# ASSESSMENT OF SUBJECTIVE MOTOR LEARNING ABILITY USING OF N400 ERP SIGNAL

A thesis submitted towards the partial fulfillment of the requirements for the degree of Master of Engineering in Biomedical Engineering Course affiliated to Faculty of Engineering and Technology, Jadavpur University


Submitted by Neelakshi Ganguly

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# CERTIFICATE OF RECOMMENDATION

We hereby recommend that the thesis entitled "***Assessment of subjective motor learning ability using of N400 ERP Signal***" carried out under my supervision by Neelakshi Ganguly may be accepted in partial fulfilment of the requirement for awarding the Degree of Master in Biomedical Engineering of Jadavpur University. The project, in our opinion, is worthy for its acceptance.

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# DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

I hereby declare that this thesis contains literature survey and original research work by the undersigned candidate, as part of his **Master of Engineering in Biomedical Engineering** studies during academic session 2020-2022.

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by this rules and conduct, I have fully cited and referred all material and results that are not original to this work.

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I owe a deep sense of gratitude to my respected thesis advisor Prof(Dr.) Amit Konar, Professor of Cybernetics and Cognitive Neuroscience, Dept. of Electronics and Tele-Communication Engineering, Jadavpur University for his esteemed guidance, invaluable suggestions, constant encouragement and affection at every stage of the entire tenure of the project without which I could not have finished the work.

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# CHAPTER-1

# NEUROSCIENCE

Humans develop their motor skills through learning. Such learning is a gradual development process experienced by people over the years. This project is concerned with the detection of the motor learning ability of human subjects in a Brain-Computer Interface (BCI) setting. An experimental setup is arranged to examine the muscle activation by motor execution signal. The experiment includes 4-time windowed steps in a sequence. In the first window, the subject is commanded to fix her attention to an on-screen fixation cross. In time window 2, the subject is commanded to execute a motor task (such as picking up a bottle containing water). In Time-window 3, the subject executes the task and releases a motor execution (ME) signal, followed by an N400 signal. The motivation of such an experiment is to check possible learning of the sequence of muscle activation signal amplitudes in 3 distinct cases. The cases include: i) gradual increase in the volume of water in the bottle, ii ) gradual decrease in volume of water in the bottle, and iii) a specific pattern of water volumes (for example, 0.5L, 0.75L, and 1L in 3 consecutive experimental trials) in the bottle repeated over cycles. The N400 signal is found to appear approximately 250MS away from the occurrence of the MI signal in the third window, in case the subject recognizes the repeated sequence. The motivation of the above experiment is to determine whether the subject can recognize the repetition of the sequence and learn the sequence. In case, the subject learns the sequence, she will be liberating the N400 signal after a short span of the release of the ME signal. The study of the above issues largely depends on the detection of the N400 signals. The N400 signal, on the other hand, requires classification by a classifier. A SVM model is proposed to classify the learning skills and fluctuations generated in the brain lobes during the process. In this model only crisp values are given as the input and clear and output is also in the crisp form. As this model works well when there is a clear demarcation of classes , it adds a special value as it directly finds out through the classification of the N400 signal that skill is learned or not, opposed to models where interim or partial results are also obtained for specifics i.e. it eliminates any partial learning. Therein lies the novelty of this method compared to others where the degree of membership (here it is analogous to learning) rather than definite value is focused. Thus any disturbances or noises get automatically eliminated which increases the efficiency further. Computational time is also much less compared to any such contemporary method. Due to all these various properties of the proposed model, it outperforms the traditional classifiers and is the most effective method of classification for this line of work. Here the specific focus lies on the N400 signal which is an oddball signal due to its monotonic decreasing nature. The negative peak of the N400 signal decreases as the subjects learn the skill. Here the change in the amplitude is given the focus rather than the absolute magnitude of the signal.

In this particular section, an overall idea about the various principles and methodology used in the study of detecting motor learning skills of human subjects from the response of the brain-computer interface is provided. The Figure provides an explicit description of the overall process taking place.

At first with the help of 13 Ag/AgCl2 electrodes from different brain regions: prefrontal(Fp1 and Fp2), frontal lobe(Fz, F3, F4, F7, and F8), and basal temporal lobe(A1, A2, and Aav) EEG signals are captured. The EEG signals are then analyzed with the help of software to find the activation regions of the brain. The majority of the motor response has been obtained from the frontal lobe. Through extensive review, it has been found that there is a predominance of N400 in the frontal-cortex region. All the voluntary movements are controlled by the primary cortex region and in the study. The primary concern in the paper is voluntary movements. In the experiment an appreciable amount of N400 signal has been found in this region which also proves the above-stated statement. 4 different sets of stimuli by varying the volumes of water, was provided to the brain to prepare and test the subject. Thus experiment is performed under two phases 1)Training phase 2)Testing phase. At first in four segments by increasing the volume of water the subject is trained and made habituated with the weights. In the second part in four segments but in decreasing order of volume of water the subject is trained. In the training phase in each part, a block of 20 trials is provided. In the testing phase, these 40 trials are provided in random order. The EEG signals are then filtered with the help of a band filter of order 10 and a cut-off frequency of 0.2 to5Hz. Two sets of BCI signals are specifically focused here , they are ERD/ERS and N400. All kinds of noises and physiological produced artifacts are eliminated with the help of a filter.

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## 1.3 Neural Activities

The central nervous system (CNS) generally consists of nerve cells and glia cells, which are located between neurons. Each nerve cell consists of axons, dendrites and cell bodies. Nerve cells respond to stimuli and transmit information over long distances. A nerve cell body has a single nucleus, and contains most of the nerve cell metabolism, especially that related to protein synthesis. The proteins created in the cell body are delivered to other parts of the nerve. An axon is a long cylinder, which transmits an electrical impulse and can be several meters long in vertebrates (giraffe axons go from the head to the tip of spine). In humans the length can be a percentage of a millimetre to more than a metre. An axonal transport system for delivering proteins to the ends of the cell exists and the transport system has "molecular motors" which ride upon tubulin rails. Dendrites are connected to either the axons or dendrites of other cells and receive impulses from other nerves or relay the signals to other nerves. In the human brain each nerve is connected to approximately 10 000 other nerves, mostly through dendritic connections. The activities in the CNS are mainly related to the synaptic currents transferred between the junctions (called synapses) of axons and dendrites, or dendrites and dendrites of cells. A potential of 60–70 mV with negative polarity may be recorded under the membrane of the cell body. This potential changes with variations in synaptic activities. If an action potential travels along the fibre, which ends in an excitatory synapse, an excitatory following neuron. If two action potentials travel along the same fibre over a short distance, there will be a summation of EPSPs producing an action potential on the postsynaptic neuron providing a certain threshold of membrane potential is reached. If the fibre ends in an inhibitory synapse, then hyperpolarization will occur, indicating an inhibitory postsynaptic potential (IPSP) .Following the generation of an IPSP, there is an overflow of cations from the nerve cell or an inflow of anions into the nerve cell. This flow ultimately causes a change in potential along the nerve cell membrane. Primary transmembranous currents generate secondary inonal currents along the cell membranes in the intra- and extra-cellular space. The portion of these currents that flows through the extracellular space is directly responsible for the generation of field potentials. These field potentials, usually with less than 100 Hz frequency, are called EEGs when there are no changes in the signal average, and called DC potential if there are slow drifts in the average signals, which may mask the actual EEG signals. A combination of EEG and DC potentials is often observed for some abnormalities in the brain, such as seizure (induced by pentylenetetrazol), hypercapnia, and asphyxia . We next focus on the nature of action potentials.

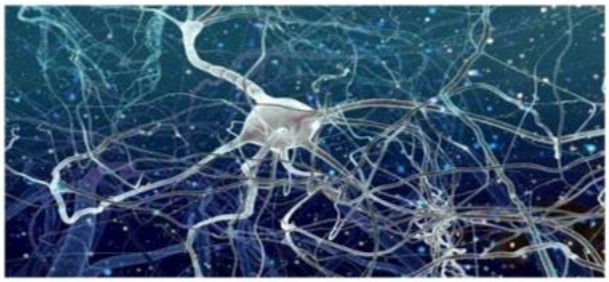
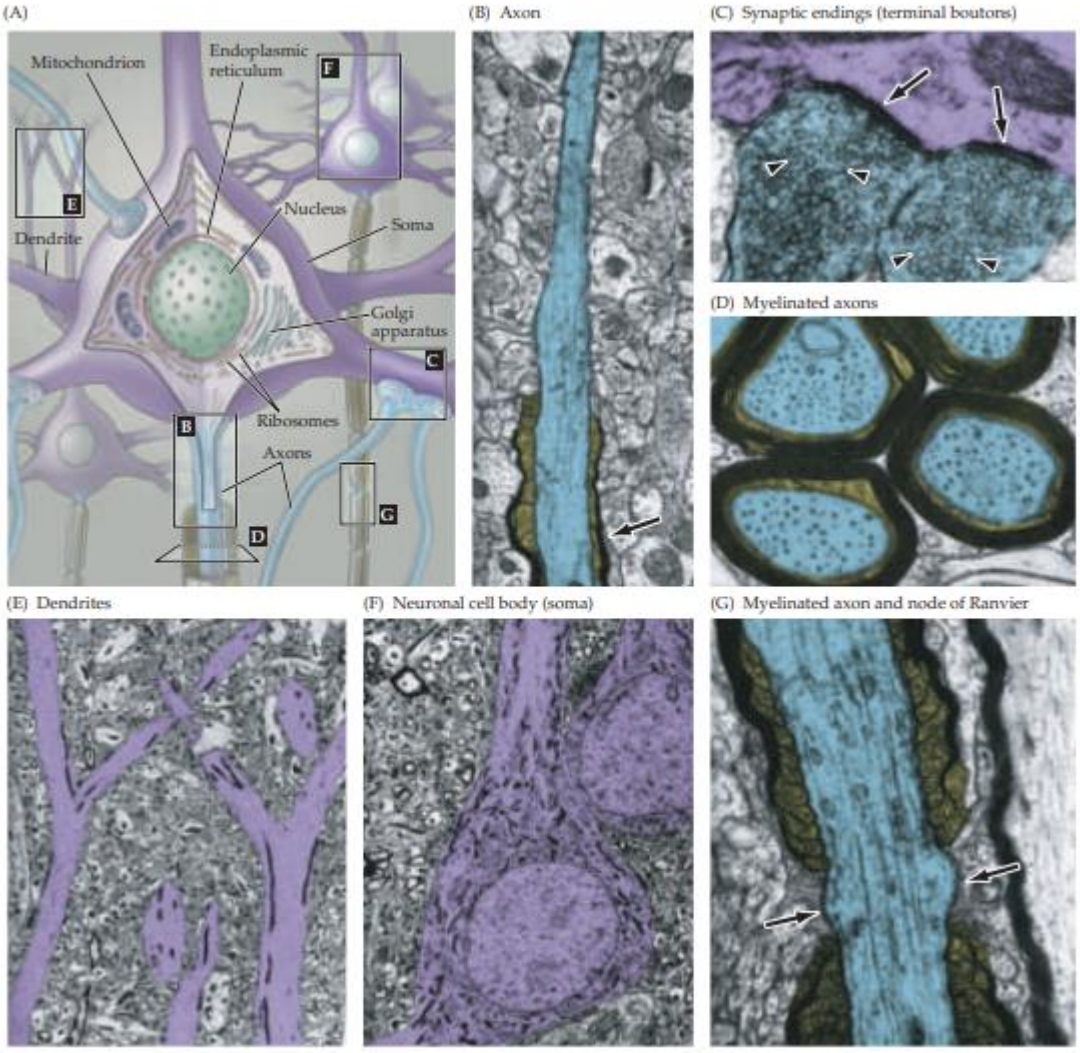


Fig 1: Neural Activity

# 1.4 Neurons


(A)
Mitochondrion
Endoplasmic reticulum
F
E
Nucleus
Soma
Dendrite
Golgi apparatus
C
Ribosomes
B
Axons
G
D
(B) Axon
(C) Synaptic endings (terminal boutons)
(D) Myelinated axons
(E) Dendrites
(F) Neuronal cell body (soma)
(G) Myelinated axon and node of Ranvier

## 1.5 Neuroglial Cells

Neuroglial cells—also referred to as glial cells or simply glia—are quite different from nerve cells. Glia is more numerous than neurons in the brain, outnumbering them by a ratio of perhaps 3 to 1. The major distinction is that glia does not participate directly in synaptic interactions and electrical signaling, although their supportive functions help define synaptic contacts and maintain the signaling abilities of neurons. Although glial cells also have complex processes extending from their cell bodies, these are generally less prominent than neuronal branches, and do not serve the same purposes as axons and dendrites.

The term glia (from the Greek word meaning "glue") reflects the nineteenth-century presumption that these cells held the nervous system together in some way. The word has survived, despite the lack of any evidence that binding nerve cells together is among the many functions of glial cells. Glial roles that are well-established include maintaining the ionic milieu of nerve cells, modulating the rate of nerve signal propagation, modulating synaptic action by controlling the uptake of neurotransmitters at or near the synaptic cleft, providing a scaffold for some aspects of neural development, and aiding in (or impeding, in some instances) recovery from neural injury. There are three types of glial cells in the mature central nervous system: astrocytes, oligodendrocytes, and microglial cells Astrocytes, which are restricted to the brain and spinal cord, have elaborate local processes that give these cells a starlike appearance (hence the prefix "astro"). A major function of astrocytes is to maintain, in a variety of ways, an appropriate chemical environment for neuronal signaling. Oligodendrocytes, which are also restricted to the central nervous system, lay down a laminated, lipid-rich wrapping called myelin around some, but not all, axons. Myelin has important effects on the speed of the transmission of electrical signals. In the peripheral nervous system, the cells that elaborate myelin are called Schwann cells. Finally, microglial cells are derived primarily from hematopoietic precursor cells (although some may be derived directly from neural precursor cells). They share many properties with macrophages found in other tissues, and are primarily scavenger cells that remove cellular debris from sites of injury or normal cell turnover. In addition, microglia, like their macrophage counterparts, secrete signaling molecules—particularly a wide range of cytokines that are also produced by cells of the immune system—that can modulate local inflammation and influence cell survival or death. Indeed, some neurobiologists prefer to categorize microglia as a type of macrophage. Following brain damage, the number of microglia at the site of injury increases dramatically. Some of these cells proliferate from microglia resident in the brain, while others come from macrophages that migrate to the injured area and enter the brain via local disruptions in the cerebral vasculature.

## 1.6 Action Potentials

The information transmitted by a nerve is called an action potential (AP). APs are caused by an exchange of ions across the neuron membrane and an AP is a temporary change in the membrane potential that is transmitted along the axon. It is usually initiated in the cell.

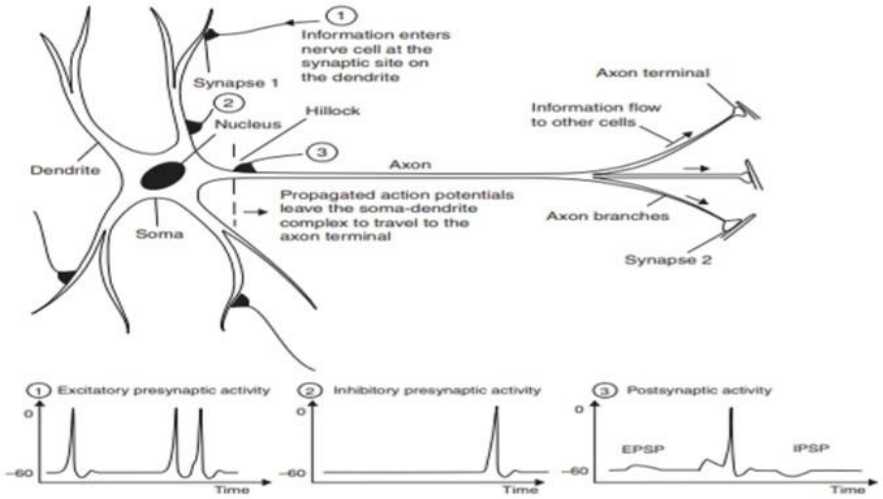



Fig 4: The neuron membrane potential changes and current flow during synaptic activation recorded by means of intracellular microelectrodes.

Action potentials in the excitatory and inhibitory presynaptic fibre, respectively, lead to EPSP and IPSP in the postsynaptic neuron body and normally travels in one direction. The membrane potential depolarizes (becomes more positive) producing a spike. After the spike reaches its peak amplitude the membrane repolarizes (becomes more negative). The potential becomes more negative than the resting potential and then returns to normal. The action potentials of most nerves last between 5 and 10 milliseconds. The conduction velocity of action potentials lies between 1 and 100 m s–1. APs are initiated by many different types of stimuli; sensory nerves respond to many types of stimuli, such as chemical, light, electricity, pressure, touch and stretching. On the other hand, the nerves within the CNS (brain and spinal cord) are mostly stimulated by chemical activity at synapses. A stimulus must be above a threshold level to set off an AP. Very weak stimuli cause a small local electrical disturbance, but do not produce a transmitted AP. As soon as the stimulus strength goes above the threshold, an action potential appears and travels down the nerve.

## 1.7Neural Circuits

Neurons never function in isolation; they are organized into ensembles or neural circuits that process specific kinds of information and provide the foundation of sensation, perception and behavior. The synaptic connections that define such circuits are typically made in a dense tangle of dendrites, axons terminals, and glial cell processes that together constitute what is called neuropil (the suffix -pil comes from the Greek word pilos, meaning "felt";). The neuropil is thus the region between nerve cell bodies where most synaptic connectivity occurs. Although the arrangement of neural circuits varies greatly according to the function being served, some features are characteristic of all such ensembles. Preeminent is the direction of information flow in any particular circuit, which is obviously essential to understanding its purpose.

Nerve cells that carry information toward the brain or spinal cord (or farther centrally within the spinal cord and brain) are called afferent neurons; nerve cells that carry information away from the brain or spinal cord (or away from the circuit in question) are called efferent neurons. Interneurons or local circuit neurons only participate in the local aspects of a circuit, based on the short distances over which their axons extend. These three functional classes—afferent neurons, efferent neurons, and interneurons—are the basic constituents of all neural circuits. A simple example of a neural circuit is the ensemble of cells that subserves the myotatic spinal reflex (the "knee-jerk" reflex). The afferent neurons of the reflex are sensory neurons whose cell bodies lie the dorsal root ganglia and whose peripheral axons terminate in sensory endings in skeletal muscles (the ganglia that serve this same of function for much of the head and neck are called cranial nerve ganglia). The central axons of these afferent sensory neurons enter the the spinal cord where they terminate on a variety of central neurons concerned with the regualtion of muscle tone, most obviously the motor neurons that determine the activity of the related muscles. These neurons constitute the efferent neurons as well as interneurons of the circuit. One group of these efferent neurons in the ventral horn of the spinal cord projects to the flexor muscles in the limb, and the other to extensor muscles. Spinal cord interneurons are the third element of this circuit. The interneurons receive synaptic contacts from sensory afferent neurons and make synapses on the efferent motor neurons that project to the flexor muscles; therefore they are capable of modulating the input–output linkage. The excitatory synaptic connections between the sensory afferents and the extensor efferent motor neurons cause the extensor muscles to contract; at the same time, the interneurons activated by the afferents are inhibitory, and their activation diminishes electrical activity in flexor efferent motor neurons and causes the flexor muscles to become less active. The result is a complementary activation and inactivation of the synergist and antagonist muscles that control the position of the leg. A more detailed picture of the events underlying the myotatic or any other circuit can be obtained by electrophysiological recording. There are two basic approaches to measuring the electrical activity of a nerve cell: extracellular recording (also referred to as single-unit recording), where an electrode is placed near the nerve cell of interest to detect its activity; and intracellular recording, where the electrode is placed inside the cell.

Extracellular recordings primarily detect action potentials, the all-or-nothing changes in the potential across nerve cell membranes that convey information from one point to another in the nervous system. This sort of recording is particularly useful for detecting temporal patterns of

action potential activity and relating those patterns to stimulation by other inputs, or to specific behavioral events. Intracellular recordings can detect the smaller, graded potential changes that trigger action potentials, and thus allow a more detailed analysis of communication between neurons within a circuit. These graded triggering potentials can arise at either sensory receptors or synapses and are called receptor potentials or synaptic potentials, respectively. For the myotatic circuit, electrical activity can be measured both extracellularly and intracellularly, thus defining the functional relationships between neurons in the circuit.

The pattern of action potential activity can be measured for each element of the circuit (afferents, efferents, and interneurons) before, during, and after a stimulus. By comparing the onset, duration, and frequency of action potential activity in each cell, a functional picture of the circuit emerges. As a result of the stimulus, the sensory neuron is triggered to fire at higher frequency (i.e., more action potentials per unit time). This increase triggers a higher frequency of action potentials in both the extensor motor neurons and the interneurons. Concurrently, the inhibitory synapses made by the interneurons onto the flexor motor neurons cause the frequency of action potentials in these cells to decline. Using intracellular recording, it is possible to observe directly the potential changes underlying the synaptic connections of the myotatic reflex circuit.

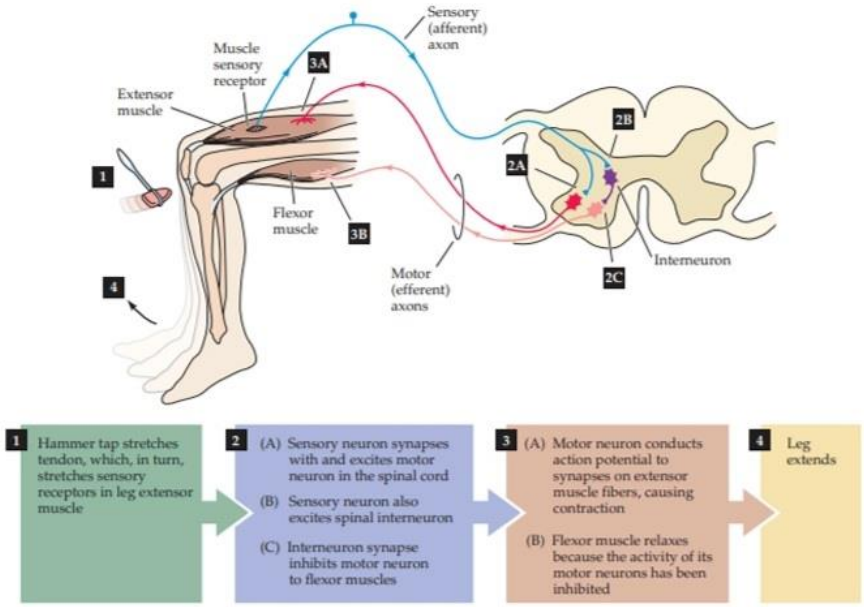



Fig 5: A simple reflex circuit, the knee-jerk response (more formally, the myotatic reflex), illustrates several points about the functional organization of neural circuits.

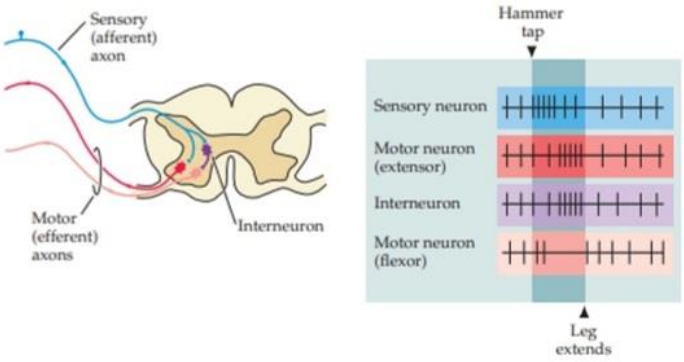



Fig 6: Relative frequency of action potentials (indicated by individual vertical lines) in different components of the myotatic reflex as the reflex pathway is activated. Notice the modulatory effect of the interneuron

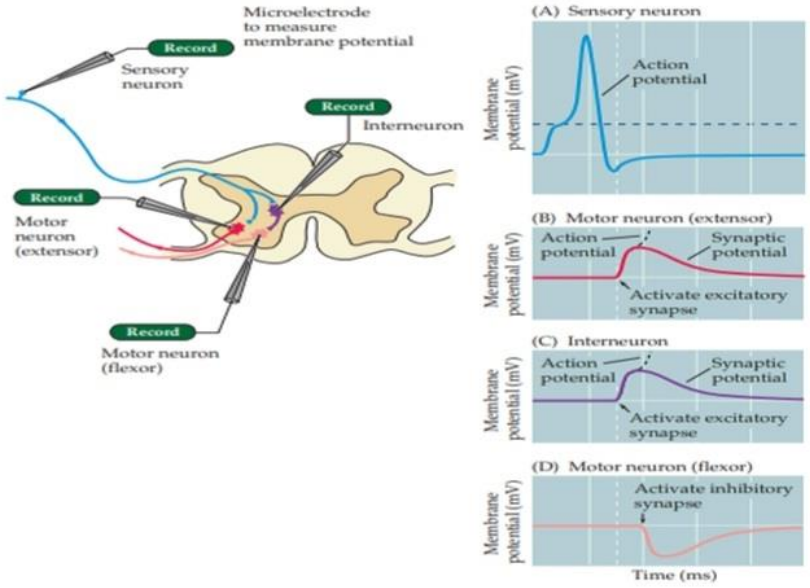



Fig 7: (A) Action potential measured in a sensory neuron. (B) Postsynaptic triggering potential recorded in an extensor motor neuron. (C) Postsynaptic triggering potential in an interneuron. (D) Postsynaptic inhibitory potential in a flexor motor neuron.

## 1.7 Overall Organization of the Human Nervous System

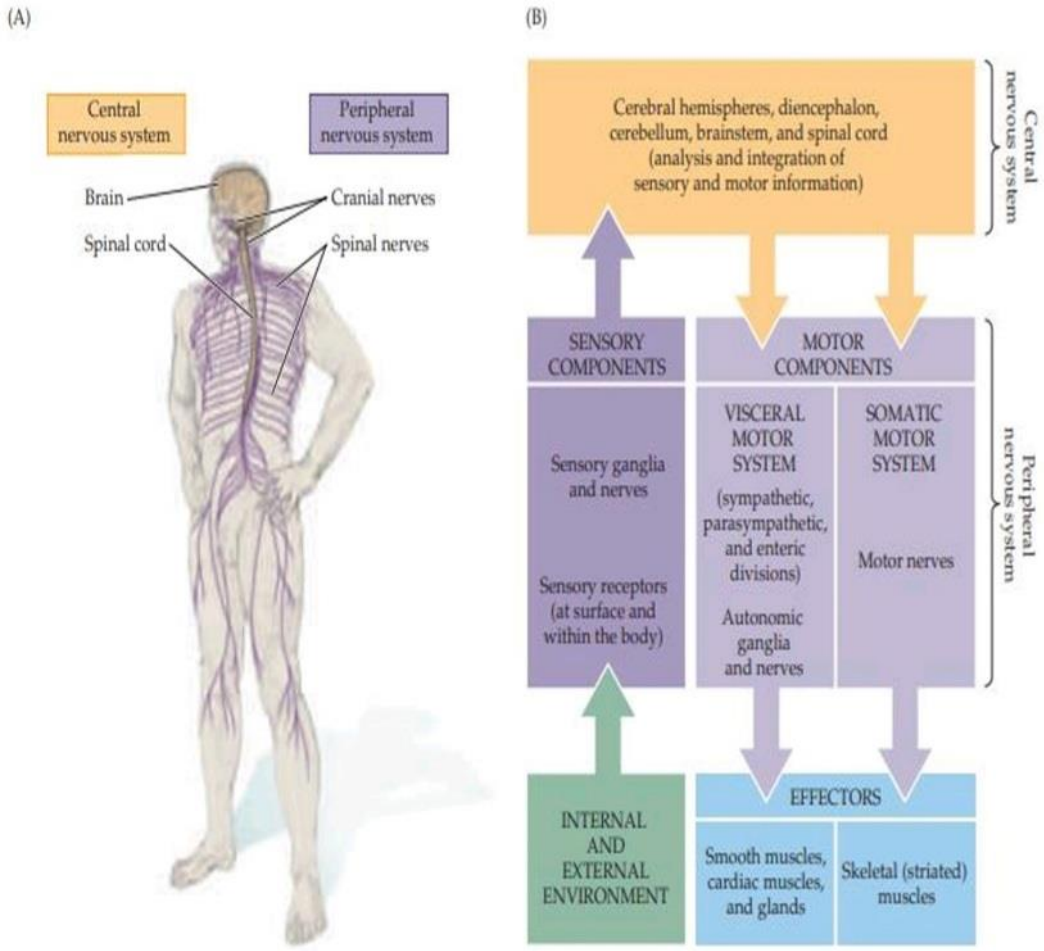



Fig 8: The major components of the nervous system and their functional relationships. (A) The CNS (brain and spinal cord) and PNS (spinal and cranial nerves). (B) Diagram of the major components of the central and peripheral nervous systems and their functional relationships. Stimuli from the environment convey information to processing circuits within the brain and spinal cord, which in turn interpret their significance and send signals to peripheral effectors that move the body and adjust the workings of its internal organs.

# CHAPTER-2

# BRAIN COMPUTER INTERFACE

Humans develop their motor skills through learning. Such learning is a gradual development process experienced by people over the years. This project is concerned with the detection of the motor learning ability of human subjects in a Brain-Computer Interface (BCI) setting. An experimental setup is arranged to examine the muscle activation by motor execution signal. The experiment includes 4-time windowed steps in a sequence. In the first window, the subject is commanded to fix her attention to an on-screen fixation cross. In time window 2, the subject is commanded to execute a motor task (such as picking up a bottle containing water). In Time-window 3, the subject executes the task and releases a motor execution (ME) signal, followed by an N400 signal. The motivation of such an experiment is to check possible learning of the sequence of muscle activation signal amplitudes in 3 distinct cases. The cases include: i) gradual increase in the volume of water in the bottle, ii ) gradual decrease in volume of water in the bottle, and iii) a specific pattern of water volumes (for example, 0.5L, 0.75L, and 1L in 3 consecutive experimental trials) in the bottle repeated over cycles. The N400 signal is found to appear approximately 250MS away from the occurrence of the MI signal in the third window, in case the subject recognizes the repeated sequence. The motivation of the above experiment is to determine whether the subject can recognize the repetition of the sequence and learn the sequence. In case, the subject learns the sequence, she will be liberating the N400 signal after a short span of the release of the ME signal. The study of the above issues largely depends on the detection of the N400 signals. The N400 signal, on the other hand, requires classification by a classifier. A SVM model is proposed to classify the learning skills and fluctuations generated in the brain lobes during the process. In this model only crisp values are given as the input and clear and output is also in the crisp form. As this model works well when there is a clear demarcation of classes , it adds a special value as it directly finds out through the classification of the N400 signal that skill is learned or not, opposed to models where interim or partial results are also obtained for specifics i.e. it eliminates any partial learning. Therein lies the novelty of this method compared to others where the degree of membership (here it is analogous to learning) rather than definite value is focused. Thus any disturbances or noises get automatically eliminated which increases the efficiency further. Computational time is also much less compared to any such contemporary method. Due to all these various properties of the proposed model, it outperforms the traditional classifiers and is the most effective method of classification for this line of work. Here the specific focus lies on the N400 signal which is an oddball signal due to its monotonic decreasing nature. The negative peak of the N400 signal decreases as the subjects learn the skill. Here the change in the amplitude is given the focus rather than the absolute magnitude of the signal.

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## 2.3 BCI-Related EEG Features

### A)Readiness Potential and Its Detection

An early indication of movement can be realised from the so-called readiness potential, Bereitschaftspotential (BP), which is the German word for readiness potential, or pre-motor potential. This is a transient signal hump which appears just before the movement around the brain motor region. This was discovered by Helmut Kornhuber and Luder Deecke at the University of Freiburg in Germany in 1964. The BP is much (10 to 100 times) smaller than the EEG alpha rhythm and it can be seen only by averaging, relating the electrical potentials to the onset of the movement. Figure 13.1 illustrates a typical BP together with the onset of voluntary hand (or finger) movement. A time–frequency–space approach, such as that in [32], may be followed to detect and characterize the BP. This method uses PARAFAC-based tensor factorization [71] to detect the BP and differentiate between left- and right-hand (or finger) movements. Detection and tracking of BP over trials is important in monitoring the rehabilitation process in humans.

### B)ERD and ERS

ERD is due to blocking of alpha activity just before and during the real or imagery (imaginary)movement. A simple measure of ERD is given as:

$$\text{ERD Level} = \frac{P(f,n) - P_{\text{ref}}(f)}{P_{\text{ref}}(f)}$$

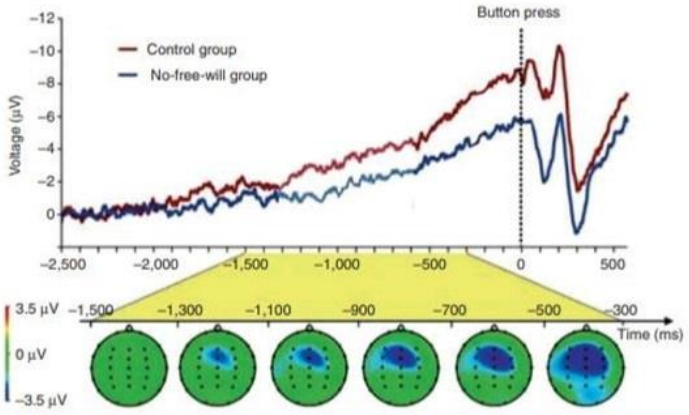



Fig 10: Readiness potential elicited around the finger movement time instant 0

where P(f,n) is the value of a signal power at a given time–frequency point of an average power map, and Pref( f ) is an average power during some reference time calculated for frequency f. This represents the level of rhythmic activity within the alpha band just before or during the movement. Any attention dramatically attenuates the alpha rhythms, while an increase in task complexity or attention results in an increased magnitude of ERD. Increased cellular excitability in thalamo-cortical systems results in a low amplitude desynchronised EEG. So ERD may be due

to the electrophysiological correlate of various activated cortical regions involved in processing sensory or cognitive information or production of motor reaction. Involvement of more neurons increases the ERD magnitude. In the BCI context, explicit learning of a movement sequence, for example, key pressing with different fingers, is accompanied by an enhancement of the ERD over the contralateral central regions. As the learning progresses and becomes more automatic the ERD decreases. The cortical mu rhythm is of particular interest in BCI, mainly because it can be modulated/translated through imagery and can be monitored via a non-invasive technique. The overall alpha band may be divided into lower and higher alphas. Lower alpha (6–10 Hz) is a response to any type of task and topographically is spread over almost all the electrodes. Higher alpha ERD, restricted to parieto-occipital areas, is found during visually presented stimulations. The level of ERD is closely linked to semantic memory processes; those with good memory show a larger ERD in the lower alpha band . In an auditory memory task, the absence of an ERD can be explained by the anatomical localization of the auditory cortex below the surface. Detection of the auditory ERD from the EEGs is often difficult.

As related to BCI, voluntary movement also results in a circumscribed desynchronization in the upper alpha and lower beta bands, localized over sensorimotor regions . The ERD starts over the contralateral rolandic region and, during the movement, becomes bilaterally symmetrical with execution of movement. It is of interest that the time course of the contralateral mu desynchronization is almost identical to brisk and slow finger movement, starting about 2 s prior to movement onset. Generally, brisk and slow finger movements have different encoding processes. Brisk movement is pre-programmed and the afferents are delivered to the muscles as bursts. On the other hand, slow movement depends on the reafferent input from kinaesthetic receptors evoked by the movement itself. Finger movement of the dominant hand is accompanied by a pronounced ERD in the ipsilateral side, whereas movement of the non-dominant finger is preceded by a less lateralized ERD . Circumscribed hand area mu ERD can be found in nearly every subject, whereas, a foot area mu ERD is hardly localised close to the primary foot area between both hemispheres. In another study with cortical electrodes, it was discovered that mu rhythms are not only selectively blocked with arm and leg movements, but also with face movement. The ECoG captures more detailed signals from smaller cortical areas than the conventional EEG-based systems. These signals also contain low-amplitude high-frequency gamma waves. Consequently, ECoG-based BCIs have better accuracy and require shorter training time than those of EEGs . In ERS, however, the amplitude enhancement is based on the cooperative or synchronisedbehaviour of a large number of neurons. In this case, the field potentials can be easily measured even using scalp electrodes. It is also interesting to know that approximately 85% of cortical neurons are excitatory, with the other 15% being inhibitory.

**C)Transient Beta Activity after the Movement**

This activity, also called post movement beta synchronization (PMBS) is another interesting robust event starting during the movement and continuing for about 600 ms. It is found after finger or foot movement over both hemispheres without any significant bilateral coherence. The frequency band may vary from subject to subject; for finger movement the range is around 16–21 Hz whereas for foot movement it is around 19–26 Hz . The PMBS has similar amplitude for brisk and slow finger movements. This is interesting since brisk and slow movements involve different neural pathways. Moreover, this activity is significantly larger with hand as compared

to finger movement . Also, larger beta oscillations with wrist as compared to finger movement can be interpreted as the change of a larger population of motor cortex neurons from an increased neural discharge during the motor act to a state of cortical disfacilitation or cortical idling . This means movement of more fingers results in a larger beta wave. Beta activity is also important in the generation of a grasp signal, since it has less overlap with other frequency components .

**D)Gamma Band Oscillations**

Oscillation of neural activity (ERS) within the gamma band (35–45 Hz) has also been of interest recently. Such activity is very obvious after visual stimuli or just before the movement task. This may act as the carrier for the alpha and lower beta oscillations, and relate to binding of sensory information and sensorimotor integration. Gamma, together with other activities in the above bands, can be observed around the same time after performing a movement task. Gamma ERS manifests itself just before the movement, whereas beta ERS occurs immediately after the event.

**E)Long Delta Activity**

Rather than other known ERS and ERD activities within alpha, beta, and gamma bands a long delta oscillation starts immediately after the finger movement and lasts for a few seconds. Although this has not been reported often in the literature, it can be a prominent feature in distinguishing between movement and non-movement states. The main task in BCI is how to exploit the behaviour of the EEGs in the above frequency bands before, during, and after the imaginary movement, or after certain brain stimulation, in generation of the control signals. The following sections address this problem.

## 2.4 Major Problems in BCI

A simple and very popular BCI system set-up is illustrated in Figure . Feature extraction and classification of the features for each particular body movement is the main objective in most of the BCI systems. As mentioned previously, the main problem in BCI is separating the control signals from the background EEG. Meanwhile, cortical connectivity, as an interesting identification of various task-related brain activities, has to be studied and exploited. Detection and evaluation of various features in different domains will then provide the control signals.

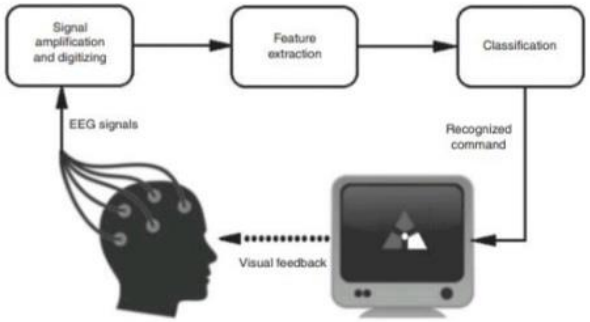



Fig 11(A): A typical BCI system using scalp EEGs when visual feedback is used

## 2.5 Pre-Processing of the EEGs

In order to have an artifact-free EEG to extract the control signals, the EEGs have to be restored from the artefacts such as eye-blinking, electrocardiograms (ECGs), and any other internal or external disturbing effects. Eye-blinking artefacts are very clear in both frontal and occipital EEG recordings. ECGs on the other hand can be seen more over the occipital electrodes. Many attempts have been made by different researchers to remove these artefacts. Most of the noise and artefacts are filtered out by the hardware provided in new EEG machines. As probably the most dominant remaining artefact, interfering eye blinks (ocular artefact; OA) generate a signal within EEGs that is of the order of ten times larger in amplitude than cortical signals, and can last between 200 and 400 ms. There have been some studies by researchers to remove OAs. Certain researchers have tried to estimate the propagation factors, as discussed in [79] based on regression techniques in both the time and frequency domains. In this attempt there is a need for a reference electrooculogram (EOG) channel during the EEG recordings. PCA and SVMs have also been utilized for this purpose [80]. In these methods the EEGs and OAs are assumed statistically uncorrelated. Adaptive filtering has also been utilized [81]. This approach has considered the EEG signals individually and, therefore, ignored the mutual information amongst the EEG channels. ICA has also been used in some approaches. In these the EEG signals are separated into their constituent independent components (ICs) and the ICs are projected back to the EEGs using the estimated separating matrix after the artefact-related ICs are manually eliminated [82]. In [83] a BSS algorithm based on second-order statistics separates the combined EEG and EOG signals into statistically independent sources. The separation is then repeated for a second time with the EOG channels inverted. The estimated ICs in both rounds are compared, and those ICs with different signs are removed. Although, due to the sign ambiguity of the BSS the results cannot be justified, it is claimed that by using this method the artefacts are considerably mitigated. As noticed, there is also a need to separate EOG channels in this method. In a robust approach the EEGs are first separated using an iterative SOBI following by SVM to effectively remove the EOG artefacts [84]. The method can also be easily extended to removal of the ECG artefacts. The proposed algorithm consists of BSS, automatic removal of the artefact ICs, and finally reprojection of the ICs to the scalp, providing artifact-free EEGs. This is depicted in Figure 13.3. Iterative SOBI as previously discussed has been effectively used to separate the ICs in the first stage. In the second stage only four features were carefully selected and used for classification of the normal brain rhythms from the EOGs. These features are as follows: Feature I: A large ratio between the peak amplitude and the variance of a signal suggests that there is an unusual value in the data. This is a typical identifier for the eye blink because it causes a large deflection on the EEG trace. This is described mathematically as:

$$f_1 = \frac{\max(|\mathbf{u}_n|)}{\sigma_n^2} \quad \text{for} \quad n = 1, \ldots, N$$

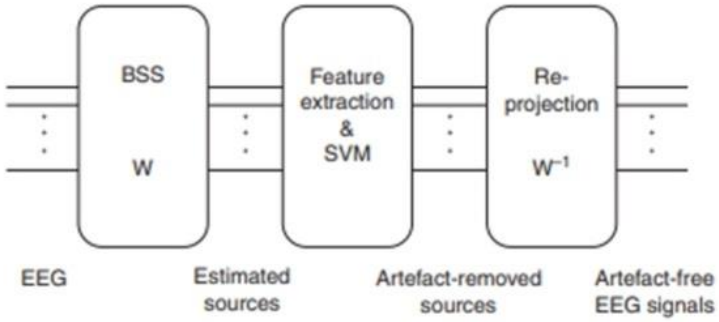



Fig 11(B) : A hybrid BSS–SVM artefact removal system

where un is one of the N ICs, max(.) is a scalar valued function that returns the maximum element in a vector, σn is the standard deviation of un, and | . | denotes absolute value. Normal EEG activity is tightly distributed about its mean. Therefore, a low ratio is expected while the eye-blink signals manifest a large value.

Feature II: This is a measure of skewness which is a third-order statistics of the data, defined as:

$$f_2 = \left| \frac{E\left\{\mathbf{u}_n^3\right\}}{\sigma_n^3} \right| \quad \text{for} \quad n = 1, \ldots, N$$

for zero mean data. The EEG containing eye blink typically has a positive or negative skewness since the eye-blinking signal has a considerably larger value for this feature. Feature III: The correlation between the ICs and the EEG signals from certain electrodes is significantly higher than those of other ICs. The electrodes with most contributed EOG are frontal electrodes FP1, FP2, F3, F4 and occipital lobe electrodes O1 and O2 (in total, six electrode signals) The reference dataset, that is, the EEG from the aforementioned electrodes, is distinct from the training and test datasets. This will make the classification more robust by introducing a measure of the spatial location of the eye-blinking artefact. Therefore, the third feature can be an average of the correlations between the ICs and the signals from these six electrodes:

$$f_3 = \frac{1}{6} \sum_{i=1}^{6} \left( \left| E\left\{ x_i^0(n) u(n+\tau) \right\} \right| \right) \quad \text{for} \quad n = 1, \ldots, N$$

where $x_i^0(n)$ are eye blinking reference signals, and i indexes each of the aforementioned electrode locations. The value of this feature will be larger for ICs containing an eye blinking artefact, since they will have a larger correlation for a particular value of τ in contrast to ICs containing normal EEG activity. Feature IV: The statistical distance between distributions of the ICs and the electrode signals which are more likely to contain EOG is used. This can be measured using the Kullback–Leibler (KL) distance defined as:

$$f_4 = \int_{-\infty}^{\infty} p(u(n)) \ln \frac{p(u(n))}{p(x_{\text{ref}})} \mathrm{d}u(n) \quad \text{for} \quad n = 1, \ldots, N$$

where p(.) denotes the pdf. When the IC contains OA the KL distance between its pdf and the pdf of the reference IC will be approximately zero, whereas the KL distance to the pdf of a normal EEG signal will be larger. An SVM with an RBF nonlinear kernel is then used to classify the ICs based on the above features. Up to 99% accuracy in detection of the EOG ICs has been reported [84]. After the artefact signals are marked, they will be set to zero. Then, all the estimated sources are re-projected to the scalp electrodes to reconstruct the artefact-free EEG signals. The same idea has been used directly for extraction of the movement-related features [85] from the EEGs. In this work it is claimed that without any long-term training the decision as to whether there is any movement for a certain finger or not can be achieved by BSS followed by a classifier. A combination of a modified genetic algorithm (GA) and an SVM classifier has been used to condition and classify the selected features.

**A)Multidimensional EEG Decomposition**

All movement-related potentials are limited in duration and in frequency. In addition, each channel contains the spatial information of the EEG data. PCA and ICA have been widely used in decomposition of the EEG multiple sensor recordings. However, an efficient decomposition of the data requires incorporation of the space, time, and frequency dimensions. Time–frequency (TF) analysis exploits variations in both time and frequency. Most of the brain signals are decomposable in the TF domain. This has been better described as sparsity of the EEG sources in the TF domain. In addition, TF domain features are much more descriptive of the neural activities. In [86], for example, the features from the subject-specific frequency bands have been determined and then classified using linear discriminant analysis(LDA).

In a more general approach the spatial information is also taken into account. This is because the majority of the events are localized in distinct brain regions. As a favourable approach, joint space–time–frequency classification of the EEGs has been studied for BCI applications. In this approach the EEG signals are measured with reference to digitally linked ears (DLE). DLE voltage can be easily found in terms of the left and right earlobes as V
DLE e = Ve − 1 2 VA1 + VA2

where VA1 and VA2 are, respectively, the left and right earlobe reference voltages. Therefore, the multivariate EEG signals are composed of the DLE signals of each electrode. The signals are multivariate since they are composed of the signals from multiple sources. A decomposition of the multivariate signals into univariate classifications has been carried out after the segments contaminated by eye blink artefacts are rejected . There are many ways to write the general class of TF distributions for classification purposes . In the above work the characteristic function (CF) M(θ,τ ) as in

$$C(t,\omega)=\frac{1}{4\pi^2}\int_{\tau=-\infty}^{\infty}\int_{0}^{2\pi}M(\theta,\tau)\mathrm{e}^{-\mathrm{j}\theta t-\mathrm{j}\tau\omega}\mathrm{d}\theta\mathrm{d}\tau$$

for a single channel EEG signal, x(t), assumed continuous time, (a discretized version can be used in practice) is defined as

$$M(\theta, \tau) = \phi(\theta, \tau) A(\theta, \tau)$$

$$A(\theta, \tau) = \int_{-\infty}^{\infty} x^* \left(u - \frac{1}{2}\tau\right) x \left(u + \frac{1}{2}\tau\right) e^{j\theta u} du$$
$$= \int_{0}^{2\pi} \hat{X}^* \left(\omega + \frac{1}{2}\theta\right) \hat{X} \left(\omega - \frac{1}{2}\theta\right) e^{j\tau\omega} d\omega$$

and X^ (ω) is the Fourier transform of x(t), which has been used for classification. This is a representative of the joint TF auto-correlation of x(t). ϕ(θ,τ ) is a kernel function which acts as a mask to enhance the regions in the TF domain so the signals to be classified are better discriminated. In [37] a binary function has been suggested as the mask. In the context of EEGs, as multi-channel data, a multivariate system can be developed. Accordingly, the multivariate ambiguity function (MAF) of such a system is defined as:

$$\mathbf{MA}(\theta, \tau) = \int_{-\infty}^{\infty} \mathbf{x} \left(t + \frac{\tau}{2}\right) \mathbf{x}^{\mathrm{H}} \left(t - \frac{\tau}{2}\right) e^{j\theta t} dt$$

where (.)H denotes conjugate transpose. This ambiguity function can also be written in a matrix form as:

$$\mathbf{MA}(\theta, \tau) = \begin{bmatrix} a_{11} & \dots & a_{1N} \\ . & . & . \\ . & . & . \\ a_{N1} & \dots & a_{NN} \end{bmatrix}$$

where

$$a_{ij} = \int_{-\infty}^{\infty} x_j^* \left(t - \frac{\tau}{2}\right) x_i \left(t + \frac{\tau}{2}\right) e^{j\theta t} dt$$

The diagonal terms are called auto-ambiguity functions and the off-diagonal terms are called cross-ambiguity functions. MAF can, therefore, be an indicator of the multivariate time–frequency–space autocorrelation of the corresponding multivariate system. The space dimension is taken into account by the cross-ambiguity functions.

**B)Space–Time–Frequency Method**

It is desirable to exploit the changes in EEG signals in time, frequency, and space (electrodes) at the same time. The disjointedness property of the brain sources may not be achievable in time, frequency or space separately due to the strong overlaps of the sources in each domain. However, in a multidimensional space the sources are more likely to be disjoint. Such a property may be exploited to separate and localize them. An early work in [89] represents this idea. The block diagram in Figure 13.4 illustrates the steps of the approach. The above concept may be studied in the framework of tensor factorization where the signal variations in all possible dimensions can be considered at the same time. The PARAFAC and Tucker methods explained in previous chapters are

the two main approaches. Here, application of PARAFAC to BCI particularly for artefact removal is discussed. Another direction in BCI research is to evaluate the cortical connectivity and phase synchronization for characterization of continuous movement. The work on this area is, however, limited. Multivariate autoregressive (MVAR) modelling followed by directed transfer functions (DTFs) and evaluation of the diagonal and off-diagonal terms has been the main approach.

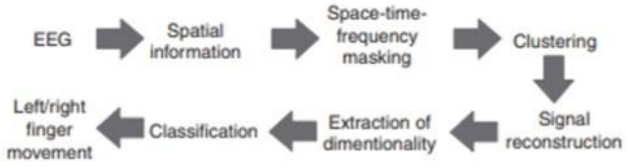



Fig 12: Classification of left/right finger movements using space–time–frequency decomposition

However, as comprehensively discussed in Chapter 8, there are other approaches for this evaluation. One application of the MVAR is discussed in a later section of this chapter. The contrast of MAF is then enhanced using a multidimensional kernel function and the powers of cross-signals (cross-correlation spectra) are used for classification [37]. Using this method (as well as MVAR) the location of the event-related sources can be tracked and effectively used in BCI.

**C)Parallel Factor Analysis**

In this approach the events are considered sparse in the space–time–frequency domain and no assumption is made on either independence or uncorrelatedness of the sources. Therefore, the main advantage of PARAFAC over PCA or ICA is that uniqueness is ensured under mild conditions, making it unnecessary to impose orthogonality or statistical independence constraints. Harshman [90] was the first researcher to suggest that PARAFAC be used for EEG decomposition. Harshman, Carol, and Chang [91] independently proposed PARAFAC in 1970. Mocks reinvented the model, naming it topographic component analysis, to analyse the ERP ¨ of channel × time × subjects [92]. The model was further developed by Field and Graupe [93]. Miwakeichi et al. eventually used PARAFAC to decompose the EEG data to its constituent space–time–frequency components [94]. In [87] PARAFAC has been used to decompose the wavelet transformed event-related EEG given by the inter-trial phase coherence. Figure 13.5 and 13.6 show, respectively, the space–time–frequency decomposition of the 15 channel EEG signals recorded during left and right index finger movement imaginations. Spectral contents, temporal profiles of the two identified factors, and the topographic mapping of EEG for the two factors are shown in these figures. Accordingly, space–time–frequency features can be evaluated and used by a suitable classifier to distinguish between the left and right finger movements (or finger movement imagination) [95]. In an experiment the I × l × K size X was formed by applying finite difference implementation of a spatial Laplacian filter [96] to 15 channels of the EEG and then transformed to the TF domain using complex Morelet's wavelets w(n,f0) as:

$$EEG_{\text{filtered}} = EEG_i(n) - \frac{1}{4}\sum_{l \in N_i} EEG_l$$

and

$$\mathbf{X}(n) = |w(n, f_0)EEG_{\text{filtered}}|^2$$

The surface Laplacian filter may be considered as a spatial highpass filter. Combining PARAFAC with another signal processing modality, such as BSS or beamforming, can be used effectively for the removal of EEG artefacts. Figure 13.7 represents the results using PARAFAC combined with beamforming [97]. In this approach the solution to the beamforming problem is used as a spatial constraint into the PARAFAC.

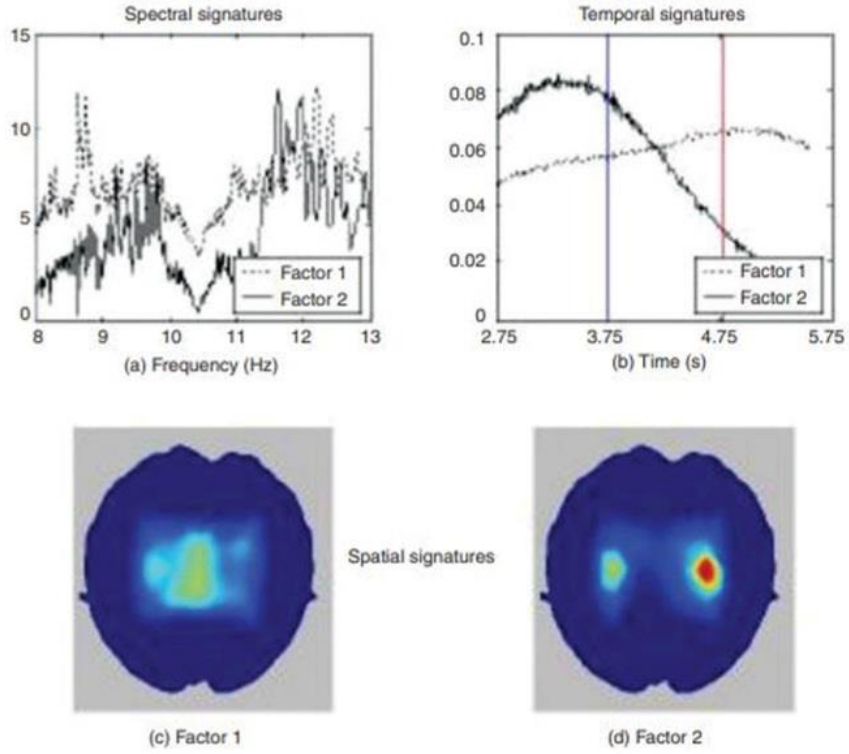



Fig 13(A) : Sample space–time–frequency decomposition of the 15 channel EEG signal recorded during left index movement imagination. The factor demonstrated with the solid line indicates a clear ERD in the contralateral hemisphere: (a) spectral contents of the two identified factors, (b) temporal signatures of the factors, the onset of preparation and execution cues are shown in light and dark patches, respectively, (c) and (d) represent topographic mapping of EEG for the two factors (see Plate 14 for the coloured version)

## 2.6 Detection and Separation of ERP Signals

Utilization of the ERP signals provides another approach in BCI design. The ERP-based BCI systems often consider a small number of electrodes to study the movement-related potentials of certain body organs. However, in recent works multichannel EEGs have been used, followed by an efficient means of source separation algorithm in order to exploit the maximum amount of information within the recorded signals.. As stated previously, these systems are initiated by introducing certain stimulations of the brain. As soon as the movement-related ERP components are classified the system can be used in the same way as in the previous sections. In single trial applications the ERP components can be tracked in order to evaluate the state of the brain during BCI.

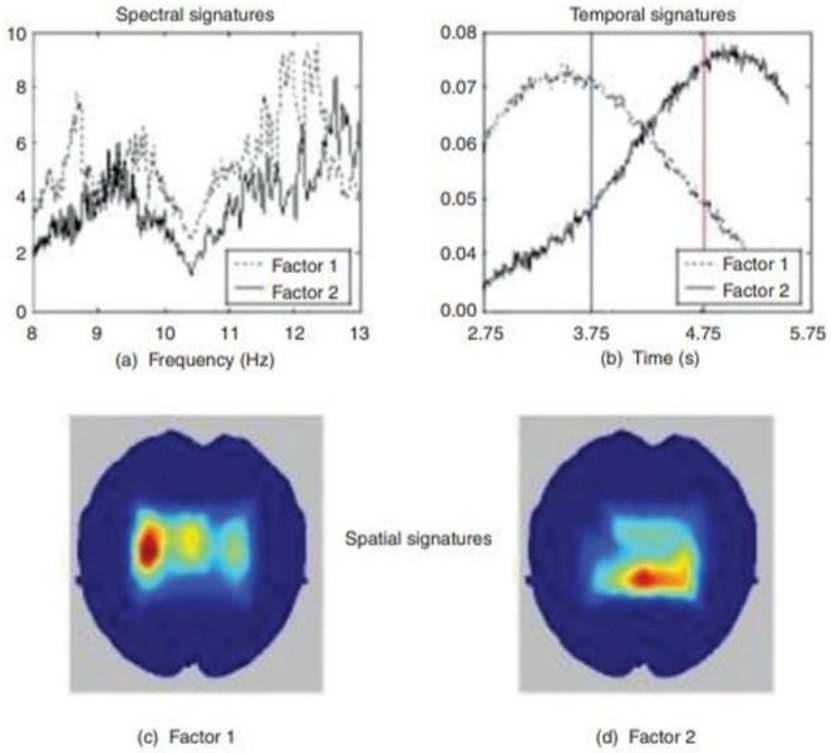



Fig 13(B): Sample space–time–frequency decomposition of the 15 channel EEG signal recorded during right index movement imagination. The factor demonstrated with the solid line indicates a clear ERD in the contralateral hemisphere: (a) spectral contents of the two identified factors, (b) temporal signatures of the factors, the onset of preparation and execution cues are shown in light and dark patches, respectively, (c) and (d) show topographic mapping of EEG for the two factors.

**A)Estimation of Cortical Connectivity**

The planning and the execution of voluntary movements are related to the pre-movement attenuation and post-movement increase in amplitude of alpha and beta rhythms in certain areas of the motor and sensory cortex [98, 99]. Also it has been found that during movement planning, two rhythmical components in the alpha frequency range, namely mu1 and mu2, play different

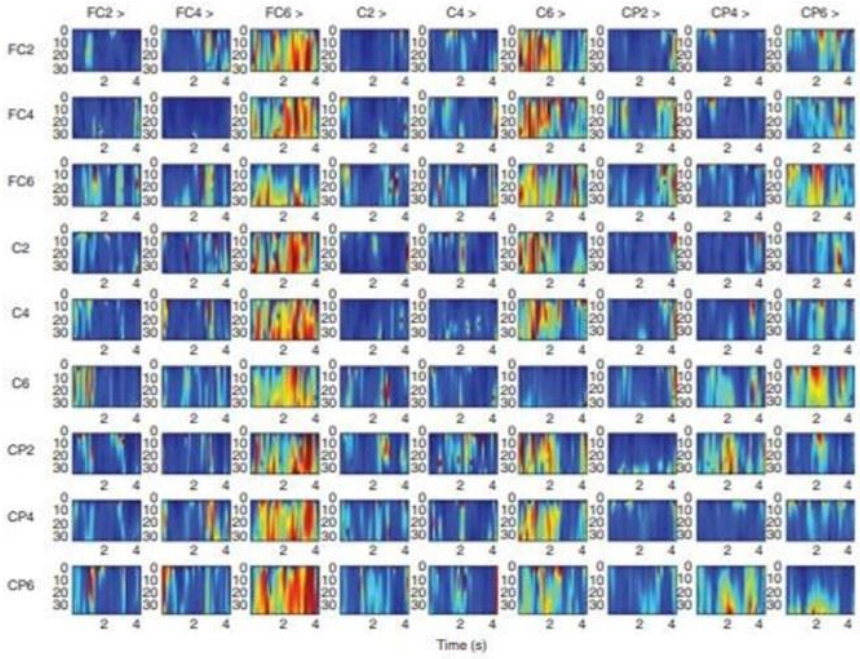



Fig 15: Illustration of source propagation from the coherency spectrum for the specified EEG channels for the left hand

where V is the variance matrix of the model noise, N is the data length for each channel, and k is the number of channels. The transitions in the DTF patterns can be illustrated for different EEG channels for left and right hands finger movements as depicted in Figure 13.8 and 13.9, respectively. The direction of the signal source movement is realised from the cross-correlations between signals, which are computed for different time shifts in the procedure of correlation R(n) matrix estimation. These time shifts are translated into phase shifts by transformation to the frequency domain. The phase dependences between channels are reflected in the transfer matrix. The DTF values express the direction of a signal component in a certain frequency (not the amount of delay) [105]. Analysis of the DTF values, however, will be difficult when the number of channels increases, resulting in an increase in the number of MVAR coefficients.

**B)Application of Common Spatial Patterns**

CSPs are probably the most effective feature selection algorithms used in BCI for feature selection and classification. In early 2000 in a 2-class BCI set-up, Ramoser et al. [52] proposed application of common spatial patterns that learned to maximize the variance of bandpass filtered EEG signals from one class while minimizing their variance from the other class. Formally, the CSP (w) minimizes the Rayleigh quotient of the spatial covariance matrices to achieve the variance imbalance between the two classes of data X1 and X2, and is defined using:

$$J(\mathbf{w}) = \frac{\mathbf{w}^{\mathrm{T}}\mathbf{X}_1^{\mathrm{T}}\mathbf{X}_1\mathbf{w}}{\mathbf{w}^{\mathrm{T}}\mathbf{X}_2^{\mathrm{T}}\mathbf{X}_2\mathbf{w}} = \frac{\mathbf{w}^{\mathrm{T}}\mathbf{C}_1\mathbf{w}}{\mathbf{w}^{\mathrm{T}}\mathbf{C}_2\mathbf{w}}$$

where T denotes transpose, Xi is the data matrix for the ith class (with the training samples as rows and the channels as columns) and Ci is the spatial covariance matrix of ith class signals, assuming a zero mean for EEG signals. As was stated in Chapter 6, the CSP problem is often solved by the generalized eigenvalue equation:

$$\mathbf{C}_1\mathbf{w} = \lambda\mathbf{C}_2\mathbf{w}$$

or C−1 2 C1w = λw. In detection and recognition of 2-class patterns in BCI the CSP is widely used as an effective approach. Most of the existing CSP-based methods exploit covariance matrices on a subject-by-subject basis so that inter-subject information is neglected. CSP and its variants have received much attention and have been one of the most efficient feature extraction methods for BCI. However, despite its straightforward mathematics, CSP overfits the data and is highly sensitive to noise. To address these shortcomings, recently it has been proposed to improve the CSP learning process with prior information in terms of regularization terms. Lotte et al. reviewed, categorized and compared 11 different regularized CSP approaches: from regularization in the estimation of the EEG covariance matrix to several different regularization methods such as composite CSP , regularized CSP with generic learning , regularized CSP with diagonal loading and invariant CSP . They applied these methods to the EEGs recorded from 17 patients and verified the superiority of CSP with Tikhonov regularization in which the optimization of J(w) is penalized by minimizing w2, hence, minimizing the influence of artefacts and outliers. Regularization of w can also be used to reduce the number of EEG channels without compromising the classification score. Farquhar et al. converted CSP into a quadratically constrained quadratic optimization problem with -norm penalty and Arvaneh et al. used l1/l2 -norm constraint. Recently, in a computationally expensive quasi -norm-based principle has been applied to achieve a sparse solution for w.

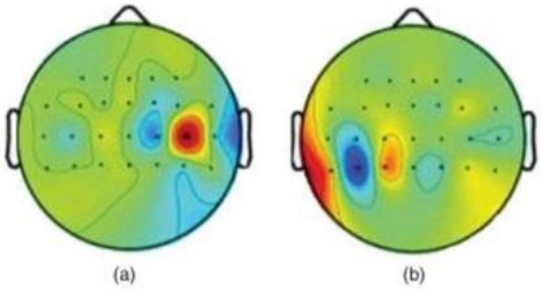



Fig 16: The results of applying CSP to classify the cortical activity of the brain for both (a) left and (b) right hand movements

**C)Multiclass Brain–Computer Interfacing**

Often a good model for performing a full BCI task or detection of various body movements becomes useful and important. This cannot be achieved if a robust multiclass classifier is not in

place. Most cases in the literature refer to two-class problems which can be solved using efficient classifiers, such as SVM. For general applications multiclass classifiers such as neural networks (NNs) have always been an option. The efficiency or computational complexity of such algorithms has usually been under question. Two new classification approaches for BCI have been introduced in . One of these classifiers is based on the distance to the Riemannian mean and the other one works in the Riemannian tangent space. Obviously, the popular classification algorithms, such as LDA, SVM, and NNs, cannot be implemented directly in the Riemannian manifold since they are based on projections into hyperplanes. In this BCI approach consider short-time segments each including Ts sample of EEG signal or trials in the form of a matrix Xi = [xt+Ti ... xt+Ti+Ts−1] ∈n×Ts which corresponds to the ith trial of real or imagined movement started at time Ti. Define Pi as the n × n sample covariance matrix as:

$$\mathbf{P}_i = \frac{1}{T_s - 1}\mathbf{X}_i\mathbf{X}_i^{\mathrm{T}}$$

**D)Cell-Cultured BCI**

Most of the information about this type of BCI comes from the public media and university websites. Researchers have built devices to interface with neural cells and entire neural networks in cultures outside animals. Neurochips powered by neuroelectronics have been developed to enable stimulating, sampling and recording from neurons directly [121]. A neurochip is a chip (integrated circuit/microprocessor) that is designed for the interaction with neuronal cells. It is made of silicon that is doped in such a way, that it contains EOSFETs (electrolyte-oxide-semiconductor field effect transistors) that can sense the electrical activity of the neurons (action potentials) in the above-standing physiological electrolyte solution. It also contains capacitors for the electrical stimulation of these cells.

frequency properties of the signals may be exploited. This eventually leads to a dissimilarity measurement denoted as d(m) between the adjacent EEG frames, where m is an integer value indexing the frame and the difference is calculated between the m and (m − 1)th (consecutive) signal frames. The boundary of the two different segments is then defined as the boundary between the m and (m − 1)th frames provided d(m) >ηT, where ηT is an empirical threshold level. An efficient segmentation is possible by highlighting and effectively exploiting the diagnostic information within the signals with the help of expert

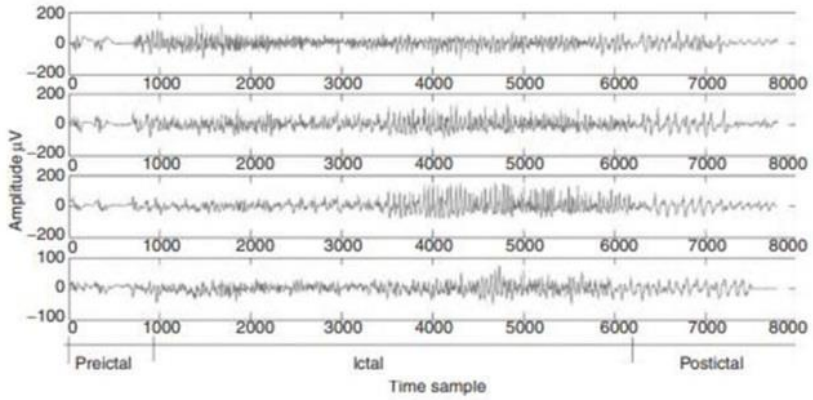



Fig 17: An EEG set of tonic-clonic seizure signals including three segments of preictal, ictal, and postictal behavior

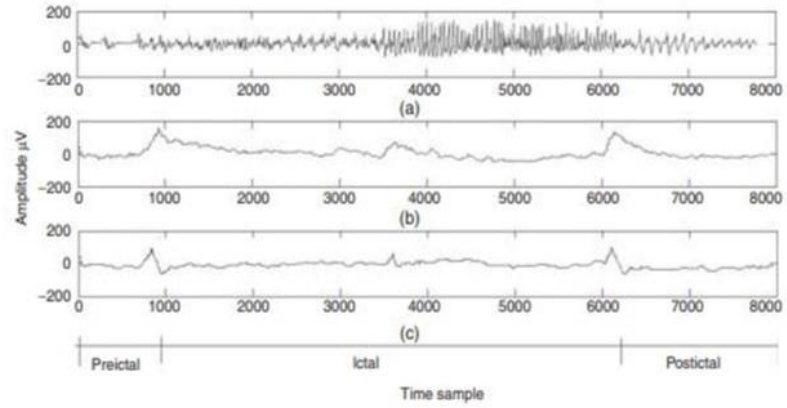



Fig 18: (a) An EEG seizure signal including preictal ictal, and postictal segments, (b) the error signal and (c) the approximate gradient of the signal, which exhibits a peak at the boundary between the segments. The number of prediction coefficients p = 12

where ∇m(.) denotes the gradient with respect to m, approximated by a first order difference operation. Figure  shows the residual and the gradient defined in equation . Finally, a fifth criterion d5(m) may be defined by using the AR-based spectrum of the signals in the same way as STFT for d3(m). The above AR model is a univariate model, that is, it models a single channel EEG. A similar criterion may be defined when multichannel EEGs are considered [12]. In such cases a multivariate AR (MVAR) model is analysed. The MVAR can also be used for characterisation and quantification of the signal propagation within the brain and is discussed in the next section. Although the above criteria can be effectively used for segmentation of EEG

# CHAPTER-4
# CLASSIFICATION AND CLUSTERING OF BRAIN SIGNALS

## 4.1 Introduction

Separating or dividing the data, objects, samples, and so on into a number of classes is called clustering. Clustering methods are unsupervised and only the number of clusters may be identified and fed into the clustering algorithm by the user. Classification of data is similar to clustering except the classifier is trained using a set of labelled data before hand. Therefore, classification of the test data is supervised since the main criterion for classification is somehow similarity of the test data to a category of labelled data. In practice, the objective of classification is to draw a boundary between two or more classes and to label them based on their measured features. In a multidimensional feature space this boundary takes the form of a separating hyperplane. The art of the work here is to find the best hyperplane, which has maximum distance from all the classes while the members of each class are as close to each other as possible. There is always an ambiguity in clustering or classification with regard to what features to use and how to either extract or enhance those features. PCA and ICA have been two very common approaches. This is an open question but in identification of ERPs, common spatial patterns (CSP) have been more common and indeed successful. Therefore, CSP is briefly reviewed in this chapter. In the context of biomedical signal processing, especially with application to EEG signals, the classification of the data in feature spaces is often required. For example, the strength, locations, and latencies of P300 subcomponents may be classified not only to detect if the subject has Alzheimer's disease but also to determine the stage of the disease. As another example, to detect whether there is a left or right finger movement in the BCI systems one needs to classify the time, frequency, and spatial features. There have been several clustering and classification techniques developed within the last forty years. Amongst them artificial neural networks (ANNs), linear discriminant analysis (LDA), hidden Markov modelling (HMM), k-mean clustering, fuzzy logic, and support vector machines (SVMs) have been very popular. These techniques have been developed and well explained in the literature [1]. The explanation of all these methods is beyond the objective.

. However, here we provide a summary of a SVM since it has been applied to EEG signals for the removal of the eye-blinking artefact [2], detection of epileptic seizures [3], detection of evoked potentials (EPs), classification of left and right finger movement in BCI [4], and many other issues related to EEGs [5]. Unlike many mathematical problems in which some form of explicit formula based on a number of inputs results in an output; in classification of data there is no model or formula of this kind. In such cases the system should be trained to be able to recognise the inputs. Many classification algorithms do not perform efficiently when

1. The number of features is high

2. There is a limited time for performing the classification
3. There is a non-uniform weighting amongst the features
4. There is a nonlinear map between the inputs and the outputs
5. The distribution of the data is not known
6. The convergence is not convex (monotonic), so it may fall into a local minimum.

There are two types of machine learning algorithms for classification of data; supervised learning and unsupervised learning. In the former case the target is known and the classifier is trained to minimise a difference between the actual output and the target values. Good examples of such classifiers are support vector machines (SVM) and the multilayered perceptrons (MLPs). In unsupervised learning, however, the classifier clusters the data into the groups having farthest distances from each other. A popular example for these classifiers is the k-means algorithm. On the other hand, to estimate the features many algorithms can be used. These algorithms are often capable of changing the dimensionality of the signals to enhance their separability. Independent component analysis (ICA) as , principal component analysis (PCA), and also tensor factorization can be used to generate/estimate the necessary features. These features can then be clustered or classified. CSP on the other hand, exploits spatial filters in order to discriminate between two classes. This approach and its extensions have become very popular in the EEG feature detection, with particular application to BCI. This method has been very successful mainly because it exploits the variations in the electrode space. In the following sections we briefly explain the most popular approaches that is, LDA, SVM and CSP for classification and the k-mean algorithm for clustering the data

## 4.2 Linear Discriminant Analysis

Linear discriminant analysis (LDA) is a method used to find a linear combination of features which characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier. In LDA it is assumed that the classes have normal distributions. Like PCA, LDA is used for both dimensionality reduction and data classification. In a two-class dataset, given the a priori probabilities for class 1 and class 2 are respectively p1 and p2, and class means and overall mean as μ1, μ2, and μ, and the class variances as cov1 and cov2.

$$\mu = p_1 \times \mu_1 + p_2 \times \mu_2$$

Then, within-class and between-class scatters are used to formulate the necessary criteria for class separability. Within-class scatter is the expected covariance of each of the classes. The scatter measures for multiclass case are computed as:

$$S_w = \sum_{j=1}^{C} p_j \times cov_j$$

where C refers to the number of classes and

$$cov_j = (\mathbf{x}_j - \mu_j)(\mathbf{x}_j - \mu_j)^T$$

Slightly differently, the between-class scatter is estimated as:

$$S_b = \frac{1}{C}\sum_{j=1}^{C}(\mu_j - \mu)(\mu_j - \mu)^T$$

Then, the objective is to find a discriminant plane such as w to maximize the ratio of between-class to within-class scatters (variances);

$$J_{LDA} = \frac{\mathbf{w}S_b\mathbf{w}^T}{\mathbf{w}S_w\mathbf{w}^T}$$

## 4.3 Support Vector Machines

Amongst all supervised classifiers, SVM is the one which performs well in the above situations [6–11]. The concept of SVM was initiated in 1979 by Vapnik [11]. To understand the concept of SVM consider a binary classification for the simple case of a two-dimensional feature space of linearly separable training samples) S = {(x1, y1) ,(x2, y2) ,...,(xm, ym)} where X∈Rd is the input vector and y∈ {−1,1} is the class label. A discriminating function could be defined as

$$f(\mathbf{x}) = \operatorname{sgn}(\langle \mathbf{w}, \mathbf{x}\rangle + b) = \begin{cases} +1 & \text{if } \mathbf{x} \text{ belongs to the first class } \bullet \\ -1 & \text{if } \mathbf{x} \text{ belongs to the second class } \circ \end{cases}$$

In this formulation w determines the orientation of a discriminant plane (or hyperplane). Clearly, there are an infinite number of possible planes that could correctly classify the training data. An optimal classifier finds the hyperplane for which the best generalising hyperplane is equidistant or farthest from each set of points. Optimal separation is achieved when there is no separation error and the distance between the closest vector and the hyperplane is maximal.

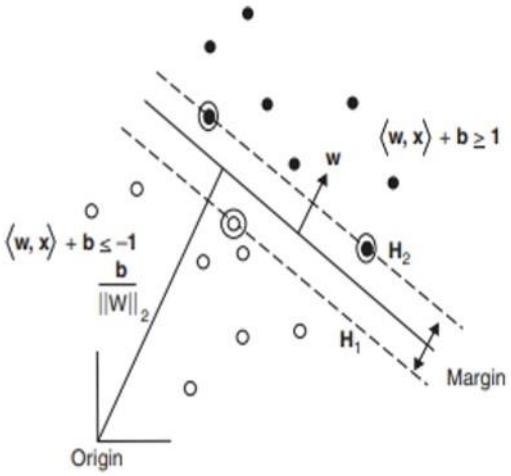



Fig 19: The SVM separating hyperplane and support vectors for the separable case

One way to find the separating hyperplane in a separable case is by constructing the so-called convex hulls of each data set. The encompassed regions are the convex hulls for the data sets. By examining the hulls one can then determine the closest two points lying on the hulls of each class (note that these do not necessarily coincide with actual data points). By constructing a

plane that is perpendicular and equivalent to these two points an optimal hyperplane should result and the classifier should be robust in some sense.

In the design of an optimal separating hyperplane often a few points, referred to as the support vectors (SVs) are utilised (e.g. the three circled data points in Figure 6.1). In places where the data are multidimensional and the number of points is high a mathematical solution rather than graphical solution will be necessary. To formulate an SVM, start with the simplest case: linear machines trained on separable data (as we shall see, the analysis for the general case; nonlinear machines trained on non-separable data results in a very similar quadratic programming problem). Again label the training data $\{x_i, y_i\}$, $i = 1,\ldots, m$, $y_i \in \{-1, 1\}$, $x_i \in R^d$.

Define the "margin" of a separating hyperplane as in and, for the linearly separable case, the algorithm simply looks for the separating hyperplane with largest margin. The approach here is to reduce the problem to a convex optimisation problem by minimising a quadratic function under linear inequality constraints. To find the plane farthest from both classes of data, the margin between the supporting canonical hyperplanes for each class is maximised. The support planes are pushed apart until they meet the closest data points, which are then deemed to be the support vectors.

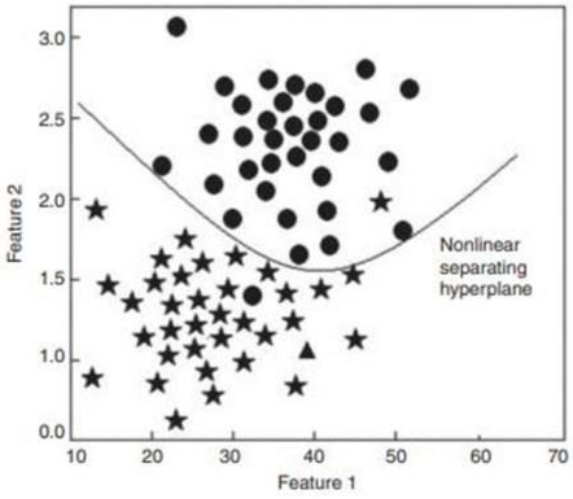



Fig 20: Nonlinear discriminant hyperplane

This means that the explicit mapping need not be known or calculated, rather the innerproduct itself is sufficient to provide the mapping. This simplifies the computational burden dramatically and, in combination with the inherent generality of SVMs, largely mitigates the dimensionality problem. Further, this means that the input feature inner-product can simply be substituted with the appropriate Kernel function to obtain the mapping whilst having no effect on the Lagrangian optimisation theory.

## 4.4 k-Means Algorithm

The k-means algorithm [17] is an effective and generally a simple clustering tool that has been widely used for many applications, such as in [18]. This algorithm divides a set of features (such as points in Figure 6.4) into k clusters. The algorithm is initialised by setting 'k' to be the assumed number of clusters. Then, the centre for each cluster, k, is identified by selecting k representative data points. The next step in the k-means clustering algorithm after initialization is to assign the remaining data points to the closest cluster centre. Mathematically, this means that each data point needs to be compared with every existing cluster centre and the minimum distance must be found. This is performed most often in the form of error checking (which will be discussed shortly). Before this though, new cluster centres are calculated. This is essentially the remaining step in k-means clustering: once clusters have been established (i.e. each data point is assigned to its closest cluster centre), the geometric centre of each cluster is recalculated. The Euclidian distance of each data point within a cluster from its centre can be calculated. It can be repeated for all other clusters, whose resulting sums can themselves be summed together. The final sum is known as the sum of within-cluster sum-of-squares. Consider the within-cluster variation (sum of squares for cluster c) error as εc:

$$\varepsilon_c = \sum_{i=1}^{n_c} d_i^2 = \sum_{i=1}^{n_c} \left\| x_i^c - \bar{x}_c \right\|_2^2 \quad \forall c$$

$$\bar{x}_c = \frac{1}{n_c} \sum_{i=1}^{n_c} x_i^c$$

$$E_k = \sum_{c=1}^{k} \varepsilon_c$$

Ek is the total error.

The overall k-means algorithm may be summarized as: 1. Initialization i. Define the number of clusters (k). ii. Designate a cluster centre (a vector quantity that is of the same dimensionality as the data) for each cluster, typically chosen from the available data points. 2. Assign each remaining data point to the closest cluster centre. That data point is now a member of that cluster. 3. Calculate the new cluster centre (the geometric average of all the members of a certain cluster). 4. Calculate the sum of within-cluster sum-of-squares. If this value has not significantly changed over a certain number of iterations, stop the iterations. Otherwise, go back to Step 2.

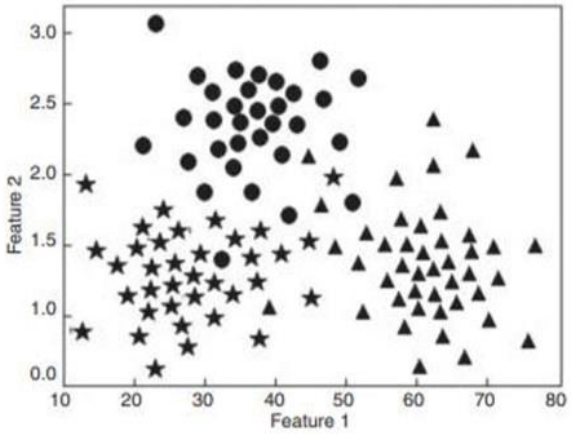



Fig 21: A two-dimensional feature space with three clusters, each with members of different shapes (circle, triangle, and asterisk)

## 4.5 Common Spatial Patterns

CSP is a popular feature extraction method for EEG classification. CSP aims at estimating spatial filters which discriminate between two classes based on their variances. The CSP (w) minimises the Rayleigh quotient of the spatial covariance matrices to achieve the variance imbalance between the two classes of data X1 and X2. Before applying the CSP the signals are bandpass filtered and centred. The CSP approach aims to find a spatial filter w∈ c such that the variance of the projected samples of one class is maximized while the other's is minimized. The CSP are estimated by the following maximization .

$$\mathbf{w}^{(CSP)} = \arg\max_{\mathbf{w}} \frac{Tr(\mathbf{w}^T\mathbf{C}_1\mathbf{w})}{Tr\left(\mathbf{w}^T\mathbf{C}_2\mathbf{w}\right)}$$

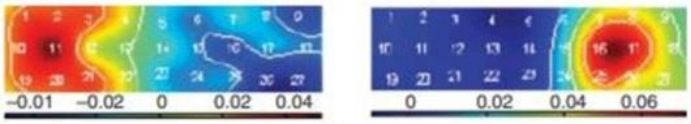
where C1 and C2 are the covariance matrices of the two clusters X1 and X2. This optimization problem can be solved (though this is not the only way) by first observing that the function J(w) remains unchanged if the filter w is rescaled, that is, J(kw) = J(w), with k as any real constant. Hence, extremizing J(w) is equivalent to extremizing wTC1w subject to the constraint wTC2w = 1 as it is always possible to find a rescaling of w such that wTC2w = 1.

$$L(\lambda, \mathrm{w}) = \mathbf{w}^T\mathbf{C}_1\mathbf{w} - \lambda(\mathbf{w}^T\mathbf{C}_2\mathbf{w} - 1)$$

This is a standard eigenvalue problem; the spatial filters extremizing equation (6.32) are then the eigenvectors of M = C−1 2 C1 which correspond to its largest and lowest eigenvalues. When using CSP, the extracted features are the logarithm of the EEG signal variance after projection onto the filters w. The eigenvalue λ measures the ratio of variances of the two classes. CSP is suitable for classification of both spectral [21] and spatial data. It is based on the fact that the power of the latent signal is larger for the first cluster than for the second cluster. Applying this approach to separation of event-related potentials (ERPs) enhances one of the classes against

the rest. This allows a better discrimination between the two classes and can be separated more easily. In early 2000 in a 2-class BCI set-up, Ramoser et al. [23] proposed application of CSP that learned to maximise the variance of bandpass filtered EEG signals from one class while minimizing their variance from the other class. Currently, CSP is widely used in BCI where the signals are changed by evoked potentials or movement.

$$\mathbf{w}_i^{(CSP)} = \arg\max_{\mathbf{w}} \frac{\left\|\mathbf{w}^T\mathbf{X}_1\right\|_1}{\left\|\mathbf{w}^T\mathbf{X}_2\right\|_1} = \arg\max_{\mathbf{w}} \frac{\sum_{k=1}^{m}\left|\mathbf{w}^T\mathbf{x}_{1k}\right|}{\sum_{l=1}^{n}\left|\mathbf{w}^T\mathbf{x}_{2l}\right|}$$




(a) (b)

Fig 22: The CSP patterns related to (a) right-hand movement and (b) left-hand movement. The EEG channels are indicated by numbers which correspond to three rows of channels (electrodes) within the central and centro-parietal regions (see Plate 3 for the coloured version).

# CHAPTER-5

# EXPERIMENT

## TITLE: ASSESSMENT OF SUBJECTIVE MOTOR LEARNING ABILITY USING ERP N400

## I. INTRODUCTION

Humans develop their motor skills through learning. Such learning is a gradual development process experienced by people over the years. This project is concerned with the detection of the motor learning ability of human subjects in a Brain-Computer Interface (BCI) setting. An experimental setup is arranged to examine the muscle activation by motor execution signal. The experiment includes 4-time windowed steps in a sequence. In the first window, the subject is commanded to fix her attention to an on-screen fixation cross. In time window 2, the subject is commanded to execute a motor task (such as picking up a bottle containing water). In Time-window 3, the subject executes the task and releases a motor execution (ME) signal, followed by an N400 signal. The motivation of such an experiment is to check possible learning of the sequence of muscle activation signal amplitudes in 3 distinct cases. The cases include: i) gradual increase in the volume of water in the bottle, ii ) gradual decrease in volume of water in the bottle, and iii) a specific pattern of water volumes (for example, 0.5L, 0.75L, and 1L in 3 consecutive experimental trials) in the bottle repeated over cycles. The N400 signal is found to appear approximately 250MS away from the occurrence of the MI signal in the third window, in case the subject recognizes the repeated sequence. The motivation of the above experiment is to determine whether the subject can recognize the repetition of the sequence and learn the sequence. In case, the subject learns the sequence, she will be liberating the N400 signal after a short span of the release of the ME signal. The study of the above issues largely depends on the detection of the N400 signals. The N400 signal, on the other hand, requires classification by a classifier. A SVM model is proposed to classify the learning skills and fluctuations generated in the brain lobes during the process. In this model only crisp values are given as the input and clear and output is also in the crisp form. As this model works well when there is a clear demarcation of classes , it adds a special value as it directly finds out through the classification of the N400 signal that skill is learned or not, opposed to models where interim or partial results are also obtained for specifics i.e. it eliminates any partial learning. Therein lies the novelty of this method compared to others where the degree of membership (here it is analogous to learning) rather than definite value is focused. Thus any disturbances or noises get automatically eliminated which increases the efficiency further. Computational time is also much less compared to any such contemporary method. Due to all these various properties of the proposed model, it outperforms the traditional classifiers and is the most

effective method of classification for this line of work. Here the specific focus lies on the N400 signal which is an oddball signal due to its monotonic decreasing nature. The negative peak of the N400 signal decreases as the subjects learn the skill. Here the change in the amplitude is given the focus rather than the absolute magnitude of the signal.

## II. System overview

In this particular section, an overall idea about the various principles and methodology used in the study of detecting motor learning skills of human subjects from the response of the brain-computer interface is provided. The Figure provides an explicit description of the overall process taking place. At first with the help of 13 Ag/AgCl2 electrodes from different brain regions: prefrontal(Fp1 and Fp2), frontal lobe(Fz, F3, F4, F7, and F8), and basal temporal lobe(A1, A2, and Aav) EEG signals are captured. The EEG signals are then analyzed with the help of software to find the activation regions of the brain. The majority of the motor response has been obtained from the frontal lobe. Through extensive review, it has been found that there is a predominance of N400 in the frontal-cortex region. All the voluntary movements are controlled by the primary cortex region and in the study. The primary concern in the paper is voluntary movements. In the experiment an appreciable amount of N400 signal has been found in this region which also proves the above-stated statement. 4 different sets of stimuli by varying the volumes of water, was provided to the brain to prepare and test the subject. Thus experiment is performed under two phases 1)Training phase 2)Testing phase. At first in four segments by increasing the volume of water the subject is trained and made habituated with the weights. In the second part in four segments but in decreasing order of volume of water the subject is trained. In the training phase in each part, a block of 20 trials is provided. In the testing phase, these 40 trials are provided in random order. The EEG signals are then filtered with the help of a band filter of order 10 and a cut-off frequency of 0.2 to5Hz. Two sets of BCI signals are specifically focused here , they are ERD/ERS and N400. All kinds of noises and physiological produced artifacts are eliminated with the help of a filter.

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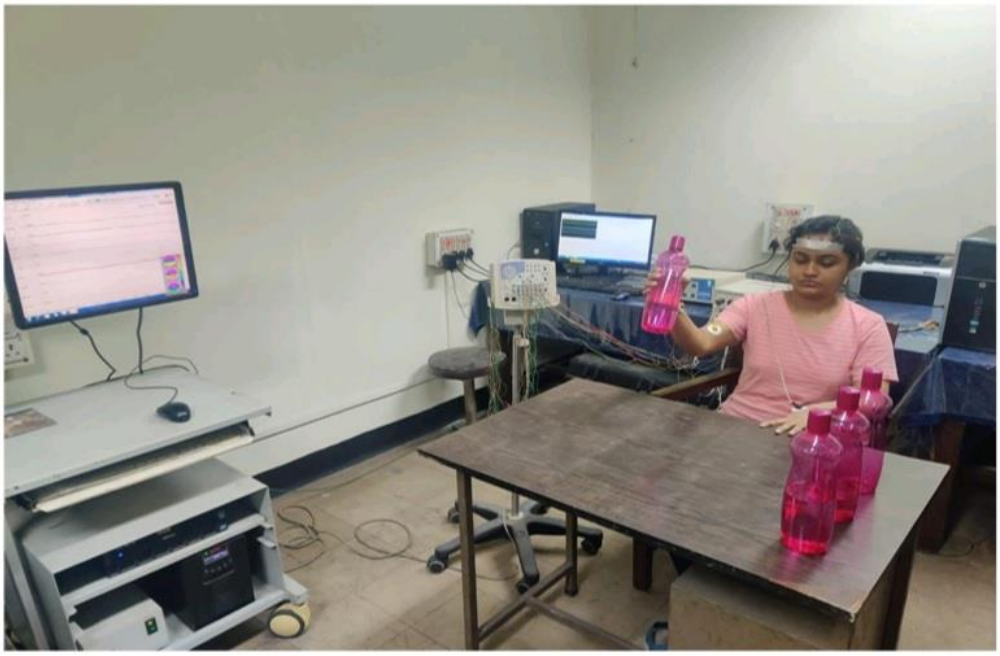

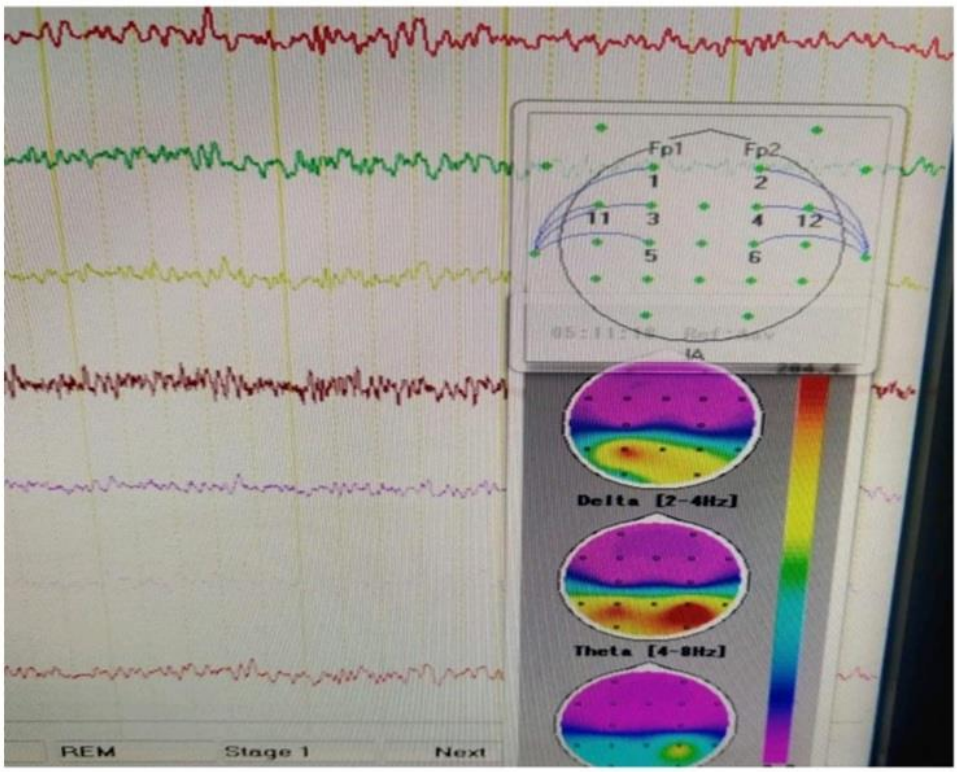
Fp1
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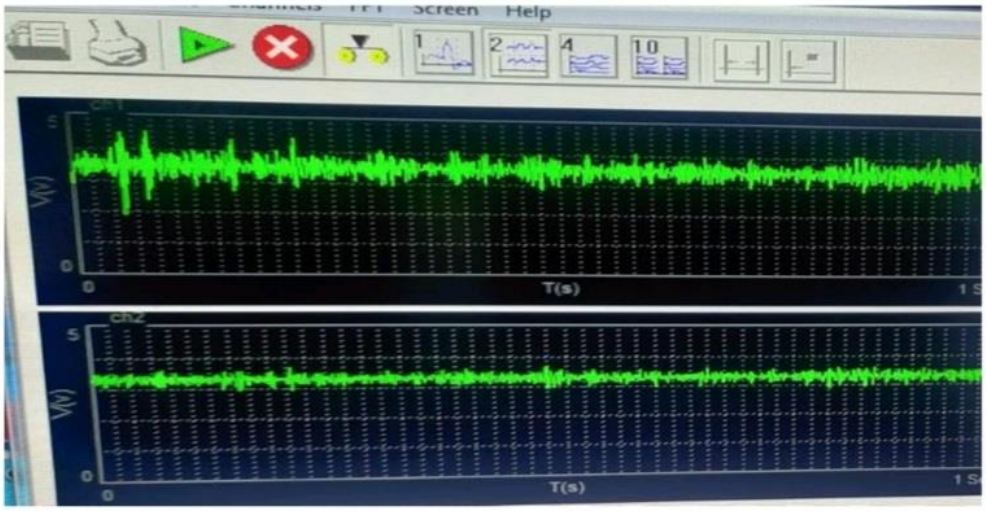
Next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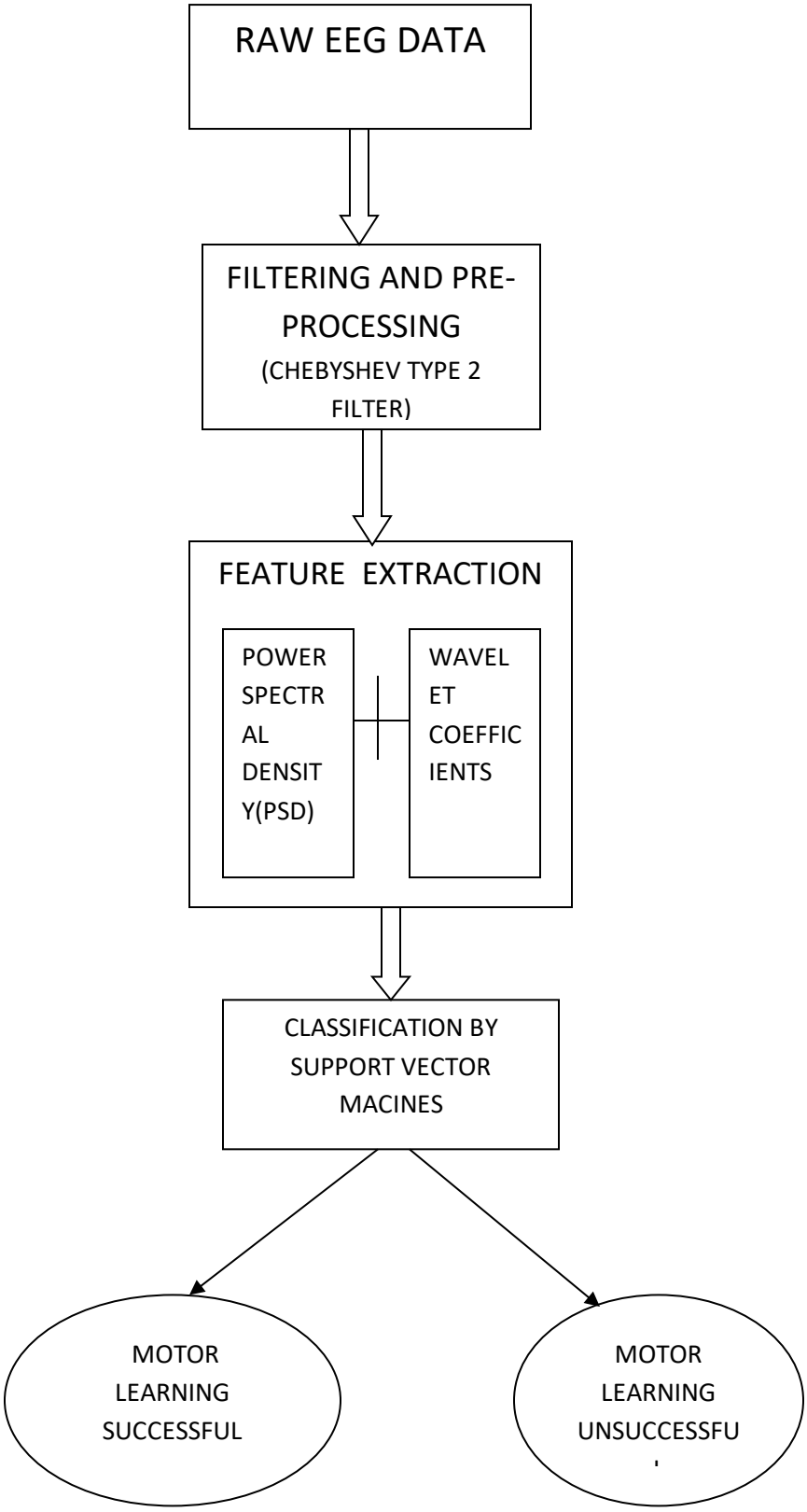
## III. SCHEMATIC DIAGRAM



# IV. PROPOSED METHODS FOR N400 DETECTION

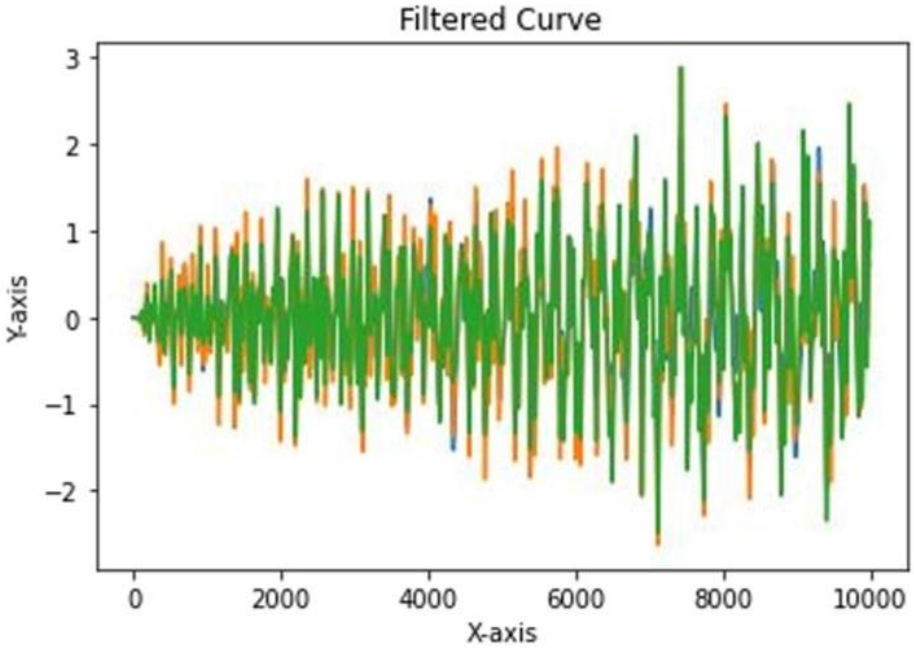
## A. Pre-processing and Filtering

In this particular work both the involvement of the cognitive and motor regions are involved. This inturn bring the ERD/ERS signals. Both the signals are highly time-locked albeit not phase-locked moreover these signals are extremely frequency band specific, therefore proper signal processing is utmost necessary to bring the absolute result. Here atfirst we are performing the filtering of the signals from each node. Then filtering of data specific to trials is also performed. Once we get the results it is averaged. Process is repeated for each trial like during 25%, 75% , 100% of the volume etc. In this particular work focus has been kept only on N400 signal

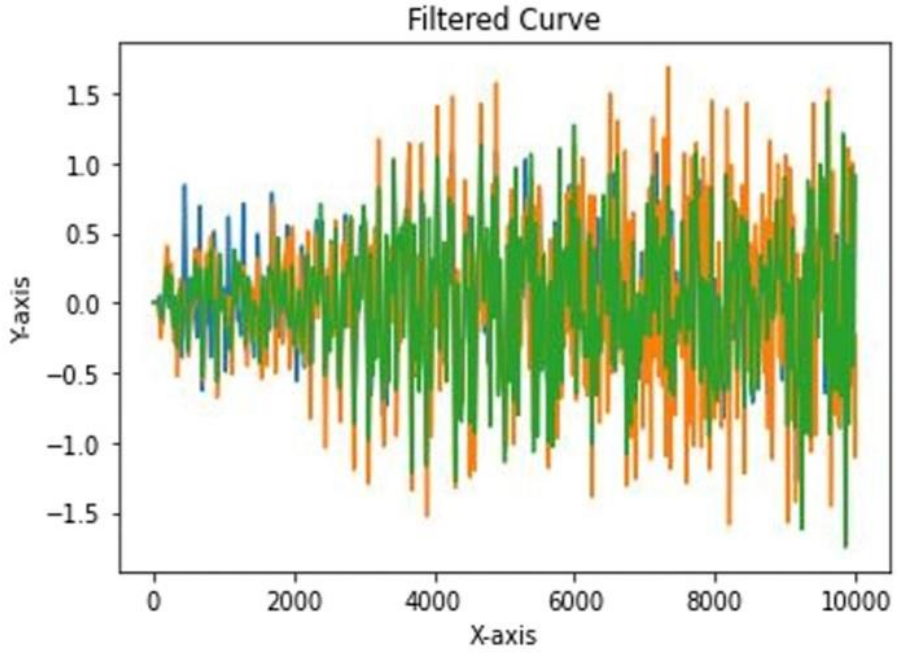
In this part EEG signals are going to be processed with the goal to recognize the BCI signals. The BCI signals that is involved here is mainly N400. It has been found that N400 dominate in the fronto-central lobe. Most of the N400 are collected from Fz, F3, F4, F7, and F8 electrodes. It has have seen during the second phase of the experiment that during the testing phase if the person is able to recognize the volumes the negativity decreases.

EEG trials are filtered at first by Chebychev filtering method to remove the different kinds of noise like common mode noise, thermal noise, power-line interfearance, undesired physiological signals and also help in removal of the physiological artefacts like shivering of the hands. These filters are taken into consideration cause

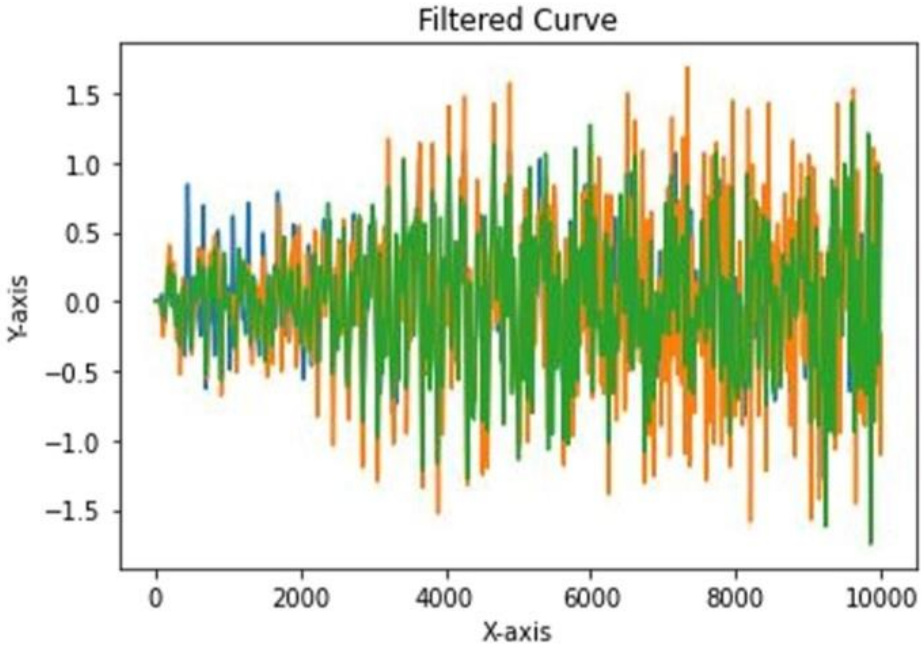
**Filtering Results:**



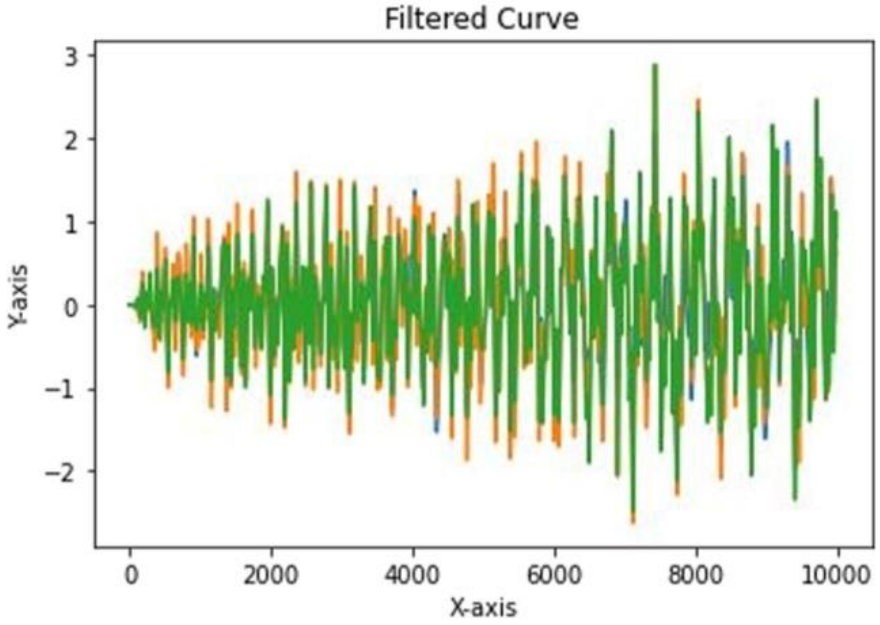

Filtered Graph for Cz electrode(Full Volume)




Filtered Graph for Cz electrode(75% Volume)




Filtered Graph for Cz electrode(50% Capacity)




Filtered Graph for Cz electrode(25% Capacity)

## B. Feature Extraction

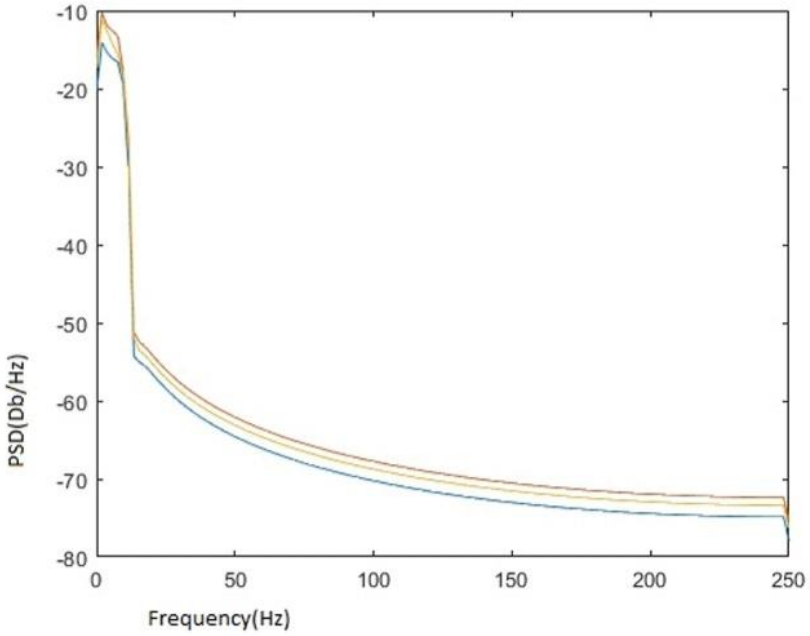
### Power spectral estimates

Spectral density methods extract information from a signal to describe the distribution of its power in the frequency domain. The power spectral density (PSD) is defined as the Fourier transform (FT) of the signal's autocorrelation function, provided that the signal is stationary in a wide sense . Thus for an EEG signal segmenting the complete time series data would be an ideal approach. The measure for power spectral estimates is commonly divided into two methods; Non-parametric method and parametric method.

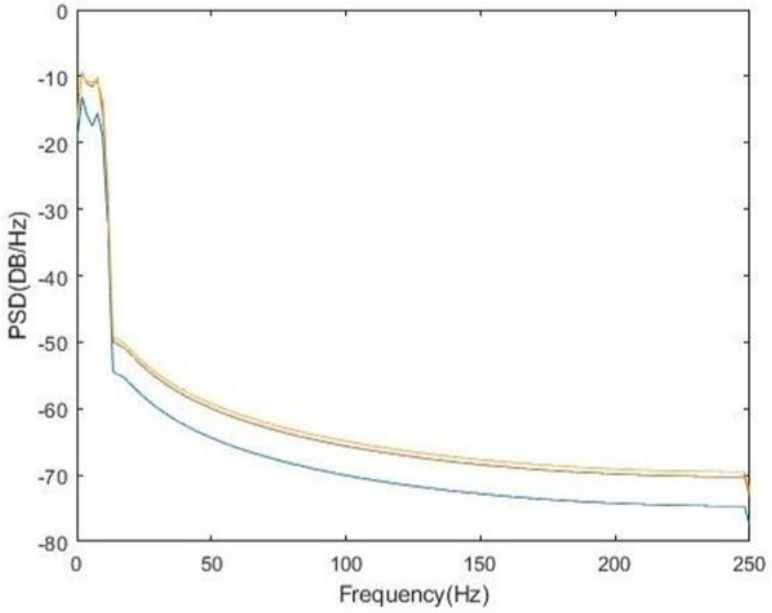
The Welch's method fall into non-parametric method which, divides the times series data into overlapping segments, computing a modified periodogram of each segment and then the PSD estimates is averaged. Let xm(n) = x(n+mN), n=0,1,…N-1, denote the mth block of the signal x ∈ C MN, with M denoting the number of blocks. Then the Welch PSD estimate is given by

$$R_x(w_k) = \sum_{m=0}^{M-1} | DFT_k(x_m) |^2$$

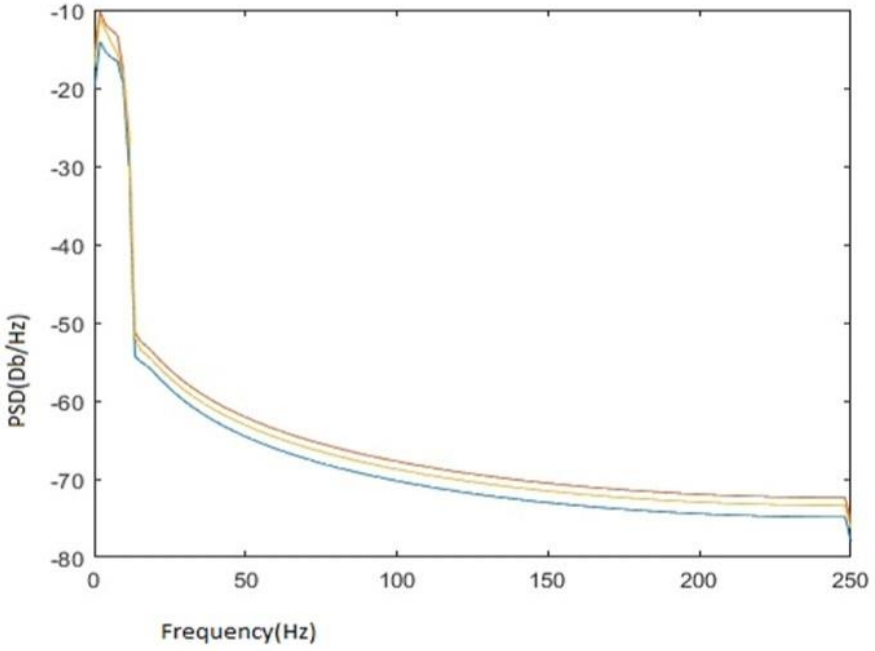
**PSD RESULTS:**



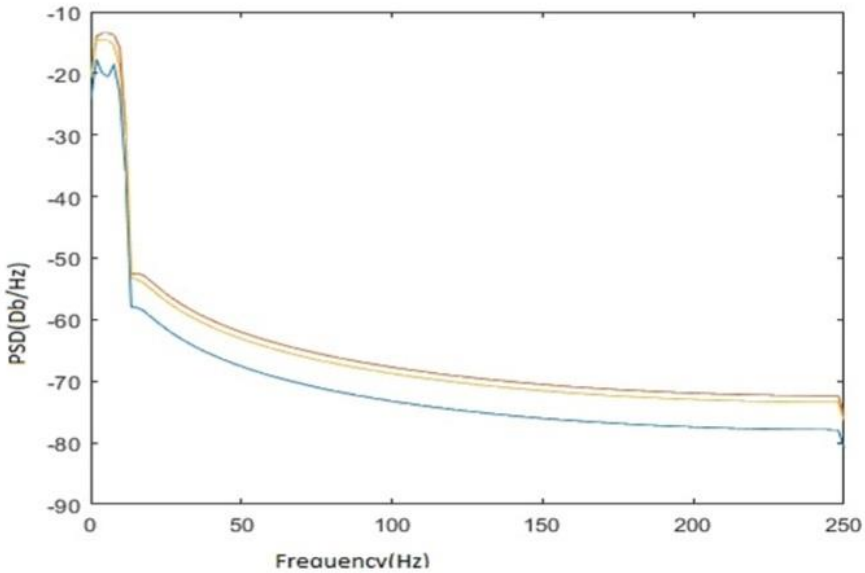

PSD Graph for Cz electrode(100% Capacity)




PSD Graph for Cz electrode(75% Capacity)




Graph for Cz electrode(50% Capacity)




PSD Graph for Cz electrode(25% Capacity)

## Wavelet Coefficient Decomposition

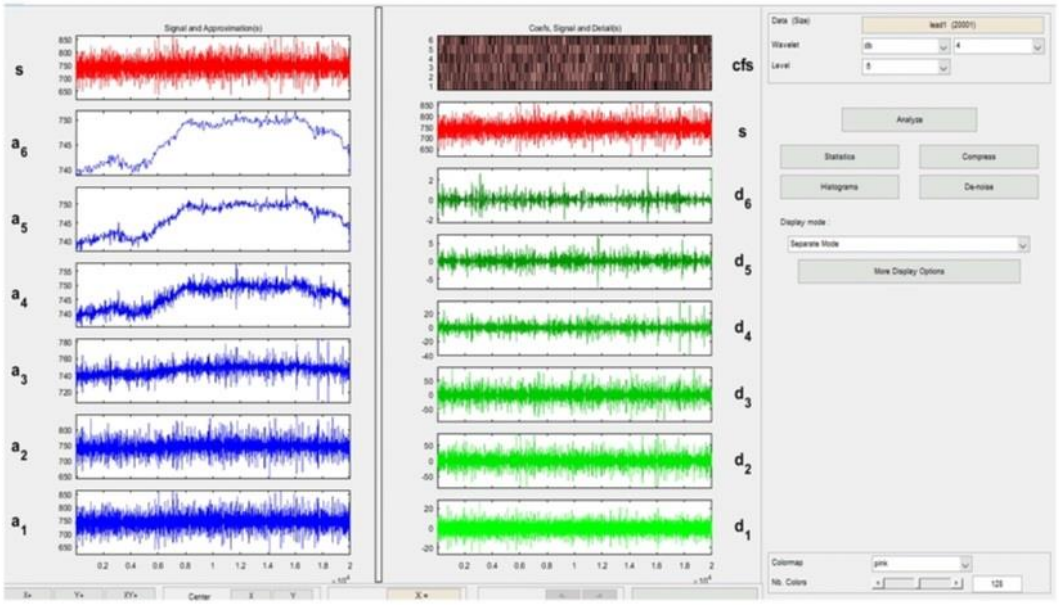
Decomposing a signal into a set of basis functions are known as wavelets. These wavelets are obtained from a single prototype wavelet called the mother wavelet by dilations, contractions and shifting, which is the fundamental approach of wavelet transformation. The mother wavelet function Ψa,b(t) is given as:

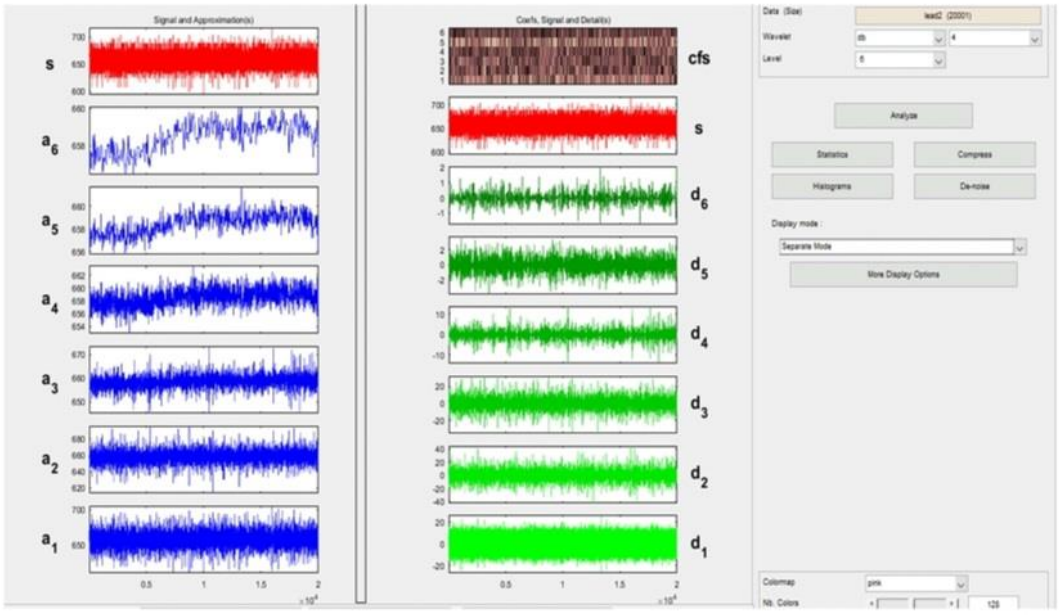
$$\Psi_{a,b}(t) = 1/\sqrt{a}\ \Psi(t\text{-}b/a)$$

R, a∈ where, a,b >0, and R is the wavelet space and 'a' and 'b' are the scaling factor and shifting factor respectively. The property of wavelet transformation to discriminate both temporal and spatial domain parameters make it an inevitable tool for feature extraction from EEG signals. The time frequency tradeoff encountered by short time Fourier transforms (STFT) is being overcome by wavelet transformations with their multi-scale approximation allowing effective localization of the signal with various spatio-temporal characteristics. Thus for a non-stationary signal like EEG, it is an effective analysis tool. The discrete wavelet transforms analyzes the signals at different resolutions by decomposing the signal into coarse approximation and detail information. Each level includes two digital filters and two down-samplers by 2. The down-sampled outputs of the first high-pass and low-pass filters provide the detail D1 and approximation A1, respectively. The first approximation is further decomposed and the process is continued, until the desired level of decomposition is obtained.

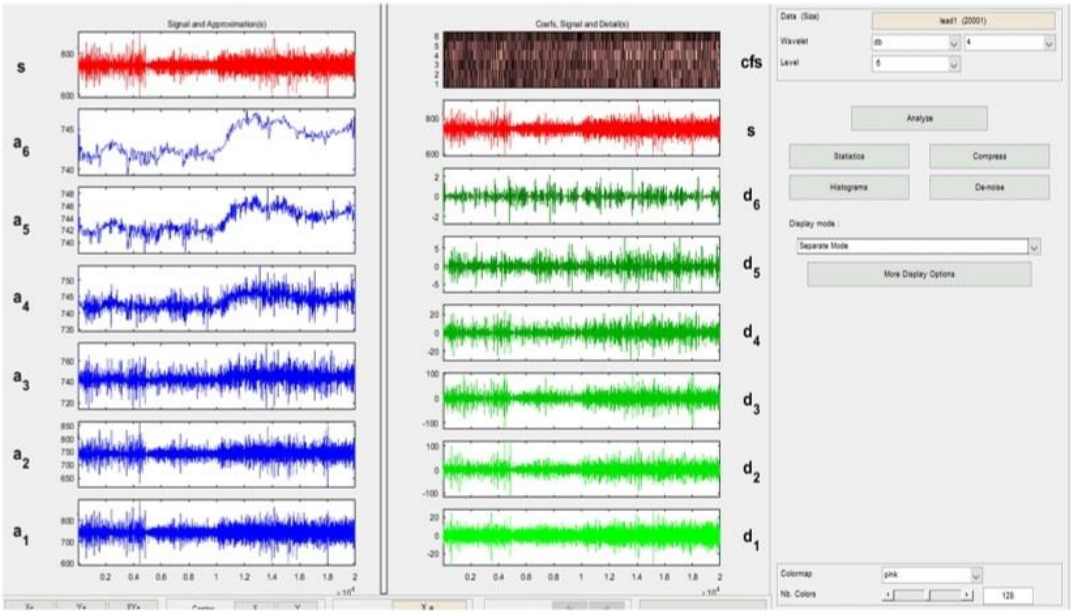
## Experimental Results:

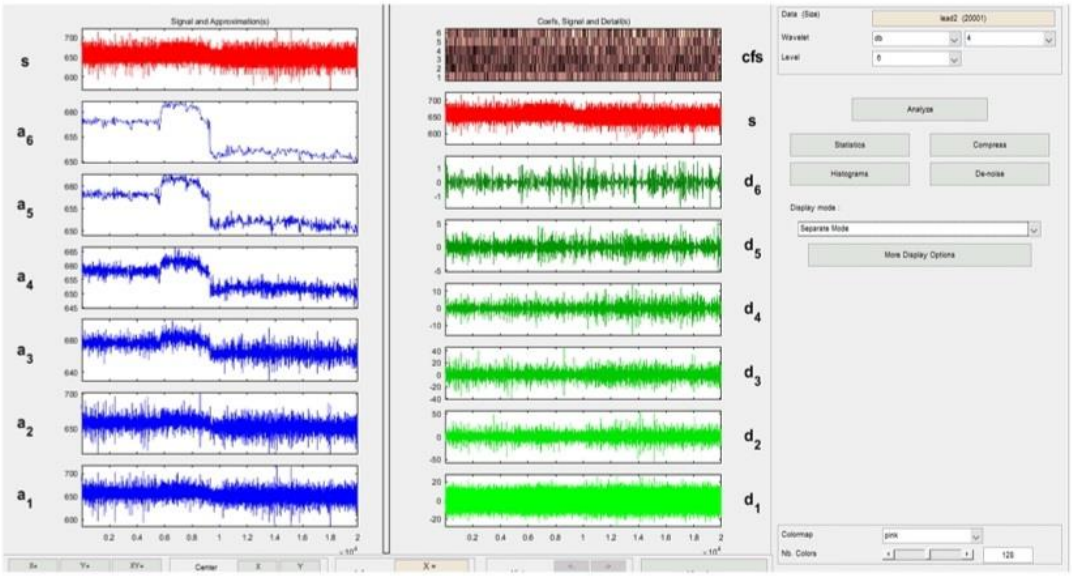
Wavelet coefficients for 100% Capacity



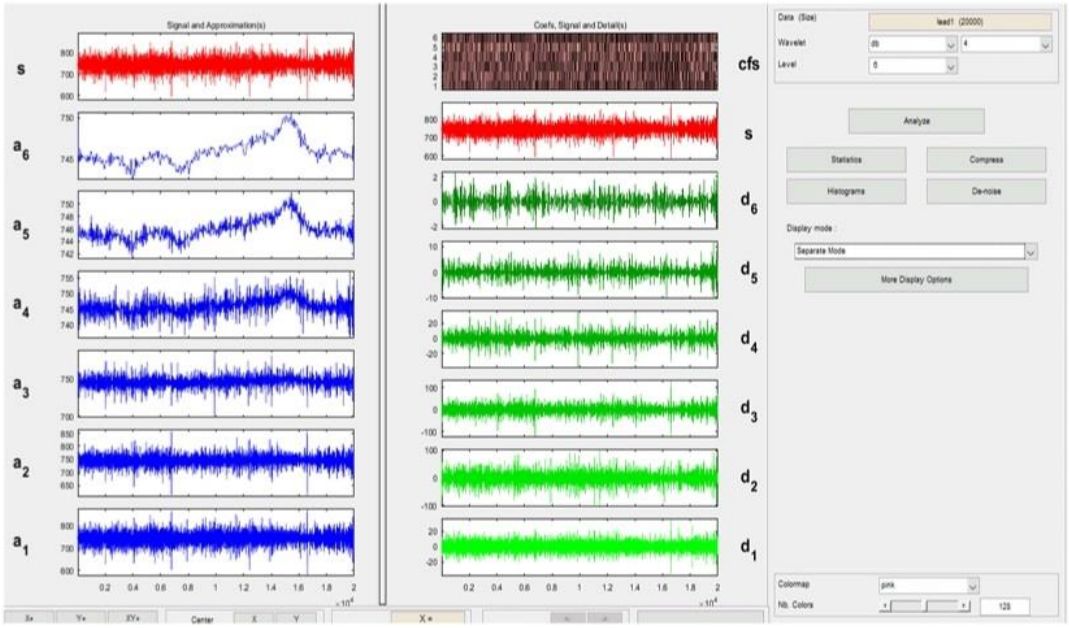



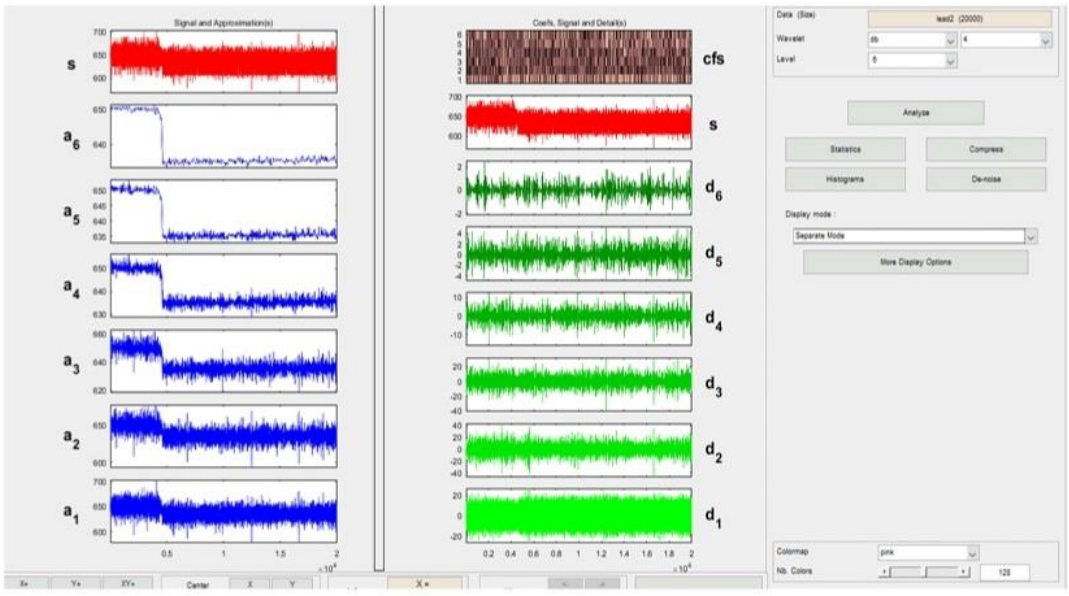
Wavelet coefficients for 50% Capacity



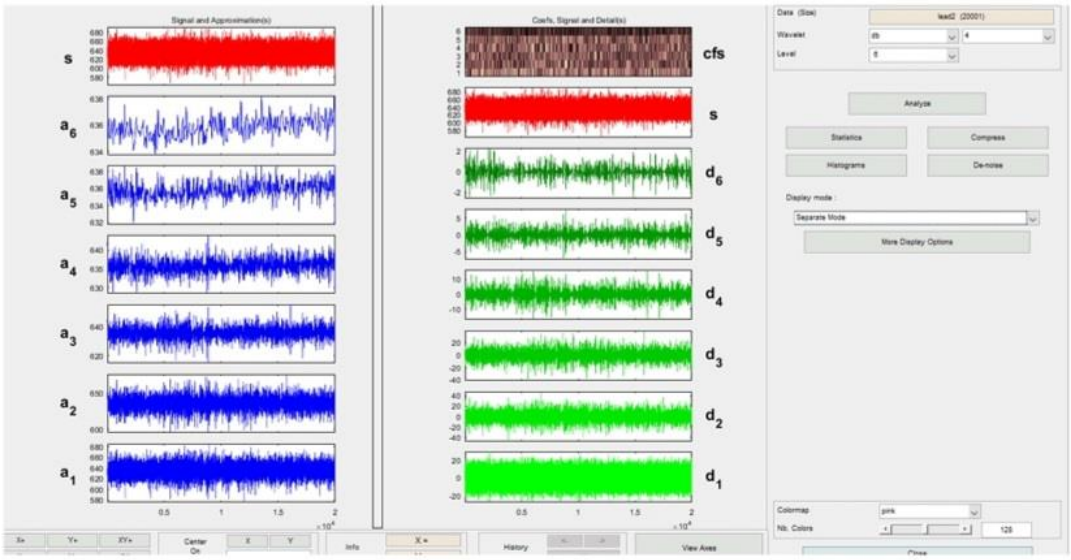



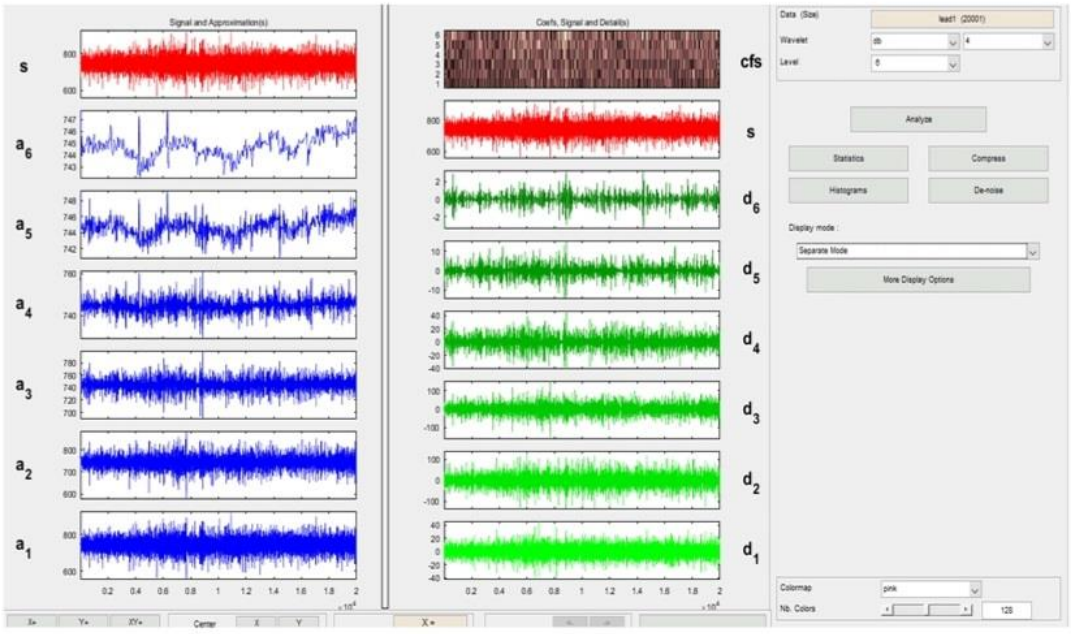
Wavelet coefficients for 25% Capacity



Wavelet Coeffiecient for 75% Capacity



## C. Classification

### Support Vector Machines

Statistical learning theory being the basis of support vector machines (SVM) provides a new approach to pattern recognition. Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. They belong to a family of generalized linear classifiers. SVM training always finds global minimum and its performance depends upon the selected kernel, where the user chooses only the error penalty parameter. The foundations of Support Vector Machines (SVM) have been developed by Vapnik and gained popularity due to many promising features such as better empirical performance. The formulation uses the Structural Risk Minimization (SRM) principle, which has been shown 1345 to be superior, to traditional Empirical Risk Minimization (ERM) principle, used by conventional neural networks. SRM minimizes an upper bound on the expected risk, where as ERM minimizes the error on the training data. If the training data is labelled as {xi , R∈ {−1, 1}, xi ∈ yi}, i = 1, …. , l, yi d . Suppose there is some hyperplane which separates the positive from the negative examples (a "separating hyperplane"). The points x which lie on the hyperplane satisfy w.x + b = 0, where w is normal to the hyperplane, b / w is the perpendicular distance from the hyperplane to the origin, and w is the Euclidean norm of w. Let d+ (d−) is the shortest distance from the separating hyperplane to the closest positive (negative) example. The "margin" of a separating hyperplane is defined as d+ + d−. The aim of linear support vector algorithm is to find the hyperplane with largest margin. Let us assume that all the training data satisfy the following constraints:

$$\boldsymbol{x}_i.\ \boldsymbol{w} + b \geq +1 \ for\ y_i = +1$$
$$\boldsymbol{x}_i.\ \boldsymbol{w} + b \leq -1 \ for\ y_i = -1$$

The above two equations can be combined to obtain the following resultant:

$$y_i(\mathbf{x}_i\ .\ \mathbf{w} + b) - 1 \geq 0 \quad \forall\ i$$

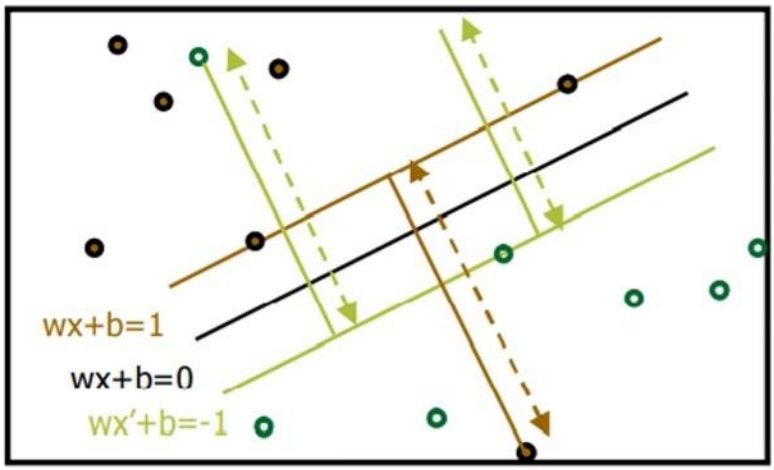
Considering the points for which the equality in (3) holds, these points lie on the hyperplane H1: xi . w + b = b / w is the−1, where w is the normal and 1 perpendicular distance from the origin. Similarly, the points for which the equality in Eq. (11) holds lie on the hyperplane H2: xi . w + b = −1. Hence d+ = d− = 1/ w and the margin is d+ + d− = 2 / w .

When the vectors are separated by non-linear region, the SVM uses a kernel function to map the data into a different space where a hyperplane can be used for separating the vectors. Certain function that corresponds to an inner product in some expanded feature space is referred to as kernel function. According to Mercer's theorem, every semi positive definite symmetric function is a kernel. Kernel function transforms the data into higher dimensional space to make it possible for the separation of the vectors (Fig. 13). The dot product becomes K (xi ,xj)= ϕ(xi) T ϕ(xj) when every data point is mapped into high-dimensional space via some transformation Φ: x → ϕ(x). The kernel matrix, Kij ≡ K (xi , xj), is a Gram matrix (a matrix of dot products (Horn, 1985)) in H (i.e. the Euclidean Space) [28]. It is necessary to choose l training

points such that the rank of the matrix Kij increases without limit as l increases. The radial basis function is given by:

$$K(x^t, x) = \exp\left[-\frac{\|x^t - x\|^2}{\sigma^2}\right]$$

which defines a spherical kernel where t x is the centre and σ, supplied by the user defines the radius.




In the literature, Support Vector Machine has been widely used on EEG data; research on EEG based emotion recognition , motor learning recognition using frequency domain features and Support Vector Machine (SVM) was done by Wang et al. (2011). Though other regression in binary results can also be used to build this model, in the literature, Support Vector Machine is the most widely used method in this field. Also, Support Vector Machine is suitable because of the sparse dataset the experiment uses. The technique used will build a prediction model based on several different brainwaves, which include frequency band less than 4Hz (i.e. Delta), frequency band between 4 and 7 Hz (i.e., Theta), frequency band 8–15 Hz (i.e., Alpha), frequency band 16–31 Hz (i.e., Beta) and frequency bigger than 32Hz (i.e., Gamma).

Electroencephalography (EEG) is a complex bioelectrical signal. Analysis of which can provide researchers with useful physiological information. In order to recognize and classify EEG signals, a pattern recognition method for optimizing the support vector machine (SVM) . The EEG signal is preprocessed, with its time domain features being extracted and directed to the SVM as feature vectors for classification and identification

**Experimental Results:**

```
accuracy: 0.9254385964912281
precision: 0.9333333333333333
recall 0.9402985074626866
              precision    recall  f1-score   support

           0       0.91      0.90      0.91        94
           1       0.93      0.94      0.94       134

    accuracy                           0.93       228
   macro avg       0.92      0.92      0.92       228
weighted avg       0.93      0.93      0.93       228


Process finished with exit code 0
```

# N400 PLOTS



FREQUENCY(Hz)

For Cz full Volume



FRQUENCY(Hz)

For Cz 25% Volume



FREQUENCY(Hz)

For Cz 75% Volume



FREQUENCY(Hz)

For Cz 50% Volume

# CHAPTER-6

# CONCLUSION

A novel approach to assess the subjective motor-learning ability by utilizing the N400 event related potential (ERP) signal acquired from the scalp of the subjects. The N400 signal is liberated from the brain of human subjects with high negative amplitude at the early stage of the motor-learning task and the negativity of the amplitude is reduced after the completion of the motor learning process. The experiment is conducted to execute a motor learning task by picking up a bottle of water containing different volumes such as 0.25 L, 0.5 L, 0.75 L, and 1 L with a specific pattern repeated over cycles. The novelty of the research lies to classify the learning ability of subjects in 3 distinct levels (like High, Medium, and Low). Another important aspect of the present research is to determine the subjective abnormality in memory learning tasks by analyzing the repetition effect of the N400 signal. The Friedman statistical test is performed to confirm the superiority of the proposed technique with other competitive techniques at a 95% confidence level.

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