BCI BASED DIGITAL SECURITY CHECKING BY MULTI-SENSORY PERCEPTUAL MODALITIES

A thesis submitted towards partial fulfilment

of the requirements for the degree of

Master of Engineering in BIOMEDICAL ENGINEERING

Submitted by

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CERTIFICATE OF RECOMMENDATION

This is to certify that the thesis entitled **"BCI based Digital Security Checking by Multi-sensory Perceptual Modalities"** is a bonafide work carried out by **Tabassum Hossain** under our supervision and guidance for partial fulfilment of the requirement of Master of Engineering (Biomedical Engineering) in School of Bio-Science and Engineering, during the academic session 2017-2019.

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I hereby declare that this thesis contains literature survey and original researchwork by the undersigned candidate, as part of his **Master of Engineering (BIOMEDICAL ENGINEERING**) studies during academic session 2017-2019.

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

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Preface

In early days'scope of Brain-Computer Interfacing or BCI was very limited to interact with computer using very few interface devices such as mouse, keyboard or using any graphical user interface and from then people started to realise that translating thoughts into real action can no longer be considered to be a material of fiction. Now in these days it has spread its arms towards developing sophisticated multimodal system which can interact with almost all environment. New era of BCI includes interfacing with joystick, steering wheel, bio sensors and which ultimately used for actuating robots, driving a car or can be used for gaming purpose.

Initially the prime focus for developing the BCI technology was for rehabilitative purpose but gradually its application has covered making collaborative system, information processing, cognitive robotics, perception engineering and also the amusement and entertainment field. Now Brain Computer Interaction Researchers are trying to explore the possibilities of allowing more sensory channels possible. They are concerned with implicit form of input information that input that is not explicitly performed to direct any computer or machine to do something. Researchers attempt to infer information from various physiological signals to understand the mental state and intent so that system can adapt themselves in order to support their task. Among various physiological signals this thesis concentrates on Electroencephalographic signal and fNIRS signal.

Brain Computer Interfacing is a multidisciplinary field and it not only encompasses the Computer Engineering but also the various area of cognition, sensors, machine learning, neuro-physiology, psychology, signal detection and processing, source localization, pattern recognition, clustering and classification.It conceptualizes, monitors, measures and evaluates the complex neurophysiological state and infer the required actuating signal needed to interface with robot or any other man- machine device and along with that it has become most emergent area of research in this era of technology.

Though BCI is not limited to any particular application but here the thesis mainly focuses on its prime application, i.e. Rehabilitative application. Thesis is composed of 7 chapters where chapter 1 discusses the introductory concept of BCI. Chapter 2, 3 and 4 Chapter 3 discusses the methods and techniques of olfactory perception and pathway detection using both Electroencephalography and Functional Neat Infrared Spectroscopy. Chapter 5 describes the application of BCI in personal device security. This chapter also sheds some light on using olfactory perception for personal identification, thereby, opening a new domain in research. Chapter 6 describes the application of odour perception. Concluding remarks and Future Scope has been given in Chapter 7.

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1. INTRODUCTION

Brain- computer interface [1] or man-machine interface is a direct communication pathway between an enhanced brain and an external device. BCI system measures the activity of the central nervous system (CNS) [2] and converts it into artificial output that replaces, restores enhances or improves the CNS activity, thereby changing the ongoing interactions between the CNS and its external environment. The history of BCI begins with Hans Berger's discovery with electrical activity of the human brain and development of electroencephalography (EEG) [1]. In 1924, Berger first recorded the human brain activity by means of EEG and was able to identify the alpha waves (8-3 Hz) by means of EEG traces.

This state-of-the-art technology is useful for people who are suffering from extreme neuro-moto disabilities like Amyotropic Lateral Sclerosis (ALS) [3], Celebral Palsy, stroke, spinal cord injury etc. Through this tecnique, brain signals are collected from the brain which helps in restoring the ability to the patients who have lost their sensory and motor functions. BCI finds its applications in various fields like medicine [4], rehabilitation [4] and as an assistive device like in cochlear implants [5], artificial limb [6], retinal prosthetic devices [5] etc. With the recent advancement in the study of neuroscience, brain- computer interfacing can be safely extended to non-medical applications like gaming [7], device control [7], user-state monitoring [7] and many more.

1.1. Perception

Perception [8] is our sensory experience of the world around us and involves both recognizing environmental stimuli and actions in response to these stimuli. The term perception derives from the Latin word *perceptio,* and is the organization, identification, and interpretation of sensory information in order to represent and understand the presented information, or the environment. The perceptual process allows us to experience the world around us. Through the perceptual process, we gain information about properties and elements of the environment that are critical to our survival. Perception not only creates our experience of the world around us, it allows us to act within our environment.

Perception includes the five senses- touch, sight, sound, smell, and taste. It also includes what is known as proprioception, a set of senses involving the ability to detect changes in body positions and movements. It also involves the cognitive processes required to process information, such as recognizing a familiar face or detecting a familiar scent.

Practically, perception can be divided into five categories:

- **Visual perception:** The ability to see and interpret light information within the visible spectrum that arrives to our eyes. The region of our brain responsible for visual perception is the occipital lobe (primary visual cortex V1 and secondary visual cortex V2).
- **Auditory perception:** Ability to receive and interpret information on the arrival in our ears by frequency waves within the audible region through any medium. The area of the brain responsible for auditory perception is the temporal lobe (primary auditory cortex A1 and secondary auditory cortex A2).
- **Touch, somatosensory or Haptic perception**: The capacity to intepret information of pressure or vibration received on the surface of our skin. Parietal lobe of the brain is in charge of basic stages in haptic perception (primary somasensory cortex S1 and secondary somatosensory cortex S2).
- **Smell or olfactory perception**: The ability to interpret information of chemical substances dissolved in the air (smell). The olfactory bulb (primary olfactory cortex) and the piriform cortex (secondary olfactory cortex) are responsible for the basic stage of olfactory perception.
- **Taste or taste perception**: The ability to interpret information from chemical substances dissolved in saliva (taste). The main brain regions in control of the basic stages are the primary taste areas G1 (postcentral inferior gyrus, parietal ventral lobe, anterior insula, fronto-parietal medial operculum) and secundary taste areas G2 (caudolateral frontal orbital cortex and anterior cingulate cortex).

There are other senses present in our body which allows perception of body balance, gravity, heat or coldness, pain, itching, state of our internal organs, presence of a magnetic field etc. The main concern of this thesis is only olfactory perception.

1.2. Olfactory Perception

Olfaction or olfactory perception [9] is a chemoreception that forms the sense of smell. It is a process that begins in the nose with the stimulation of olfactoy sensory neurons and terminates at the higher cerebral centres, making us conciously aware of an odor when activated. Olfactory sense is, in terms of evolution, one of the oldest senses, allowing the organisms with receptors for the odorant to identify hazards, pheromones and food. It integrates with other senses to form the sense of flavor. For most living creatures and for mankind smell is one of the most important ways of interaction with the environment. In humans, this awareness is generally confirmed by verbal reports while in animal studies some sort of odor detection or discrimination task is used. In mammals, olfactory stimuli are received and processed by multiple systems- the main olfactory system, vomeronasal, and the septal organ system. Activation of the trigeminal, vagal, glossopharyngeal receptors in the respiratory tract may contribute to the perceptual experience.

The olfactory system is a part of the sensory system that is used for smelling or olfaction. Majority of mammals and reptiles have a main olfactory system and an accessory olfactory system. The main olfactory system detects airborne substance while accessory olfactory system detects fluid-phase stimuli. The senses of smell and taste or gustatory substance are often referred together as the chemosensory system, as they both provide the brain with information about the chemical composition of objects through a process called *transduction* [10].

1.3. Importance of Olfactory Perception

The main functions of olfactory perception are- searching food, avoid predators and disease and social communication. Its role in detection of food has resulted in a unique dual mode sensory system. Environment odorants are inhaled via external nostrils while volatile chemicals in food arrive via the nasopharynx, contribute to the flavor. This arrangement allows the brain to link the consequences of eating with a food's odor and later on use this information in search of food.

Recognizing an odorant—a food, mate, or predator—requires the detection of complex chemical blends against a noisy chemical background. The brain solves this problem in two ways. Firstly by rapid adaptation to background odorants so that new odorants stand out. Secondly by pattern matching, the neural representation of an odorant to prior olfactory experiences.

This account is consistent with olfactory sensory physiology, anatomy, and psychology. Odor perception, and its products, may be subject to further processing—olfactory cognition. While olfactory cognition has features in common with visual or auditory cognition, several aspects are unique, and even those that are common may be instantiated in different ways. These differences can be productively used to evaluate the generality of models of cognition and consciousness. Finally, the olfactory system can breakdown, and this may be predictive of the onset of neurodegenerative conditions such as Alzheimer's, as well as having prognostic value in other disorders such as schizophrenia.

1.4. Brain-computer Interface

Brain-computer interface (BCI) is a collaboration between a brain and a device that enables signals from the brain to direct some external activity, such as control of a cursor or a prosthetic limb [6]. The interface enables a direct communications pathway between the brain and the object to be controlled [11]. In the case of cursor control, for example, the signal is transmitted directly from the brain to the mechanism directing the cursor, rather than taking the normal route through the body's neuromuscular system from the brain to the finger on a mouse.

By reading signals from an array of neurons and using computer to translate the signals into action, BCI can enable a person suffering from paralysis to write a book or operate and control a motorized wheelchair or prosthetic limb through thoughts alone. Current brain-interface devices require deliberate conscious thought; some future applications, such as prosthetic control, are likely to work effortlessly. One of the biggest challenges in developing BCI technology has been the development of electrode devices and surgical methods that are minimally invasive. In the traditional BCI model, the brain accepts an implanted mechanical device and controls the device as a natural part of its representation of the body. Much current research is focused on the potential on non-invasive BCI.

The following processing stages are involved in BCI:

- Signal acquisition
- Preprocessing.
- Feature Extraction.
- Classification.
- Application interface.

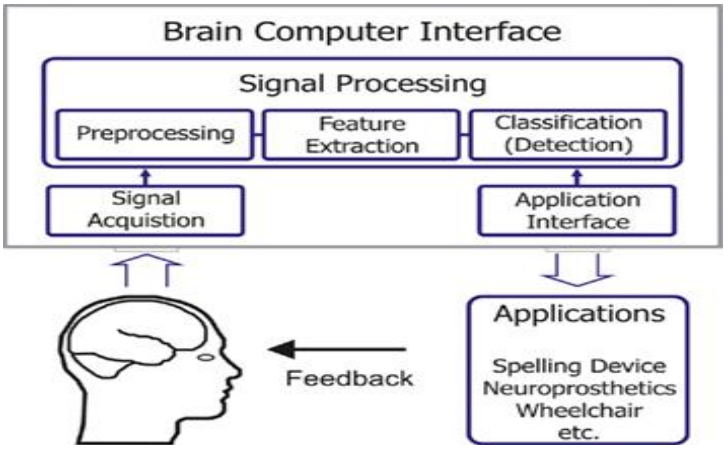

Fig: Processing stages of Brain-computer Interface.

BCI incorporates several well-known modalities [1], [12] like electroencephalography (EEG), magnetoencaphalography (MEG), functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), Postron Emission Topography (PET)etc. Among them, the widely used modality is EEG due to its non-invasive characteristics, superior temporal resolution [13] and low cost.

In EEG based BCI, the signals are captured from the scalp using surface electrodes. The field potentials of EEG are measured by different paradigms like P300 [1] Steady State Visually Evoked Potentials (SSVEP) [1], Event-related Desynchronization /Event-related Synchronization (ERD/ERS) [1], ErrP (Error-related Potential) [1], Slow Cortical Potentials [1] and others.

1.4.1. Types of BCI

(a) Invasive BCI

Techniques that allow recording from individual neurons in the brain that involve some form of surgery, wherein a part of the skull is removed, an electrode/ implant is placed in the brain and then the removed part of the skull is replaced is called an invasive technique [1]. Invasive BCI have been developed to enable the direct communication between the brain and a computer or another external device. Unlike non-invasive BCI that have a lower spatial resolution, invasive BCI have the potential to record the activity of single neurons. The clinical long-term aim of these interfaces has always allowed severely paralyzed individuals to regain some autonomy and to increase their quality of life. In recent years, several groups could show that complex movements, with multiple degrees of freedom, can be decoded from the recorded brain signals. At the same time, this technology has also made it possible to *peek* into living and intact human brains on a single neuron level while the person is thinking and acting.

This method is usually employed on animals like monkeys and rats. The recording itself is not painful as the brain has no pain receptors but the recovery process can be painful and involves risk and infection. The recording procedure can be done on both anesthsized as well as awake animals. In case of humans, invasive recordings are taken only in clinical settings such as during a brain surgery or during monitoring a patient's abnormal brain activity.

The major advantage of invasive technology is that they allow recording of action potential at the milliseconds timescale. This contrasts with noninvasive technique which measure indirect correlates of neural activity, such as blood flow, that occur at a coarser timescale (hundreds of milliseconds). Invasive techniques in both humans and animals require the involvement of electrodes.

In invasive modalities, microelectrode arrays need to be implanted inside the skull that involves significant health risks. Two invasive modalities can be found in BCI literature: electrocorticography (Ecog) [14], which places electrodes on the surface of the cortex, either outside the dura mater (epidural electrocorticography) or under the dura mater (subdural electrocorticography), and intracortical neuron recording which implants electrodes inside the cortex. Firstly, we need to address tissue acceptance of the microelectrode, for which proposals exist for electrodes with neurotropic mediums that promote neuronal growth to improve biocompatibility. Secondly, a link between the microelectrode and external hardware that uses wireless technology is required to reduce the risks of infection. And thirdly, the continuous stress caused by plugging and unplugging the recording system may lead to tissue damage or system failure. Non-neuronal cells known as glial cells surround the implanted device, which leads to the formation of scar tissue and then an insulatins sheath around the implant, thereby increasing the impedance of the electrodes. This biological response to the device can result in significant reduction in recording quality over time, decreasing its usefulness in carrying out brain-computer interfacing.

(b) Non-invasive BCI

Techniques that do enables recording from the scalp surface, without the requirement of any surgery or removal of a part of the scalp is called non-invasive techniques [1]. Noninvasive approaches have successfully been used by severely and partially paralyzed patients to enable basic forms of communication and to control neuroprostheses. Non-invasive approaches have outstanding utility in BCI applications, motor recovery has been limited, because of the need for brain signals with a higher resolution.

Various modalties used in non-invasive approaches are- fMRI, EEG, fNIRS, PET etc. Among these, EEG is given the preference due to its superior temporal resolution, portability and low cost.

1.4.2. Electroencephalograpy (EEG)

Electroencephalography is a popular non-invasive technique for recording signals from the brain using electrode placed on the scalp. It measures the electric activity of the brain caused by the flow of electric currents during synaptic excitations of the dendrites in the neurons and is extremely sensitive to the effects of secondary currents. Billions of electrically charged neurons located within the brain constantly exchange ions with the extracellular environment to maintain the resting membrane potential and to propagate action potential. The volume conduction of these ions by means of their mutual interactions can be measured by electrodes on the brain surface. The difference in the voltages between any two electrodes can be recorded over time by a voltmeter giving the EEG signal. However the electric potential generated by an individual neuron is too small to be picked up.

Currents tangential to the scalp are no recorded by EEG. Also, currents originating deep in the brain are also not detected by EEG as voltage fields fall off with the square of the distance from the source [1]. Thus, EEG predominantly captures electrical activity in the cerebral cortex whose columnar arrangement of neurons and their proximity to the skull favors recording by EEG. Though the spatial resolution of EEG is poor, the temporal resolution is very high.

. Our brain consists of six lobes which has their pre-defined individual activities. These are

i) pre-frontal, ii) frontal, iii) motor cortex, iv) parietal, v) temporal and vi) occipital lobes.

Their structure and functions are stated below:

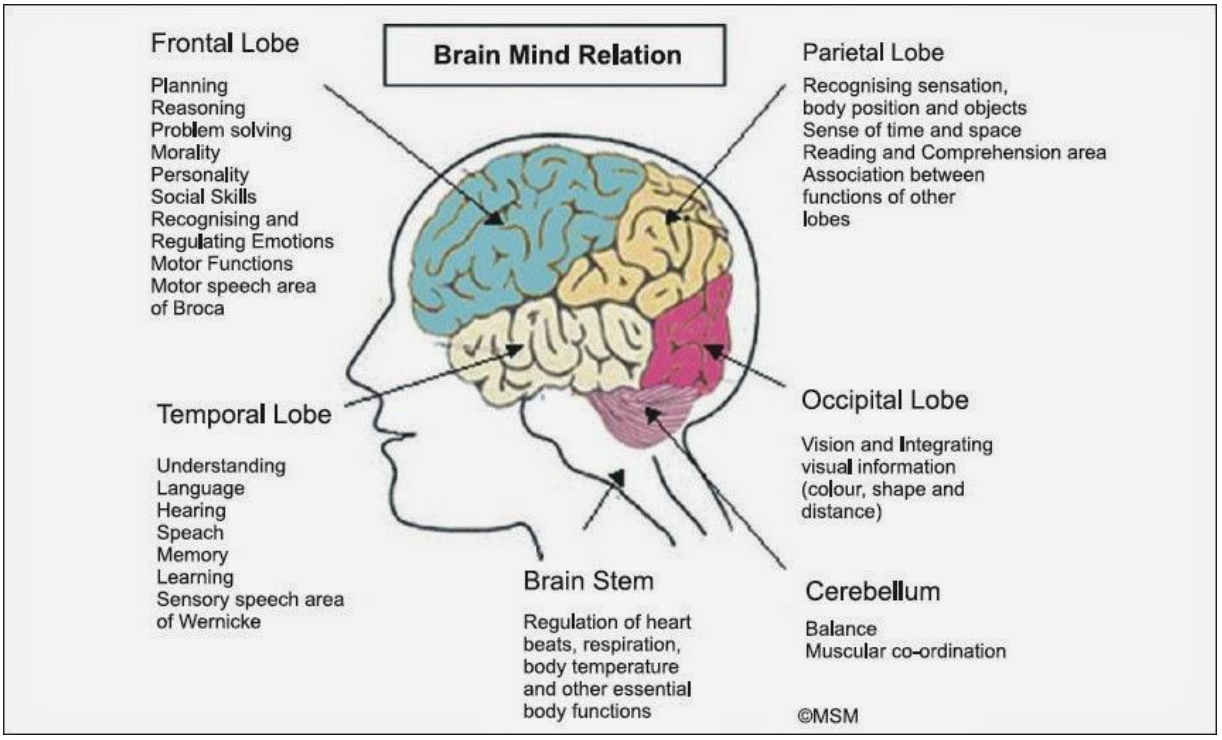

Fig 1.1: Brain lobes and their functions

EEG signals are easily recorded through electrodes placed on the scalp, in a widespread recording manner, thus the signals are of poor quality as they have to cross the scalp, skull, and many other layers. This means that EEG signals in the electrodes are weak, hard to acquire and are of poor quality. This method is moreover severely affected by background noise generated either inside the brain or externally over the scalp. Amplitude of EEG signal voltage ranges from 1 to 100 µV peak-to-peak at low frequency (0.5 to 100 Hz) at the cranial surface [15]. The recording system consists of electrodes, amplifiers, A/D converter, and a recording device. The electrodes acquire the signal from the scalp then the amplifiers process the analog signal to amplify the EEG signals so that the A/D converter can digitalize the signal in a more accurate fashion. Finally, the recording device stores and displays the data. EEG signal comprises a set of signals which may be classified according to their frequency.

Table 1.1: EEG frequency bands

Band	**Frequency(Hz)**	**Implication**
Delta	up to 4	Sleep, continuous-attention tasks, low arousal levels, no movements
Theta	4 – 8	Drowsiness, recall, imagery, creative mental states
Alpha	8 – 13	relaxation, meditation, tranquil conditions, associated with inhibition control
Beta	13 – 30	Alert, active, busy, or anxious thinking, active concentration, movement, sensorimotor ryhthms

Gamma	above 30	cross-modal sensory processing, short-term memory matching of recognized objects

1.4.3. Function Near Infrared Spectroscopy (fNIRS)

Functional near infrared spectroscopy is an optical technique for measuring changes in the blood oxygenation level caused by increased neural activity in the brain. This type of brain imaging is based on detecting the near-infrared light absorbance of hemoglobin in the blood with and without oxygen [1].

Functional near infrared imaging relies on the fact that infrared light can penetrate the skull and enter a few centimeters in the cortex. Infrared emitters placed on the scalp send infrared light through the skull. This light is partially absorbed and partially reflected back through the skull, where it is detected by the infrared detectors. Infrared light is absorbed differently based on the oxygen concentration of the blood, providing a measure of underlying neural activity.

Like EEG, a number of electrodes called “optodes” are evenly spaced across the head, allowing one to construct a 2-D map of the neural activity across the brain surface. Functional near infrared imaging, however, is restricted by design to measuring neural activity close to the skull, unlike fMRI, which can image deep regions of the brain. On the other hand, unlike fMRI, subjects are not restricted in their movement as they are not lying down within an MR scanner. Functional near infrared imaging is not as susceptible to muscle artefacts (compared to EEG) because it relies on optical rather than electrical measurements. It is also much less expensive than fMRI and is portable like EEG.

1.5. Realization of Olfactory Perception using BCI

This thesis aims at developing an idea of olfactory perception by different odourants. olfaction, being an integral part of brain-computer interfacing (BCI), follows the basic scheme of BCI in order to classify the classes of smell. It includes hardware to acquire brain signal as well as software to decode these brain signals in order to process further. Electroencephalogram (EEG), often referred to as the recording device of the electrical activities of brain collected from the electrodes placed on the human scalp, plays a vital role to deliver the information about physiological changes in the brain by odour perception.

In the odour perception, the subject was mader to smell different odourants with eyes closed. The basic idea of this thesis is to develop an olfactory pathway in the human brain. The various odourants act as stimuli. The human nasal cavity contains multiple sensory and

olfactory structures. The nasal mucosa with its complex innervation detects the danger substances in the air and stimulates the protective reflexes. Healthy olfactory mucosa allows for appreciation of pleasant aromas and food flavors. The olfactory nerve, in concert with the trigeminal nerve, serves as a main interpreter and modulator of chemosensory information. The part of the brain this arrives at first is called the olfactory bulb, which processes the signal and then passes information about the smell to other areas closely connected to it, collectively known as the limbic system.

The limbic system comprises a set of structures within the brain that are regarded by scientists as playing a major role in controlling mood, memory, behaviour and emotion. It is often regarded as being the old, or primitive, part of the brain, because these same structures were present within the brains of the very first mammals. Knowing this helps us to understand why smell plays such an important role in memory, mood and emotion.

Then the brain activity is recorded by the EEG as well as fNIRS electrodes. They decode all the activities of the brain and interface with the computer. Here in this thesis, the olfactory pathway is measured through touch perception.

1.6. Scope of the Thesis

This thesis attempts to realize a BCI model which acquires EEG signals for olfactory perception, remove noises and extract significant EEG features from the filtered data and finally determine the olfactory pathway and its various applications.

1.7. Summary

In this chapter we describe olfactory perception and different types of touch perceptions. Also describe the importance of touch perception. In our thesis we use Brain-Computer Interface to differentiate between known and unknown smell. In the next chapter 2, we describe the methods and techniques used in our study. In section 2.2, we describe the overall system, which includes data acquisition techniques, per-processing and filtering, feature extraction and feature classification methods. Section 2.3 describes elaborately all feature extraction technique like Power Spectral density, Wavelet Transform, Hjorth Parameter and Autoregressive Parameter. Then in section 2.4, feature classification techniques Support Vector Machine (SVM), Back Propagation Neural Network (BPNN) and Interval Type-ii Fuzzy Sets (IT2FS) are described. The experimental steps and results are given in chapter 3.In chapter 4, we detected the olfactory pathway by various techniques. In chapter 5, we discussed a BCI-based security, utilizing olfactory perception. Chapter 6 consists of application of odour perception. Conclusion and future direction are discussed in chapter 7.

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2. METHODS AND TECHNIQUES FOR OLFACTORY PERCEPTION

2.1. Introduction

BCI is an artificial intelligence system that can recognize a certain set of patterns in brain signals following five consecutive stages: signal acquisition, preprocessing, feature extraction, classification, and the control interface. The signal acquisition stage captures the brain signals and may also perform noise reduction and artefact processing. The pre-processing stage prepares the signals in a suitable form for further processing. The feature extraction stage identifies discriminative information in the brain signals that have been recorded. Once measured, the signal is mapped onto a vector containing effective and discriminant features from the observed signals. In this section the block diagram of the BCI technology which includes data acquisition unit for collect data, pre-processing and filtering unit, features extraction and features classification unit shall be discussed. The next section explains the several methods of feature extraction techniques like power spectral density [1], wavelet transform [2], Hjorth parameter [3], autoregressive parameter [4]. Following this, we shall describe the classification techniques used in BCI system like Support Vector Machine (SVM) [5], Back Propagation Neural Network (BPNN) [6], Interval Type- II Fuzzy (IT2FS) [7] sets in the next section. Then in chapter 3 we shall thoroughly discuss the experiment performed and its relative result.

2.2. The overall system

This section describes the basic steps of Brain-Computer Interface (BCI) required for olfactory perception. Olfaction, as it largely falls under the domain of BCI, follows the preliminary steps including data acquisition, preprocessing, features extraction, data classification units and control interface in order to determine the correct class of odours.

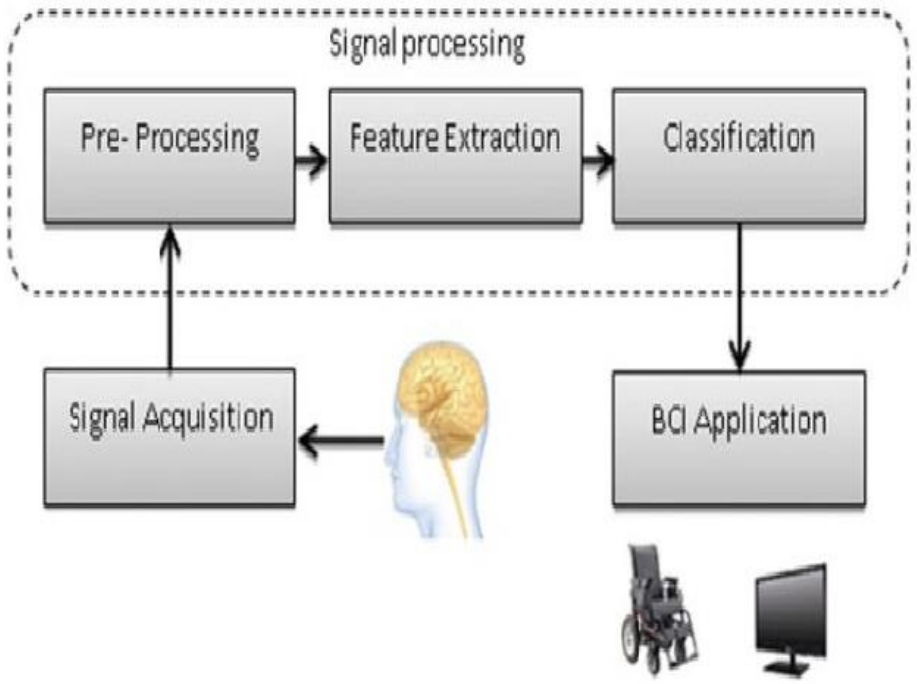

Fig 1.2: The overall system.

2.2.1. Data Acquistion

In this step raw signals are captured which reflects the user's brain activity. Stimulus is given to a subject and all the sensory information is delivered through the afferent nerves by action potential [12] and processed in the primary sensory cortex. These sensations from the receptors are carried by nerves to the spine and then ascend to the brain. In this regard, we can use different invasive and non invasive devices, but the most common one is Electroencephalography.

2.2.2 Preprocessing & Filtering

In this step, the raw EEG signals are filtered in their required frequency bands, where the information related to user intention is dominant. It also serves the purpose of eliminating various noises arising from the environment, muscle movement and power line interferences (50 or 60 Hz).

2.2.3. Feature Extraction

Different type cognitive activities result in different patterns of brain signals. BCI is seen as an olfactory perception system that classifies each signal into a class according to its features. BCI extracts some features from brain signals that reflect similarities to a certain class as well as differences from the rest of the classes. The features are measured or derived from the properties of the signals which contain the discriminative information needed to distinguish their different types. The design of a suitable set of features is a challenging issue. The information of interest in brain signals is subdued due to noise and brain signals comprise a large number of simultaneous sources. A desired signal could be overlapped in time and space by multiple signals from different brain tasks. In many scenarios, it is not enough to use simple methods such as band pass filters to extract the desired band power. Brain signals are inherently non-stationary. Time information about when a certain feature occurs should be obtained. Therefore, feature exteaction is performed to extricate the information which lies hidden or overlapped within other signals or noise. Multiples features can be extracted from several channels and from several time segments before being concatenated into a single feature vector. One of the major difficulties in BCI design is choosing relevant features from the vast number of possible features. Therefore, we employ feature extraction.

2.2.4. Classification of Feature Vectors

The next step of feature extraction is classification of feature vector. The aim of the classification step in a BCI system is recognition of a user's intentions on the basis of a feature vector that characterizes the brain activity provided by the feature step. Classification algorithms use the features extracted as independent variables to define boundaries between the different targets in feature space. Classification algorithms can be developed via either offline, online or both kinds of sessions. The offline session involves the examination of data sets, such as BCI competitions data sets, which are collected from an adaptive or closed-loop system.

Classification algorithms have traditionally been calibrated by users through supervised learning using a labeled data set. It is assumed that the classifier is able to detect the patterns of the brain signal recorded in online sessions with feedback. However, this

assumption results in a reduction in the performance of BCI systems, because the brain signals are inherently non-stationary. On the one hand, the patterns observed in the experimental samples during calibration sessions may be different from those recorded during the online session. On the other hand, progressive mental training of the users or even changes in concentration, attentiveness, or motivation may affect the brain signals. Therefore, adaptive algorithms are essential for improving BCI accuracy. Adaptation to non-stationary signals is particularly necessary in asynchronous and non-invasive BCIs [8]. Apart from the fact that supervised learning is not optimal for non-stationary signals classification, large data sets and, thus, long initial calibration sessions are usually required to achieve acceptable accuracy. Semi-supervised learning has been suggested to reduce training time and to update the classifier in the online session on a continuous basis. In semi-supervised learning, the classifier is initially trained using a small labeled data set, after which the classifier is updated with on-line test data.

2.3. Data Acquistion

2.3.1. Data Acquisition for EEG signals.

The EEG potentials were recorded at 10-20 EEG [13] electrodes, positions over the scalp shown in fig. 2, with a cap and integrated electrodes. These electrodes measure the weak (5-100 μV) electrical potentials generated by brain activity. Each electrode consists of a ware leading to a disk that is attached to the scalp using conductive paste or gel. Each pair of electrodes is denoted by a channel name, shown in Table I. In the data acquisition is performed using Micromed Digital Acquisition system at a 256 samples per second sampling frequency.

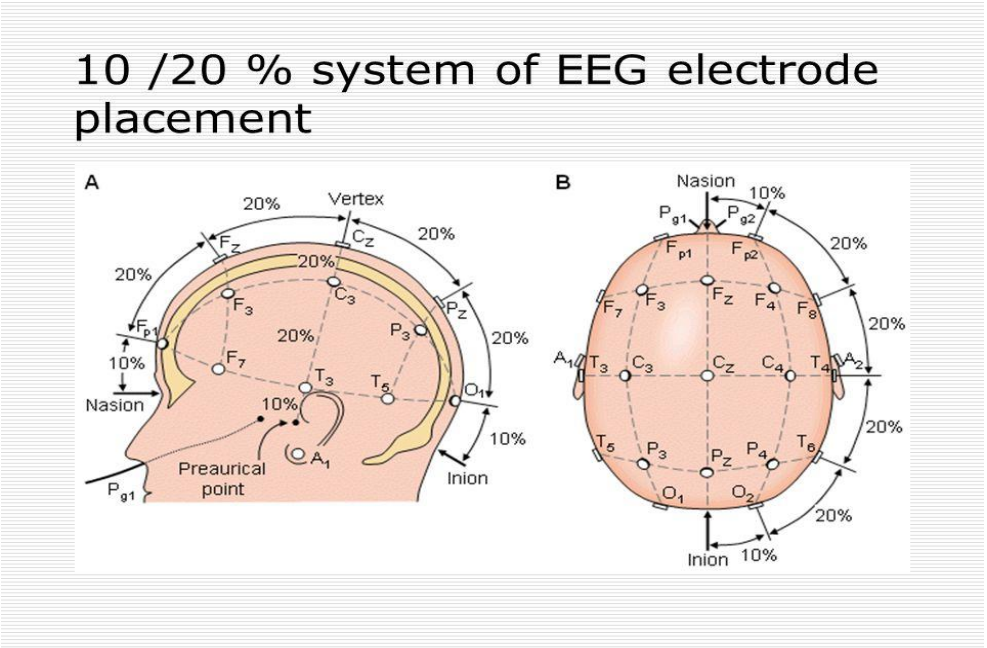

Fig1.3: International 10-20 EEG electrode placement

2.3.2. Data Acquisition for fNIRS signals

BCI utilizes cerebrum signals to gather data on the user's intentions. The initial phase in building up an fNIRS-BCI framework is to obtain useful brain signals. The subject was asked to inhale different kinds of odours which are procured generally from the pre-frontal lobe. The emitter-detector distance is normally kept inside a particular range, as it assumes a vital part in fNIRS estimation. For instance, an expansion in emitter-detector distance relates to an increase in imaging depth. To quantify hemodynamic response [9] signals from the cortical regions, a emitter-detector division of around 3 cm was proposed. A division of under 1 cm may contain just skin-layer contribution, though more than 5cm division may produce weak results ans subsequently, An appropriate number of emitter and detector sets for satisfactory extraction of neuronal action differ upon the kind of brain signals that are utilized for different BCI problems.

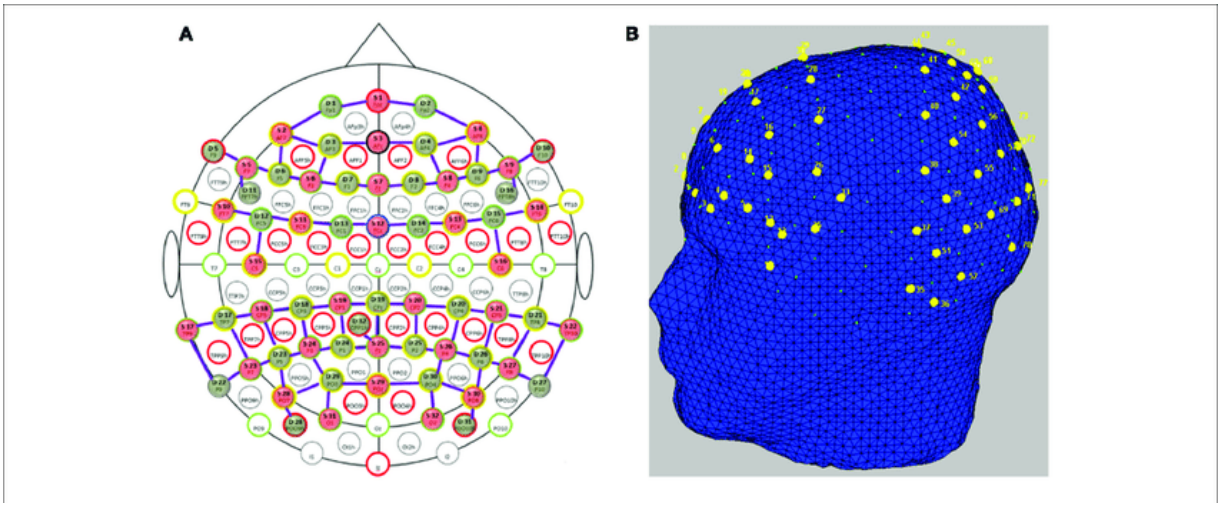

Fig 1.4: fNIRS probe placement- a topological layout

2.4. Preprocessing

2.4.1. Preprocessing of EEG data

The pre-processing block deals with filtering the recorded signals and remove the noise. It is important to maximize the signal-to-noise ratio (SNR) as many noise sources encounters with the raw signals. The filters are designed in such a way that they do not introduce any change or distortion to the signal. High pass filters [10] with a cutoff frequency of usually less than 0.5 Hz are used to remove the noise of very low frequency components. On the other hand low pass frequency passes the frequency of 40-70 Hz. Therefore, it is important to select an appropriate band pass filter which satisfies both the condition of low and high pass filters.

2.4.2. Preprocessing of fNIRS data

The obtained fNIRS signals can contain different noises, which can be grouped into instrumental noise, physiological noise and experimental noise. Since the experimental error and instrumental noise are not associated with the brain activities, it is ideal to remove them before changing over the raw optical density signals to the concentration changes of HbO and HbR by using modified Beer-Lambert law [11].

2.5. Noise and Artefacts Removal

2.5.1. Instrumental Noise Removal

Instrumental noise incorporates to system due to abnormalities present in the EEG and fNIRS equipment or brought on by the surrounding condition. It generally includes high frequencies. Such high frequency can be effortlessly evacuated by a low-pass filter (for example, 3∼5 Hz of frequency). Besides, by limiting the variety of the outside light, instrument noise can be reduced.

2.5.2. Physiological Noise Removal

Physiological noises can be incorporated within the system due to heartbeat or pulse (1∼1.5 Hz), breath (0.2∼0.5 Hz), Mayer waves (∼0.1 Hz), which are identified with blood pressure fluctuation [14]. A few strategies including band-pass filtering, PCA, Independent component analysis (ICA) and adaptive filtering methods have been utilized to expel them.

Removals of Experimental Errors

Movement artifacts like head movements, due to the movement of optodes from the alloted positions, may cause experimental errors. This can bring about a sudden change in the light, producing a spike-like noise. A few strategies for movement artifact removal have been proposed in the writing; the Wiener filtering based strat- egy [15], Principal Component Analysis(PCA)- based filtering [16], wavelet-analysis based techniques, Savitzky-Golay filters [17], and others.

Noise Removal Using Band-Pass Filtering

Since the frequency ranges of previously mentioned physiological signals are typically known, a band-pass filter can be considered. Some EEG and fNIRS based BCI contemplates have demonstrated promising outcomes utilizing a straightforward low-pass, or a high- pass, or a band-pass filtering technique to expel physiological noises [18].

2.6. Feature Extraction for Olfactory Perception

Different type cognitive activities result in different patterns of brain signals. BCI is seen as an olfactory perception system that classifies each signal into a class according to its features. BCI extracts some features from brain signals that reflect similarities to a certain class as well as differences from the rest of the classes. The features are measured or derived from the properties of the signals which contain the discriminative information needed to distinguish their different types. The design of a suitable set of features is a challenging issue. The information of interest in brain signals is subdued due to noise and brain signals comprise a large number of simultaneous sources. A desired signal could be overlapped in time and space by multiple signals from different brain tasks. In many scenarios, it is not enough to use simple methods such as band pass filters [22] to extract the desired band power. Brain signals are inherently non-stationary. Time information about when a certain feature occurs should be obtained. Therefore, feature exteaction is performed to extricate the information which lies hidden or overlapped within other signals or noise. Multiples features can be extracted from several channels and from several time segments before being concatenated into a single feature vector. One of the major difficulties in BCI design is choosing relevant features from the vast number of possible features. Therefore, we employ feature extraction.

2.6.1 Autoregressive Parameters

The use of an Autoregressive (AR) [19] model for biosignals has been very popular. This is mainly because the AR model estimation can be done by efficient algorithms even online, AR modeling has shown efficient representation of the stochastic behavior of signals and also it provides the "maximum entropy spectral estimation", meaning that a small number of parameters provide accurate description of the signal spectrum without the need for averaging. The AR model is a simple parametric model for a time series. It can be described by (2.6.11) and (2.6.1.2) for a discreet time signal y_k, the index k being an integer to denote discrete, equidistant time points. Here x_k is a zero-mean-Gaussian-noise process [20] with variance σ^2, y_{k-I} with $i = 1$ to p are the p previous sample values, p being the order of the AR model and a_i being the AR model parameters.

$$y_k = a_1 * y_{k-1} + \ldots + a_p * y_{k-p} + x_k$$

$$x_k \text{ is computed as } N\{0, \sigma^2\} \qquad (2.6.1.1)$$

The AR model can be observed to be a linear filter with a random noise input as illustrated in figure below:

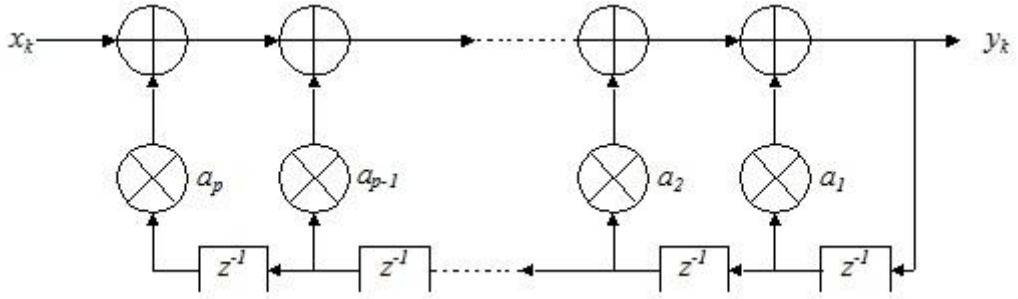

Figure 2.1 AR Model as a Linear Filter with a Random Noise Input

The AR model is used for any wide sense stationary stochastic time-series. Wide-sense stationary means the mean of the data is constant and the autocorrelation depends only on the time lag.

$$x_k = \text{constant}; \langle x_k x_{k-d} \rangle = r_d \qquad (2.6.1.2)$$

For calculating the AR parameters, there are different methods, but we will only discuss the Yule-Walker method [21].

Yule-Walker Method

The AR model of order *p*, AR (*p*), given by (2.6.1.1) can also be written as

$$y_k = \sum_{i-1}^{p} a_i y_{k-i} + x_k \qquad (2.6.1.3)$$

By convention, the series y_k is assumed to have zero mean. The method involves multiplying the above equation by x_{k-d}, where *d* is the delay; then averaging and normalizing the result. Repeating the process for *d*=1 to *p*, yields the following set of linear equations called the Yule-Walker equations [23] whose matrix form is given by

$$\begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \vdots \\ \gamma_p \end{bmatrix} = \begin{bmatrix} \gamma_0 & \gamma_{-1} & \gamma_{-2} & \cdots \\ \gamma_1 & \gamma_0 & \gamma_{-1} & \cdots \\ \gamma_2 & \gamma_1 & \gamma_0 & \cdots \\ \vdots & \vdots & \vdots & \ddots \\ \gamma_{p-1} & \gamma_{p-2} & \gamma_{p-3} & \cdots \end{bmatrix} \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \vdots \\ \varphi_p \end{bmatrix}$$

Fig2.2: Yule-Walker equations in matrix form

2.6.2. Power Spectral Density (PSD)

Power Spectral Density (PSD) measures how the signal power is distributed at different frequencies. Power spectral density is used as a feature because different classes of EEG distinguish from each other by having different power in different frequency ranges. PSD is also easily measurable and observable. Two different estimation techniques for PSD are existent: parametric and non-parametric.

Parametric power spectral density estimation involves fitting an appropriate model to the data, a parametric estimation method to calculate the values of the model parameters and the evaluation of the frequency response of the model which gives an estimate of the PSD of the data. An Autoregressive model is used commonly for fitting the data in the parametric method. In this work, as a parametric power spectral density estimation method, the signal responses are modeled using an AR model by the Yule Walker Method [21] and then the frequency response of the system is evaluated. Rearranging (2.6.1.3), we can write

$$y_k - \sum_{i=1}^{p} a_i y_{k-i} = \mathrm{x_k} \qquad (2.6.2.1)$$

In the frequency domain (2.6.2.2) can be rewritten as (2.6.2.3) from where the transfer function of the system is obtained. Here a_i values denote the AR parameters of the model that are determined using the Yule Walker equations.

$$y_z\left(1 - \sum_{i=1}^{p} a_i z^{-i}\right) = x_z \qquad (2.6.2.2)$$

$$\Rightarrow H(z) = \frac{y_z}{x_z} = \frac{1}{1-\sum_{i=1}^{p} a_i z^{-i}} \qquad (2.6.2.3)$$

$$\Rightarrow H(f) = \frac{1}{1-\sum_{i=1}^{p} a_i e^{-if(2\pi f)}} \qquad (2.6.2.4)$$

Using (2.6.2.4) the power spectrum $P_y\,(f)$ of the series y_k is given by (2.6.2.5) where $P_x\,f$ is the power spectrum of the white noise process x_k given by its variance.

$$P_y(f) = |H(f)^2| P_x(f) = \frac{P_x(f)}{|1-\sum_{i=1}^{p} a_i e^{-if(2\pi f)}|^2} \qquad (2.6.2.5)$$

For a time varying signal such as EEG, the complete time series should be divided into segments to determine its PSD. As a non-parametric approach PSD is evaluated using Welch

Method [24] that splits the signal into overlapping segments, computes the periodograms of the overlapping segments from their Fourier Transforms, and averages the resulting periodograms to produce the power spectral density estimate. The Welch method reduces noise in the estimated power spectra in exchange for reducing the frequency resolution. The steps are as follows:

The signal is split up into overlapping segments

The overlapping segments are then windowed i.e. after the data is split up into overlapping segments, the individual data segments have a window applied to them (in the time domain).

Then periodogram is calculated by computing the discrete Fourier transform, and then computing the squared magnitude of the result. The individual periodograms are then time-averaged, which reduces the variance of the individual power measurements. The result is a series of power measurements vs. frequency.

PSD is also alternatively referred to as Band Power Estimate (BPE) [25] in this work as the power of the signal at different frequency bands are taken as features. For example, say, we are interested in extracting EEG features in the range 4-30Hz then we compute the values of the power spectrum in the 27 integer frequency points in 4-30Hz range as 27 feature values. These features are also computed per channel of the EEG signals.

2.6.3. Welch

Welch [24] is the well-known feature extraction technique of EEG signal by overlapping the windowed signal sections and averaging the periodograms. The important steps of the method are listed below:

- Division of the time series data into overlapped segments,
- Computing a modified periodogram of each segment,
- Averaging the PSD estimates.

Welch periodogram works in such a way that the vector x is segmented into eight sections of equal length, each with 50% overlap. Any remaining (trailing) entries in x that cannot be included in the eight segments of equal length are discarded. Each segment is windowed with a Hamming window that is the same length as the segment.

2.6.4. Wavelet Transform

Wavelet Transform is a mathematical tool widely used for extracting information from many different kinds of data, such as audio or image data, among others. Wavelet Transform is particularly suitable when signals are not stationary, because it provides a flexible way of representing the time-frequency of a signal. Wavelets are functions of varying frequency and limited duration that allow simultaneous study of the signal in both the time and the frequency domain, in contrast to other modalities of signal analysis such as Fourier transform (FT) [26]. Fourier Transform provides only an analysis of the signal activity in the frequency domain. Fourier Transform gives information about the frequency content, but it is not accompanied by information on when those frequencies occur. The Wavelet transform overcomes this drawback by decomposing the signal in both the time and the frequency domain at multiple resolutions, by using a modulated window that is shifted along the signal at various scales. Wavelet decomposition is of two types including i) continuous wavelet transform (CWT) and ii) discrete wavelet transform.

2.6.4.1. Continuous wavelet transform

Continuous wavelet transform (CWT) is defined as the convolution of the signal $x(t)$ with the wavelet function $\psi_{s,\tau}(t)$:

$$w(s,\tau)=\int\infty-\infty x(t)\psi*s,\tau\ (t)dt \qquad (2.6.3.1)$$

$w(s, \tau)$ is the wavelet coefficient that corresponds to the frequency associated with the scale s and the time τ of the wavelet function $\psi_{s,\ \tau}(t)$, and the symbol *'*'* expresses the complex conjugation. The wavelet function $\psi_{s,\tau}(t)$ is a dilated and shifted version of a *mother wavelet* $\psi(t)$:

$$\psi s,\tau\ (t)=1s\sqrt{}\psi(t-\tau s) \qquad (2.6.3.2)$$

The CWT introduces a lot of redundancy and complexity since it involves the analysis of a signal at a very high number of frequencies using multiple dilations and shifting of the mother wavelet. Discrete wavelet transform (DWT) was introduced to reduce this redundancy and complexity. The Wavelet transform is a convolution of the wavelet function ψ (t) with the signal x(t). Orthogonal dyadic discrete wavelets are associated with scaling function υ (t). The scaling function can be convolved with the signal to produce approximation coefficients S.

2.6.4.2. Discrete wavelet transform

A discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. If we consider discrete sequence $s(n)$, defined for n= 0,1,….., the resulting coeffients in the series expansion are called Discrete Wavelet Transform (DWT) of *s(n)*. DWT is expressed as,

$$W_{\varphi}(j_0, k) = \frac{1}{\sqrt{M}} \sum_n s(n) \varphi_{j0,k}(n) \qquad (2.6.3.3)$$

$$W_{\psi}(j, k) = \frac{1}{\sqrt{M}} \sum_n s(n) \psi_{j,k}(n) \qquad (2.6.3.4)$$

Where, $j \geq j_0$ and s(n), $\varphi_{j0,k}(n)$ and $\psi_{j,k}(n)$ are functions of discrete variables n=0,1,….., M-1.

2.6.5. Hjorth Parameter.

Hjorth parameter, in the present context has been used to compute the quadratic mean and the dominant frequency of EEG signals on each side of brain. Hjorth parameters were originally developed for various online EEG analyses.

Hjorth activity: The activity parameter represents the signal power, the variance of a time function. This can indicate the surface of power spectrum in the frequency domain. This is represented by the following equation

$$\text{Activity} = \text{var}(y(t)). \qquad (2.6.4.1)$$

Where y(t) represents the signal.

Hjorth mobility: The mobility parameter represents the mean frequency or the proportion of standard deviation of the power spectrum. This is defined as the square root of variance of the first derivative of the signal *y(t)* divided by variance of the signal *y(t)*

$$\text{Mobility} = \sqrt{\frac{var\left(\frac{d(y(t))}{dt}\right)}{var(y(t))}} \qquad (2.6.4.2)$$

Hjorth complexity: The Complexity parameter represents the change in frequency. The parameter compares the signal's similarity to a pure sine wave, where the value converges to 1 if the signal is more similar.

$$\text{Complexity} = \frac{Mobility\left(\frac{d(y(t))}{dt}\right)}{Mobility\,(y(t))} \qquad (2.6.4.3)$$

We tried to apply the same approach, as developed for the first two Hjorth parameters, to this third parameter, assuming that the mean value of the bandwidth was smaller at the side of the seizure onset zone than at the other side, but the results were not significant. Then, the difference between the mean of complexity signals from the right side and the left side of the brain seemed not to be a relevant measure of lateralization. Nevertheless, the use of complexity could probably be interesting for localization.

2.7. Feature Selection

Feature selection is the process where we automatically or manually select those features which contribute most to our prediction variable or output in which contribute most to our prediction variable or output in which we are interested in. The two types of feature selection used here are: Principal component analysis and differential evolution.

2.7.2. Principal Component Analysis (PCA)

Feature extraction, as described above, gives rise to feature sets of large dimensions and thus direct employment of all these features in the classification procedure is computationally expensive. To overcome this issue, feature selection is performed on the feature set. In this process, the most significant features are selected and the redundant information is discarded thereby reducing the dimensionality of the feature set. This paper employs the method of Principal Component Analysis (PCA) [16] for the feature selection purpose.

A (N x M) dimensional feature set F is processed by the PCA to obtain a (1 x M) feature vector S, where, N is the number of features extracted for each EEG channel and M defines the number of channels considered. The steps involved in performing this analysis are outlined below.

Normalization

Let the feature vector obtained from the EEG signal of the i_{th} channel be expressed as,

$$f_i = [f_{1i} \;\; f_{2i} \;\; \ldots\ldots \;\; f_{Ni}]^T \qquad (2.7.1)$$

The elements of this vector are normalized using the following transformation,

$$f_{ji} \leftarrow \frac{f_{ji}}{\sum_{j=1}^{N} f_{ji}} \qquad (2.7.2)$$

Mean adjust

Each normalized feature vector is adjusted around zero mean by using the formula,

$$\mathbf{f_{ji} \leftarrow f_{ji} - \overline{f_i}}$$

Where $\mathbf{\overline{f_i}}$ is the mean of the feature vector obtained for i_{th} channel and it is described below;

$$\frac{1}{N}\sum_{j=1}^{N} f_{ji} \qquad (2.7.3)$$

Covariance matrix evaluation

The covariance matrix [28] C corresponding to the (N x M) dimensional feature set F is obtained as,

$$C = \frac{1}{(N-1)} F.F^{T} \qquad (2.7.4)$$

This C matrix is of dimension (N x N).

Evaluation of eigenvalues and eigenvectors

The eigenvalues of the covariance matrix C are evaluated by finding the roots of the equation given in ().

$$|C - \lambda I| = 0 \qquad (2.7.5)$$

As C is a (N x N) matrix, a total of N number of eigenvalues are obtained. The eigenvectors EV corresponding to the eigenvalues are then determined such that condition () is satisfied.

$$C.\mathbf{EV} = \lambda.\mathbf{EV} \qquad (2.7.6)$$

In this case, each eigenvector EV is of dimension (N x 1).

Evaluation of principal component

The eigenvector [27] corresponding to the largest eigenvalue λ_1 is considered as the principal component PC of the feature set.

Projection of feature set along the principal component

The feature set F is projected along the vector PC in order to obtain the (1 x M) feature vector S that best describes the feature set. This projection is done by employing the following formula,

$$\mathbf{S = PC'}.F \qquad (2.7.6)$$

Thus a (N x M) dimensional feature set is reduced to a (1 x M) dimensional feature vector that is used in the subsequent classification phase.

2.7.3. Differential Evolution

From a set of feature vectors, Differential Evolution (*DE*) [29] can be used to select relevant features, which performs better than the others, in terms of yielding better classification accuracy in a given classifier.

Initially 'N' dimensional feature vectors are presented to *DE*. The vectors also represent the candidate solutions. The feature vectors representing the candidate solution evolve through the generations. For the i_{th} vector at generation G is represented as follows,

$$\vec{F}_i(G) = [\, f_{i,1}(G),\ f_{i,2}(G), \ldots . f_{i,N}(G)] \qquad (2.7.7)$$

The present generation is designated as G which can assume values 0, 1, 2... $G_{\max}$ for the subsequent generations.

A theoretical upper and lower bound is provided to each parameters in the problem. The above procedure helps to get a better search result. For the initial solution, each individual vector is randomized in such a manner that it covers the entire search space but constrained by theoretical bounds given below,

$$\left.\begin{aligned} \vec{F}_{\min} &= [\, f_{1-\min},\ f_{2-\min}, \ldots . f_{N-\min}] \\ \vec{F}_{\max} &= [\, f_{1-\max},\ f_{2-\max}, \ldots . f_{N-\max}] \end{aligned}\right] \qquad (2.7.8)$$

The j_{th} component of i_{th} vector is initialized as follows,

$$f_{i,j}(0) = f_{j-\min} + rand_{i,j}(0,1) \times (f_{j-\max} - f_{j-\min}) \qquad (2.7.9)$$

Here $rand_{i,j}(0,1)$ represents any random number from a uniform distributionbetween 0 to 1. The obtained new vector goes through process of mutation, crossover and selection. The subsequent sections describe the above procedures briefly.

A. Mutation

The next step is to create a donor vector $\vec{D}_i(G)$ corresponding to each feature vector $\vec{F}_i(G)$ in the present generation, by mutation and re-combination. Mutation can take place in many ways, some popular mutation process are described below,

$$\text{Process1} : \vec{\mathrm{D}}_{\mathrm{i}}(G) = \vec{F}_{k_1^i}(G) + h(\vec{F}_{k_2^i}(G) - \vec{F}_{k_3^i}(G)) \qquad (2.7.10)$$

$$\text{Process2} : \vec{\mathrm{D}}_{\mathrm{i}}(G) = \vec{F}_{best}(G) + h(\vec{F}_{k_1^i}(G) - \vec{F}_{k_2^i}(G)) \qquad (2.7.11)$$

$$\text{Process3}: \vec{\mathrm{D}}_{\mathrm{i}}(G) = \vec{F}_i(G) + h(\vec{F}_{best}(G) - \vec{F}_i(G)) + h(\vec{F}_{k_3^i}(G) - \vec{F}_{k_4^i}(G)) \tag{2.7.12}$$

$$\text{Process4}: \vec{\mathrm{D}}_{\mathrm{i}}(G) = \vec{F}_{best}(G) + h(\vec{F}_{k_1^i}(G) - \vec{F}_{k_2^i}(G)) + h(\vec{F}_{k_3^i}(G) - \vec{F}_{k_4^i}(G)) \tag{2.7.13}$$

$$\text{Process5}: \vec{\mathrm{D}}_{\mathrm{i}}(G) = \vec{F}_{k_1^i}(G) + h(\vec{F}_{k_2^i}(G) - \vec{F}_{k_3^i}(G)) + h(\vec{F}_{k_4^i}(G) - \vec{F}_{k_5^i}(G)) \tag{2.7.14}$$

Here $k_1^i, k_2^i, k_3^i, k_4^i$ and k_5^i are randomly chosen integers within the range [1, NP]. It is also ensured that those integers are different from index i. 'h' is a scaling factor and $\vec{F}_{best}(G)$ mentioned in the equation is the best performing feature vector that obtains minimum cost value when subjected to minimize a certain objective function.

In general, the mutation procedure is designated by $DE\,a/b/c$, where a represent the original feature vector, b represents the number of difference vector considered for recombination and c is the type of crossover.

B. Crossover

Once the donor vector is created, crossover takes place to increase the potential diversity of solution. The donor vector $\vec{\mathrm{D}}_{\mathrm{i}}(G)$ exchanges components with feature vector $\vec{F}_i(G)$ under the crossover procedure.Mainly two types of crossover procedure is undertaken for the present study.

a) Exponential Crossover

Here an integer l is chosen randomly within the dimension of the vector, i.e.[1, N].

The l_{th} position is marked on the feature vector $\vec{F}_i(G)$, and exchange between feature vector and donor vector starts at the marked position. Another integer Z within the above-mentioned interval is taken randomly. Z specifies the number of component that a donor vector exchanges with original feature vector. A new trial vector $u_{i,j}(G)$ is specified below,

$$u_{i,j}(G) = \begin{cases} \vec{\mathrm{D}}_{\mathrm{i,j}}(G) \text{ for } \mathrm{j} = \langle l \rangle_N, \langle l \rangle_{N+1} \cdots \\ f_{i,j}(G) \text{ for all other } \mathrm{j} \in [1, \mathrm{N}] \end{cases} \tag{2.7.14}$$

$\langle l \rangle_N$ is a modulo function [30] with modulus N. Another parameter R_c is also considered to control the crossover rate.

b) Binomial Crossover

Here a number is chosen randomly within the range 0 to 1. The random number is instantiated independently for each instance over each component. If the chosen number is

less than or equals to the crossover rate R_c, binomial crossover is performed on each component of the feature vector. The new trial vector is obtained as follows,

$$u_{i,j}(G) = \begin{cases} \vec{\mathrm{D}}_{\mathrm{i,j}}(G) \text{ if } \mathrm{rand(i,\ j)} \le R_c \\ f_{i,j}(G) \text{ otherwise} \end{cases} \qquad (2.7.15)$$

C. Selection

It is of at most importance to maintain the population size constant throughout the generations. Therefore, all the new trial vectors goes through the process of selection to qualify for the next generation.

At the next generation, $G = G + 1$, the selection procedure is maintained as follows,

$$\vec{F}_i(G+1) = \begin{cases} \vec{\mathrm{U}}_{\mathrm{i}}(G) \text{ if } \vec{\mathrm{U}}_{\mathrm{i}}(G) \le \gamma(\vec{F}_i(G)) \\ \vec{F}_i(G) \quad \text{otherwise} \end{cases} \qquad (2.7.16)$$

γ is the particular objective function, which need to be minimized. Lower the value of function better is the result.

2.8. Classifiers for Olfactory Perception

The aim of the classification step in a BCI system is recognition of a user's intentions on the basis of a feature vector that characterizes the brain activity provided by the feature step. Classification algorithms use the features extracted as independent variables to define boundaries between the different targets in feature space. Classification algorithms can be developed via either offline, online or both kinds of sessions. The offline session involves the examination of data sets, such as BCI competitions data sets, which are collected from an adaptive or closed-loop system.

Classification algorithms have traditionally been calibrated by users through supervised learning using a labeled data set. It is assumed that the classifier is able to detect the patterns of the brain signal recorded in online sessions with feedback. However, this assumption results in a reduction in the performance of BCI systems, because the brain signals are inherently non-stationary. On the one hand, the patterns observed in the experimental samples during calibration sessions may be different from those recorded during the online session. On the other hand, progressive mental training of the users or

even changes in concentration, attentiveness, or motivation may affect the brain signals. Therefore, adaptive algorithms are essential for improving BCI accuracy. Adaptation to non-stationary signals is particularly necessary in asynchronous and non-invasive BCIs. Apart from the fact that supervised learning is not optimal for non-stationary signals classification, large data sets and, thus, long initial calibration sessions are usually required to achieve acceptable accuracy. Semi-supervised learning has been suggested to reduce training time and to update the classifier in the online session on a continuous basis. In semi-supervised learning, the classifier is initially trained using a small labeled data set, after which the classifier is updated with on-line test data.

The classifiers mainly used in this paper are: Support Vector Machine (SVM), Back Propagation Neural Network, Type-I Fuzzy and Type-II Fuzzy.

2.8.2. Support Vector Machine (SVM)

Support vector machine (SVM) [5] is one of the suprvised learning models associated with learning algorithms that analyze data used for classification and regression analysis. It is a non-probabilistic binary classifier used for linearly separable classification problems. It can also be extended to tackle non-linear classification problems too. The main postulate of SVM classification is to detect a *maximum margin hyperplane* that separates two classes of data.

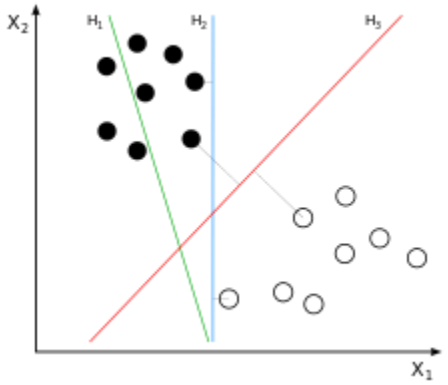

Fig: Support Vector Machine Classifier

To demonstrate linear binary classification with SVM, let us consider two classes C_1 and C_2. The training feature space consists of i= [1, N] instances of 'd' dimensional feature vectors $\mathbf{x_i}$ and class labels y_i where $y_i = 1$for $\mathbf{x_i} \in C_1$ and $y_i = -1$ for $\mathbf{x_i} \in C_2$. The equation of hyperplane for a set of points $\mathbf{x}$ is given by (2.8.1), where $\mathbf{w}$ denotes the direction of hyperplane and $\frac{b}{||\boldsymbol{w}||}$ denotes the offset of the hyperplane from the origin along the

direction normal to **w**.

$$\mathbf{w}^T\mathbf{x} + b = 0. \qquad (2.8.1)$$

To select the hyperplane that divides the two classes of data with the maximum margin, the two hyperplanes are given by (2.8.2) which are considered while trying to maximize the distance the distance between them or the margin, which is geometrically denoted by $\frac{2}{||\boldsymbol{w}||}$.

$$\left.\begin{aligned}\mathbf{w}^T\mathbf{x} + b &= 1\\ \mathbf{w}^T\mathbf{x} + b &= -1\end{aligned}\right\} \qquad (2.8.2)$$

To classify the data points to lie in either of the two classes they must be on either side of this margin which is ensured by the condition (2.8.3)

$$\left.\begin{aligned}\mathbf{w}^T\mathbf{x_i} + b \geq 1 \text{ for } \mathbf{x_i} \in C_1\\ \mathbf{w}^T\mathbf{x_i} + b \leq -1 \text{ for } \mathbf{x_i} \in C_2\end{aligned}\right\} \qquad (2.8.3)$$

Now, the selection of the maximum margin hyperplane is basically an optimization problem that tries to maximize *J(***w***)* given by (2.8.4) subjected to the constraint of (2.33). (2.33) is obtained by combining the two equations presented in (2.8.3). The nearest training data points of either class that are closest to the maximum margin hyperplane and are the basis of the building of this hyperplane are called the 'support vectors'.

$$J(\mathbf{w}) = \frac{1}{2}||\boldsymbol{w}||^2 \qquad (2.8.4)$$

2.8.3. Back Propagation Neural Network (BPNN)

The back-propagation neural network was developed by Rumelhart *et al.* as a solution to the problem of training multi-layer perceptrons. The fundamental advances represented by the BPNN were the inclusion of a differentiable transfer function at each node of the network and the use of error back-propagation to modify the internal network weights after each training epoch.

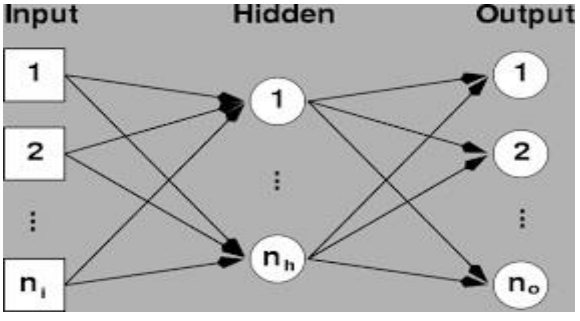

Fig: Architecture of Back Progation Neural Network

The BPNN was chosen as a classifier primarily because of its ability to generate complex decision boundaries in the feature space [31]. There is even work suggesting that a BPNN, under appropriate circumstances, can approximate Bayesian posterior probabilities at its outputs [32]. This is significant because a Bayesian classifier provides the best performance possible (i.e., lowest error rate) for a given distribution of the feature data. As with other non-parametric approaches to pattern classification, it is not possible to predict the performance of a BPNN *a priori*. Furthermore, there are several parameters of the BPNN that must be chosen, including the number of training samples, the number of hidden nodes, and the learning rate.

Based on the work of Baum and Haussler [33], it is possible to place a bound (m) on the number of training samples needed to *guarantee* a particular level of performance on a set of test samples drawn from the same distribution as the training data. Specifically, if at least m samples are used to train a network with W weights and N nodes such that a fraction equal to $1 - \frac{\epsilon}{2}$ of them are classified correctly, then one can be confident that a fraction $1-\epsilon$ of future test samples from the same distribution will be classified correctly, where

$$m \geq 0(\frac{W}{\epsilon} log \frac{N}{\epsilon}) \qquad (2.8.5)$$

As a specific example, to guarantee no more than a 10% error in classifying the test data, the number of training samples should be equal to roughly 10 times the number of weights in the network. For a typical network generated below, this represents a requirement for 5000-10000 training samples. It is simply not tractable to generate that many images. Fortunately, this bound does not preclude the possibility of generating a successful classifier using fewer training samples, as many studies have empirically demonstrated.

2.8.4. Interval Type-II Fuzzy Sets

An Interval Type-2 Fuzzy Set induced classifier is developed to classify 20 dimen- sional data points into three classes: LOW, MODERATE and HIGH. An example of a classifier rule is given below:

IF

For all channels F 1, F 2, F 3 are HIGH
and F 4, F 5, F 6, and F 7 are LOW

THEN

For all the channels then cognitive load is HIGH

Each feature is represented by a Gaussian membership function (MF) [34], the mean and variance of which are obtained from experimental instances. Repeated experiments with different subjects result in a set of Gaussian MFs over individual feature axis with shifted mean values. The collection of the obtained Gaussians mem- bership functions is summarized as a Interval Type-2 Fuzzy Set (IT2FS): their min- imum/maximum yield the lower(LMF)/ upper (UMF) membership functions. Thus, for seven features there will be

seven IT2FS.

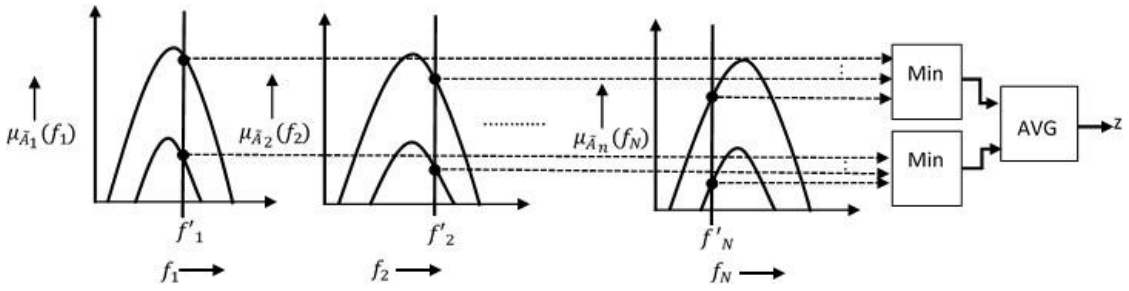

Fig: Explanation of IT2FS

$f_1, f_2, ..., f_N \in$ set of 20 features selected by feature selection algorithm.

Let, $\mu_{\tilde{A}_j(f_i)}, i = 1, \ldots, N, j = 1, \ldots, 7$, N Gaussian Interval Type-2 membership functions for features $f_1, \ldots, f_N$. Suppose, $f_1 = f_1^J, f_2 = f_2^J, \ldots, f_N = f_N^J$ measurement points. Define now:

$$Z_{min,j} = \min\{\underline{\mu}_{\tilde{A}_j}(f_i^J) \mid i = 1, \ldots, N\} \qquad \ldots..(2.8.6)$$

$$Z_{max,j} = \min\{\bar{\mu}_{\tilde{A}_j}(f_i^J) \mid i = 1, \ldots, N\} \qquad \ldots\ldots(2.8.7)$$

Where $\bar{\mu}_{\tilde{A}_j}(f_i^J)$ and $\underline{\mu}_{\tilde{A}_j}(f_i^J)$ denote the jth UMF and the LMF.

$$Z_j = \frac{Z_{max,j} + Z_{min,j}}{2} \qquad (2.8.8)$$

the average degree of firing strength (2.8.8)of a rule for the given measure- ment points, $f_1^J, f_2^J, \ldots, f_N^J$.

After computing the firing strength of all the rules for the measurements $f_1^J, f_2^J, \ldots, f_N^J$, the rule with the highest firing strength is selected to produce the output class listed in its consequent

2.9. References

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3. HEMODYNAMIC RESPONSE FOR ODOUR CLASSIFICATION

fNIRS [1] is relatively new, which uses near infrared lights in the range of 650 1000 nm wavelength to measure the change in oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) concentration in brain regions. fNIRS has its advantage as it is low cost, portable, and mainly it produces low noise (com- pared to fMRI). fNIRS data is not susceptible to electrical noise, unlike EEG or MEG as it is an optical neuroimaging modality. fNIRS measures the changes in blood flow due to neuron firings in local capillary network. Hemoglobin is an oxygen carrier, thus the changes in HbO and HbR concentration level after a neural activation can be measured. A near-infrared (NI) light emitter detector pairs with two or more operating wavelength is used in fNIRS devices [2]. The NI light discharged into the scalp diffuses through the brain tissues bringing about numerous scattering of photons. Some of these photons leave the head in after going through the cortical area of the brain, where in the chromophores (i.e.,HbO and HbR)are changing in time. These left photons are then recognized by utilizing the detectors. Since HbO and HbR have distinctive absoption coefficients for different wave lengths of NI light, the connection between the leaving photon intensity and the occurrence photon intensity can be utilized to compute the progressions of the changes of HbO and HbR concentration along the way of the photons by applying the modified Beer-Lambert's law[3].

3.1. Working Principle of fNIRS

fNIR imaging is based on the principle of Beer Lambert Law, which characterizes a linear relationship between absorption of EM radiation and the concentration of the desired absorptive material in a given medium. The full law incorporates elements representing the absorption coefficient (wavelength ward) and path length. In spite of the fact that initially defined for transmittance, it is appeared to be compelling for diffusion/scattering too. The estimations are at first taken as received photon concentration, which can freely be named as "received power". For biological fNIR imaging, baseline data is first accumulated. This perusing is viewed as the "transmitted power". Using these we can compose the law as:

$$Absorbance = -\log(\frac{recieved\ power}{transmitted\ power}) \qquad (3.1)$$

3.2. Experimental Setup

Ten five healthy volunteers took part in this experiment. None of them had any abnormal medical records and were all aged between 18-29 years. All the participants were assigned to inhale four kinds of different odourants with their eyes closed. The odourants were covered in four small bottles of same sizes. Each of the subjects were given each odourant for 5 seconds and 10 seconds break between two different odourants to eliminate the effect of the previous

stimulus. All the participants were informed about the experimental objective and possible limitations. Experimental data for each instance is recorded after removal of base line.

Fig 3.1: The subject is inhaling the odourant with her eyes closed

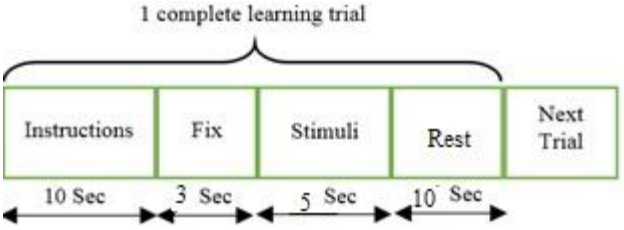

Fig 3.2: Timeline of Stimuli Presentation

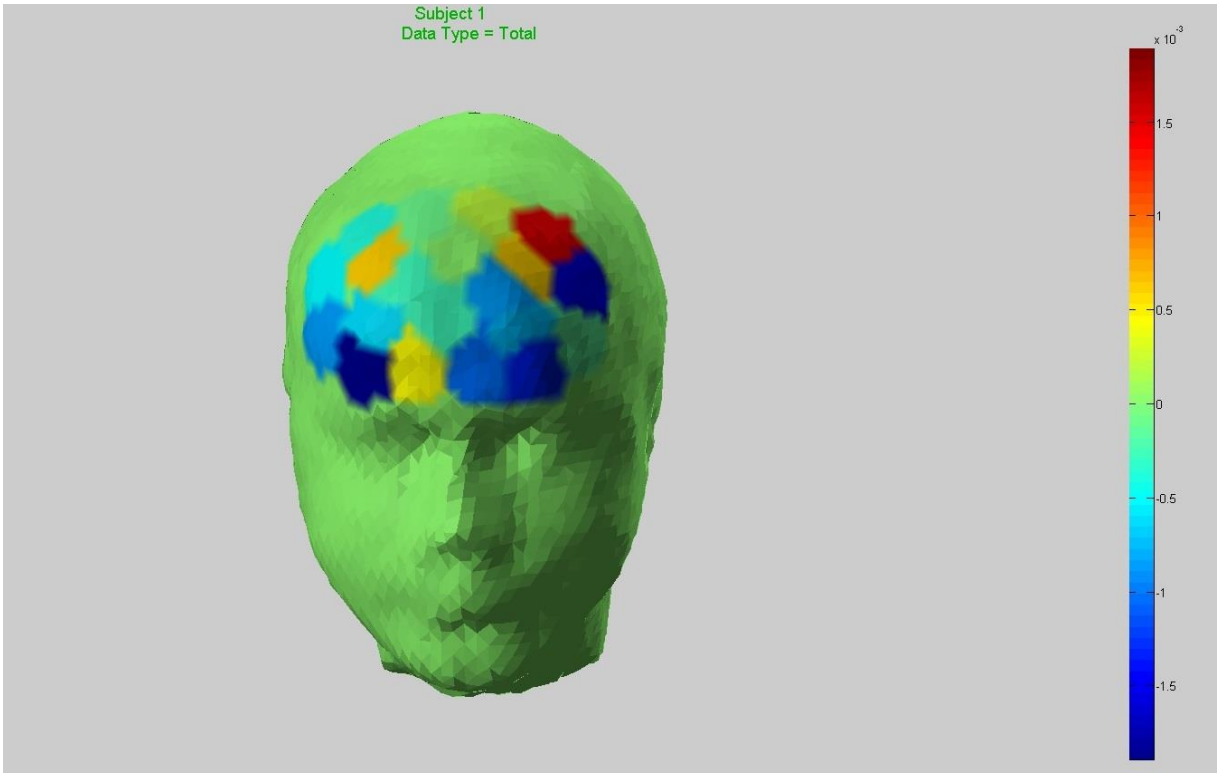

Fig 3.3: Brain activation region using fNIRS. The green patches shows the area with most activation while the red patches shows the area with least activation

3.3. Data Acquisition

The total experimental procedure is conducted at Artificial Intelligence Labora- tory, Jadavpur University over a period of 20 days. The whole-brain fNIRS is recorded using NIRX fNIRs. This fNIRs system has a recording frequency of 2 Hz and the IR light penetrates into 1.25 cm of cortical tissues. The data acquisition and visualization is performed using NIRX studio software.

3.4. Normalization of Raw data

Let C_{HbO} and C_{HbR} be the concentration of oxyhemoglobin (*HbO*) and deoxyhe- moglobin (*HbR*) respectively, measured in mili-mol/litre. We take maximum and minimum of C_{Hbo} and C_{HbR} in each session. Let $Max_{C_{HbO}}$ and $Min_{C_{HbO}}$ be the maximum and minimum concentration of *HbO* in a session. Then we normalize C_{HbO} by:

$$\hat{C}_{HbO} = \frac{C_{HbO} - Min_{C_{HbO}}}{Max_{C_{HbO}} - Min_{C_{HbO}}} \qquad (3.2)$$

Similarly, we normalize C_{HbR} by:

$$\hat{C}_{HbR} = \frac{C_{HbR} - Min_{C_{HbR}}}{Max_{C_{HbR}} - Min_{C_{HbR}}} \qquad (3.3)$$

where the parameters used in the last equation has meaning similar to those defined for C_{HbO}. It is needless to mention here that such transformation returns normalized C_{HbO} and C_{HbR} in $[0, \hat{1}]$ We also verified that the data set obtained within a session are normally distributed, i.e., all data points lie within $\mu \pm 3\sigma$, (i.e., within three standard deviations of the mean values).

3.5. Preprocessing and Noise Removal

A digital filter with a pass band of (0.1-0.4 Hz) is used to eliminate the undesirable signals in the above band. The Chebyshev filter[4] from well-known digital filters realized with Butterworth [5] and Chebyshev technology is selected for it has the faster roll-off than Butterworth. In addition, an independent component analysis (ICA)[6] is performed to remove physiological noise from mixed signals allowing the restoration of the primary cortical activity related signals.

3.6. Feature Classification

The classifier used in out study was Interval Type-2 fuzzy sets. An Interval Type-2 Fuzzy Set induced classifier is developed to classify 20 dimensional data points into three classes: LOW, MODERATE and HIGH. An example of a classifier rule is given below:

IF

For all channels F 1, F 2, F 3 are HIGH and F 4, F 5, F 6, and F 7 are LOW

THEN

For all the channels then cognitive load is HIGH

Each feature is represented by a Gaussian membership function (MF) [7], the mean and variance of which are obtained from experimental instances. Repeated experiments with different subjects result in a set of Gaussian MFs over individual feature axis with shifted mean values. The collection of the obtained Gaussians membership functions is summarized as a

Interval Type-2 Fuzzy Set (IT2FS): their min- imum/maximum yield the lower(LMF)/upper(UMF) membership functions as stated in chapter 2.7.

3.7. Relative Performance Analysis

Performance analysis shows that Interval Type-II Fuzzy classifier gave better response than the conventional SVM and BPNN classifiers. The performance metrics are given below.

Table 3.7.1: Claasifier Accuracy of the IT2FS classifier

Learning Features Level/class	PSD	AAR	Hjorth Parameter	Proposed fNIRS Technique
Level 1	79.952	76.405	73.221	89.15
Level 2	73.14	76.210	71.489	81.8
Level 3	71.548	74.346	66.86	85.92

Table 3.7.2: Classifier Performance based on Classification Accuracy of the Classifiers

Learning Level/Class	SVM	BPNN	IT2FS
Beginner	72.86	75.89	89.15
Intermediate	73.450	77.182	81.8
Expert	72.458	77.623	85.92

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4. PHASE SYNCHRONY AND CAUSALITY ANALYSIS OF BRAIN SIGNALS TO DETERMINE SIGNAL TRANSDUCTION PATHWAYS IN OLFACTORY PERCEPTION

Determining the signal transduction pathways in the brain is an interesting arena of research in modern brain sciences [1].This work proposes an interesting approach to determine the olfactory processing pathways in the brain of the subjects by acquiring the EEG signals during the odour processing phase of the subjects. In order to perform the present analysis, two basic steps are undertaken on the acquired EEG signals after pre-processing and filtering. The steps include: i) phase synchrony analysis [2]- [3] and ii) Granger causality analysis [4] of the acquired EEG signals.

4.1. Block Diagram of the overall system

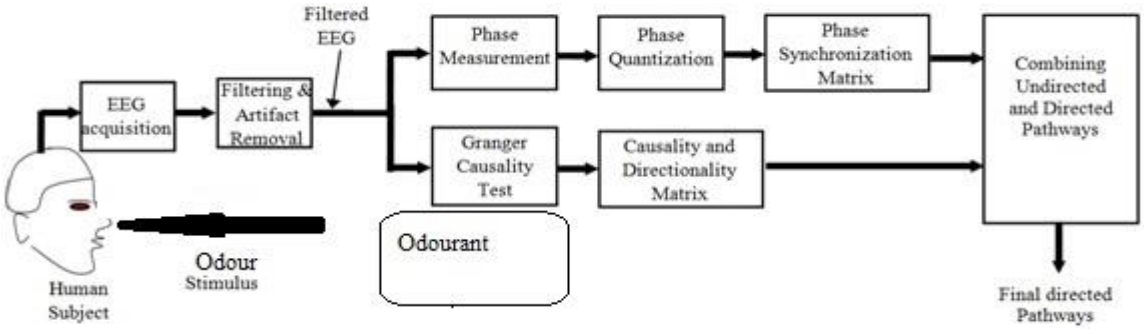

Fig 4.1: The overall system

The figure above provides a summary of the proposed scheme to de- termine the directed pathways representing signal transduction routes in the brain during olfactory perception.

4.2. Phase Computation of EEG Signals

Given a time-domain signal x(t), we obtain Fourier transform [5] of x(t) to gain frequency domain information. Finally,

$$F\{f(t)\} = Re\{t\} + j\, Im\{t\} \qquad (4.1)$$

Where Re{t} and Im{t} are real. The phase information of F {f(t)} is given by

$$\omega(t) = \tan^{-1}\frac{Im(t)}{Re(t)} \qquad (4.2)$$

Unfortunately, computing Fourier transform at each time point t of a signal is tedious and computationally expensive. One approach to address this drawback is to replace Fourier transform by Hilbert transform [6].

$$H(u)(t) = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{u(\tau)}{\tau - t} = \text{Re(t)} + \text{Im(t)} \qquad (4.3)$$

Here too, the phase $\varphi(t)$ is obtained similarly as above. For a given time-varying EEG signal x(t), we then obtain for a referred interval $0 \leq t \leq nT$ where T is sampling interval of the EEG

signal and n is an integer identifying the highest number of samples being used depending on the selected perception problem.

4.3. Phase Quantisation

Though the phase relationship between 2 brain lobes taking part in perceptional process are in phase-synchrony, yet show difference in phase. This type of problem arises because of presence of noise in the EEG signals due to artefacts like eye blinking and undesirable motor noise, parallel thoughts [7]. The approach is to quantize the phase $\varphi(t)$ into uniform levels to overcome the problem.

Let $\varphi\hat{}(t)$ be the quantized interval obtained by,

$$\varphi\hat{}(t) = b\frac{\varphi(t)}{N}c \qquad (4.4)$$

Where b, c denotes the results of integer division. The smaller the value of N, the larger is the quantised $\varphi(t)$($\varphi\hat{}(t)$), at the cost of loss in phase information. Again, the larger the value of N, the $\varphi\hat{}(t)$ is too small in finding similarity between $\varphi 1\hat{}(t)$ and $\varphi 2\hat{}(t)$ of 2 channels woul be difficult. A moderate value of N=37 is chosen to have 10^{o} quantized interval for the phase range [180^{o}, 180^{o}]. Two channels, having same $\hat{\varphi}(t)$, i.e., $\hat{\varphi}1(t) = \hat{\varphi}2(t)$ are perused to have phase-synchrony. The definition of phase-synchrony for n channels also extends the definition of 2 channels.

4.4. Finding Topological Connectivity

At the time *t*, suppose 6 channels C_1,C_5,C_7,C_9,C_{11} and C_{13} are in phase synchrony, of which C_7 has the highest activation, then we construct a graph at time *t*

At time point *t* + *T* , let C7 has the highest activation and C_1,C_5,C_9,C_{11} and C_{13} have phase symmetry, then the signaling behavior between time *t* and *t* + *T* is such that there is a central node corresponding to the electrode having the maximum activation, which is in turn connected to multiple nodes having phase synchrony among them.

A percentage degree of correct scores evaluation of directed areas in the graphs is computed by the following formulation. The percentage degree of graph mismatching is given by

$$Percentage\ score = \frac{D-d}{D} X\ 100 \qquad (4.5)$$

Using this score, we can determine the relative performance of the proposed tehnique with the existing one.

4.5. Granger-causality Test

Granger Causality test[4] is widely used to understand relationship between multiple time series components. When two time-series are tested for Grangers causality, it is checked whether the first series have a causal effect on the second series or vice versa. For example in our case, comparing the values of the P_3 and the $F\ p_1$ nodes, we take the null hypothesis H0: P_3 do not Granger-cause $F\ p_1$ and test it against the test parameters. We assume that P_3 would be the independent variable and $F\ p_1$, the dependent variable two or more channels spatially located apart carries important message about direct neural transduction pathways between distinct lobes.

Although the phase-synchrony analysis provides the neural basis of brain-lobe connectivity during the olfactory perceptual- process, it hardly can offer any information about direction of signal-flow between pairs of lobes. Fortunately, there exist several approaches to determine the directional connectivity between pairs of signal sources and sinks. A few among them that need special mention includes Granger causality [4], transfer-entropy [8] and cross-correlation [9] techniques. Granger causality analysis aims at determining the influence of one stationary signal on a second one. Transfer-entropy measures the information-transfer from one signal to the other. Granger causality is preferred to other existing approaches of signal directivity analysis for its high time-efficiency. This inspired us to employ Granger causality analysis to label the directivity in the edges of the unlabelled edged- graph obtained by phase-synchrony analysis. Ultimately, a pathway is obtained during the perceptual process. It is interesting to note that the graphs obtained by the above process have dissimilarity, signifying the involvement of different lobes at various time instances during perception of the odourants.

The significance of the present work is 2-fold. First, this work demonstrates a novel approach to determine the signal transduction pathways in olfactory perceptual processes. This might be utilized as a diagnostic tool to determine the brain lobes unable to participate in the generic signal transduction pathways used for analysis of olfactory-perception. It also opens up a new vista of knowledge that the signal transduction pathways for various odours which are distinct, thereby interpreting parallel pathways for multiple odour information processing.

4.6. Performance Analysis

After performing Hilbert Transform, the electrodes, between which had the highest phase

angel, were synchronous whereas, the electrodes pairs which had less phase angle were not synchronous. The lobes are: Pre-frontal (Fp), Frontal (F), Parietal (P), Motor Cortex (C), Temporal (T), Occipital(O).

For every iteration, we found that, odd number electrodes (e.g: F3, F7 etc) as well as even number electrodes (e.g. F4, F8) were synchronous whereas, a combination of odd and eve electrodes were non-synchronous.

The Granger-causality test shows the olfactory pathway which is depicted below:

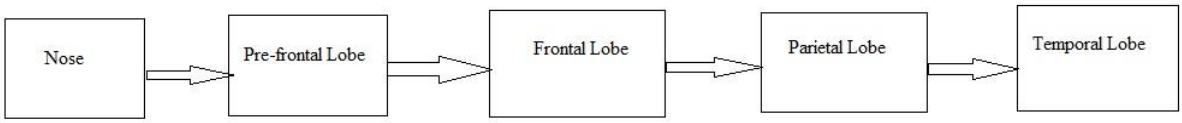

Fig 4.6: Olfactory pathway detected by Granger causality test

4.7. References

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5. OLFACTORY RESPONSE BASED PERSONAL IDENTIFICATION

5.1 Introduction

This chapter proposes a novel approach to recognize people based on their response to aromatic stimuli. Various aromatic stimuli are used as input to the subject and the brain response to each stimulus is used as the subjective identity of the person. It is noted that the brain response to a given stimulus is unique, consequently opening up a new territory of research. The proposed area is new and thus can be used for online security checking of people.

5.2. Proposed Scheme

The proposed BCI based user authentication scheme comprises dual stage verification process. In the first phase, the user is subjected to visual authentication process whereas in the next stage, user goes through an auditory authentication process. The details of this methos id explained below.

In the first phase a matrix (3X3) of spatially located circles appear on the computer screen. Each of the circles in the matrix flickers with different frequencies. Now the user needs to select any five different circles from the spatially located ones. During the locking phase user can select any five circles from the available options but at the time of unlocking, the must select the same circles which he had chosen during the locking phase. The user can mentally select the circles with real-time feedback of SSVEP[] brain signals to the system. When he fixes his gaze on a particular flickering circle, SSVEP signal is generated in the visual cortex of the occipital lobe. The signal is modulated by the flickering frequency of the circle he is gazing at. Mentally selected circles are traced by decoding the particular SSVEP signal liberated in the subject's brain.

Changes in the brain potential are captured by Electroencephalography. The subject is equipped with surface electrodes placed over his scalp to record the brain activity. SSVEP signal is recorded over the visual cortex goes through sequential steps of preprocessing, feature extraction and classification.

In this scheme, the user needs to store numerical digits in each of the previosuly selected circles. Here the user mentally utters any number (starting from 0 to 9) he wishes to store, along with

that, a headphone is placed over the ears of the subject where numbers starting from 0 to 9 are spelled randomly.

It is observed that whenever the randomly spelled numbers matches with the mentally uttered number, a particular brain signal namely auditory P300[1] is generated. Now the system having prior information of temporl sequence of spelled numbers can easily detect the imagined number by compring the latency of P300 occurrence with the temporal sequence of spelled numbers.

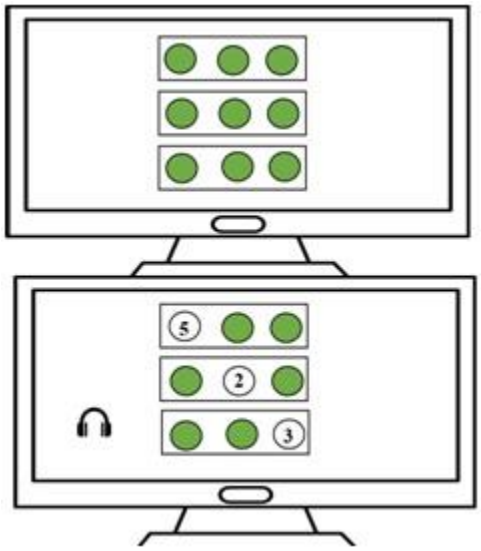

Fig 5.1: Illustration of scheme

5.3. Brain Signature Patterns Used

Among the widely known modalities in BCI literature, the two used in this experiement are Steady State Visually Evoked Potential (SSVEP) and Visual/Auditory P300.

5.3.1. Detection of SSVEP

SSVEP signal is characterised by its nature of reproducing the flickering waveform in the visual cortex of the brain, modulated by the external visual flickering perceived by the subjet. SSVEP is best observed in the frequency domain. The subject when gazes at a particular flickering source, EEG study confirms that a particular brain pattern is generated in the visual cortex of the occipital lobe consequently. Frequency domain representation of generated SSVEP signal reveals the band-power of the signal increases around the source frequency and its harmonics.

5.3.2. Detection of P300.

Auditory P300 is observed mainly over the pre-frontal, parietal and anterior cingulate cortex of the human brain. The signal is charactrized by the appearance of positive peak after an average

time of 300ms on recognizing any infrequent stimulus or desired stimulus in a train of frequent stimuli. P300 signal corresponds to largest positive peak after N1-P2 complex.

5.4. Preprocessing

Recorded raw EEG signal contains noise and artefacts, which arises from power line frequency, involuntary muscle movemnt and eye blinking. In order to remove those artefacts and noises, the EEG signal passes through 6th order low pass elliptical filter of cutoff frequency 20Hz. Apart from the time domain filtering, EEG signal also passes through the method of spatial filtering to get more localized signal. Common average referncing (CAR)[2] is done to remove the influence of far field sources. Average of all electrodes is subtracted from each individual electrode in CAR filtering.

5.5. Feature Extraction

5.5.1. Canonical Correlation

Cannonical correlation (CCA)[3] finds out the underlying covariance or correlation structure between two sets of random variables, in terms of linear combination. It is most suitable for detection of SSVEP as the process involves detecting particular stimulus frequency from recorded EEG signal from multiple channels. The optimization procedure involved here [rovides a better signal-to-noise ratio.

For two sets of random variables $X \in R^{P_1 XQ}$ and $Y \in R^{P_2 XQ}$, CCA attempts to find out two such linear combinations, $C_X \in R^{P_1}$ and $C_Y \in R^{P_2}$ for which the linear combination given below

$$\tilde{x} = C_X^T X \qquad (5.1)$$

$$\tilde{y} = C_Y^T Y \qquad (5.2)$$

Produces maximum correlatin subjected to maximization of objective function given below,

$$\max \rho = \frac{E[\tilde{x}\tilde{y}]}{\sqrt{E\left[\tilde{x}\tilde{x}^T\right] E\left[\tilde{y}\tilde{y}^T\right]}} \qquad (5.3)$$

$$= \frac{C_X^T X Y^T C_Y}{C_X^T X X^T C_X \, C_Y^T Y Y^T C_Y} \qquad (5.4)$$

Where ρ denotes the maximum correlation coefficient for linear transform C_X and C_Y.

5.5.2. Emperical Mode Decomposition (EMD)

This method uses Emperical mode decomposition [4]to extract the features of the raw signal. EMD is most suitable for signal with mixed scale of frequencies, such as where slow oscillations are superimposed with fast oscillation. EEG is non-stationary in nature, which makes it unsuitable for decomposition using fixed basis functions such as Fourier Transforms, Wavelet Decomposition. EMD works based on the phenomenon of decomposing the initial sequence into Intrinsic Mode Functions (IMF) [5]. IMF will have following properties:

(1) No of extrema is one greater than the no of zero crossing.
(2) Local average will be zero implying the average of upper envelope and lower envelope will be zero.

After excecuting the sifting process [6], the EEG signal x(n) can be written as

$$x(n) = \sum_{i=1}^{N} \hat{f}(n) \qquad (5.5)$$

Where $\hat{f}(n)$ denotes the IMFs derived from the EEG signal.

Feature vector has been obtained for two different class of signal, i.e., trial containing the P300 evidence $P_1(n)$ and $P_2(n)$. EMD algorithm was applied separately to both categories of signal. Now these two signals can be expressed as linear combination of IMFs as described below.

$$P_1(n) = \sum_{i=1}^{N_1} \widehat{f_{1,i}}(n) \qquad (5.6)$$

$$P_2(n) = \sum_{i=1}^{N_2} \widehat{f_{2,i}}(n) \qquad (5.7)$$

Where N_1 and N_2 denote the number of IMFs obtained for two categories of signal respectively. Now each of the EEG trials can be expressed in terms of the IMFs obtained fo above two catergories of signal.

$$x(n) = \sum_{i=1}^{N_1} a_{1,i} \widehat{f_{1,i}}(n) = \widehat{x_1}(n) \qquad (5.8)$$

Or can be written as,

$$x(n) = \sum_{i=1}^{N_2} a_{2,i} \widehat{f_{2,i}}(n) = \widehat{x_2}(n) \qquad (5.9)$$

5.6. Classification

In this oresent work, a variant of RNN[7], called ERNN has been used to find he existence of P300 evidence from the EEG features fed to the concerned ERNN. The choice of ERNN as an estimation component was primarily influenced by the knowledge of its potential of characterizing any finite state machine with suitable numbers of hidden units and connecting weights.

Suppose, the input *X(t)* is and *I* X 1 vector at time t and *Z(t)* is and *J* X 1 output vector of the hidden layer at time *t*. Let, $\bar{X}(t)$ and $\bar{Z}(t)$ denote the values of X(t) and Z(t), appended by a bias value. Basically, the inputs at the current time instance and the output of the hidden units at previous time instance activated by the choice of sigmoid function results in the outputof the hidden layer at current time step. Moreover, output of each visible unit is nothing but the weighted sum of the hidden layer outputs appended by the bias value.

$$Z(t) = \psi[H\bar{X}(t) + SZ(t-1)] \qquad (5.10)$$

$$Y(t) = V\bar{Z}(t) \qquad (5.11)$$

Here, H is a J X (I+1) dimensional feed forward weight matrix, S is a J X J dimensional recurrent weight matrix and ψ is a sigmoide activation function. In this scheme, Particle Filter (PF) [8] and Extended Kalman Filter (EKF)[9] are partially combined to train the ERNN.

5.7. Experimental Results and Discussion

Fifteen volunteers took part in the experiment. Among them 9 were males and6 were females with all of them in age group 18-30. Medical history showed no evidence of any critical illness, ear disease or any kind of surgery that the participants underwent. All objectives and procedures were made clear to the participants beforehand. A consent form was duly signed by the volunteers stating their willingness to participate in the experiment. All other safety and ethical issues were addressed according to Helsinki Declaration of 1970 revised in 2000[].

5.7.1. Perfomance Analysis of Classifiers

For the SSVEP detection, CCA is compared with standard SVM classifier where PSD is used as a feature vector. In case of auditory and visual P300 detection, proposed EKF_PF trained ERNN is compared with standard SVM, BPNN, and IT2FS classifiers. It is observed that in each case proposed classifier outperforms the other ones. Comparison is drawn in terms of a) Classification Accuracy (CA), b) Precision Value (PR), c) Sensitivity/Recall Value (RC), d) Specficity and e) Miss Rate (MR).

Table 5.1: SSVEP Decoder Performance

Algorithm	CA%	PR%	RC%	SP%	MR%
CCA	95.6	91.2	94.8	92.4	10.2
PSD+SVM	82.1	78.5	82.5	80.9	16.7

Table 5.2: Visual P300 Decoder

Algorithm	CA%	PR%	RC%	SP%	MR%
BPNN	77.8	74.5	76.9	77.6	21.6
EKF-PR ERNN	86.5	84.7	86.7	85.6	12.3
SVM	81.4	77.9	82	79.7	16.8
IT2FS	84.4	80.5	84.3	83.5	14.5

Table 5.3: Auditory P300 Decoder

Algorithm	CA%	PR%	RC%	SP%	MR%
BPNN	77.8	74.5	76.9	77.6	21.8
EKF-PR ERNN	83.5	75.5	84.3	82.1	14.8
SVM	79.2	76.5	80.3	78	18.1
IT2FS	82.1	78.9	82.5	80.5	16.7

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6. **APPLICATIONS OF ODOUR PERCEPTION**

Olfaction in human has connections with memory, language and neuro-vegetative areas. One of the significant roles of olfaction is the influence in taste and personalities. Experiments are undertaken here to analyse the olfactory perception of human being. Olfactory perception is very useful in detecting early stages of Alzheimer's disease, Schizophrenia and it is also useful in tea tasting industries.

Smell and Memory

The sense of smell is closely linked with memory, probably more so than any of our other senses. Those with full olfactory function may be able to think of smells that evoke particular memories; the scent of an orchard in blossom conjuring up recollections of a childhood picnic, for example. This can often happen spontaneously, with a smell acting as a trigger in recalling a long-forgotten event or experience.

Smell and Emotion

In addition to being the sense most closely linked to memory, smell is also highly emotive. The perfume industry is built around this connection, with perfumers developing fragrances that seek to convey a vast array of emotions and feelings; from desire to power, vitality to relaxation.

On a more personal level, smell is extremely important when it comes to attraction between two people. Research has shown that our body odour, produced by the genes which make up our immune system, can help us subconsciously choose our partners.

t is likely that much of our emotional response to smell is governed by association, something which is borne out by the fact that different people can have completely different perceptions of the same smell. Take perfume for example; one person may find a particular brand 'powerful', 'aromatic' and 'heady', with another describing it as 'overpowering', 'sickly' and 'nauseating'. Despite this, however, there are certain smells that all humans find repugnant, largely because they warn us of danger; the smell of smoke, for example, or of rotten food.

The Psychological Impact of Smell Loss

Given that our sense of smell clearly plays an important part in our psychological make-up, in addition to it being one of the five ways in which we connect with the world around us, its absence can have a profound impact. Anosmia sufferers often talk of feeling isolated and cut-off from the world around them, and experiencing a 'blunting' of the emotions. Smell loss can affect one's ability to form and maintain close personal relationships and can lead to depression. An important issue here is the fact that smell loss is invisible to all but the patient.

Research has shown that loss of olfactory function can be an indicator of something far more serious. Smell loss occurs with both Parkinson's disease and Alzheimers, and studies have indicated that a diminishing sense of smell can be an early sign of the onset of both conditions, occurring several years before motor skill problems develop.

7. **CONCLUSION AND FUTURE DIRECTION**

Brain Computer Interfacing is a powerful tool, which helps to communicate with machine using ones neural activity. EEG and fNIRS devices come here as a medium of neuroimaging which is cost effective and user friendly. Brain signals are useful biomarkers for understanding working memory and executive performance or any kind of perception. Therefore, both EEG and fNIRS devices could be an effective BCI application to measure prefrontal hemodynamics using these specific brain regions.

Chapter 2- 4 deals with olfactory perception and various methods and techniques for its study, chapter 5 describes how BCI could be used as a security system to make it more robust. It also slightly touches upon using olfactory pathway for personal identification. The aromatic stimuli are used here as input and the subjects's brain response is the output. In this way, one could ensure proper security because brain signalling pathway for a particular odourant/aromat is unique to every human being . This could be a new research territory and can also be used in online security checking of humans.