Brain Signal Analysis For Classification Of Touch-Induced Affective Emotion

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

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The forgoing thesis is hereby approved as a creditable study of an engineering subject carried out and presented in a manner satisfactory to warrant its acceptance as a prerequisite to the degree for which it has been submitted. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn therein but approve the thesis only for the purpose for which it is submitted.

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DECLARATION OF ORIGINALITY AND COMPLIANCEOF 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 accordancewith 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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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPER 1

INTRODUCTION

Brain computer interfacing is a new domain of science which combines the field of neuroscience, machine learning, signal processing and electronics to solve neural problems and study brain activity for different tasks.

First, human brain is activated giving any kind of stimulus, be it audio stimulus (hearing any type of sound), visual stimulus (showing image or video), olfactory stimulus or motor imagery task. Then the brain signal is recorded invasively (micro electrode array or ECoG) or non-invasively (EEG, fNIR). The next process is signal acquisition where the raw signal is sampled and converted to digital numerical value for computer and ADC and display. In this stage band pass filtering is done to get the signals only of desired frequency band. Next, in the pre-processing stage, artefacts are removed and important features are extracted for further study. Then machine learning algorithms are used for pattern recognition, mapping etc. In this step, it generates a control signal depending on the patterns received in the input. This control signal results change in functions, it helps to move a mind-controlled wheelchair or a prosthetic arm. The user can feel the changes in environment by the sensors and these data act as a feedback to human brain for further improvement and modifications.

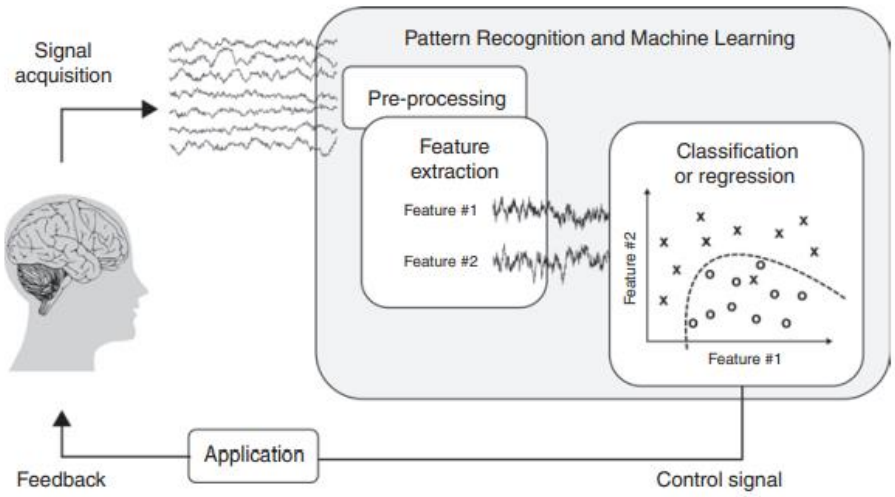


Figure 1 : Basic components of BCI

Nowadays, BCI is exploring new applications in medical field. It helps In sensory restoration. BCI based cochlear implants are developed for deaf and visual implants for blinds. In case of cochlear implants, a signal processor is placed outside the ear which implements feature extraction and signal processing of the sound wave signal received by a microphone. The sound signals are decomposed into frequency components and transmitted by a external transmitter. This transmitter delivers the sound signal to a receiver that is placed inside the brain, in the form of radio frequency. Then the received signal is converted to electrical pulses which is delivered to the nerve fibres via electrode arrays and stimulate the auditory nerves.

BCI is also used in motor restoration of stroke persons and paralyzed individuals. Also it is used to control upper limb prosthesis.

Stimulating the deep region of human brain is used to cure Parkinson's decease. Study of brain signal for different stimulus can be used to detect psychological disorders like depression.

CHAPTER 2

ABSTRACT

This thesis paper introduces a novel approach to categorize the hemodynamic response of subjects due to arousal of touch induced affection classes such as Respect, Love, Fondness and Devotion using a TSK-based Type-2 Fuzzy classifier. The main contribution of the paper is to design the novel TSK-based Interval Type-2 Fuzzy classifier to classify the finer changes in affective emotions using the hemodynamic response of a subject, when she comes in contact with her mother, spouse, child and also conveys her prayer to a model/sculpture of God by holding it with her palms. Experiments undertaken reveal that the brain activation patterns vary in different sub-regions over distinct time-windows for individual emotions. Relative performance analysis and statistical validation confirm the superiority of the proposed TSK-based Interval Type-2 Fuzzy classifier. Moreover, the proposed scheme has successfully been applied for assessing subjective sensitivity of healthy as well as psychiatric disordered people.

CHAPTER 3

THEORY AND BASIC KONWLEDGE

I) BIOMEDICAL SIGNALS

Biological potential is produced at a cellular stage. The electrochemical activity of excited cells is the cause of the bio potential. Inside the cell there is an ionic conductor which is separated from surrounding by a semipermeable membrane. This membrane is semipermeable and filters ion selectively. As a result some ions are able to bypass in the membrane without any interruption whereas rest of the ions cannot pass.

Cell is the fundamental component of muscular, nervous and glandular tissue. In general, cells have two types of potential: i) when they are stimulated they have **Active Potential**, ii) when they are at rest they have **Resting Potential**.

- **Resting Potential-** The body fluid that surrounds the cells contain ions (Na^+, K^+, Cl^-) which helps to conduct the electrical potential. The semipermeable cell membrane only allows the flow of potassium ions potassium ions (K^+) through it but stops sodium ions (Na^+) even if they have high concentration. This results high concentration of ions of sodium outside the cell and high concentration of ions of potassium inside the cell. As sodium ion is more positive compared to potassium ion, the inner surface of the cell is negative compared to outer surface. This unequal charge distribution results an electric potential across the cell membrane which is called Resting Potential. The amount of internal resting potential is -90 mV with respect to the outer surface of cell membrane. In this condition the cell is called **Polarized**.
- **Active Potential**- When the cell is stimulated or excited, positive ions from outside the cell starts to flow inside the cell resulting outer surface of the cell membrane negative with respect to inner surface. As a result, the cell potential becomes 20 mV. In this condition the cell is **De-polarized**.

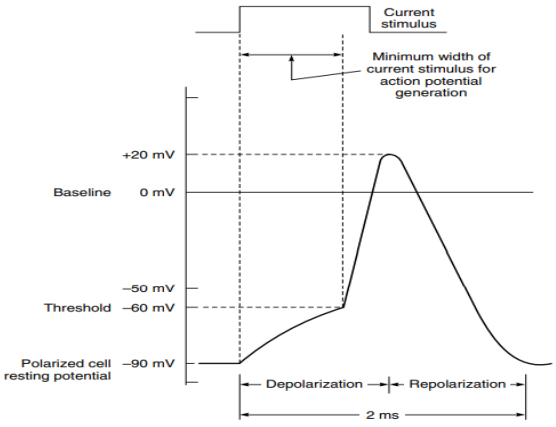


Figure 2: Cell potential waveform

- **Stimulus Threshold** – There is a minimum value of stimulus that should be applied to depolarize a cell otherwise no action potential will be generated. This minimum value of stimulus is called Stimulus Threshold.
- **Refractory Period** – After stimulation, the cell takes a period of time to get back its pre-stimulus phase. As energy is generated during action potential due to metabolisms in the cell and this metabolism requires time to complete. The total time is referred as Refractory Period.

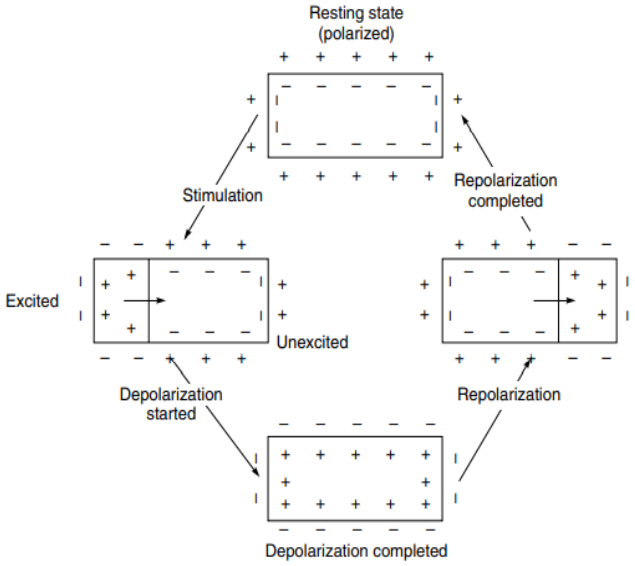


Figure 3: Depolarization and repolarization of a cell

Charges from excited cells migrate to unexcited cell areas through the body fluids and results an electric current. The flow of electric current produces potential difference inside and outside the body. These potential differences can be measured placing electrodes at any two part of the body surface. These potential differences play important role for diagnosis and therapy.

The recording of electrical signals that represent the cardiac function is known as Electrocardiography (ECG).

Electroencephalography (EEG) is the recording of electrical activity related to the function of the brain.

Electromyography (EMG) is the recording of electrical activity that is produced by the skeletal muscles.

Electrooculography is the technique to record corneo- retinal resting potential.

Electroretinography is the technique to record electrical activity generated by cells in retina.

II) BASIC NEUROSCIENCE

Neuron is the primary computing part of the nervous system. As the connections between neurons are of plastic nature, it allows the brain network to adopt new inputs when circumstances change.

There is high concentration of sodium, calcium, chloride ions in the outer part of the neuron membrane. Similarly, high concentration of potassium ions and anions are in the inner side of neurone membrane. The lipid bi-layer membrane of neuron only allows selective ions to flow inside. The resting potential across the neuron membrane is -70 mV.

When a neuron is stimulated or excited by other neurons then there is a sudden rise of Na^+ inside the neuron cell membrane. So at the membrane, potential rises and after that, concentration of K^+ ions start increasing and the potential drops. This quick up down of membrane voltage is called active potential.

The neuron is made of soma which is actually a cell body. The Soma is connected to dendrites having several branches. The single branch is axon. Function of axon is to convey the output spike to other adjacent neurons. Many axons are covered by a white sheath. This is called myelin which increases the propagation speed of spike for long path. The axons with myelin sheath, connecting different brain regions are known as white matter. On the other hand, the regions containing the cell bodies are known as grey matter.

The connection between two neurons is known as Synapses which can be electrical but generally chemical in nature and play an important role in communication. A synapse is the gap between the axon of one neuron (called the presynaptic neuron) and a dendrite (or soma) of another neuron (called the postsynaptic neuron). When a presynaptic neuron generates an active potential, it results the release of neurotransmitter ions into synaptic cleft. Neurotransmitters are chemical natured and are connected to ionic channels, that are receptors, on the postsynaptic neuron, making the channels. As a result, the local diaphragm voltage of the postsynaptic cells experience influence.

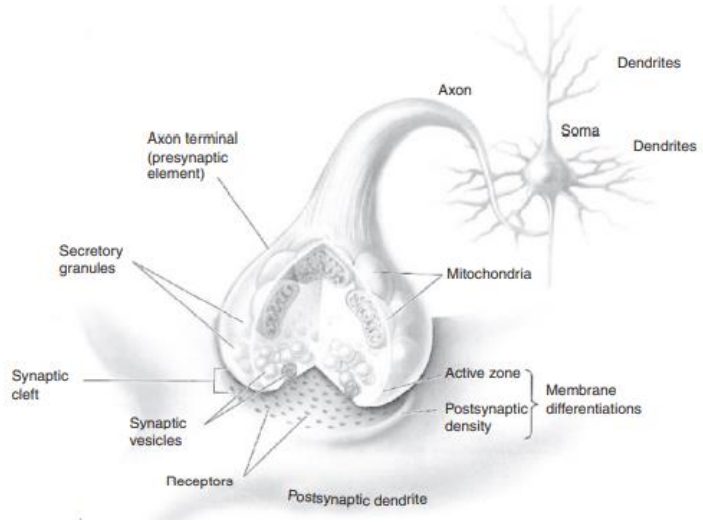


Figure 4: Dendrites, soma, axon, and synapse

Synapses can be two types-excitatory or inhibitory.

- Excitatory synapses- there is brief increase in neighbourhood membrane of cell voltage in postsynaptic cell. This grow in voltage is termed as an **excitatory postsynaptic potential (EPSP)**. EPSPs contribute to greater probability of a spike firing by postsynaptic cell.
- Inhibitory synapses - it results inhibitory postsynaptic potentials (IPSPs).IPSPs temporarily cut down localized membrane voltage of postsynaptic cell.

  A neuron is termed as excitatory /inhibitory depending on nature of synapse it develops with postsynaptic neurons. A particular one can built one unique synapse. So, if excitatory neuron demands to stimulate a second one, first former need to excite the “interneuron”. Later this excited interneuron stimulates the desired neuron.

When a neuron is excited with strong inputs from its synapses, its membrane potential crosses a neuron-specific the threshold, generating a spike. This phenomenon turns a neuron into a hybrid AD device: digital inputs 0 and 1 are expressed as analog changes of localized cell membrane voltage and addition of these changes appear generally at soma. If the addition of changes at the soma crosses the cut off value, a spike is generated. This threshold model is a useful distraction in neuro modelling and ANN.

Synaptic Plasticity

The most complex thing in case of adaptive nature of brain is the potentiality of neurons in changing the strength of neural connections through synaptic plasticity. There are various types of synaptic plasticity that have been found from experiments, they are-long-term potentiation (LTP) and long-term depression (LTD). For both cases, the changes in synaptic plasticity last for hours or even days. In case of spike timing dependent plasticity (STDP), the polarity of synaptic change is determined by comparative timing of input as well as output spikes. In case of depression (short term), the plasticity is quick but temporary.

LTP- It is major synaptic plasticity. Correlated firing of the two neurons increases the strength of a synaptic connection between two neurons. If a neuron named as A causes neuron B for fire, the connection strength between A and B must be grow. LTP is generally observed in the hippocampus and the neo-cortex.

LTD- In this case, there is a decrease in the strength of a synaptic connection due to un-correlated firing of 2 neurons which are participating. LTD is found very distinctly in cerebellum. But this coincides with LTP in hippocampus, neo-cortex..

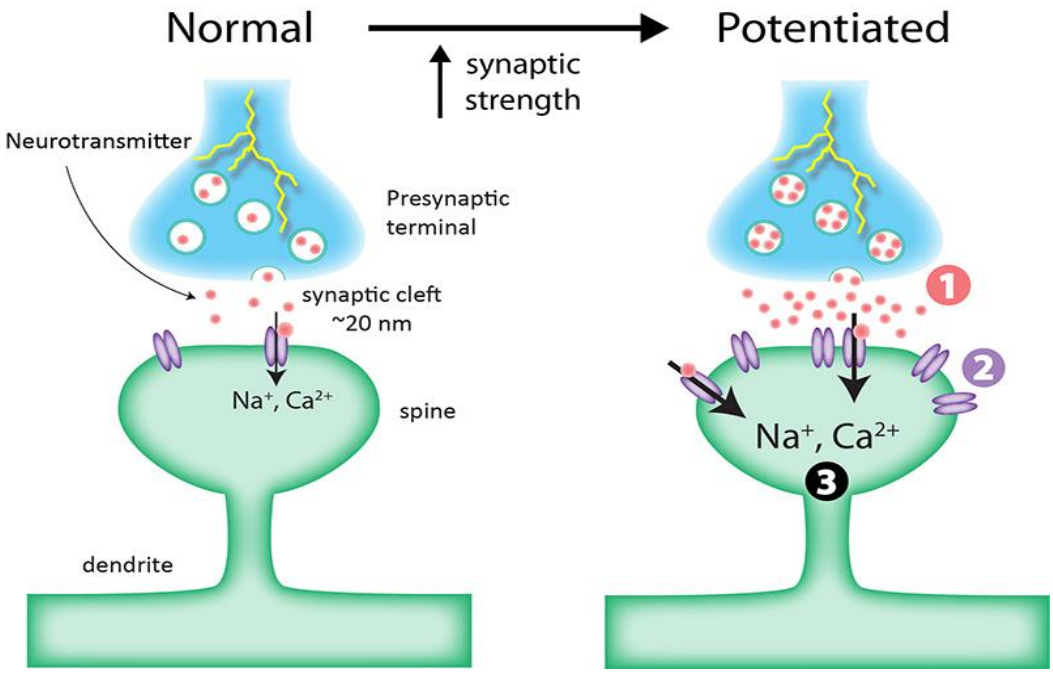


Figure 5: Synaptic plasticity

STDP- In case of LTP/LTD, presynaptic neuron and a postsynaptic neuron are stimulated simultaneously, which manipulate the firing rate the neurons without manipulating the timing between the generated spikes. Several studies disclosed that accurate timing of spikes help to find out change in synaptic strength, if it is positive or negative. This synaptic plasticity is denoted as Spike Timing Dependent Plasticity (STDP). In a unique kind of STDP, the presynaptic spike generates slightly before the postsynaptic spike, strengthening the synapses. But if the presynaptic spike occurs slightly after the postsynaptic spike, the synaptic strength is decreased. It is called the Hebbian STDP.

Short-Term Facilitation and Depression – It causes corresponding synapses to perform like temporal filters according to the patterns of input spiking. In short-term depression (STD), the effect of every consecutive spike in sequence of input spikes is declined in comparison with foregoing spike. So, when the neuron receives huge number of spikes in input, first one has the best effect with later ones giving lesser changes in the membrane voltage until equilibrium point is achieved, subsequent spikes having the same decreased effect on postsynaptic neuron. When each successive spike has a larger effect than its predecessor, until a saturation point is reached, it I called Short-term facilitation or STF. Both STD and STP are valuable in regulating cortical network dynamics, gating effects of spike trains as input coming to postsynaptic neurons.

III) BRAIN STRUCTURE, ANATOMY AND FUNCTIONS

Two concerned parts of human nervous system are - the central nervous system (CNS) and the peripheral nervous system (PNS).

a) **Central nervous system (CNS) –** have two parts, brain and spinal cord. Brain uses nerves to send and receive message from rest of the body. Spinal cord is main route that carries motor-control commands from brain to muscles of body and sensory feedback data received from muscles and skin to brain. Also, neurons of spinal cord participate in localized feedback loops. This loops control reflexes like rapid withdrawal of finger when unintentionally touch any item that hurts.

b) **Peripheral nervous system (PNS)**- nerves that spread from CNS all over body make the PNS. It relays the signals and information from the brain and spinal cord to other part of body. It has 2 parts.

- **Somatic nervous system –** nerves under this PNS controls the movements.
- **Autonomic nervous system**- this nervous system controls natural activities of body like breathing, heart pumping etc.

Structure Of Brain-

There are many different clusters of neurons, known as nuclei and regions in brain. Base of brain has three parts- **medulla**, **pons**, **mid brain**. They together build **brain stem** which carries all commands and information from the brain to the rest of the body.

Basic functions such as breathing, blood pressure, sleep, arousal etc. that are regulatory in nature, are controlled by the medulla and pons.

A major part of the midbrain is the **tectum and tegmentum.** **Tectum** has two parts- **inferior** and **superior colliculus**. The main function of tectum is to control the eye movements and visual and auditory reflexes. Tegmentum also has parts like the **reticular formation,** modulating reflexes in muscles, perception of pain, and breathing.

The **cerebellum** is known as “little brain”. It is complexly structured neural network located at base of brain. It plays important role for the coordination of movements.

Diencephalon is the upper part of the base of the brain. It has two parts- the **thalamus** and the **hypothalamus**. The thalamus is principal “relay station” as it transfers all data from sensory organs to neo-cortex. It has involvement in feedback loops with neo-cortex through cortico-thalamic feedback junctions that exist between these 2 regions.Hypothalamus is involved to regulate feeding, fighting, fleeing, and mating and other basic needs of organism.

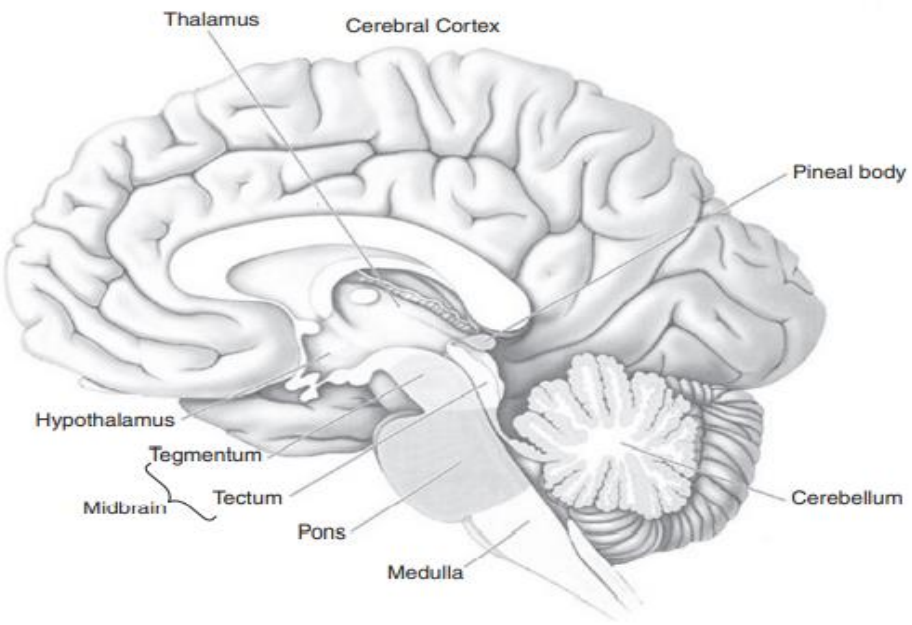


Figure 6: Major regions in Brain

There are two cerebral hemispheres, which are situated furthest from the brain. It has several parts like the i) **neo-cortex**, ii) **basal ganglia**, that is important in motor control and action selection, iii) **hippocampus**, plays an important role for memory and learning, besides spatial cognition. iv) **amygdala**, has involvement in regulating emotion.

The neo-cortex is the top most part of the brain and is about one-eighth inch thick. This is made of about billion neurons, distributed into 6 layers. Every single neuron makes 10,000 synaptic connections with others resulting trillion connections. The pyramidal neuron is the most common type of neuron in cortex. The surface of cortex is complex, with fissures and famous as **sulci** and ridges known as **gyri**.

Neo-cortex is functionally specialized which means that every single area of the cortex is specialized for definite function. For example, near back of head, there is occipital area which involves in visual processing. Parietal area is situated toward top of head and plays an important role in reasoning, that is spatial in nature and processing of motion. Recognising visual, auditory signal is controlled by temporal areas (towards side of head). Frontal areas are activated during doing complex cognitive functions.

Inputs in cortex predominantly come to middle layers whereas output leave from upper and lower layers. According to this input-output pattern, cortex is represented as a network made of sensory and motor areas.

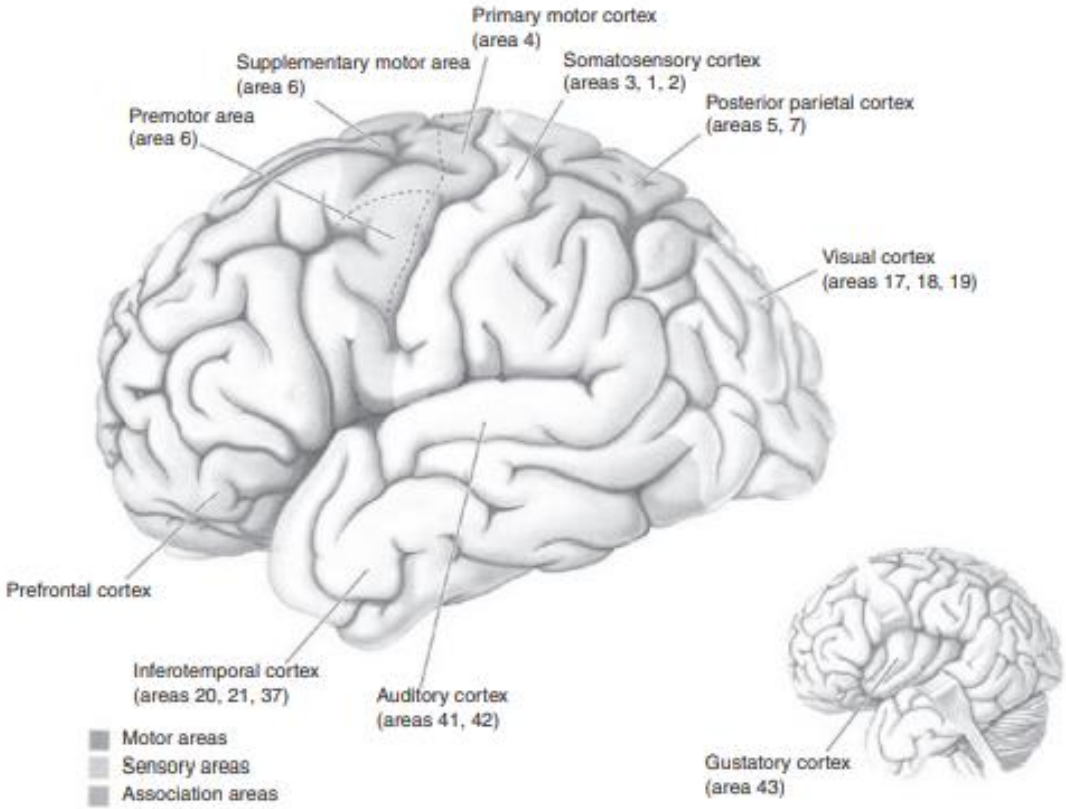


Figure 7: Major areas of neocortex

The ventral stream identifies form and colour of objects and helps in object and face recognition. The dorsal stream identifies motion and reasoning for spatial relations. Even having functional differences, different areas of cortex are similar anatomically which is remarkable. This phenomenon suggests that cortex applies special algorithm to process information.

IV) RECORDING SIGNALS FROM THE BRAIN

The technologies to record brain activity are mainly two types. When brain signals are recorded detecting changes in electrical potentials in neurons using electrodes, it is called **invasive techniques**. On the other hand, recording signals from large populations of neurons is called **non-invasive techniques** for example electroencephalography or EEG. In case of fMRI, there is indirect detection of neural activity which measures changes in blood flow. This change is result of growing neural activity in a certain part of brain. Also brain function can be determined finding minute changes in the field of magnet over the skull as a result of neural activity (MEG).

a) Invasive Techniques

Bio-signal recording from individual neurons in the brain needs invasive techniques. It needs some form of surgery, a part of the skull is removed, an electrode or implant is placed in a certain region of the brain, and the removed part of the skull is placed again. The recording itself is not painful because the brain has no internal pain receptors, but the surgery and recovery process can cause pain and involves risks such as infection. In the case of humans, invasive recordings are done only in medical settings. Invasive recordings are suitable to use as they can record the action potential of neuron at the millisecond timescale. It is different from non-invasive techniques at the point that non-invasive techniques measure indirect correlates of neural activity, for example- blood flow, ocuuring at a coarser timescale (hundreds of milliseconds).

- **Microelectrodes**- A microelectrode is made of a very fine wire or other electrical conductor and is used to make contact with brain tissue. A typical electrode measures around 1µm in diameter. It is generally made of tungsten or platinum iridium alloy and is insulated except at the tip. In some cases neuroscientists use a glass micropipette electrode filled with a weak electrolyte solution which has same composition to intracellular fluid.

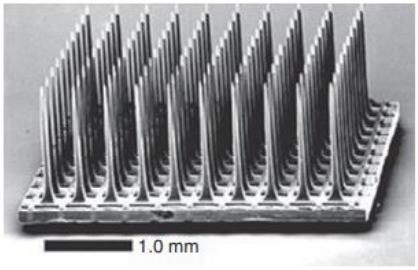


Figure 8: Micro electrode arrays

- **Intracellular Recording –** It measures the potential difference between the inside of the cell (tip of the intracellular electrode) and an external electrode (reference electrode) placed in the extracellular fluid outside the cell ("ground").
- **Extracellular Recording-** It measures the potential difference between the tip of the extracellular electrode (placed near but outside the neuron) and a ground electrode.
- **Multi-electrode Arrays-** they are arranged in a grid-like structure to form a multi electrode array of dimension m × n to record signals from large number of neurons. In the grid like structure the values of m and n range between 1 and 10. Implantable arrays such as micro wire, silicon-based and flexible micro electrode arrays can be used for brain-computer interfacing. Michigan and Utah arrays are example of silicon based arrays. The Michigan array records signal along the total length of the electrodes, rather than just at the tips. Higher density and higher spatial resolution than micro wire arrays is also observed in case of both the arrays. Flexible arrays are made of polyimide, parylene and as a result can better match to the mechanical properties of brain tissue and diminish the probability of shear-induced inflammation that can be caused by silicon-based arrays. Multi electrode arrays are better than conventional single-electrode systems due to its increased spatial resolution. As it is possible to record simultaneously from a group of neurons that helps to study complex types of information like position or velocity signals that could be useful for controlling prosthetic devices.
- **Electrocorticography (ECoG)-** Electrocorticography (ECoG) is an invasive technique to record brain signals by placing electrodes on the surface of the brain. A surgery is required to replace a part of the skull and implant the electrodes on the brain surface. Generally to study seizure activity in epilepsy patients, ECoG is done. A grid or strip of m × n electrodes is implanted, where the values of m and n vary between 1 and 8. The grid electrodes are usually placed at 10 mm to 1 cm distance. The electrodes can record the normal movements of the brain.

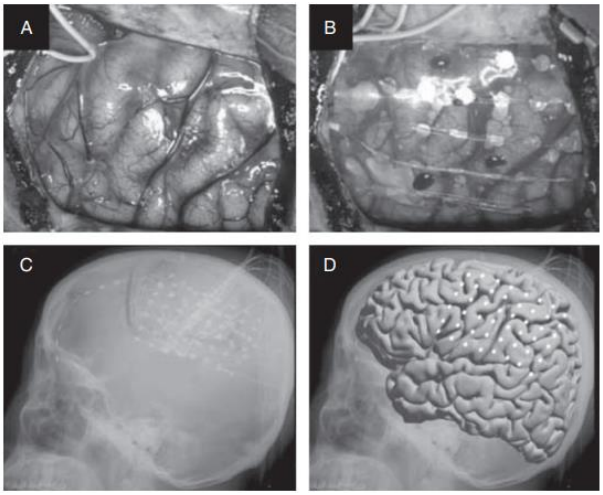


Figure 9: ECoG electrodes inside brain

ECoG electrodes can record the electrical fluctuations caused by the coherent activity of large populations of neurons but single-cell electrodes and multi electrodes are unable to do so. ECoG electrodes do not directly measure the spikes, rather they record the signal from the input currents received by the dendrites of cortical neurons, particularly in the upper layers of the cerebral cortex. A particular type of ECoG cannot penetrate the blood-brain barrier. So they are safer than multi electrode arrays that are implanted inside the brain.

Advantage of ECoG includes (1) greater spatial resolution than non-invasive techniques, (2) broader spectral bandwidth (the upper range is 0–200 Hz versus the lower range is 0–40 Hz), (3) amplitude is higher (upper range 50–100 µV versus lower range - tens of µV), and (4) comparatively less vulnerability to artifacts such as muscle activity and ambient noise as it is closer to the neural activity.

Disadvantages of ECoG include: (1) At present it can be used in surgical settings, (2) only surgically relevant portions of the brain can be recorded, and (3) the result can be fluctuated and manipulated due to drugs or patient-related conditions such as seizures.

b) Non-invasive technique

- **Electroencephalography (EEG)** - Electroencephalography (EEG) is a popular non-invasive technique to record brain activity placing surface electrodes on the scalp. EEG signals represent the summation of rhythmic postsynaptic potentials which appear as surface waveform from many thousands of neurons. These neurons are distributed radially to the scalp. So tangential currents I the scalp are not detected by EEG.

  EEG predominantly records the electrical activity in the cerebral cortex, whose columnar arrangement of neurons and proximity to the skull are suitable for the EEG recording. But EEG is unable to detect current from deep brain because the voltage field is inversely proportional to square of the distance from the source.

  EEG has a poor spatial resolution but good temporal resolution. There are different layers of brain tissues; they are-meninges (innermost part), cerebrospinal fluid (protects brain), skull and scalp. These different layers performs volume conduction and act as low pass filter to decrease the magnitude of original signal and intervene between the signal source (all type of neural activity in the cortex) and the sensor on the scalp, resulting poor spatial resolution.

Figure 10: EEG setup

The recorded EEG signals are in the range of a few tens of microvolts. So to make these signals usable, preamplifiers, amplifiers with high common mode rejection ratio are used. Preamplifiers and amplifiers with high CMRR ratio and SNR (Signal to Noise ratio) amplify the signal and filter out noise.

Weak EEG signals are effected different types of artefacts caused by movements, physiological functions like heart rate, eye blinking, respiratory function etc. Electrical power supply equipment results an artefact due to 50 Hz power line interface. This 50 Hz noise is eliminated using a notch filter.

Physiological noises like noises due to respiration rate results large artefacts in the EEG signal, the frequency of these artefacts are close to that

of EEG signals. As a result, the two type of signals overlap and cannot be separated using low band pass filter. So to eliminate this kind of artefacts, adaptive filtering, PCA (Principal Component Analysis), ICA (Independent Component Analysis) are done.

Band pass filters like Butterworth filter, Chebyshev filter, Elliptical filter are used to eliminate noises in the frequency range of 0.1 to 0.4 Hz resulted due to heartbeat and mayer waves.

Motion artefacts are caused due to head movement, hand movement, chewing etc. These type artefacts are removed using common average referencing. As precaution, subjects are advised to avoid any kind of movement.

Also, changing skin-electrode impedance and variation in psychological activity of the subject like boredom, stress, depression or frustration cause additional noises.

To reduce error in signal due to impedance of dead cell, a conductive gel or paste is used into the holes of the cap before placing the electrodes. This conductive gel helps to pass the electric signal using active ions present in the gel.

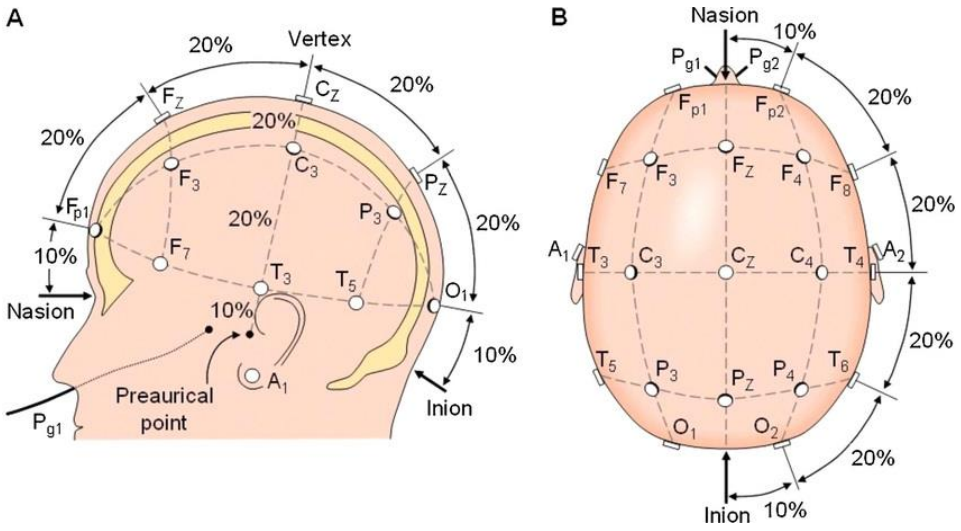


Figure 11: 10-20 system Montage

The international 10–20 system is used to standardize electrode locations on the scalp. The mastoids reference electrodes are placed in each ear (A1 and A2). Other two reference electrodes are placed on nasion and inion which are used to measure the skull perimeters in the transverse ande median planes. The one is placed at the top of the nose (nasion). It is in the level of the eyes. The other electrode is placed in the junction of head and neck (inion). The total scalp perimeter is divided into 10 percent and 20 percent intervals and the electrodes are placed according to that montage. F_P electrodes record the frontal polar region, F represents the frontal lobe. Also C records

the central region, T records the temporal regions, P records the parital region and O records the occipital region. The even numbers of electrodes denote right side and odd numbers denote left side of the head.

Bipolar or unipolar electrodes can be used for measuring EEG. Bipolar electrodes are useful as they measure voltage difference between a pair of electrodes. On the other hand, unipolar electrodes measure the potential of each electrode with respect to a neutral electrode. After that all scalp channel values are averaged and then the result is subtracted from each channel. This method is called common average referencing or CAR.

In brain, individual neurons are the origin of the rhythmical potential. These waves have characteristic frequency ranges and are used to determine different functional states of the brain. Delta waves have the lowest frequency ranging from 0.5-4 Hz and are detected when adults are asleep or from babies.

Theta waves (4-8 Hz) represent drowsiness or dreaming condition. This frequency range generally describes unconscious condition.

Alpha waves are recorded from the occipital region in case of awake persons who are in a relaxed mode.

Beta waves (13–30 Hz) are detected from the parietal and frontal lobes and generated when a person is alert and active.

Gamma waves have the highest frequency range (30-50 Hz), and are recorded when the subject is involved in mental maths or any kind of work involving short-term memory and multisensory integration. High gamma activity (70 Hz and above) are also found in motor tasks.

A special kind of alpha wave is mu rhythm (8–12 Hz). It is recorded from sensorimotor areas when the subject is in stationary condition (no movement) and is decreased when the subject performs a movement or imagines performing a movement. The mu wave plays an important role in modern BCI applications.

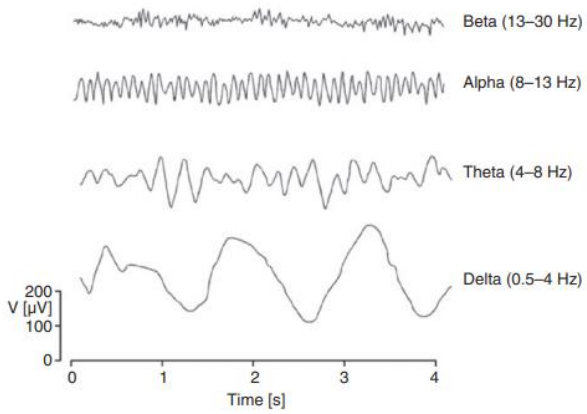


Figure 12: EEG signals of different frequencies

- **Magnetoencephalography (MEG)-** It detects the field of magnet produced by brain activity using quantum interference devices which are superconducting. In the setup, during the experiment a subject sits in a chair keeping the head inside the device and responds to stimuli on a screen by pressing buttons on a handheld device.

  The similarity between MEG and EEG is in both the cases signals are generated from the total effect of ionic currents flowing in the dendrites when receiving synaptic inputs from other neurons. A field of magnet is orienting orthogonally which is produced from the ionic current and is detected by MEG. These current sources should have similar orientation else they would cancel out.

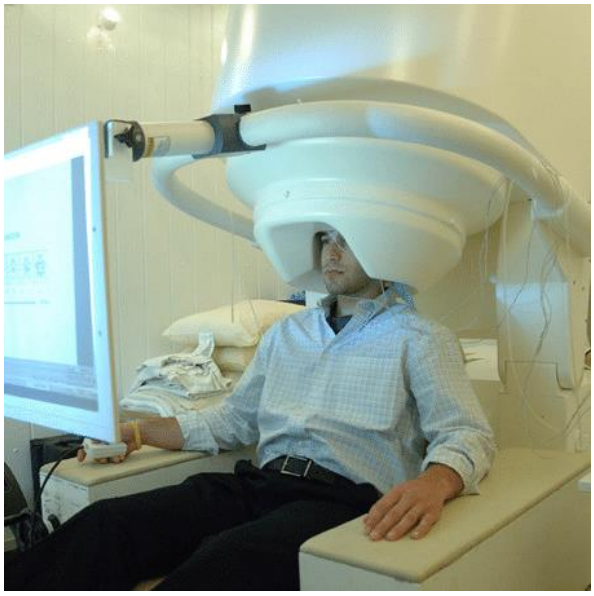


Figure 13: Setup of MEG

MEG is sensitive only the currents that are flowing tangential to the scalp as a result detect the orthogonally oriented magnetic field. So MEG can measure activity from cortical sulci rather than the gyri. But EEG is sensitive to both regions. On the other hand, MEG systems are more expensive, bulky and not portable compared to EEG. Also external magnetic signals, including the earth's own magnetic field causes noise so a magnetically shielded room is required for the experiment.

MEG directly measures the neural activity, not metabolic activity of neurons like fMRI, fNIR or PET and as a result it has high temporal resolution Also, MEG is more advantageous than EEG because the magnetic fields produced due to neural activity and measured by MEG are not violated by the skull and the scalp and the tissue layer of brain Thus, MEG offers better spatial resolution than EEG and independence from the head geometry.

- **Positron Emission Tomography (PET)-** It is an indirect, non-invasive method to measure brain activity from the metabolic activity. Radioactively labeled, metabolically active chemicals that are called as a radio tracer, are injected into the bloodstream and are transported to the brain. These chemicals make the brain region fluorocent.

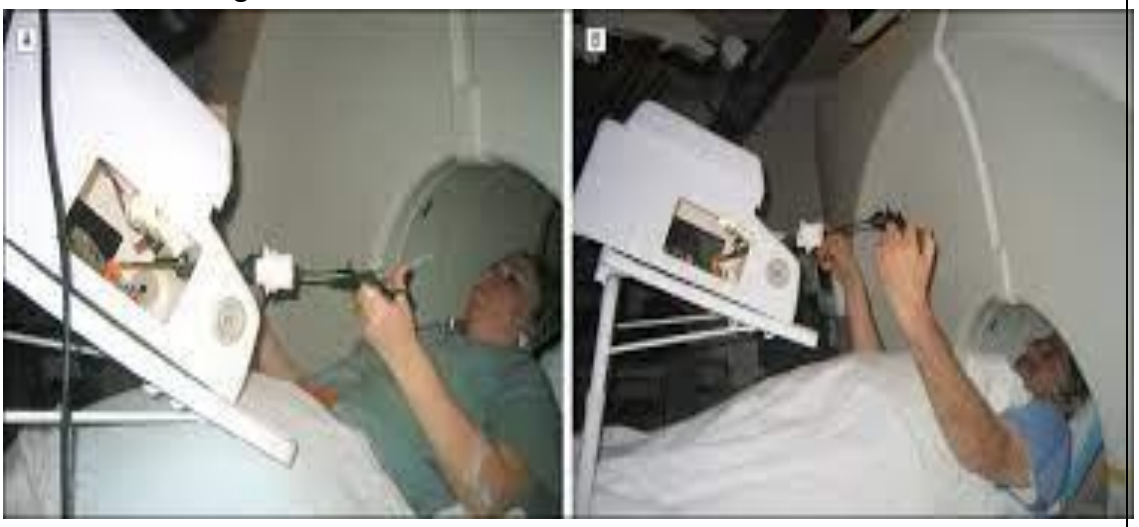


Figure 14: Setup for PET

Generally the most used radiotracer is a modified glucose, named as FDG (Fluro Deoxy Glucose). PET has low temporal resolution compared to EEG but has a high spatial resolution**.** Injection of radioactive chemicals into the body is a major disadvantage. Also the rapid decay of radioactivity results decrease in time limit of the experiments.

Sensors in PET are able to detect radio tracer as they make their travel path in the brain fluorescent due to metabolic activity in brain. From this data, two-dimensional and three-dimensional images representing the amount of brain activity are generated.

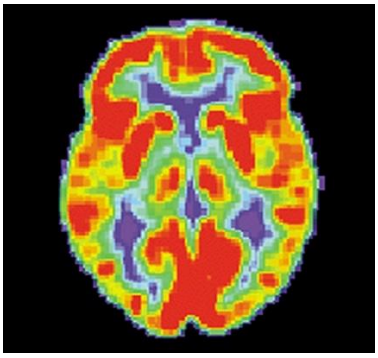


Figure 15: Brain image in PET

- **Functional Magnetic Resonance Imaging (fMRI)**- It detects the changes in blood flow when certain brain region is activated during particular task, by indirectly measuring neural activity in the brain. It is well known that active neurons consume more oxygen, and oxyhemoglobin carries this excess oxygen to the brain through the blood. There is a dilation of local capillaries due to neural activation resulting highly replacement of oxygen-depleted blood by oxygenated blood in that active brain lobe.

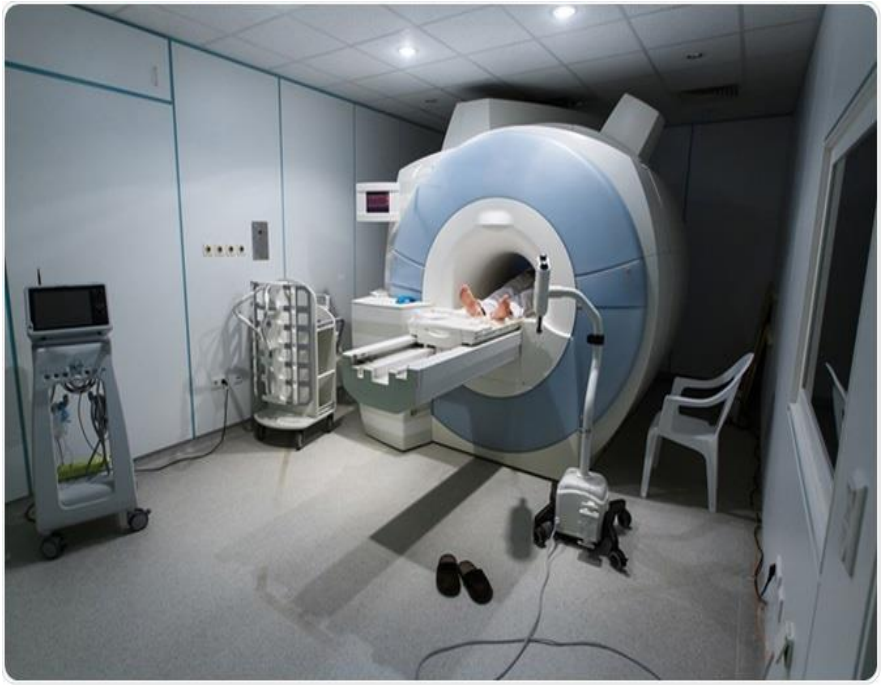


Figure 16: Setup for fMRI

In case of fMRI, the hemodynamic response is slow compared to that of EEG as the former records brain signal indirectly by measuring the hemodynamic response of brain.

The de-oxygenated hemoglobin is more magnetic than oxygenated hemoglobin and using this theory fMRI produce images which represent different cross sections of human brain and show enhanced activation in particular areas during a neural activity.

Blood oxygenation level dependent or (BOLD) response is the signal recorded by fMRI. During the experiment, subjects are lied down and their head is positioned inside the fMRI scanner. Subjects can be stimulated with visual stimulus like as image, or audio stimulus like sounds or by any kind of touch stimulus to activate certain region of brain.

fMRI has a good spatial resolution, typically in the 1–3 mm range, is much higher than other non-invasive techniques such as EEG and MEG. However, its temporal resolution is poor. Also it is not portable and expensive also which are the drawbacks.

- **Functional Near Infrared (fNIR) Imaging-** It is an optical, non-invasive technique to measure changes in blood oxygenation level when there is an increase in neural activity in the brain. It uses source- detector pairs of near infra-red to detect near-infrared light absorbed by the chromophores like oxyhaemoglobin and deoxyhaemoglobin, providing an indirect window into brain activity.

Figure 17: Setup for fNIR

In case of functional near infrared imaging, infrared light is emitted to the scalp by sources placed in the scalp and penetrates the skull. This penetration results multiple scattering of photons through the scalp. Some of these photons are partly reflected from the scalp and are detected by the detectors placed on the scalp. Rest of the photons travel through the scalp and different layers of tissue and get reflected from cortical part of brain. Different neural activity results different level of oxygen consumption in the blood capillaries and so different level of infrared light is for different task. It is seen that blood containing oxyhaemoglobin absorbs more infrared (800-900nm wavelength) and reflects more red light whereas, blood containing deoxyhaemoglobin absorbs more red light and reflects more infrared light. So by measuring the amount of reflected infrared light from different region of brain for different neural activity, the region of activation is determined. Generally the change of concentration of HbO and HbR is detected from the relationship between exiting-photon intensity and incident-photon intensity, using the Beer Lambert's law.

$$A = \varepsilon c l$$

A	Absorbance	
ε	Molar absorption coefficient	$M^{-1}cm^{-1}$
c	Molar concentration	M
l	optical path length	cm

Figure 18: Beer Lamberts Law

Generally, fNIR is used to record the neural activity of two main regions of brain- the primary and the prefrontal part of motor cortex. Brain signals generated during motor imagery task, also motor execution are recorded from the specific part of cortex. On the other hand, prefrontal cortex is activated when the subject performs music imagery, mental arithmetic etc.

The source- detector pairs are arranged in a particular distance. Generally, the distance between source and detectors are in the range from 1 to 5cm. But 3 cm distance is taken as standard. Separation of 1 cm will record infrared recorded from skin layer. Also, exceeding 5 cm distance results inefficient signals with low magnitude due to volume conduction.

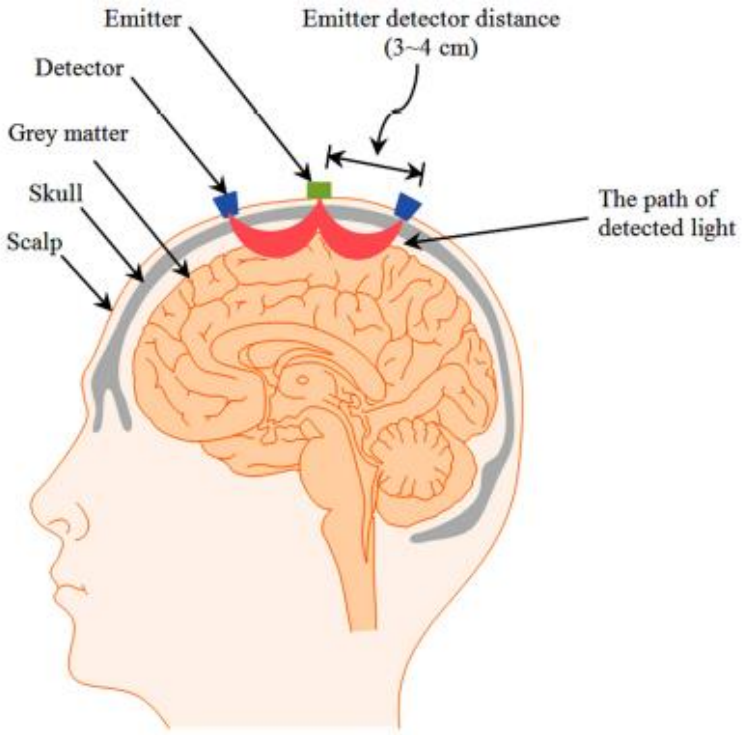


Figure 19: Source-detector arrangement in fNIR

The fNIR device is less heavy, less expensive and less difficult than fMRI. In case of fMRI subjects are restricted from any kind of movement as they are lied down within an MR scanner. But it also have some disadvantages- it is more sensitive to noise and offers less spatial resolution compared to fMRI. Also it is unable to measure neural activity of brain close to the scalp compared to fMRI which can image deep regions of brain.

Similar to EEG, using a number of equally arranged “optodes”, are a group of emitters and detectors, covering the whole surface area of the head helps in the construction of a 2D map of neural activity of the whole brain. Functional near infrared is not as susceptible to muscle artefacts (compared to EEG) because it works on the principle of optoelectronics rather than electrical measurements. It is less expensive than fMRI and also portable. fNIR gives good spatial resolution compared to EEG but gives poor temporal resolution. It is preferred to use fNIR as EEG uses wet electrodes which sometimes result poor electrode skin conductivity.

Compared to EEG, brain signal recording using hemodynamics (fMRI and fNIR) shows delay in response making the signal generation slow. In case of fNIR, the drawback can be resolved measuring the initial dip (decrese of HbO and increase of HbR when neuron fires) instead of hemodynamics.

V) STIMULATING BRAIN

Brain can be stimulated using invasive and non-invasive technique.

- **Invasive technique**

a) Microelectrodes- the glass microelectrodes are used to record intra-cellular activity of a cell as well as to stimulate the cell by supplying current into it. In this way, these electrodes are used to depolarize or polarize the cell.

The platinum-iridium microelectrodes are used for extracellular recording. But they are also used to stimulate the cells. Generally they activate the local population of neurons near the electrode rather than a single neuron.

A popular use of deep brain stimulation (DBS) is implanting larger electrodes surgically into the brains of Parkinson's patients. The electrical pulses are delivered continuously to different regions of brain to activate that region and relieve symptom like Alzheimer disease, tumors and gait problems. Microelectrodes are also used in cochlear implants to stimulate the auditory nerve.

b) Direct Cortical Electrical Stimulation (DCES)- A semi-invasive method for stimulating neurons in the brain is to use electrodes on the surface of the cortex as discussed above for electrocorticography(ECoG). Electric current is delivered across bipolar electrodes on the brain surface, usually in the form of short pulses of alternating polarity. The effect is limited to the several thousands of neurons in the local cortical tissue near the electrode pair. Stimulation effects are rapid in their onset and offset, coinciding with the duration of stimulation.

DCES can produce "positive" effects such as generating movements or causing particular sensations, or "negative" effects such as the disruption of a movement or behaviour. DCES is typically used in a clinical setting for mapping the location of sensory, motor, memory, and language functions in the brains of neurosurgery patients. Its potential for providing direct feedback during brain-computer interfacing remains to be explored.

c) Optical Stimulation- laser illumination can be used to depolarize neuron. Two-photon laser illuminations are used to excite specific single neurons in brain slices from visual cortex. The laser is applied tangentially to the membrane of the cell. The excitation can be changed by changing both the intensity and wavelength of illumination. The excitation is quickly removed when illumination is discontinued. Optogenetic stimulation is used in genetic modification to make only certain neurons responsive to illumination, using cell-specific method.

Further, increasing the light intensity tends to increase the firing rate of the neurons.

- **Non-invasive technique**
  a) **Transcranial Magnetic Stimulation (TMS)**- its activity depends on the relationship between electricity and magnetism and the process of electromagnetic induction. A field of magnet is generated when a current passes in the coil. This magnetic field is perpendicular to the direction of the current. If a second coil is placed within the magnetic field, a current is generated in a direction opposite the first flow.

     In case of TMS, a plastic-enclosed coil of wire is placed on the surface of the skull. It develops a changing field of magnet which is rotated perpendicular to the plane of the coil. This field of magnet penetrates the skin and skull without any distortion and produces a current to the brain according to law of magnetic induction. This current stimulates the neurons

     The technique is able to activate the superficial layers of the brain as the magnetic field can penetrate to a maximum depth of about 3 to 5 cm into the brain. The TMS is advantageous as it is non-invasive and its use is not restricted to patients. But poor localization of the area of stimulation and high power requirement compared to invasive techniques are its disadvantages.

  b) **Transcranial Ultrasound**- it uses ultrasound technology to stimulate brain region non- invasively. Generally an ultrasonic (frequency greater than human hearing range, >20 kHz) mechanical pressure wave (sound wave) is used which is called ultrasound. Ultrasound is transmitted through solid structures, including bone and soft tissues, making it well suited for non-invasive medical applications.

     The high-intensity ultrasound stimulates the neuron through thermal effects. But this thermal affect can damage brain tissue. So now low-intensity pulsed ultrasound is used to activate neuron without thermal effects, resulting tissue damage.

     Pulsed ultrasound offer better spatial resolution than TMS as it can stimulate brain regions 1–2 mm in diameter, greater in the case of TMS.

- ## Recording electrodes

Bioelectric signals are recorded from the body surface before they are amplified for subsequent record and display. Recording electrodes are used for this purpose. Electrodes are required to measure physiological parameters by the impedance method and also for electrotherapy to stimulate irritable tissues. A transfer of ionic conduction of the tissue to the electronic conduction is carried out by electrodes for important measurements.

The main two types of electrodes are

a) **The surface electrodes** – the potential difference from the tissue surface is recorded when placed over body surface but in this recording process no live tissue is damaged.
b) **The deep-seated electrodes** –they find electric voltage difference which is developed inside the living tissue.

Electrodes are necessary for the recording of bioelectric signals and they should be chosen carefully. Also the electrodes and the gel should be comfortable for the patients so that they can wear it for long periods and no artefacts are produced. In order to avoid movement artefacts and to achieve good contact (low contact impedance), electrolyte or electrode paste is usually used at the junction of electrode and the surface of the signal source.

Electrodes for EEG

The EEG signals are recorded from scalp or directly from the cerebral cortex. Silver Chloride (NaCl) discs are the most commonly used electrodes for EEG (electroencephalogram) recording. The diameters of electrodes are 6–8 mm. These electrodes are made up of silver plates coated with silver chloride. It is important to reduce the contact impedance between skin and electrode surface to acquire better signals. The electrode–tissue impedance depends on several factors like interrupting layer; be it skin preparation or hair etc. electrode's surface area, and temperature of the electrolyte. Also a proper and stable contact is required so that movement of subject does not dislocate the electrodes and cause motion artefacts. So an electrolytic paste is used to make contact with the scalp and reduce contact impedance. They have ac resistance ranging from 3–20 kW.

Figure 20: Different types of electrodes

Sometimes needle electrodes are used to record specific EEG recordings when they are inserted in the subcutaneous region and are small in size.

Silver pellet electrodes are coated with a small pad of cloth, have high dc resistance and are advantageous to record electrical activity from the exposed cortex.

Another type of EEG electrode is made of multiple silver wires which have silver chloride coating and are placed together in a rigid plastic cup that is filled with jelly. An electrolyte bridge connects the tissue and the wires to avoid the disturbance of the jelly with the electrode metal due to scalp movement. The silver wires are used as the output lead to avoid metal junction. The wide surface area and excess of NaCl solution help in stability.

VI) BASIC RECORDING SYSTEM

In medical recorders, preamplifier and the main amplifier are the main part of signal processing. These amplifiers are designed properly to achieve requirements like input impedance, gain, signal to noise ratio, common mode rejection ratio and frequency response properties for a better production of signal in input terminal.

Generally biological signals have magnitude of micro volt or mV range which cannot be processed properly by filters and analog to digital converters. So amplification is the first necessity. Also, compatible input signal is required for the display or recording system. So normalization of the electrical signals is required for each transducer. The signal conditioner plays an important role in normalization of recorded signal as it adjusts adjust all signals output to a common signal level. On the other hand, the signal conditioners also adjustment gain and frequency response. Also an important part of recording system is different types of writing system like pen recorder, using galvanometer, the recorder using inkjet and the potentiometric recorder.

Signal Amplification: bio-signals recorded by the transducers from human body are very small in magnitude and so amplification is a necessity to increase amplitude of the signal in input that will satisfy the need of the recording as well as display system and also the range of the analog-digital convertor. These are low-level measurement, amplifying and recording signals of micro volt. As a result of amplification, resolution and sensitivity increase. Electrical noise is unwanted in recording system as it produces error and sometimes over shadow the main desired signals. To avoid environmental noise, signal conditioners are placed closer to the signal source, which results in an improvement in the signal-to-noise ratio.

Frequency Response: Nowadays instruments are able to handle signals having different range of bandwidths, be it dc signal or signal with frequency up to 1000 Hz. Electrical or mechanical filters are unable to extract useful signals from the noisy input as their bandwidths overlap. In case of instruments used for low frequency information recording, the requirements are not fulfilled. On the other hand, the one which can reproduce this type of data are more allowing to external disturbance and, so, they should be designed to nullify the probability of data distortion by noise. Bio signals frequently have low frequency parts. To have a satisfactory reproduced signal, the amplifiers should have very good frequency response. This response should be less than one Hz. For amplifiers that are RC-coupled,

weak frequency response is kept in limits using the reactance of the inter stage coupling capacitors. In case of medical application, to achieve the low frequency response, the amplifier with great values of coupling capacitance is used. Large value capacitors are the reason of blocking in amplifier for high-level signal in input, arising due to switching transients or other high-level inputs. Due to long time constant introduction by high value coupling capacitors, several seconds may pass before the discharging of capacitors to the normal levels. This type of problem is not present in directly coupled amplifiers due to absence of coupling capacitors. Amplifiers which are direct coupled type, results perfect frequency response for low range of frequencies, but at the same time it has tendency to drift-a slow change in output without any relation with the input signal that is put in to the amplifier. Frequency response for RC-coupled amplifier does not expand up to dc, causing no drift. Medical amplifiers are advantageous for having these two types of coupling in a single amplifier. In that case, all stages are direct coupled excluding only one stage. That excluded stage is RC coupled, preventing the drift in output. Necessary precautions are followed to prevent blocking for overdrive. This is obtained by automatic rapid discharge of coupling capacitor when overdriving input occurs.

Filtering: A filter amplifies only the specified range of frequencies and cancels out others. There are mainly four distinct types of filters.

i) **High-pass Filter**- it selects the signals with frequencies above a certain cut off frequency, amplifies them and attenuates other frequencies.

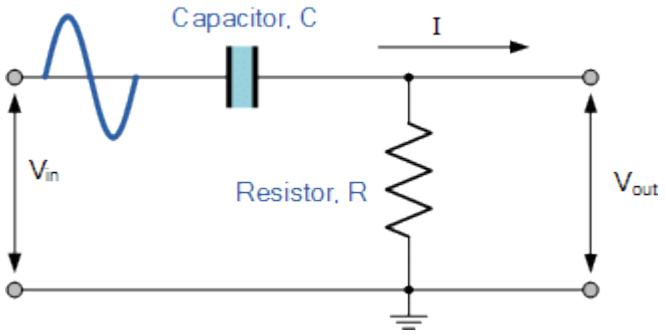


Figure 21: RC network as High pass filter

ii) **Low-pass Filter**- it amplifies signals with frequencies below a certain cut off frequency and attenuates rest of the signals.

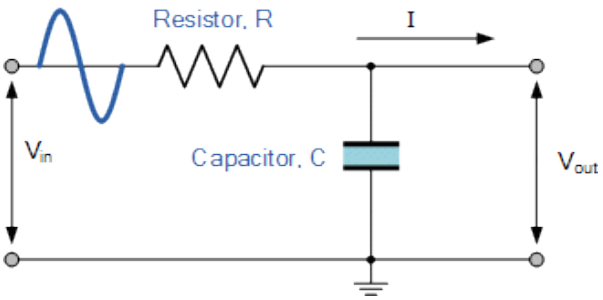


Figure 22: RC network as Low pass filter

iii) **Band-pass Filter**- only frequencies within a certain band undergo amplification.

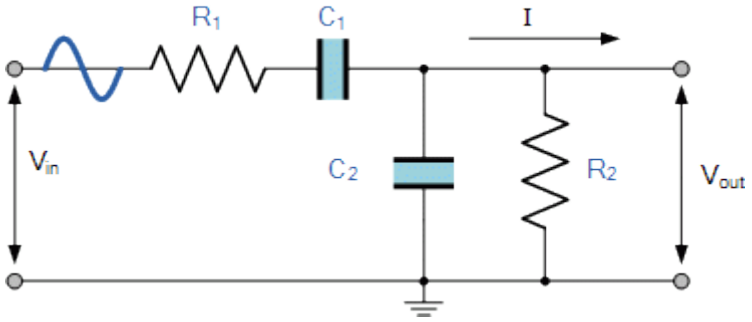


Figure 23: RC network as Band pass filter

iv) **Band- stop Filter-** all frequencies have an amplification except those in a particular band.

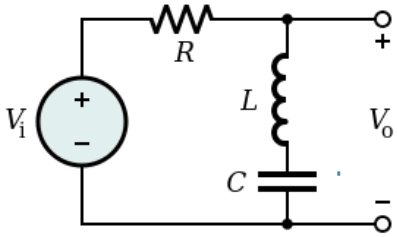


Figure 24: RLC network as Band stop filter

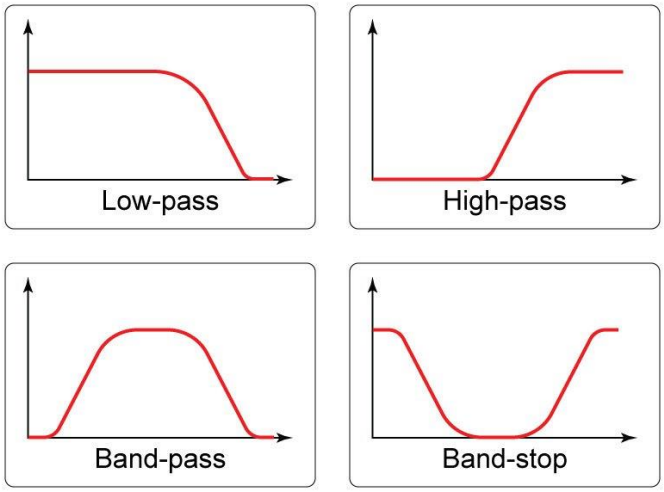


Figure 25: Bode plot of 4 kinds of filters

Filters are designed following various methods.

- Passive filters are made of only components like resistors, capacitors and inductors which are passive in nature.
- Active filters are made of amplifier and also with components that are passive providing better result.
- Operational amplifiers are used in active filters as gain blocks.
- Digital filters use ADC for the conversion of a signal to its digital form. In the next stage they filter the digitized signal using high-speed digital computing techniques.

Almost all measuring and recording applications have 50 Hz noise from power lines or supply instruments. So low-pass filters like notch filters are used to attenuate this 50 Hz noise.

Filters can be classified as digital and analog filters.

Analog filter- it operates inputs that are analog in nature and produces outputs which are also analog in nature. These filters are based on the mathematical operator of differentiation.

Digital filter- it processes and generates digital data. This are based on addition, multiplication and delay operators.

Digital filters are advantageous than analog filters as they are not effected by temperature, external intervention, drift in voltage in comparison with analog filters. Their response is reproducible as well as predictable. Also the product performance is represented by software simulation.

Isolation: Signal conditioners with isolation can prevent measurement problem caused due to improper grounding of the instruments. The isolating device uses transformer, capacitive coupling technique to carry signal from source without physical contact or galvanic link to the measurement device. Also blocking high voltage flow and rejecting common mode voltages (high magnitude) is done by isolating device.

Excitation: Transducers like thermistors need external voltage source or current source for excitation purpose otherwise they cannot become active. This excitation is provided by signal conditioning section of instruments.

Linearizaion: Many transducers, for example thermocouples have a non-linear reaction to changes. Signal conditioners have hardware-based or software-based linearization technique to study and record this non- linear response.

- **Preamplifier**- Conventional preamplifiers offer a wide range of input sensitivities. They can reject noise or unwanted signal components by using its low pass filter property. In biomedical measurements, different amplifiers are used for different purpose.
  (i) AC/DC universal amplifiers are used in intracellular measurements using fluid-filled electrodes or extracellular measurement using metal microelectrodes. They have low drift for dc, capacity neutralization, their leakage current is low and they also have current injection.
  (ii) ECG amplifier helps to select all the 12 leads and provides patient isolation
  (iii) Transducer amplifier is used on blood pressure transducers (strain gauge for example), resistance temperature instruments.
  (iv) A dc amplifier is used in standard thermistor probes to measure temperature accurately.

  There are different kinds of amplifiers- Differential amplifier, DC amplifier, AC coupled amplifier, instrumentation amplifier etc.

  a) **Differential amplifier**- there are three input terminals in a differential transducer. One terminal is located at the reference potential and rest two represent live terminals. This is important to find out the difference in voltage between two live terminals which have changing amplitude

with different rates and various patterns. Voltages generated from cardiac activity are recorded from arms and legs, and brain-generated voltages recorded from the scalp require differential amplifiers.

The differential amplifier is very useful in recording system as it performs well to nullify common-mode interfering signals which are recorded along with the important bio signals and act like noise. Differential amplification is good as it is stable and versatile as it is a direct coupled amplifier. Temperature change is one of the causes of excessive drift in other configurations. But differential amplifier is insensible to temperature change resulting greater stability. It is a versatile amplifier as it can be used where floating inputs, floating outputs are required or grounded inputs and grounded outputs are main requirements.

Common mode rejection describes the property of the amplifier to eliminate common voltages in two input leads. This property is very important and it is denoted by the ratio of common-mode input and differential input. This is called common mode rejection ratio (CMRR) which is an important characteristics of differential amplifier. CMRR is normally expressed as decibels. Preamplifiers are designed to have a high CMRR to bypass only wanted signals using amplifier and eliminate all unimportant signals in the preamplification stage.

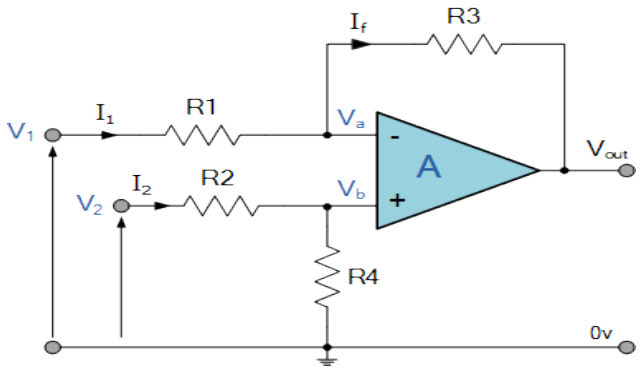


Figure 26: Differential amplifier circuit

To get a high CMRR, a matched pair of transistors is used in the input stage of the preamplifier. To provide maximum negative feedback for inphase signals, a large tail resistance is used in the long tailed pair. This long-tailing technique is used to improve the CMRR without compromising with desired the gain requirement for concerned signal. Use of an active long-tail can also provide very high CMRR. High input

impedance is very necessary for a high CMRR. Also to reduce effect of high impedance of electrode, a high input impedance of preamplifier is required.

b) **Instrumentation amplifier**- The differential amplifier has the following limitations:

• It has input impedance in a limited range. So it draws low current from the source and loads.

• CMRR is limited to 60 dB in general cases. 60 dB CMRR is not enough for advanced biomedical instrumentation systems.

An improved version of the differential amplifier is used nowadays to overcome the limitations. It is a device having precision differential voltage gain. Three op-amps and seven resistors are used to design an instrumentation amplifier. Basically, a basic differential amplifier can be turned into an instrumentation amplifier by simply adding a buffer amplifier with it.

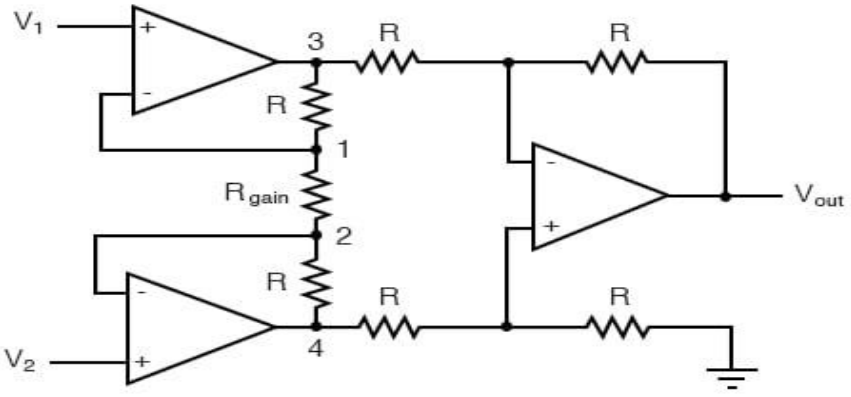


Figure 27: Instrumentation amplifier circuit

$$\frac{V_0}{V_1 - V_2} = 1 + \frac{2}{a}$$

Here a= R_g/R, V_0 is difference between voltage of two input terminals.

The instrumentation amplifier has following important properties are:

• One resistor is used to set the voltage gain from input which is differential (V1 – V2) to single terminal output.

• Both the inputs have very high input resistance which do not change if the gain is varied.

• Output voltage does is independent of common-mode voltage only at difference. The op-amps cannot cope with when the inputs are prone to high voltage spikes, which, but this problem is solved by instrumentation amplifier as it uses back-to-back connected diodes at the inputs.

The instrumentation amplifier offers the following advantages:

• Extremely high input impedance

•Very high CMRR

• High slew rate

• Bias and offset current are minimal

• Consume low power.

• Minimal performance deflection when source impedance changes

• In case of amplifier and source, may provide independent reference levels

VII) SIGNAL PROCESSING

In this chapter, different signal-processing methods are used to process raw signals recorded by electrodes. Every signal can be represented in two domains- time domain and frequency domain. In time domain analysis, every data is measured at a successive time interval. Time domain analysis of biomedical signals is done for display and recording purpose. On the other hand, data is described by the amplitude of sinusoidal and cosine components for different range of frequencies. in case of frequency domain analysis. The signals are represented as sine and cosine wave with phase and amplitude as y-axis and frequency in x-axis.

A) Frequency Domain Analysis- In case of non-invasive recording like EEG, fNIR etc. the signal are able to record correlated tasks of a group of neurons only.

i) Fourier Analysis- almost all bio signals are time varying. So to analyse the signal, transient analysis of the test signals are required. Fourier analysis is a basic mathematical tool which is used to generate spectrum of a given signal. In Fourier analysis, the signal is decomposed into a weighted sum of sine and cosine waves of different frequencies. For example, a step function has a constant positive value for some time and then becomes a constant negative value, and then again the original positive value. Using this frequency domain analysis the step function can be approximated by adding sine waves of different frequencies, each weighted by a different coefficient (amplitude). So the step function can be decomposed into different sine waves with various frequencies and various amplitudes. The signals are decomposed during the time range of (-T/2) to (T/2), into a weighted sum of sine and cosine waves of different frequencies. The decomposition of periodic signal is called Fourier series and the decomposition of finite energy signal is called Fourier transform. Fourier transform generally connects the time domain and frequency domain. For a time varying signal s(t), Fourier transform is defined as

$$\begin{aligned} \boldsymbol{s(t)} &= \frac{\boldsymbol{a_0}}{\boldsymbol{2}} + \boldsymbol{a_1 cos(wt) + a_2 cos(2wt) + \cdots b_1 sin(wt) + b_2 sin(2wt)}.. \\ &= \frac{\boldsymbol{a_0}}{\boldsymbol{2}} + \boldsymbol{\sum_{n=1}^{\infty} a_n cos(nwt) + \sum_{n=1}^{\infty} b_n sin(nwt)} \\ &= \frac{\boldsymbol{a_0}}{\boldsymbol{2}} + \boldsymbol{\sum_{n=1}^{\infty} a_n cos(2\pi fnt) + \sum_{n=1}^{\infty} b_n sin(2\pi fnt)} \end{aligned}$$

Here w is angular frequency and f is ordinary frequency.

$$a_n = \frac{2}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} s(t)\cos(nwt)\,dt$$

$$b_n = \frac{2}{T}\int_{-T/2}^{T/2} s(t)\sin(nwt)\,dt$$

The value $\frac{a_0}{2}$ is the average (DC value) of the input signal over the interval –T/2 to T/2.

$$\frac{a_0}{2} = \frac{1}{T}\int_{-T/2}^{T/2} s(t)dt$$

ii) **Discrete Fourier Transform (DFT)** - For BCI applications, the brain signals are typically sampled at discrete time intervals. The discrete Fourier transform (DFT) takes a time series S(t) as input, sampled at time points t = 0, …, T-1 and transforms it to the corresponding complex Fourier coefficients:

$$\boldsymbol{C(n) = \frac{1}{T}\sum_{n=0}^{T-1} S(t)e^{-jnwt}}$$

The inverse discrete Fourier transform (IDFT) is similarly defined as:

$$S(t) = \sum_{n=0}^{T-1} C(n)e^{jnwt}$$

Here,

Amplitude A(n)= $\sqrt{Re(C(n))^2 + Im(C(n))^2}$

Phase φ(n) = arctan (Im(C(n)),Re(C(n)))

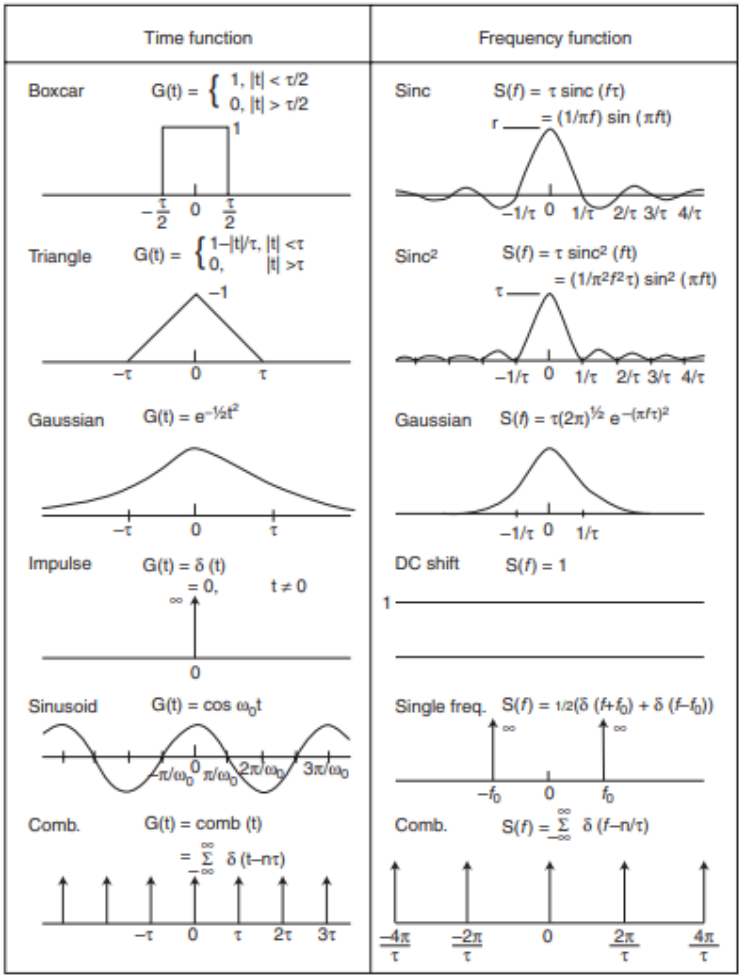


Figure 28: Examples of time-varying signals and their Fourier transforms.

iii) **Fast Fourier Transform** - Fourier Transform becomes time consuming when a large number of points are considered. So Fast Fourier Transform (FFT) algorithm is used to solve the problem. It expands the signal into sine and cosine functions. For each discrete segment of the signal, frequency spectrum is calculated. A set of coefficients represents the output of the FFT. The amplitude portion of the component is represented by the cosine part which is multiplied by the coefficient A. On the other hand, the phase portion is represented by y the sine component which is multiplied by the coefficient B. Each component in the FFT series is denoted as:

$$A\cos(wt) + iB\sin(f)$$

Where, w = Angular frequency of the component

A stands for a FFT coefficient

B stands for another FFT coefficient

f stands for phase angle of the component

i is the imaginary number,

t denotes time

In FFT method, it is assumed that the signal is stationary. The stationary signals are not sensitive to its variable features. But this assumption is not practical for biomedical signals as they are non-stationary having very large complex time frequency characteristics. So these non- stationary signals satisfy the stationary condition when the signal is divided into short segment blocks. In these short segment blocks, the small part of the test signal can be assumed to be stationary. This short segmentation of biomedical signals is known as Short-Time FourierTransform (STFT). But there is disadvantage of this technique that is segmenting a signal into desired length. During segmentation, a short analysis window results poor frequency resolution. This problem can be solved using a long analysis window but that results non-stationarity in that window.

iv) **Spectral features-** Many BCI systems prefer features which are obtained from the extraction of the power spectrum of a recorded brain signal such as EEG over a time interval. First FFT is used to compute the power signal. Then the power in a specific frequency band is used as a spectral feature for classification or any kind of advanced analysis. For example, the power in the mu band (8-12 Hz) can be used as a feature in a BCI to study motor imagery.

B) **Wavelet Transform-** It is a new signal processing method**.** This transformation technique acts like a mathematical tool and functions like a microscope. It is enable to display individual parts of the signal when the adjusting the focus properly. During transformation, the scale is varied when moving along the sequence. As a result, the wavelet transform shows good time resolution at high frequencies. At low frequencies it shows good frequency resolution. Wavelet transform is used in spatial filtering, edge detection, feature extraction, pattern recognition etc. It is demonstrated as a bank of filters for the decomposition of a single signal into multiple signal bands. Wavelet transform is advantageous as the signal features are easily extracted. Wavelet transform is better than conventional FFT in case of selecting features and reducing noise. On the other hand in case of signal analysis, adaptive filtering is able to adjust itself continuously for good performance in a changing circumstance. The

correction algorithm reshapes the signals.

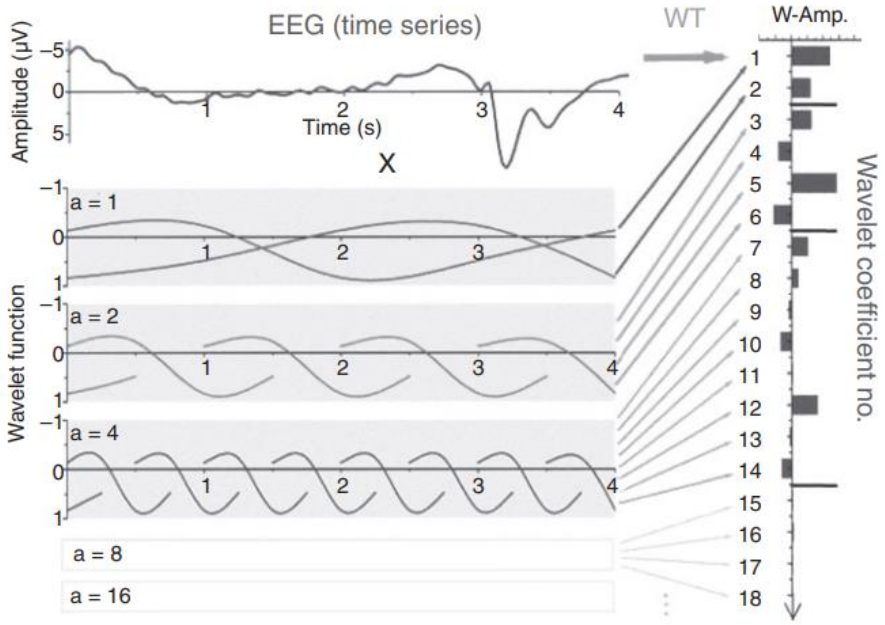


Figure 29: Wavelet transform of EEG signal

C) Time domain analysis

i) Hjorth Parameters- It computes three important features of a time-varying signal that are- the mean power, the root mean square frequency spread and the root mean square frequency. These three features can be detected from first and second derivative of the signal and are known as "normalized slope descriptors". Three Hjorth parameters are "activity", "mobility" and complexity. They are denoted as-

$A = a_0$

$$M = \sqrt{\frac{a_2}{a_0}}$$

$$C = \sqrt{\frac{a_4}{a_0}}$$

Here a_0 is the mean power, a_2 is the variance of the first derivative of the test signal, a_4 is the variance of the second derivative of the test signal. Hjorth parameters are preferred in EEG analysis they compute faster than other methods. This is due to the fact that this analysis uses variance.

ii) Fractal Dimension- fractional dimension represents the self- similarity of a signal. Self-similarity explains the phenomenon of similarity of a part of signal compared to the whole signal. This similarity is repeated in a definite time interval. Generally, Higuchi fractal dimension is used in EEG analysis. The fractal dimension for a brain

signal is calculated using a sliding window. The fractal dimension for EEG range between 1.4 to 1.7 and higher the value, higher is the spiking activity.

iii) **Autoregressive (AR) Modeling** - natural signals tend to be correlated over time and so this method is used. The next measurement can be predicted using the values of the previous measurements.

$$x_t = \sum_{i=1}^{p} a_i x_{t-i} + \in$$

Here p is the order of the AR model. It determines the window of past input to calculate the present input. The p is determined using cross validation. Here a_i is the set of coefficients and x_t denotes the current measurement. Also $\in$ is the zero mean white noise process.

iv) **Kalman Filtering -** It is the best of all Bayesian filtering algorithms. For both the dynamics and measurement probabilities, linear Gaussian models are used to derive a Kalman filter. Kalman filter uses a Gaussian distribution having specific mean and co-variance, to maintain the estimation of the hidden state of the environment. A linear equation for dynamics is used to predict the new time step using the previous time steps. At time t, new input is used to correct the predicted mean and variance and generate a new estimate defined by the corrected variance and mean.

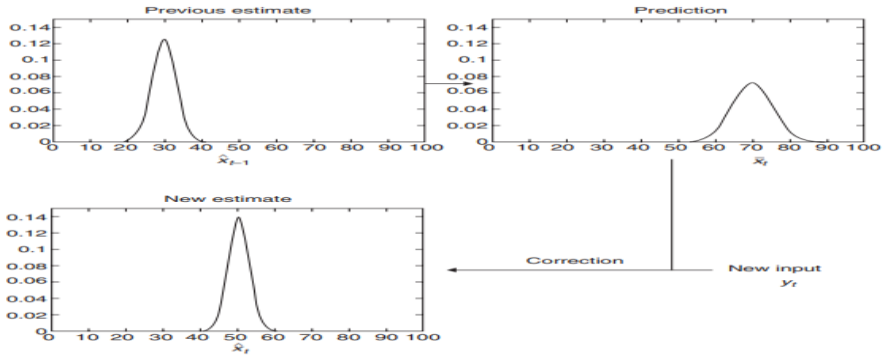


Figure 30: Kalman Filtering

v) **Particle filtering-** It is used to measure the posterior distribution over hidden state in case of non-linear non-Gaussian process. It is also a kind of Bayesian filtering**.** To approximate the posterior, it uses population of samples. In this type of filtering, a set of particles are used to represent the samples present in the prediction distribution. Then every sample is provided a weight and a new measurement value according to its preference. Next, the particles are resampled according to the probability that is proportional to their weights. At last, a new set of particles are obtained representing prediction distribution when they are propagated in time according to the transition probability distribution.

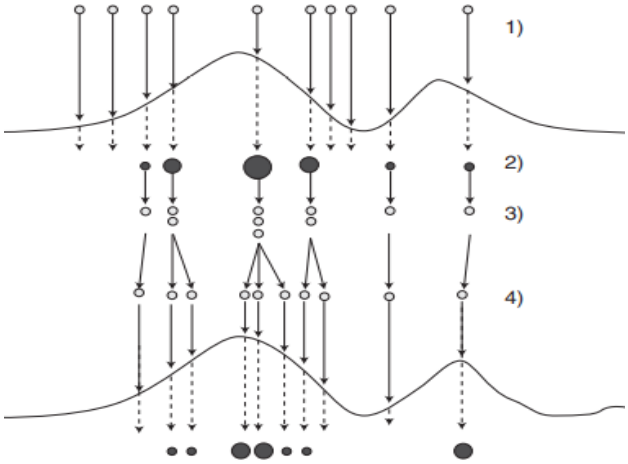


Figure 31: Particle filtering

D) **Spatial Filtering-** it takes brain signals recorded from several channels as input and transforms them in one channel output. Generally to improve local activity, reduce the common noise appearing in several channels and to decrease the dimensionality of recorded brain signal for better classification and computation this type of filtering is used. It helps to maximize the discrimination between different classes.

i) **Bipolar filtering-** here the difference between two electrodes is considered.
ii) **Laplacian filtering-** first the average of four near neighbour electrodes are calculated and then the result is subtracted from each electrode.
iii) **Common average referencing-** here average of all electrodes are calculated and then the result is subtracted from each electrode.
iv) **Principal component analysis (PCA)-** it finds out the hidden variability in the data and reduce the dimension for easy evaluation. Like most of the biological signals, in EEG signals also N electrodes record L dimensional signal resulting a huge number of features which is very tough to evaluate. PCA tries to find out the common rhythms appearing in multiple electrodes and reduce the dimensionality.

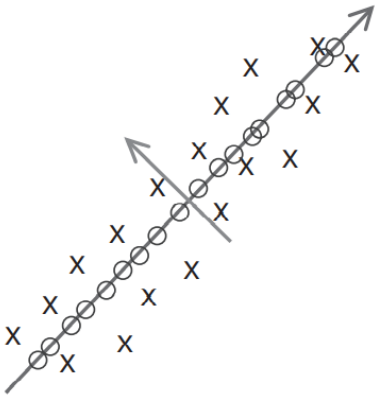


Figure 32: Principle Component Analysis

This figure can be used to explain the PCA properly. PCA finds the direction of maximum variance in data. For this two dimensional data the direction of diagonal vector represents the direction of maximum variation. On the other hand, the second directional vector is perpendicular to the first vector and is short in length. This short arrow represents the amount of data lost in this reduction process as most of the data are considered along the longer vector. PCA can be used in motion artefact removal during fNIR measurement as the data fluctuation is covariant. The performance of PCA depends on the number of eigen vectors to be removed and the number of channels. For small number of channels, PCA is not suitable for noise reduction.

v) Independent Component Analysis (ICA)- to separate noise signals from mixed signals ICA is used. But in this process, the original hemodynamic response is restored. ICA identifies noise signals from their spectral densities. In case of physiological noise removal (like respiration, heart- beat etc), ICA outperforms all other low pass filters. ICA overcomes the disadvantages of PCA as it uses statistical independence rather than decorrelation. All the ICA components are stistically independent after decomposition.

VIII) ARTEFACT REMOVAL

Physiological signals contain noise signals generated by artefacts. To get optimized result, filtering is needed to get only important signals for processing. Some common artefacts that results noise in signal are

- Artefacts generated due to 50 Hz power supply line.
- Uncontrolled physiological activities like respiration and heart rate generate rhythmic artefacts.
- Artefact is also observed during the recording of Galvanic Skin Response when the skin impedance changes due to sweats, mental stress etc.
- EOG and ERG recorded artefacts that are resulted due to eye movement and eye blinking. This type of artefacts results high amplitude deflection of brain signals.
- Muscle artefacts occur due to movement of head, eating etc.

All these artefacts have different frequencies and so they need different methods of filtering

A) Notch filter- it is a band pass filter. Signals are transformed into frequency domain by FFT and then the particular frequency band is attenuated and finally inverse FFT is done to get the signal in time domain. A filter called Notch is used that cancels the power source and power providing instruments' noise of a frequency 50 Hz.

B) Band pass filter- Band pass filters like Butterworth filter, Chebyshev filter, Elliptical filter are used to eliminate noises in the frequency range of 0.1 to 0.4 Hz resulted due to heartbeat and mayer waves.

C) Filtering using PCA and ICA- Physiological noises like noises due to respiration rate results large artefacts in the brain signal, the frequency of these artefacts are close to that of brain signals. As a result, the two type of signals overlap and cannot be separated using low band pass filter. So to eliminate this kind of artefacts, adaptive filtering, PCA (Principal Component Analysis), ICA (Independent Component Analysis) are done. Generally ICA and PCA are very helpful to eliminate EOG artefacts.

D) Common average referencing- Motion artefacts are caused due to head movement, hand movement, chewing etc. These type artefacts are removed using common average referencing. As precaution, subjects are advised to avoid any kind of movement.

IX) FEATURE EXTRACTION

After the signals are processed, they are classified or mapped using different features of the signals. Brain generates signals of large dimensions which are not suitable for classification. So important features are extracted for better classification.

Heuristic methods- In this method, kurtosis, mean, variance, slope, skewness etc are used as feature for the classification. These parameters are generally determined from the shape of hemodynamic signals after the noise elimination.

Filter Coefficients- filter coefficients obtained from Kalman Filtering, wavelet transform are used in feature extraction of fNIR signals.

Genetic algorithms are also used in feature extraction.

In case of fNIR, mean and slope values of HbO, HbR are used in feature extraction. Generally HbO signals are more suitable in fNIR feature selection because it is more stable than the other signals.

X) CLASSIFICATION TECHNIQUES

Different brain signals are identified by the user using different classification techniques and are converted into control signals for application purposes. Generally, classification algorithms are designed by users using supervised learning in the training phase. In the testing phase the classifiers are provided test signals to divide them into existing classes.

LDA

It is the mostly used classifier in BCI due to its simplicity. Discriminant hyper planes are used to separate data set into different classes. It requires less computation and so very popular in online BCI. A normal data distribution is assumed by LDA with an equal covariance matrix in both classes. The separating hyper plane is obtained when the distance between the two classes' mean is maximized and interclass variance is minimized. This algorithm tries to separate the two projected classes 1 and 2 in the direction of vector v which is found in the feature space. During the separation of two more classes, the variance is maintained as small as possible by maximizing Fisher's criteria.

$$J(v) = \frac{v^T S_b v}{v^T S_w v}$$

Here S_b is between class and S_w is within class scatter matrix.

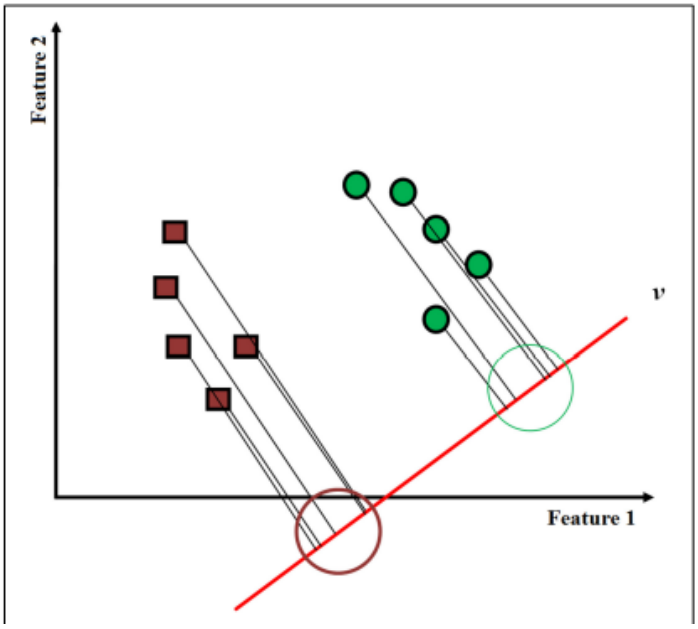


Figure 33: LDA classification depicting the best separating hyperplane

$$S_b = (m_1 - m_2)(m_1 - m_2)^T,$$
$$S_w = \sum_{x_n \in C1} (x_n - m_1)(x_n - m_2)^T + \sum_{x_n \in C2} (x_n - m_1)(x_n - m_2)^T$$

Here group mean of class C1 is represented by m_1 and m_2 represents the group mean of class C2. On the other hand, x_n represents the samples.

SVM

It is a linear classifier. The main aim of this classifier is to maximize the distance between the nearest training points and the separating hyper planes which is denoted in the 2D feature space by

$$f(x) = r.x + b,$$

Here, r, $x \in R^2$ and $b \in R^1$. Optimal solution can be obtained if the cost function is minimized.

$$J(r, \xi) = \frac{1}{2}\|r\|^2 + C.\sum_{n=1}^{z} \xi_n,$$

Satisfying the condition,

$$(x_n.r + b) \geq 1 - \xi_n \text{ for } y_n = +1,$$
$$(x_n.r + b) \geq -1 + \xi_n \text{ for } y_n = -1,$$
$$\xi_n \geq 0 \; \forall \; n,$$

Here user chooses the positive regularization parameter C. This classifier improves the capability of generalize. Though it is a linear classifier, using Kernel functions like Gaussian functions can help it to do non-linear function, increasing the classification accuracy.

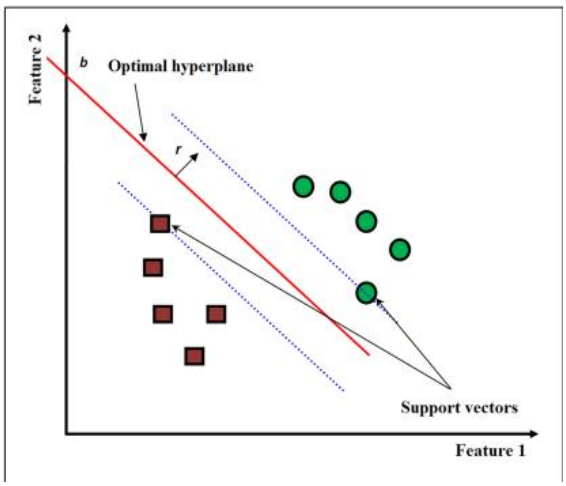


Figure 34: SVM classification

ANN

It is a non- linear classifier that mimics human brain activity while performing any neural activity. In case of pattern recognition, ANN is widely used. It can understand the post –training capability to recognise the set of training data related patterns. ANN is constructed by several artificial neurons to draw decision boundaries with non-linear characteristics. ANN are generally used in variety of architectures like Gaussian classifier, RBF neural network etc

. **KNN**

It is one of the simplest algorithms. The dataset is divided into two groups. The group of data with highest population is used as training set and divided into different classes. Now data from test set is introduced to the classifier wand a user defined K value is provided where K is number of nearest neighbours. Euclidean distances of test value from all K points are calculated and nearest neighbours are determined. Finally the test data is assigned to the category which contains maximum number of neighbours.

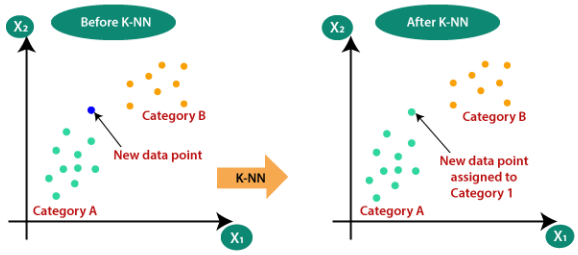


Figure 35: KNN classification

These four are most commonly used classifiers in BCI. But nowadays Convolutional Neural Network (CNN), SNN etc are used for better result in some cases.

CHAPTER 4

REVIEW OF LITERATURE

Since the beginning of the human civilization, 'touch' is adopted as a fundamental modality of nourishment specially for children and people suffering from psychological distresses (including stress, anxiety and depression) [1], [2]. However, the role of 'soft touch' in inducing affection is emphasized very recently in scientific publications [3], [4]. The true understanding of touch perception from the points of view of changes in activation of different brain regions remained a virgin area of research in brain and cognitive sciences till this date. This paper explores the possibility of inducing 4 different classes of affective emotions by touching one subject's palm by her family members (spouse, child and parents). It makes an attempt to assess the true 'nature of affection' (love, fondness, respect and devotion) aroused in a subject during the period of contact of her palm with her individual family members as well as a sculpture of God/Goddess she is habituated to worship, directly from the hemodynamic response of her brain.

Similar works have been undertaken recently [5] using EEG-based BCI. EEG offers the advantage to responding to instantaneous changes in the input stimuli. However, due to poor spatial resolution, it is unable to localize the brain activation regions precisely, and also fail to provide the accurate degree of activations at different brain regions because of volume conductivity of the scalp [6]. Functional Magnetic Resonance Imaging (f-MRI) [7] is a good choice to get rid of the above problems. However, because of excessive cost of the f-MRI device, most of the small BCI labs in the world cannot afford it. Rather, these labs utilize functional Near Infrared Spectroscopy (f-NIRs) [8] to determine the brain activations at different locations in the brain. In this paper, we would deal with f-NIRs device to capture the brain activations. These devices measure oxygenated and de-oxygenated blood concentrations, thus offering the degree of activation in a brain region based on the consumption of oxygen in the local tissues of the region. It is noteworthy that during arousal of an emotion, one or more activation regions in the brain are found active. The natural question that appears immediately: can we recognize the emotion of a person from his brain activation regions? This paper will ultimately give an answer to this important question. The approach adopted to handle the present problem is outlined next.

First, the brain regions responsible for a selected affective emotion are identified. It is important to learn that for the four classes of emotion chosen, the common brain regions are temporal and pre-frontal lobes. However, there exist temporal variations in the activation patterns within the sub-regions of an activated region. For instance, if the emotion refers to love, the affected brain regions show high activations first in the hippocampus (temporal lobe) and then shifts towards Orbito-frontal cortex (in the pre-frontal lobe). In case of parental respect, a high activation first appears in Orbito-frontal cortex, which has a gradual shift towards the temporal region. These observations jointly

reveal that the training instances to be developed should include temporal variation in the regions. After the emotions are aroused, we ask the subject about his/her feeling and thus fix up the emotion as the class and the temporal variations in the regions as the features to develop the training instances.

Any traditional classification algorithm could be employed to train the classifiers by the generated training instances. However, because of intra-subjective and inter-subjective variations, a fuzzy classifier is a better choice [9]. In this paper, a Takagi-Sugeno-Kang (TSK) [10]-[11] based Interval Type-2 Fuzzy Classifier is employed to handle the present problem. Takagi-Sugeno-Kang (TSK) based model is advantageous to its competitor Mamdani based model with respect to structure of the fuzzy rules. Both the Mamdani and Takagi-Sugeno-Kang (TSK) model include similar antecedent part, but they differ in the consequent side [12]. While Mamdani based rules have a fuzzy quantified proposition of the output variable in the consequent, TSK-based model employs a linear function of the antecedent variables as the consequent. So, the variable in the consequent can be obtained in defuzzified form, and needs no additional defuzzification and type-reduction [13].

CHAPTER 5

EXPERIMENTAL METHODOLOGY

This section gives a brief description of the principles and methodologies that have been undertaken to classify four distinct affection classes from the hemodynamic response of the subjects. The touch induced affective emotion classification is performed in five steps: (a) Time-windowing and Data acquisition b) Normalization of the raw f-NIRs signals, (c) pre-processing and artifact removal, (d) feature extraction and selection from the filtered f-NIRs data and (e) classification. Fig. 1 provides the basic block diagram of touch induced affective emotion classification using f-NIRs device.

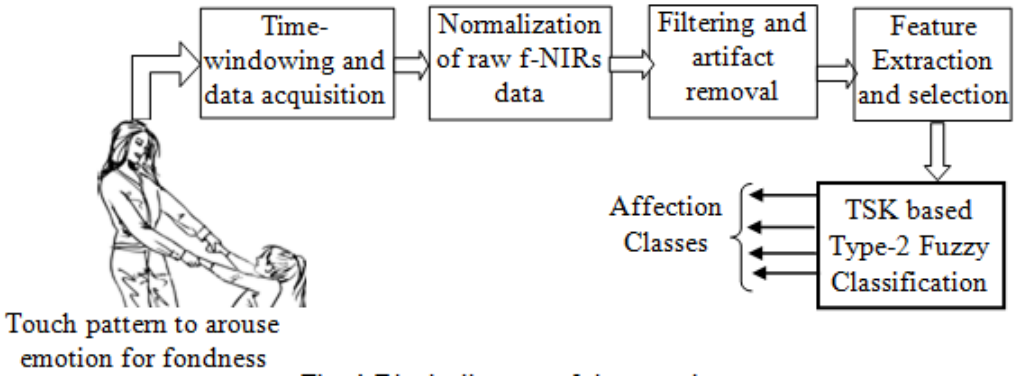


Figure 36: Bloch diagram of the complete system

A) Time-windowing and Data acquisition

In the present context, the f-NIRs data acquisition is carried out over various time-windows across trials. Each trial includes 4 distinct touch patterns for the arousal of four emotions such as Devotion, Respect, Love and Fondness. The subject arouses her affective emotions, when she comes in contact (due to touch) with her better half, child, mother and model of any god or goddess over a certain time-intervals. The hemodynamic response is acquired from the scalp of the subject for 60s duration with a time interval (rest period) of 30s. Consequently, the total duration of each trial is 330s containing (60s × 4) = 240s for 4 distinct touch patterns and (30s × 3)s = 90s for 3 rest periods. The experiment includes 10 such trials in a session. Each session starts with 3s fixation cross. To overcome the contamination effect between two successive trials, an interval of 30s time gap is maintained over a session. Each session is repeated for 5 times in a day. Fig. 2 provides one timing diagram of trials over a session.

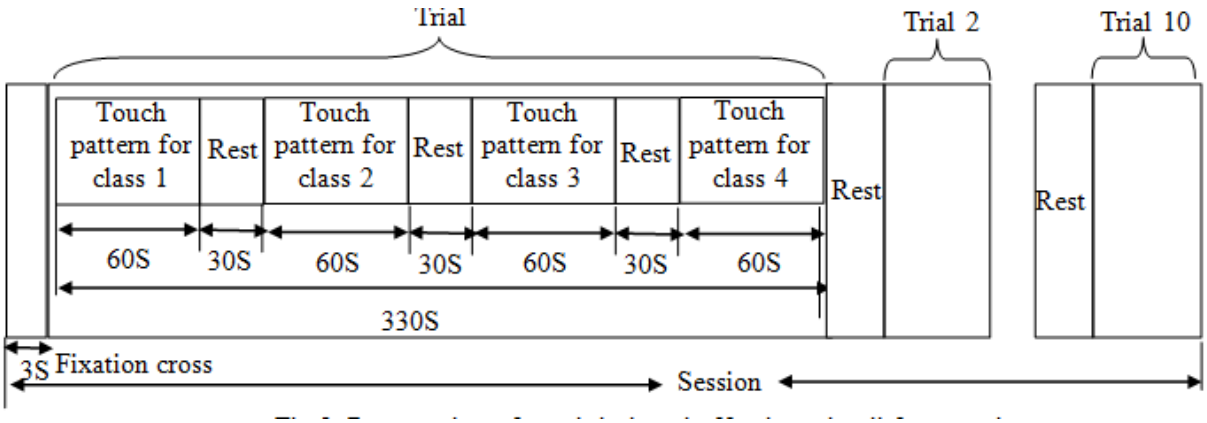


Figure 37: Presentation of touch-induced affection stimuli for a session

B) Normalization of raw f-NIRs data

The following principle is adopted for the normalization of the Hemodynamic response. Let $C_{HbO_\alpha}(t)$ be the oxygenated hemoglobin concentration of α-th channel at time *t*. Similarly, $C_{HbR_\alpha}(t)$ be the de-oxygenated hemoglobin concentration of α-th channel at time *t*. The normalization of $C_{HbO_\alpha}(t)$ and $C_{HbR_\alpha}(t)$ at a given channel are evaluated by the following 2 parameters:

$$^{\max}C_{HbO} = Max_t(C_{HbO_\alpha}(t) : t_0 \le t \le T, \forall \alpha) \quad (1)$$

$$^{\min}C_{HbR} = Min_t(C_{HbR_\alpha}(t) : t_0 \le t \le T, \forall \alpha) \quad (2)$$

where t_0 and T stands for the starting and the completion time points of a trial of experiment for a particular touch pattern of a specific subject [14].

The cerebral oxygen change in the temporo-prefrontal part is normalized in [0,1] by the following equation.

$$d_\alpha(t) = \frac{(C_{HbO_\alpha}(t) - C_{HbR_\alpha}(t))}{^{\max}C_{HbO}(t) - ^{\min}C_{HbR}(t)} \quad (3)$$

The sampling frequency of the particular device used in the experiment is 7.8 Hz. During the training phase, each touch pattern having 60 × 7.8 = 468 samples/s.

C) Artefact Removal from normalized f-NIRs data

Due to the non-stationery characteristics of brain signals, the acquired f-NIRs signals are not free from artefacts. To eliminate the artefacts from the raw EEG signals, three individual steps are undertaken. In the first step, the *Common Average Referencing (CAR*) [15] has been performed to eliminate the motion artefacts.

Let $d_\alpha(t)$ be the normalized oxygen consumption of channel α at time *t* and $d_{avg}(t)$ be the average oxygen consumption over all channels(=20) at time *t.* Thus the *common average referenced* signal $CAR_\alpha(t)$ for channel α = 1 to 20 is evaluated by

$$CAR_\alpha(t) = d_\alpha(t) - d_{avg}(t). \quad (4)$$

In the second step, the $CAR_{\alpha}(t)$ signals are passed through the Elliptical filter [16] which is a band pass filter having the order of 10, to eliminate the biological artefacts like eye ball rotation, blinking the eye leads, heart rate, respiration etc. The pass band frequency of the Elliptical band pass filter is (0.1-8) Hz. Finally, the independent component analysis (ICA) [17] has been performed to determine the highest correlation between f-NIRs signals acquired from other channels.

D) Feature Extraction and selection

To extract the important set of features from the filtered f-NIRs signals, the 60s time interval for each touch pattern is divided into 6 equal time frames. Two groups of features (one is group of static features and the other is dynamic features) are extracted from each time frame. Static features include mean variance, skewness, kurtosis, average energy and the dynamic features include the changes in static features between two consecutive time frames [18].

In the present application, (5×6=) 30 static features and (5×5=) 25 dynamic features, altogether (30+25=) 55 features are extracted for a given channel. Thereby, from 20 channels yield 55x20 = 1100 features for each trial of a given touch pattern. Next, from 1100 features, 50 best features are selected using Evolutionary algorithm for classifier training. Here, the popular Differential Evolution (DE) algorithm has been used because of its simplicity, low computational cost [19], [20].

Now, to classify 4 emotions, each session includes 10 trials and 5 such sessions are prepared for each touch pattern. Consequently, for 30 healthy subjects 30 × 5 sessions × 10 trials/session = 150 trials are generated for each touch pattern.

Finally, for 4 touch patterns 4×150 = 600 training instances are fed to the proposed TSK based Interval type-2 fuzzy classifier to classify 4 distinct emotions aroused from the hemodynamic response of a subject.

E) Proposed TSK-based Interval Type-2 fuzzy (TSK-IT2Fs) Classifier design

A novel TSK based Interval Type-2 Fuzzy (IT2F) classifier model has been presented here to classify 4 affective emotions of a subject from their acquired hemodynamic responses.

Let, $f_1, f_2, \ldots, f_n$ represent n number of features that are extracted from the respective channel positions in the brain of a person during the experimentation. The experiment is performed over 5 sessions in a day, where each session comprises 10 experimental trials. Let, $f_{i,j}$ is $\tilde{A}_{i,j}$ is a fuzzy proposition utilised to build up the forerunner part of the required fuzzy rule *j*. For the construction of $\tilde{A}_{i,j}$, intra-session and inter-session variations has been considered.

Suppose, $f_{i,h,s,j}$ be *i*-th feature extracted on session *s* for the h^{th}*trial* of rule *j*. For a session s, the mean and the variance of the i^{th} *feature* of that rule are given by

$$\bar{f}_{i,s,j} = (\sum_{h=1}^{10} f_{i,h,s,j})/10 \quad (5)$$

$$\sigma^2_{i,s,j} = \sum_{h=1}^{10} (f_{i,s,h,j} - \bar{f}_{i,s,j})^2 / 10. \quad (6)$$

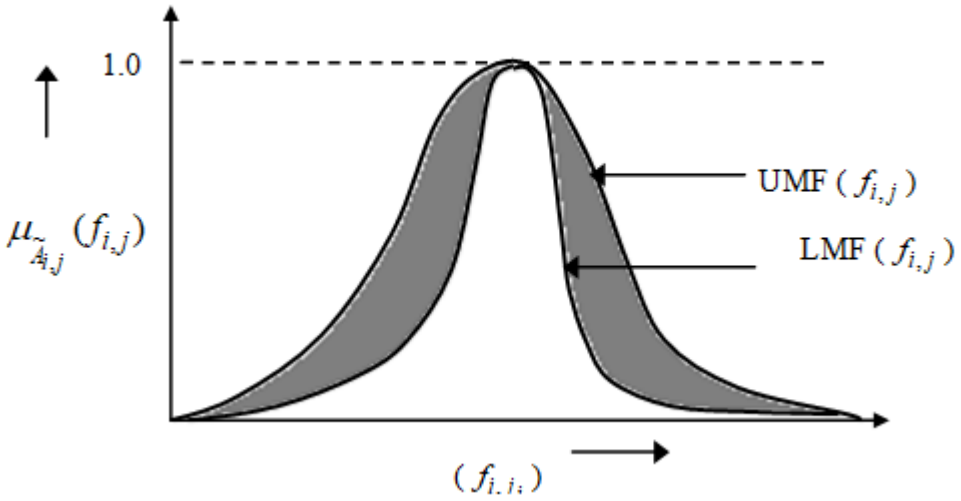


Figure 38: Construction of $\mu_{\tilde{A}_{i,j}}(f_{i,j})$

Now, a type-1 Gaussian MF $G(\bar{f}_{i,s,j}, \sigma^2_{i,s,j})$ is constructed to model the intra-session variation of *i*-th feature extracted from rule *j*.

Now, the Upper MF (UMF), of feature *i* of *j*-th rule is considered as

$$UMF(f_{i,j}) = \bar{\mu}_{\tilde{A}_{i,j}}(f_{i,j}) = G_{i,j}(\bar{f}_{i,s,j}, \sigma^2_{i,s,j}) \quad (7)$$

where,

$$G(\bar{f}_{i,s,j}, \sigma^2_{i,s,j}) = \exp[-(f_{i,s,j} - \bar{f}_{i,s,j})^2 / 2\sigma^2_{i,s,j}] \quad (8)$$

Now, to construct the Lower MF (LMF) of $f_{i,j}$, we consider the concentration [9] of the UMF.

Mathematically,

$$LMF(f_{i,j}) = Con(\bar{\mu}_{\tilde{A}_{i,j}}(f_{i,j})) = (\bar{\mu}_{\tilde{A}_{i,j}}(f_{i,j}))^2. \quad (9)$$

Fig. 3 provides the construction of the membership functions of the IT2F sets.

The TSK model proposed here employs type-2 fuzzy rules, where the *j*-th rule is given by $If\ f_1 \text{ is } \tilde{A}_{1,j},\ f_2 \text{ is } \tilde{A}_{2,j},\ldots,\ f_n \text{ is } \tilde{A}_{n,j}, Then\ y_j = \sum_{i=1}^{n} a_{i,j} * f_i + b_j$. Here, $f_1, f_2,\ldots, f_n$ together denotes a measurement point, and y_j denotes the signal power of the temporo-prefrontal region to classify effective emotion classes.

The co-efficient $a_{i,j}$ and b_j used in the classifier model are evaluated by classical least min-square technique [21], [22].

The proposed TSK-based IT2Fs model undertakes the following steps in order (Fig. 4).

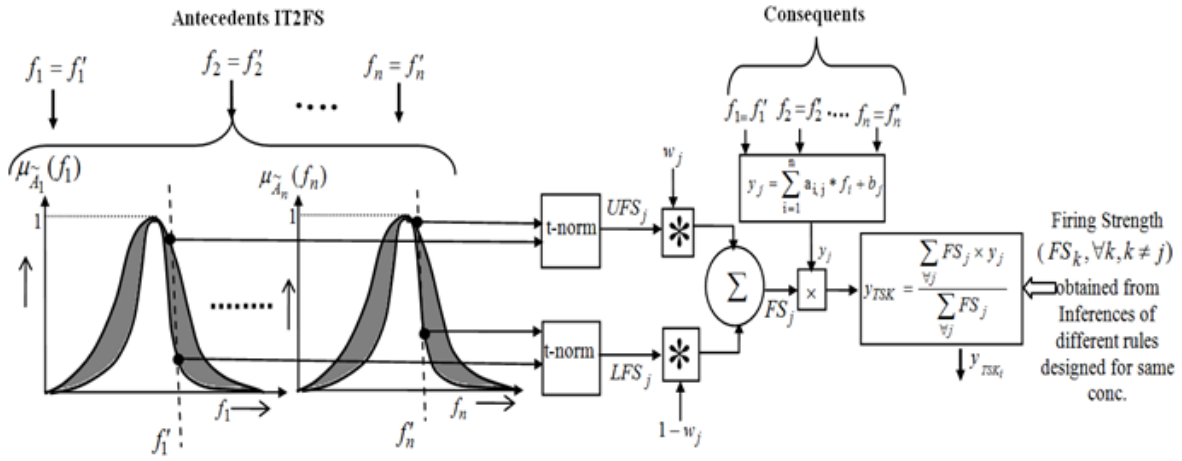


Figure 39: Architecture of Proposed TSK based Interval Type-2 Fuzzy Classifier

1. For the *j*-th rule, computation of UFS or Upper Firing Strength as well as the LFS or Lower Firing Strength at the given measurement point $f_1 = f_1', f_2 = f_2',\ldots, f_n = f_n'$ are depicted by eq. (10) and (11) respectively.

$$UFS_j = \min[\bar{\mu}_{\tilde{A}_1}(f_1), \bar{\mu}_{\tilde{A}_2}(f_2),\ldots, \bar{\mu}_{\tilde{A}_n}(f_n)] \quad (10)$$

$$LFS_j = \min[\underline{\mu}_{\tilde{A}_1}(f_1), \underline{\mu}_{\tilde{A}_2}(f_2),\ldots, \underline{\mu}_{\tilde{A}_n}(f_n)] \quad (11)$$

2. Next, the (FS_j) for rule *j* is evaluated by using the product of the weighted summation of UFS_j and LFS_j. The weights are all in the range between [0, 1] so, one of the weights can be w_j and the other one is $1-w_j$. Thus, for rule *j*, the FS or the firiging Strength will be,

$$FS_j = w_j . UFS_j + (1-w_j) . LFS_j . \quad (12)$$

Finally, to select the weight optimally, Evolutionary algorithm (EA) has been used.

3. In case of resulting response of the type-2 TSK- based type-2 fuzzy classifier model is computed by

$$y_{TSK} = \frac{\sum_{\forall j} FS_j \times y_j}{\sum_{\forall j} FS_j}, \tag{13}$$

where FS_j is the firing strength of the *j*-th rule.

Now, to classify four emotions classes from the measure of y_{TSK}, we divide the interval $[0, {y_{TSK}}^{\max}]$ into 4 non-overlapped partitions, where each partition is segregated from its neighbors by two partition-boundaries. Thus for 4 partitions, we need to insert three partition boundaries. Let α_1 through α_3 be three boundaries in $[0, y_{TSK}]$, such that ${y_{TSK}}^{Max} > \alpha_3 > \alpha_2 > \alpha_1 > 0.$

Now, the boundaries α_1 through α_3 are evaluated by an Evolutionary algorithm. The motivation in the present context is to choose the parameters α_1 through α_3, so as to maximize the classification accuracy for a given set of training instances of affection classification.

CHAPTER 6

EXPERIMENT AND RESULTS

Experiments are undertaken in two different phases, one is the Training phase and the other one is the test phase. In the training phase, weights: w_j and $(1-w_j)$ for each rule j are tuned in order to maximize the classification accuracy for training instances of each class. After the training phase is over, we go for the test phase, where the affection-class of an unknown instance of brain response is provided as an input, and the class of affection is determined using the pre-trained IT2 fuzzy classifier.

A) Experimental framework and f-NIRs data acquisition

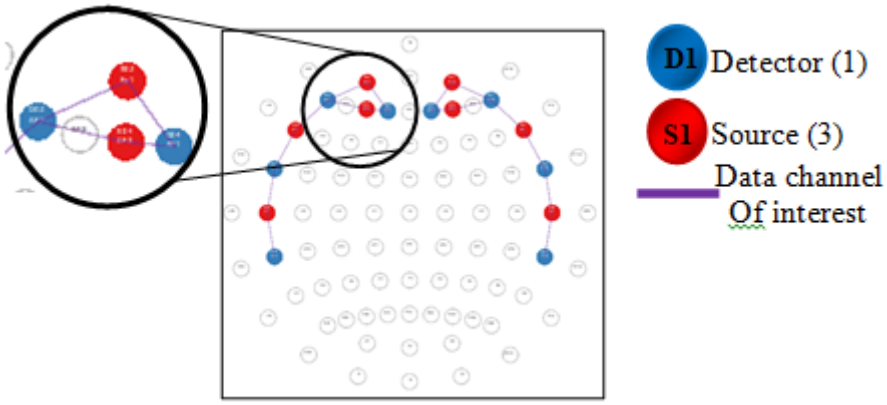


Figure 40: Source-detector connection of Temporo-prefrontal cortex 8×8 montage

Figure 41: Setup for Experiment

This interesting experiment has been conducted in Artificial Intelligence laboratory of Jadavpur University, Kolkata, India [23]. The arrangement for the experiment is shown in Fig. 5(a). A whole brain f-NIRs device, manufactured by NIRx Medical Technologies LLC, has been used which captures the hemodynamic response of every

subject [24]. The f-NIRs device includes 8 Infrared sources and 8 Infrared detectors, which form 8 × 8 = 64 channels and placed over the scalp of the subject. Among 64 channels, 20 nearest neighboring source-detector pairs are utilized to execute the experiment (Fig. 5(b)). The experiment has been performed over ten healthy and normal volunteers (mostly women), in the age between 25-32 years, with her husband, mother and her own child. Each women volunteer are requested to arouses their emotions, when they come in physical contact with their husband, mother and their 2 to 4 years old child.

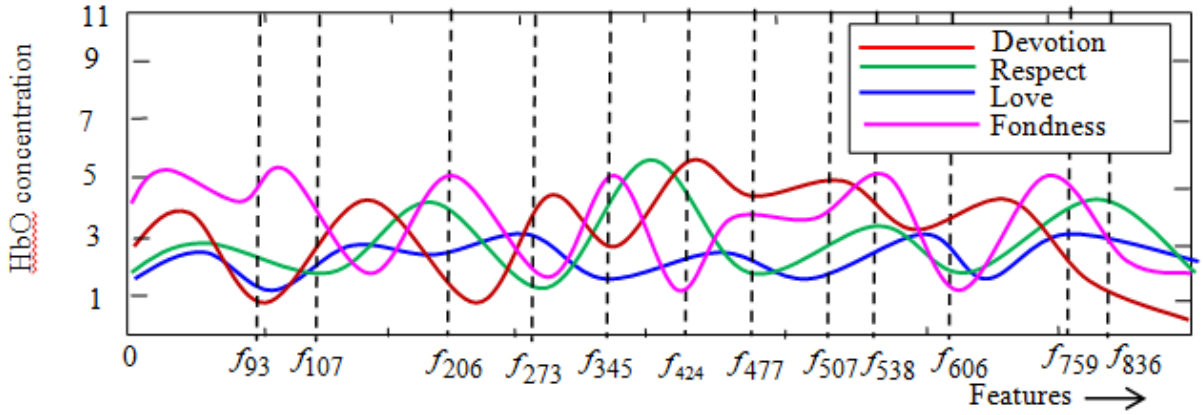


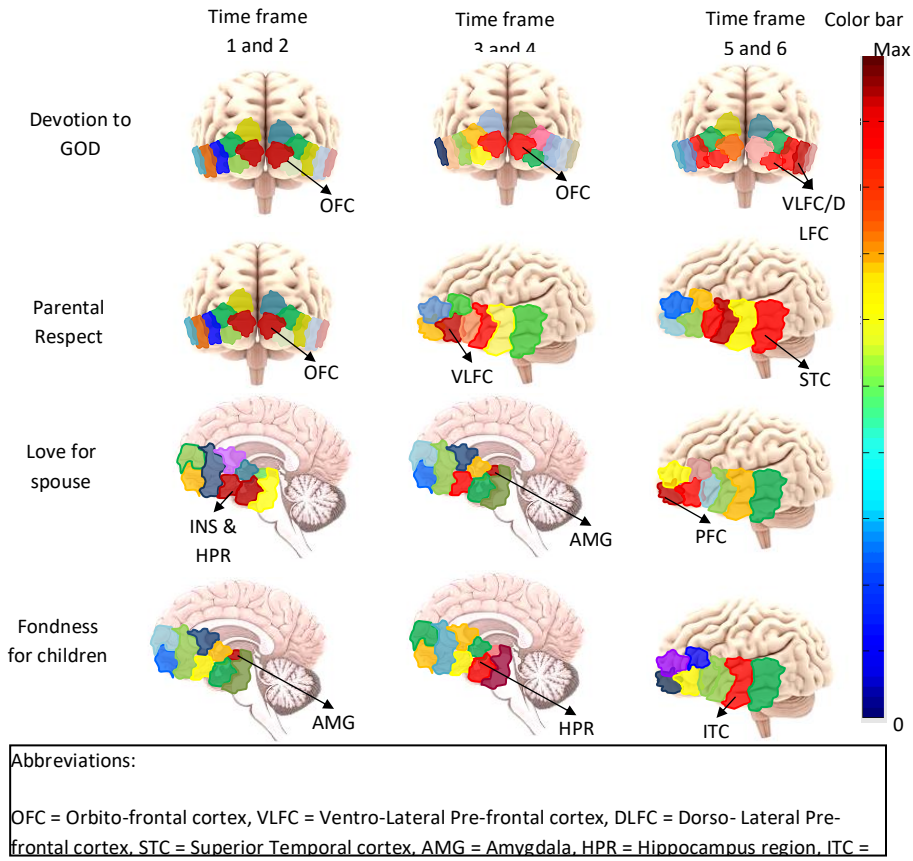
Figure 42: Feature level discrimination between mean HbO concentrations for four affective emotions

B) Experiment 1: (Automatic Feature Extraction to discriminate 4 affective emotions)

The main focus of the current experiment is to discriminate f-NIRs features that are recorded for 4 affective emotions aroused by the subjects. We adopt Differential Evolutionary (DE) algorithm to select the best possible f-NIRs features from the extracted f-NIRs features. DE selects most significant 50 features from a large dimension (=1100 features) feature sets. 12 best features among 50 optimal features are depicted in Fig. 6 to categorize 4 affective emotions aroused from the hemodynamic response of a subject. It can be seen from the figure, feature f_{93} (mean HbO concentration obtained from channel 4, f_{107} (mean HbO concentration obtained from channel 12), f_{206} (mean HbO concentration obtained from channel 18), f_{273} (mean HbO concentration obtained from channel 20), f_{345} (standard deviation of HbO concentration obtained from channel 15), f_{424} (standard deviation of HbO concentration obtained from channel 16), f_{477} (standard deviation of HbO concentration obtained from channel 19), f_{507} (avg. energy obtained from channel 7), f_{538} (avg. energy obtained from channel 10, f_{606} (avg. energy obtained from channel 14), f_{759} (avg. energy obtained from channel 19), f_{836} (skewness obtained from channel 17), have the maximum inter-class separation.

C) Experiment 2: Analysing Topographical Map for Individual Emotions

This investigation aims to identify the relative changes in the topographical images for four seperate emotions. The below figure illustrates the brain activation regions and their hemodynamic load distribution in brain lobes over different time frames. To capture the temporal features of the cognitive task, the total duration of acquired f-NIRs data has been divided into 6 time frames. It is observed from the plot that the brain activation is shifted from one region to another over different time frame. For example, the Orbito-frontal cortex (OFC) is highly activated for the first four time frames then it shifts towards Ventro/Dorso lateral Pre-frontal cortex (VLFC/DLFC) for the emotion aroused due to Devotion. For emotion parental respect, the activation shifts from OFC to VLFC and finally the Superior Temporal cortex (STC) is highly activated in the last two time frames. Similarly, the Insular (INS) and Hippocampus regions (HPR) are highly activated for the emotion of love and then the activation shifts to pre-frontal cortex (PFC) through Amygdale (AMG). Hippocampus regions (HPR) and Inferior Temporal cortex (IFC) for the next time frames.



Abbreviations:

OFC = Orbito-frontal cortex, VLFC = Ventro-Lateral Pre-frontal cortex, DLFC = Dorso- Lateral Pre-frontal cortex, STC = Superior Temporal cortex, AMG = Amygdala, HPR = Hippocampus region, ITC =

Figure 43: Identification of activation regions and their shifts for individual affective emotions in 6 various

D) Experiment 3: Variation in Hemoglobin Concentration for Intra and inter-subjective assessment

The prime motivation of this experiment is to determine the intra and inter-subjective variations in oxy-hemoglobin concentration (HbO) and de-oxy-hemoglobin concentration (HbR) of a particular time frame (such as 20 to 40 seconds) of a selected channel (here, channel 4). It is clearly observed from the experimental results, that the changes in the hemodynamic load takes place in the selected time-window for all subjects. Fig. 8 (a-b) provides the variation in hemodynamic load distribution for two selected subjects over four distinct emotions. It is apparent from the plot, that the amplitude of concentration of de-oxy-hemoglobin (HbO) and oxy hemoglobin (HbR) of subject 5 is increased than subject 9 in the same selected time frame.

To minimize this intra-and inter-subjective variations, Type-2 fuzzy classifier is employed in this paper.

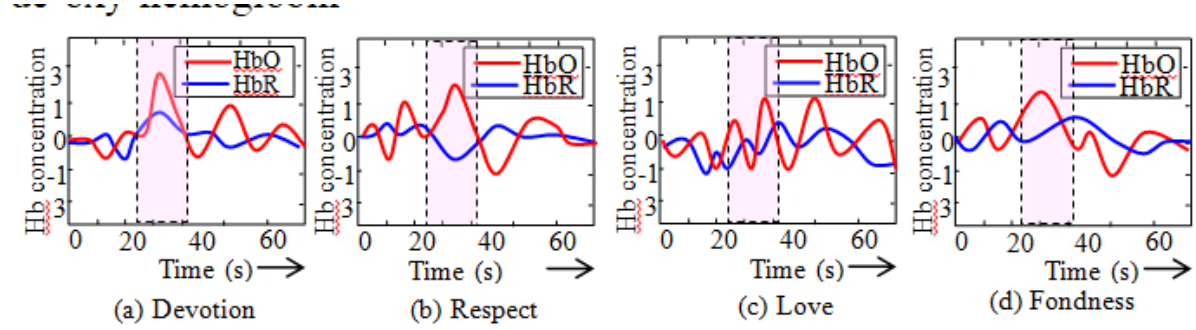


Figure 44: Changes in Hemoglobin concentration for four distinct affections of subject 5

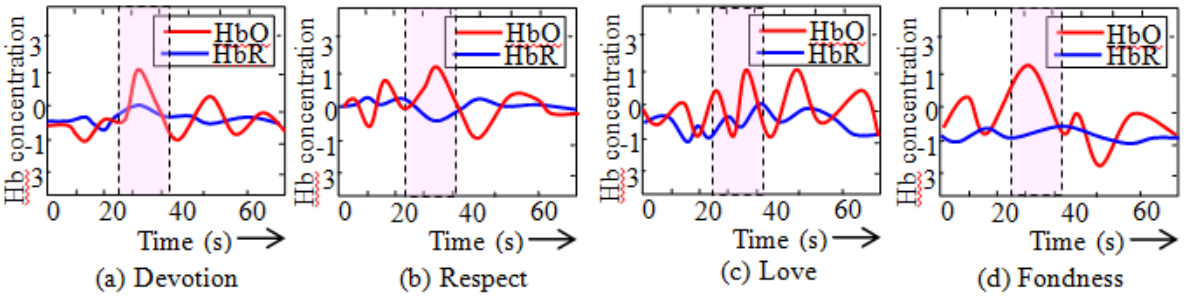


Figure 45: Changes in Hemoglobin concentration for four distinct affections of subject 9

CHAPTER 7

DISCUSSION

Performance Analysis Of The Classifier and Its Statistical Validation

The section explains the performance analysis of this proposed classifier at four individual levels. First, The per centum value of True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) have been evaluated for every emotion class. Table-1 gives the result of calculation of TP, TN, FP and FN value for a selected (Fondness) class over the existing classifiers. This is apparent from the table that the suggested TSK-based Type-2 Fuzzy system yields better performance over its competitors. Second, a comparative study has been undertaken in Table-2 to determine the performance of suggested f-NIRs based classification technique over the EEG- based classification, depending on four metrics: Sensitivity (SEN), Classification Accuracy (CA), Specificity (SPE), and F1-score [25]. Which are formally introduced by equations (14), (15), (16), and (17) respectively.

$$CA = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

$$SEN = \frac{TP}{TP + FN} \tag{15}$$

$$SPE = \frac{TN}{TN + FP} \tag{16}$$

$$F1\ score = \frac{2TP}{2TP + FP + FN} \tag{17}$$

Classifiers	TP%	TN%	FP%	FN%
LSVM classifier [26]	79.0%	78.9%	21.1%	21.0%
KSVM-RBF Kernel classifier [27]	82.7%	80.8%	19.2%	17.3%
KSVM- polynomial kernel [28]	83.3%	84.6%	15.4%	16.7%
BPNN [29]	87.1%	88.8%	11.2%	12.9%
Genetic Algorithm based Type-1 Fuzzy classifier [30]	78.1%	76.8%	23.2%	21.9%
Difference Evolution (DE) based IT2Fs classifier [31]	90.0%	91.8%	8.2%	10.0%
Type-2 fuzzy-RBF- perception neural net (T2F-RBF-PNN) [14]	98.3%	97.0%	3.0%	1.7%
Mamdani-based IT2FS [16]	95.5%	96.2%	3.8%	4.5%
Proposed TSK-based IT2FS	**98.9%**	**97.7%**	**2.3%**	**1.1%**

Table1- Comparative Study of the proposed Classifier over Existing ones

Affective emotion classes	EEG based Classification accuracy [5]				f-NIRs based Classification accuracy(proposed)			
	CA (%)	SPE	SEN	F1-score (%)	CA (%)	SPE	SEN	F1-score (%)
Devotion	78.9	0.78	0.79	78.3	92.6	0.93	0.92	92.5
Respect	79.9	0.85	0.75	79.5	94.7	0.95	0.94	94.8
Love	83.7	0.80	0.85	82.9	95.7	0.96	0.95	96.0
Fondness	82.5	0.85	0.82	82.9	93.5	0.94	0.92	93.7

Table 2-Comparative performance of proposed study of f-NIRs and EEG based classification accuracy (standard deviation) of affective emotions

It is observed from Table - 2 that the performance of this new f-NIRs based classifier is enhanced over the EEG-based classification technique by a large margin. Third, Table-3 describes the evaluation of the relative performance of the suggested classifier. The proposed TSK-based Interval Type-2 Fuzzy algorithm outperforms to its competitors by a significant level. Finally, the popular Mc-nemar's test [32] has been performed to evaluate statistically. According to this Mc-Nemar's test, the value of z-score can be defined as

$$z = \frac{(|n_{01} - n_{10}| - 1)^2}{n_{01} + n_{10}} \qquad \textbf{(18)}$$

Classifier Used	Classification Accuracy (Standard Deviation) for four affective emotions			
	Devotion	Respect	Love	Fondness
LSVM classifier[26]	66.7 (0.049)	68.2 (0.042)	66.8 (0.044)	68.0 (0.045)
KSVM-RBF Kernel classifier [27]	71.2 (0.039)	70.9 (0.044)	71.3 (0.034)	70.4 (0.035)
KSVM- polynomial kernel [88]	73.8 (0.039)	74.6 (0.022)	73.3 (0.029)	73.6 (0.055)
BPNN [29]	76.6 (0.049)	77.2 (0.042)	76.8 (0.044)	78.3 (0.045)
Genetic Algorithm based Type-1 Fuzzy classifier [30]	65.2 (0.069)	65.8 (0.062)	65.1 (0.064)	66.4 (0.064)
Difference Evolution (DE) based IT2Fs classifier [31]	80.5 (0.029)	81.3 (0.044)	81.7 (0.056)	81.1 (0.055)
type-2 fuzzy-RBF-perception neural net (T2F-RBF-PNN) [14]	89.2 (0.020)	89.7 (0.022)	90.6 (0.024)	89.5 (0.028)
Mamdani-based IT2FS [16]	91.8 (0.015)	92.7 (0.016)	92.5 (0.011)	92.0 (0.014)
Proposed TSK-based IT2FS	**95.2 (0.009)**	**95.6 (0.008)**	**95.0 (0.011)**	**96.3 (0.011)**

Table3- Mean Classification Accuracy in percentage (standard deviation) of Classifiers

where, n_{01} denotes the number of classes misclassified by the proposed classification algorithm X but not by the other standard classification algorithm Y. Similarly, n_{10} indicates the number of classes that are wrongly classifier by Y and not by X. The results of statistical validation are presented in Table-4. The above analysis confirms that the null hypothesis for the standard classifiers are not accepted because the z-score of all the other classifiers crossing the value $\chi^2_{1,0.95} = 3.84$.

Classifier name	*m*	*n*	z	Comments on acceptance/ rejection of hypothesis
LSVM [26]	6	17	4.34	Rejected
KSVM-RBF Kernel [27]	20	63	21.2	Rejected
KSVM- polynomial kernel [28]	13	33	8.53	Rejected
BPNN [29]	17	67	28.5	Rejected
Genetic Algorithm based Type-1 Fuzzy classifier [30]	13	37	10.5	Rejected
Difference Evolution (DE) based IT2Fs classifier [31]	23	49	8.68	Rejected
type-2 fuzzy-RBF- perception neural net (T2F-RBF-PNN) [14]	19	35	4.16	Rejected
Mamdani-based IT2FS [16]	31	97	33.0	Rejected
Proposed TSK-based IT2FS	**7**	**16**	**2.78**	**Accepted**

Table 4- Statistical performance analysis for suggested algorithm using McNemar's Test

CHAPTER 8

CONCLUSION

The paper introduced a novel approach to affective emotion classification using hemodynamic brain response by employing TSK-based IT-2 Fuzzy classifier. The proposed design requires adaptation of 2 weights w_j and $(1-w_j)$ for each rule *j*, which are optimally selected during the training phase to maximize the classification accuracy of all the affection classes. In the test phase, the pre-trained classifier is utilized to classify unknown instances of brain hemodynamic responses corresponding to test data for 4 classes: devotion, respect, love and fondness.. Experiments undertaken confirm the superiority of the said technique over the state-of-the-art techniques, including both classical fuzzy, Type-2 Mamdani based fuzzy and non-fuzzy standard techniques. The proposed TSK-based fuzzy classifier would find interesting applications in sensitivity assessment of healthy and psychiatric disordered people.

CHAPTAR 9

FUTURE SCOPE

There is still a subtle problem that needs to be clarified at the beginning. How do we ensure that the emotions we capture from the subject are inherently accurate? For instance, touching wife's palm by her husband may not ensure transmission of love, in case the wife is aware of her husband's psychological involvement with a number of girlfriends. Similarly, a touch by a mother to her daughter may not result in a glimpse of respect in the daughter, if the latter dislikes her mother. This took a lot of time to identify individuals for the experiments. The inter-personal relationships of the subject with spouse, parents and children were asked, and the subject was chosen after confirmation that she/he has a good relation with his/her family members. So, now we can ensure that a touch by a spouse at the palm of the subject may yield love, while a touch by parents result in a matter of respect in the subject, and so on.

But sometimes the subject's brain response is showing abnormal behaviour, for example the particular brain region is not activating for a stimulus which is showing activation of that region for other healthy subjects. So we can guess this particular subject may be in some early stage of any neurological problem which has not displayed any symptoms now. So early detection of psychological disorders like Alzheimer's disease, Parkinson's disease can be done.

CHAPTAR 10

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