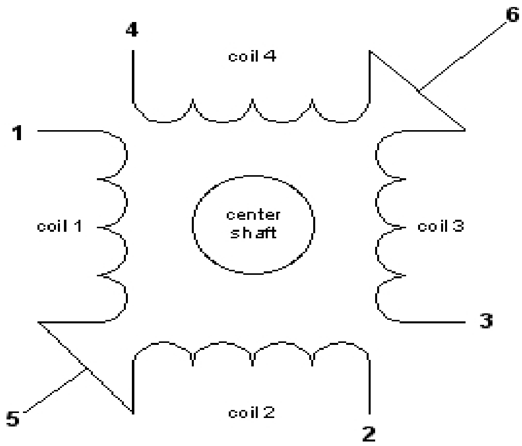


Fig 7.3: Working of Stepper motor

7.2 ATMEGA16 Microcontroller

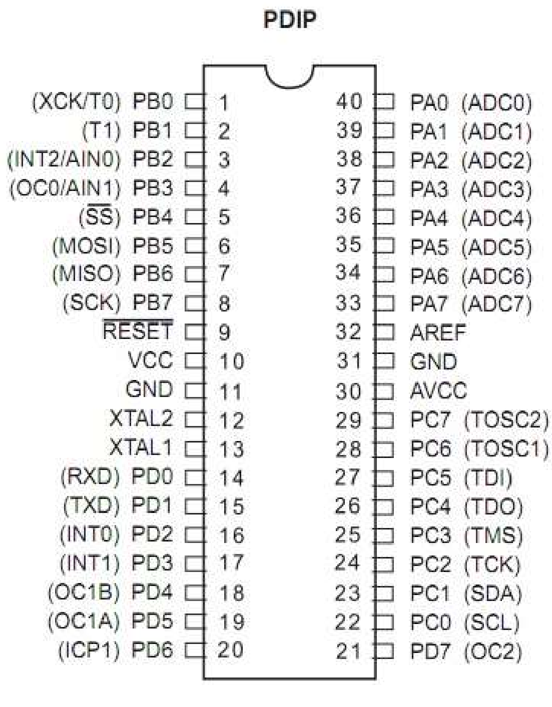


Fig 7.3: ATMEGA16

- Port PD0 (RXD) and PD1(TXD): These ports are used for serial communication.
- Port B: This port has 8 pins (B0 to B7) and is used for driving stepper motors.

7.3 Interfacing the Serial / RS232 Port

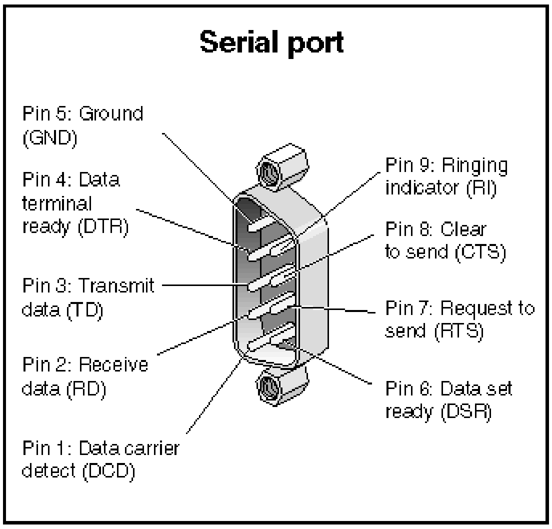


Fig 7.4: RS232 Port

The Serial Port is harder to interface than the Parallel Port. In most cases, any device you connect to the serial port will need the serial transmission converted back to parallel so that it can be used. This can be done using a UART. On the software side of things, there are many more registers that you have to attend to than on a Standard Parallel Port. (SPP).

Fig7.5: Robot with Atmega16 microcontroller

7.4 Interfacing Robot with Matlab

Atmega16 Microcontroller is serially connected to Matlab. IC Max232 is used for interfacing microcontroller and RS232 of the computer or Laptop. Stepper Motors are connected to the Port B of the controller. L293D ICs are used to interface microcontroller and motors. Two power supplies are used, one for providing 5V for operation of microcontroller and the other providing 12 V for driving the motors.
Neural Network classifies the input EEG signal into one of the five classes as shown in table below. According to this output a number between 1 to 5 is send serially from matlab to the microcontroller which decides the motion of the Robot.

Microcontroller is programmed using Bascom. The program instructs the microcontroller to drive motors in various directions according to the serial input which are the ASCII values of numbers 1 to 5.

Classifier Output	**Microcontroller Input**	**Motion of the Robot**	**Left Motor**	**Right Motor**
{1,-1,-1,-1,-1} Arth c	49 (Ascii value of 1)	Forward motion	Forward Rotation	Forward Rotation
{-1,-1,-1,-1, 1} Rotation	50	Left Motion	Backward Rotation	Forward Rotation
{-1,-1,-1, 1,-1} Move r	51	Right Motion	Forward Rotation	Backward Rotation
{-1, 1,-1,-1,-1} Arth s	52	Backward Motion	Backward Rotation	Backward Rotation
{-1,-1, 1,-1,-1} Relax	53(Ascii value of 5)	Stop	No Rotation	No rotation

.

8

Findings and Conclusion

- We conclude that all the activity is from 9.4 to 10.3 Hz.
- We conclude that
    - Maximum EEG activity occurs at 'p3' electrode which is the left side of parital lobe.
    - Minimum EEG activity occurred at 'f4' electrode which is the right side of the frontal lobe with the exception for Complex arithmetic calculations which has at electrode 'p4', right side of parital lobe.
- We saw the most apt wavelet was found out to be 'bior 3.7'in case of our EEG signal classification.
- In earlier stages of the project, binary hidden units in MLP network were used which were later changed to sigmoid and an increase in accuracy was seen.
- We also found Delta Learning Law to be better than Perceptron Learning Law.
- It was also noted during various trials of training, number of hidden layer units is not proportional to the accuracy in the training, and neither is number of hidden layers.
- The low accuracy (68.75%) of the network can be accounted to the fact that temporal data was classified in static classifier (MLP). The Wavelet Transform although converts the temporal data into static data and it reduces the input size but the reduction in input size and faster processing costs in the reduction in accuracy.

9

References

[1] B.Yegnanarayana," Artificial Neural Network", Prentice-Hall of India Private Limited, India, February 2001

[2] J. M. Zurada.," Introduction to Artificial Neural Network Systems", Jacio Publishing House, Mumbai, 2006.

[3] R. Polikar, "The Wavelet Tutorial", Second Edition http://users.rowan.edu/~polikar/wavelets/wtpart1.html

[4] E. Haselsteiner and G. Pfurtscheller," Using Time-Dependent Neural Networks for EEG Classification, IEEE transactions on rehabilitation engineering, Vol. 8, No. 4, December 2000

[5] S. Seung, "Multilayer perceptrons and backpropagation Learning", 9.641 Lecture 4: September 17, 2002

[6] Y. Bengio, N. Le Roux, P. Vincent, O. Delalleau, P. Marcotte, "Convex Neural Network", Dept. IRO, Universit´e de Montréal

[7] A. Proch´azka and J. Kukal, "Wavelet Transform Use for Feature Extraction and EEG Signal Segments Classification", ISCCSP 2008, Malta, 12-14 March 2008

[8] S. Sanei and J.A. Chambers, "EEG Signal Processing", John Wiley & Sons, West Sussex

[9] http://en.wikipedia.org/wiki/Electroencephalography.

[10] http://serendip.brynmawr.edu/bb/kinser/Structure1.html.

[11] http://www.ebme.co.uk/arts/eegintro/eeg2.htm

[12] http://en.wikipedia.org/wiki/Neural_network.

[13]http://dsp.vscht.cz/konference_matlab/MATLAB07/prispevky/bartosova_prochazka/bartosova_prochazka. pdf

[14] http://www.medical-illustrations.ca/?s=brain