

Investigating MUSIC Algorithm in Neural Information Processing: Robust Feature Extraction for Emotional State Classification from Multichannel EEG Signals

by

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A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
M.Sc. in Computer Science

Department of Computer Science and Engineering
Brac University
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3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
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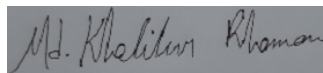
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Ethics Statement

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- 1) This material is original work, which has not been previously published elsewhere.
- 2) The manuscript is not being considered for publication anywhere at this time.
- 3) The writers' research and analysis are reflected in the publication wholly and truthfully.
- 4) The paper appropriately acknowledges the efforts of co-authors and co-researchers.
- 5) The findings are discussed in the context of previous and ongoing research.

The norms of the Ethical Statement can have serious implications if they are broken.

I agree to the aforementioned declarations and certify that this submission adheres to Solid State Ionics' rules as described in the Authors' Guide and the Ethical Statement.

List of Publication

- **M.S.A. Hossain**, M. A. Rahman, and A. Chakrabarty, "MUSIC Model based Neural Information Processing for Emotion Recognition from Multichannel EEG Signa" in IEEE Sponsored 8th Internation Confernece on Signal Processing and Integrated Networks (SPIN), India, August 25-27, 2021 (**Accepted for Publication**)
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Abstract

The major challenge in any electroencephalogram (EEG) classification task lies with in the dilemma of feature extraction, as raw time series signal provide little correlated information, yet it holds colossal varieties of hidden feature patterns. Frequency domain transformations are considered state of the art to tackle such complexity. Nevertheless such conventional feature extraction techniques for instance; discrete wavelet transformation (DWT), short time Fourier transform (STFT), differential entropy or classical non-parametric power spectral density (PSD) estimation models are computationally expensive as they demonstrate high computational complexity and extensive run time. Consequently artificial intelligence driven multi channel EEG based systems struggles to process neural information in real time and such barrier minimizes the dynamics of relevant human computer interaction (HCI) and brain computer interaction (BCI) applications. Multiple Signal Classification Algorithm (MUSIC) is an eigen decomposition based parametric PSD estimation model, which solely uses linear transformation rather than computing windowed periodiogram from autocorrelated function of the targeted signal for transformation. Hence MUSIC algorithm should demonstrate lesser time complexity and run time than contemporary classical non-parametric PSD models. Nevertheless this particular model is relatively unexplored for such feature extraction task specifically in the area of emotion recognition, as the model is difficult to implement in terms of EEG signals which demonstrate random behaviour. Our research investigates the performance of MUSIC algorithm in feature extraction task for emotion recognition from multi channel EEG signals and compares its performance with conventional classical non parametric models. It also clarifies the complexity in subspace estimations for EEG waveforms through in detailed analysis, which are indispensable parameters for implementing any eigen decomposition based models in such particular cases. Our proposed model derived state of the art 5-fold cross validation accuracies of 97% and 97.4% for Multi Layer Perceptron (MLP) network and Hybrid Long Term Short Memory (LSTM)-MLP network, respectively on the SEED emotional dataset. The proposed MUSIC model optimizes 95% – 96% run time comparing with conventional classical non-parametric techniques for feature extraction. With exceptional 0.01 *sec.* machine specific run time for feature extraction task, the proposed model shows great prospect in real time applications. Network performance and advanced visualization techniques demonstrate the MUSIC model based feature space holds significant superiority over non-parametric model generated feature space. Additionally the research also found extensive flaws in the widely popular SEED dataset, which were ignored in previously. Over 17% trials were found to hold multiple corrupt channel resulted from external artifacts, which should have effected previously conducted researches. Our research also discusses the effects of such flawed trial in network performance.

Keywords: Multiple Signal Classification Algorithm, Neural Information Processing, Multilayer Perceptron Network, Data Visualization, Brain Computer Interfacing, Human Computer Interaction, Biomedical Signal Processing.

Dedication

This thesis is dedicated to each and every mentor I have been blessed with during my journey through life so far. Each of them had played an indispensable role in shaping my life and career as a researcher. May this research work leads the beginning of another exciting journey.

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To me this research resembles a wonderful adventure and I have enjoyed every bit of this journey as I was blessed with amazing mentors. I am extremely grateful to my thesis supervisor Associate Professor Dr. Amitabha Chakrabarty and my co-supervisor Assistant Professor Dr. Md. Asadur Rahman for their continuous support and guidance towards the completion of this research. I am also thankful to my current employer and principal investigator Professor Dr. Khondkar Siddique Rabbani, along with my current team lead Dr. Zihad Tarafdar for providing immense moral support and substantial leniency in work place, which were indispensable to complete this thesis work. Furthermore, I would like to acknowledge the partial financial support provided by the International Science Programme (ISP) of Uppsala University, Sweden and Relevant Science & Technology Society (RSTS) for conducting this research. Last but not the least, I consider myself extremely lucky as I am blessed with an amazing family. My family have always been the prime source of motivation, support and inspiration not only throughout this journey but all round my life so far.

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

ANN Artificial Neural Networks

BCI Brain Computer Interaction

CNN Convolution Neural Networks

DBN Deep Belief Network

DoA Direction of Arrival

DWT Discrete Wavelet Transformations

EEG Electroencephalogram

fMRI Functional Magnetic Resonance Imaging

fNIRS Functional Near Infrared Spectroscopy

HCI Human Computer Interaction

HMM Hidden Markov Model

LSTM Long Short-Term Memory

MLP Multi Layer Perceptron

MUSIC Multiple Signal Classification

PCA Principle Component Analysis

PSD Power Spectral Density

RNN Recurrent Neural Networks

STFT Short Time Fourier Transforms

SVM Support Vector Machines

Chapter 1

Introduction

1.1 Feelings and Emotions in Consciousness

Professor Dr. Antonio Damasio in his book “The Strange Order of Things : Life, Feeling and the Making of Cultures” has argued that feelings and human emotions have been the sole influence in initiating progress. For example the prime motive behind development of efficient anesthetics is to mitigate human feeling of discomfort. The author presented a delicate and intriguing explanation behind the development of culture and progress of civilization in a diversified perspective of human feeling and emotions. These important aspects of human behavior particularly, emotion is highly correlated with human consciousness. Each of them is indispensable for the co-existence of the other [15]. The phenomenal evolution of medical imaging modalities in recent times, have facilitated us to explain more of such complex investigations [42]. As a consequence, relevant fields which focuses on the application of the theoretical and hypothetical aspects of neuroscience have experienced immense advancements [116].

In the late 1920s, psychiatrist Dr. Hans Berger invented EEG and recorded the first EEG brain waves in order to interpret psychophysiology of mental diseases. Though Hans Berger’s psychophysiological research later became the foundation of modern brain imaging modalities, correlation of EEG brain waves with psychological states remained ambiguous for a prolonged period. After world war 2, in the 1950s EEG experienced clinical use in neural disorder (specifically epilepsy and seizures) diagnosis, but substantial correlation with mental diseases remained quiet challenging [8], [9]. But in the recent past, advancements in hardware provided enormous computational capabilities. This has lead to opportunities, which were previously nonexistent in the study of EEG recordings. Hybrid neural imaging techniques such as, simultaneous acquisition of fMRI and EEG recordings, granted delicate information regarding the neural dynamics of cognition [14]. Recent researches have discovered fascinating insights, about the correlation of EEG features with various cognitive processes, by describing complex phenomena such as, neural oscillation and neural microcircuits [44]. Wearable brain activity recording devices such as EEG and fNIRS (functional near infrared spectroscopy) can now provide correlated information about cognitive behaviors such as memory, perception and emotions [47], [76], [92].

As discussed previously, feelings and emotions are the prime motive behind the progress of civilization. As observing such cognitive states with wearable devices has become accessible, it has unfolded new dimensions for research and development

beyond our imaginations. In the process, the fields of HCI, BCI and Neuromarketing [26] have experienced massive breakthroughs. Such breakthroughs have also radically transformed associated fields such as virtual reality, assistive technologies and numerous other domains.

1.2 Application of EEG Based Emotion Recognition in BCI & HCI

EEG based emotion recognition have seen a wide range of applications in recent years, it's application ranges from clinical environment to ensuring biometric based security in ATMS [25]. EEG emotional recognition techniques are also being used to evaluate clinical therapies for cancer patients [62]. Such emotion recognition based BCI systems are also playing key roles in observing cognitive states of critical patients in ICU [103] and patients with consciousness disorder [75]. Recently similar EEG based emotion recognition systems have seen use in tele-medicine and e-health applications for treating patients with psychological disorder, as such systems can provide a decent overview of the psychological states of the patient [41]. EEG based emotion recognition systems have also showed great potentials in ensuring passwordless secured transactions in ATM by only monitoring cognitive state of the user [94], [107].

In HCI research, EEG emotional and attention analysis has been a decisive framework for assessing the competence of m-learning platforms [97]. Virtual reality based e-learning educational platforms have witnessed considerable increase in efficiency, with the integration of EEG headsets. By evaluating learners mental states, such system tweaks the learning environment for optimum efficiency [63]. Modern BCI technologies are capable in ensuring safe driving, as driver's EEG features provide highly correlated information regarding their stress levels and mental states [11], [17]. Motor impairment is a common phenomena in post-stroke patients and in patients suffering from spinal cord injuries. In such instances, BCI systems can now restore lost sensorimotor functions with advanced neurorehabilitation robotics [43], [93]. Wearable EEG headgears are now currently revolutionizing the mobile gaming industry, by providing a medium for user interaction with virtual reality based systems. Such interaction is solely based on the analysis of users emotional states and motor imagery states [105]. Researches in consumer neuroscience has demonstrated, EEG recordings of consumers emotional states can provide highly correlated information regarding their product preferences and liking. Such knowledge describing consumer behavior is now being portrayed as a decisive aspect for contemporary marketing schemes [57], [74], [90].

1.3 Limitations of Existing EEG Feature Extraction Techniques

A superficial work flow of EEG based BCI and HCI is illustrated in figure 1.1. The fundamental obstacle in any BCI based application is the feature extraction task. Machine learning and deep learning algorithms for instance, SVM, ANN, CNN, LSTM and other sequential models have always been considered as the state of the

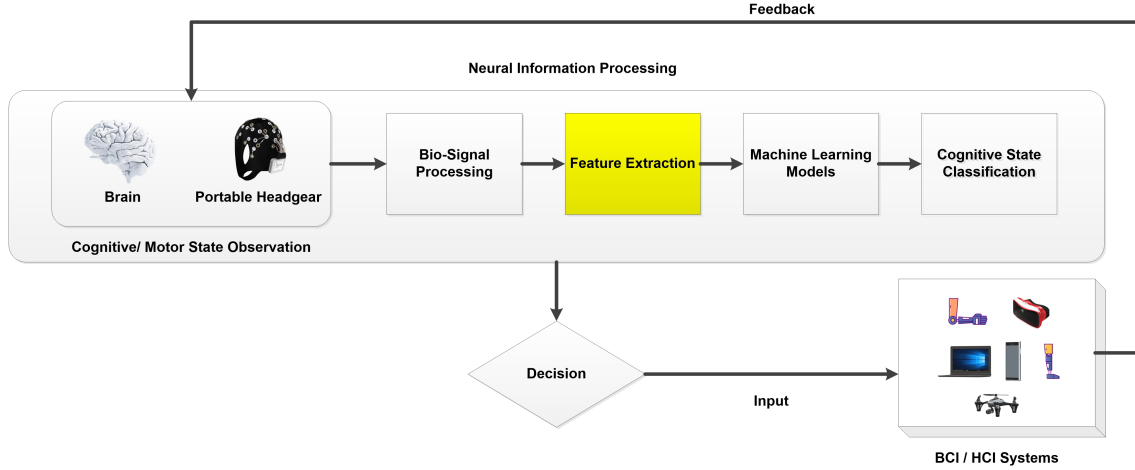


Figure 1.1: Brief Workflow of EEG based BCI & HCI Systems

art in EEG brain signal classification tasks [59], [73], [81]. However in such classification tasks the major challenge lies within the dilemma of feature extraction. Raw time series signal provide little correlated feature information, yet it holds colossal varieties of hidden feature patterns. Standard deviation, absolute deviations, statistical norms and other statistical parameter computations have received admiration in time series feature extraction tasks, as t and p-values for such statistical features have demonstrated considerable correlations [99]. Overlapping windowing techniques in raw time series data have also shown potentials, as it eradicates the risk of hidden feature patterns in time series [87]. Having said that, frequency domain transformations in particular DWT, STFT, non-parametric classical power spectral estimators, parametric based autoregressive power spectral estimator models can be considered as the state of the art in EEG feature extraction tasks [31], [73], [101]. Nevertheless the particular frequency domain estimators comes with expensive computational cost, as they have higher computational complexity and considerably extensive run time. Our investigations has shown, mean run time for computing nonparametric welch power spectrum estimation in a intel CORE-i5 processor(32 GB DDR4 RAM, 512GB SSD Memory), for a 240 seconds (downsampled to 200 HZ) 62 channel EEG recording is 30.5 seconds. Such extensive run time minimizes the dynamics of HCI and BCI applications, by shrinking real time data processing capabilities in systems with comparatively lesser configurations. Real time data processing in such cases demands spark or hadoop based distributed computational systems [46], [61], [104].

1.4 MUSIC Algorithm in Cognitive Research

PSD Estimators which uses parametric eigen analysis models should have a lesser time complexity, as it solely uses linear transformations rather than computing windowed periodigram from autocorrelated functions [2]. Parametric eigen analysis based PSD estimators, specifically models which uses eigen matrix decomposition principles have seen little exploration in EEG feature extraction tasks. One reason behind the unpopularity of such PSD estimators is, such models requires some preceding information regarding the signal. For instance, the MUSIC algorithm demands esti-

mations about the signal’s subspace dimension and noise thresholding parameters. In terms of complex random signals analogous to EEG, such parametric information are ambiguous and generates complexity.

The MUSIC algorithm have given incredible results in detecting DoA through PSD estimation, specifically in the radar and communication research [24], [51], [67]. Successful implementation of MUSIC models extents to the domain of structural engineering in corrosion monitoring [70]. Previously , the MUSIC model has been very successful in EEG source localization, due to its efficiency in DoA estimation [7], [12], [48], [56]. However, as a consequence of its complexity in terms PSD estimation of random signals, a limited number of researches have been conducted to investigate its possible use in EEG feature extraction tasks [10], [16], [20], [23], [37]. Particularly in terms of psychological feature extraction, almost no research can be seen which focuses on the possible implementation of the MUSIC model.

1.5 Aim, objective and Outcome of the Research

In this paper we investigated the use of MUSIC model in EEG emotional feature extraction task, on publicly available SEED dataset. The feature extraction model uses parametric based eigen matrix decomposition for estimating power spectral density. Our research also explains the complex concept of estimating subspace dimensions for EEG waveforms in unique cases through detailed analysis. As estimation of subspace dimentionality are indispensable in implementing any eigen analysis based parametric PSD estimators, we believe our findings will benefit a wide spectrum of future EEG information processing researches. An enormous amount of researches have already been conducted on the SEED dataset, unfortunately no researches had focus on a thorough investigation on the attribute and characteristics of the dataset [29], [32], [36], [39], [49], [53], [65], [99]. Our investigation have also revealed some fascinating attributes of the SEED dataset, which had unknowingly effected previously conducted researches on this popular EEG waveform dataset. Figure 1.2 illustrates the fundamental objectives of this reasearch through mapping of problem statements. Figure 1.3 illustrates the core objective of this research through a simplified block diagram.

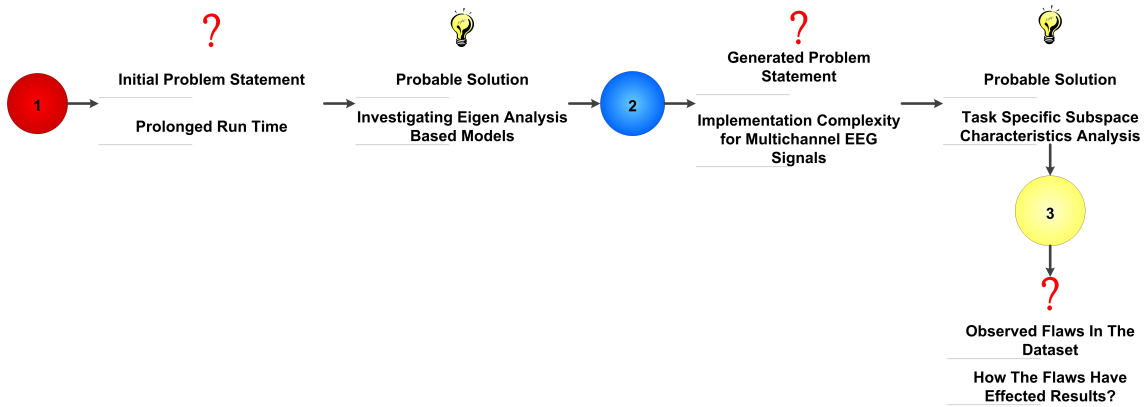


Figure 1.2: Problem Statement Mapping

The novelty of this research work are specifically states as follows:

- The research discusses extensive flaws in the SEED emotional dataset through three dimensional time series visulization. Such observation also creates immense scope for future researches on this dataset.
- The article discusses specific complex characteristics of non-stationary EEG signals, which construct complexity for implementing Eigen decomposition based parametric feature extraction models for such bio-signals.
- The research analyses the quality of the extracted MUSIC model based feature spaces through high dimensional visualization and network performance evaluation.
- Finally, the research conducts machine specific run time comparison of proposed MUSIC model based feature extraction technique with conventional non-parametric feature extraction technique.

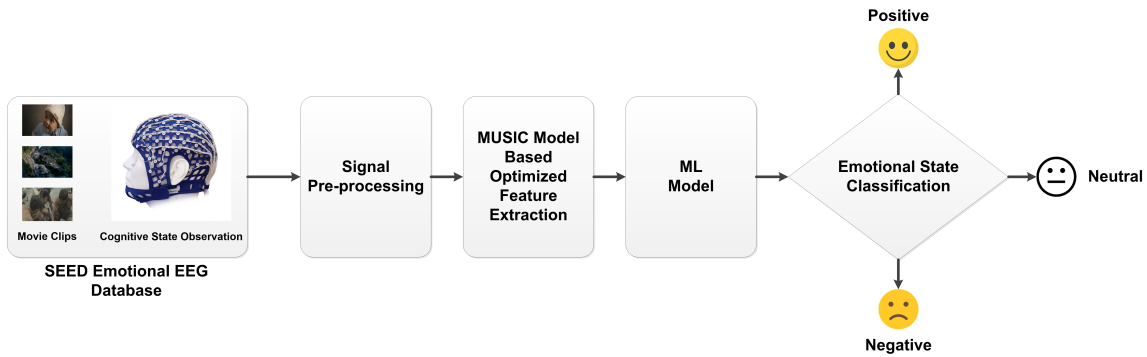


Figure 1.3: Block diagram explaining the core objectives

1.6 Thesis Outline

Remaining part of the thesis report has been organized as follows:

- Chapter 2 provides an overview of the prerequisite background knowledge from the domain of biomedical engineering.
- Chapter 3 briefly reviews the literature of existing state of the art researches in feature extraction task for neural information processing and implementation of MUSIC algorithm in several other domains,
- Chapter 4 gives an overview of the dataset and findings from the investigation on the dataset characteristics,
- Chapter 5 discusses the research methodology in details,
- Chapter 6 contains detailed evaluation of the proposed method,
- Chapter 7 illustrates the concluding remarks for this research,
- Finally, Appendix A and Appendix B discusses about the developed modules and code bases for MUSIC model based feature extraction task and three-dimensional visualization of large scale multi-channel EEG data, respectively. Both of the repository have been made public.

Chapter 2

Background Comprehension

The brain is called "the command panel of the human body". It is a part of the central nervous system (CNS). The average weight of the human brain is approximately 1.5 kg or 3.3 lb which is around 2% of the human body. But the fact is "brain demands 17% of the cardiac output and 20% of the human body's oxygen consumption", which means it is metabolically one of the most active organs. Interestingly, the brain's metabolic activity varies in different regions as it is not a homogenous organ. Therefore, the metabolic activity of any brain region denotes the distinct functional activity which can be radiographically imaged.

In this chapter we discuss the basic brain structure and physiology, which are prerequisites for understanding the origin of neural action potential or neural activity. Then we provided an brief summary about different types of bio-signals. Finally, we discuss about the origin of neural action potentials and fundamentals EEG in observing such neural activity.

2.1 Anatomy, Functions and Regulatory Behaviours of Human Brain

The brain is a multi-functional organ as the brain controls intelligence, personality, emotion, motor skills, memory, automatic functions, etc. Basically, five senses (sight, smell, taste, touch, and hearing) act as the input of the brain. The brain receives inputs as chemical and electrical signals and processes output signals according to those inputs. Sometimes, the brain stores inputs as memory. Each part of the brain has distinct functions and abilities.

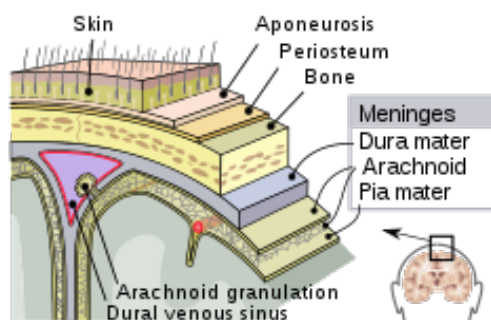


Figure 2.1: Three layers of meninges [4]

The brain is wrapped by three types of meninges: the dura mater, the arachnoid mater, and the pia mater (Figure. 2.1). These meninges layers are also continuously found in the spinal cord.

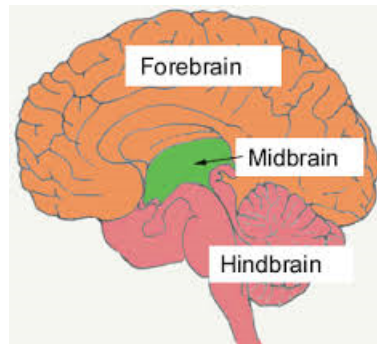


Figure 2.2: Three parts of human brain [4]

The brain can be divided into three regions considering the phylogenetic principles and ontogenetic growth. They are:

- Hindbrain/ Rhombencephalon
- Midbrain/ Mesencephalon
- Forebrain/ Prosencephalon

During embryonic development, the dorsal surface ectoderm generates a neural tube which subsequently develops the brain and spinal cord. Basically, three primary ganglia are generated from the neural tube which eventually makes up the brain by forming these three parts of the brain [4], [5], [19] These regions are elaborately described.

2.1.1 Hindbrain/ Rhombencephalon

The rhombencephalon or the hindbrain is subdivided into the following parts:

- Medulla oblongata
- Pons
- Cerebellum.

These parts can be identifiable at week 22 of embryonic development. The medulla oblongata is connected to the spinal cord, it's like a communication port between the brain and the spinal cord. Pons lies above the medulla which connects the brain stem and the cerebellum. The brainstem incorporates the midbrain, pons, and medulla oblongata.

Medulla oblongata plays a vital role in terms of maintaining homeostasis as many centers and nuclei lie within the medulla oblongata. Such as the cardiovascular center, the respiratory rhythmicity centers, the nucleus gracilis and nucleus cuneatus, the olivary nucleus, the sensory and motor nuclei of cranial nerves VIII, IX, X, XI, and XII, etc. Functions of medulla oblongata are given below:

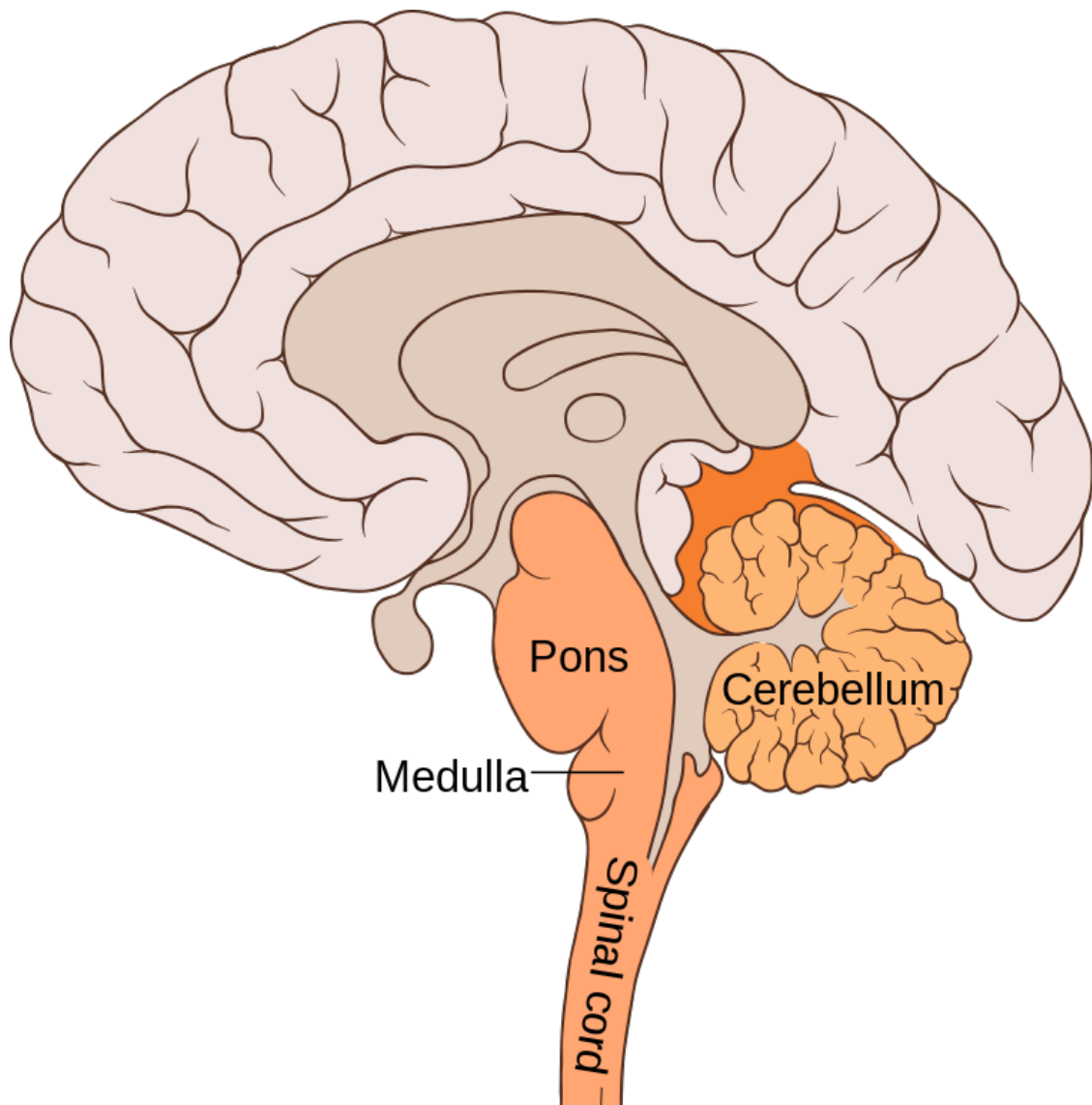


Figure 2.3: Parts of Hindbrain (Sagittal View) [5]

- It has a role in the cardiovascular system by maintaining heart rate, peripheral vasculature, and the strength of contractility of the heart muscle.
- It receives afferent information from set a baseline for respiratory rate.
- It transfers afferent information to the thalamus and cerebellum.
- It regulates blood pressure by baroreceptors.
- It regulates coughing, vomiting, sneezing, and swallowing by serving as a “reflex center”.

Pons is located between the medulla oblongata and midbrain and it is the thickest part in the brainstem region. It is also called “the pons Varolii” which means “bridge of Varolius”. Cranial nerves V, VI, VII, and VIII are generated from this part. Functions of the pons are illustrated below:

- It has a sensory role in taste, hearing, and equilibrium.

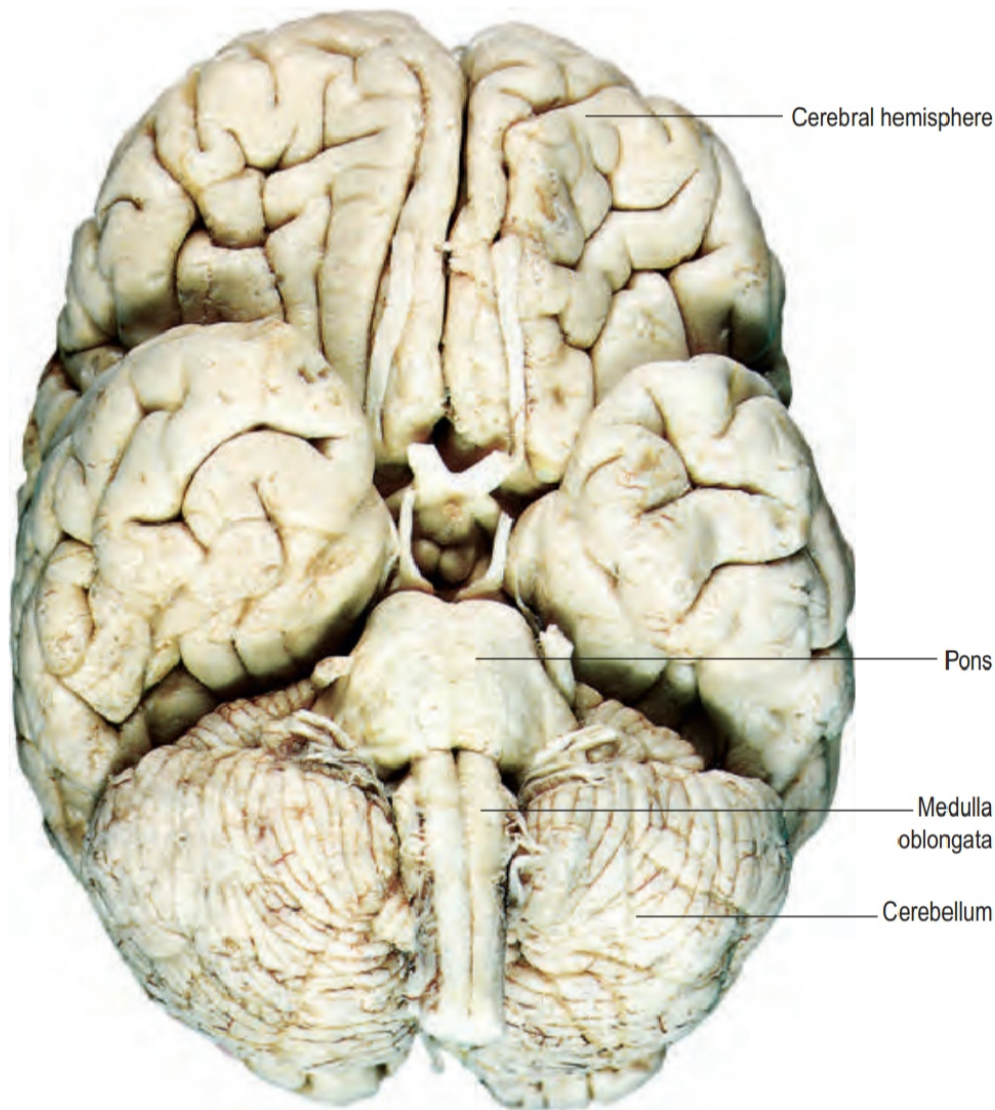


Figure 2.4: Parts of Hindbrain (Transverse View) [5]

- It has a role in touch pain sensation.
- It has a motor role in lateral eye movement, facial expression, chewing, swallowing, body fluids like urine, tears, saliva, nasal and oral mucus secretion.
- it controls sleep, respiration, and body posture.
- It is related to generating dreams and sleep paralysis.

The cerebellum is the largest part in the Rhombencephalon region which contains more than the total number of neurons (almost 100 billion) though it is only 10 % of total brain mass. Tiny granule cells are the most common type of neuron cells in the cerebellum and also in the brain. But its Purkinje cells are the most distinguishable neuron cells as they are extraordinarily large, dendrites are formed like a flat tree and their axons go to deep nuclei and synapse with output neurons. There are two cerebral hemispheres (right and left) which are connected by the “vermis” made up the entire cerebellum part. Several sulci and fissures divide it into multiple lobes,

lobules, and folia. The outer layer or surface cortex of it is gray matter and the inner layer is white matter. The brainstem is attached to the cerebellum by three pairs of cerebellar peduncles. A pair of inferior peduncles by which most spinal input signals launch into the cerebellum is connected to the medulla oblongata, a pair of middle peduncles by which the rest of the entire brain input signals enter the cerebellum are connected to the pons and cerebellar output signals go out by a pair of superior peduncles which are connected to the midbrain. The functions of the cerebellum were mostly unknown till the 1950s. Most of its current known functions have been discovered by researching cerebellar damage of humans and animals. The cerebellum has multiple numbers of independent modules and its combination with motor or non-motor areas will demonstrate a distinctive behavioral pattern. The functions of the cerebellum are given below [4], [5], [19], [38],

- It maintains muscle contraction and motor coordination. For this reason, people with cerebellar lesions have problems with coordinating and locomotion.
- It controls emotions, linguistic, and various non-motor and sensory activities.
- It maintains spatial, timing, and sound difference related perception.
- It helps planning and scheduling works .
- It controls precise and intentional skill-related movement, therefore only humans can perform intricate works like writing.

2.1.2 Midbrain/ Mesencephalon

The mesencephalon or the midbrain is smallest the part of the brainstem which connects the forebrain and the hindbrain. Midbrain is subdivided into three parts:

- Tectum/ Quadrigeminal Plate (dorsal part)
- Tegmentum (central part)
- Crura Cerebri/ Cerebral Peduncle (ventral part)

The cerebral aqueduct separates two regions, the tectum, and the tegmentum; it is surrounded by periaqueductal grey and continues the circulation of cerebrospinal fluid. Substantia Nigra is responsible for separating the tegmentum from the cerebral peduncle. Two pairs of cranial nerve nuclei, the trochlear (CN IV) and the oculomotor (CN III) are located ventral to periaqueductal grey. The tectum contains four bulges named the corpora quadrigemina. The upper pair is known as the superior colliculi, whereas the lower pair is known as the inferior colliculi. In the tegmentum part, red nuclei are visible which has a connection with the cerebellum, and reticular formation which is an array of interconnected nuclei is also located here. The corticospinal nerve tracts are carried by the cerebral crus which is a bundle of nerve fibers. Cerebral Peduncles are two large fiber bundles, each of those fiber bundles has a connection with the cerebral cortex, the brainstem, and the spinal cord [16]. The functions of the midbrain are [1], [4], [5], [19], [21], [38], [113],

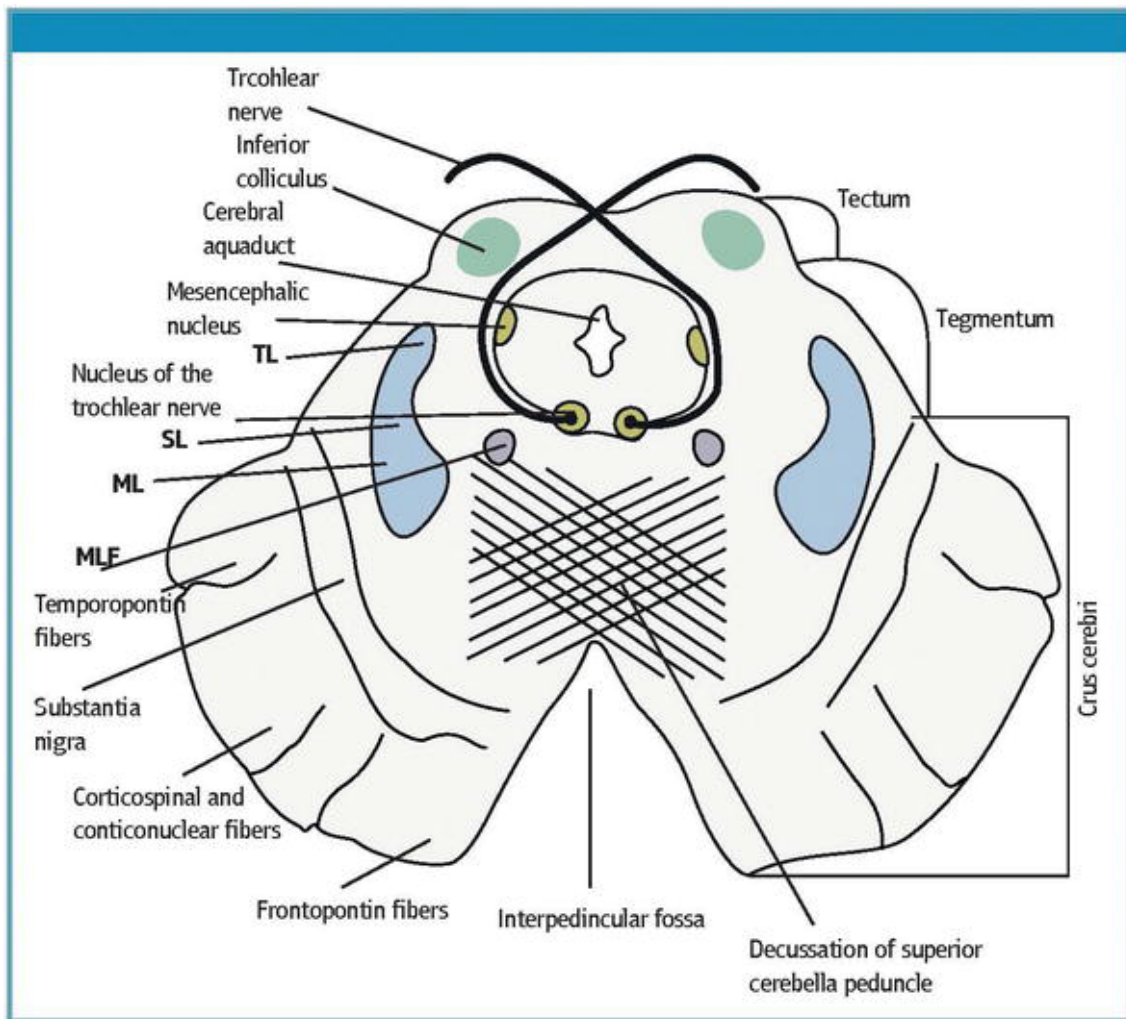


Figure 2.5: Midbrain segments (cross section through inferior colliculus) [19]

- The superior colliculi control visual attention, visual reflexes (pupil dilation and contraction, blinking, focusing), visual tracking of moving objects, and eye movement according to a stimulus
- The inferior colliculi transmit signals from the inner ear to the brain (especially thalamus) and control reflexive actions in response to sound
- The substantia nigra and ventral tegmental area produce dopamine which is essential in motor control, motivation, pleasure, decision making, emotion, reinforcement, etc.

2.1.3 Forebrain/ Prosencephalon

The prosencephalon is the largest part of the human brain and it contains two parts:

- Diencephalon

- Telencephalon

The diencephalon originates from the foremost primary cerebral vesicle [18]. It is also known as “tween brain” as it controls metabolism. It is further divided into three structures:

- Thalamus
- Hypothalamus
- Epithalamus

The thalamus is a gray matter, located in the dorsal region of the diencephalon, which lies between the cerebral cortex and midbrain. All sensory signal has to pass through the thalamus before entering cerebral cortex; that’s why it is called “gateway of the cerebral cortex”. It is equally divided into two halves (right and left). Some branches of the posterior cerebral artery like the polar artery, inferolateral arteries, posterior choroidal arteries, and paramedian thalamic-subthalamic arteries provide blood supply to the thalamus. The thalamus is interconnected with some parts of the cerebrum (sensory thalamus and sensory cortex, motor thalamus and motor cortex, limbic thalamus and limbic cortex). The functions of the thalamus part are described below:

- Human conscious perception depends on the information of the cerebral cortex. It acts as a relay and filters sensory information before passing to the cerebral cortex region
- It also acts as a relay of motor signals from the cerebellum to the cerebrum and regulates feedback loops to the basal nuclei and the cerebral cortex
- Particular regions of the thalamus combining with the prefrontal cortex have a role in paying attention, working memory, and quick decision making. The study clarifies that the mediodorsal thalamus controls connectivity of circuit and helps to take real-time decisions
- It regulates sleep and wake states
- The thalamus is a vital part in terms of generating antisaccade eye movement in primates
- It contributes to the limbic system’s function like memory and emotion-related functions

The hypothalamus is the most ventral part of the diencephalon. It elongates posteriorly to the mammillary bodies containing 3-4 mammillary nuclei and anteriorly to the optic chiasm. It is a part of the limbic system and the pituitary gland is connected to it. It is smaller in size (4 cm²) but has some vital roles in the body. They are:

- The hypothalamus controls pituitary gland activities by secreting hormones. Growth, reproduction, stress, and metabolism are regulated by the anterior pituitary gland which is controlled by hypothalamic hormones like Thyrotropin-releasing hormone (TRH), Corticotropin-releasing hormone (CRH), Dopamine, Growth-hormone-releasing hormone (GHRH), Gonadotropin-releasing hormone (GRH), Somatostatin. The hypothalamus releases two hormones like oxytocin and vasopressin that stores in the posterior pituitary gland and maintains uterine contraction, lactation, and water reabsorption and excretion
- The hypothalamus coordinates the autonomic nervous system by influencing functions like heart rate, blood pressure, pupillary response, etc. It also controls emotional response and fight or flight response
- The hypothalamic thermostat controls sympathetic and parasympathetic response according to temperature
- It controls the hunger and thirst for water by arcuate nucleus and osmoreceptors. The arcuate nucleus contains some receptors for two types of hormones that control hunger and energy expenditure. Whilst, osmoreceptors monitor the osmolarity of blood and stimulate thirst during dehydration. In case of dehydration, the hypothalamus secretes antidiuretic hormone that conserves body water
- The hypothalamus initiates and coordinates reproductive functions which are distinguishable in terms of sex
- The hypothalamus involves in the maintenance of sleep and the circadian rhythm of the body
- It is an important part of the memory conservation of the brain. Severe memory deficit appears in case of lesion formation in this region

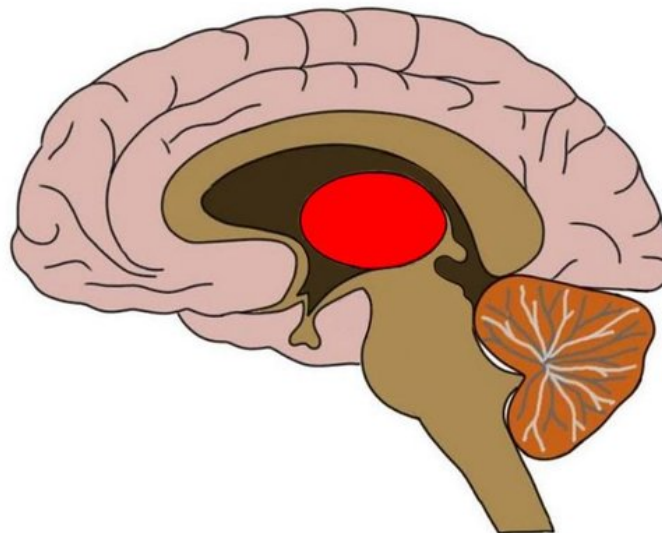


Figure 2.6: Thalamus (red colored region) [19]

The epithalamus is the small mass of tissue that is in the posterior part of the diencephalon. It comprises the pineal gland, habenular nuclei, and a thin roof over the third ventricle. The functions are demonstrated below:

- The limbic system is connected to other regions of the brain with the help of the epithalamus
- It controls motor pathways, energy conservation, and emotions
- Secretion of melatonin by the pineal gland is regulated by it.

The telencephalon develops to the cerebrum which is the largest part of the brain. It contains the cerebral cortex, the hippocampus, the olfactory bulb, and the basal ganglia. This is situated at the vertex position of the central nervous system (CNS). Two cerebral hemispheres are equally sized and divided by the longitudinal fissure but attached by the corpus callosum. The surface area of the cerebrum is enormous (approximately 2500 cm²) but the cerebrum easily fits in the cranial cavity due to the gyri formation or folding of the surface. Sulci divide each cerebral hemisphere into anatomically different lobes:

- Frontal Lobe
- Parietal Lobe
- Occipital Lobe
- Temporal Lobe
- Insula

The frontal lobe is the largest lobe among the five lobes of the hemisphere. The central sulcus and the lateral sulcus separate the frontal lobe from the parietal lobe and the temporal lobe, respectively. The frontal lobe is responsible for activities related to functions like skeletal movement, eye movement, speech, and speech production. It integrates non-task-based memory that stores in the brain. Some of its emotional and cognitive functions are: emotional control, judging, planning, foresight, decision making, motivation, etc.

The parietal lobe is situated in the uppermost region of the brain. The central sulcus, the parieto-occipital sulcus, and the lateral sulcus separate it from the frontal lobe, the occipital lobe, and the temporal lobe, respectively. The parietal lobe is well known for its sensory functions like touch, heat, pain, etc. It is responsible for two-point discrimination by touch, graphesthesia, and localization of touch.

Coordination of multisensory tasks, language processing, the memory of stimuli, and numerical awareness are also parts of its functions. The occipital lobe is located at the back of the brain and it is called the visual center of the brain where vision is first precepted and processed. It has an important role in the recognition of face, object, and color. It also deals with spatial perception, movement, memory, and distance-related functions. The binocular perception is achieved by combining two images received by two occipital lobes to one image which helps humans to obtain better spatial perception. The temporal lobe is separated from the frontal lobes and the parietal lobes by the lateral sulcus; the lateral fissure is situated on top of it.

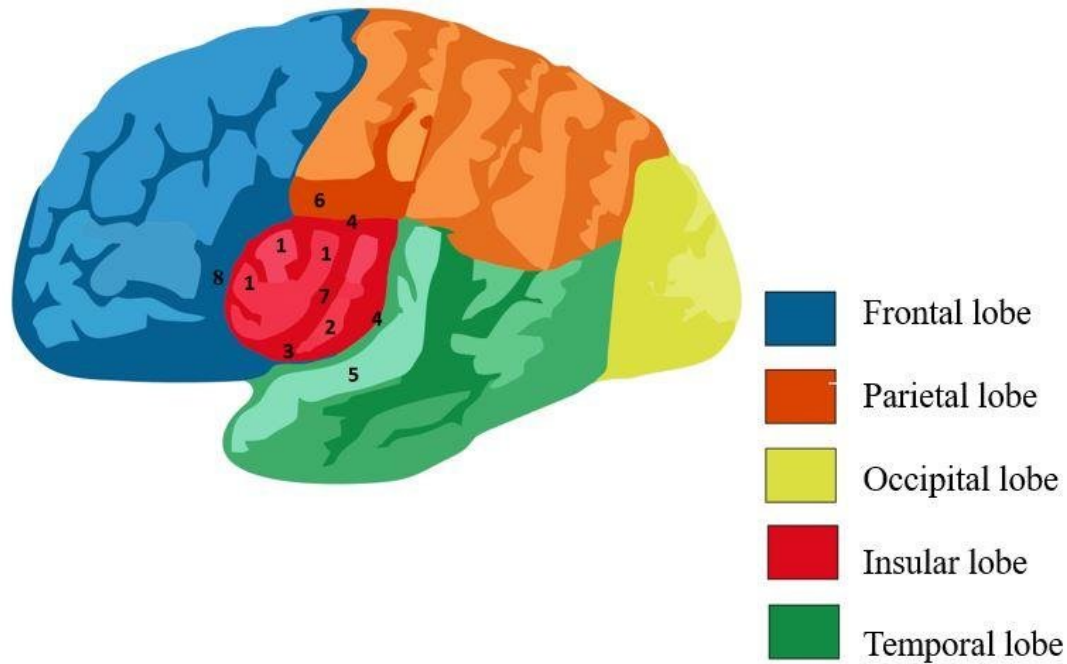


Figure 2.7: Five lobes of the cerebrum [19]

The temporal lobe involves in the formation of explicit long-term visual memory. It is also essential in storing auditory and verbal memory. Damage in this part causes permanent or temporary amnesia. It plays an important role in language recognition and processing. Hearing, smell, and learning are also included in its area of function. The insula is a small part of the cerebral cortex which is located within the lateral sulcus. It concerns with taste, pain, cardiovascular homeostasis, and visceral sensation. It has an important role in consciousness, addiction, and empathy towards other individuals. The limbic system is located on the medial side of each of the cerebral hemispheres and it consists of some important components like the cingulate gyrus, the amygdala, and the hippocampus. It is called the center of emotion and learning. It has an impact on the endocrine system and the autonomic nervous system. The hippocampus plays an important role in memory consolidation which converts short-term memory to long-term memory and navigation-related spatial memory. On the other side, the amygdala deals with memory, decision, and emotional responses.

The basal ganglia are a group of subcortical nuclei which are located deep within the white matter. They have intense communication with the cerebral cortex, the thalamus, and the brainstem. The basal ganglia deal with "feedback mechanism" to the cerebral cortex and modulation cognitive and emotional response. By filtering the excitatory input to the cerebral cortex, the basal ganglia prevent unwanted excessive movements [1], [4], [5], [19], [21], [22], [38], [113].

2.2 Bio-signals

The biosignal denotes a sort of signal possessing space, time, or space-time information that is generated from a biological event. The biological event may be electrical,

mechanical, or chemical activities of a living being. The biosignal is essential in the case of medical diagnosis or study of any physiological mechanism of a biological event by analysis methods like filtering, amplifying, digitization, processing, or storing. Along with these conventional methods, digital processing methods like wavelet analysis, artificial intelligence, and averaging of the signal are utilized to upgrade the quality. The biosignal can be classified as being of a particular nature like either being continuous or discrete and either being deterministic or random. Electrical circuits, or computer, or a combination of both execute the analysis procedure of the biosignal. Followings are sources of biosignals [28]:

- **Bio-electric Signals:** The electrochemical changes in nerve and muscle cells generates low amplitude and frequency bioelectric signals. Basically, the flow of ions through the cell membrane (the action potential), generated by stimulus, is transmitted by activated cell to cell which eventually creates an electrical field. That causes a change in extracellular potential which can be measured by bioelectrodes. Examples are: electrocardiogram (ECG), electromyogram (EMG), electroencephalogram (EEG), and electrogastrogram (EGG).
- **Bio-magnetic Signals:** Living organs develop a weak magnetic field which can be measured by accurate magnetic sensors or SQUID (superconducting quantum interference device). Examples are: magnetoencephalogram (MEG), Magnetoneurography (MNG), Magnetogastrography (MGG), and magnetocardiography (MCG).
- **Biochemical Signals:** Amount of various biochemical agents like ions (Ca^{2+} and K^{+}), partial pressure of oxygen and carbon dioxide, glucose, etc., which are known as biochemical signals contains essential information of the physiological system.
- **Bio-mechanical Signals:** Biomechanical signals are produced by mechanical activities (motion, pressure, displacement, etc.) of a living being. Waveform representing changes in pressure can indicate the systolic pressure and the diastolic pressure.
- **Bio-acoustic Signals:** Acoustic noise generated by biological systems is known as bioacoustics signals. Example: Bioacoustic signal of the heart valve denotes its functionality.
- **Bio-optical Signals:** The light-induced by biological events generates bio-optical signals which can be measured with the help external medium. Example: Fluorescence generated by the amniotic fluid is essential to monitor the fetus.

2.3 Neural Action Potential and Electroencephalogram (EEG)

The electroencephalogram records the electrical potential of the brain by an electrophysiological mentoring method. It is a graphical representation of the potential differences in brain function of two regions during a course of time. The extracranial

EEG follows a noninvasive procedure and records the electrocerebral activity with the help of electrodes placed on the surface of the scalp.

2.3.1 Origin of Neural Action Potential

The intracranial EEG records detailed and precise information of brain function with the help of surgically implanted electrodes that target specific parts of the brain.

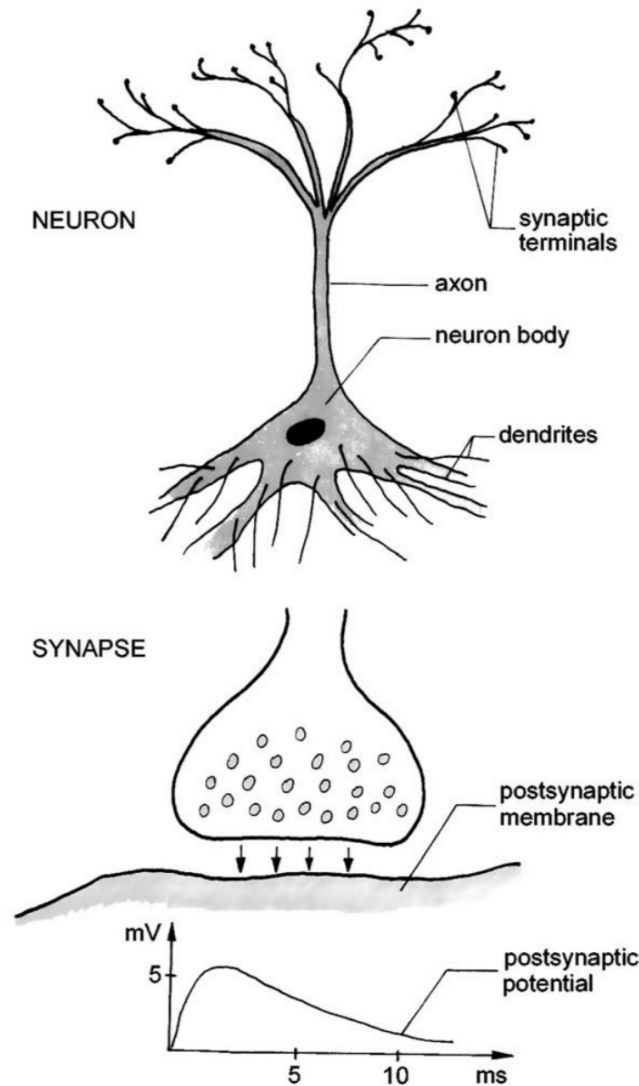


Figure 2.8: Neuron, Synapse and Action Potential

The resting potential is -80 mV for both of the brain cells, glial cells, and nerve cells, which active transport of K^+ (to inside of the cell) and Na^+ (to the outside of the cells). When the stimulus exceeds the threshold, The influx of Na^+ to the cell leads to an increase in the potential and changes in the polarity of the nerve cell ($+30$ mV), this case is known as the action potential.

However, due to subsequently decreased permeability for Na^+ and increased permeability for K^+ turns the potential inside of the cell negative again. The action

potential reaches the synapse, the mediator is released which causes a potential difference across the neighbor's postsynaptic membrane. The influx of the Na^+ turns the neuron to be less negative which generates the excitatory postsynaptic potentials (EPPs). On the contrary, when neurons become more negative, the inhibitory postsynaptic potentials (IPPs) are generated. The amplitude of the postsynaptic potentials is around 5 – 10 mV with a time span of 10 -50 msec. The sources of the EEG waveforms are the synchronously generated postsynaptic potentials.

2.3.2 EEG Acquisition Setup

The extracranial EEG (conventional EEG) procedure starts with preparing the skin as the interface between surface and electrode has a resistance below 5 kOhm. In order to prepare the skin, a cleaning site with diluted alcohol or light abrasion can be essential. Electrodes are either attached to cables or embedded in caps or nets. The placement of electrodes is very important for interpretation or comparing results.

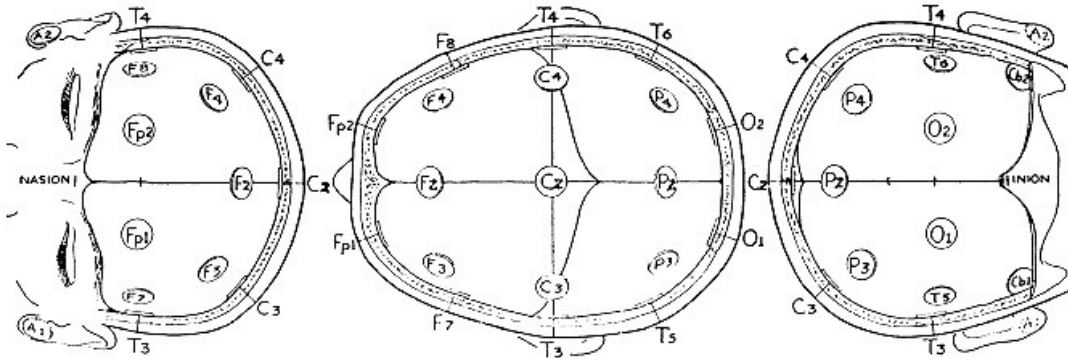


Figure 2.9: Electrode placements for 10-20 System

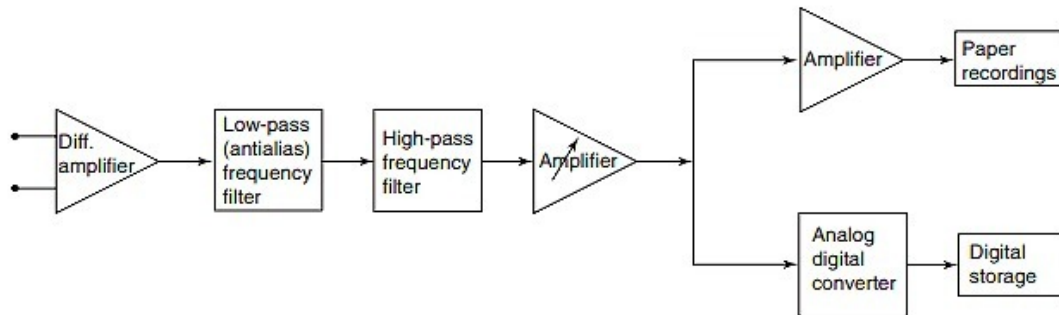


Figure 2.10: Simplified EEG Block-diagram

The international 10-20 electrode system defines the placement of electrodes regarding the application. To identify the lobes of the cerebrum, each electrode has a distinct index regarding the lobe: Fp (pre-frontal), F (frontal), T (temporal), P (parietal), O (occipital), and C (central). Though the central lobe doesn't exist, the "C" electrode can be crucial in detecting the stages of sleep. The electrodes which are labeled with "z" or 0 denote the midline sagittal plane of the brain and act as the reference points. The odd and even numbers represent the electrodes placed on

the left and the right side of the brain respectively. The “A” (also referred to as “M”) indicates the electrodes placed on earlobes.

Generally, 19 electrodes are placed on the scalp in such a manner that they cover up the entire scalp with an interval of 10 – 20% distance between them. In some cases, more or fewer electrodes are used considering the subject (fewer electrodes for infants and more electrodes for better spatial resolution of the desired region).

A series of stimulations like eye closure, mental activity, sleep, intermittent photic stimulation is needed to induce desired EEG activity. The differential amplifier’s two inputs are connected to the electrode and the reference electrode which amplifies the signal by 1000 – 100000 times or 60 -100 dB of voltage gain. The analog signal has to be filtered before entering the output section. The high-pass filter (0.5-1 Hz), the low pass filter (35-70 Hz), and the notch filter are used for filtering the analog signal. The output can be either analog (pen paper-based) or digital (computer or oscillator). In the case of digital output, the analog to digital converter is required according to the purpose. The awake state of a normal subject is characterized by 10-100 μ V in EEG; the amplitude of EEG increases rapidly (500-1500 μ V) in the case of epilepsy. The montage consists of series of EEG channels which is essential for display and lateralizing and localizing information.

There are several kinds of montage used in the EEG, such as sequential montage (each channel denotes the voltage difference of two neighbor electrodes), referential montage (each channel denotes the voltage difference of an electrode and a reference electrode), average referential montage (each channel denotes the voltage difference of an electrode and average of all outputs), and Laplacian montage (each channel denotes the voltage difference of an electrode and the weighted average of adjacent electrodes).

2.3.3 EEG Bands and Waveforms

Neurological conditions, metabolic disorders, and drug addiction affect the normal EEG pattern. The EEG has several distinguishable rhythms which are described in Table 2.1:

EEG Bands	Frequency Range (Hz)	Characteristics
Delta	0.5 to 4	Sleep wave
Theta	4 to 8	Indicates partial cognitive states
Alpha	8 to 13	Main feature during awake state
Beta	13 to 30	Focused state
Gamma	greater than 30	Information processing and voluntary movements

Table 2.1: EEG Bands

2.3.4 EEG Artifacts

The artifacts in the EEG signal interfere with the actual EEG signals. The artifacts of the EEG are described below:

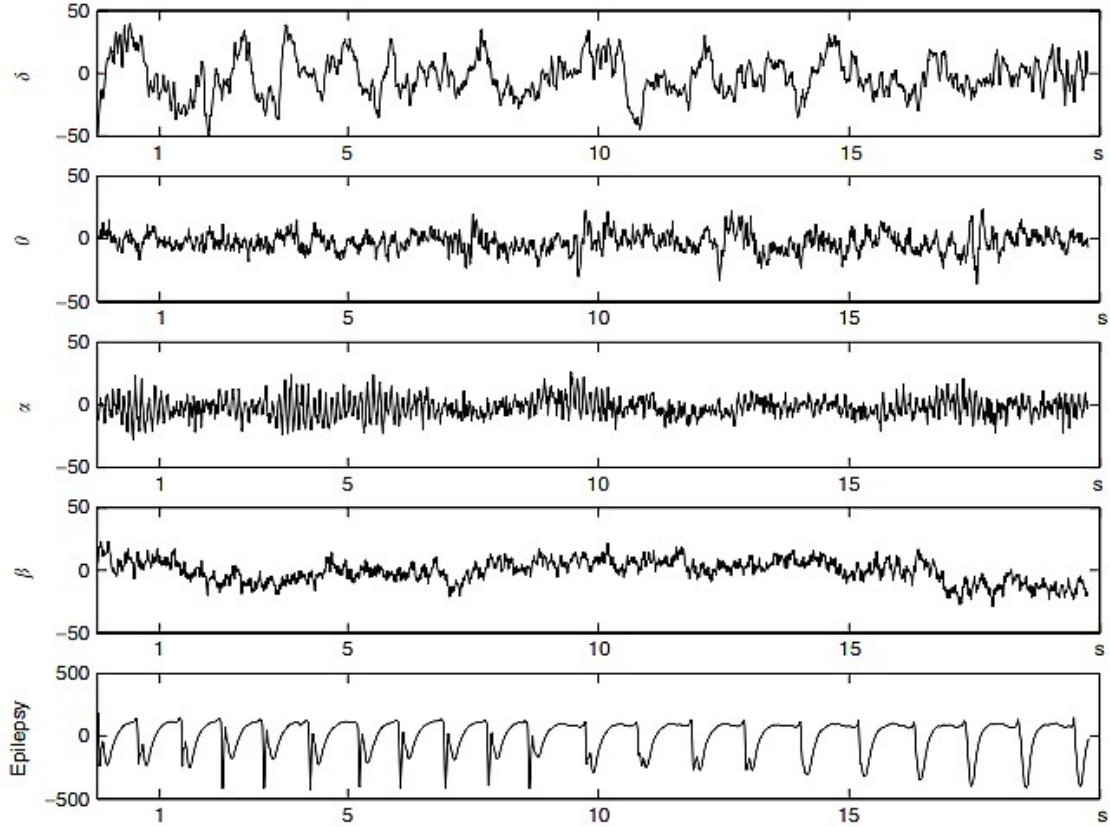


Figure 2.11: The figure illustrates different EEG bands: delta band (0.5 to 4 Hz), theta band (4 to 8 Hz), alpha band (8 to 13 Hz), beta band (13 to 30 Hz) and epileptic seizure waveform (from the top)

1. **Physiological artifacts:** non-cerebrum induced signals are considered as physiological artifacts. Some of the physiological EEG artifacts are given below:
 - **EOG (eye) artifacts:** Eye blinking, eye movements, extraocular muscle activities can distort signals by changing the amplitude level.
 - **EMG (Muscle) artifacts:** Muscle contraction can produce an unwanted signal in the EEG.
 - **ECG (cardiac) artifacts:** ECG can distort the EEG signals by overlapping, though the amplitude is low. ECG artifact is also known as pulse artifact.
 - **Perspiration-induced artifacts:** perspiration overlaps the EEG signal by changing the electrical baseline of the electrodes.
 - **Respiration-induced artifacts:** it is common in the sleep EEG which is induced by movement of chest and head while inhaling and exhaling.
2. **AC electrical and electromagnetic fields induced artifacts:** AC power sources and wires can create electrical and electromagnetic fields which can be observed in the EEG by appearing a large spike of 50 or 60 Hz.
3. **Incorrect reference placement induced artifacts:** Not properly placement of reference channel can lead to abrupt changes in the EEG.

4. **Patient's movement-induced artifacts:** patient movements (arm movements, head movements, walking) can overlap delta and theta bands in lower frequencies.
5. **Electrode pop induced artifacts:** Changing contact potential between the electrode and the scalp can lead to this artifact.
6. **Wire movement induced artifacts:** The movement of wires which connect the electrodes and the amplifier can distort the EEG signal by overlapping.

2.3.5 Handling EEG Artifacts

To remove artifacts, one of the conventional methods is to discard the epochs of the artifact enriched data ($>\pm 100$ V). Another method is to utilize spatial and frequency band filters. However, these methods have some cons also, like loss of essential data, overlapping, etc. Recent studies show that independent component analysis (ICA) techniques can be effective to deal with the artifacts.

2.3.6 EEG Applications

The EEG is extensively used in both clinical and research fields. It is an important part of neuroscience, cognitive science, cognitive psychology, neuromarketing, and neurolinguistics-related research. EEGs are playing crucial roles in the study of mental disabilities. Combining with PET, it can be helpful to monitor drug effects in the brain. The EEG is essential for the diagnosis of epilepsy. It can be useful in the diagnosis and treatment of several other disorders or conditions like brain tumor, brain damage, stroke, sleep disorders, encephalopathy, encephalitis, etc. Comparing to other methods to study the brain function like functional magnetic resonance imaging (fMRI), positron emission tomography (PET), single-photon emission computed tomography (SPECT), etc., the EEG provides some disadvantages like:

- Poor spatial resolution,
- Not useful in the case of detecting the source of activities like effects of the drug,
- Relatively time-consuming during preparation as a long time is needed to properly connect multiple electrodes at the exact locations,
- Poor signal to noise ratio.

Despite having these disadvantages, the EEG provides some advantages to the users. The followings describe the advantages of the EEG:

- Relatively lower cost,
- Noninvasive procedure for the surface EEG,
- Relatively smaller in size,
- No radioligands or magnetic field is needed,

- Higher temporal resolution in millisecond range,
- Not claustrophobic,
- Relatively tolerant of movement of the subject (even having a method for reducing movement induced artifacts).

Finally, the combination of EEG and machine learning can be essential in the automatic analysis of diseases (dementia, epilepsy, etc.) and mental states. The EEG-based brain-computer interface can be an important part of the communication and rehabilitation of people who have limited motor response. [\[13\]](#), [\[18\]](#), [\[28\]](#)

Chapter 3

Literature Review

The domain of HCI and BCI are now rapidly flourishing, as wearable devices for efficiently observing human cognitive states are becoming more accessible. Emotion recognition based systems have broader spectrum of application in both of these domains. Recent HCI researches have enhanced e-learning experience by dynamically changing learning environment through EEG emotional and attention analysis. EEG based advanced cognitive state analysis is also ensuring save driving by predicting drivers concentration and stress levels [91]. The application of EEG based mental state also extends to the domain of marketing and consumer behavior. Recent studies in neuro-marketing and consumer neuroscience have shown, consumer emotional states highly correlates with the their liking and preferences of specific products [90]. Most of the recent researches in EEG emotional state classification tasks focus on implementing new classification techniques such as; spiking neural networks and graph neural networks. Nevertheless the real complexity in such classification task lies in the efficiency of feature extraction methods, as time series signals of EEG recording demonstrate lightly correlated features. For extracting highly correlated feature set from such signals with random characteristics, frequency domain transformations are comparatively efficient. Wavelet Transformation, Short Time Fourier Transformation and non-parametric PSD estimators are highly popular for such feature extraction tasks. According to the review of Wang and Wang, 2021 on EEG feature extraction task, non-parametric PSD estimation models and differential entropy models are the mostly used feature extraction techniques in recent researches.

3.1 Overview of Conventional EEG Feature Extraction Techniques

As previously discussed, the major challenge in any EEG classification task is feature extraction from raw time series signal. For extracting psychological feature information from EEG waveform, past researches have explored multitudinous varieties of methods. Table 3.1 gives an overview of existing researches in psychological state feature extraction task from multi-channel EEG signals.

Duan, Zhu, and Lu, 2013 and Zheng, Zhu, Peng, *et al.*, 2014 calculated differential entropy for δ , θ , α , β and γ frequency bands for selected channels, follow-

Authors	Feature Extraction Method	Classification Method
W. Zheng et al.[54]	Non-parametric PSD Model	Sparsed Correlation Analysis
Z. Yin et al. [109]	Non-parametric PSD model	SVM
L. Piho et al. [98]	Non-parametric PSD model and Wavelet	KNN
D. Nath et al. [95]	Non-parametric PSD model	LSTM
E. S Pane et al. [80]	Non-parametric PSD model	Random Forest
H. Dabas et al. [55]	Non-parametric PSD model	Naive Bias
M.A.Rahman et al.[100]	Non-parametric PSD model and PCA	Artificial Neural Network
Q. Gao et al. [89]	Non-parametric PSD model and STFT	SVB
M.A.Rahman et al.[117]	Non-parametric PSD topographic map	CNN
H. Cui et al. [88]	Non-parametric PSD topographic map	CNN
W. L. Zheng et al. [71]	Differential Entropy	Disciminative Graph Regularization
Y. Yang[66]	Differential Entropy	Hierarchical Network
W. L. Zheng et al. [40]	Critical Frequency Band Investigation	Deep Belief Network
F. Wang et al.[106]	STFT	CNN
J. Liu et al. [58]	STFT	SVM
R. Nawaz et al. [96]	STFT	SVM
G. Zhao et al. [69]	STFT	SVM
H. Zamanian et al. [68]	Wavelet based decomposition	
A. Bhattacharyya et al.[112]	Wavelet based decomposition	Random Forest
W. Zheng et al.[86]	Differential Entropy	Discriminative graph regularized
T. Song et al. [102]	Differential Entropy	DCNN
T. Zhang et al. [85]	Differential Entropy	RNN
J. Yang et al. [108]	Differential Entropy	Bidirectional LSTM
Y. Luo et al.[60]	Data augmentation approach	Generative adversarial network
X. Wu et al.[83]	Connectivity Network	SVM
F. Yang et al.[84]	High dimensional features	ST-SBSSVM

Table 3.1: Relevant Researches in Psychological Feature Extraction Task from Multi-channel EEG Waveforms

ing 512 points STFT with non overlapping windows. Extracted features had the best prediction results in hybrid model incorporating DBN and HMM. Differential entropy computation from the transformed sequence had the time complexity of $O(KN \log N)$, where K and N represents "number of electrodes" and "sample size" respectively. Zhao, Ge, Shen, *et al.*, 2018 explored both STFT and PSD estimations for extracting features from 7 classes of emotional states. For feature extraction task Gao, Wang, Wang, *et al.*, 2020 experimented an unique method of feature fusion. It fuses features from PSD estimations and features extracted from WT. The extracted fusion feature was represented as;

$$\begin{aligned}
X_{FusionFeature} &= \begin{bmatrix} X_{PSD}, X_{WEE} \end{bmatrix} \\
&= \begin{bmatrix} \alpha_1, \dots, \alpha_{48}, \beta_1, \dots, \beta_{72} \end{bmatrix} \subset R
\end{aligned} \tag{3.1}$$

Pane, Wibawa, and Purnomo, 2019 used hybrid feature extraction techniques, which uses non-parametric Welch model for PSD estimation. Yin, Liu, Chen, *et al.*, 2020 extracted subject independent features from PSD estimations and statistical parameters. Rahman, Hossain, Hossain, *et al.*, 2020 at first extracted channels from **Frontal, Prefrontal, Central, Parietal** and **Occidental lob** by excluding the rest of the channels from each trial of 64 channels. Then reduced selected 35 channels to 5 channel trials with PCA. The research uses classic Welch PSD estimation model for transformation and extracted statistical features from the transformed spectra.

As the literature review so far suggests, non-parametric classical estimator models are widely used for PSD estimator based psychological feature extraction. EEG neural functional signals can be contemplated as a random processes with stationary intervals. Theoretically FT for such signals do not exist, as random processes posses finite power rather than finite energy. But FT of the auto correlation function derives the PSD of such random processes. For a signal $x(t)$, time averaging auto correlation function can be stated as the following,

$$\mathbf{R}_{xx}(\tau) = \frac{1}{2T_\theta} \int_{-T_\theta}^{T_\theta} x^*(t)x(t+\tau) dt \tag{3.2}$$

Fourier Transform of the above time averaging auto correlation function will derive the PSD function, $\mathbf{P}_{xx}(F)$ of the signal $x(t)$. The expected value, $\Gamma_{xx}(F)$ in the limit $T_\theta \rightarrow \infty$ denotes the actual PSD, which can be expressed as,

$$\begin{aligned}
\Gamma_{xx}(F) &= \lim_{T_\theta \rightarrow \infty} E \left[\mathbf{P}_{xx}(F) \right] \\
&= \lim_{T_\theta \rightarrow \infty} E \left[\frac{1}{2T_\theta} \left| \int_{-T_\theta}^{T_\theta} x(t)e^{-j2\pi Ft} dt \right|^2 \right]
\end{aligned} \tag{3.3}$$

Equation 3.2 and equation 3.3 are the principle hypothesis behind Periodogram, which is the fundamental of any non parametric PSD estimators. If $L\{x(n)\} = X(f)$, then for the sequence $x(n)$ with N number of samples, the Periodogram is expressed as,

$$\begin{aligned}
\mathbf{P}_{xx}(f) &= \frac{1}{N} \left| \sum_{n=0}^{N-1} x(n)e^{-j2\pi fn} \right|^2 \\
&= \frac{1}{N} \left| X(f) \right|^2
\end{aligned} \tag{3.4}$$

Non-parametric Bartlett, Welch and Blackman-Turkey estimator methods are just the modifications of the above denoted fundamental Periodogram equation (3.4).

The widely used Welch model, modified equation 3.4 by firstly subdividing the full sequence to L overlapping segments and secondly taking the average from all the computed windowed Periodogram. When each segment is of size M with D number of overlapping samples and factor of normalization U , the Welch estimator $\mathbf{P}_{xx}^W$ can be expressed as,

$$\begin{aligned}\mathbf{P}_{xx}^W &= \frac{1}{L} \sum_{i=0}^{L-1} \tilde{\mathbf{P}}_{xx}^{(i)}(f) \\ &= \frac{1}{L} \sum_{i=0}^{L-1} \left[\frac{1}{MU} \left| \sum_{n=0}^{M-1} x_i(n)w(n)e^{-j2\pi fn} \right|^2 \right]\end{aligned}\quad (3.5)$$

The quality factor, Q_A for such PSD estimation is measured by the ration of its squared spectrum power estimation ($E[\mathbf{P}_{xx}^A(f)]$) to its spectrum power variance, ($\text{Var}[\mathbf{P}_{xx}^A(f)]$). Welch estimator model represents a better quality factor than its contemporary non-parametric methods (such as, Bartlett method). For 50% overlapping windows, the Welch Quality Factor is expressed as,

$$Q.F_{(Welch)} = 1.39N\Delta f \quad (3.6)$$

N and Δf represents signal length and frequency resolution respectively. Equation 3.6 states, PSD estimation accuracy increases with increasing signal length and frequency resolution for the Welch method. Computational complexity for the Welch model (with 50% overlapping windows) and Bartlett method are expressed as,

$$Total_Number_of_Computation_{(Welch)} = N \log_2 \frac{5.12}{\Delta f} \quad (3.7)$$

$$Total_Number_of_Computation_{(Bartlett)} = \frac{N}{2} \log_2 \frac{0.9}{\Delta f} \quad (3.8)$$

Though Welch estimators performs better in spectrum estimations with enhanced quality factor, in terms of time complexity Welch estimator requires larger number of computations comparing to contemporary methods. Still due to its spectral estimation accuracy, the welch method is hugely popular for feature extraction in EEG information processing tasks [2], [3], [45], [52].

3.2 MUSIC Model in DoA Estimation

MUSIC models are widely used in array signal processing due to increased performance in DoA estimation. DoA computations are based on signal spatial spectrum estimation. The phase differences among the signal array elements leads to signal azimuth estimation, which is the fundamental of DoA estimation. The phase difference in signal azimuth estimation is expressed as,

$$\varphi = e^{-j2\pi \frac{d \sin \theta}{\lambda}} \quad (3.9)$$

d and λ are "inter-spacing among signal array elements" and "signal wavelength" respectively. DoA estimation model architecture consist of target space, observation

space and estimation space. Target space represents signal sources, whereas observation space represents signal detector arrays. Estimation space constitute of signal azimuth computation and spectrum estimations.

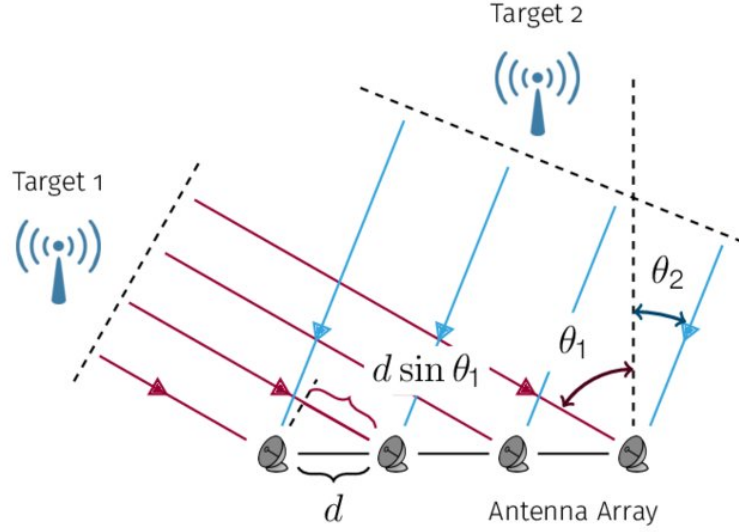


Figure 3.1: Direction of Arrival Estimation Model in Radar Communication [\[64\]](#)

MUSIC algorithm possesses some unique characteristics which include, capability of simultaneously processing signals from multiple sources and capacity of real time processing in specific conditions along with providing extraordinary precision. Owing to such features of the algorithm, the MUSIC model have performed significantly better than contemporary techniques in estimating DoA. Eigenspace algorithms (MUSIC, root MUSIC in particular) also have reduced time complexity as they only use linear transformation for spectrum estimation. MUSIC algorithm uses characteristics decomposition of signal covariance matrix, by producing two orthogonal matrices of signal subspace and noise subspace. The orthogonal matrices derives the following spectrum function,

$$P_{(music)}(\theta) = \frac{1}{a^H(\theta)E_nE_n^H a(\theta)} \quad (3.10)$$

E_n, E_n^H represents the signal noise subspace and hermitian matrix of the signal noise subspace respectively. Signal spectrum is computed using equation 3.10. Detecting the spectrum peaks from the computed spectrum derives the DoA estimation [\[24\]](#), [\[35\]](#), [\[51\]](#), [\[64\]](#).

3.3 MUSIC Model in EEG Source Localization

MUSIC algorithm is an eigen decomposition based parametric PSD estimator model. MUSIC methods have demonstrated incredible efficiency in Direction of Arrival (DoA) estimation tasks and the algorithm was adapted for evoked source localization in neuroscience research. Mosher, Baillet, and Leahy, 1999 pioneered such technique in EEG source localization, Giri, Kumar, and Gandhi, 2018 conducted EEG source localization in harmonic domain and Jatoti, Kamel, and Musavi, 2017 estimated active brain sources using MUSIC spectrum analysis.

EEG Source localization is a complex DoA estimation task. Reconstruction and localization of neural functional sources plays a key role in improving the performance of noninvasive brain imaging technologies. MUSIC algorithms performs tremendously in such localization tasks by minimizing gross errors, providing independence from model ordering and lastly by allowing modeling of distributed functional sources. MUSIC localization techniques in such cases have produced significant results compared to SPECT scans and MRI scan, in terms of precisely localizing functional neural regions [7], [12], [34], [48], [56], [79].

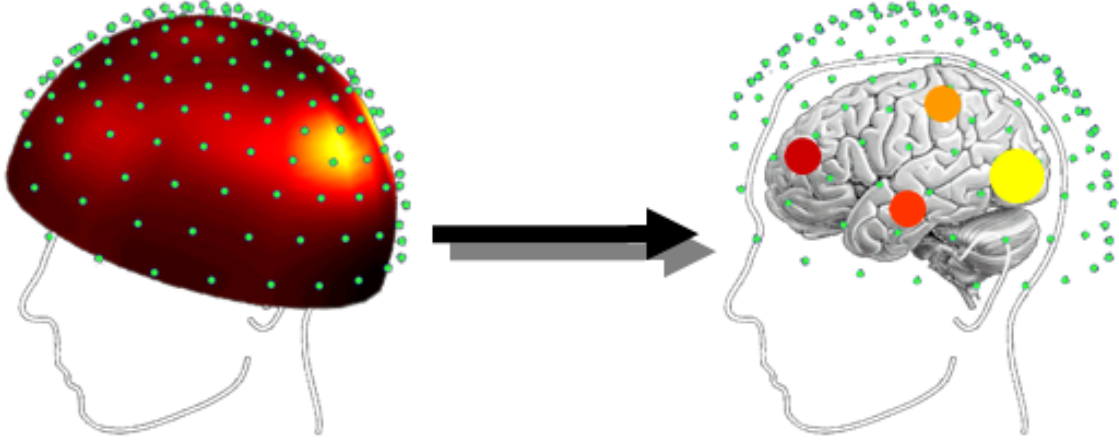


Figure 3.2: EEG Function Neural Source Localization [[34], [79]]

3.4 MUSIC Model in EEG Feature Extraction

Unlike source localization with DoA estimation tasks, very few researches can be found which explore MUSIC algorithm in EEG feature extraction task. Among that few researches, Übeyli, 2009, Alkan, Koklukaya, and Subasi, 2005, Naghsh-Nilchi and Aghashahi, 2010 explored eigen analysis based methods (in particular Pisarenko method and MUSIC method) for extracting features in epilepsy classification task. The extracted features were tested on RNN, ANN, MLP and Logistic Regression. Siuly and Li, 2015 used similar techniques in feature extraction along with PCA for reducing the number of feature dimension space. Lastly no significant researches can be found, which specifically focuses on exploring MUSIC model based approach for extracting psychological feature information from functional EEG signals.

3.5 Scope of Research in the SEED Dataset

Non-parametric models estimate PSD through Fourier transformation of the autocorrelation functions. Such techniques are computation intensive. On the contrary, parametric eigen analysis based PSD estimation models uses solely linear transformation and as a result demonstrates lower computational complexity. On this basis parametric eigen decomposition based techniques such as, MUSIC model holds potentials for efficient spectrum feature extraction from random time series signals. Nevertheless such parametric based PSD estimation models are relatively unexplored in EEG feature extraction tasks. Specifically for the widely used SEED [39]

[29] EEG waveform dataset for emotion recognition no prior researches are available, which investigate the performance of parametric eigen analysis based PSD estimation models in feature extraction.

Rahman, Hossain, Hossain, *et al.*, 2020 used a unique method of PCA and t-stat analysis for feature extraction in EEG emotion recognition task. Zheng, 2017 explored grouped sparse canonical correlation analysis in predicting three distinct emotional states. For the same dataset Zheng and Lu, 2015 and Chen, Miao, Yang, *et al.*, 2019 used differential entropy based feature extraction technique and investigated critical frequency bands with deep belief network. Yang, Wu, Zheng, *et al.*, 2018 and Jin, Luo, Zheng, *et al.*, 2017 both also used differential entropy based feature extraction technique for emotion recognition tasks.

This research focuses on investigating the performance of MUSIC algorithm in such feature space extraction. At first from the SEED multi channel EEG dataset, features are extracted by implementing the MUSIC model for deep learning based emotion recognition task. Then the performance of the MUSIC model in such feature extraction task was evaluated through intense feature space visualization and comparing the classification accuracy with existing high performance classification methods for the dataset.

Chapter 4

Dataset

4.1 Description

Our experimented method for extracting feature informations from EEG brain waves was evaluated on a publicly available EEG dataset, which is widely known as SEED dataset. The Seed dataset is prepared by BCMI laboratory of Shanghai Jiao Tong University.



Figure 4.1: Arrangement for 62 Channel EEG Brain Wave Acquisition in Brain-like Computing and Machine Intelligence Laboratory, Shanghai Jiao Tong University. [Source: [seed dataset description page](#)]

The selected EEG waveform dataset represents human emotions of three classes, naming; Neutral Emotion State, Positive Emotion State and Negative Emotion State. The distinct emotional states were evoked by showing film clips to each of the subjects. Each film clip is easy to interpret and evokes a single desired targeted emotion. The total number of subjects for the experiment were 15, with each subject undergoing 15 trials for each of the emotional states. The total elapsed time for

EEG waveform acquisition in each trial is 305 seconds, with each trial represents 62 channel EEG brain waves of a subject.

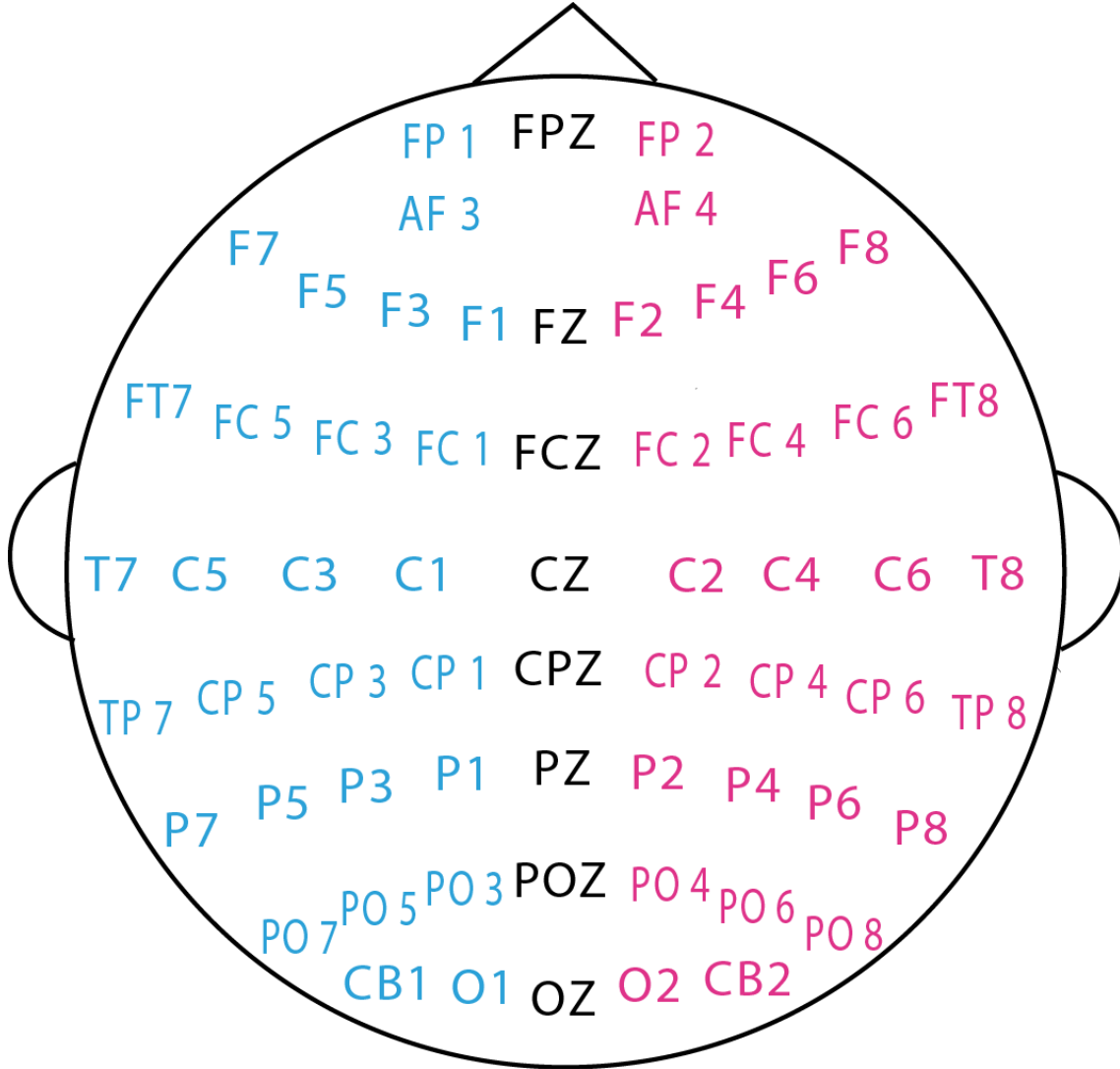


Figure 4.2: Placement of EEG electrodes for EEG brain wave acquisition during the experiment. [Source: [seed dataset description page](#)]

For each of the trails, the acquisition involved four distinct phases;

- Phase One: Subjects were given a hint regarding the content of the upcoming film clip. Elapsed time for Phase one is 5 seconds.
- Phase Two: Selected movie clips were exhibited to the subject. Elapsed time for each clip was 240 seconds.
- Phase Three: Subjects were given time to self assess the presented film clip. Elapsed time for phase three was 45 seconds.
- Phase Four: Subjects were apprised to relax. Elapsed time for the last phase was 15 seconds.

The Nyquist's Sampling Theorem states that;

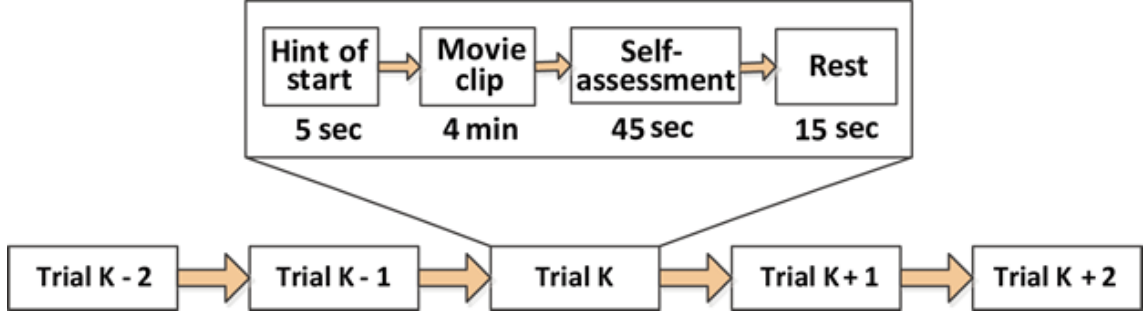


Figure 4.3: Protocol for EEG brain wave acquisition for each subject. [Source: [seed dataset description page](#)]

$$2 \times f_{Nyquist} \leq f_s \quad (4.1)$$

Where $f_{Nyquist}$ is the maximum frequency of a signal which has been sampled at f_s . As each trial data was downsampled to 200 Hz, after downsampling each trial data holds the information band of 0 Hz to 100 Hz. The downsampling was followed by a 0 Hz to 75 Hz bandpass filter. After downsampling and filtering, each trial retains the information of 0 Hz to 75 Hz band EEG waveform of 62 channels. The works of Duan, Zhu, and Lu, 2013 and Zheng and Lu, 2015 have meticulously discussed the detailed methodology for constructing the dataset. The seed dataset has total of 675 trials, with 225 trials representing each of the three classes of emotional states.

4.2 Insights

In this research we have used the statistical visualization Seaborn library for data visualization. 3D contour plots of the raw time series data revealed intriguing characteristics of the dataset. It was found 17% of the total 675 trials contains at least one overshooting channel out of total 62 channels. EEG evoked potential ranges from 10 μ V to 100 μ V, on the other hand EMG evoked potential is in millivolt level [82]. However some of the channels exhibited evoked potentials which ranges up to 5mV. The existence of such overshooting channels could be resulted from electrode leakage or any other arbitrary issues during data acquisition.

Figure 4.4 shows 3D contour plots of faultless trials from subject 4 and figure 4.5 represents 3D contour plots of trials with overshooting/ corrupted channels. In figure 4.4, evoked potentials ranges up to 200 μ V for all the emotional states which is within the evoked neural potential range. At the same time the contour plots for the time series signals are distinguishable for the three psychological states. In figure 4.5 (a), channel 45 (P1) contains recorded evoked potentials of 2500 μ V or 2.5mV and channel 56 (PO6) contains recorded evoked potentials which ranges upto 10000 μ V or 10mV, which lies within the voltage band of EMG signals.

Figure 4.6 (a) represents an ideal channel for EEG recording. In (a),(b),(c),(d) and (e) of figure 4.6, the raw signal was filtered using an IIR filter with butter-worth window for removing eye blink artifacts and baseline noise. Then an 500 impulse FIR filter with hamming window was used for extracting α , β and γ frequency

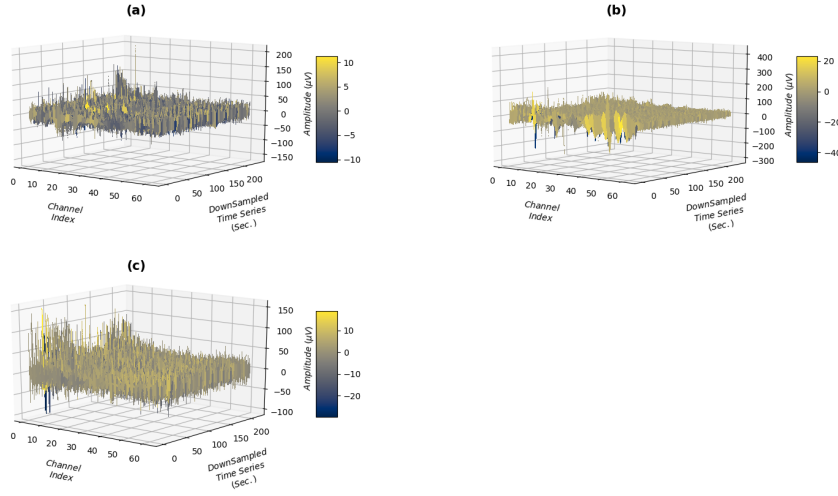


Figure 4.4: 3D visualization of faultless trials (a) subject: 4, state: negative, trial: 3 (b) subject: 4, state: neutral, trial: 15 (c) subject: 4, state: positive, trial: 13

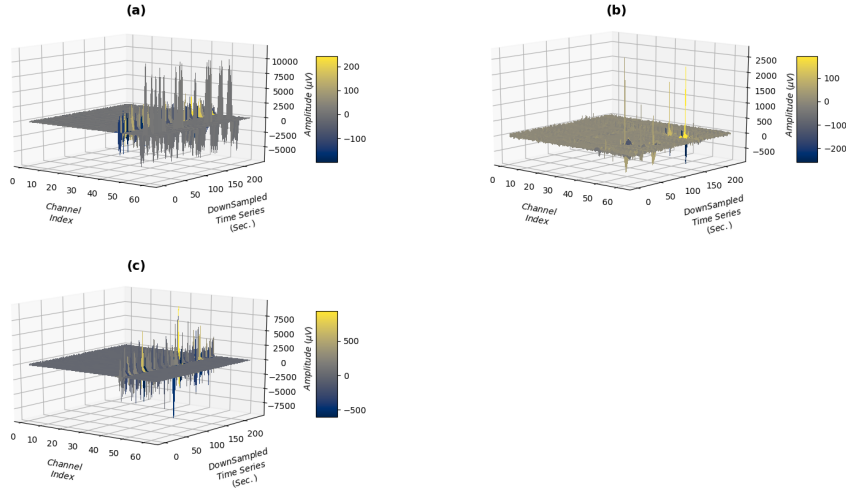


Figure 4.5: 3D visualization of faulty trials with overshooting/ corrupted channels (a) subject: 1, state: negative, trial: 3 (b) subject: 1, state: neutral, trial: 4 (c) subject: 1, state: positive, trial: 15

bands, which contains the relevant psychological state information. A portion of the whole signal is presented in the mentioned figure. Figure 4.6 (b) represents a periodic saturation curve and definitely does not represent any correlated evoked neural activity, as well as the voltage band ranges up to 5mV. Figure 4.6 (c), (d) and (e) all represents overshooting portions of larger time series signals. The maximum value of overshooting channels voltage bands ranges from 0.6mV to 10mV. In each of the cases multiple overshoots are observed in the channels.

The 3D contour plots for the full dataset is available [here](#). Trials from subject

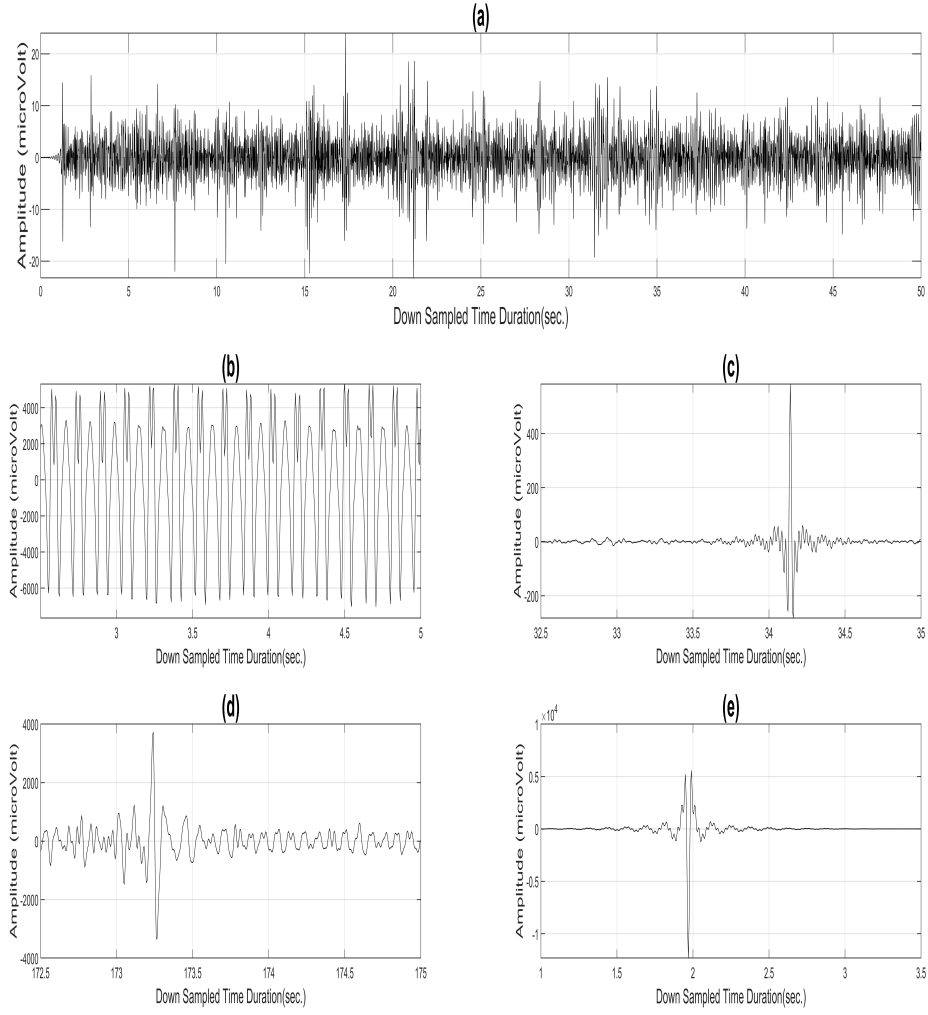


Figure 4.6: Visualization of corrupted channels in respect to faultless ideal channel
 (a) representing: ideal channel, subject: 1, state: negative, trial: 3, channel: FP1
 (b) representing: corrupted channel, subject: 1, state: negative, trial: 3, channel: PO6
 (c) representing: corrupted channel, subject: 1, state: negative, trial: 1, channel: FP2
 (d) representing: corrupted channel, subject: 1, state: positive, trial: 10, channel: P1
 (e) representing: corrupted channel, subject: 15, state: negative, trial: 10, channel: C1

1 demonstrated most faulty trials with 100% trials from negative state containing corrupt channels, neutral and positive states holds 60% and 66% trials containing multiple corrupt channels respectively. Subject 9 have demonstrated least faulty trials with no trials containing any corrupt channels. Table 4.1 represents the total distribution of trials with overshooting corrupt channels.

Subject No	Neg. State	Neu. State	Pos. State
Subject 1	15	9	10
Subject 2	2	null	4
Subject 3	1	null	1
Subject 4	1	null	null
Subject 5	6	null	2
Subject 6	12	2	2
Subject 7	null	2	null
Subject 8	null	null	2
Subject 9	null	null	null
Subject 10	1	2	3
Subject 11	null	null	null
Subject 12	null	3	3
Subject 13	8	null	null
Subject 14	3	1	1
Subject 15	15	2	3
Total	64	21	31

Table 4.1: Distribution of Trials with Overshooting Corrupt Channels

4.3 Augmentation

Figure 4.7 represents phase wise brain activity for an arbitrary subject-trial. The phase wise brain activity is clearly distinguishable and also varies with amplitude. Phase wise segmentation is indispensable for efficient data augmentation in this particular case, due to the unique process of data acquisition. Each augmented trial should contain portion of information from all the four phases of parent trials, this demands phase wise data separation at the beginning of data augmentation process (unless data augmentation is performed by generating completely new data, ex: implementation of Generative Adversarial Network Models). As per the data acquisition documentation for the dataset, total original/ acquisition time duration for a trial, $T_{original}$ is

$$\begin{aligned}
T_{original} &= T_{phase\ 1} + T_{phase\ 2} + T_{phase\ 3} + T_{phase\ 4} \\
&= 5sec. + 240sec. + 45sec. + 15sec. \\
&= 305sec.
\end{aligned} \tag{4.2}$$

If the down-sampled signal length is L , then end point $\mathbf{P_n}$ for a distinct phase $\mathbf{n}$ can be computed as,

$$\mathbf{P_n} = \frac{L}{T_{original}} \sum_{i=1}^n T_{phase\ i} \tag{4.3}$$

The down-sampled phase duration, $T_{phase\ i}^{sampled}$ will vary with the down-sampled signal length, L . Using equation 4.3 phase end points and starting points were calculated for precise visualization and data augmentations. Figure 4.8 illustrates the proposed data augmentation technique for this dataset.

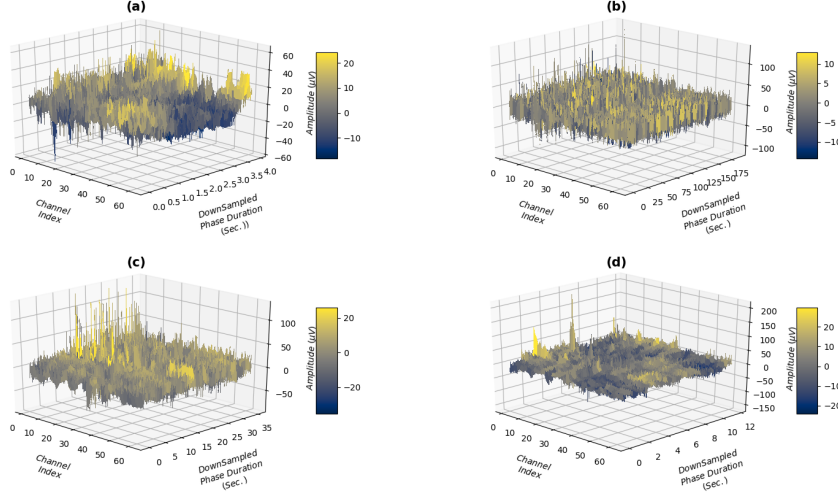


Figure 4.7: Phase wise visualization for subject: 4, state: negative, trial: 3 (a) phase 1: brain activity while conveying hint of the clip (b) phase 2: brain activity during showcasing of the clip (c) phase 3: brain activity during self assessment (d) phase 4: brain activity during rest state

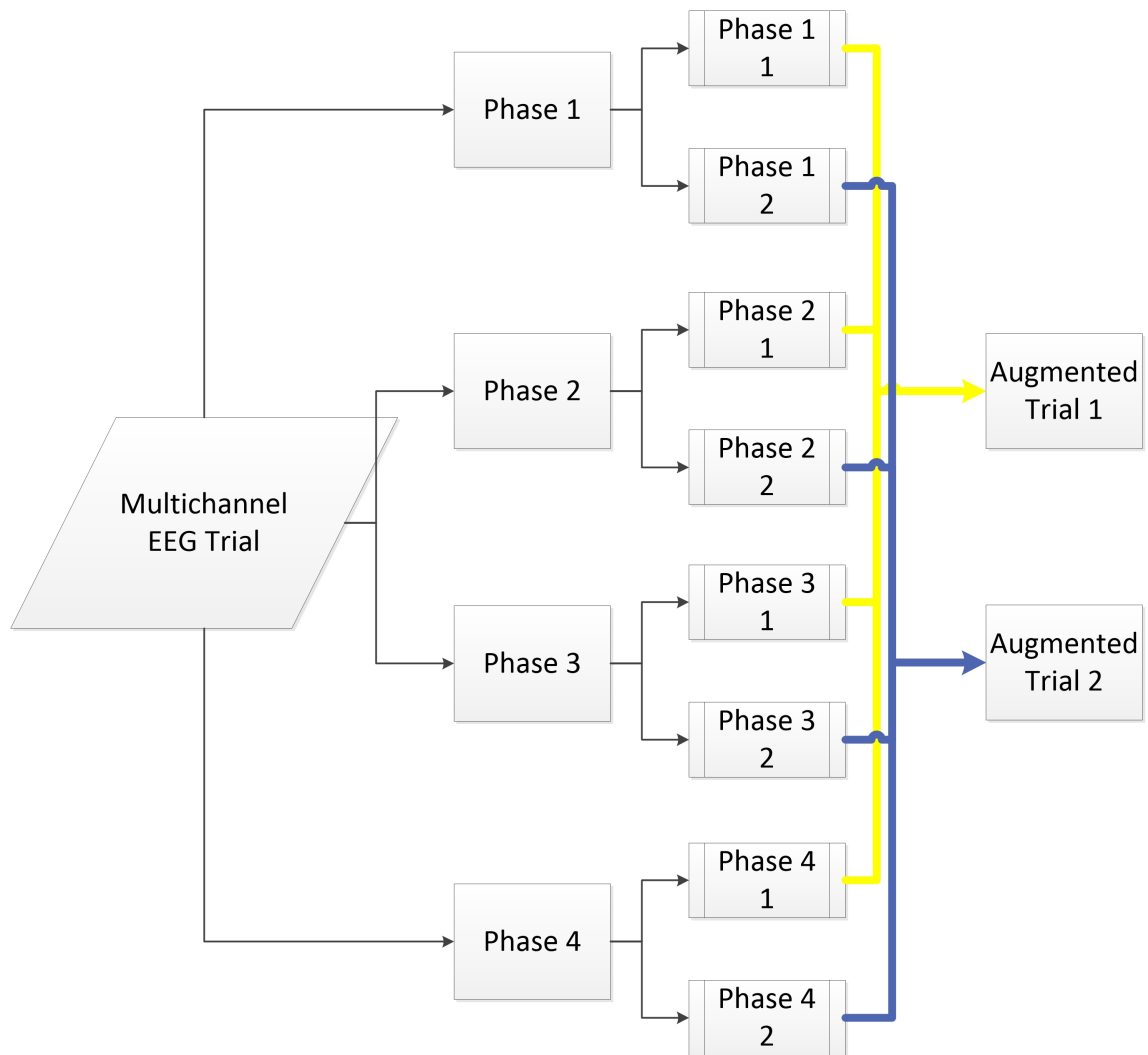


Figure 4.8: Proposed data augmentation technique.

Chapter 5

Methodology

Figure 5.1 explains the work process of the conducted research briefly. Trial separation for each of the subjects were conducted manually from the parent database. Data visualization have provided undiscovered unique characteristics of the SEED dataset, which have been discussed in details previously. Before pre-processing detailed analysis of signal filters are conducted to derive the optimal method. The parametric MUSIC model requires specific estimation about the signal character, such requirement makes the model difficult to implement in terms of signals with random characteristics. The algorithm analysis part explores such complexities in terms of implementing MUSIC model for feature extraction tasks.

The pre-processing includes implementation of derived optimal signal filters and time series dimensionality reduction. Multiple methods are introduced in each of the steps. The feature space includes raw transformed frequency spectrum as well as extracted statistical features from the frequency spectrum. Each of the method are tested on keras sequential MLP network, LSTM network and hybrid neural networks (consisting of keras functional MLP-LSTM networks). Each of the steps are discussed briefly from here.

5.1 Signal Filtering

As previously discussed all trials were downsampled to 200 Hz and holds the information band of 0 Hz to 75 Hz. Before specific psychological information band extraction, a 2nd ordered butter-worth IIR Bandstop filter with half power frequency band of 48 Hz to 52 Hz is implement. The notch filter is responsible for removing any baseline noise. The butterworth function can be mathmatically denoted as [6],

$$|H(j\Omega)|^2 = \frac{1}{1 + \left(\frac{\Omega}{\Omega_c}\right)^{2k}} \quad (5.1)$$

were k denotes the number of order and Ω_c represents the cutoff frequency. Figure 5.2 represents comparison of raw signal and notch filtered signal to remove the baseline noise for an arbitrary trial. It demonstrates that the frequency spectrum for the signal are almost similar and the channel is not effected by such artifact. It is observed that, the dataset do not demonstrate basline noise artifact. Eyeblink artifacts are handled with the EAWICA toolbox [27], [33] after notch filtering.

The raw signal are then filtered to extract the relevant neural bands holding emotional state information. To deduct an optimal and time efficient filtering method

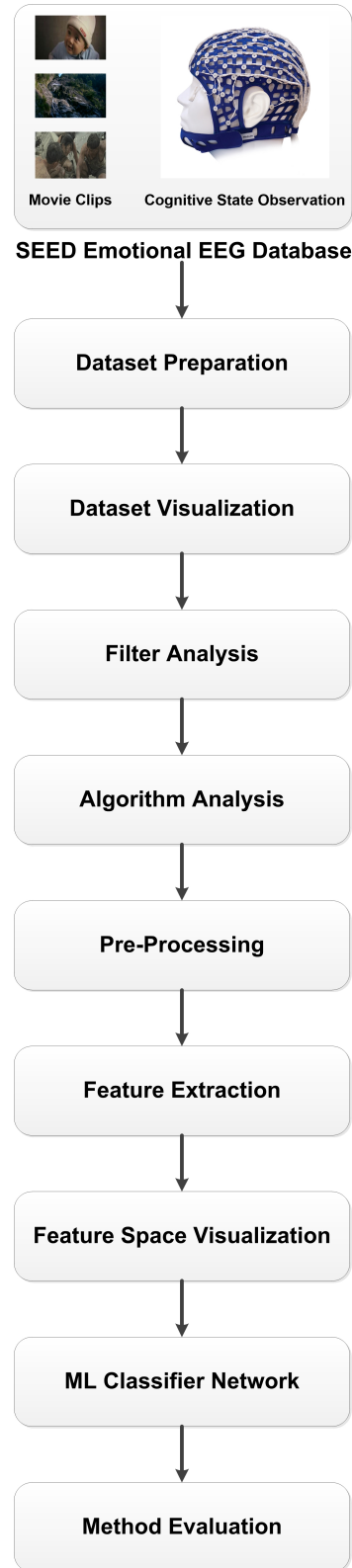


Figure 5.1: Flow diagram explaining brief research methodology

FIR Hamming window, FIR Kaiser window and FIR Chebyshev window were tested. Figure 5.3 output comparison of different FIR filters. For 4Hz to 40Hz band the chebyshev window has a sharper cutoff. On the other hand kaiser window and hamming window demonstrated similar performance. But as hamming window possesses

a better time complexity function, a higher order FIR hamming window of 500 data points is chosen. Equation for Hamming window and Kaiser window can be mathematically denoted as,

$$H_{hamming}(n) = 0.54 - 0.46 \cos \frac{2\pi n}{M-1} \quad (5.2)$$

$$H_{kaiser}(n) = \frac{\sqrt{\left(\frac{M-1}{2}\right)^2 - \left(n - \frac{M-1}{2}\right)^2}}{\left(\frac{M-1}{2}\right)} \quad (5.3)$$

In equation 5.2 and 5.3 M denotes the size of the window in time series. [2]

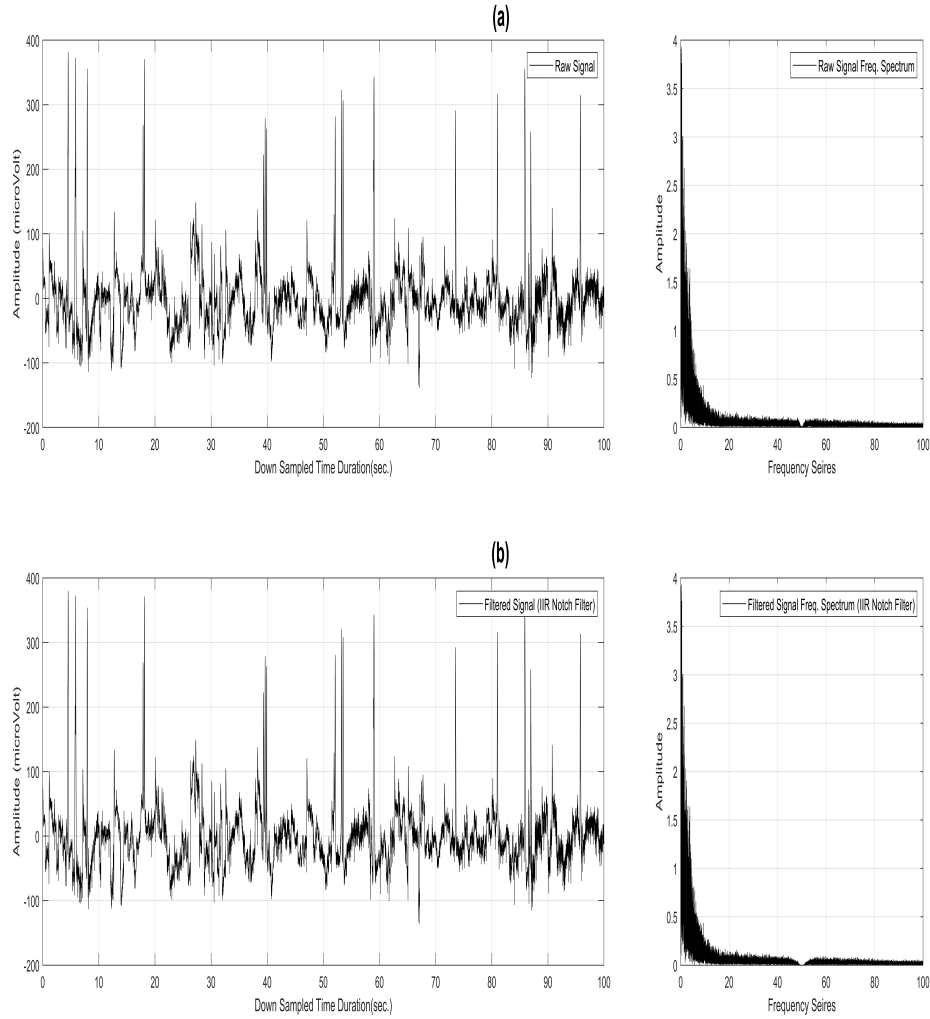


Figure 5.2: Comparison of raw signal vs IIR notch filtered signal for subject: 15, state: negative, trial: 10, channel: FP1 (a) raw time series signal of downsampled first 100 seconds and fft transformed spectrum (b) filtered time series signal of downsampled first 100 seconds and fft transformed spectrum

Figure 5.4 represents phase wise fft transformed frequency spectrum after notch and bandpass filtering with varying cutoff. EEG waveform holds 5 major bands; δ , θ ,

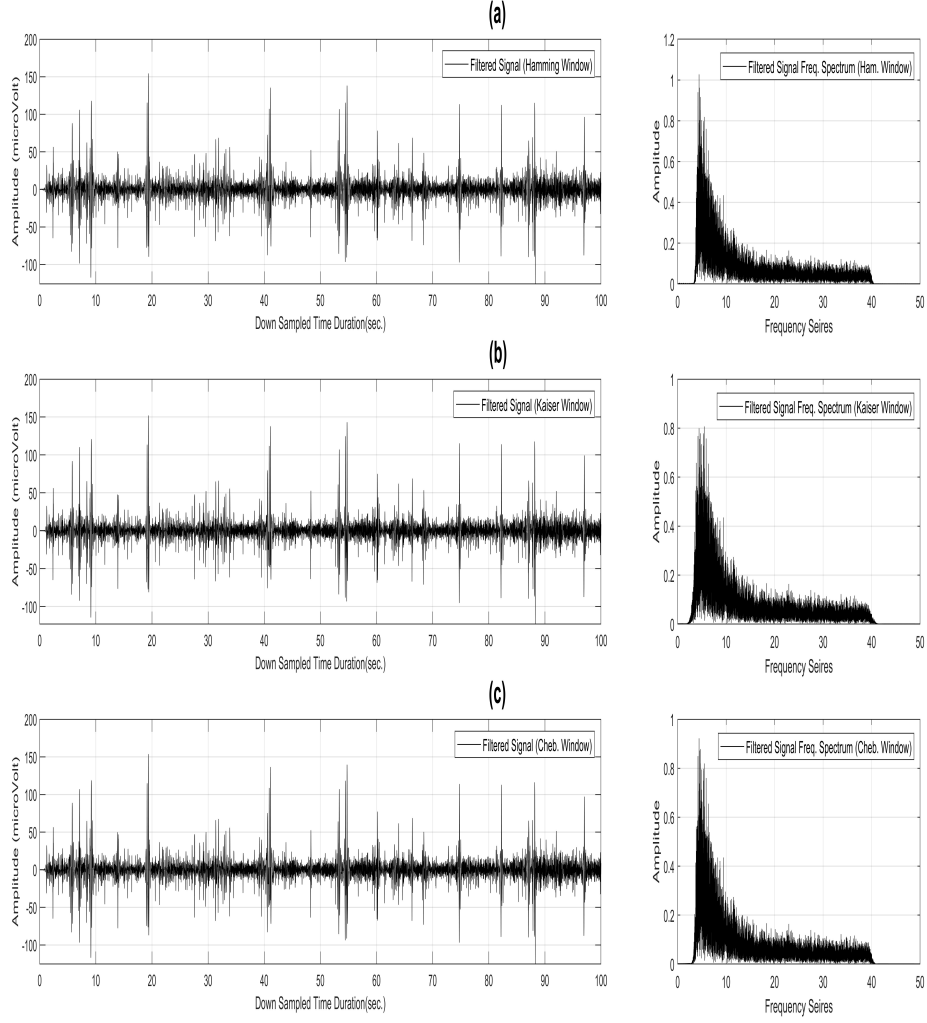


Figure 5.3: Comparison of different higher order 4 Hz to 40 Hz FIR bandpass filter implementations for subject: 15, state: negative, trial: 10, channel: FP1 (a) FIR Hamming Window (b) FIR Kaiser Window (c) FIR Chebyshev Window

α , β and γ wave. As δ band represents sleep waves and θ band represents deeply relaxed phase, both of them can be ignored for information extraction. Our bands of interest should only represent attention and concentration states, as they are relevant to the experiment. As a result, only α , β and γ bands are our targeted extraction bands. Figure 5.4 demonstrates that, a bandpass filter of 8Hz to 40Hz extraction band do not exclude information from any specific phases. The visualization also demonstrates that, α band is dominant across all the four phases.

5.2 MUSIC Model

The concept of signal and noise subspace is crucial for understanding the fundamentals of MUSIC algorithm. The vector, $[x_1(n) \ x_2(n) \ x_3(n) \ \dots \ x_p(n)]$ can be considered as the signal subspace vector of an arbitrary signal $y(n)$ if,

$$y(n) \equiv [x_1(n) \ x_2(n) \ x_3(n) \ \dots \ x_p(n)] \quad (5.4)$$

If, $[x_{p+1}(n) \ x_{p+2}(n) \ x_{p+3}(n) \ \dots \ x_L(n)]$ vector represents the noise subspace for the signal, then the signal $y(n)$ can be represented as,

$$y(n) = x_1(n) + x_2(n) + \dots + x_p(n) + x_{p+1}(n) + x_{p+2}(n) + \dots x_L(n) \quad (5.5)$$

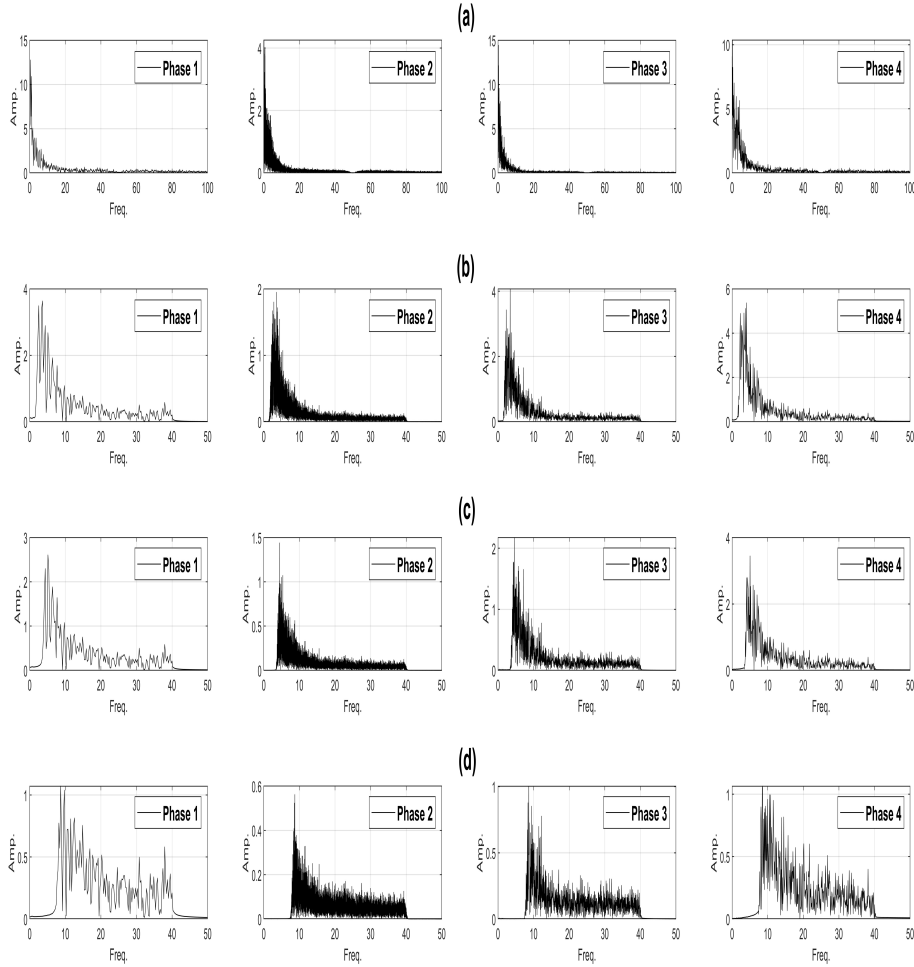


Figure 5.4: Phase wise fft transformed frequency spectrum after implementing different frequency band FIR and IIR filters for subject: 15, state: negative, trial: 10, channel: FP1 (a) IIR notch filter (b) IIR notch filter and 2 Hz to 40 Hz FIR hamming window (c) IIR notch filter and 4 Hz to 40 Hz FIR hamming window (d) IIR notch filter and 8 Hz to 40 Hz FIR hamming window

Here p represents the number of signal subspace. MUSIC algorithm estimates the power spectral density of the targeted signal $y(n)$ by, decomposing the signal auto correlation function Γ_{yy} to it's auto correlated function of signal subspace Γ_{xx} and

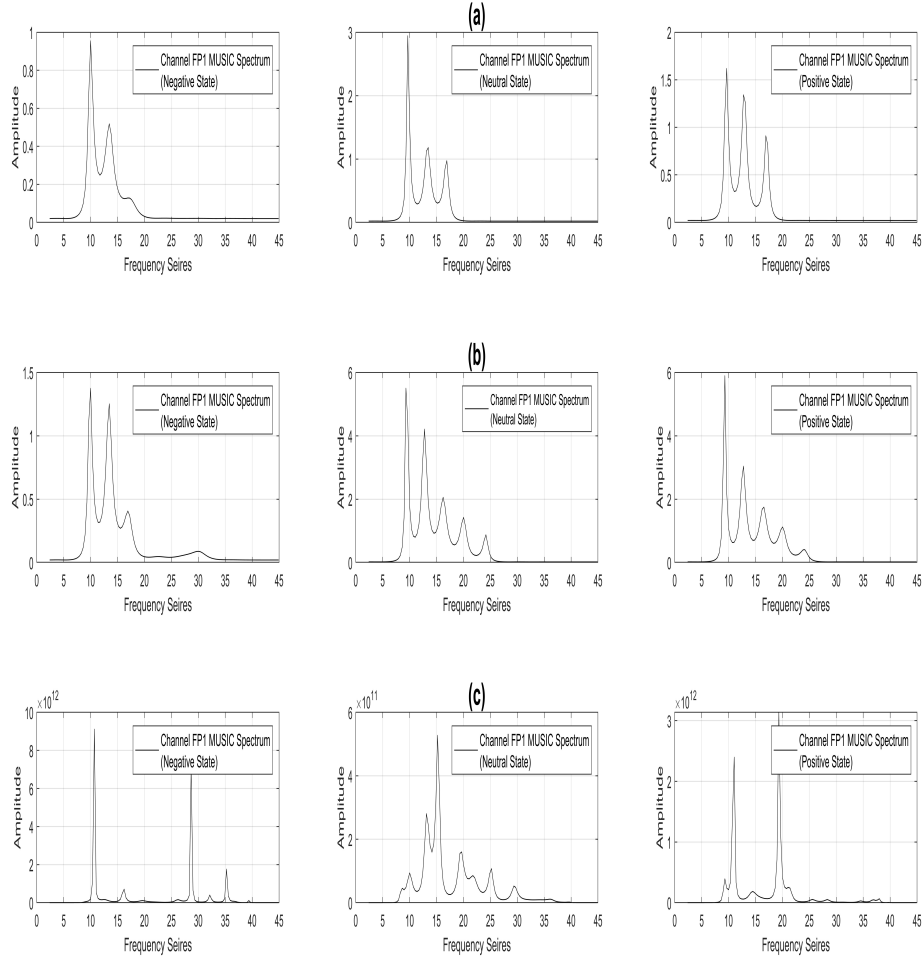


Figure 5.5: MUSIC transformed power spectrum density spectrum with varying signal subspace estimation for subject: 15, state: negative, trial: 10, channel: FP1 (a) considering δ , θ , α , β and γ bands as signal subspace vector (b) considering α , β and γ bands as signal subspace vector (c) undefined signal subspace vector

noise subspace σ_w . The signal subspace and the noise subspace are orthogonal to each other. The concept can be mathematically expressed as;

$$\Gamma_{yy} = \Gamma_{xx} + \sigma_w^2 I \quad (5.6)$$

The dimension of Γ_{yy} is $L \times L$ and rank is p (number of subspace), where $p < L$. Equation 5.6 can be furthered simplified into,

$$\Gamma_{yy} = \sum_{i=1}^p \lambda_i v_i v_i^H + \sigma_w^2 v_i \sum_{i=p+1}^M v_i v_i^H \quad (5.7)$$

λ_i represents the non zero eigenvalues for the range of $i = 1$ to p . v_i is the eigenvector and v_i^H is the Hermitian conjugate of the eigenvector. The term, $\lambda_i v_i v_i^H$ represents each signal subspace element of $y(n)$. Equation 5.7 fully decomposes the targeted

signal and is considered the fundamentals of the MUSIC model. The targeted signal can be represented as the complex sinusoidal vector $s(\omega)$,

$$s(\omega) = [1 \quad e^{j\omega} \quad e^{2j\omega} \quad \dots \quad e^{(M-1)j\omega}] \quad (5.8)$$

The eigenvectors in noise subspace v_{noise} is denoted as,

$$v_{noise} = [v_{p+1} \quad v_{p+2} \quad v_{p+3} \quad \dots \quad v_k] \quad (5.9)$$

Then the MUSIC model frequency estimator $P_{MUSIC}(\omega)$ is stated as,

$$P_{MUSIC}(\omega) = \frac{1}{\sum_{k=p+1}^M |s^H(\omega)v_k|} \quad (5.10)$$

$s^H(\omega)$ is the Hermitian conjugate of the vector $s(\omega)$. After calculating the peaks (estimated frequencies) of $P_{MUSIC}(\omega)$, the power spectrum can be calculated from the following Pisarenko Harmonic equation [2], [7], [12], [35], [56].

$$\begin{bmatrix} \cos \omega_1 & \cos \omega_2 & \dots & \cos \omega_p \\ \cos 2\omega_1 & \cos 2\omega_2 & \dots & \cos 2\omega_p \\ \vdots & \vdots & \dots & \vdots \\ \cos p\omega_1 & \cos p\omega_2 & \dots & \cos p\omega_p \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_p \end{bmatrix} = \begin{bmatrix} \gamma_{yy}(1) \\ \gamma_{yy}(2) \\ \vdots \\ \gamma_{yy}(p) \end{bmatrix} \quad (5.11)$$

Vergallo and Lay-Ekuakille, 2013 implemented MUSIC algorithm for brain source localization and their findings suggest that the neural signal band is consist of three source dipoles. As per their research, for an arbitrary EEG channel the number of signal subspace depends mostly on the extracted information bands. $[\delta \quad \theta \quad \alpha \quad \beta \quad \gamma]$ can be generalized as the subspace vector for an arbitrary channel holding all neural information bands. But as discussed previously, in this particular case our targeted neural information bands only lies in the range of 8 Hz to 40 Hz. For this the number of subspace, p in this particular case can be estimated as 3 and the subspace vector can be denoted as, $[\alpha \quad \beta \quad \gamma]$. The figure 5.5 also clarifies the estimated subspace vector. In figure 5.5(a) the three peaks clearly states the presence of α , β and γ bands, as the peaks can be found near 10 Hz, 15 Hz and 20 Hz for all the states. All the five bands are considered for calculating the spectrum in figure 5.5(b), but the spectrum do not demonstrate any peaks near δ and θ bands (1 Hz to 8 Hz). Which clarifies the absence of these two information bands in the target signal. The number of subspace are undefined ($p = \infty$) in figure 5.5(c) and the spectrum is calculated by only thresholding the eigenvalues for noise subspace. The spectrum for negative state gives three major peaks which lies in the α (peak at 10 Hz), β (peak at 27 Hz) and γ (peak at 35 Hz) bands. Each of the state spectrum in figure 5.5(c) are clearly distinguishable and clarifies the estimated signal subspace vector for the targeted EEG channels. Thus for the whole dataset transformation, the MUSIC spectrum is calculated considering $p = 3$.

5.3 Pre-Processing and Feature Extraction

Figure 5.6 and figure 5.8 explains pre-processing and feature extraction method which excludes the corrupt/ overshooting channels. Following the literature in Rah-

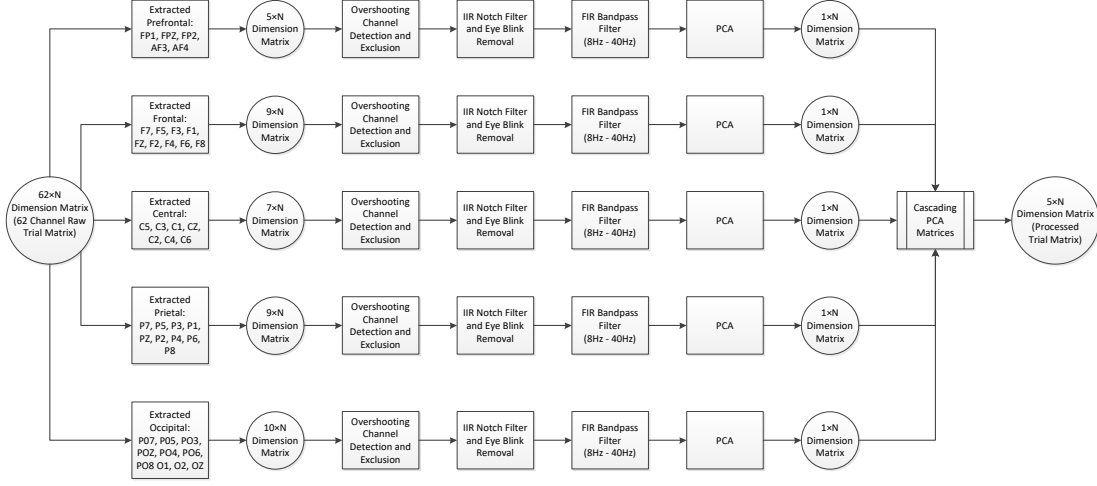


Figure 5.6: Flow diagram for channel exclusion and dimensional reduction

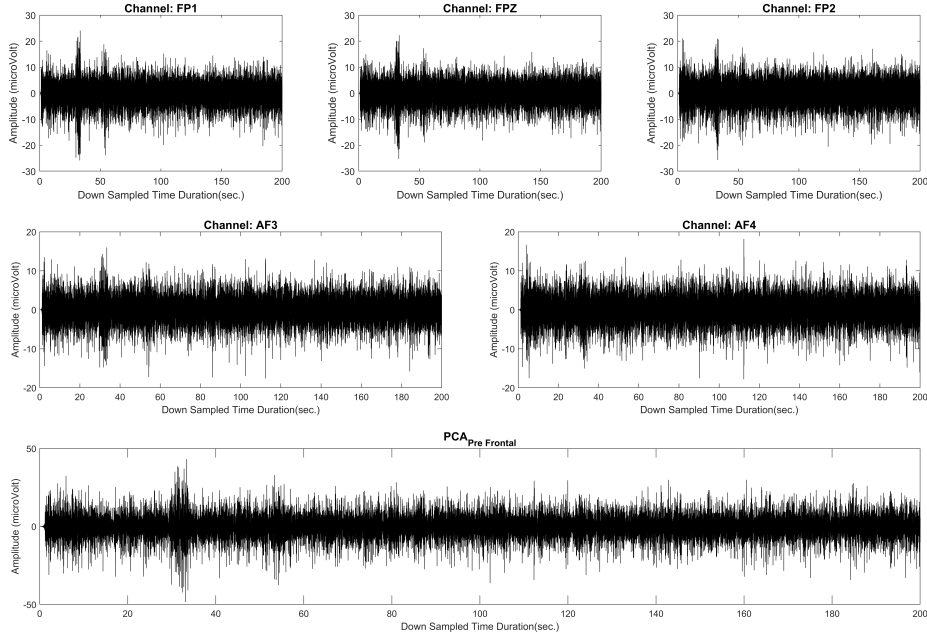


Figure 5.7: Visualization of the constructed Prefrontal PCA band (channels: FP1, FPZ, FP2, AF3 and AF4, subject: 4, state: negative, trial: 13)

man, Hossain, Hossain, *et al.*, 2020 only prefrontal, frontal, central, parietal and occipetal channels are extracted, excluding the rest of the 22 channels. Each channel band matrix ($M \times N$, M represents the number of channels and N represents the number of data points) then filtered for handling baseline noise and eye blink artifact removal. After the initial filtering corrupt/ overshooting channels are excluded for each $M \times N$ channel band matrices, followed by a 8 Hz to 40 Hz bandpass FIR filter for extracting the relevant information band. Each clean channel band matrix are then reduced to a single channel ($1 \times N$ dimensional vector) using principal component analysis (PCA). Each PCA vector are then cascaded to form the reduced $5 \times N$

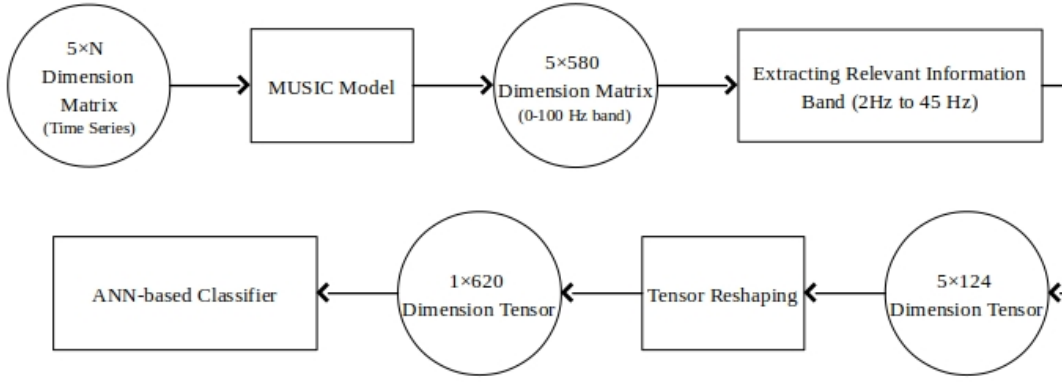


Figure 5.8: Flow diagram explaining feature extraction process for 5×124 Tensor from reduced $5 \times N$ dimension trials

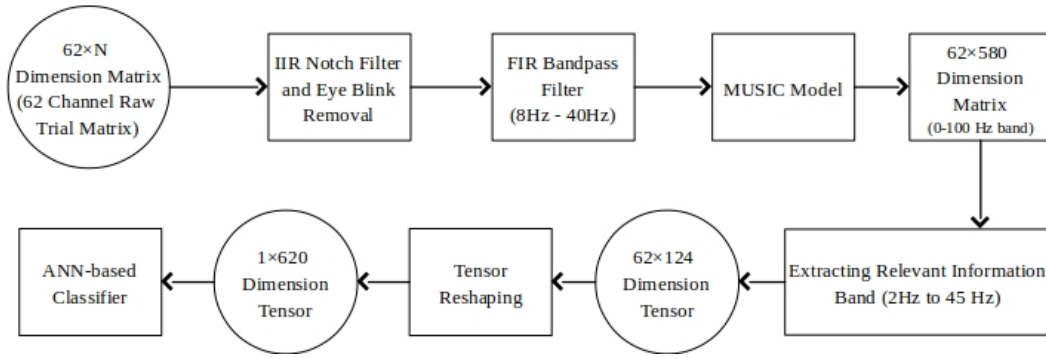


Figure 5.9: Flow diagram explaining feature extraction process for 62×124 Tensor from raw $62 \times N$ dimension trials

dimensional trial vector. The work flow is designed to gain the maximum computational efficiency. Lastly, figure 5.9 demonstrated the pre-processing and feature extraction methods which includes the overshooting channels.

The pre-processed time series matrices were then transformed using a MUSIC model with a window of 50 overlapping data points. From the transformed spectrum the band of 2 Hz to 45 Hz were extracted before statistical feature extraction and forming the tensor matrix.

5.4 Training and Method Evaluation

For training and evaluation k-Fold cross validation technique is followed, where the value of k is considered as 5. The dataset is splitted in 5 equal folds, then the networks are repeatedly trained on 4 folds and tested on the remaining one fold. The average accuracy from the five training;testing incident is evaluated, due to folding each trial got the chance to appear in both training and testing set for atleast once. We also explored the concept of Batch Normalization and Dropout on each of the networks. Batch normalization layer normalizes weights from all of the nodes and thus increases the training speed. Dropout layers randomly drops nodes to remove network biasness. Figure 5.10 illustrates the fundamental concept of dropout. Each feature matrix are evaluated on MLP networks, LSTM network and hybrid MLP-LSTM networks. Apart from k-fold cross validation, random training;testing data

ratios are also used to get further intuition about the feature space.

Multilayer Perceptron Network

For both of the feature spaces a fully connected 2 layer MLP network (L_1 : 512 nodes, L_2 : 248 nodes) with relu activation function and a softmax classification layer are used.

Hybrid Network (MLP-LSTM)

The hybrid MLP-LSTM network is consist of 2 LSTM layers with 100 nodes each (L_1 and L_2), two perceptron layer (L_3 : 512 nodes, L_4 : 248 nodes) and a softmax classification layer. The activation function used in this network is of type Relu.

LSTM network

The LSTM network is consist of 2 LSTM layers with 100 nodes each (L_1 and L_2) and a softmax classification layer. For k-fold cross validation the LSTM network is not tested, the network is tested on random spliting with fixed spliting ratios.

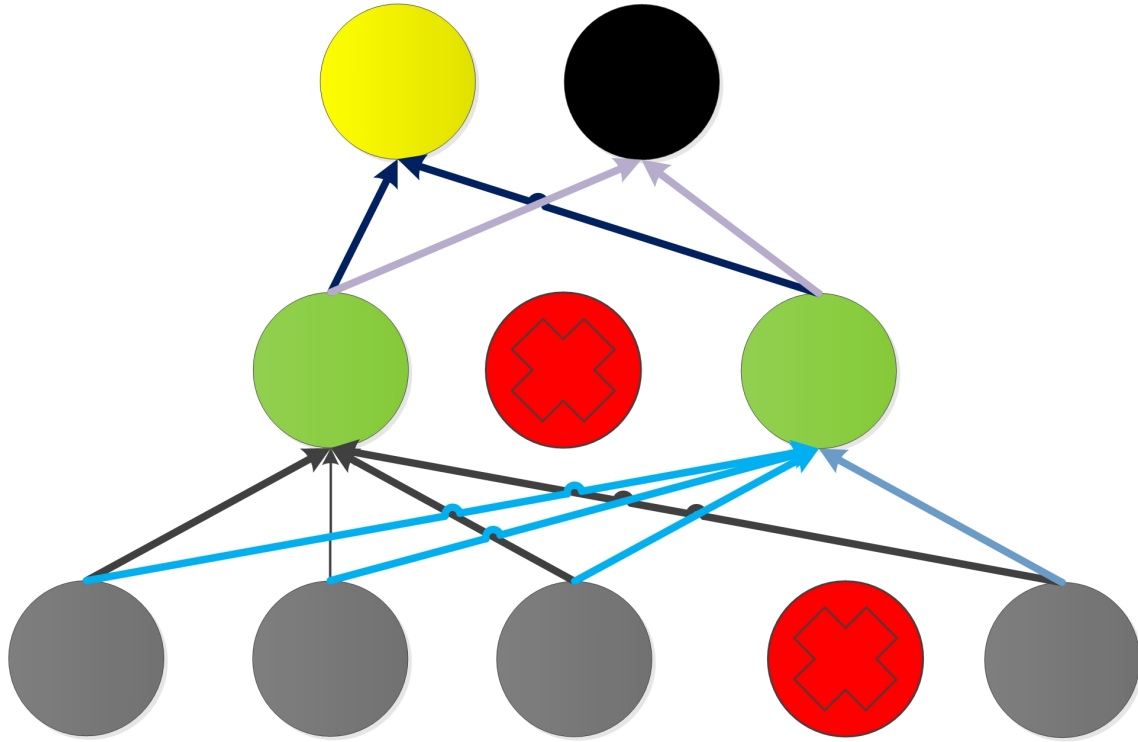


Figure 5.10: The concept of dropout

Chapter 6

Result and Discussion

The MUSIC algorithm is widely used in array signal processing and source localization due to extreme efficiency in DoA Estimation. Nevertheless the parametric eigen decomposition based power spectral density estimator model is comparatively unexplored in feature extraction tasks in emotion recognition, due to its complexity in implementation. In this research, we investigated the performance of parametric eigen decomposition based MUSIC model for feature extraction task in subject dependent emotion recognition from multi channel EEG recordings. In the investigated task, the MUSIC model based approach showed superiority than existing feature extraction techniques in terms of class separability and feature space quality.

For the feature set constructed from the $62 \times N$ dimensional pre-processed signal matrix (considering all 62 channels), subject wise 5 fold cross validation accuracy from the hybrid LSTM-MLP network is 97.4%. Proposed technique can be considered as the state of the art for this dataset, by comparing with existing high performance subject wise classification models (Table 6.5).

The observed subject wise accuracy from the reduced signal matrix is 90%. Which is superior than the observed subject wise accuracy from investigations which uses non-parametric feature extraction model and utilizes similar signal pre-processing technique.

As our additional findings suggest, specific trials from the seed dataset hold corrupted channels demonstrating voltage bands much higher than desired EEG voltage bands. This channels can be considered as EMG artifacts or caused due to electrode leakage current, and do not demonstrate any EEG information. Till now, no research has handled these specific channels demonstrating corrupt data. As discussed earlier for such particular cases, we have excluded the corrupt/ overshooting channels and then reduced the number of channels with PCA. In this case the feature space is constructed from a $5 \times N$ dimensional reduced signal matrix. From this distinct feature space which excludes the corrupted channels, subject wise 5 fold cross validation accuracy from the MLP network is 86.53 %.

6.1 5-Fold cross validation from feature space constructed without channel reduction

Fig 6.1 represents subject wise 5 fold cross validation accuracies from the MUSIC feature space without reducing the number of channels, where the dimension for each trial feature is 62×124 . The MLP network demonstrates 100% accuracy for 6 out of 15 subjects. The hybrid LSTM-MLP network demonstrates such remarkable state of the art performance for 7 subjects. Both the networks achieved over 97% classification accuracy for 13 subjects out of 15.

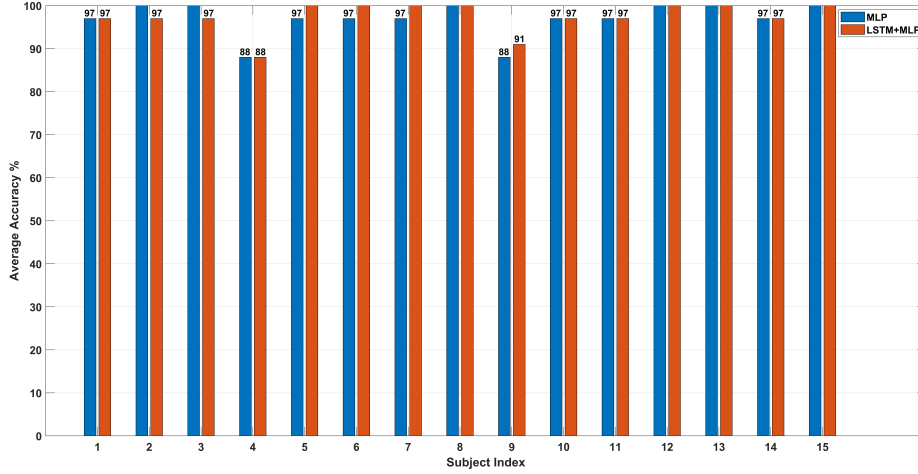


Figure 6.1: Subject wise 5 fold cross validation accuracy from MUSIC feature space considering all 62 channels

Fig 6.3 and fig 6.2 represents subject wise precision, recall and F1 scores for both of the networks on this particular feature space. The exceptionally high precision values suggest that, both the networks are extremely efficient in predicting true values for each of the states across all subjects.

Table 6.1 summarizes the observed state wise average Precision, Recall and F1 scores for this specific method. All of the average metric values are over 96.5%, which suggest both the feature space and the networks demonstrates excellent performance in each of the state classification tasks.

Network	Metric	Neg. (%)	Neu. (%)	Pos. (%)
MLP	Precision	97.78 %	96.82 %	97.53 %
	Recall	97.51 %	97.22 %	97.22 %
	F1 Score	97.34 %	96.65 %	96.89 %
LSTM-MLP	Precision	99.08 %	98.91 %	96.76 %
	Recall	97.28 %	96.95 %	98.34 %
	F1 Score	97.85 %	97.56 %	97.11 %

Table 6.1: Average Precision, Recall and F1 Score from MLP and LSTM-MLP networks considering all 62 channels

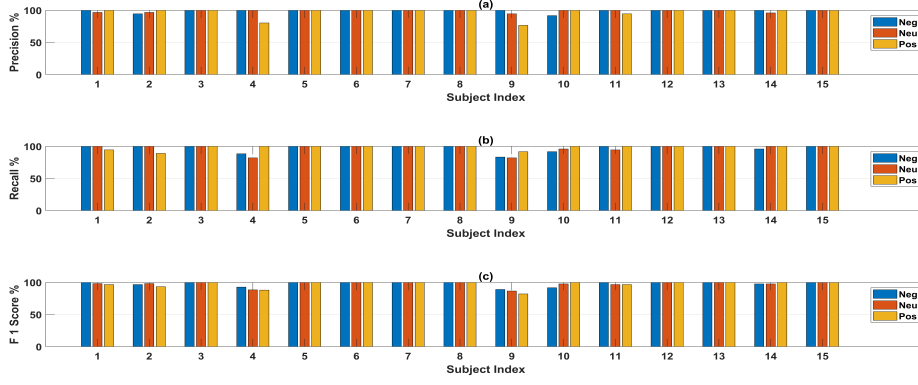


Figure 6.2: Observed (a) precision (b) recall and (c) F1 scores from the hybrid LSTM-MLP classifier considering all 62 channels

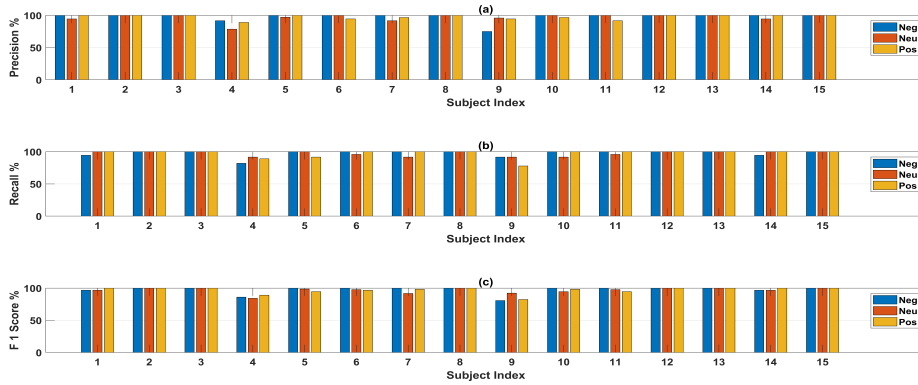


Figure 6.3: Observed (a) precision (b) recall and (c) F1 scores from the MLP classifier considering all 62 channels

6.2 5-Fold cross validation from feature space constructed after channel reduction

The 6 fold cross validation classification accuracy for subject 15 was observed to be a staggering 100% for both 70% training data and 50% training data. The classification accuracy for subject 14 and subject 13 with 50% training data was observed to be near 95%. With 70% training data the classification accuracy was over 90% for 13 subjects. The 6 fold cross validation classification accuracy was over 90% for 11 subjects with 50% training data. MUSIC feature space for each of the subject except subject 4 and subject 9 have provided average accuracy of over 93%. The PCA plots for subject 4 and subject 9 shows comparatively lower correlated feature space for the MUSIC method and thus resulted in lesser accuracy than other subjects.

The tabular Fig. 6.5 provides a detailed performance overview for the proposed

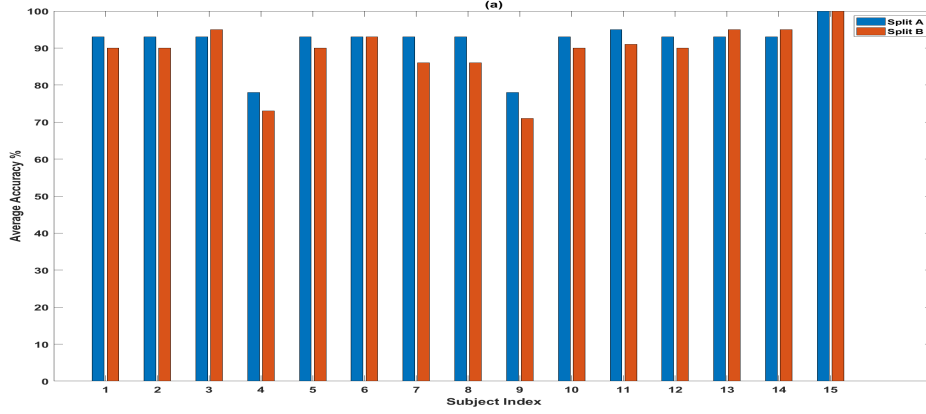


Figure 6.4: Subject wise 5 fold cross validation accuracy from MUSIC feature space constructed after channel reduction, which includes corrupt channels

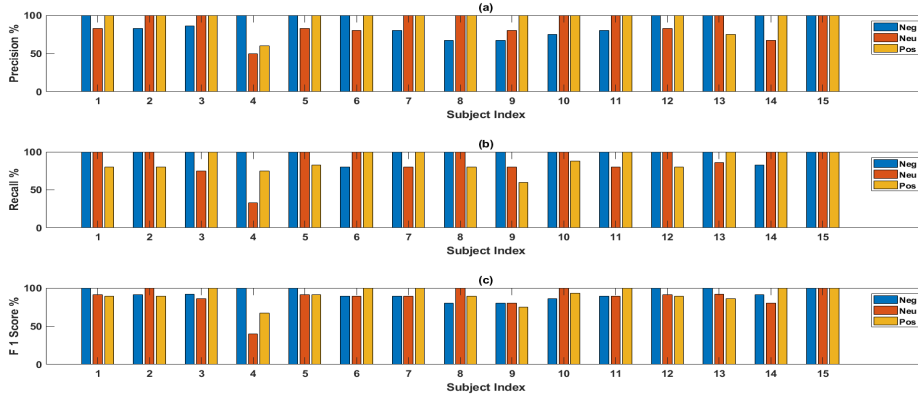


Figure 6.5: Observed (a) precision (b) recall and (c) F1 scores from the MLP classifier

method. The model demonstrate better precision for predicting trials from Positive class, as the average precision for the Positive class is 95%. The average precision from the Negative and Positive classes are 89.2% and 88.4% respectively. The Negative class shows a maximum average recall score of 97.5% from the MUSIC feature space classification method. The average recall score for the Neutral and Positive classes are 89% and 88.4% respectively. The model demonstrates the maximum average F1 score of 92.5% for the Negative class. Average F1 score for the Positive and Neutral classes are observed to be 91.2% and 88% respectively.

6.3 5-Fold cross validation from feature space constructed after exclusion of corrupt channels

The subject wise 5 fold cross validation accuracies for the feature space which excludes the overshooting/ corrupt channels prior to reducing the number of channels with PCA, are represented in fig 6.6. The dimension for each of the trial feature is 5×124 for this distinct method. Both the networks performed satisfactory across all

subjects except subject 4 and 9. Both the networks demonstrate average accuracy of over 90% when subject 4 and subject 9 are excluded.

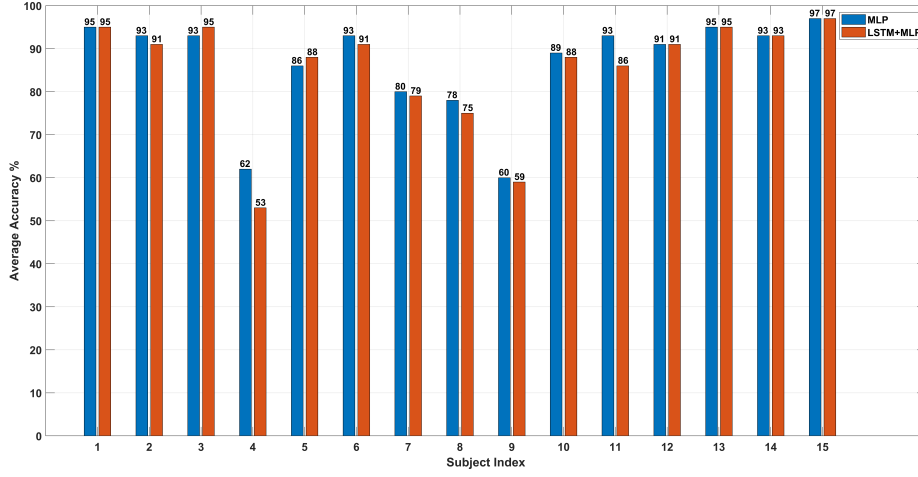


Figure 6.6: Subject wise 5 fold cross validation accuracy from MUSIC feature space excluding the corrupt channels

Fig 6.8 and fig 6.7 represents subject wise Precision, Recall and F1 score for this method. As the F1 scores suggests, for subject 4 the hybrid network failed to predict neutral and positive states. On the contrary, the MLP network achieved satisfactory performance in predicting neutral states for this particular subject with 85.33 % F1 Score.

Table 6.2 summarizes the observed subject wise Precision, Recall and F1 scores for further evaluating the feature space and network performance. Both the networks comparatively performs better in predicting the negative states, for this particular feature space.

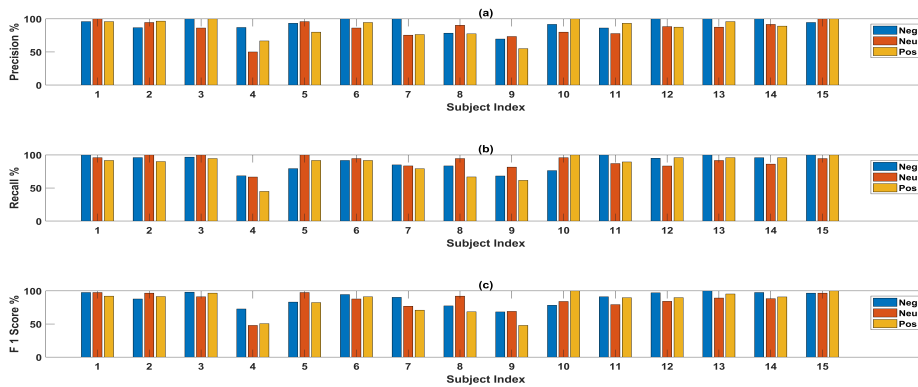


Figure 6.7: Observed (a) precision (b) recall and (c) F1 scores from the hybrid LSTM-MLP classifier excluding the corrupt channels

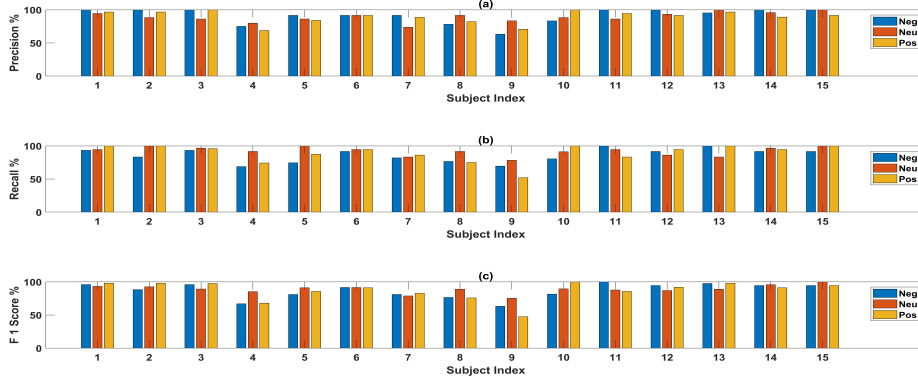


Figure 6.8: Observed (a) precision (b) recall and (c) F1 scores from the MLP classifier excluding the corrupt channels

Network	Metric	Neg. (%)	Neu. (%)	Pos. (%)
MLP	Precision	91.36%	89.28%	89.55%
	Recall	85.91%	92.17%	89.17%
	F1 Score	86.94%	89.05%	87.10%
LSTM-MLP	Precision	92.20%	85.14%	87.20%
	Recall	89.06%	90.33%	85.93%
	F1 Score	88.74%	85.30%	83.88%

Table 6.2: Average Precision, Recall and F1 Score from MLP and LSTM-MLP networks with excluding the corrupt channels prior to channel reduction

6.4 Arbitrary feature set splitting with fixed *Training* : *Testing* ratios

For deriving further intuition about the the quality of the feature extraction methods, the research undertakes additional network training with random dataset splitting retaining fixed training data:testing data splitting ratios. Three *training* : *testing* data split ratios of 50 : 50, 60 : 40 and 70 : 30 are investigated on MLP, LSTM and hybrid LSTM-MLP networks. Average accuracy from four random splitting incident for each case are represented in table 6.3. On the MLP network the channel reduction technique demonstrated 93.81%, 96.16% and 97.8% for 50 : 50, 60 : 40 and 70 : 30 *training* : *testing* data ratios, respectively. In other cases all three models demonstrated comparatively similar high performance. Such performance illustrate the quality of MUSIC model based feature extraction technique across diverge network architectures.

Pre-processing method	Train:Test ratio	Network	Avg. Acc.
Includes all 62 channels	50 : 50	MLP	97.22%
		LSTM	93.14%
		LSTM-MLP	98.39%
	60 : 40	MLP	97.58%
		LSTM	94.31%
		LSTM-MLP	98.50%
	70 : 30	MLP	99.53%
		LSTM	95.68%
		LSTM-MLP	99.76%
Excludes corrupt channels	50 : 50	MLP	93.81%
		LSTM	86.56%
		LSTM-MLP	93.17%
	60 : 40	MLP	96.16%
		LSTM	88.45%
		LSTM-MLP	93.86%
	70 : 30	MLP	97.80%
		LSTM	91.92%
		LSTM-MLP	96.54%

Table 6.3: Average accuracies from arbitrary data splitting with fixed
Training : Testing ratios

6.5 Subject Independent Classification Accuracies

The subject independent classification accuracy are represented in figure 6.9, it represent network performance from 5 fold cross validation. The higher dimension feature space, which is constructed considering all 62 channels demonstrated superiority over the feature space constructed after reduction of channels.

For the feature space where the dimension of each trial matrix is 62×124 the LSTM network showed better performance over the MLP network. The LSTM network has a subject independent accuracy of 90% for the feature space which includes all 62 channels, and 75% for the feature space which excludes the corrupt channels.

The precision-recall and F1 scores provides a detailed overview of the network performance. For the higher dimensional feature space, both the network performed better in classifying the negative state. Figure 6.10 represents observed precision for both the network where the dimension of each trial is 62×124 . Here the observed precision from the LSTM network is 95%, 88%, and 89% for the negative, neutral, and positive states, respectively. Figure 6.11 illustrates observed recall for this specific feature space from both of the networks.

The F1 scores provides an overview of both precision and recall scores. Figure 6.12 illustrates that both the networks performed well in classifying each of the states.

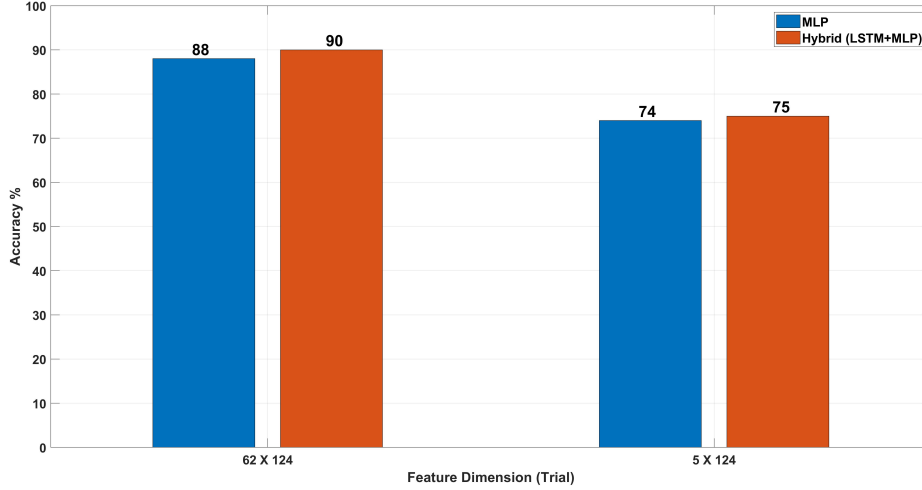


Figure 6.9: Subject independent k fold classification results

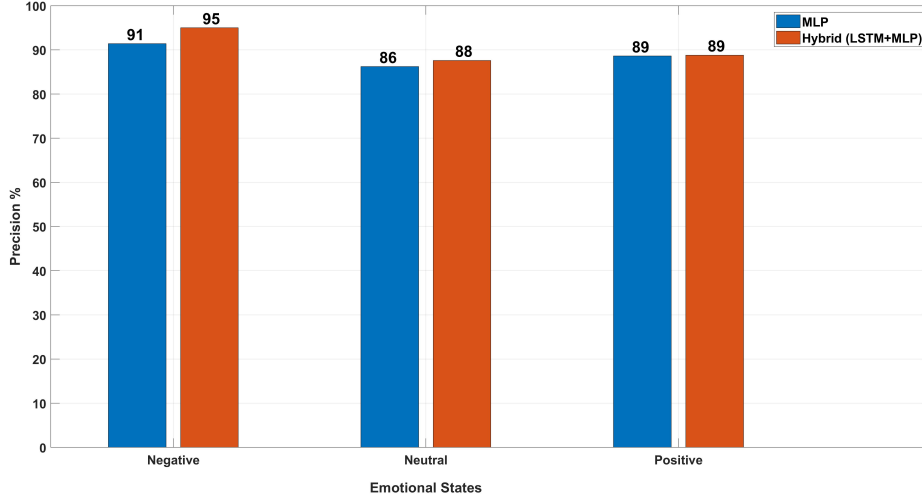


Figure 6.10: Observed precision from the network, where the dimension for each trial feature is 62×124

For the feature space constructed after channel reduction figure 6.13, figure 6.14, and figure 6.15 illustrates precision, recall, and f1 scores, respectively.

Our investigated methods for subject independent classification have been compared with existing high performance classification methods on this dataset. Table 6.4 illustrates such comparison. From the comparison it is eminent that, the MUSIC based feature extraction method outperforms the non-parametric approaches by a large margin. M. A. Rahman et al. [100], F. Javier et al. [114], and Lan et al. [77] achieved 80%, 79%, and 72% classification accuracy with non-parametric based feature extraction techniques. With 90% classification accuracy from the LSTM network, our proposed technique also showed superiority over other feature extraction techniques such as, auto-encoder or windowed time series approach for subject independent classification.

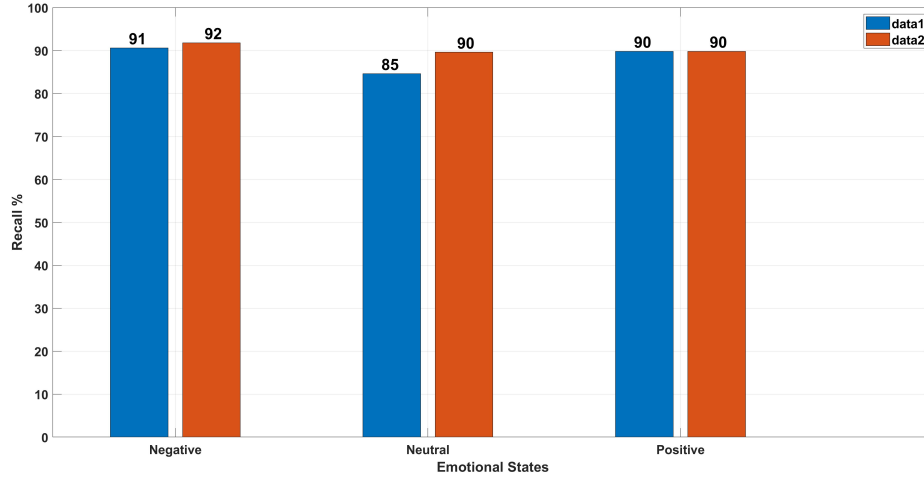


Figure 6.11: Observed recall from the network, where the dimension for each trial feature is 62×124

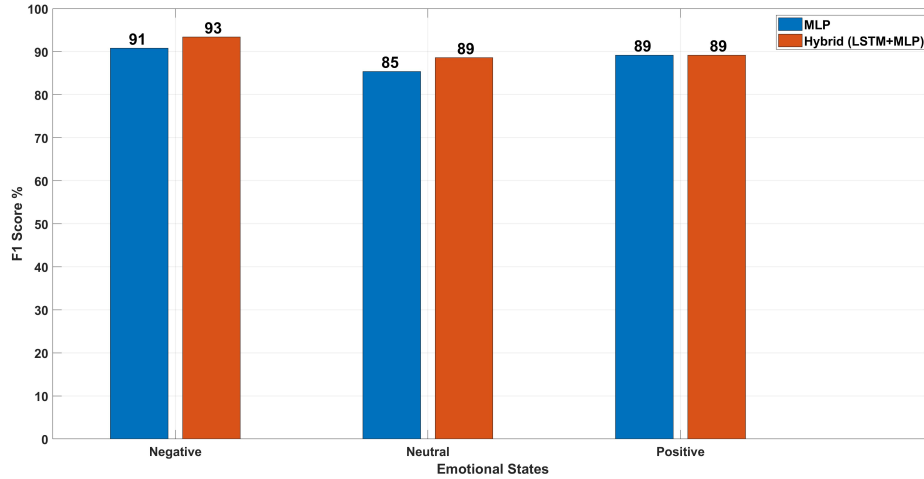


Figure 6.12: Observed F1 Score from the network, where the dimension for each trial feature is 62×124

Author and Research	Feature Extraction Method	Classification Method	Average Accuracy
Lan et al. [77]	Differential Entropy	Logistic Regression	72%
Arjun et al. [111]	Attention Driven Higher Dimensional Features	DNN	76%
Y. Cimtay et al. [87]	Windowed Time Series	CNN	78%
F. Javier et al. [114]	Non-parametric	MLP	79.6%
M.A.Rahman et al.[100]	PCA and non-parametric Welch model	Artificial Neural Network	80%
Li et al [78]	Auto-encoder Based	LSTM	84.2%
Proposed Method	MUSIC model (Includes all 62 channels)	MLP network Hybrid LSTM-MLP network	88% 90%
Investigated Method (No prior investigation exist)	MUSIC model (Excludes corrupt channels)	MLP network Hybrid LSTM-MLP network	74% 75%

Table 6.4: Performance comparison for subject independent classification approach, with existing researches on emotional state classification for the SEED dataset

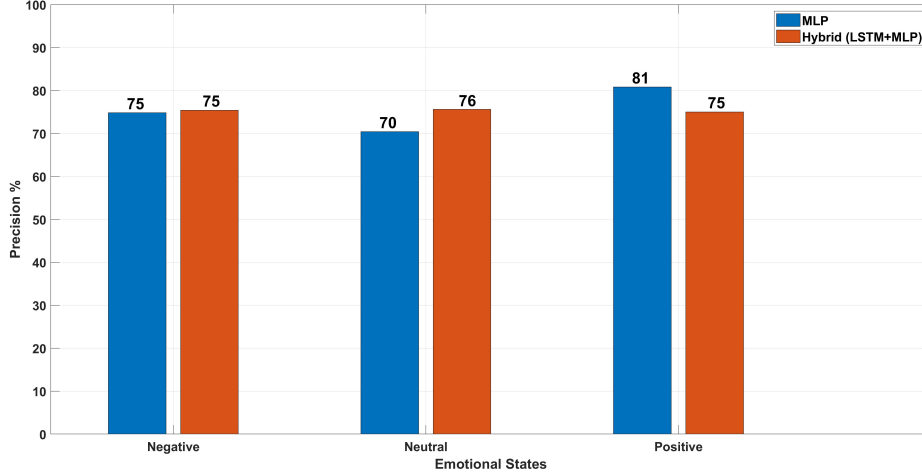


Figure 6.13: Observed precision from the network, where the dimension for each trial feature is 5×124

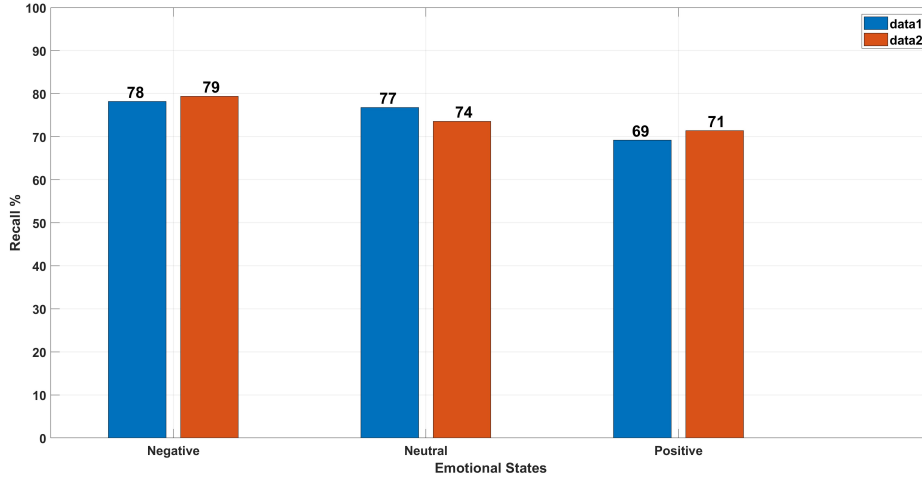


Figure 6.14: Observed recall from the network, where the dimension for each trial feature is 5×124

6.6 Effects of overshooting/ corrupt channels

Our research also implements higher dimensional visualization techniques for interpreting the influence of the corrupted channels in the feature space. Fig 6.16, represents three dimensional visualization of the constructed MUSIC feature space for a trial demonstrating neutral stage of subject 1. In fig 6.16 (a), the feature space is constructed from $62 \times N$ dimensional signal matrix, which includes the corrupted channels for this particular trial. In fig 6.16 (b) and fig 6.16 (c) the feature space is constructed from $5 \times N$ dimensional reduced signal matrix, but only the later representation excludes the corrupted channels through peak finding. The overshooting channels for this particular trial lies in the parietal and occipital bands.

Correspondingly in the 62×124 dimensional MUSIC feature space for the trial, spectrum values for the rest of the channels are suppressed due to much higher

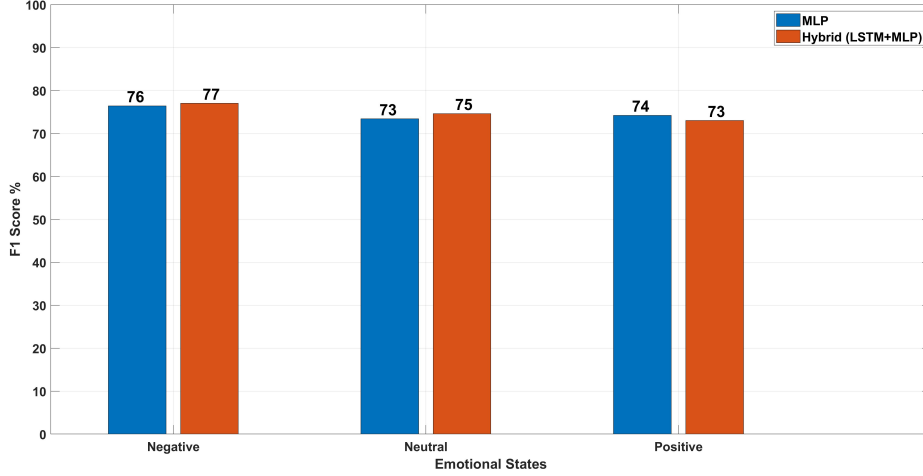


Figure 6.15: Observed F1 Score from the network, where the dimension for each trial feature is 5×124

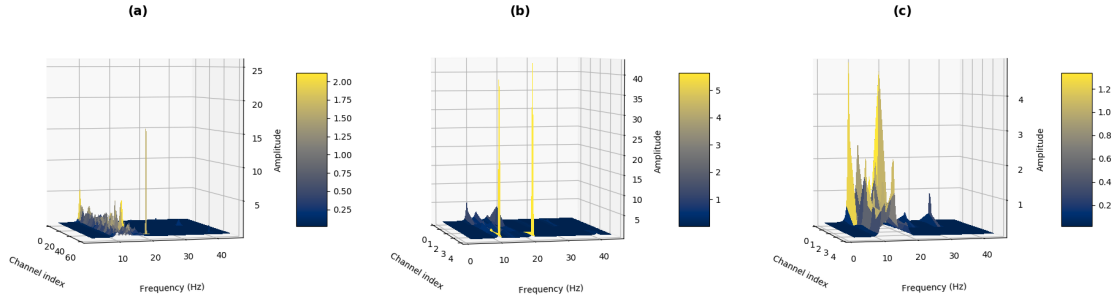


Figure 6.16: Three dimensional visualization of the computed MUSIC spectrums for subject: 1, state: negative, trial: 5 (a)considering all 62 channels (b)reducing the number of channels (c) excluding the corrupt channels prior to channel reduction

peaks generated from the overshooting channels in the β band. The feature space extracted from the reduced signal matrix which also includes these overshooting channels, the $PCA_{occipital}$ and $PCA_{parietal}$ bands similarly suppress the spectrum from rest of the bands. Removing the corrupt / overshooting channels from the Occipital and Parietal bands provide the true spectrum distribution across all PCA bands, which is represented in the fig. 6.16 (c).

Subsequently it can be observed in fig. 6.16 (a) and fig. 6.16 (b), the presence of the corrupt channels generates high peaks which demonstrates β band components. When the particular overshooting channels are excluded the β components are significantly reduced and α band is dominating across all channels. Additionally in such a case the presence of the γ band can also be observed, which is absent when the corrupted channels are present in the feature space. The high amplitude peaks in the β bands suggests the presence of EMG artifacts in the trial due to the corrupted channels. The corrupt/ overshooting channels demonstrate similar effects across all subjects.

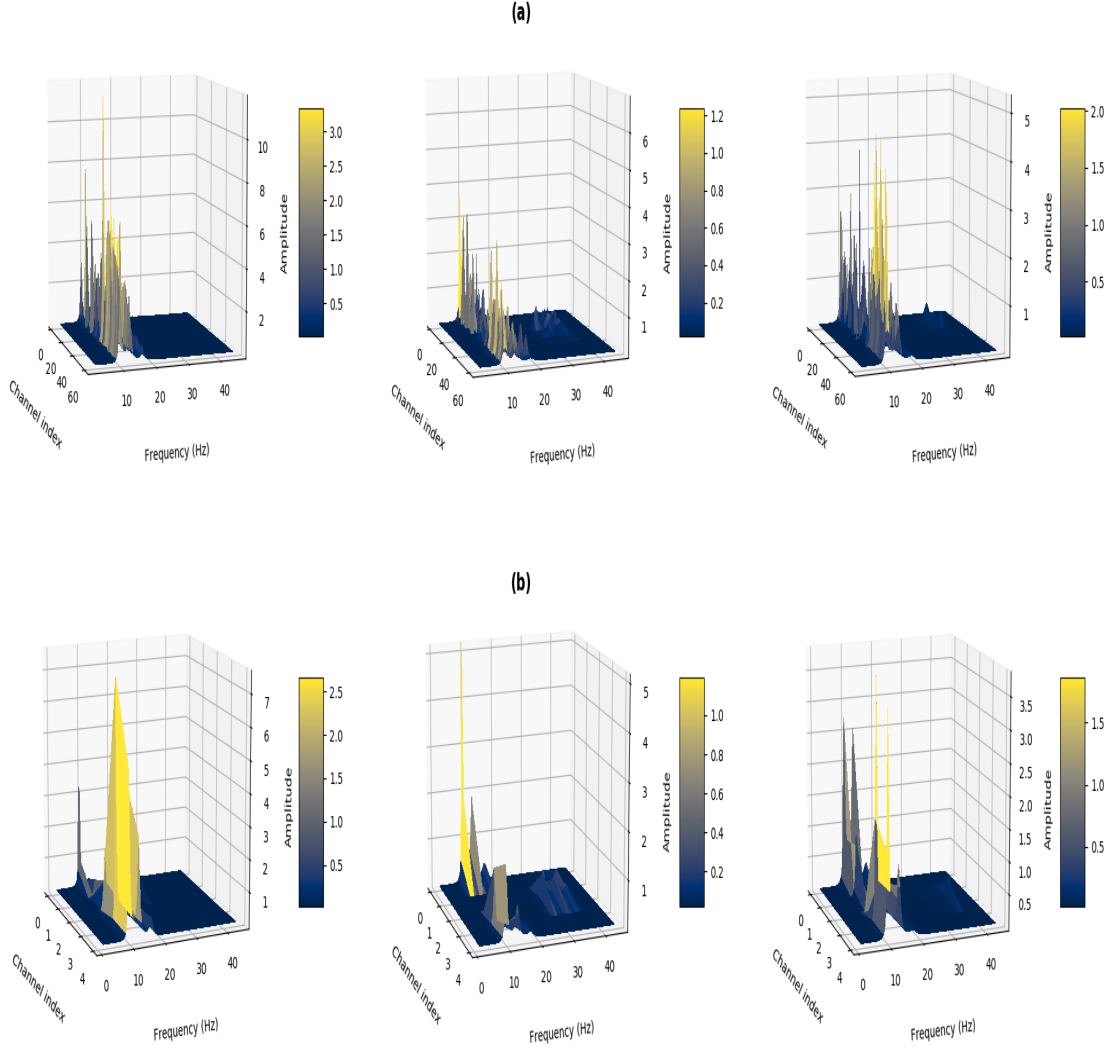


Figure 6.17: Three dimensional visualization of the computed MUSIC spectrum for negative state (left), neutral state (middle) and positive state (right) of subject:12, trial: 14 (a) considering all 62 channels (b) excluding the corrupt channels prior to channel reduction

Fig. 6.17 and fig. 6.18 represents feature space for subject 12 from MUSIC spectrum and non-parametric (Welch) spectrum, respectively. As evident from the figure, MUSIC model demonstrates superiority in localizing the signal subspace bands. For fig. 6.17 (a) and fig. 6.17 (b), the weight of the α band is significantly higher across all the spectrums. The MUSIC spectrum visualizations interpret that, α band is dominant for each of the states but varies with amplitude. For the frontal and central channels, γ components are also observed for the neutral and positive states. Both 62×124 and 5×124 dimensional feature space demonstrates presence of similar signal subspace bands.

For the MUSIC model it is observed from the visualizations, each state demonstrates exact frequency bands but significantly varies with amplitude. This behaviour arises a problem in feature scaling. Feature scaling may reduce class separability in this unique case, as bands in different classes may be scaled into adjacent values. Due

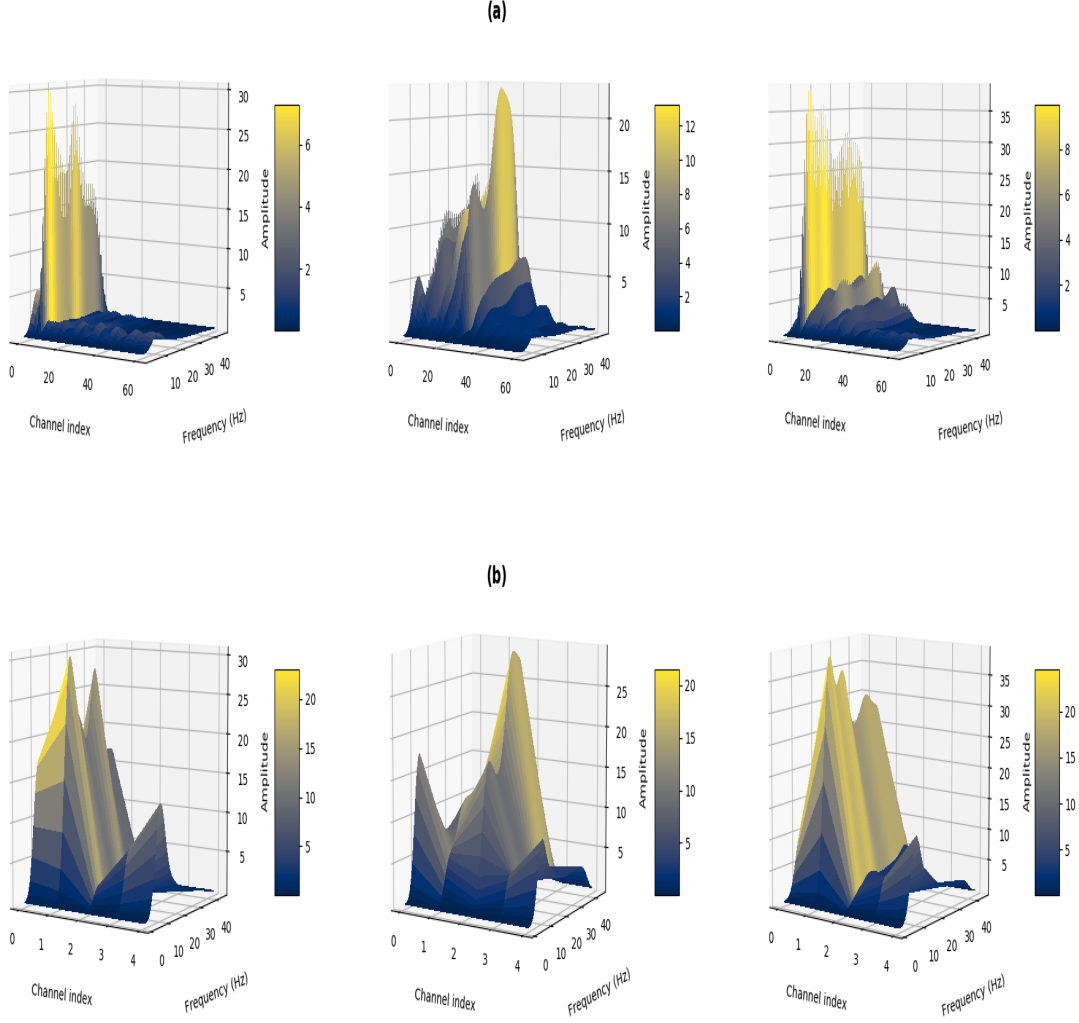


Figure 6.18: Three dimensional visualization of non-parametric (Welch) spectrum for negative state (left), neutral state (middle) and positive state (right) of subject:12, trial: 14 (a) considering all 62 channels (b) excluding the corrupt channels prior to channel reduction

to this finding feature space was not scaled before network training.

For the non-parametric feature space in fig. 6.18 (a) and fig. 6.18 (b), spectral variation for the signal sub space bands can be observed. Unlike the MUSIC model, the non parametric spectrums can not localize specific signal subspace bands across the trial. $PCA_{occipital}$ band from the non-parametric feature space demonstrates significant spectral weights for the δ and θ components, which should have been absent due to prior FIR filtering.

6.7 Comparison of features space quality

The k-fold validation results and the feature space visualization techniques both suggest that, by reducing the number of channels the quality of the MUSIC feature space is significantly reduced. The results from both of the pre-processing techniques for constructing the MUSIC feature space are summarized in table ?? . The network performance on the $45 \times 62 \times 124$ dimensional feature space is exceptionally higher than the feature space constructed by reducing the number of channels. Moreover, the hybrid network demonstrates slightly better performance than the MLP network for the feature extraction method which includes all 62 channels.

The research undertook extensive data visualization to better understand the extracted feature characteristics and behavior from the MUSIC model. From fig. ?? it can be observed that, the α and the β bands holds the most weights in the spectrum for each of the states, but significantly varies with amplitude. The positive spectrum also demonstrate significant weights in the γ bands across all subjects.

6.7.1 PCA Visualization

The first three principal components holds around 65% to 95% information for the entire feature space, consequently three dimensional visualization of these three principal components can provide explicit information. The PCA visualization in fig. 6.19 and fig. 6.20 demonstrates the quality for each of the feature spaces, as the visualization can interpret class separability. In this regards the MUSIC model also demonstrates superiority over classical non-parametric approach of feature extraction, for both of the signal pre-processing approaches.

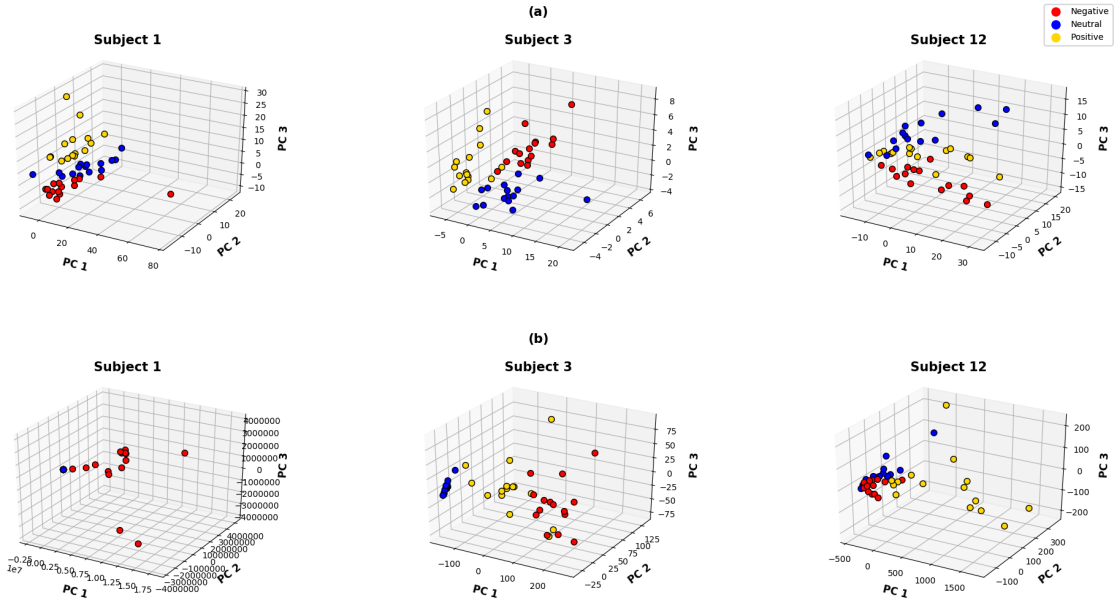


Figure 6.19: Three dimensional Principal Component visualization of (a) the computed MUSIC feature space and (b) non-parametric (Welch) feature space considering all 62 channels

Fig. 6.19 (a) represents the MUSIC feature space and fig. 6.19 (b) represents the non-parametric (Welch) feature space, from the pre-processed $62 \times N$ dimensional

signal matrix. Fig. 6.20 (a) and fig. 6.20 (b) represents MUSIC and Welch feature spaces, respectively for $5 \times N$ dimensional reduced signal matrix. For both of the figures feature spaces which are generated from MUSIC model form more separable clusters. As demonstrated in the visualization, Welch feature space of subject 1, clearly can not distinguish neutral and positive states when all 62 channels are considered. On the contrary, with the exact identical signal pre-processing approach PCA plots from MUSIC models demonstrates comprehensive class separability. From fig. 6.20 (b) it can be observed that in terms of reducing the number of channels, conventional non-parametric Welch model demonstrate much lesser efficiency in extracting desirable feature quality.

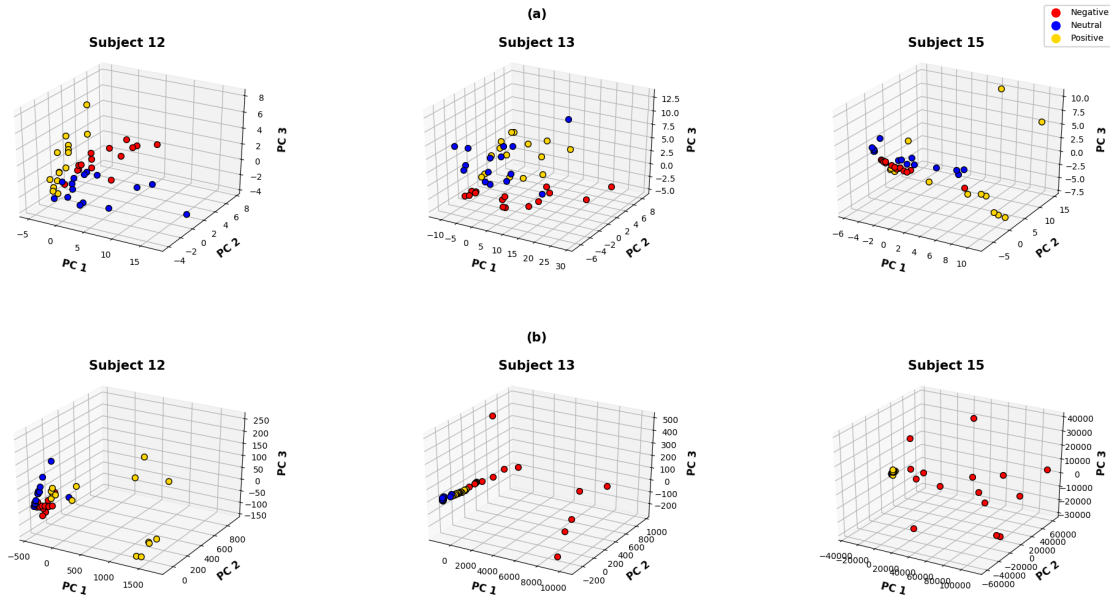


Figure 6.20: Three dimensional Principal Component visualization of (a) the computed MUSIC feature space and (b) non-parametric (Welch) feature space after excluding the corrupt channels prior to channel reduction

From comparing fig. 6.19 (a) and fig. 6.20 (a), it is eminent that the quality of the feature space is significantly decreased when the number of channels are reduced. The subject wise accuracies from k-fold cross validation also clarifies such behaviour. Fig. 6.21 and fig. 6.22 demonstrates three dimensional principal component visualization for feature space extracted from MUSIC model and Welch model (non parametric PSD estimator model), where number of channels were reduced without excluding the overshooting channels. The PCA visualizations explains the results in Tabular Fig. 6.4. The visualization assist to compare among the quality of these two feature spaces. The MUSIC feature space demonstrates better class separability than the Welch feature space, as the MUSIC feature space forms more specific clusters in most cases.

From comparing fig. 6.19 (a) and fig. 6.20 (a), it is eminent that the quality of the feature space is significantly decreased when the number of channels are reduced. The subject wise accuracies from k-fold cross validation also clarifies such behaviour.

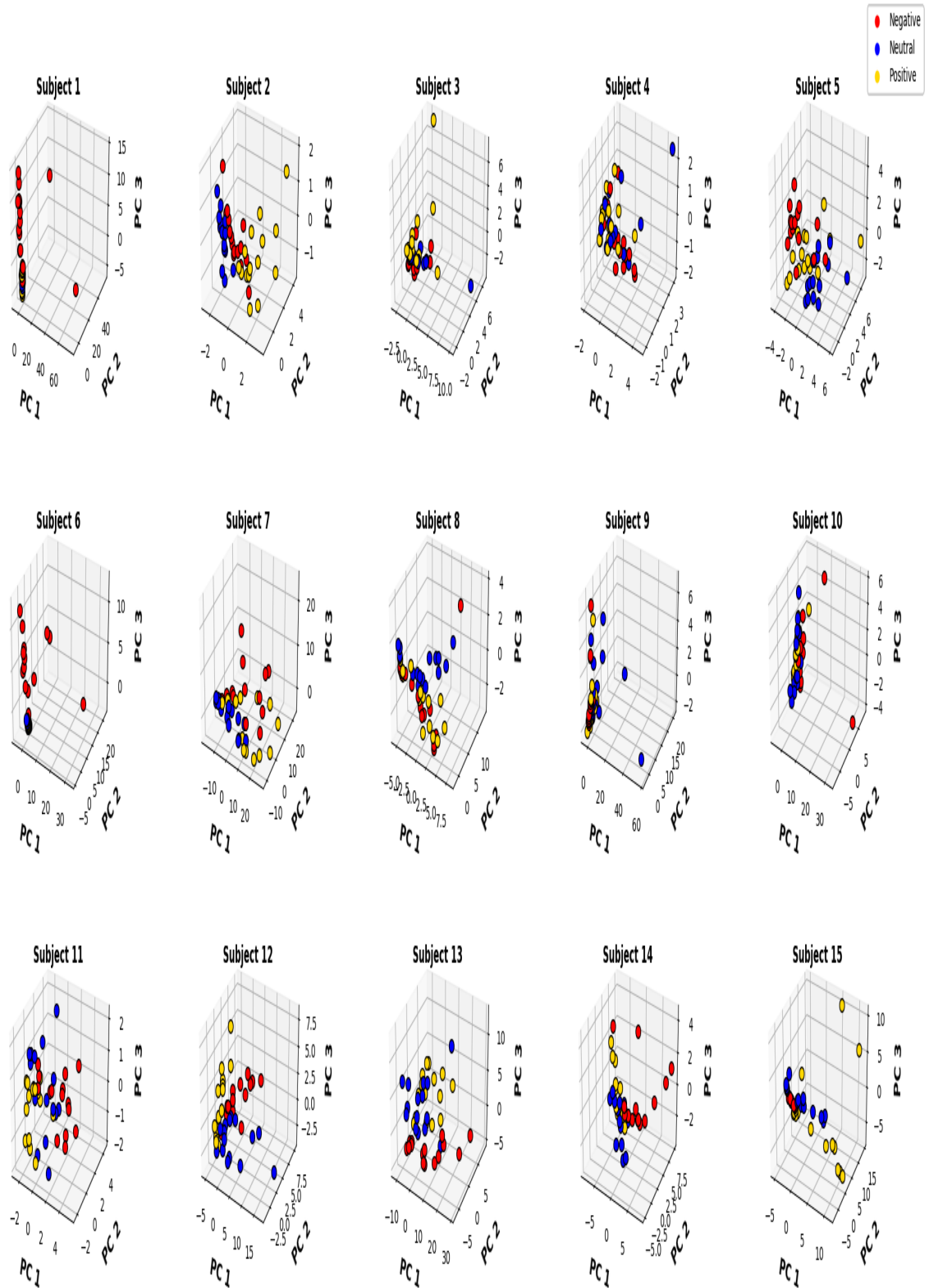


Figure 6.21: Three dimensional Principal Component visualization for feature space from computed MUSIC spectrum, where channels were reduced without the exclusion of overshooting channels

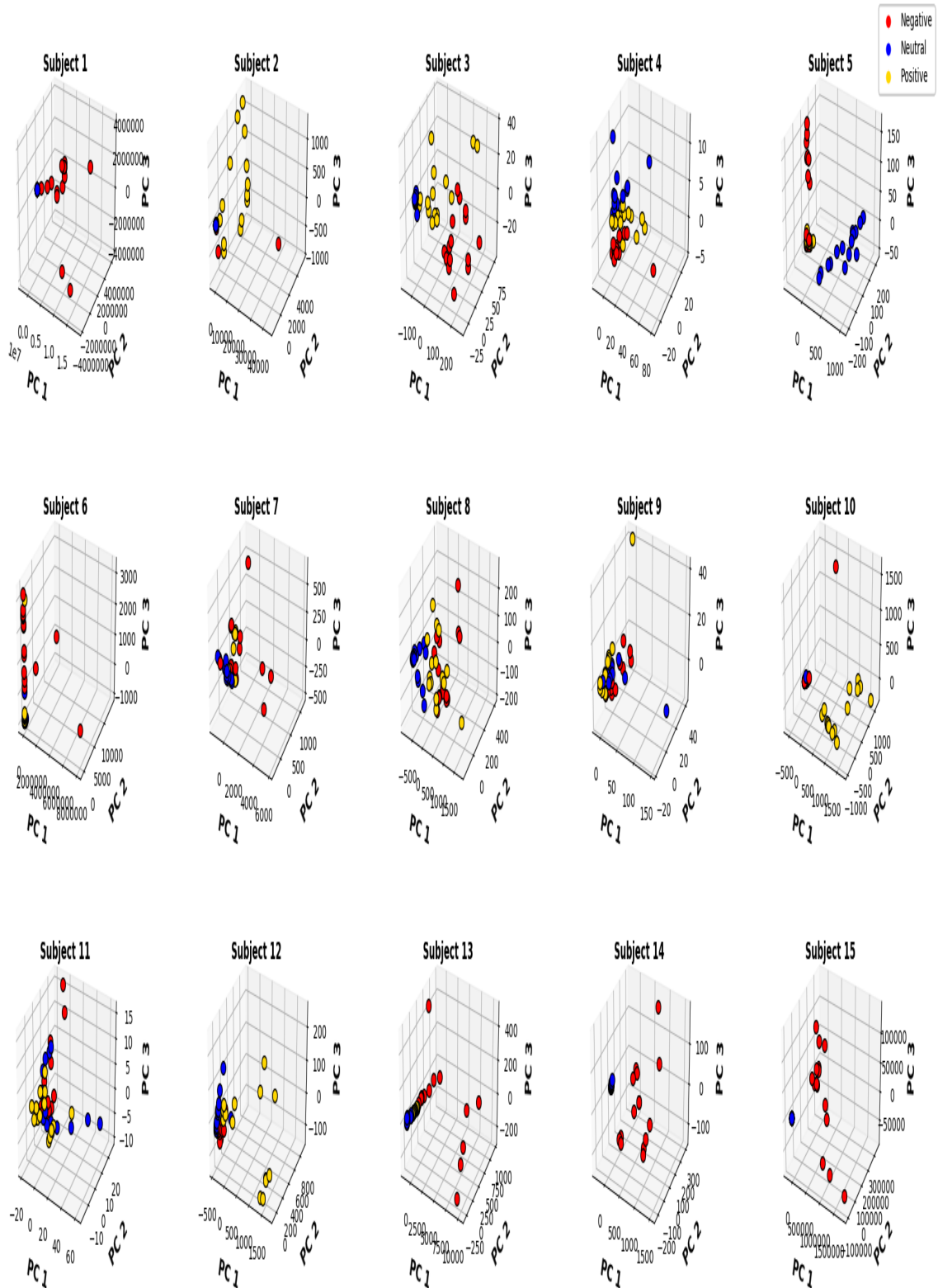


Figure 6.22: Three dimensional Principal Component visualization for feature space from computed Welch spectrum, where channels were reduced without the exclusion of overshooting channels

6.7.2 Higher dimensional visualization

Parallel coordinate plot and swarm plots represents critical information such as, class separability and correlation among variables regarding the visualized dataset [115].

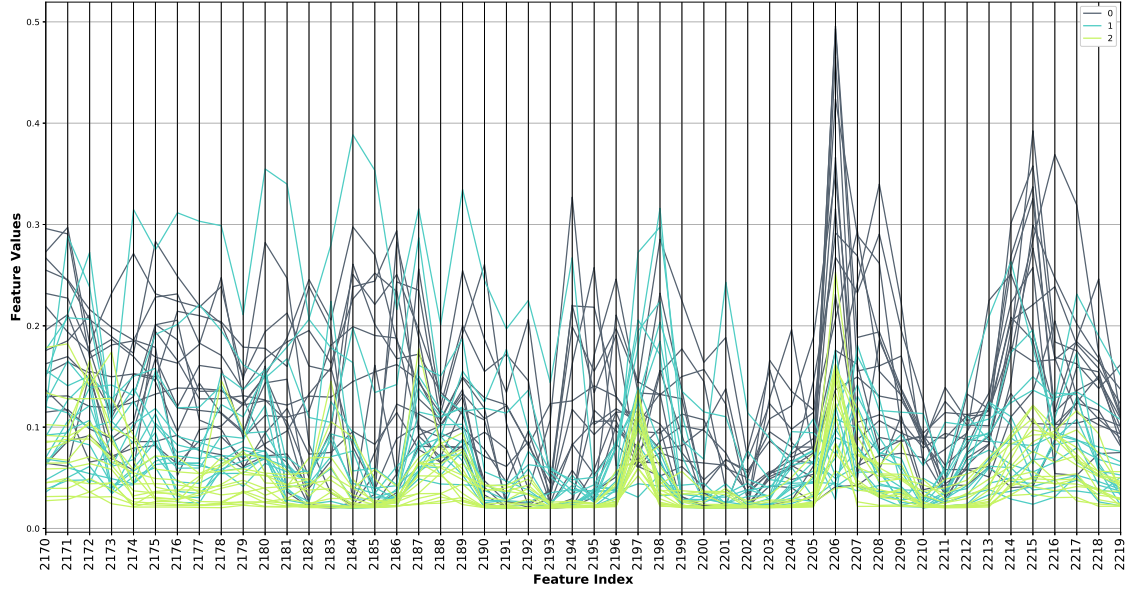


Figure 6.23: Parallel coordinate visualization for subject 11 considering all 62 channels: feature index 2170 to 2220

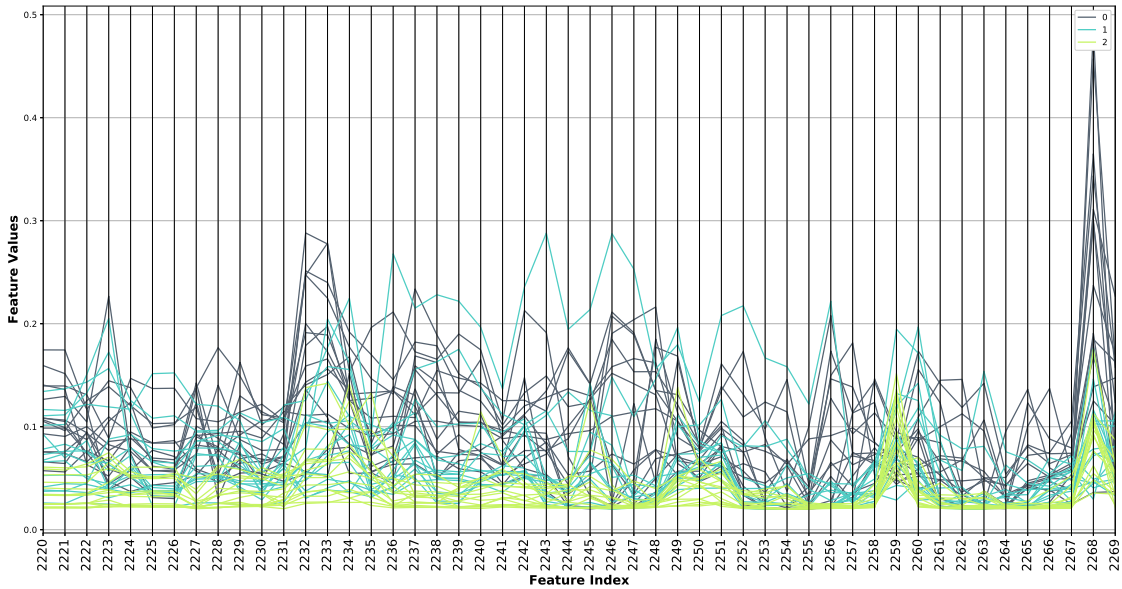


Figure 6.24: Parallel coordinate visualization for subject 11 considering all 62 channels: feature index 2220 to 2270

Parallel coordinate plot and swarm plots also represent similar feature attributes which spectral contour plots and three-dimensional PCA plots demonstrate. Though parallel coordinate plots primarily exhibit correlation among each feature index, in

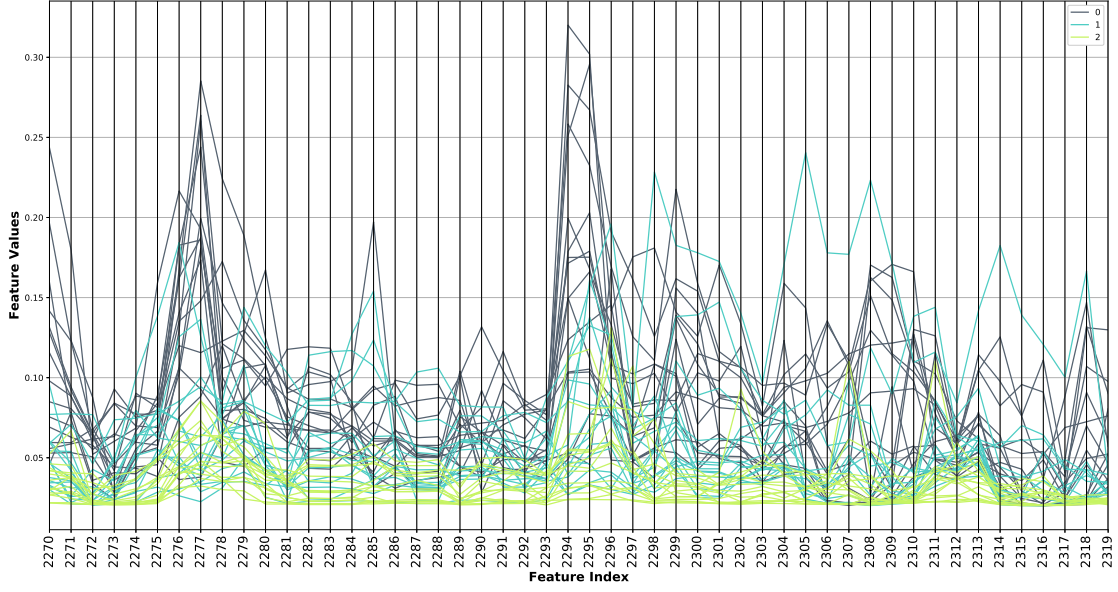


Figure 6.25: Parallel coordinate visualization for subject 11 considering all 62 channels: feature index 2270 to 2320

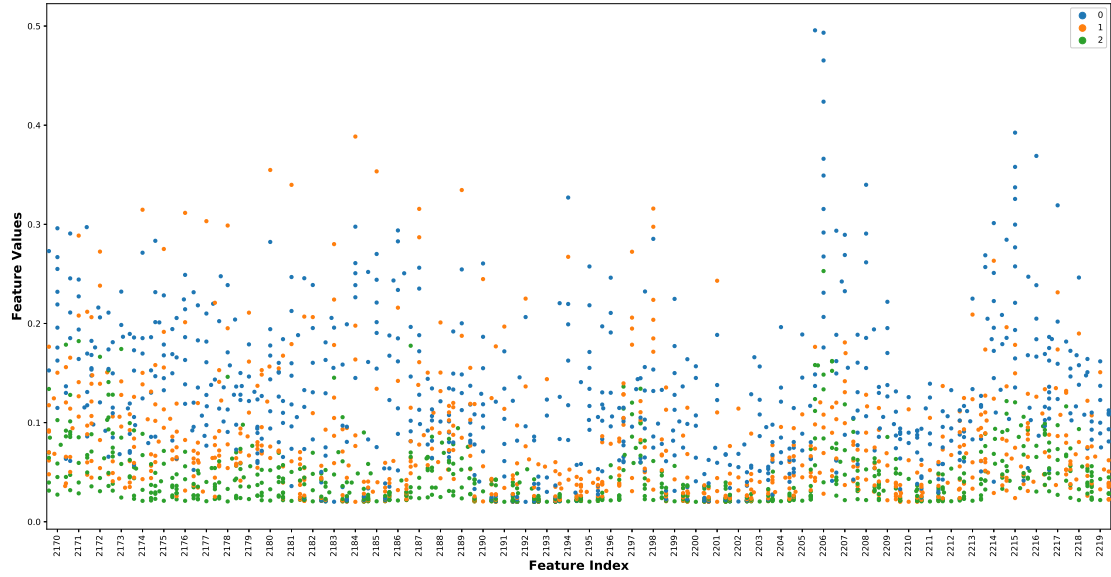


Figure 6.26: Swarm Plot visualization for subject 11 considering all 62 channels: feature index 2170 to 2220

this particular case such correlation can not demonstrated across all the feature indexes due to higher number of features. Rather selected feature index bands are visualized, which contributes the most to the model due to higher class separability. The swarm plots represents exact computational points for the network.

The higher dimensional visualizations also demonstrate some of the same feature characters which have been observed from the spectrum contour plot. The feature indexes which holds the spectrum information of α , β and γ bands are visualized in the parallel coordinate plots and they describes the separability of the classes in these selected bands. The swamp plot for both the subjects shows exact computational

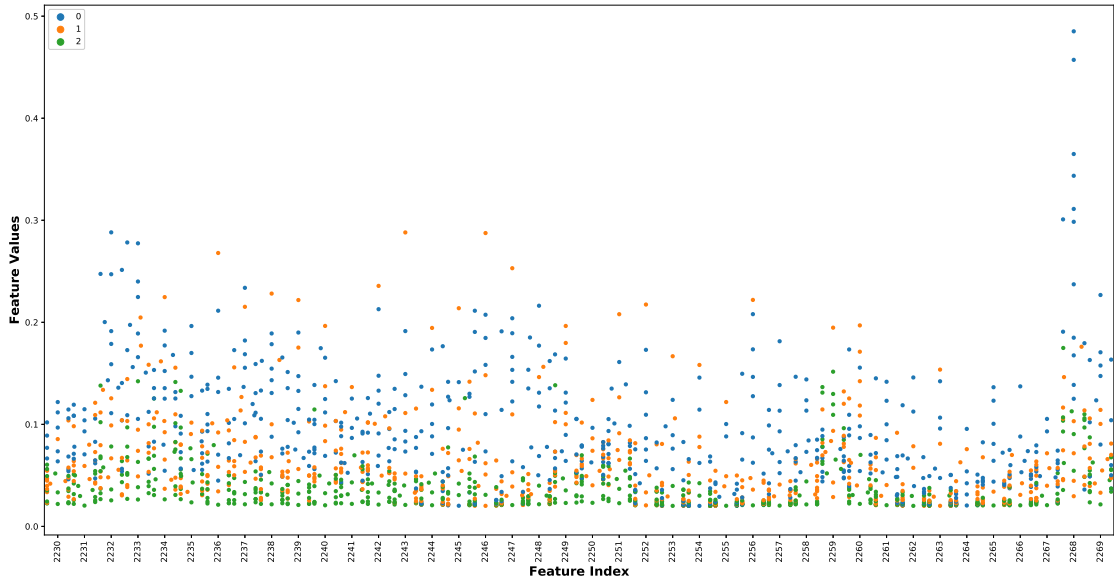


Figure 6.27: Swarm Plot visualization for subject 11 considering all 62 channels: feature index 2220 to 2270

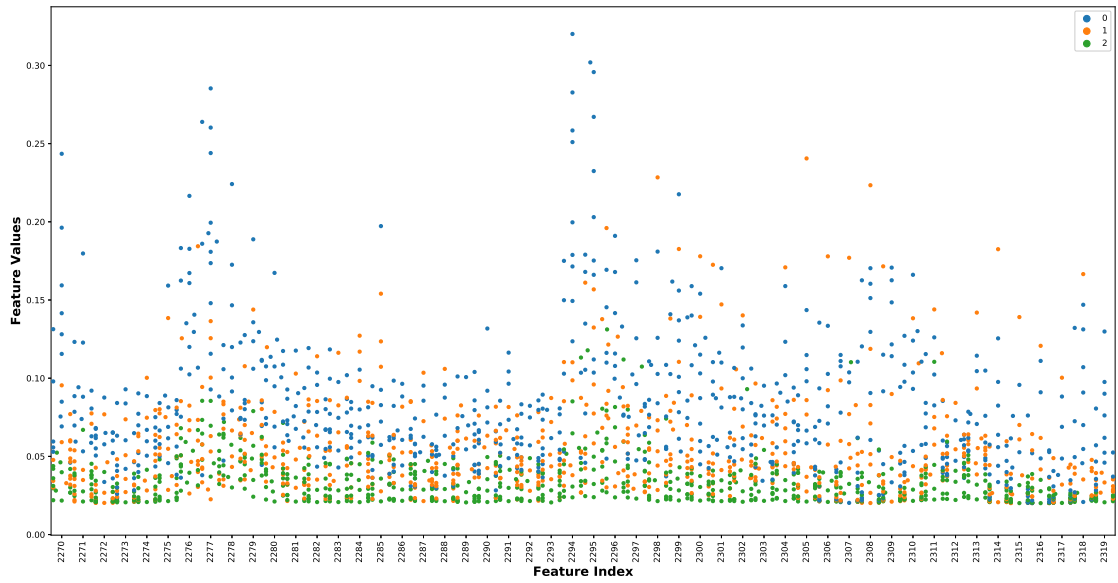


Figure 6.28: Swarm Plot visualization for subject 11 considering all 62 channels: feature index 2270 to 2320

points used by the MLP network in these regions. For subject 11, feature data in the index bands of 100 to 120, 150 to 170 and 200 to 240 show very good classes separability, as they significantly varies with amplitude. For subject 15 feature data in the index band of 120 to 140, 140 to 160 and 170 to 200 demonstrate similar behaviour.

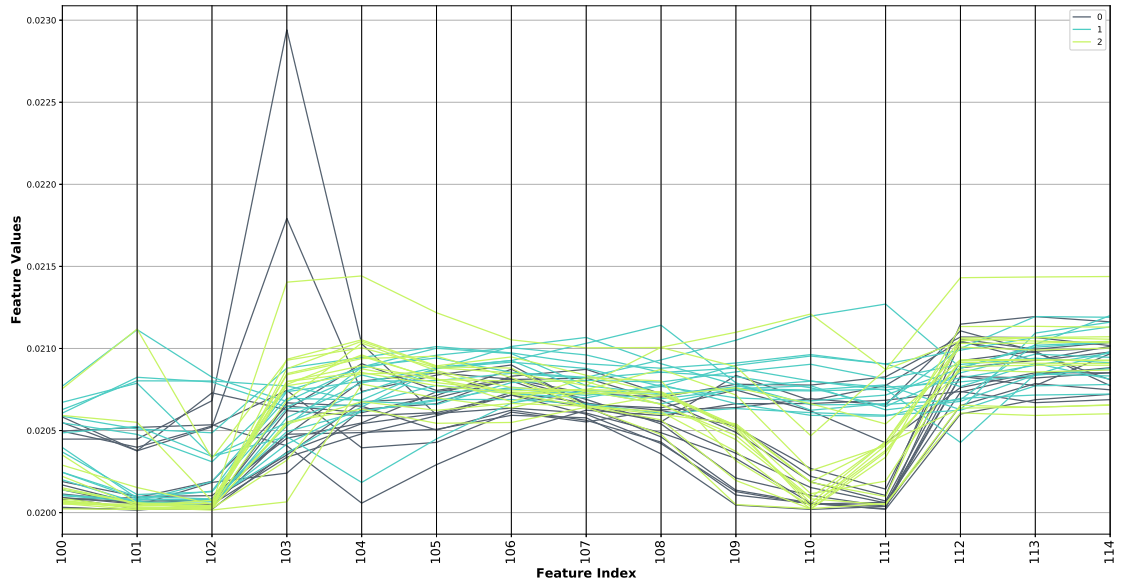


Figure 6.29: Parallel coordinate visualization for subject 5 considering all 62 channels: feature index 100 to 115

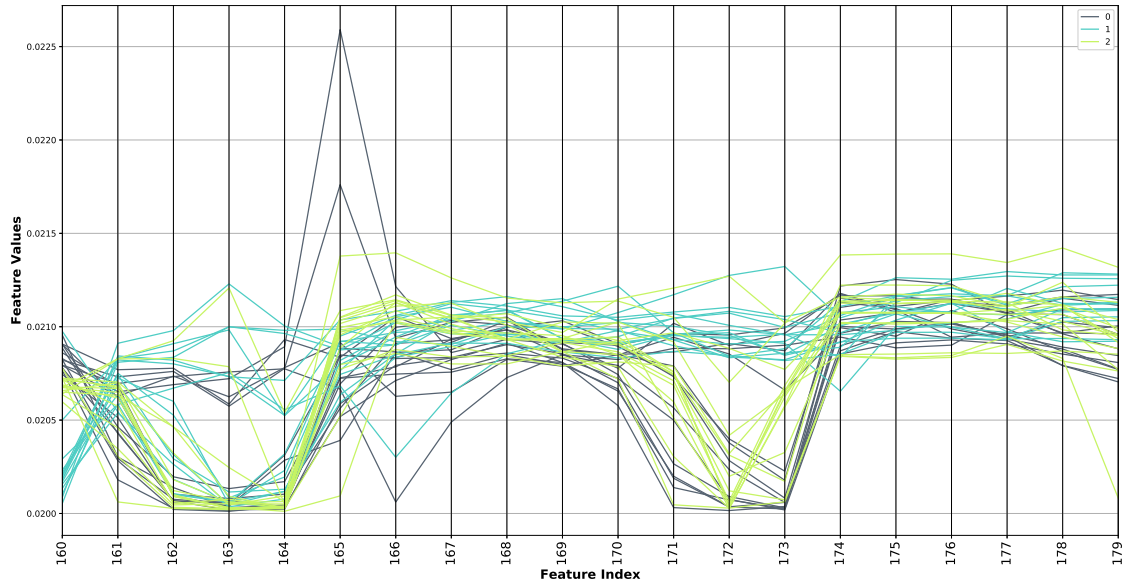


Figure 6.30: Parallel coordinate visualization for subject 5 considering all 62 channels: feature index 160 to 180

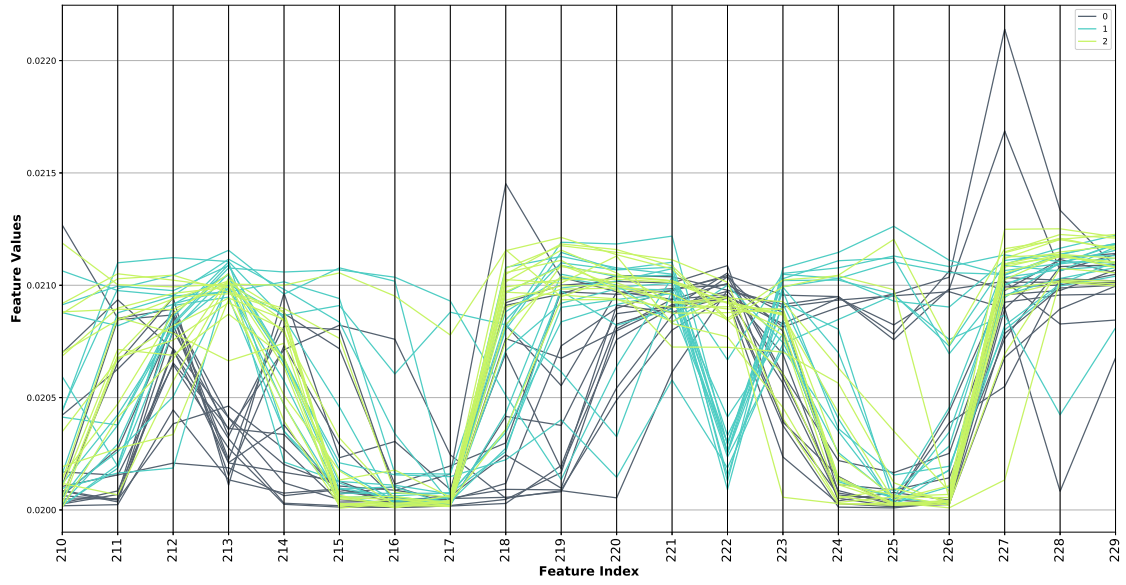


Figure 6.31: Parallel coordinate visualization for subject 5 considering all 62 channels: feature index 210 to 230

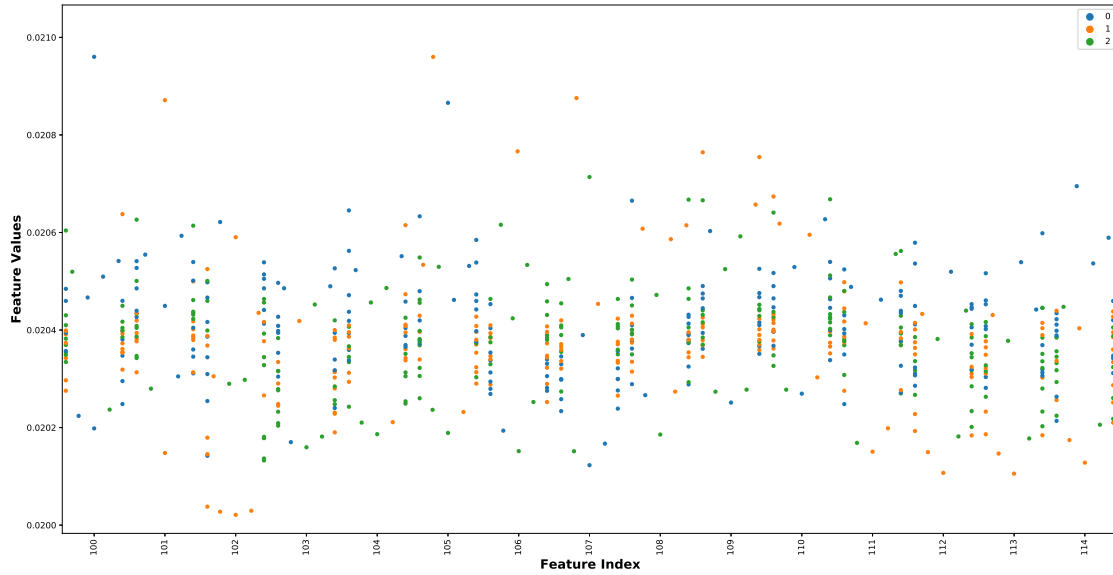


Figure 6.32: Swarm Plot visualization for subject 5 considering all 62 channels: feature index 100 to 115

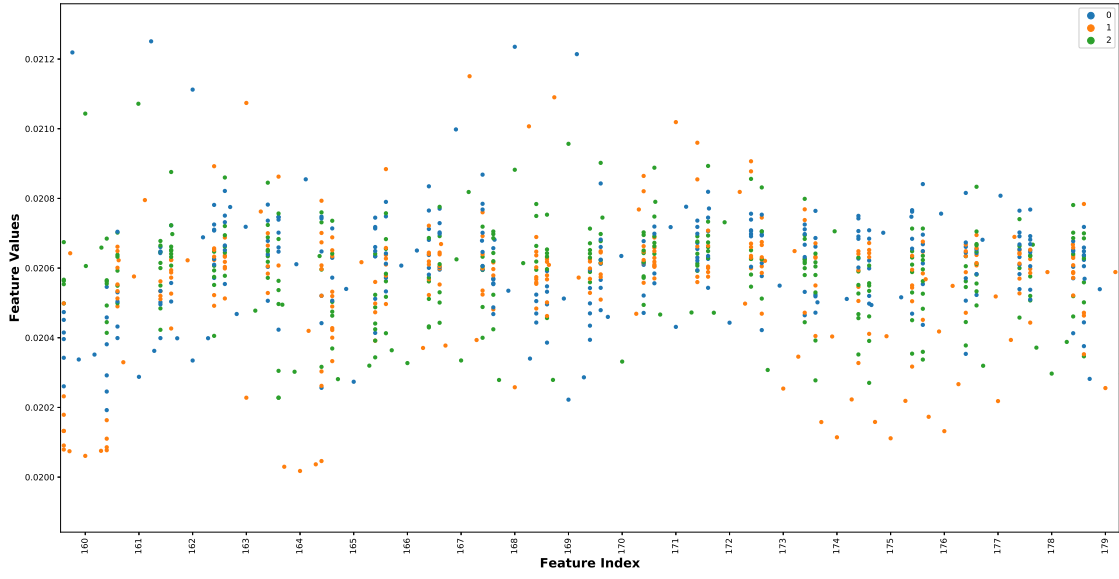


Figure 6.33: Swarm Plot visualization for subject 5 considering all 62 channels:
feature index 160 to 180

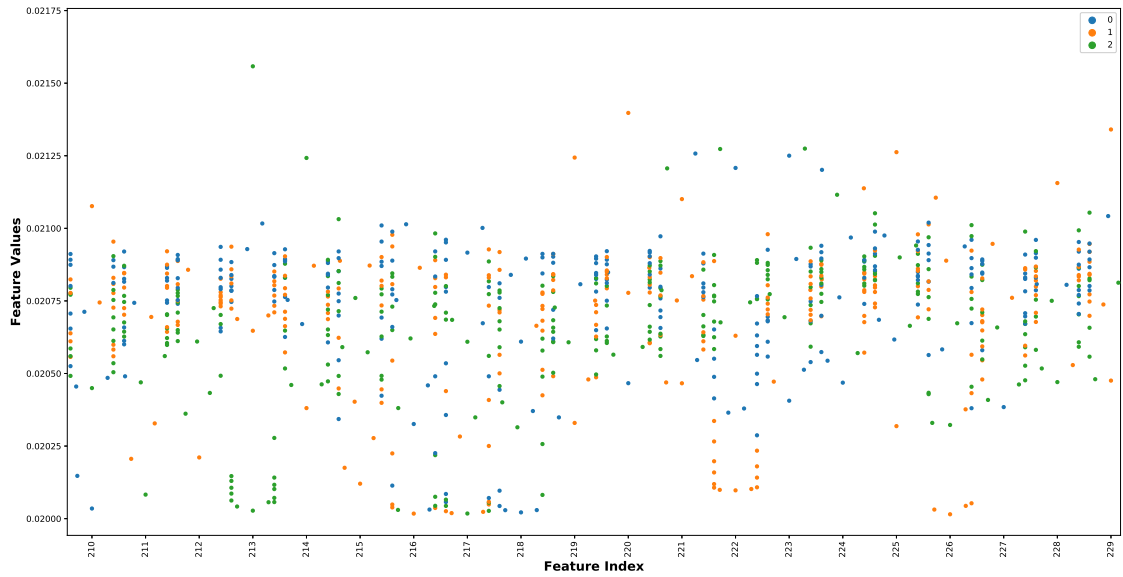


Figure 6.34: Swarm Plot visualization for subject 5 considering all 62 channels:
feature index 210 to 230

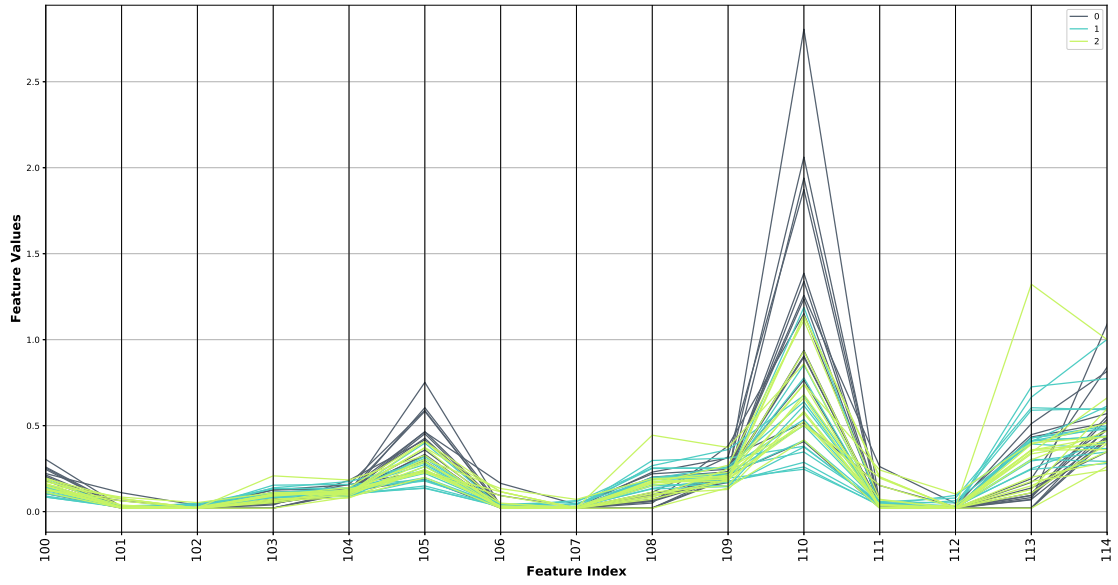


Figure 6.35: Parallel coordinate visualization for subject 5 after excluding the corrupt channels prior to channel reduction: feature index 100 to 115

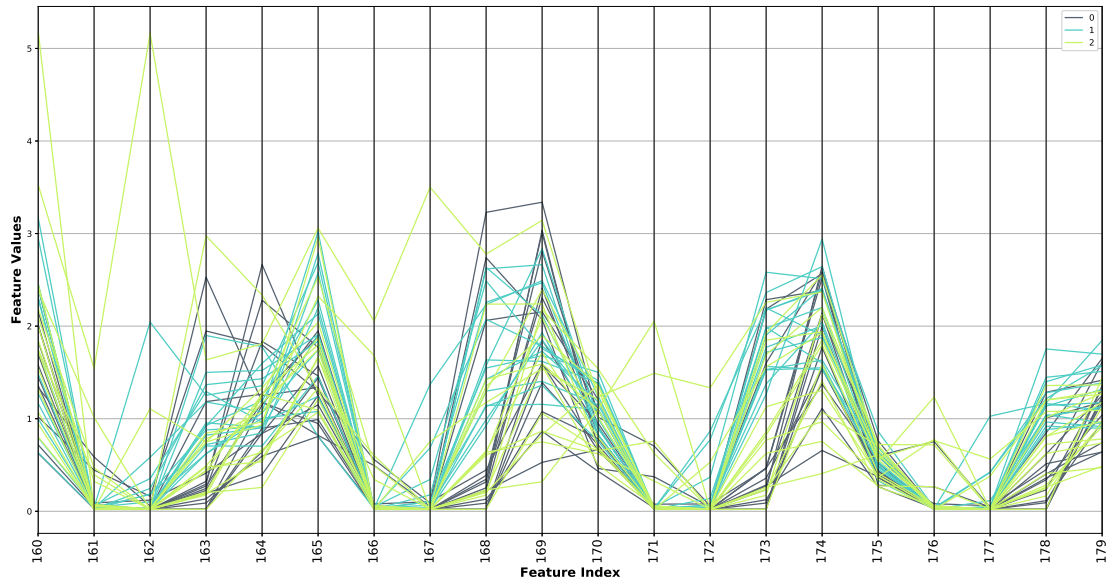


Figure 6.36: Parallel coordinate visualization for subject 5 after excluding the corrupt channels prior to channel reduction: feature index 160 to 180

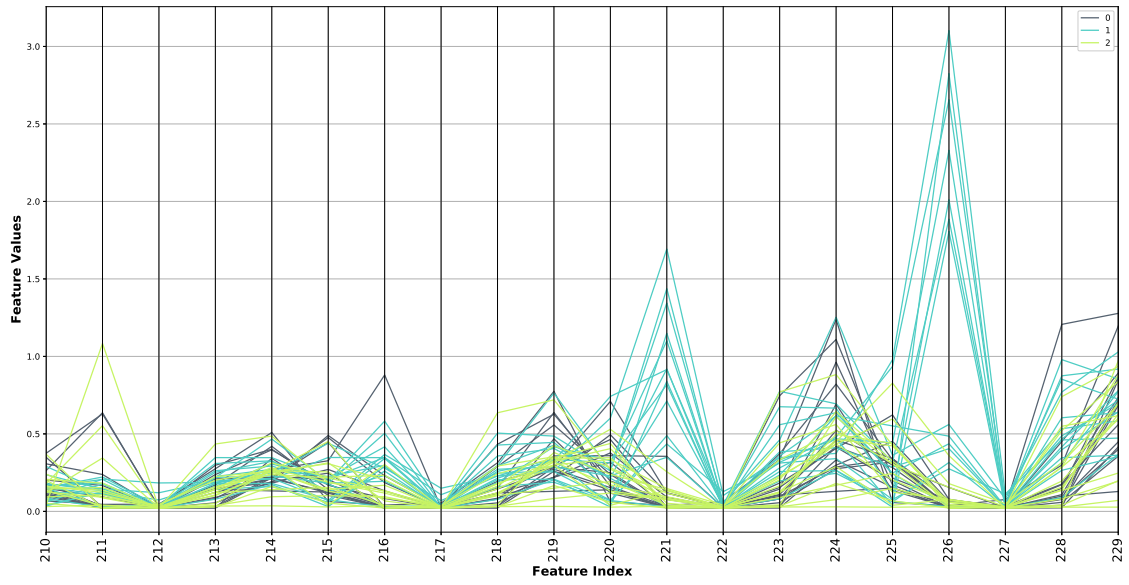


Figure 6.37: Parallel coordinate visualization for subject 5 after excluding the corrupt channels prior to channel reduction: feature index 210 to 230

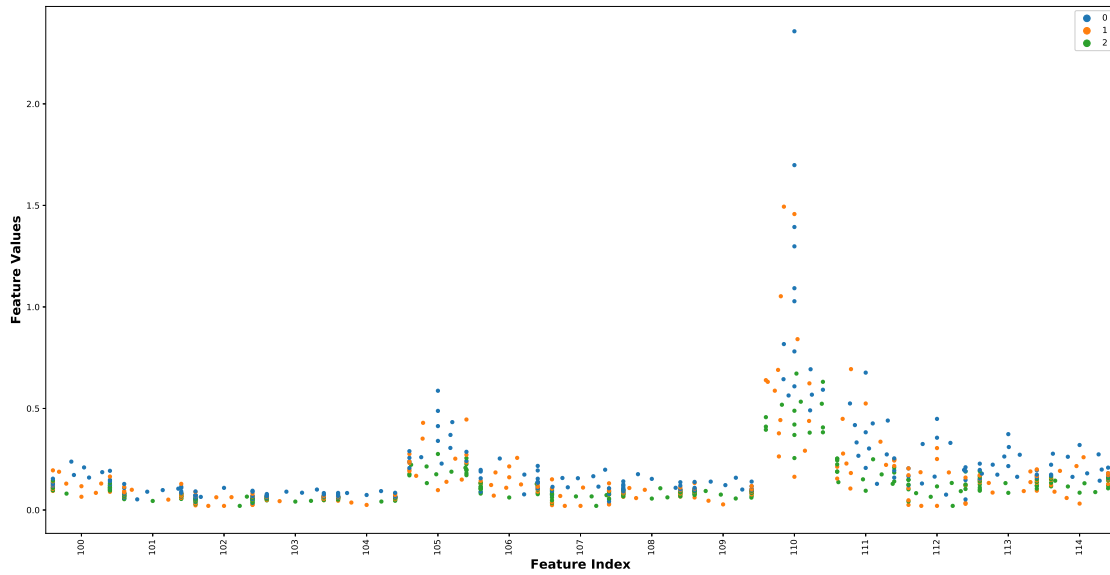


Figure 6.38: Swarm Plot visualization for subject 5 after excluding the corrupt channels prior to channel reduction: feature index 100 to 115

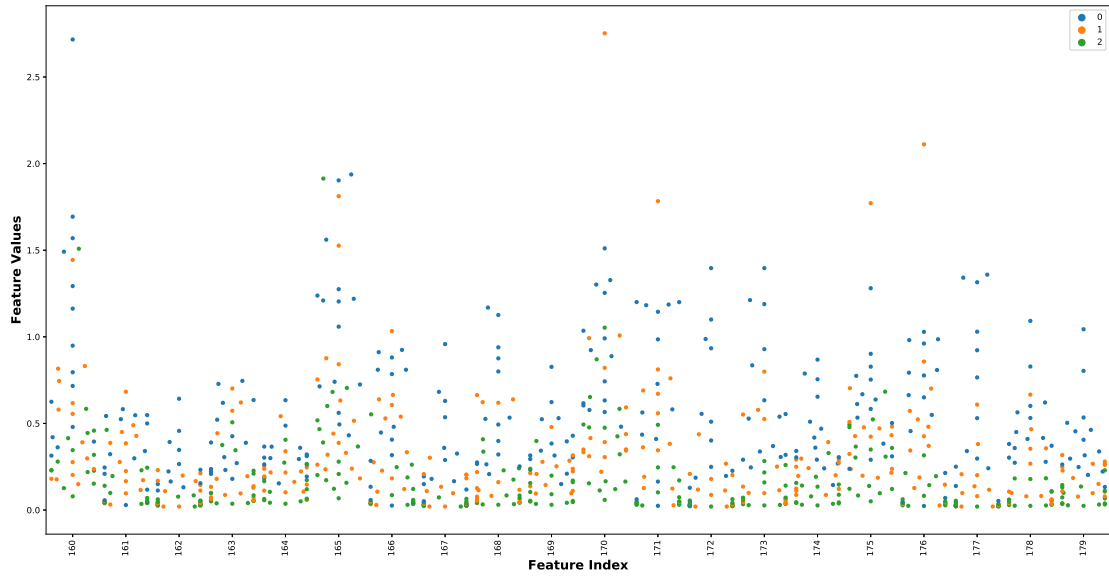


Figure 6.39: Swarm Plot visualization for subject 5 after excluding the corrupt channels prior to channel reduction: feature index 160 to 180

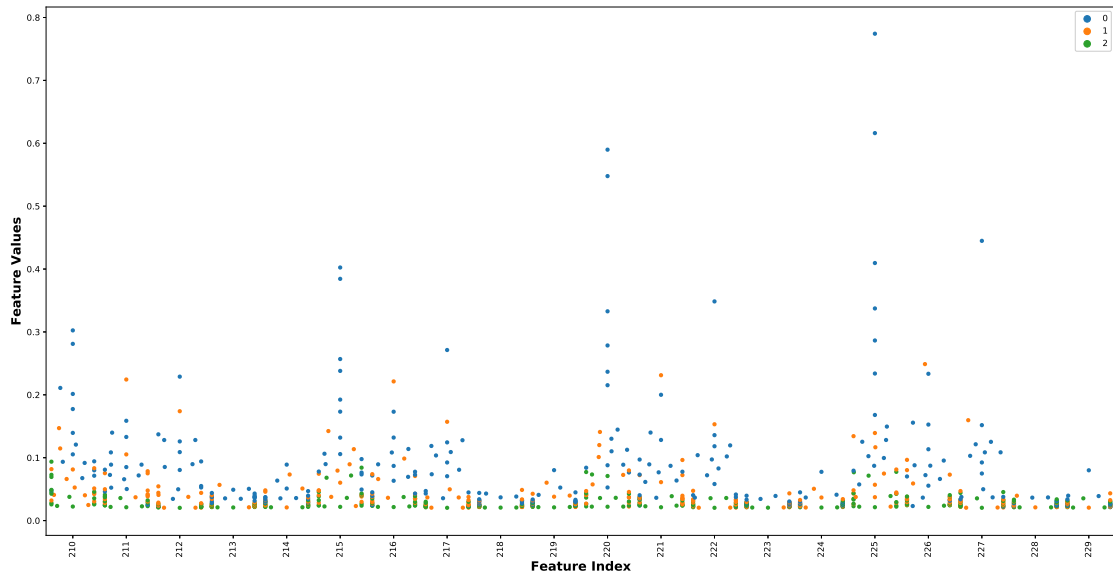


Figure 6.40: Swarm Plot visualization for subject 5 after excluding the corrupt channels prior to channel reduction: feature index 210 to 230

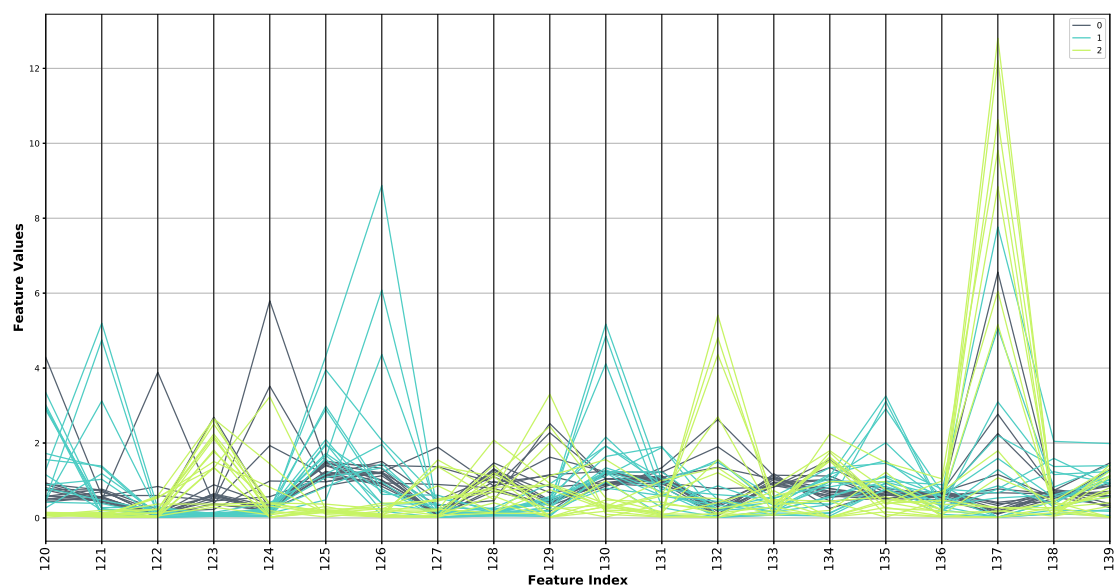


Figure 6.41: Parallel coordinate visualization for subject 15 without excluding the corrupt channels prior to channel reduction: feature index 120 to 140

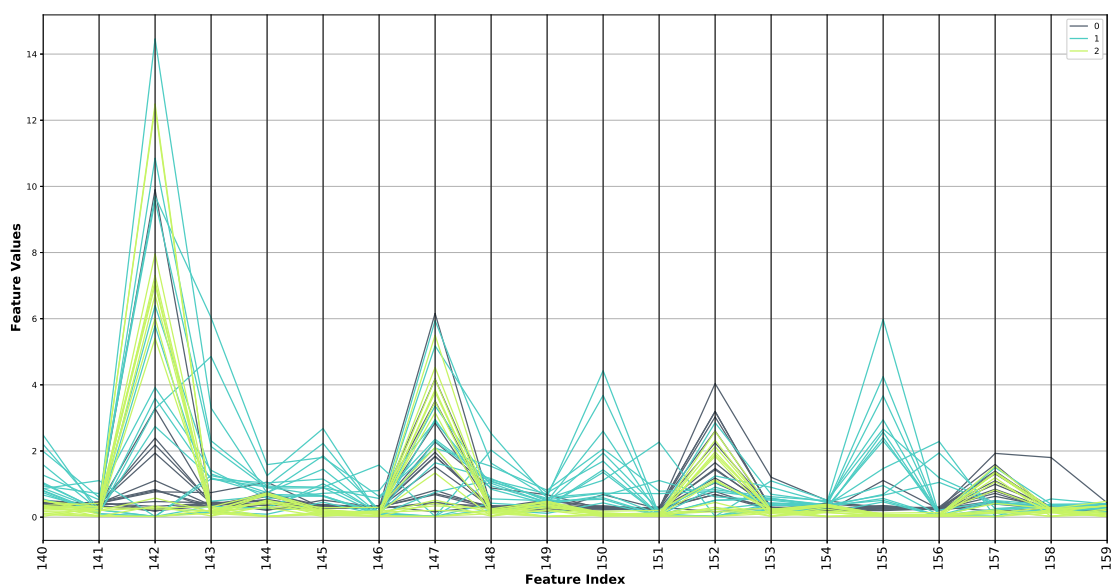


Figure 6.42: Parallel coordinate visualization for subject 15 without excluding the corrupt channels prior to channel reduction: feature index 140 to 160

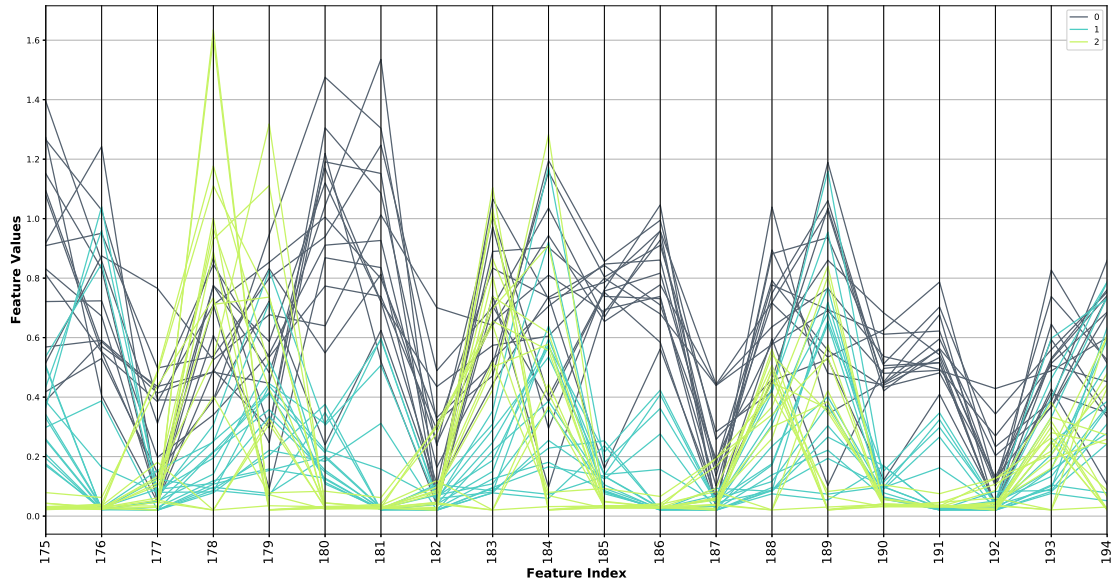


Figure 6.43: Parallel coordinate visualization for subject 15 without excluding the corrupt channels prior to channel reduction: feature index 175 to 195

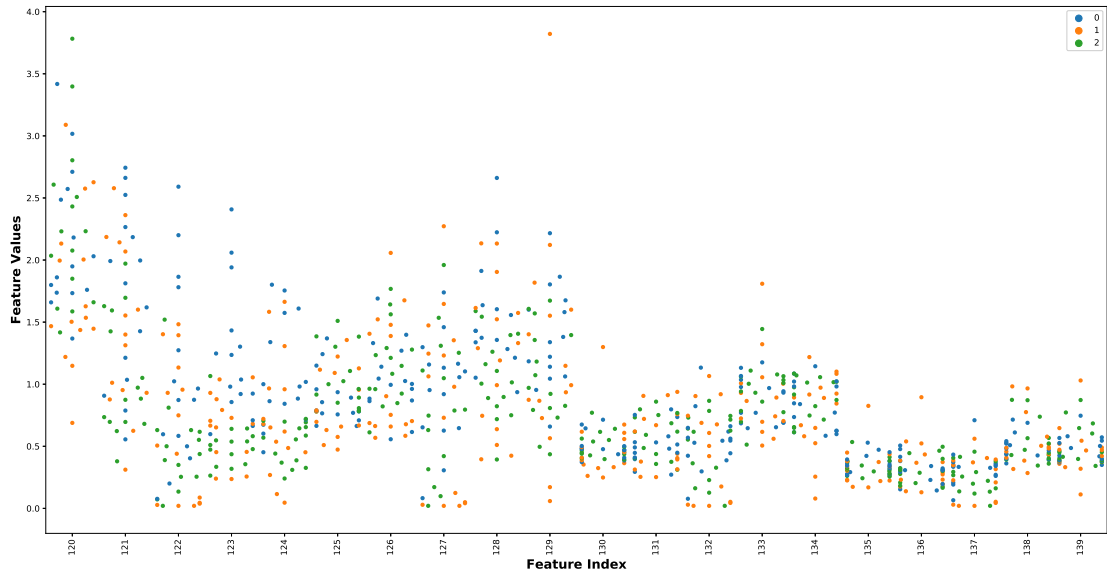


Figure 6.44: Swarm Plot visualization for subject 15 without excluding the corrupt channels prior to channel reduction: feature index 120 to 140

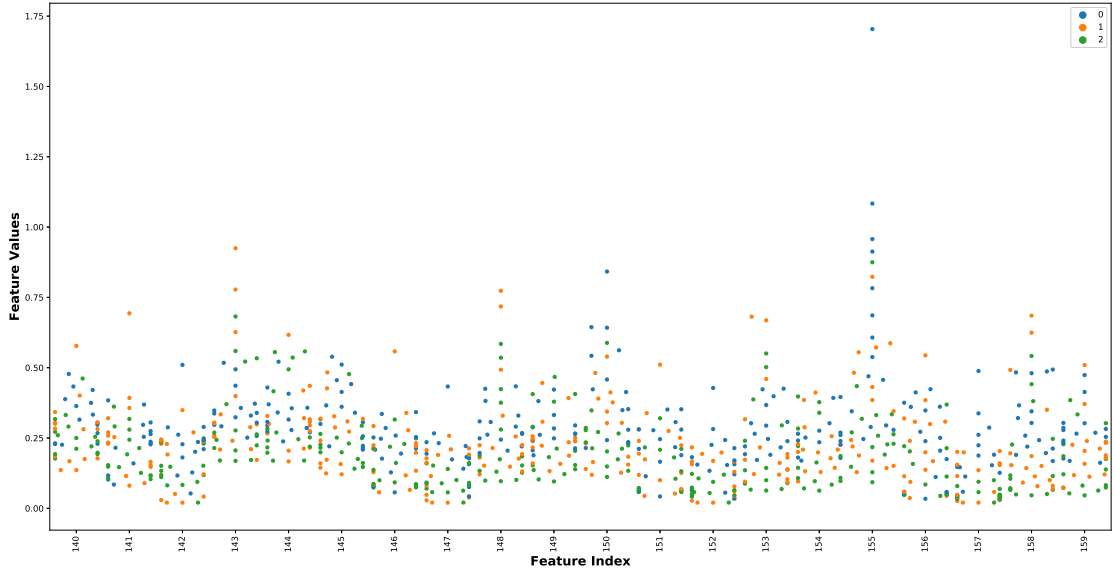


Figure 6.45: Swarm Plot visualization for subject 15 without excluding the corrupt channels prior to channel reduction: feature index 140 to 160

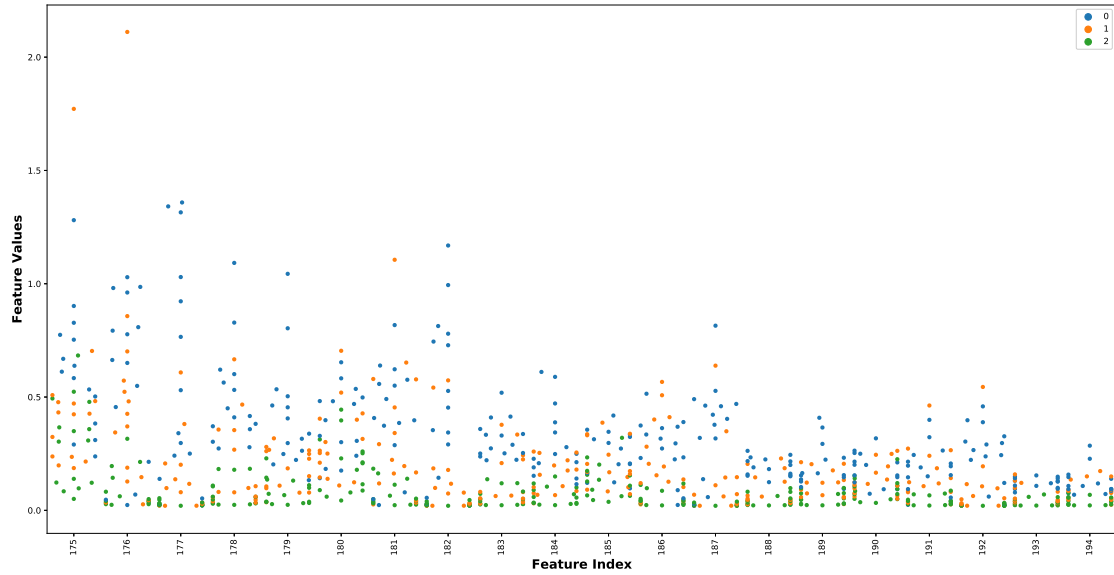


Figure 6.46: Swarm Plot visualization for subject 15 without excluding the corrupt channels prior to channel reduction: feature index 175 to 195

6.8 Activation Pattern with Neural Stimulation

Figure 6.47, figure 6.47, and figure 6.47 represents EEG topographies for three distinct emotional classes. It can be observed, the neural activation pattern varies with targeted evoke. Negative states demonstrate high neural activation across all regions. On the contrary, topographies from the neutral and positive classes demonstrate similar neural activation maps.

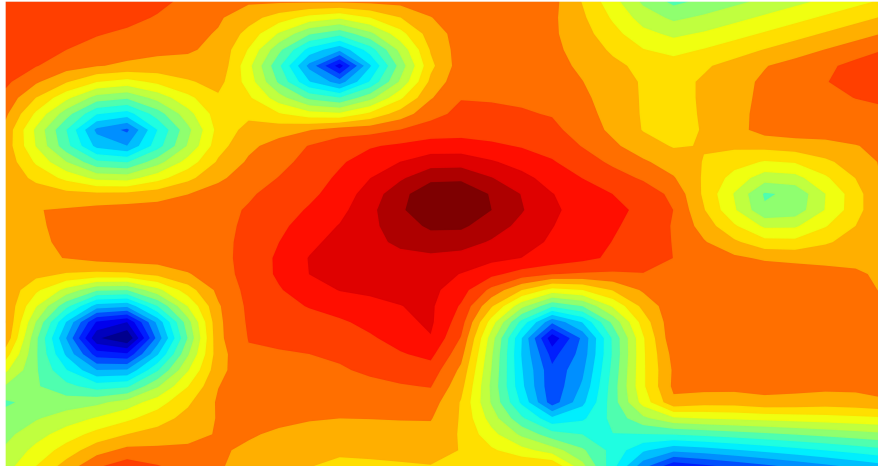


Figure 6.47: Neural activation topography of an arbitrary trial representing negative state from subject 15

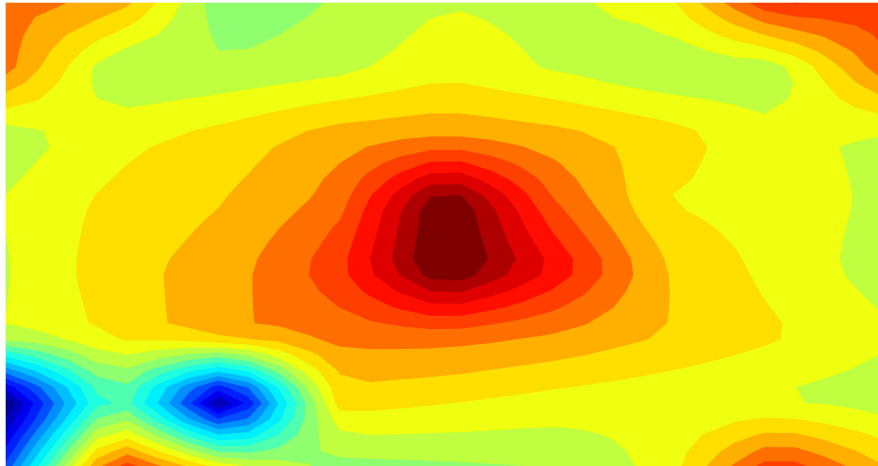


Figure 6.48: Neural activation topography of an arbitrary trial representing neutral state from subject 15

The topographies illustrates that, in terms of both positive and neutral states the central regions exhibits high neural activity. On the other hand, for the negative state prefrontal, frontal, parietal, occipetal and central regions exhibits high neural activity.

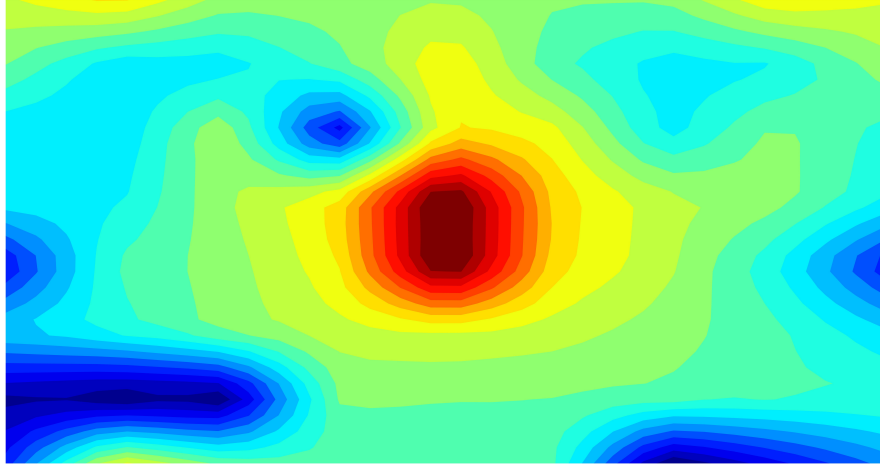


Figure 6.49: Neural activation topography of an arbitrary trial representing positive state from subject 15

Figure 6.47, figure 6.47, and figure 6.47 represents EEG topographies for three distinct emotional classes. It can be observed, the neural activation pattern varies with targeted evoke. Negative states demonstrate high neural activation across all regions. On the contrary, topographies from the neutral and positive classes demonstrate similar neural activation maps.

The attributes of the targeted evokes are mainly responsible for such similarities. During the acquisition phase, film clips were shown to participants which evoked single targeted emotion. For the neutral and positive states, the demonstrated film clips were similar in genre. Due to such similar evoke types, these two classes demonstrated similar topography. The topographies explain network performance in terms of predicting each class. Due to such similarities F1 scores for neutral and positive class were lower than the F1 scores for negative class.

6.9 Comparison of results with existing researches

Comparing with existing high performance classification techniques on this particular SEED dataset, our 97% and 97.4% subject dependent classification accuracy on MLP and Hybrid LSTM-MLP networks suggest that the proposed MUSIC model can be considered state of the art for such feature extraction task. Table 6.5 makes detailed comparison with existing works. M.A Rahman et al. [117] explores Welch based brain topography for feature extraction and CNN for classification task, which achieved around 94% accuracy. M.A.Rahman et al. also used exact same signal preprocessing techniques that are followed in this research but used non-parametric Welch model for feature extraction. A. Bhattacharyya et al. [112] explored modified wavelet based decomposition for feature extraction and auto-encoder based random forest for classification, this particular approach also achieved accuracy level of around 94%. W. Zheng et al. [54] used parametric PSD estimation models and F. Wang et al. [106] used STFT for emotional feature extraction task which achieved 86.65% and 90.5% accuracy, respectively. As it is evident from the comparison,

our proposed approach achieves significant improvement. Additionally, none of the existing researches made any investigation which consider the corrupt channels.

Author and Research	Feature Extraction Method	Classification Method	Average Accuracy
Jin et al. [50]	Differential Entropy	Domain Adaptive Network	79.19%
W. L. Zheng et al. [71]	Differential Entropy	Disciminative Graph Regularization	79.28%
W. L. Zheng et al [40]	Critical Frequency Band Investigation	Deep Belief Network	86.08%
Y. Yang[66]	Differential Entropy	Hierarchical Network	86.42%
M.A.Rahman et al.[100]	PCA and non-parametric Welch model	Artificial Neural Network	86.57%
W. Zheng et al.[54]	Non-parametric Model	Group Sparse Canonical Correlation Analysis	86.65%
Y. Luo et al.[60]	Data augmentation approach	Generative adversarial network	87%
X. Wu et al.[83]	Connectivity Network	SVM	87%
F. Yang et al.[84]	High dimensional features	ST-SBSSVM	89%
F. Wang et al.[106]	STFT	CNN	90.59%
W. Zheng et al.[86]	Differential Entropy	Discriminative graph regularized	91%
A. Bhattacharyya et al.[112]	Wavelet based decomposition	Random Forest (Autoencoder based)	94.4%
M.A.Rahman et al.[117]	Welch topographic map	CNN	94.63%
Proposed Method	MUSIC model (Includes all 62 channels)	MLP network Hybrid LSTM-MLP network	97% 97.4%
Investigated Method (No prior investigation exist)	MUSIC model (Excludes corrupt channels)	MLP network Hybrid LSTM-MLP network	86.53% 85.07%

Table 6.5: Performance comparison with existing researches on emotional state classification for the SEED dataset

As discussed previously the dataset contains a large number of trials, which holds multiple corrupt/ overshooting channels. These overshooting channels were ignored in previous researches on this dataset. Nevertheless, due to the existence of these particular channels in the feature space the network will demonstrate biasness. Such biasness will affect network performance on an external dataset, which does not hold such flawed channels. Thereby these specific channels should be excluded prior to feature extraction. Our investigated approach of removing these specific channels prior to constructing the feature space has demonstrated 86.53% accuracy on the network. This article is the first research to observe such extensive flaws in the SEED dataset.

6.10 Computation Time Analysis

Fig 6.50 illustrates computation time for MUSIC model and non-parametric model based feature extraction task, along with execution time for both of the signal pre-processing methods investigated in this research. The computation time varies intensively with the length of targeted matrix and across machine specifications. Each of the task were executed in a intel CORE-i5 processor with 32 GB DDR4 RAM, 512GB SSD Memory and 4 GB NVIDIA GEFORCE GTX 960M graphics card. The length of each trial were duly considered for the computation time analysis. Table 6.6 summarizes the run time analysis.

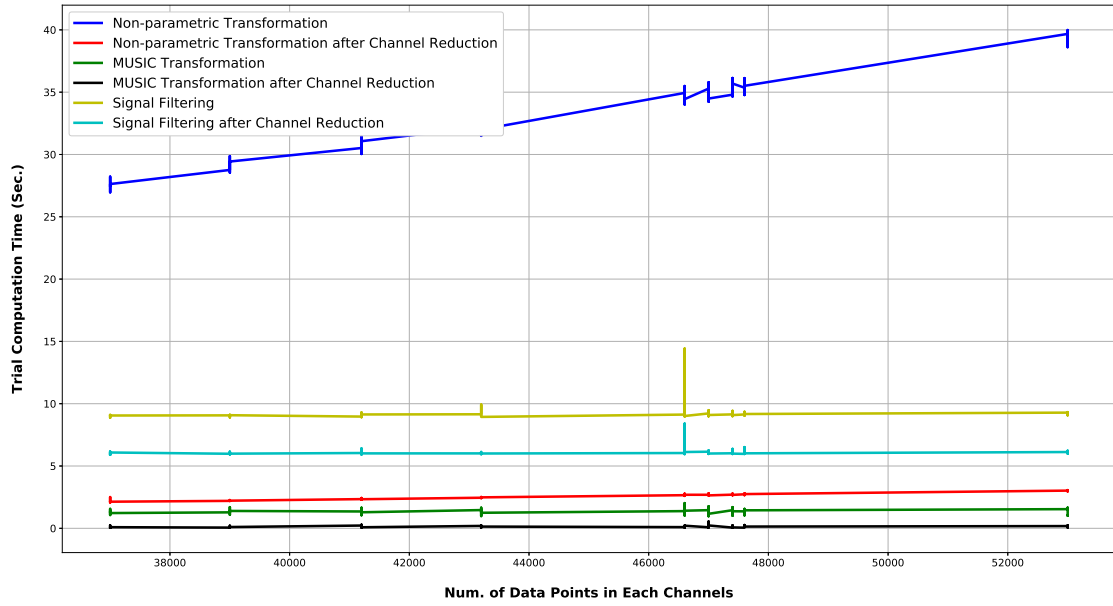


Figure 6.50: Run time comparison of various methods for multi channel EEG pre-processing and feature extraction tasks

Trial dimension	Channel length(N)	Welch (sec)	MUSIC (sec)	Optimization %
$62 \times N$	below 40000	28.30 (sec.)	1.32 (sec.)	95.33 %
	40000 to 45000	31.09 (sec.)	1.35 (sec.)	95.65 %
	45000 to 50000	35.05 (sec.)	1.38 (sec.)	96.07 %
	50000 to 55000	39.36 (sec.)	1.39 (sec.)	96.47 %
$5 \times N$	below 40000	2.37 (sec.)	0.12 (sec.)	94.94 %
	40000 to 45000	2.46 (sec.)	0.14 (sec.)	94.31 %
	45000 to 50000	2.64 (sec.)	0.13 (sec.)	95.07 %
	50000 to 55000	2.79 (sec.)	0.13 (sec.)	95.34 %

Table 6.6: Investigated computation time meta data for non-parametric feature extraction method (Welch model) vs MUSIC model

From fig 6.50 it is eminent that, non-parametric feature extraction techniques are computation heavy. Though the pre-processing techniques which considers all 62 channels enhances the quality of feature space, the technique is computationally expensive. MUSIC spectrum exhibits far greater superiority in terms of computation time. Even for a full 62 channel trial the computation time was investigates near 1.3 sec., on the contrary the non-parametric estimation models required around 28 sec. to 40 sec in a prioritized thread. As per table 6.6 illustrates, MUSIC model can optimize computation time for feature extraction tasks around 94% to 96%. With PCA based pre-processing approach, the feature extraction time is just around 0.1 seconds. The results from the computation time analysis suggests that, with implementation of MUSIC model along with PCA based pre-processing techniques EEG based BCI system can achieve comparatively real time performance.

Chapter 7

Conclusion

Owing to the complexity in implementing MUSIC algorithm for random signals, the algorithm is rarely investigated in feature extraction tasks for neural signals. In this research we investigated the performance of MUSIC algorithm in neural information processing by implementing MUSIC model based feature extraction method for emotional state recognition task from multi-channel EEG recordings. With a Hybrid LSTM-MLP network, the MUSIC model generated feature space achieves state of the art 97.4% accuracy on the SEED emotional dataset. Our investigation also finds that significant number of trials in the SEED dataset hold corrupt or overshooting channels which were previously overlooked and we have also investigated the effects of these channels on subject dependent classification task. We achieved a subject dependant emotional state classification accuracy of 86.53% after excluding these specific channels. We then compared the quality of the MUSIC model generated feature space with feature space generated implementing conventional methods. Additionally in this paper we also explored a data augmentation technique particularly for the SEED dataset, which may be further investigated for improving the performance of both subject dependant and subject independent classification tasks. Finally our computation time analysis of various methods illustrates that, MUSIC model can optimize 94% to 95% run time in similar feature extraction tasks. Such findings suggest that MUSIC algorithm has great prospect in real time BCI applications.

Appendix A Repository For EEG Feature Extraction Module

The MUSIC based feature extraction module is developed for Matlab. The code-based uses modular architecture and can be applied on any EEG dataset for feature extraction task. The module can handle different number of channels (works for 62 channels/32 channels and 16 channels EEG signals).

```
Transforming : D:\Thesis\Seed_Dataset\Subject 1\  
.....  
.....  
run_transform_subject_func = function_handle with value:  
    @run_transform_subject  
run_transform_directory_func = function_handle with value:  
    @run_transform_directory  
Transforming : D:\Thesis\Seed_Dataset\Subject 1\Negative\  
.....  
Transforming Files from : D:\Thesis\Seed_Dataset\Subject 1\Negative\  
.....  
Iteration 1 of 15 running.  
.....  
get_feature_matrix_func = function_handle with value:  
    @get_feature_matrix  
reading files from : neg_1.mat  
neg_1.mat : Extracting Principal Components and Filtering Signal...  
neg_1.mat : Completed Extraction and Filtering in 26.5142sec  
neg_1.mat : Computing Welch Spectrum...  
neg_1.mat : Completed Welch Computation in 3.7724sec  
neg_1.mat : Computing Music Spectrum...  
neg_1.mat : Completed Music Computation in 0.56592sec  
neg_1.mat : Generating Feature Matrixes...  
neg_1.mat : Saving Matrixes...&...Gathering Meta Data  
neg_1.mat : Transformation Ended Successfully  
.....  
Iteration 2 of 15 running.  
.....  
get_feature_matrix_func = function_handle with value:  
    @get_feature_matrix  
reading files from : neg_10.mat  
neg_10.mat : Extracting Principal Components and Filtering Signal...  
neg_10.mat : Completed Extraction and Filtering in 7.6112sec  
neg_10.mat : Computing Welch Spectrum...  
neg_10.mat : Completed Welch Computation in 4.041sec  
neg_10.mat : Computing Music Spectrum...  
neg_10.mat : Completed Music Computation in 0.26178sec  
neg_10.mat : Generating Feature Matrixes...  
neg_10.mat : Saving Matrixes...&...Gathering Meta Data  
neg_10.mat : Transformation Ended Successfully  
.....  
Iteration 3 of 15 running.  
.....  
get_feature_matrix_func = function_handle with value:  
    @get_feature_matrix  
reading files from : neg_11.mat  
neg_11.mat : Extracting Principal Components and Filtering Signal...  
neg_11.mat : Completed Extraction and Filtering in 8.204sec  
neg_11.mat : Computing Welch Spectrum...  
neg_11.mat : Completed Welch Computation in 4.196sec  
neg_11.mat : Computing Music Spectrum...  
neg_11.mat : Completed Music Computation in 0.20776sec  
neg_11.mat : Generating Feature Matrixes...  
neg_11.mat : Saving Matrixes...&...Gathering Meta Data  
neg_11.mat : Transformation Ended Successfully  
.....  
Iteration 4 of 15 running.  
.....  
get_feature_matrix_func = function_handle with value:
```

Figure 7.1: Sample Log 1

Github Repository

The github repository have been made public [here](#).

```
Iteration 13 of 15 running.
.....
get_feature_matrix_func = function_handle with value:
    @get_feature_matrix
reading files from : neg_7.mat
neg_7.mat : Extracting Principal Components and Filtering Signal...
neg_7.mat : Completed Extraction and Filtering in 8.5sec
neg_7.mat : Computing Welch Spectrum...
neg_7.mat : Completed Welch Computation in 3.389sec
neg_7.mat : Computing Music Spectrum...
neg_7.mat : Completed Music Computation in 0.23126sec
neg_7.mat : Generating Feature Matrixes...
neg_7.mat : Saving Matrixes...&...Gathering Meta Data
neg_7.mat : Transformation Ended Successfully
.....
Iteration 14 of 15 running.
.....
get_feature_matrix_func = function_handle with value:
    @get_feature_matrix
reading files from : neg_8.mat
neg_8.mat : Extracting Principal Components and Filtering Signal...
neg_8.mat : Completed Extraction and Filtering in 7.9218sec
neg_8.mat : Computing Welch Spectrum...
neg_8.mat : Completed Welch Computation in 4.6427sec
neg_8.mat : Computing Music Spectrum...
neg_8.mat : Completed Music Computation in 0.17501sec
neg_8.mat : Generating Feature Matrixes...
neg_8.mat : Saving Matrixes...&...Gathering Meta Data
neg_8.mat : Transformation Ended Successfully
.....
Iteration 15 of 15 running.
.....
get_feature_matrix_func = function_handle with value:
    @get_feature_matrix
reading files from : neg_9.mat
neg_9.mat : Extracting Principal Components and Filtering Signal...
neg_9.mat : Completed Extraction and Filtering in 7.9039sec
neg_9.mat : Computing Welch Spectrum...
neg_9.mat : Completed Welch Computation in 3.9025sec
neg_9.mat : Computing Music Spectrum...
neg_9.mat : Completed Music Computation in 0.12484sec
neg_9.mat : Generating Feature Matrixes...
neg_9.mat : Saving Matrixes...&...Gathering Meta Data
neg_9.mat : Transformation Ended Successfully
.....
Total transformation time for the directory : 3.3666 minutes.
.....
.....
Transforming : D:\Thesis\Seed_Dataset\Subject 1\Neutral\
.....
Transforming Files from : D:\Thesis\Seed_Dataset\Subject 1\Neutral\
.....
Iteration 1 of 15 running.
.....
get_feature_matrix_func = function_handle with value:
    @get_feature_matrix
```

Figure 7.2: Sample Log 2

7.1 Documentation for the Repository

In-detailed documentation for the repository and how each module is designed are discussed here.

7.1.1 Scripts and how they work

There are total of 7 ".mlx" scripts each holds functions for performing separate tasks and all of them reusable for any EEG dataset. The main script for running the repo is: "*transform_dataset.mlx*".

"transform_dataset.mlx", *"transform_directory.mlx"* and *"transform_subject.mlx"* script for navigating through the dataset directory. As per the dataset directory architecture and location, these scripts are required minor modifications.

"make_one_file.mlx" pre processes a single EEG trial (or file). It uses functions from *"extract_channels_script.mlx"* for reducing the number of channels with Principal Component Analysis and functions from *"spectrum_transformation_script.mlx"* for getting transformed spectrum matrices with multiple parametric and non-parametric methods.

The *"spectrum_transformation_script.mlx"* can be modified to add additional spectrum transformation methods. The *"extract_channels_script.mlx"* uses *"filter_signal_matrix_script.mlx"* for FIR and IIR filtering task. Filtering tasks is computation intensive with overlapping windows and higher orders, that's why to optimize the process relevant channels are extracted first before filtering. After extracting the channels, each *"Prefrontal"*, *"Frontal"*, *"Central"*, *"Parietal"* and *"Occipital"* bands are reduced with Principal Component Analysis. Each section of the scripts are written by following modular architecture and are reusable with minor modification.

7.1.2 Output

The repo extracts 5×124 dimensional parametric MUSIC and non-parametric Welch spectrum features from each $62 \times N$ dimensional EEG trials. It also generates an excel sheet holding meta data for computational time for each task. Figure 7.1 and figure 7.2 demonstrates sample log file for the repo.

7.1.3 Targeted Dataset

The repo is aimed to transform the SEED dataset for emotion recognition. The dataset holds 675 trials of three classes (Negative State, Neutral State, Positive State) for 15 subjects. The acquisition has been performed with a 62 electrode EEG headset. Details documentation is available [here](#).

Appendix B Repository for 3D Time Series Visualization of Multichannel EEG Dataset

Visualizing the dataset before starting analysis helps in many ways. For example; this code base visualize each trial ($62 \times N$ Dimensions) of the SEED EEG dataset. The 3D contour plots tells a lot about the dataset. It shows most of the trial contains corrupted channels, they demonstrate signals which exceeds the EEG voltage band (generally it the voltage band lies within micro volt range). Notably these corrupted overshooting channels lies mostly in "*Occipetal*" bands. All generated 3D images are available [here](#). Additionally, these channels are not affected by eye blinking activity (as eye blinking incidents were handled and matlab 1 dimensional plots for the channel demonstrates unique wave patterns). Such findings have effected the methodology of the research by opening new dimesions for exploration.

7.2 Github Repository

The github repository have been made open source and available [here](#).

7.3 Scripts

The "*run_analysis.py*" is the main script to generate and save 675 3d plots for the "SEED" multichannel EEG dataset. The "*Dataset_Analysis_Class*" needs to be modified as per the targeted dataset. The "*Mat_File*" class is for reading multichannel EEG matlab data files and generate required parameters for plotting. The "*Subject_Class*" and "*Dir_Class*" handles the plotting of each subject for the dataset.

Spectrum 3D contour plots, feature space parallel coordinate plots, swamp plots and 3D PCA plots for the whole dataset can be generated by extending the following three classes; "*Mat_File*", "*Dir_Class*" and "*Subject_Class*".

7.4 Required Libraries

mpl_toolkits.mplot3d, matplotlib, seaborn, scipy.io, numpy, pandas, os.

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