Networks-based brain computer interfaces for decoding neurophysiological dynamics

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**NETWORKS-BASED BRAIN COMPUTER
INTERFACES FOR DECODING
NEUROPHYSIOLOGICAL DYNAMICS**

TUSHAR CHOUHAN

**SCHOOL OF COMPUTER SCIENCE AND
ENGINEERING**

2019

Networks-based Brain Computer Interfaces for Decoding Neurophysiological Dynamics

Tushar Chouhan

School of Computer Science and Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirements for the degree of
Doctor of Philosophy

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Prof. Cuntai Guan

Authorship Attribution Statement

This thesis contains materials from three papers published and one paper submitted in the following peer-reviewed journal and papers accepted at conferences in which I am listed as an author.

Chapter 3 is published as

1. [T. Chouhan, N. Robinson, K. K. Ang, Vinod A. P. Binary Classification of Hand Movement Directions from EEG using Wavelet Phase-Locking. Proceedings of the International Conference on Systems, Man and Cybernetics \(IEEE SMC\), 5-8 October, 2017. DOI: 10.1109/SMC.2017.8122613](#)
2. [T. Chouhan, N. Robinson, Vinod A. P., K. K. Ang, C. Guan. Wavelet Phase-Locking based Binary Classification of Hand Movement Directions from EEG. Journal of Neural Engineering, 15 \(6\), \(2018\). DOI: 10.1088/1741-2552/aadeed](#)

The contributions of the co-authors are as follows:

- I developed the proposed algorithm, performed the data analysis and wrote the paper.
- Dr. Neethu Robinson and Dr. Kai Keng Ang supervised the technical development of the proposed methodology and analysis and provided feedback on the manuscript draft.
- Dr. Kai Keng Ang and Prof. Cuntai Guan designed the experiment for data collection.
- Prof. Vinod A. Prasad and Prof. Cuntai Guan provided feedback on the work presented and the manuscript.

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The contributions of the co-authors are as follows:

- I performed the data analysis and wrote the paper.
- Dr. Kai Keng Ang and Prof. Cuntai Guan designed the experiment for data collection.
- Dr. Kai Keng Ang, Prof. Vinod A. Prasad and Prof. Cuntai Guan provided feedback on the work presented and the manuscript.

Chapters 5 and 6 have been submitted as a full paper for review. [T. Chouhan, M. H. Black, S. Girdler, S. Bolte, T. Tan, C. Guan. Dynamic Functional Brain Networks of Autism Spectrum Disorder. Human Brain Mapping. \(*in Revision*\)](#)

The contributions of the co-authors are as follows:

- I performed the EEG data analysis, statistical analyses and wrote the paper.
- Dr. Melissa H. Black helped perform the statistical analyses and co-wrote the paper.
- Prof. Sonya Girdler, Prof. Tele Tan, Prof Sven Bolte and Prof. Cuntai Guan provided feedback on the technical and statistical work presented and the manuscript.
- Prof. Sonya Girdler, Prof. Tele Tan and Prof. Sven Bolte designed the experiment for data collection.

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I dedicate this thesis to my loving parents.

Abstract

The brain is an extremely complex organ and probably one of the greatest mysteries of the universe that has baffled scientists and thinkers for centuries. Today, one of the ways in which we understand and investigate the brain is by modelling various neural phenomena with the help of machine learning and sophisticated mathematical algorithms. Technological and scientific advancements go hand in hand. One such area of technology receiving great attention from the scientific community is brain-computer interface (BCI). A BCI is an alternate channel of communication between the brain and a computer, without the involvement of peripheral muscles, via direct transmission of brain signals to a computer.

The primary aim of this thesis is to develop and use models of dynamic interactions between brain regions which can be used in different types of applications, from machine learning to classify different types of hand movements to understanding different cognitive styles in autistic adults compared to typically developing (TD) controls.

For the first study, electroencephalogram (EEG) data was acquired from seven subjects performing centre-out hand movements in four orthogonal directions in the 2D horizontal plane. A modified form of phase-locking based estimator of inter-channel synchrony, called Wavelet Phase-Locking Values (W-PLV), was proposed to carry out binary classification of hand movements in different directions. It was hypothesized that different parts of the brain would show different connectivity patterns to carry out a fairly complex motor task. Results showed that different spatial and time-frequency patterns of pairwise inter-channel synchrony could be identified for hand movements in different directions using the proposed quantifier, thus providing evidence in support of the above hypothesis. Binary classification using the proposed features achieved satisfactory performance.

This study was then extended to investigate the flow of information between different brain regions using a simple independent component analysis (ICA)-based

method. The experimental paradigm allowed the subjects a mental preparation phase before the actual execution of hand movements. It was thus demonstrated that the task involved participation of motor as well as non-motor (cognitive) parts of the brain using a data-driven approach. Results in the EEG source space showed that during the visuomotor task, independent components derived from EEG data were not limited to the motor region but were in fact spread out throughout the cortical surface. This observation had been previously reported in other electrophysiological modalities such as electrocorticography (ECoG). Thus, results obtained from this EEG study are in agreement with the expected neurophysiology of motor action and preparation.

Having investigated the dynamic interactions between different brain regions in healthy subjects performing motor tasks, research was then conducted on more sophisticated models of dynamic brain interactions to study human behaviour in a neurodevelopmental disorder called Autism Spectrum Disorder (ASD). TD and high functioning autistic adults participated in a study to identify complex positive and negative facial emotions, using video stimuli of actors, while their EEG data was collected. While the groups performed at par in recognizing complex negative emotions, the autistic group performed significantly poorly compared to the TD controls. The aim of this research was then to obtain a dynamic functional brain networks perspective of the differences observed in the facial emotion recognition (FER) accuracy.

Features extracted from the EEG cortical source space showed dynamic cognitive processing during the FER task showing that the brain may have to reorganize its neural resources dynamically. Next, it was also seen that functional brain networks in the autistic group had a closer inclination to random networks than their TD counterparts, especially in lower frequency bands, which are typically attributed to the integration of information between long-range brain regions. A multi-temporal scale, coarse-grained connectome study was then carried out which showed that there seemed to be a spatio-spectral shift in dynamic functional connectivity during complex emotional processing from the lower frequency bands to the gamma and beta sub-bands were in the autistic group compared to TD controls. This spectral shift was seen to occur more drastically for emotions resulting in poorer recognition accuracy. Results of this work showed that psycho-cognitive theories of ASD could potentially have a basis in EEG-based dynamic functional brain networks and

provide motivation to further investigate the dynamics of brain networks to study human behaviour.

The research presented in this thesis shows that EEG-based dynamic brain interactions can be modelled to decode and investigate motor activity directly from brain data as well as analyze the sub-optimal cognitive performance in autistic adults with evidence supporting widely promoted theories in psychology. With recent advances in Deep Learning, future research can use the work presented in this research with BCIs and appropriately designed experiments to decode finer and more complex motor activity or gain better understanding of human behaviour.

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Symbols and Acronyms

Acronyms

ANOVA	Analysis of Variance
ASD	Autism Spectrum Disorder
BCI	Brain Computer Interface
CC	Clustering Coefficient
CPL	Characteristic Path Length
CSF	Cerebrospinal Fluid
CSP	Common Spatial Patterns
DTF	Directed Transfer Function
ECoG	Electrocorticography
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
EP	Evoked Potential
ERD	Event Related Desynchronization
ERS	Event Related Synchronization
FBCSP	Filterbank Common Spatial Patterns
FER	Facial Emotion Recognition
fMRI	Functional Magnetic Resonance Imaging
GC	Granger Causality
iCOH	Imaginary Part of Coherency
LDA	Linear Discriminant Analysis
MEG	Magnetoencephalography
MVAR	Multivariate Autoregressive
NBPW	Naive Bayesian Parzen Window
PCC	Pearson's Correlation Coefficient

PLV	Phase-Locking Value
ROI	Region of Interest
sLORETA	Standardized Low Resolution Electromagnetic Tomography
SMR	Sensorimotor Rhythms
SVM	Support Vector Machines
TD	Typically Developing
W-PLV	Wavelet Phase-Locking Value
WCSP	Wavelet Common Spatial Patterns

Chapter 1

Introduction

There lies a neuron, spontaneously producing electrochemical spikes, following a chain of rhythmic activations from its presynaptic neighbours to its post-synaptic counterparts. Suddenly, there is a change in its spontaneous rhythmic activity and the neuron now starts producing oscillations at a different frequency. Within moments, the neuron finds that it is not alone in this rhythmic fluctuation but is, in fact, sharing this rhythmicity with other neurons, some near, some spatially further away. And then, with another fluctuation in its activity, the neuron finds itself transiently connected with a new set of neurons, some near, some more distant. The neuron now finds huge masses of its counterparts, which like itself, are transiently locked in rapidly changing configurations, like a huge orchestra playing a jazz symphony or a troupe of dancers in incredible formations. This creates currents of ions with rapid changes leading to emerging electromagnetic fields. These fields traverse outwards, through various layers of tissue, fluid and bone until they reach the scalp. Externally attached scalp electrodes measure these electrical fields and record a potential difference. A computer reads this recorded data from multiple places of a subject's scalp, who intends to perform a certain task, inducing his neurons into dynamically reorganizing functional interrelationships. The computer decodes the subject's intention and activates an orthosis, enabling him to perform his intended activity while some neural oscillations peak and some are inhibited, turning his intention to action. Soon enough, the neuron finds itself back to its original state of spontaneity, linked to its old set of pre- and post-synaptic neighbours for some time - until the next fluctuation. This is the cycle of turning

intention into action, through an elegant new medium called ***Brain-Computer Interfaces (BCIs)***.

At the most fundamental level, BCIs involve establishing a direct link of communication between a brain and a computer. The main aim of BCIs is to develop an autonomous, computerised system capable of directly detecting the subject's thoughts and intentions and use them to carry out the tasks desired by the subject. The need for such a system in the real world can be understood in three major contexts.

Firstly, BCIs have shown huge potential in being used as non-invasive rehabilitative or restorative applications in major clinical applications such as Stroke rehabilitation [7], training for improvement of attention deficit hyperactive disorders (ADHD) in children [8]. With the help of well-established protocols that promote neuroplasticity, BCIs reinforce the patient's brain to enter into a self-repairing mechanism forming new synaptic connections that improve the neurological or mental condition of the person. BCIs used in conjunction with multiple modalities such as immersive virtual reality (VR) and augmented reality (AR) are said to carry a huge potential in motor rehabilitation [9, 10]. In Stroke rehabilitation, BCIs have been shown to outperform all other conventional methods of therapy [11]. Therefore, BCIs offer a huge potential in treating several neurological disorders non-invasively. These type of BCI systems are usually a class of active BCIs wherein the subject is required to voluntarily control the BCI by modulating his brain rhythms or reactive BCIs in which the subjects react appropriately to a cued protocol of tasks to be performed.

Secondly, BCIs are also being developed to augment the mental capacities of a healthy person such as training to maintain cognitive skills against aging related mild cognitive decline [12]. Thus, BCIs even offer a medium to tap into the huge potential of the brain, even for healthy subjects, to be more productive and acquire skills more effectively. Like the above BCIs in rehabilitative or restorative applications, these type of BCIs are also generally active or reactive BCI systems.

Thirdly, BCIs can also be used to investigate and reveal the underlying neuromechanisms of various cognitive, perceptual and motor tasks. With the help of properly designed experiments, BCIs can be used to test various hypotheses about the nature

of neural events corresponding to different situations. Thus, on a more fundamental level, BCIs can be used to reveal more insights into the working of the brain. New insights into the underlying neurodynamics of different tasks can then be used to create improved BCI systems to decode mental states more effectively, with increased precision and accuracy. Thus, science and technology related to BCI lie in a deeply symbiotic relationship with each field promoting the advancement in the other. Besides active and reactive BCI systems, another class of BCIs are well suited for this application, called passive BCIs. This type of BCI system does not require the subject to explicitly control the BCI. Instead, a BCI system is used as a passive decoder of the subject's cognitive strategies and mental variables while the subject performs a given task.

Besides the wide realization and acceptance of the aforementioned potential that BCIs offer, a number of factors have generated worldwide interest and research into the development of BCI systems. Non-invasive brain data acquisition systems that feed data, carrying relevant information about the subject's brain states, to a computer, have become much more feasible and affordable with developments in Electroencephalography (EEG) sensor technology. Advances in computational power of commercially available computers have enabled the use of AI in decoding brain states from recorded brain data. Sophisticated models built on known neurophenomena have been used in literature to decode a number of cognitive and motor variables directly from acquired brain signals. Novel multi-modal systems like AR / VR, functional electrical stimulation (FES) and soft-robotics with haptic actuators are capable of delivering high-fidelity feedback to the subject about his decoded mental state through a process called neurofeedback [13, 14]. It is often postulated that an effective feedback technique can greatly enhance the efficacy of BCI-based therapeutic applications [15].

However, BCI systems currently used are far from perfect. Non-invasively acquired data have high levels of noise, which contain a dense mixture of the original signals of interest making it difficult to draw inferences about the underlying neurodynamics of various functions. Moreover, our understanding of the working of the brain is quite incomplete. Most feature extraction algorithms are built on certain working principles that are either derived from known neurological phenomena underpinning different aspects of cognitive and motor behaviour or based on the researcher's assumption of how the brain works in different situations. The brain is so extremely

complex that it has drawn multiple fields of research into investigating its various aspects. Therefore, in the light of new scientific discoveries and knowledge about the working of the brain, older models must give way to newer techniques that better estimate and quantify the underlying neurodynamics of different tasks more effectively and help to predict the subject's mental state more accurately. This thesis provides a fresh and exciting perspective of BCI systems which carries the potential to decode the underlying neurodynamics in more comprehensive details than traditionally used BCI systems. The various chapters presented in this thesis demonstrate the ability of this perspective to be more generalizable over different types of applications, compared to traditional BCIs, including motor and cognitive domains. The factors that motivated this area of research are detailed in the next section.

1.1 Research Motivations

Until recently, the brain was considered to comprise various anatomically contiguous regions, each associated with its own special functional relationship to a cognitive, perceptual or motor function, such that, that particular region was seen to be activated while the subject engaged in the corresponding activity. Traditional BCI systems employed various signal processing methods to extract patterns of these activations or quantify task-dependent neural signatures and translate them into control commands. However, there has been a recent paradigm-shift in the way underlying neural dynamics are now perceived. Recent studies show that different anatomically distant brain regions form dynamic functional connections and it is these interactions which form the basis of all motor, cognitive and perceptual functions.

Evidence from recent studies encourage development of novel techniques to better quantify and interpret these underlying transient functional connections which would then provide more comprehensive insights about the neurological basis of movement and cognition. However, traditionally used algorithms in BCI systems neither use nor provide much information about these dynamic interactions between different brain regions. Moreover, since EEG is the most commonly used modality to acquire brain data in non-invasive BCI systems, the acquired brain data is a dense non-linear mixture of non-stationary brain signals, artifacts and

noise. This makes it very difficult to interpret the different quantified functional interrelationships and requires strict statistical analyses and verification, making the process very computationally intensive. This limits the use of such models in BCI systems.

Sensorimotor rhythms (SMR) refer to brain oscillations that are induced when the subject wishes to perform a motor action. SMR-BCIs decode movement kinematics directly from the subject's brain signals by quantifying various features from such oscillations. Most feature extraction algorithms used in such systems target discriminative activation patterns of the motor and somatosensory cortex. For bilateral tasks such as comparing left vs. right hand motor activity, clear patterns of signal power suppressions and amplifications emerge, called Event-related Desynchronization and Synchronization, respectively. However, with finer and more precise unilateral motor activity, these patterns of activations likely become increasingly complex and overlapped. Moreover, it has been known that the motor and somatosensory cortices do not produce such movements in isolation but are, in fact, part of a complete web of interactions with other regions such as the prefrontal, parietal and visual cortices. It is currently a challenge to reliably extract more comprehensive details about the nature of such interactions from EEG-based signals that may be informative about complex limb movements.

Besides motor activity, complex perceptuo-cognitive tasks like emotion recognition are known to require large-scale integration of information from distant brain regions. Using powerful neuroimaging techniques, such as functional magnetic resonance imaging (fMRI), it has been reported that disorders of emotion recognition often find altered connectivity between various brain regions. However, the electrophysiological nature of such interactions and aberrant patterns within them in neurodevelopmental disorders such as autism spectrum disorder (ASD) still remains poorly understood.

1.2 Research Objectives

This section describes the research objectives of this thesis. The main objective of this thesis is to provide a novel, networks-based approach to BCI systems. Functional brain networks describe a different set of neurophysiological phenomena that

FIGURE 1.1: Overview of networks-based BCI proposed in this thesis.

have been attributed to be the very basis of cognition, perception and motion, compared to task-induced activations of individual regions. Therefore, incorporating such interrelationships in BCI-based decoding of the neural correlates of various different processes would involve a fresh perspective to feature extraction algorithms used in SMR-BCIs as well as interpreting the neurodynamics of cognitive processes in neurodevelopmental disorders in passive-BCIs. Therefore, the aim of this thesis is to develop and use various strategies to decode and infer from such transient functional relationships which would establish a new and alternate working principle to traditional BCIs. This new approach in motor decoding in BCIs has been recently called *Network-based Brain Computer Interfaces (nBCI)* [16]. Figure 1.1 shows an overview of a Networks-based BCI system that has been used in this thesis. The major specific research objectives are listed below.

- Development of a networks-based approach to SMR-BCIs to decode and investigate the EEG-based transient functional connections that underlie different types of hand movements. As shown in Figure 1.1, this objective refers to work done in Chapters 3 and 4. This includes:
 - Developing a new networks-based working principle and appropriate feature extraction technique for effective decoding of voluntary hand movements in an EEG-based SMR-BCI.

- Validating the above working principle using experiments to decode different types of hand movements in an EEG-based SMR-BCI.
- Using effective methods to demonstrate the involvement of different cortical regions during motor activity and establishment of flow of information amongst them to verify their functional interrelationships and relevance to the motor task.
- Using a networks-based approach in passive EEG-based BCIs to study dynamic functional connections underlying a complex cognitive process such as facial emotion recognition in Autism Spectrum Disorder (ASD). As shown in Figure 1.1, this objective refers to work done in Chapters 5 and 6. This includes:
 - Developing novel hypotheses about the nature of dynamic electrophysiological functional connections underlying a facial emotion recognition task based on recent neuroimaging literature and psychology.
 - Using effective techniques to demonstrate a dynamically changing functional brain network architecture induced by the facial emotion recognition task.
 - Contrasting groups of autistic from typically developing individuals to investigate differences in whole-brain dynamic functional connections through rigorous statistical methods.
 - Presenting a basis for the apparent different cognitive styles in the autistic group compared to TD individuals, as predicted by cognitive theories, using dynamic whole brain functional connections.

Thus, the above-mentioned research challenges and objectives will be addressed in this thesis using a networks-based approach to active / reactive and passive BCI systems for motor decoding and cognitive monitoring of emotional processing.

1.3 Contributions of the thesis

An EEG-based SMR-BCI is presented in this thesis to demonstrate the ability of using functional networks-based features for extracting movement information

regarding different unilateral hand movements. Experiments were conducted with subjects performing centre-out hand movements in 4 orthogonal directions in a 2D horizontal plane, using a cued experimental protocol. The specific contributions are listed below.

- Using estimates of large-scale phase synchrony to decode hand movement directions. A phase-locking based estimator of phase synchrony using wavelet reconstruction of signals in the EEG sensor space is proposed to evaluate phase-relationships between various EEG channels within single-trials. An algorithm is developed to extract discriminative features from the latter single-trial phase-locking based method to classify hand movements in different directions.
- The time-frequency spectrum in the wavelet domain is used to investigate the presence of discriminative movement-related patterns of large-scale neural synchrony accompanying movements of the dominant hand in different directions. Different patterns of phase-based functional connections are visualized using scalp contour and connectivity plots.
- A simple independent component analysis (ICA)-based method is used to identify involvement of different brain regions in the above unilateral hand movements in different directions. A distributed network of independent components are visualized using a low resolution cortical source projection of the movement-induced independent components.
- The above contributions are used to validate a novel working principle of a networks-based approach to motor decoding in SMR-BCIs.

A passive EEG-BCI system is used to investigate the underlying dynamic functional brain networks of complex facial emotion recognition in typically developing and autistic individuals. A cued experimental protocol is used to show subjects video stimuli of actors expressing different kinds of positive and negative complex facial emotions. Subjects are then asked to identify the correct complex emotion depicted out of 4 choices displayed on a screen. Rigorous statistical analyses are carried out to investigate the nature of electrophysiological functional connectivity underlying the observed differences in emotion recognition capabilities between the two groups and the putative functional roles of different EEG frequency bands in the observed

aberrant functional connections in the autistic group compared to the typically developing individuals. The specific contributions are as follows.

- Dynamic functional connections are quantified in the EEG source space to identify the correlates of the dynamic reorganization of functional brain networks accompanying the processing of different positive and negative emotions.
- Rigorous statistical analyses are conducted to identify group differences in the reorganization of large-scale whole-brain functional networks across multiple EEG frequency bands between the autistic and typically developing individuals. Connectivity-based neural signatures of slower global processing of emotions are identified in the autistic group, as predicted by cognitive theories.
- A coarse-grained connectomic approach in the EEG source space is conducted using appropriate and rigorous statistical analyses of the functional roles of different EEG frequency bands in the observed behavioural outcome of the task.
- Summing the above observations across different types of statistical assessments, a networks-based explanation is proposed to describe an altered cognitive style in autistic individuals. The evidence obtained from the above statistical analyses are backed by recent advances in cognitive frameworks.

Thus, the above set of contributions seek to provide a functional brain networks perspective of human behaviour in a neurodevelopmental disorder using a case-control methodology with passive BCIs.

1.4 Organization of the thesis

The above contributions to the aforementioned research challenges are presented in this thesis across various chapters which are summarized as follows.

Chapter 2 presents an introduction to BCI systems and a literature review on EEG-based SMR-BCIs, conventional feature extraction algorithms as well as techniques

to evaluate neural synchrony in EEG signals. The considerations and limitations to existing techniques are also highlighted.

Chapter 3 presents the first contribution of this thesis wherein an algorithm using a phase-locking based estimator of neural synchrony is presented to test and validate a networks-based approach to motor decoding in SMR-BCIs. Binary classification of hand movements in different directions is carried out to verify presence of discriminative information in different phase-locking patterns. The latter patterns are visualized using different methods. Spatial visualizations obtained in this chapter motivated further investigation of the involvement of different brain regions in hand movements in different directions in the next chapter.

Chapter 4 presents the investigation of functional networks using a simple ICA-based method to identify different cortical sources in a wide-spread network of brain regions associated with center-out hand movements. Function connections amongst these regions are quantified to verify flow of information between the identified regions and relevance to the motor task. Results obtained in this chapter demonstrated the ability to apply the concepts of a networks-based approach to BCIs in investigating the widespread sources of motor planning and execution in healthy subjects. These results encouraged extending these approaches to investigating more complex phenomena, namely, altered emotion processing and recognition in ASD, which was done in the next chapter.

Chapter 5 investigates brain networks in passive BCIs in the EEG source space to evaluate rapid reorganizations in the functional brain network architecture accompanying complex facial emotion recognition. Quantified estimates of functional segregation and integration are contrasted between typically developing and autistic individuals to identify different patterns of local and global information processing in the two groups within multiple EEG frequency bands. Evidence is presented showing potential signatures of slower or sub-optimal global information processing in autistic individuals compared to typically developing individuals. This work demonstrated the ability of using features extracted from dynamic brain networks to study complex FER which provided motivation for further extending the used methodology to contrast the dynamic brain networks between the autistic and control groups. This was further pursued in the next chapter.

Chapter 6 uses a connectomic approach in the EEG source space to test the putative functional roles of different EEG frequency bands in the aberrant large-scale connections seen in autistic individuals. Conclusions derived from the statistical validation of different models of connectivity-based group differences is presented which provide evidence for well-known cognitive theories in autism indicating an altered cognitive style in autistic individuals compared to typically developing controls.

Chapter 7 presents a summary of the various contributions of this thesis along with a discussion of their significance. It also presents some possible future directions based on the research presented in this thesis.

1.5 List of Publications

The contents of this thesis are the contributions made by the author and reported in the following publications.

Journal Articles

1. T. Chouhan, N. Robinson, Vinod A. P., K. K. Ang, C. Guan. Wavelet Phase-Locking based Binary Classification of Hand Movement Directions from EEG. *Journal of Neural Engineering*, 15 (6), (2018). DOI: 10.1088/1741-2552/aadeed.
2. T. Chouhan, M. H. Black, S. Girdler, S. Bolte, T. Tan, C. Guan. Dynamic Functional Brain Networks of Autism Spectrum Disorder. *Human Brain Mapping*. (*in Revision*)

Conference Proceedings

3. T. Chouhan, N. Robinson, K. K. Ang, Vinod A. P. Binary Classification of Hand Movement Directions from EEG using Wavelet Phase-Locking. *Proceedings of the International Conference on Systems, Man and Cybernetics (IEEE SMC)*, 5-8 October, 2017. DOI: 10.1109/SMC.2017.8122613.

4. T. Chouhan, K. K. Ang, Vinod A. P., C. Guan. Modelling Causal Connectivity from EEG for BCI with Multi-direction Hand Movements. 7th International BCI Meeting, 21-25 May 2018.
5. T. Chouhan, N. Robinson, C. Guan. Dynamic Networks Underlying Planning and Execution of Hand Movements in Different Directions. (*In preparation*).

Chapter 2

Literature Review

2.1 Introduction - Brain Computer Interfaces

A brain-computer interface is a direct channel of communication between the brain and a computer, bypassing peripheral neural and muscular pathways, such that the computer directly uses the brain signals to decode the mental state of the subject and respond with appropriate output commands to a control device. BCIs have been a topic of intense research for more than a decade to study movement execution and imagination (motor imagery) [1, 17–20] whose applications include rehabilitation of patients afflicted with neural or spinal cord diseases, partial or full paralysis and Stroke [20–23]. In the case of totally locked-in patients, a BCI may be the only usable channel of communication with the external environment [24]. Moreover, amputees can use smart, thought-controlled prostheses to carry-out activities in a normal way[25]. Thus, BCI systems have large scope in real world applications and humanitarian technology.

In this chapter, an overview of existing literature and techniques for movement decoding as well as analyzing neurophysiological dynamics in BCIs are presented. First, different types of BCI systems found in literature are defined, followed by a brief description of the functional units of a typical BCI system. Various data modalities used in literature and motivations for using EEG are also discussed. Next, we present an overview of the neurophysiological mechanisms in sensorimotor rhythm-BCIs along with existing techniques to quantify their properties that can be used for decoding various motor activity. Lastly, we present a brief overview

of existing literature regarding decoding neural interactions from EEG. We also present the challenges to the various existing techniques.

2.2 Types of BCIs

Depending on the nature of human involvement required to evoke the neural activity of interest, BCIs can be divided into three types [26]:

1. **Active BCIs** - This type of BCIs enables the subject to voluntarily control an external device directly using his brain rhythms [27, 28]. The evoked activity is thus asynchronous and depends on the intention of the subject to voluntarily manipulate the control device. Such BCIs not only need to identify the appropriate control commands to be given to the control system depending on the subject's intention detected by the BCI systems but also needs to identify periods when the user does not wish to send any control commands to the control device.
2. **Reactive BCIs** - This type of BCI systems use a cued protocol to stimulate the subject into performing a certain task or evoke a certain neural activity [29, 30]. Thus, neural events are stimulus-locked (phase- and/or time-locked) to the cue according to which the user must respond with appropriate behaviour to enable the BCI system to work. This is the most commonly studied BCI application in literature and is typically used to collect calibration data to develop algorithms for real-time decoding and active BCI systems.
3. **Passive BCIs** - This is the most recent type of BCI application introduced in literature wherein no explicit commands are required from the subject. Instead, the BCI system uses the spontaneously evoked activity of the brain or induced activity during a certain mental task for extracting information regarding on-going neural oscillations. This type of BCI systems find use in cognitive monitoring applications where certain aspects of the subject's neurodynamics are decoded and fed back to the subject to inform him/her about his/her mental state, affective state (emotions, arousal levels)[31] or workload levels [32]. Such kinds of BCIs can also be used to complement other human-machine interface (HMI) systems to enhance the overall efficacy

of the HMI system [33]. Moreover, passive-BCIs can also be used to enhance the performance of existing active or reactive BCI systems, such as in Error Potentials, wherein a complementary passive BCI system can be used to correct misclassification errors made by the computer with regards to the subject's mental state or motor kinematic variables [34].

Thus, the main difference between active or reactive BCIs and passive BCIs is that in the former the task to be performed is decoded by the computer using the subject's brain signals and carried out. In passive BCIs, on the other hand, tasks are performed by the subject normally (without sending explicit commands to control the BCI). The computer only passively monitors the subject's brain rhythms.

2.3 Functional Units of a BCI System

A system-level view of BCIs typically breaks down the entire interaction between the brain and a computer into smaller components or modules that carry out various tasks. Figure 2.1 shows a block diagram with the functional modules that make up a typical BCI system. First, a data acquisition module is used to record brain signals which are sent to a computer that decodes relevant information from the recorded signals. Depending on whether the sensors are implanted directly into the brain or attached externally on the scalp or head, data can be acquired in invasive or non-invasive ways, respectively. As seen in Figure 2.1, the acquired data is then sent to the signal processing module where the features of interest are extracted and used for classification of the user's intended action. The classified results are then translated to commands for actuation of the control system, which the user then controls by modulating his brain state through a process called neurofeedback. This means that the actuation performed by the control system is used as feedback by the user, who then learns to manipulate his brain rhythms to perform the task as per his desire. Machine learning is typically used in BCI along with other signal processing methods [35, 36] for decoding the mental state of the subject from the recorded data. One of the advantages of using machine learning methods in BCI applications is that it is possible to get automatic subject specificity through feature selection [36–38]. For example, in an EEG-based BCI,

the system can automatically choose the most informative channels and frequency bands that help to maximise its efficiency and decoding accuracy.

FIGURE 2.1: Block diagram of a typical BCI [1].

2.3.1 Brain Data Acquisition

Brain data can be acquired using various different techniques, each having its own advantages and limitations. Each data acquisition modality is based on a particular working principle which enables it to sense and record different kinds of neural information. Figure 2.2 shows recording sites for electrophysiological measurements of different data modalities, namely, intracranial recordings, electrocorticography and electroencephalography. Some of the commonly used modalities of data acquisition are described as follows.

- **Microelectrode arrays** are an invasive technique to record brain signals. They consist of electrodes that are implanted directly inside the cortex. This technique provides excellent signal quality but is risky since it involves implanting the electrodes deep inside the skull and needs surgery. One of the successful applications of microelectrode-arrays is the brain-computer interface called BrainGate [39].
- **Electrocorticography** (ECoG) is a semi-invasive method of acquiring brain signals [40]. It has the advantages of having good temporal as well as spatial

FIGURE 2.2: Various layers of brain tissue (cortex), meninges, skull and scalp showing the layer at which EEG is recorded, as taken from [2].

resolution. However, being a semi-invasive method, it requires surgery to be performed on the subjects for implanting the electrodes [41].

- ***Electroencephalography*** (EEG) is an inexpensive and non-invasive method of acquiring electrophysiological brain data from the scalp of a subject. This involves measuring the potential differences between various points on the scalp and a certain reference point [3]. While EEG offers good temporal resolution of recorded brain data, it however, suffers from poor spatial resolution.
- ***Magnetoencephalography*** (MEG) is a non-invasive method of data acquisition of brain signals with the advantage of having good temporal resolution and better spatial resolution than EEG. MEG measures the magnetic fields on the subject's head as a result of cortical electrochemical currents [42]. However, the machine required for MEG is extremely expensive, voluminous and requires proper magnetic shielding of the room in which it is used. One of the most common types of MEG machines is called superconducting quantum interference device, or SQUID.
- ***Functional Magnetic Resource Imaging*** (fMRI) is another non-invasive technique of acquiring brain signals and provides information about brain metabolism using Blood Oxygen Level Dependent (BOLD) [43]. In spite of its high cost, it is used popularly due to its excellent spatial resolution. However, it suffers from poor temporal resolution.
- ***Function Near Infrared Spectroscopy*** (fNIRS) uses the change in haemodynamic activity in the brain due to neural activity to record brain signals. It

FIGURE 2.3: Generators of EEG signals. (a) A representation of a microcircuit configuration showing the underlying generators of EEG signals, as taken from [3]. (b) A slice of the various layers of the cortex, meninges, skull and scalp as taken from [4].

uses optodes to emit and detect optical waves in the near infrared wavelength and records data using the change in the absorption of light [44].

The research presented in this thesis entirely uses EEG as the brain data modality. Thus, specific properties about EEG are discussed in more detail below.

2.3.1.1 Why EEG?

Temporal resolution and ease of data recording

EEG is recorded as electrical signals at various points on the scalp [45]. The frequency spectrum of EEG signals of interest is typically between 0.01 Hz to 100 Hz and the nature of EEG signals is similar to pink noise [46]. This means that lower the frequency of the EEG signal, higher is its amplitude. EEG is the most popular choices for non-invasive brain data recording for decoding mental states and investigating the rapid changes in neural events underlying various behavioural attributes. The data acquisition hardware for EEG is simple, portable and low cost. Moreover, EEG data have excellent temporal resolution. Lastly, being a non-invasive technique, it is arguably the easiest and most feasible method to study brain signals as compared to other techniques.

A neurophysiological basis for EEG in cross-scale electrophysiology of neural events

Other than the aforementioned reasons of simplicity and low-cost, there are some inherent properties of EEG signals that make them suitable for the research presented in this thesis. EEG is an electrophysiological measure of brain activity formed by the cumulative activity of large ensembles of neuronal populations called microcircuits [3]. Neural oscillations caused by the rhythmic firing of large masses of pyramidal cells aligned geometrically gives rise to cortical currents which create electric fields. These electric fields travel outward from the cortex, through various layers of the meninges, cerebrospinal fluid (CSF) and skull to reach the scalp, where they are ultimately measured with electrodes. Figure 2.3 shows a representation of a microcircuit formed by geometrically aligned pyramidal cells and a view of the various layers propagated by electric fields whose source lies in the cerebral cortex containing the pyramidal cells all the way to the scalp. As compared to other neuroimaging techniques such as functional magnetic resonance imaging (fMRI), EEG signals are, thus, a more direct outcome of the cumulative rapid electrochemical exchanges between neuronal cell populations and hence reflect a direct measure of neural events on a macroscale. This functional relevance of the measured EEG signals to the underlying microcircuit configurations not only encourages development of mathematical models to reverse engineer the cortical signals of interest to study the underlying neuromechanisms (covered under “Source Localization” in Section 2.7) but in fact, has an interesting relationship with the underlying neural events which serve as the functional units of the working of the brain.

It is now well-known that neural activities occur at multiple spatial and temporal scales [5, 47, 48]. Figure 2.4 shows various different types of electrophysiological neural phenomena at various spatial and temporal scales typically studied in literature. On the spatial scale, neural dynamics vary from the *microscopic*, consisting of single neurons, to *mesoscopic*, consisting of ensembles of neurons and microcircuits, to *macroscopic*, consisting of large-scale neural activity from whole brain regions typically parcellated according to some functional and / or anatomical criteria. On the temporal scale, neural activity vary from synaptic currents and spikes occurring on the order of a millisecond, to local field potentials, occurring in few tens of milliseconds to EEG typically occurring at about hundreds of milliseconds.

It has been conjectured that neural events occurring at various spatial and temporal scales are in fact related and entwined such that there is a modulating influence of events across different spatial and temporal scales [5]. One perspective of neural

FIGURE 2.4: Multi-scale nature of neural activity as taken from [5].

events holds that the cortex can be viewed as a functional “mosaic” of different neural cell assemblies, each oscillating at a particular characteristic frequency[19]. Another perspective states that on each spatial scale, different neuronal oscillations emerge that contribute activity seen in different parts of the frequency spectrum [5]. Thus, on the one hand, higher frequency bands account for more precise and spatially localized synchrony of cell assemblies performing precise lower level feature processing through closely located synaptic events. On the other hand, lower frequency bands account for long-range integration of information from spatially different parts of the brain which are characteristic of more macroscale events. It has been postulated that bidirectional causal influences occur across different levels, braiding together the events occurring at the macro-, meso- and microscales [5, 49], as visualized in Figure 2.5. Thus, an EEG-based analysis of whole brain interactions provides a macroscale view of neural dynamics that have inherent bases in the electrophysiological synaptic events occurring in large cell populations. A new branch of computational neuroscience, called Network Neuroscience [50], is now rapidly gaining popularity with developments in effective tools to quantify and

FIGURE 2.5: Visualization of the multi-scale nature and cross-scale interaction of neural dynamics.

statistically assess such neural interactions. Given the multiscale nature of neural events, such analyses then provide comprehensive insights into the underlying neuromechanisms, linked with their putative cortical sources, that can be used to decode mental states, motor kinematics or assess group differences between healthy subjects and patients of various neurodevelopmental disorders.

Therefore, although the content of EEG data is still imperfectly understood [3], it inherently carries a huge potential to uncover rapid reorganizations of neural dynamics that give rise to human behaviour and cognition. The work presented in this thesis attempts to quantify such dynamic functional interrelationships from EEG to better understand the underlying neuromechanisms of different types of motor activity for use in BCIs. A dynamic networks-perspective is also undertaken to investigate the effect of a neurodevelopmental condition on the emotional processing ability of individuals.

Despite its advantages, EEG suffers from various limitations. The drawbacks of EEG include high noise levels and inherent non-stationarity in the recorded data. Another limitation of EEG data is that it has poor spatial resolution. Moreover, due to the smearing and conductive effect of the skull and tissues, the signals originating at the source are spatially mixed when they reach the scalp where they are recorded by the EEG electrodes. This is called Volume Conduction [46]. Hence, interpreting the content of EEG signals and decoding their relationship to the underlying microcircuit configurations that participated in their generation becomes

a challenge. Therefore raw EEG data is typically subjected to relevant preprocessing techniques in order to separate, identify and isolate the signals of interest. For more accurate results, EEG should be considered as a non-stationary stochastic process, especially over long periods of time [51]. During shorter periods, however, EEG may be considered to be quasi-stationary. Depending on the recording conditions, this short-term stationarity may last for a few seconds to a few minutes [52].

2.3.2 Preprocessing

Preprocessing techniques are those which help to clean the recorded EEG data since the latter are almost always contaminated with artefacts. The performance of BCI depends on the quality of signals that are used. Signals with low signal to noise ratio (SNR), which is often the case with EEG signals, will compromise the performance of the BCI. Thus, before any algorithm is used to extract features of interest from EEG, it is recommended to clean the signals using some preprocessing techniques.

Based on the source of these artefacts, the latter can be categorized as technical artefacts, physiological artefacts or non-physiological artefacts. Technical artefacts may arise from the improper attachment of electrodes to the scalp. Physiological artefacts arise due to the interference of biological signals with EEG, such as Electrooculogram (EOG) artefacts due to eye movements and Electromyogram (EMG) artefacts due to voluntary muscle movements. Non-physiological artefacts arise due to electromagnetic interference from heavy electrical machines near the data acquisition system, line noise due to the frequency of alternating current (AC), and so on. In order to get reliable results, it is imperative to remove such artefacts from the signals before applying algorithms to extract the features of interest.

EOG artefacts are electrophysiological signals that are generated by eye movements. These signals are picked up primarily by the frontal EEG electrodes but the resulting artefacts may also be recorded by electrodes further away, depending on the proximity of the sensors to the eyes and the direction in which the eyes are moving [53]. Eye blinking causes abrupt changes in the recorded EEG and the magnitude of these artefacts are much larger than background EEG activity. Examples of bidirectional interference from eye movements include Radial (REOG),

Vertical (VEOG) and Horizontal (HEOG) EOG signals. EMG artefacts are caused due to the electrical signals from the movement of muscles. Their shape and amplitude depend on the degree and type of muscle contraction. These artefacts are wide-spectrum and detected across the scalp [54]. There are various measures of the quality of filtered, clean signals such as signal to noise ratio (SNR) [46], signal to artifact ratio (SAR) [55], normalized mean standard error (NMSE)[56] and so on. Moreover, techniques like Pearson’s Correlation Coefficient and Mutual Information based methods can be used to determine the effectiveness of cleaned data in delivering task-dependent information [57]. Table 2.1 lists some of the commonly used preprocessing techniques.

Besides the methods listed in Table 2.1, wavelet based methods are also used. They are capable of removing various types of physiological artefacts, whose performance depends on the ability of signals of interest being decomposable using a wavelet basis function. Detail coefficients are thresholded and signals are reconstructed to remove artefacts. Wavelet-based methods are well suited for treating biomedical signals due to good time-frequency resolution trade-off.

2.3.3 Feature Extraction

This section provides an overview of features that are typically extracted from EEG to study and decode various mental state variables. We also present a brief discussion of the existing interpretations of the putative functional roles of classical EEG functional bands with respect to various task conditions.

EEG oscillations encode multiple types of neural activity corresponding to various motor, cognitive and perceptual tasks or processes. As mentioned earlier, various processes or the intention for a particular task by the subject induces a transient alignment of neural cell assemblies into a functional “mosaic” wherein each functional unit of cell assemblies oscillates at a particular dominant higher frequency corresponding to the function of that unit [19]. Thus, different tasks correlate with different patterns of oscillations in EEG. The EEG frequency spectrum is classically divided into multiple frequency bands which have been found to encode various such processes [60, 61]. Each classical EEG frequency band has been associated with multiple fundamental functions that form the basis of a complete cognitive, perceptual or motor activity. Therefore, if a feature extraction

TABLE 2.1: Frequently used Preprocessing Techniques.

Sl. No.	Method	Type of Artifacts Treated	Description	Advantages	Disadvantages	Examples
1	Regression-based Methods	Artifacts with reference channels, eg. EOG, ECG, etc.	Subtraction of regressed portion of reference waveforms from the contaminated EEG signals	Simple and computationally efficient	Need for a reference waveform or channel; direct subtraction of waveforms can result in loss of information in the case of bilateral contamination, i.e., reference channels are affected by neural activity	Linear regression [58]
2	Filtering Methods	Artifacts with reference channels, eg. EOG, ECG, EMG etc.	Iterative methods that estimate the filter coefficients using some optimization algorithms.	Automatic methods without the need of human intervention	Need for reliable a priori knowledge or reference.	Adaptive filters [54, 58], Kalman filters [59], etc.
3	Blind Source Separation Methods	Various types of physiological artefacts	Use data from all channels together and separate them into different components depending on assumptions of uncorrelatedness, independence, orthogonality, etc.	No explicit need for reference channel. Effective technique to treat a variety of artefacts together.	Different solutions are achieved on the basis of different assumptions used. Assumptions of independence in higher order statistics need sufficient data.	Independent Component Analysis (ICA), Principal Component Analysis (PCA) [46]

algorithm is capable of identifying and quantifying task-specific or task-induced patterns in the EEG oscillations, a classifier could be trained to recognize these different tasks using machine learning.

In the pipeline of a typical BCI system, once the EEG data have been cleaned using relevant preprocessing techniques, a signal processing module is used to extract the features of interest from the cleaned data that can be used by a classifier to identify the mental state of the user. Depending on the property of the neurophysiological phenomena that is informative about the user's mental state, various kinds of spectral and spatial filtering techniques have been used in literature. While higher EEG frequency bands are seen to have greater spatial localization and have been theorised to encode more precise processing and local integration of information [62, 63]. On the other hand, low frequency oscillations are more spatially widespread and are known to involve large-scale integration of information [5, 63]. Moreover, it has been reported that endogenous top-down processes correlate with increased activity and coherence in the lower frequency bands, while exogenous bottom-up processes induce coupling in higher frequency bands [61]. Top-down processes are those which involve a goal-directed perception of objects in wholesome groups, depending on a certain semantic context that help to delineate the sensory input into a meaningful entity. On the other hand, bottom-up processing refers to the integration of sensory inputs by rapidly shifting attention to salient discriminative features [64]. Since both these streams of information processing are undertaken by human perception of various stimuli [65], different patterns of interactions within and between different frequency bands are observed in EEG depending on the task and cognitive style of the subject.

The delta band (1-4 Hz) has been seen to encode inhibition of interference to mental tasks by modulating the networks whose participation might affect the performance of the task at hand. Increased concentration has been shown to correlate with increased frontal delta band activity in mental calculation and semantic tasks [66, 67]. Power increases in the delta band has also been seen during suppression of motor response in a Go/No-Go task [68, 69]. Thus, power increases in the delta band might be associated with functional cortical deafferentation or inhibition of sensory afferences that interfere with increased concentration [68]. Moreover, the delta band has also been seen to be dominant in sleep and under the influence of anaesthesia [70].

The alpha band (8-12 Hz) is seen to be involved in various perceptual and cognitive functions. It is considered to encode basic processes which are fundamental to a wide range of cognitive processes. This includes selective, anticipatory and temporal attention to ongoing tasks, and encode semantic information retrieval [60]. Selective attention enhances processing of certain kinds of stimuli which are within the attentional focus of the subject. This helps to increase processing of semantically relevant information and ignore the irrelevant details [60]. On the other hand, lower frequency bands, such as the theta band (4-7 Hz), have been associated with encoding and retrieval of new information or working-memory-based or emotion-based information retrieval [71, 72]. The theta band is also seen to encode emotional arousal [73].

The beta band (13-30 Hz) seems to serve a variety of different functions. During motor activity, together with the mu band (7.5-12.5 Hz), the beta band is shown to encode the correlates of upper and lower limb kinematics for both executed and imagined movements [19, 74]. Moreover, activity in the beta band has been found to be particularly enhanced during continuation of a current motor state and is seen to decrease when there is a change in motor function [75, 76]. In line with the aforementioned theory of the putative functional roles of lower and higher EEG frequency bands during top-down and bottom-up processing, respectively, coherence in the beta band between the frontal and parietal lobes has been reported to dominate during tasks requiring strong top-down processing while the gamma band (> 30 Hz) has been reported to show increased activation during the appearance of new stimuli and bottom-up processing [61].

The gamma band (30-100 Hz) is known to be associated with multiple functional roles such as attention, memory and awareness, as collated by recent review articles [77, 78]. The source of gamma band activity can be found in the precise fine temporal tuning of neurons during the transmission and synchronisation of information [77]. It has also been associated with emergence of visual awareness [77, 79, 80]. Burst of gamma oscillations are seen over the occipital electrodes whose latency correlates with recognition of the presented object. This also requires access to stored memory and comparison of the stimulus. Emergence of a sensory stimulus has been known to cause a gamma band response [78]. The source of gamma band activity has been found to be a distributed network of sources in the occipital, temporal, parietal and frontal regions; as well as focal sources in the occipital pole

[77]. The gamma band is most popularly known to be associated with the binding of sensory information and is therefore known to encode bottom-up processing of sensory information. However studies have also shown involvement of the gamma band in the early stages of endogenous top-down processing of information [78].

Thus EEG has been seen to contain signatures or neural correlates of a number of different processes and tasks which are typically attributed to the classical EEG frequency bands. Therefore, a feature extraction algorithm is typically used to extract relevant and discriminative information to differentiate between various possible cognitive, perceptual and motor processes intended by the subject.

2.3.4 Classification

Classifiers form the final functional unit of a typical BCI system, wherein the trained classifier identifies the class to which an incoming feature vector belongs to. Classifiers are of different types. They can be linear or non-linear, generative or discriminative, static or dynamic. *Generative* classifiers are those which assign a class to an incoming feature vector by computing the likelihood of the feature vector belonging to the various classes. It then predicts that class which has the highest likelihood or probability [81]. *Discriminative* classifiers are those which learn to distinguish between various classes with the help of discriminating boundaries or hyperplanes which divide the feature space into various regions, signifying the classes in those regions [81, 82]. *Static* classifiers are those which do not take into account the temporal variations of the features while classifying. On the other hand, *dynamic* classifiers are those which do take into account such temporal variations of features [83]. Since EEG is mostly considered to be a non-stationary signal, they tend to have significant temporal variations. Hence, dynamic classifiers have been shown to outperform static classifiers [84, 85]. Moreover, one can use more than one classifier at a time. Various types of combinations such as voting, boosting etc., have been reported in literature.

Table 2.2 summarizes the different types of classifiers used for BCI. Table 2.3 lists some of the techniques for combining classifiers. Combination of classifiers have often been reported to outperform individual classifiers. Moreover, they are known to reduce the variance in performance. Some of the most frequently used classifiers have been described below.

TABLE 2.2: Frequently Used Classifiers in BCI.

Sl. No.	Name	Properties	Advantages	Disadvantages
1	Linear Discriminant Analysis (LDA) [86]	Linear, Static, Discriminative	Simplicity, Ability to be regularized: hence better generalization capability, low computational requirement.	Performs poorly for non-linear EEG data
2	Support Vector Machines (SVM) [87]	Linear or non-linear (depending on kernel), Static, Discriminative	Simplicity, Ability to be regularized: hence better generalization capability, immunity to curse-of-dimensionality, low computational requirement	Slow speed
3	Neural Networks (NN) [88]	Non-linear, Static, Discriminative	Ability to approximate any type of continuous function, can discriminate between more than 2 classes	Susceptible to over-fitting
4	Bayesian Classifiers [86]	Non-linear, Static, Generative	Ability to fit non-linear data well, can distinguish between >2 classes, computation of probabilities helps to reject samples with high uncertainty (possible to know the confidence of classification)	Assumption of independence of features which may not be true.
5	Hidden Markov Model (HMM) [83]	Non-linear, Dynamic, Generative	Ability to use the temporal variation in the feature space for classification	Large number of parameters which need <i>a priori</i> knowledge.

TABLE 2.3: Techniques for Combining Classifiers.

Sl. No.	Name of Combination Technique	Description
1	Voting [89]	Multiple classifiers are used to classify the same feature vector. The predicted class is that which gets the highest number of votes from the classifiers. A simple voting based technique to combine multiple classifiers in an ensemble helped to improve classification accuracy by 7% in [90].
2	Boosting [86]	Successive classification using multiple classifiers, focussing on the errors made by the previous classifier. At least a 5% gain in classification accuracy was obtained using a boosting-based method in [91].
3	Stacking [92]	Layers of classifiers are used wherein the first classifier uses the feature vector for classification. The next layer of classifiers uses the results of the previous layer to identify the predicted class. Using a stacking approach helped to achieve a mean kappa=0.74 and outperform the winner of the BCI Competition IV 2a dataset with statistical significance [93].

Linear Discriminant Analysis (LDA:) LDA is one of the most widely used classifiers for BCI for binary classification. It is also called Fisher's Discriminant Analysis. LDA seeks to find a separating hyperplane such that the means of the two classes, χ_1, χ_2 are as far apart as possible while minimizing the interclass variance. Thus, it predicts a class depending on which side of the hyperplane the feature vector lies. The advantage of using LDA is that it is computationally very efficient due to its simplicity and can be regularized, giving it good generalization capability. In order to classify more than two classes, various schemes can be used, such as One Versus Rest (OVR). Equation (2.1) shows the objective function for linear discriminant analysis.

$$J(w) = \frac{w^T S_B w}{w^T S_W w} \quad (2.1)$$

where

$$S_B = (m_1 - m_2)(m_1 - m_2)^T \quad (2.2)$$

$$S_W = \sum_{i=1,2} \sum_{x \in \chi_i} (x - m_i)(x - m_i)^T \quad (2.3)$$

m_1 and m_2 are the means of the two classes χ_1 and χ_2 , respectively. LDAs have been effectively used in [94] along with regularized wavelet-common spatial patterns (WCSP) to obtain about 80% accuracy in classifying four classes of hand movements using the OVR approach.

Support Vector Machines (SVM): Besides LDA, SVM is one of the most commonly used classifier in BCI systems. This is perhaps because of the fact that SVMs are fit high-dimensional data very well, they are simple and therefore are computationally efficient. When required to fit non-linear data, they can be used with a non-linear kernel, such as the widely used Radial Basis Function (RBF) kernel, without much increase in the computational complexity. Moreover, they have various hyperparameters and regularization parameters which help SVM to generalize better and are thus able to fit high-dimensional data without being affected much by the curse-of-dimensionality. SVMs are also discriminative classifiers such that they use hyperplanes to maximize the margins between the means of classes.

The objective function to optimize for an SVM for classifying two classes $y \in \{-1, 1\}$ is as follows [95].

$$\min_{w,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1}^l \zeta_i \quad (2.4)$$

$$\text{such that } y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i \text{ and } \zeta_i \geq 0 \quad (2.5)$$

where $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ is the kernel function which transforms the feature vectors to a higher dimensional space where the classes may be better separated, C is the penalty parameter. The effectiveness of SVMs with various kinds of feature extraction techniques on EEG data has been demonstrated in [96].

Naive Bayesian Classifier: Naive Bayesian Classifier is a non-linear generative classifier [35]. This classifier predicts the class ω_m if the conditional, *a posteriori* probability $p(\omega_m|x)$ is maximum for ω_m among all ω . The classifier is called a naive classifier since it is based upon the assumption that all the features are

independent. Naive Bayesian classifiers can be used to classify more than 2 classes. Naive Bayesian classifier will be described in greater detail in Chapter 3. The Naive Bayesian classifier was used with the filter banks common spatial patterns (FBCSP) method to achieve the highest mean classification performance in BCI Competition IV 2a ($\kappa=0.569$) and 2b ($\kappa=0.600$) [36].

It is to be noted that there have recently been tremendous advances in the application of deep learning methods in BCIs. The strength of these methods lies in their ability to take as input raw or minimally pre-processed EEG data and directly extract discriminative features, forming higher levels of abstraction from the data. However, one of the major limitations of applying deep learning frameworks to EEG-based BCIs is the availability of big data that is typically required to train deep learning models. Therefore, due to the size of EEG data used in this thesis, deep learning methods have not been used in this thesis. Recent advances in deep learning-based methods for classification of EEG data have been reviewed elsewhere [97–100].

2.3.5 Considerations for Classification of EEG features

When classifying features traditionally derived from EEG, the following properties of EEG signals are to be taken into consideration.

1. *Non-stationarity of EEG*: EEG is a non-stationary set of signals, because of which there are significant temporal variations across sessions for the same subject and across subjects. Thus, the performance of the classifier may be affected because of the huge inter-trial variation in data. Moreover, responses to stimuli as observed from EEG data are time-locked. This means that it becomes important to observe their temporal variation in order to carry out accurate classification.
2. *Effect of Outliers and Noise*: EEG features of interest, such as ERPs, are often of low amplitude with significant background noise. Moreover, artefacts like EOG, etc are much higher in amplitude than EEG. The low SNR has to be treated through relevant preprocessing techniques before training a classifier. Moreover, presence of outliers affect the performance of the classifiers. Thus, it is required to have a classifier which has low variance so that it is able

to generalize better. Many regularization techniques have been proposed to enhance the generalization ability of the classifiers.

3. *Curse of Dimensionality*: The number of training examples required for training a classifier increases exponentially with the dimensions of the feature matrix. However, due to the nature of EEG data acquisition and human subjects, it is difficult to collect lots of data; while, for any practical purpose, we need sufficient number of channels to record the scalp EEG. Thus, in the cases of small datasets, the performance of the classifiers may be affected due to insufficient number of trials for training the classifier.

2.4 EEG-based SMR BCIs

Rhythmic activities such as mu, beta and gamma rhythms, called sensorimotor rhythms (SMR), recorded over the sensorimotor cortex that occur during motor execution and imagery are used to detect and predict the type of motor activity [101]. These changes manifest as power spectrum activations and depressions in the above frequency bands during various kinds of bilateral and unilateral movements. Bilateral coordination refers to the ability to coordinate both sides of the body at the same time in a controlled and organized manner. For example, stabilizing paper with one hand while writing or cutting with the other. Good bilateral integration and coordination is an indicator that both sides of the brain are communicating effectively and sharing information. This involves both excitatory and inhibitory influences between hemispheres which are reflected in the various EEG frequency bands [19, 60]. During actual movements, motor imagery or motor intention, different parts of the brain, such as the motor and parietal cortex, coordinate in order to carry out and complete the task.

Neuroscientists can use the resulting neurological phenomena, described in Section 2.5 such as slow cortical potentials, local field potentials, Event Related Desynchronization / Event Related Synchronization, Event Related Potentials etc to decode movement directories, velocity, etc [102]. A typical example of a BCI application is a sensorimotor rhythm (SMR)-based BCI that is capable of decoding the SMR processes that correspond to various kinematic variables of the intended motor activity. In such BCI systems, a feature extraction algorithm is typically

used along with machine learning to extract movement related information from these rhythms to predict the subject's intended activity.

2.5 Neuromechanisms of interest for an SMR-BCI

During movement execution and imagination of movement, called motor imagery (MI), there are certain neurophysiological phenomena observed in the scalp EEG. Among these, event-related desynchronization/ event-related synchronization (ERD / ERS) and evoked potentials (EPs) are most commonly studied in order to analyse and classify the type of motor activity. As mentioned earlier, the frequency of EEG signals are inversely related to their amplitude. Therefore, the EEG signals at the lower end of the frequency spectrum, such as the Delta (< 4 Hz) and Theta (4–7 Hz) bands have greater amplitude than the Alpha (8–12 Hz) and Beta (16–30 Hz) bands, while the Gamma (> 30 Hz) band has the lowest amplitude. Amplitude of the EEG signals in any band is known to be proportional to the number of synchronously active neural members [19]. Thus, it is postulated that there are much more slowly oscillating neural correlates in synchrony than the faster oscillating ones [19, 74].

2.5.1 Event-related Desynchronization/ Synchronization

It is known that the left side of the brain is responsible for the motor activity in the right side of the body and vice versa. ERD refers to the (contralateral) decrease in band powers during limb movements, while ERS refers to the (ipsilateral) increase in band powers during the same. ERD / ERS are observed due to changes in the activity of neurons and inter-neurons that control frequency components [19]. They are often expressed as a percentage of the band powers in the target EEG frequency band in the period of interest with reference to a baseline interval. It has been observed that ERD is enhanced while learning a new movement task and it diminishes as the task becomes familiar. ERD is known to be highly frequency-band specific and exhibit spatial localization for movement of limbs located at different sides of the body [19]. Thus, it is possible to identify these patterns in

the scalp EEG with the use of appropriate spatial filters and are a frequently used method to identify movements made.

ERD has been observed to begin around 2 seconds prior to movement-onset (hence, in the planning stage of a task) over the contralateral Rolandic region [74]. Across the EEG frequency bands, it has been observed that ERD in the lower frequencies is more topographically widespread while the topography in the higher frequency bands (mu and beta bands) is more discrete and somatotopically specific. Ipsilateral ERS has been observed to occur simultaneously with ERD in the beta band for motor imagery of upper limbs. After the termination of movement and motor imagery, contralateral ERS in the beta band has also been commonly observed. However, the precise frequency bands which show most distinct task-dependent activity are often subject-specific. Therefore, methods like Filter-bank Common Spatial Patterns (FBCSP) allow for fine-tuning the feature matrix according to the most discriminative frequency bands and spatial patterns to achieve the best classification accuracy [36, 37].

2.5.2 Evoked Potentials (EPs)

Evoked Potentials (EPs) are transient brain responses to certain stimuli [103]. These neural signatures are not generated spontaneously but are instead time-locked changes in the on-going brain rhythms, with reference to a certain stimulus, which can be interpreted as the responses of cortical neurons due to changes in the afferent activity. Thus, they are also referred to as Event Related Potentials (ERPs) when the evoked neural signature is in reference to a certain external stimulus or event. ERPs occur due to the reorganization of phases of the ongoing EEG signals. Thus, they are evoked from neuronal masses as they process information and respond to a certain stimulus. Other types of EPs include slow cortical potentials (SCPs), movement related potentials (MRPs), auditory evoked potentials (AEPs), somatosensory evoked potentials (SEPs), visual evoked potentials (VEPs) and so on [104].

ERPs and their various components can be studied in precise time instants wherein the relative amplitude and latency of each component is indicative of a certain type of neural response to the given stimulus. These features also carry information about possible pathopsychological or neurological disorders or brain conditions

that might lead to altered processing of information. However, repeated observations of the same task or action are usually required in order to extract ERP components from the high levels of noise in EEG signals which typically have low signal-to-noise ratio (SNR), high trial-to-trial variability and poor spatial resolution of EEG signals. ERPs consist primarily of 2 components: exogenous and endogenous components. Exogenous components are those which immediately follow the stimulus and are modulated by the physical characteristics of the stimulus. Endogenous components follow the exogenous components and are modulated only by complete stimulus evaluation, attention level and so on.

Error Potentials are neural responses to the perception of error [105–108]. They are a type of ERPs and so the method of detection of ErrPs is very similar to the detection of specific ERP components. Based on the cause of error, evoked ErrPs can be categorized as those made by the user and those made by the computer. Response ErrPs are those that are evoked when the user incorrectly responds to a stimulus or cue. Observation ErrPs are those that are evoked when the user observes another user make an error. The observation of errors made by a computer with regards to the intention of a subject can lead to ErrPs called Interaction ErrPs.

2.6 Conventional Techniques to Decode Motor Kinematics in EEG-based SMR-BCIs

2.6.1 Detection of ERPs

In order to detect an ERP, we can measure various characteristics of EEG signals. However, no characteristic is completely robust and may lead to faulty interpretation. For example, amplitude of ERPs are more or less arbitrary, the timing of onset / offset may be affected by component overlap, the latency of ERP components have high variability, and so on. One may choose to measure either the area or a fraction of the area under a waveform. Among the safest ways to detect ERPs is to observe their complete temporal evolution using various time windows. Moreover, known scalp locations for certain ERP components can be used to corroborate the results of the detector.

Often, spatio-temporal features, say $X \in \mathbb{R}^{M \times T}$, are extracted to detect ERP components, where M is the set of EEG channels, T is the set of time intervals and X is the matrix of EEG data averaged in the time intervals. After that, the most informative features are selected to reduce the dimension of the feature matrix which in turn helps to make the classifier more robust. Various strategies based on correlation, relevance, redundancy and mutual information may be used to select the subset of features. These selected features are then given to a classifier such as Linear Discriminant Analysis (LDA) to learn and predict new incoming data.

2.6.2 Common Spatial Patterns

Common Spatial Patterns (CSPs) are a spatial filtering based feature extraction method used to classify between two classes. The filter coefficients in CSPs are extracted by maximizing the variances of one class while minimizing that of the other. Thus, they are inherently meant for binary classification. For classifying more than two classes, they are used with a One-Versus-Rest (OVR) strategy. The objective function of CSPs is defined in (2.6).

$$J_{CSP}(w) = \frac{wX_1X_1^Tw^T}{wX_2X_2^Tw^T} = \frac{wC_1w^T}{wC_2w^T} \quad (2.6)$$

where w is the spatial filter that maximizes J_{CSP} , X_1 and X_2 are the matrix of EEG signals recorded corresponding to classes 1 and 2 respectively, C_1 and C_2 are the covariance matrices corresponding to classes 1 and 2 respectively. The solution obtained for the above is $w =$ eigenvectors of $C_2^{-1}C_1$ corresponding to the largest and lowest eigenvalues. The advantages of CSPs are that they are versatile, so they can be used for a variety of BCI applications and are computationally efficient. However, they do suffer from some drawbacks. CSPs are sensitive to noise and non-stationarities in EEG data. Moreover, when the size of training data available is small, they are also prone to overfitting [109].

In order to address the drawbacks of CSPs, a large number of variants of CSPs have been developed and reported in literature that help to address different shortcomings. These mostly occur as regularization parameters added to the objective function and/or modifications to the covariance matrices [109, 110].

2.6.2.1 Regularized CSPs

1. Regularizing the Co-variance Matrix

CSPs suffer from the noise reflected in the co-variance matrix due to raw, noisy EEG signals. Thus, if we have prior knowledge about how the co-variance matrix should look like, we can accordingly regularize it. Thus, we replace the co-variance matrices C_i with $\bar{C}_i$.

$$\bar{C}_i = (1 - \gamma)\hat{C}_i + \gamma I \quad (2.7)$$

$$\hat{C}_i = (1 - \beta)s_i C_i + \beta G_i \quad (2.8)$$

where I is the identity matrix, γ and β are user-defined regularization parameters such that $\gamma, \beta \in [0, 1]$, s_i is a constant used as a scaling parameter.

2. Regularizing the Objective Function

The idea behind regularizing the objective function is to penalize those solutions that do not satisfy a given prior. Thus, instead of a single objective function, we instead use 2 objective functions as defined below.

$$J_1(w) = \frac{w^T C_1 w}{w^T C_2 w + \alpha P(w)} = \frac{w^T C_1 w}{w^T (C_2 + \alpha K) w} \quad (2.9)$$

$$J_2(w) = \frac{w^T C_2 w}{w^T C_1 w + \alpha P(w)} = \frac{w^T C_2 w}{w^T (C_1 + \alpha K) w} \quad (2.10)$$

where α is the regularization parameter and K is the matrix that encodes the prior. Thus, $P(w) = w^T K w$.

Thus, one may use either or both types of regularization techniques above. It is seen that regularized CSPs outperform classical CSPs in terms of classification accuracies and are also more robust to noise or limited data. Then, different combinations of regularizations used, result in different variants of CSPs. A detailed list of different types of regularized CSPs can be found in [110]. Some of the important variants have been summarized in Table 2.4. Besides the variants mentioned in Table 2.4, there are other types of variants of CSP as well which have been reported to be extremely useful for certain kinds of tasks. For instance, there is the Common Spatio-Spectral Pattern (CSSP) that uses a one time-delayed sample along with the CSP algorithm [114]. An optimized variant of CSSP is the Common Sparse Spectral Spatial Pattern (CSSSP) that carries out simultaneous optimization of an

TABLE 2.4: Regularized Variants of CSP

Regularized CSP Method	Regularization Parameters	Reason for Regularization
Composite CSP (CCSP) [111]	$\alpha = \gamma = 0$; $G_i, s_i \neq 0$	Use subject to subject transfer to compensate for low number of trials by using the trials from other subjects
Regularized CSP with Generic Learning (GLRCSP) [112]	$\alpha = 0$; $\beta, \gamma, G_i, s_i \neq 0$	Use both γ and β to shrink the covariance matrix towards I and G_i , where G_i is sum of the covariance matrices of other subjects
Regularized CSP with Diagonal Learning (DLC-SPauto) [110]	$\beta = \alpha = 0$; $\gamma \neq 0$	Shrink the covariance matrix towards the identity matrix I .
Invariant CSP (iCSP) [113]	$\beta = \gamma = 0$; $\alpha \neq 0$	Regularize the objective function only. K , the co-variance matrix that encodes the prior, is modelled for the noise source
Regularized CSP from Selected Subjects (SS-RCSP) [110]	$\alpha = \gamma = 0$; $\beta \geq 0$.	Select a subset of subjects to estimate the generic covariance matrix
CSP with Tikhonov Regularization (TRCSP) [110]	$\gamma = \beta = 0$; $\alpha \geq 0$.	Regularize the objective function to penalize large weights. Quadratic terms are used. Thus, $P(w) = w^T w (K = I)$.
Spatially Regularized CSP (SRCSP) [110]		Use the spatial information of electrodes and create smooth filters.

arbitrary FIR filter in the CSP algorithm [115]. Filter bank CSP (FBCSP) uses a filter bank to filter the incoming EEG signals into various frequency bands before using extracting features using one of the CSP algorithms [36, 37]. More recently Wavelet CSPs (WCSP) and modified WCSP were used such that a wavelet-based filter bank was used to reconstruct the EEG signals at the various wavelet levels prior to carrying out CSP and Spatially Regularized CSP feature extraction methods, respectively [94, 116, 117].

An inherent property of the above CSP-based methods is that they are inherently activation-based methods. They are capable of extracting discriminative patterns of spatio-spectral activations on the scalp for identifying between different classes.

However, while they have been seen to be informative about different kinds of simple hand movements, they carry little information about the dynamic interactions that take place between different brain areas during different tasks. Activation maps derived EEG data carry information about the power amplifications and depressions at different channel locations and EEG frequency bands. On the other hand, estimates of synchrony, also called functional connectivity, provide information about the dynamic functional relationship between different regions. The latter carries rich information about dynamic neural interrelationships that have been attributed to be the basis of all cognitive, motor and perceptual actions. The next sections describe an overview of popularly used methods in literature to estimate such functional associations between different brain regions.

2.7 EEG-based Source Localization

As mentioned earlier, scalp EEG signals have an inherent basis in the activity of cortical microcircuits. Therefore, it is often of interest to researchers to identify and re-engineer the underlying cortical sources of neural activity from the EEG signals recorded from the scalp. This transformation from the sensor to source space can aid EEG analysis and decoding of various neurological phenomena [118]. There are various reasons which encourage this transformation. Firstly, EEG suffers heavily from volume conduction and spatial smearing. This means that the propagation of electric fields generated by cortical source currents through various layers of the meninges, cerebrospinal fluid, skull and scalp, causes them to get mixed non-linearly from different cortical regions. This renders it impossible to accurately represent the underlying distribution of cortical activations, hereby referred to as the “source space”, by scalp signals alone, also called the “sensor space”. This problem is further exacerbated by the limited number of electrodes that are typically used to record EEG signals from the scalp. Thus, scalp electrodes that are used to measure EEG are vastly outnumbered by their corresponding cortical sources, making the reverse mapping of EEG signals and their underlying microcircuit configurations an ill-posed problem.

In order to reduce the effect of volume conduction and enhance the spatial resolution of EEG, various methods have been proposed in literature to solve the aforementioned ill-posed problem of EEG-based source localization. A common

strategy undertaken by various techniques to mitigate this issue is to use prior knowledge in terms of anatomical conditions to restrict the number of sensor-to-source mappings. Thus, even though theoretically, there exist an extremely large number of solutions for the latter, the total number of permissible mappings shrinks considerably by setting the anatomical priors. This prior knowledge is encoded in the forward model which consists of the lead-field matrix containing a transformation matrix of tessellated points or vertices representing sources on a multi-layer anatomical model of the head. Each layer represents various layers of cortex, cerebrospinal fluid and skull.

A linear transformation between the source and sensor space describes the principle of EEG-based source localization, as given below.

$$E = \zeta S + \eta \quad (2.11)$$

Where E stands for the $N \times T$ matrix measured EEG signals, N is the number of EEG channels, T is the total number of time points recorded, ζ is the lead field matrix of dimensions $N \times m$, where m is the number of sources, S is a matrix of dimension $m \times T$ which corresponds to the source signals to be estimated and η is the noise perturbation term.

Thus, assuming the multi-layer anatomical forward model as representations of the various layers of cortex, meninges, CSF and skull, Maxwell's equations can be solved to estimate the underlying current generators of the EEG signal space. This is referred to as the inverse problem. Since the spectrum of EEG signals that are typically analyzed are $\ll 1000$ Hz, quasi-static approximations are applied to Maxwell's equations which can then be solved to estimate the cortical signals for a given number of tessellated vertices, using given conductivity and permeability values of each layer. Various algorithms have been proposed in literature for solving the inverse problem, such as low resolution electromagnetic tomography analysis (LORETA) [119], standardized LORETA (sLORETA) [120], local autoregressive average (LAURA), minimum norm estimation (MNE), linearly constrained minimum variance (LCMV) [121] and so on. After the above transformation, certain regions of interest relevant to the task under analysis are selected, typically based on *a-priori* knowledge or whose dynamics are to be investigated.

FIGURE 2.6: Long-range brain networks as adapted from [6]

2.8 Decoding EEG-based Neural Synchrony

A number of studies have shown that neural cell assemblies in different brain regions form transient functional connections in order to perform any cognitive, motor or emotional activity [6, 50, 122]. It has been further postulated that long-range interactions, as visible through macroscale electrophysiological and neuroimaging recordings, underlie such complex activity [5]. A growing amount of evidence seems to suggest that these functional connections are in fact dynamic reciprocal connections, synchronizing anatomically segregated regions of the brain [5]. The phase of the measured brain signals is said to be crucial in establishing these long-range reciprocal connections. Some studies have postulated that the need for synchronized cell assemblies is to enable coordinated effort to carry out a certain task within the time-span of a typical cognitive function that typically takes tens to hundreds of milliseconds [5, 6]. A single neuron would not be able to activate other cells within the assembly within such a short period of time. However, a coordinated and synchronized spiking of multiple such neurons would then enable activation of other cells within the assembly. The phase of the spiking activity of these neurons is thus an important criterion in establishing synchrony within the assembly. Thus, as a correlate of large ensembles of such neuronal masses, phase-synchrony is also observed in EEG signals and has been widely used to study the functional connections that underlie various activities. Figure 2.6 shows a depiction of (transient) cell assemblies with reciprocal connections within and between cell assemblies.

2.8.1 Quantifying phase synchrony between EEG signals

Phase synchronies are often used to analyze brain activity, especially during movement, motor imagery, perceptual and cognitive tasks [123–127]. Some of the established techniques to study phase synchronies include Phase Locking Values (PLV) and Phase Locking Statistics (PLS) [127]. Phase and phase-synchrony based features have been used earlier to analyze and classify left vs. right hand and tongue motor imagery [128]. Phase-locking based features were also used to study movement execution of right vs. left index finger tapping in [125]. The study found significant differences in the phase-locking patterns between the two types of movements and between cued and self-initiated tapping. Moreover, significant phase-locking was reported due to motor execution and planning in the delta and theta frequency bands.

2.8.1.1 Phase-Locking Values (PLV)

Phase locking has been commonly used to study the dynamics of non-linear and non-stationary systems (for e.g. the phase locked loop). Hence, phase locking is a relevant measure to study EEG signals since the brain is a dynamic, non-linear and non-stationary system. It is also robust to fluctuations in amplitude in EEG which may not provide much information as compared to relative phase based features. Thus, phase-locking values measure the variability of relative phase between two signals. If the distribution of the relative phase (as a function of time or trials) is uniform, then the phase-locking value is very small and almost equal to 0. On the other hand, if the relative phase is consistent across time/trials, then the phase-locking is almost equal to or very near 1 [129].

Computation of Phase Locking Values (PLV) PLVs can be computed in the following way. First, the signal is bandpass filtered in the required narrow-band of interest using a finite impulse response (FIR) filter. Next, the filtered signal is used to carry out convolution with a wavelet centered at the desired frequency. The result is then used to extract the instantaneous phase of the signal. The authors

in [130] use Gabor wavelet as defined in (2.13) which is centered at frequency f .

$$s_1(t) = p_1(t) * h_{bp}(t) \quad (2.12)$$

$$G(t, f) = \exp\left(\frac{-t^2}{2\sigma_t^2}\right) \exp(j2\pi ft) \quad (2.13)$$

$$q_1(t) = s_1(t) * G(t, f) \quad (2.14)$$

where $p_1(t)$ is the raw EEG signal, $h_{bp}(t)$ is the FIR band-pass filter, $s_1(t)$ is the resultant narrowband signal, $G(t, f)$ is the Gabor wavelet as used in [130], $q_1(t)$ is result of the convolution with the Gabor wavelet and is used to extract the instantaneous phase of the signal. An alternative way that is frequently used to extract the phase of the narrowband signal is by using the Hilbert Transform [131, 132].

$$V = \left| \frac{1}{N} \sum \exp j(\Delta\phi) \right| \quad (2.15)$$

where $\Delta\phi$ is the phase difference between two signals and $|\cdot|$ denotes the mean absolute value.

2.8.1.2 Phase Locking Index (PLI)

Phase Locking Index (PLI) is aimed to reduce the sensitivity of the estimator of phase-synchronies to the common source problem and volume conduction in EEG [133]. Although it is not completely immune to these problems, it is less affected by them as compared to phase coherence (PC), an established measure for estimating phase-synchronies [129]. PLI can take into the account the mean around which the phase-differences are distributed. Some studies state that when the distributions of phase-differences are symmetric around 0 or π , it is most likely due to the common source problem. In such cases PLI values are 0. This is discussed in more detail in Section 2.8.1.4. However, if the distribution is not uniform or is asymmetric, then PLI is higher [134].

Trial-averaged Phase Locking Index (PLI) is computed as below.

$$I_{c,l}(x, y, t) = \left| \frac{1}{T_c} \sum_{trials \in c} \text{sign}(\phi_x(t) - \phi_y(t)) \right| \quad (2.16)$$

PLI is known to be a more robust estimator of phase-locking in EEG. PLVs are unable to discriminate between zero phase-difference and non-zero phase-difference

based phase-locking. Therefore, they suffer from common-source problem. PLIs are able to circumvent this situation as they are zero for zero phase-difference values. PLI values are thus sensitive to the mean of the distribution of phase-differences and not just the variance which is the case with PLVs.

2.8.1.3 Observations on the sample estimator of PLVs

The following are some of the observations of the sample estimator of PLV [129].

- It is a biased but consistent maximum likelihood estimator of PLVs. The bias depends on the true distribution of PLVs. Therefore, if $\hat{V}_{sample}$ is the sample estimator of the true value of PLV V , with N being the number of samples over which PLV is estimated as a mean, then $E\{\hat{V}_{sample}\} > V$ and $\lim_{N \rightarrow \infty} \hat{V}_{sample} = V$.
- $\hat{V}_{sample}$ is a function of N . As N increases, $\hat{V}_{sample}$ converges to the true value of PLV. It is seen that for $N > 50$, $\hat{V}_{sample} \approx V$. Moreover, for higher absolute values of PLV, the difference between $\hat{V}_{sample}$ and V is very small, even for a fixed value of N . As the absolute value of V decreases, the difference between $\hat{V}_{sample}$ and V increases.
- It is possible to obtain an unbiased estimator for $\hat{V}^2$ regardless of the distribution of the relative phase. Moreover, it is also equal to the measure of Vinck's Pairwise Phase Consistency (PPC). The observations for $\hat{V}_{sample}$ above are consistent with those of $\hat{V}_{sample}^2$. Moreover, the variance increases when using the unbiased estimator of $\hat{V}^2$ than when using the biased estimator of the same.

2.8.1.4 Limitations of PLVs and PLIs

Phase-locking values at the sensor space suffer from the common source problem. That is, a single source may contribute to more than one sensor after volume or current conduction and result in equal time lags at the sensors. Hence, the relative phases centered around 0 may be contributed by spurious phase-locking due to the common source. However, there is no way to identify such spurious phase-locking using PLVs alone in their traditional sense. Therefore, PLV estimates in

the EEG sensor space should be interpreted with caution. Moreover, PLVs may lead to false interpretations when EEG or MEG is measured with respect to a common electrode. When EEG signals are re-referenced to a common channel, the subtraction of similar waveform components from that channel may also contribute to falsely high phase-locking values. This is primarily because PLVs are not able to identify the mean of the distribution of the values that are used for computing the PLVs. Instead, it is an indicator of the variance of the individual values that make up the distribution. Hence, a high variance in the values leads to lower PLV values, implying more randomness in the data. The opposite holds in the case of distribution with low variance. Hence, when the values are centered symmetrically around zero phase-difference or π then the resulting PLV is higher. It is this case of zero-phase difference that is more commonly associated to the common source problem.

However, not all zero-phase difference PLV values are due to volume conduction. Some studies have demonstrated that there is indeed useful information in the zero-phase PLVs which cannot be explained by volume conduction [132]. Thus, rigorous statistical analyses are typically carried out on PLV estimates to identify important task-induced phase-synchrony between signals and eliminate spurious phase-synchrony. The statistically significant PLV values have also been called phase locking statistics (PLS). In its original form, PLVs need repeated observations of the task under investigation to estimate phase-synchrony and thus are limited to trial-averaged analyses. Moreover, since the underlying distribution of phase-spectra needs to be empirically obtained, permutation-based techniques are commonly used to generate the null distribution for the aforementioned statistical testing. However, such Monte Carlo methods are typically meant for offline analysis due to their iterative nature making it almost impossible to use such estimates in single-trial decoding of motor activity in BCI systems.

PLI exploits the asymmetry of phase-differences to quantify and better estimate true phase-synchronies. Thus, PLIs may miss out on linear but functionally meaningful interactions near zero phase-differences. Along with the common source problem, near zero phase-differences can also be because of actual, functionally relevant, linear interactions between sources and sensors. However, PLI does not account for such interactions and will nullify them as well. Lastly, PLI is not completely immune to volume conduction but is less affected by it.

2.8.1.5 Coherency, Coherence and Correlation

Coherence between a pair of signals either derived from different EEG channels or from different sources is one of the most commonly used estimators of neural synchrony. The pair of signals between which coherence is to be estimated is usually subjected to narrow band-pass filtering at the frequency of interest. Coherency is a complex number that is estimated using the following equation:

$$C_{xy}(f) = \frac{S_{xy}(f)}{S_{xx}(f)S_{yy}(f)} \quad (2.17)$$

where S_{xx} and S_{yy} are the autospectrum of the two signals x and y , respectively at the frequency f and S_{xy} is the cross-spectrum of x and y .

Coherence is then computed as the absolute value of the complex value of coherency, given by (2.17).

$$Coh_{xy}(f) = |C_{xy}(f)| \quad (2.18)$$

A closely related time-domain analogue of coherence is correlation. The time-domain series of the two signals, after narrow band-pass filtering are then used to compute the correlation using the following equation.

$$r(f) = \frac{C_{xy}(f)}{C_{xx}C_{yy}} \quad (2.19)$$

where C_{xy} is the cross-covariance between the two signals x and y , C_{xx} and C_{yy} are the auto-covariance matrices of the two signals.

2.8.1.6 Imaginary part of Coherency

It has been postulated that coherence measures suffer from spurious connectivity estimates due to volume conduction, especially at the sensor space. Therefore, it has been proposed to only use the imaginary part of coherency in (2.17) which would not have any contribution of the instantaneous spurious connections due to volume conduction [135]. This was then called imaginary part of coherency or iCOH, given by the following equation.

$$iCOH_{xy}(f) = \text{imag}(C_{xy}(f)) \quad (2.20)$$

2.8.2 Model-based Estimation of Functional Connectivity

All of the aforementioned estimators of synchrony or functional connectivity were model-free quantifiers. This means that they can be used directly to quantify the interrelationships between different signals, without having to pre-specify a model or hypothesis about the nature of interaction are thus non-parametric estimators. In some cases, it might be preferred to study a particular hypothesized model of interaction between different regions or sources. For this purpose, the interactions between these regions of interest can be modelled using various parametric approaches.

The most typical methodology is to fit a multivariate auto-regressive (MVAR) model to a given set of signals. The coefficients of this fit model is then used to derive various indicators of functional relationships. Moreover, using the concept of Granger Causality, it is also possible to model the Granger-causal (GC) interactions to assess the direction of flow of information between various sources or regions. Granger causality is assessed using the following concept. P is said to Granger-cause Q if the observation of the present and past values of P improve the prediction of the future instances of Q over and above the present and past values called Q [136].

Popular estimators of directed (GC), model-based quantifiers of functional connections are Directed Transfer Functions (DTF) [137] and Partial Directed Coherence (PDC) [138] which can be estimated as described below.

A multivariate autoregressive model A of order p is fit to the signal matrix $X(t)$ and noise matrix $E(t)$ using the following equation [139].

$$X(t) = \sum_{j=1}^p A(j)X(t-j) + E(t) \quad (2.21)$$

then, the frequency domain representation of equation (2.21) is given by the following.

$$E(f) = A(f)X(f) \quad (2.22)$$

$X(f)$ can then be written as:

$$X(f) = A^{-1}(f)E(f) = H(f)E(f) \quad (2.23)$$

The above transfer function $H(f)$ can then be used to compute DTF and PDC as follows.

$$DTF = \frac{|H_{xy}(f)|^2}{\sum_m |H_{im}(f)|^2} \quad (2.24)$$

$$PDC = \frac{A_{xy}(f)}{\sqrt{a_j^*(f)a_j(f)}} \quad (2.25)$$

2.9 Summary

In this chapter, an overview of a typical BCI system was presented. Existing techniques to implement the functional units of a typical BCI system, including data collection, feature extraction and classification were detailed. A number of data modalities were listed and motivations for using EEG as the data modality of choice in this thesis were discussed. Decoding strategies for a traditional SMR-BCI were explained along with some well known neural signatures accompanying different motor actions. Next, traditional techniques to decode neural interactions derived from EEG were discussed. The motivation for investigating such neural interrelationships beyond examining task-based power spectra were also presented.

The goal of SMR-BCIs is to decode various movement kinematic variables directly from brain signals. Moreover, passive BCIs are used to monitor cognitive processes under different situations. The collected data are then used to extract the neural correlates of the induced cognitive process. The following chapters in this thesis present contributions to BCI research using a functional networks-approach to motor decoding in SMR-BCIs and investigating the underlying mechanisms of Autism Spectrum Disorder during a complex facial emotion recognition task in a passive BCI.

Chapter 3

Classification of Hand Movement Directions from EEG using Wavelet Phase-Locking Values (W-PLV)

3.1 Introduction

The primary objective of an SMR-BCI is to decode the intention of and identify between different kinds of movements from the subject's brain signals. Voluntary motor actions, as opposed to reflex or rhythmic motor actions, are said to be goal-oriented [140]. The brain is known to create internal representations of a program to carry out a certain movement. Each motor action involves the modulation of a number of different parameters such as force, grip, speed, velocity and trajectory which are referred to as motor kinematics. Moreover, these parameters are differently associated with each of the various parts of the limb that are together coordinated by the brain in a synergy to complete a full motor action. This

Contributions made to this chapter have been published in

1. T. Chouhan et al., "Wavelet phase-locking based binary classification of hand movement directions from EEG", Journal of Neural Engineering, 2018
2. T. Chouhan et al., "Binary classification of hand movement directions from EEG using wavelet phase-locking", Proceedings of IEEE SMC, 2017

internal representation of the motor activity in the brain is called a motor program [140]. Therefore, in order to decode and recreate the intended movement by the subject, an SMR-BCI should be capable of decoding these kinematic variables corresponding to different parts of the limb.

Neural Correlates of Direction Tuning

The ability to make and therefore decode limb movements in different directions comes from a property of neurons called direction tuning [141]. This means that the firing rate of a certain neuron may depend on the direction of arm movement such that it peaks when a movement is made in a certain direction only. It is then said to preferentially encode the particular direction of movement. When plotted as a function of all directions, the firing rate of such neurons is often seen to follow a cosine function, thus being given the name of “cosine tuning” [74]. Therefore, in order to decode movement directions from EEG signals, appropriate feature extraction algorithms should be used which can quantify patterns of direction tuning generated by large masses of neuronal populations. An overview of existing techniques to decode direction-specific information from EEG are described below.

Amplitude and phase are two important properties of any signal. While the amplitude is related to the intensity of a signal, the phase corresponds to the rhythmic component in the brain oscillation. There are a number of amplitude based features that have been used in literature for decoding the parameters related to limb kinematics. For the purpose of studying arm movements and motor imagery from EEG, the most frequently used methods rely on an amplitude-based spatial filtering technique called Common Spatial Pattern (CSP) [142]. As outlined in Chapter 2, many variants of CSP have been proposed in literature to classify different hand movements from EEG [37, 110, 116, 117]. For the purpose of classifying and analysing hand movements in four orthogonal directions in a 2D plane, Spatially Regularized Wavelet Common Spatial Patterns have been shown to perform well with a multi-class classification accuracy of about 80% [94] and binary-class classification accuracy of 71.25% [117].

Neurophysiological Interpretation of Phase-Synchrony in Motor Tasks

In the recent past, a number of studies have reported rich motor-related information in the phase of electrophysiological data from humans and non-human primates [141, 143–145]. Interestingly, among the various kinematic variables decoded from different electrophysiological modalities, information related to movement direction

have been consistently reported to be decoded from the phase of low frequency signals. While the spectral perturbations in higher frequency bands such as the mu, beta and gamma bands have long been known to correlate with motor activity [1, 74], a growing amount of evidence seems to suggest the phase of the lower frequency electrophysiological data to be more informative about movement directions than spectral (amplitude) properties [141, 143, 144]. Peaks in neuronal firing during preferred movement directions have been said to be closely related to phase modulations [143]. Thus, what is observable as directionally tuned neuronal firing in single and multi-unit studies have been shown to correspond with low frequency phase of macroscale recordings such as intracranial EEG and ECoG. Thus, large-scale phase-synchrony in the lower frequencies from macro-recording modalities could be an important indicator of widespread and similarly tuned neuronal ensembles in micro-recordings. Although a number of studies have demonstrated higher decoding accuracy of movement directions using the phase of ECoG and intracranial EEG (iEEG) signals [143, 144], EEG-based studies on the same have rarely been reported on finer hand movements. Among the few phase-based studies using EEG, phase-locking based methods such as phase-locking value (PLV) have been used to investigate the trajectory of large-scale inter-region synchrony during bilateral motor tasks [145]. Even in such motor activity, PLVs showed task-induced increase in long-range phase based interactions in the delta band. It was hypothesized that executing movements would require the interaction between multiple non-motor regions of the brain. It has been postulated that phase-synchrony forms the neural basis of large-scale interactions in the brain that enable complex cognitive and motor tasks and that the human cortex dynamically reorganizes into different functional networks during various motor activities [6].

Various studies across a range of electrophysiological modalities have also reported widespread transient networks as established by phase-based large-scale interconnections during the preparation and execution of reaching tasks [146–150]. With the help of precise brain mapping methods, a number of cortical regions have been found to contain directionally tuned neuronal assemblies. These regions include the primary motor [143, 146, 149], premotor [147], frontal [143], prefrontal [148], parietal and posterior parietal regions [150], precentral gyrus [147] and medial regions such as the dorsal anterior cingulate cortex [143]. The decoding performance and direction tuning curves across these various studies show that such a heterogeneous continuum of directionally tuned neurons and neuronal ensembles show

spatiotemporal windows of peak direction tuning. This means that than an underlying distributed network enabling different movement directions may be revealed by estimating the phase-synchrony between the firing rates of these directionally tuned ensembles. Considering the cross-scale influence of firing rates of directionally tuned neuronal assemblies in multiple brain regions and their putative effects on the phase of low frequency components of various modalities of electrophysiological recordings, this chapter seeks to verify the consistency of these observations in EEG recordings of healthy human subjects. In order to test this hypothesis, it is important to select an appropriate estimator of phase synchrony capable of identifying the most discriminative patterns in the underlying large-scale interconnections that differentiate different movement directions. Thus, various options of estimators are reviewed below.

Estimators of Phase Synchrony in Motor Tasks

From the previous section, the motivation to study phase-based features of EEG and their relationship with movement directions can be derived. Some popularly used phase-based features are reviewed below which include a number of phase-based feature extraction methods reported in literature [127, 130, 131, 133]. As mentioned previously in Chapter 2 these include phase lag index (PLI) [133], phase-locking value (PLV) [123, 127, 130], phase slope index (PSI) [151] and imaginary part of coherency (iCOH) [135, 152]. Such phase-based features are typically used to study synchrony between different parts of the brain, called functional connectivity [124, 127, 130]. In some studies, they have been used as feature extraction methods to classify motor imagery of different limbs and actual movement of hands versus rest [123, 132, 153]. Moreover, some studies also show that a combination of amplitude and phase-based features perform better than either type of features leveraging on the fact that both methods essentially estimate different types of neural activity and their respective influence on the measured brain signals [123, 154, 155]. During actual movement execution, amplitude-based CSPs and their numerous variants have been shown to estimate event-related desynchronization/synchronization (ERD/ERS) very well in the mu and beta sensorimotor rhythms [94, 110, 142].

Out of the various estimators of phase synchrony, literature seems to suggest that PLVs may be most suited to classify different motor directions as they have been

used in prior studies to test similar hypotheses in other electrophysiological modalities [145]. The working principle of PLVs can be understood as follows. Like other estimators such as PLI and iCOH, it is a measure of the consistency of the phase between different signals. Those pairs of signals which maintain a near constant phase-difference with respect to each other are said to be synchronized in phase and thus functionally related; while those whose phase-difference varies randomly with respect to each other are said to be functionally unrelated. However, unlike other estimators of phase-synchrony, PLVs do not discriminate between zero and non-zero phase-difference but only estimates the consistency of the phase-difference. Depending on the hypothesis in question, a researcher may choose to select those functional networks that contain either or both zero and non-zero phase-difference between pairs of signals and these functional connections have been said to reveal different types of underlying neurophysiological properties [132]. However, for testing the hypothesis in this chapter, it is only required to identify discriminative transient phase-based functional connections and there is no basis to choose a particular value of phase-difference. Rather, biasing the estimator towards a particular value of phase-difference may cause the feature extraction algorithm to miss out on certain important and discriminative connections for different movements [132]. This may be one of the reasons why PLVs have been used for classification of different motor activity [123, 145, 156]. PLVs have been shown to provide important time-domain information for identifying different types of movements such as self-paced or cued movements and have been used to identify channel-pairs that seem to be in task-dependent synchrony [125]. PLVs have also been used to study sensorimotor rhythms during motor imagery and to control BCIs [128, 157, 158]. Thus, in line with such previous studies, the working of PLVs are chosen as the guiding principle of the proposed feature extraction algorithm, namely Wavelet PLVs.

Thus, as outlined in the previous chapter, phase-synchrony estimators provide a comprehensive picture of large-scale brain interactions that underlie cognitive, perceptual and motor tasks. While activation-based methods such as regularized CSPs have been shown to be effective in quantifying movement induced spatio-spectral activations and depressions, they do not provide any information on the transient functional interactions between different brain regions to carry out different tasks. Therefore, building on the prior theories and evidence showing reorganization of

large-scale neural phase-synchrony during different visuomotor tasks, in this chapter, a phase-locking based feature extractor of movement induced phase-synchrony is proposed to identify hand movements in different directions. It was hypothesized that due to the cross-scale influence of neural synchrony and interactions, as described in Chapter 2, EEG signals would show differing patterns of phase-synchrony corresponding to different types of movements of the same hand. We thus propose a networks-based approach to BCIs as an alternate strategy to decode hand movement directions from EEG using the estimators of EEG-based functional networks. While there has been a dramatic surge in the number of studies in the last few years to study brain interactions during various perceptuo-cognitive tasks, to the best of our knowledge, an nBCI approach has rarely been reported in literature to decode centre-out movements of the same (dominant) hand in different directions. Contributions made to this chapter have been published in [159].

3.2 Experiment Design

The purpose of this study is to identify discriminative patterns using phase-locking based features in the EEG sensor space in order to carry out binary classification of hand movement directions using a wavelet filter-bank. Various visualization schemes help to investigate the wavelet levels and temporal variation in synchrony between channels. The results of each stage in the proposed algorithm has been analyzed and with attempts to interpret them for possible neurophysiological significance.

3.2.1 Data Acquisition

The experiments were performed at the Neural Signal Processing Laboratory of Institute of Infocomm Research, Agency for Science, Technology and Research, Singapore. EEG was recorded using a Neuroscan SynAmps 128 channel amplifier of which the 118 EEG channels were used to record the data sampled at 250 Hz. Out of the remaining 10 auxiliary channels, two channels were used to record Electrooculogram (EOG). Data was collected from seven subjects (ages 25 – 36 years, mean age 31 years $\pm$ 4.4 [SD], right-handed, all male) performing right hand centre-out movements in the horizontal plane in four orthogonal directions, namely

“north”, “east”, “south” and “west” denoted by $d1$, $d2$, $d3$ and $d4$ respectively. Each subject was seated on a chair with his right forearm attached to the MIT Manus robot which recorded kinematic parameters such as direction and trajectory of movements [160]. A computer screen displayed distinct cues for movement direction and onset of movement. The experimental timeline has been illustrated in Figure 3.1. The trial began at the home screen which lasted for about 2 seconds followed by a rest period of 3 seconds during which the subjects held the MIT MANUS robot in the centre position. The cue for getting ready for hand movement was displayed at the end of the rest period followed by the cue for the direction in which movement is to be performed which signalled the start of the preparation interval. As it was a randomized controlled experiment, in each trial the direction prompted was chosen randomly by a computer. The preparation interval which lasted for 2 seconds was followed by a cue for onset of movement. This cue for movement onset was identical for all directions. Subjects were instructed to carry out the movement as soon as they received the cue for onset of movement and to complete the movement within 0.5 seconds. At the end of the task, the subject was informed that the trial was complete. A total of 160 trials per subject were conducted (40 trials per direction) for 6 subjects, S1 to S6 and 140 trials (35 trials per direction) for subject S7. The total time for each trial took around 10 seconds. For this study, a subset of 35 EEG electrodes spanning the sensorimotor cortex, as shown in Figure 3.1, and 2 EOG electrodes are used.

3.3 Proposed Methodology

3.3.1 Preprocessing of EEG Data

The acquired signals have to be preprocessed to enhance their quality and remove artefacts due to eye movements (EOG) and muscle activity known as Electromyogram (EMG). In this study, 2 seconds of data are considered for each trial, which correspond to the interval between 1 second prior to movement onset cue to 1 second after it, as shown in Figure 3.1. Thus, there are 500 samples of EEG data corresponding to 2 seconds per trial. All data processing is done in MATLAB. Firstly, the acquired signals are low pass filtered at 96 Hz using a zero phase

FIGURE 3.1: Experimental timeline of each task and the set of 35 EEG electrodes that have been used for this study which include F5, F3, F1, Fz, F2, F4, F6, FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P5, P3, P1, Pz, P2, P4 and P6. The symbols above the timeline show the various cues, relative positions on the screen and the time instants at which they were displayed to the subjects during each trial.

Chebyshev Type II filter. The filter order is determined from the data using MATLAB's `cheby2ord(·)` function which calculates the minimum order required to meet the filter design specifications. The cut off frequency is 96 Hz with less than 3dB of passband ripple and 40 dB of stopband attenuation. Notch filtering is performed to remove line frequency at 50 Hz using a second order IIR notch filter (`iirnotch(·)` in MATLAB). Since the data acquisition hardware had a lower cut-off frequency of 0.05 Hz, the spectrum of EEG signals used in this study is between 0.05 – 96 Hz. Independent Component Analysis (ICA) is then carried out on the signals for EOG artefact removal based on correlation with the EOG signals [161]. The components with highest correlation with the EOG signals are nullified. The conditioned EEG signals are then back-projected to the sensor space. Surface Laplacian is then used to remove the higher frequency artefacts due to EMG [162]. Apart from EOG and EMG artefacts, we did not find any evidence of electromagnetic field interference in the EEG data. More details of the above pre-processing techniques can be found in [94].

3.3.2 W-PLV based Feature Extraction

The method used for single-trial binary classification of hand movement directions in this chapter uses Symlets5 wavelet to successively decompose and reconstruct the preprocessed EEG signals at various frequency bands. These narrowband signals are then used for extracting Wavelet Phase-Locking Values (W-PLV) as features for single-trial binary classification. A correlation-based channel-pair selection technique (feature selection) is used and wavelet levels corresponding to frequency ≤ 12 Hz are included. This frequency range includes the mu band that is typically used to study movement and motor imagery parameters, besides the slow cortical potentials (SCPs) [163, 164]. We use 5×5 nested cross-validation to assess the performance of our binary classification algorithm. Feature selection is only done on the training set which is then applied to the test set. The results of the classification performance reported are then the average accuracy on the test set over all 5 runs of 5-fold cross-validation. We also investigate the contribution of different wavelet levels to the classification performance achieved and attempt to find evidence of information through various trial-averaged methods.

3.3.2.1 Wavelet Reconstruction

As mentioned earlier, there has been a growing amount of evidence in literature suggesting the rich presence of movement direction information in the lower frequency components of electrophysiological data. Earlier works investigating the presence of kinematic information in lower frequencies have used CSP-based methods which are a way of deriving spatial filters using the spectral properties of EEG data belonging to different classes. In order to investigate lower frequencies wavelets were used to enhance the effectiveness of CSP based methods in the lower frequencies [94, 116, 117]. However, recent studies claim that particularly in the lower frequencies, the phase of electrophysiological data is more informative about movement directions than spectral changes [141, 143, 145]. Therefore, the objective of this work is to use a phase-based method, namely PLVs, to investigate the presence of direction-dependent information in the phase of lower EEG frequencies, which can be extracted effectively using wavelets.

As in previous works, wavelets offer an effective way of analysing EEG signals since they offer excellent frequency resolution in the lower frequencies and temporal resolution in higher frequencies [165, 166]. The prototype functions are dilated and scaled to shift across time and frequency which are then used as basis functions for analysing and reconstructing the EEG signals [165, 167]. For digital signal processing, instead of performing Continuous Wavelet Transform, we perform Discrete Wavelet Transform by discretizing the translation and dilation parameters as this helps to remove redundancy caused by continuous parameters. This discretization is done on a dyadic grid to get the resultant spectrum division as illustrated in [167]. As for the choice of the prototype wavelet, prior work in wavelet reconstruction based CSPs showed that Symlets5 wavelet provided the highest accuracy compared to other Symlets and Daubechies wavelets. Therefore, the choice of Symlets5 is retained in this work [167].

The equations below describe the Discrete Wavelet Transform used in the wavelet reconstruction of EEG signals.

$$X_w(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} h^*\left(\frac{t-b}{a}\right) x(t) dt \quad (3.1)$$

$$a = a_0^m \quad (3.2)$$

$$b = na_0^m b_0 \quad (3.3)$$

$$X_w(m, n) = a_0^{-m/2} \int_{-\infty}^{\infty} h(a_0^{-m} t - nb_0) x(t) dt \quad (3.4)$$

where $a_0 = 2$ and $b_0 = 1$ making $h^*(\cdot)$ an orthonormal conjugate of basis function obtained from the translation and dilation of the prototype wavelet function, $m, n \in \mathbb{Z}$. Thus, (3.4) is the Discrete Wavelet Transform derived from the Continuous Wavelet Transform in (3.1).

The above discrete wavelet transform, using orthonormal wavelet bases functions, results in non-overlapping frequency bands. As understood from the concept of multiresolution analysis using wavelets, if V_i with $I \in \mathbb{Z}$ corresponds to the space of band limited functions with frequencies in the interval $(-2^{-i}\pi, 2^i\pi)$ and U_i is the orthogonal complement of V_i , spanning frequencies $(-2^{-i+1}\pi, -2^{-i}\pi) \cup (2^{-i}\pi, 2^{(-i+1)}\pi)$. Thus, at every level i of wavelet decomposition, the signal is half-band low pass filtered and half-band high pass filtered. Every stage is followed by a down-sampling factor of 2. As a result, two sets of coefficients are obtained,

called the approximate and detailed coefficients. The next stage of wavelet decomposition then further decomposes the approximate coefficients until a maximum of $L_w = \log_2(T)$ is achieved. Starting from $i = 0$, the frequency bands corresponding to each level are given by the following equations.

$$(2^{-i}f_{high}, 2^{-i+1}f_{high}), \text{ for } i = 1 \text{ to } L_w \quad (3.5)$$

$$(f_{low}, 2^{-i+1}f_{high}), \text{ for } i = L_w + 1 \quad (3.6)$$

In this study, 500 samples of data are divided into 9 wavelet levels. The frequency bands corresponding to the 9 wavelet levels are: 0.05–0.375, 0.375–0.75, 0.75–1.5, 1.5–3, 3–6, 6–12, 12–24, 24–48 and 48–96 Hz. We consider wavelet levels from 1 to 6 (1 being the wavelet level corresponding to the lowest frequency band) and ignore wavelet levels 7 to 9. This is because the higher wavelet levels (7 to 9) are broadband EEG frequency bands and phase-locking values are usually computed for narrow EEG frequency bands. Moreover, wavelets 1 to 6 already include SCPs and the mu band which are typically used to study motor activity.

3.3.2.2 Wavelet-Phase Locking Value

PLV is a measure of phase synchronization between a pair of signals and is computed using the phase-difference between the pair of signals [124]. A constant phase-difference would imply perfectly synchronized signals and would result in a high PLV of 1. If the signals vary randomly with respect to each other then the PLV is 0. We use PLV to identify pairs of EEG channels that show synchronous relationships for different hand movement directions.

PLVs can be computed from the phase of a narrowband signal computed using the Hilbert Transform as defined in equations (3.7) and (3.8) [131].

$$x_h(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau \quad (3.7)$$

$$\phi_x(t) = \arg(x(t) + jx_h(t)) \quad (3.8)$$

where $x_h(t)$ is the result of the Hilbert Transform of the narrowband signal $x(t)$ that is obtained by computing the integral taken in the sense of Cauchy principal

value, $\arg(\cdot)$ is the argument function that computes the instantaneous phase of the signal, denoted by $\phi_x(t)$.

Once we compute the instantaneous phase of the signal, the trial-averaged PLV between 2 channels x and y are computed using equations (3.9) and (3.10).

$$\epsilon(x, y, t) = \exp j(|\phi_x(t) - \phi_y(t)|) \quad (3.9)$$

$$V_{d,l}(x, y, t) = \left| \frac{1}{T_d} \sum_{\text{trials} \in d} \epsilon(x, y, t) \right| \quad (3.10)$$

where $x(t)$ and $y(t)$ are the EEG signals from channels x and y at wavelet level l , $t \in [1, N]$ where N is the number of time samples (500) in each trial, $d \in D$ where D is the set of all directions = $\{d1, d2, d3, d4\}$ as shown in Figure 3.1. T_d is the number of trials corresponding to direction d . $\epsilon(x, y, t)$ is a measure of the single trial phase-locking between the two channels at time t and $V_{d,l}(x, y, t)$ is the PLV calculated as the average over all the trials belonging to that direction. Since we compute the PLV values after performing wavelet reconstruction of the signals, we call them Wavelet-PLV or W-PLV.

For an offline analysis of channel-pairs showing statistically significant phase-synchrony for different movement directions, we carry out the following analysis. W-PLV values computed above are then used to compute W-PLS values, with the help of a statistical randomization test as follows. At every reconstructed wavelet level and for a given pair of electrodes, a surrogate W-PLV distribution is generated for every time instant. This is done by randomly labelling and shuffling the data for one of the channels in every channel pair and re-computing the W-PLV values. This process is repeated 10 times the sample size, T_d for each subject to generate the surrogate distribution. Then the original W-PLV values are compared against this surrogate distribution using the Student's t-test to calculate W-PLS, using a similar technique as in [130]. As shown in equation (3.11), we check for a significance level of $\alpha = 0.001$ and accept the W-PLV values if they are found to be significant, else the corresponding W-PLS values are taken as 0. For 5-fold cross validation, the sample size T_d includes the training data wherein there are 32 trials per direction for subjects S1 to S6 and 28 trials per direction for S7.

$$S_{d,l}(x, y, t) = \begin{cases} V_{d,l}(x, y, t) & \text{if } p\text{-Value} \leq \alpha \\ 0 & \text{otherwise} \end{cases} \quad (3.11)$$

where $S_{d,l}(x, y, t)$ is the W-PLS value for direction class d and wavelet level l .

In order to carry out single trial classification, we use single trial W-PLVs as features from all combinations of channel-pairs, similar to prior studies proposing a modified form of phase-synchrony to study single-trials [6, 127]. Instead of averaging over corresponding samples across trials, to estimate phase-locking within a trial, the estimates are averaged over multiple samples within a specified time window. This results in a single-trial estimate of phase-synchrony although at the cost of reduced temporal resolution under the hypothesis that transient phase-relationships underlying a certain task will be stable for a certain minimum duration of the task. Thus, given a channel pair (x, y) , we calculate the single trial PLV by using equation (3.12).

$$\epsilon_{k,l}(x, y) = \left| \frac{1}{N} \sum_{t=1}^N \epsilon_k(x, y, t) \right| \quad (3.12)$$

where $\epsilon_{k,l}(x, y)$ is the single trial W-PLV for the k^{th} trial at wavelet level l .

3.3.2.3 Pearson's Correlation Coefficient based Channel-pair Selection

As mentioned earlier, in this study we use 35 channels which are directly above the motor cortex. There are 595 combinations of channel-pairs for which we can compute W-PLV at every wavelet level. For 6 wavelet levels, there are a total of 3570 features that can be computed using W-PLV which would lead to a high dimensional feature matrix for single trial classification. Therefore, we use Pearson's Correlation Coefficient (PCC) to select the best channel-pairs from each wavelet level that show most discriminative information for a given pair of directions (for binary classification). PCC is often used in statistics to test both, the qualitative as well as the quantitative nature of the correlation between two variables [168].

The correlation coefficient r varies between -1 and 1 such that when $r = 1$ the variables have perfect positive correlation, i.e., they increase and decrease together

perfectly; and when $r = -1$ the variables have perfect negative correlation, i.e., they have perfectly opposite trends.

We use PCC in our method to select channel-pairs which have the highest PCC values with the class labels, as shown in equations (3.13) and (3.14).

$$Z_1 = [V_{di,l}(x, y, t), V_{dj,l}(x, y, t)] \forall t \in [1, N] \quad (3.13)$$

$$Z_2 = [L_1, L_{-1}] \quad (3.14)$$

where the vector Z_1 of length $2N$ contains the appended trial-averaged W-PLV values for binary-classes (di, dj) where $(di, dj) \in D$ and $di \neq dj$, for a channel-pair (x, y) at wavelet level l , Z_2 is a vector of length $2N$, whose elements, vectors L_1 and L_{-1} , are each of length N and contain labels 1 and -1 respectively. We compute PCC for all combinations of channel-pairs, at every wavelet level and sort them in descending order from which we select the channel-pairs corresponding to the highest positive and negative PCC values. In this study, we select 10 channel-pairs each corresponding to the correlation values from both ends of the sorted PCC values resulting in 20 channel-pairs at every wavelet level. $\tau_{di,dj,l}$ contains this set of channel-pairs selected for a set of binary-classes (di, dj) at every wavelet level l . The corresponding values of single trial WPLV calculated using 3.12 are stored in $\mathbf{F}$. This is then the feature matrix that is used for single-trial classification.

3.3.2.4 Naive Bayesian Parzen Window Classifier (NBPW)

A Naive Bayesian Parzen Window classifier is used for binary classification, which employs Bayes Rule to predict the class which has maximum posterior probability $p(d|f)$ as computed in equation (3.15) [37].

$$p(d|f) = \frac{p(f|d)p(d)}{p(f)} \quad (3.15)$$

where $p(d|f)$ is the posterior probability for direction d and feature f wherein f is a feature vector $\in \mathbf{F}$ that corresponds to the W-PLV values computed for a channel-pair selected in $\tau_{d_1,d_2,l}$. For 2 classes, the probability $p(f)$ is calculated as follows.

$$p(f) = \sum_{d=1}^2 p(f|d)p(d) \quad (3.16)$$

Since it is a naive classifier, it assumes that all the features are independent. On the basis of this assumption, the conditional probabilities are calculated as follows.

$$p(f|d) = \prod_{j=1}^d p(f_j|d) \quad (3.17)$$

$$\hat{p}(f_j|d) = \frac{1}{n_d} \sum_{i \in I_d} \phi(f_j - \bar{f}_{i,j}, h) \quad (3.18)$$

where $\hat{p}(f_j|d)$ is the Parzen Window estimator of the conditional probability $p(f_j|d)$, n_d is the number of data samples belonging to class d , I_d is the set of indices of training data trials $\in d$, ϕ is a smoothing kernel function with a smoothing parameter as defined in [37].

3.3.2.5 Algorithm

The steps in the binary classification algorithm, illustrated in Figure 3.2, are summarized in this section as follows. The dataset is pre-processed and segregated into training and test sets for 5×5 nested cross-validation. For a pair of binary classes, d_i and $d_j \in \{d1, d2, d3, d4\}$ and $d_i \neq d_j$, the training data is used to compute the trial averaged W-PLV values. As mentioned earlier, we use only the lower 6 wavelet levels corresponding to the frequency bands 0.05 – 0.375, 0.375 – 0.75, 0.75 – 1.5, 1.5 – 3, 3 – 6 and 6 – 12 Hz respectively. Like the methodology proposed in [169], we select channel-pairs using Pearson's Correlation Coefficient. However, instead of trial-averaged W-PLS values as used in [169], we use the trial averaged W-PLV values for channel-pair selection. This is because computation of W-PLS is extremely complex and time-consuming as it is heavily iterative. For this study, we use W-PLS values only to visually inspect the data. Since we are using PCC to select the best channel-pairs at every wavelet level, it is expected that the channel-pairs with significant W-PLV values would be picked automatically.

Feature selection is only done using the training data. As we select 20 channel-pairs per wavelet level, there are a total of 120 features selected over all 6 wavelet levels. These selected channel-pairs are then used to compute the single-trial W-PLV values from the training set to train the NBPW classifier. After 5 runs of 5-fold cross-validation, we report the average classification accuracy over the test

FIGURE 3.2: Proposed methodology for binary classification using W-PLV.

set. The steps have been summarized in Algorithm 1 and illustrated in Figure 3.2.

Algorithm 1: Wavelet-PLV based Binary Classification

- 1: Segregate trials into training and test sets for 5×5 cross-validation
 - 2: **for** each cross-validation fold **do**
 - 3: **for** trials $\in$ training set and binary-class (d_i, d_j) **do**
 - 4: Compute $V_{d,l}(x, y, t) \forall t \in [1, N], d = \{d_i, d_j\}$ for all combinations of (x, y)
 - 5: Perform PCC at every wavelet level l and choose subset of channel-pairs $\tau_{d_i, d_j, l}$
 - 6: **end for**
 - 7: $\mathbf{F}_{train} = v_{k,l}(x, y) \forall \text{ trials} \in \text{training set } \forall (x, y) \in \tau_{d_i, d_j, l}$.
 - 8: Train NBPW Classifier
 - 9: $\mathbf{F}_{test} = v_{k,l}(x, y) \forall \text{ trials} \in \text{test set } \forall (x, y) \in \tau_{d_i, d_j, l}$.
 - 10: Test the performance of the NBPW classifier on test set and calculate classification accuracy
 - 11: **end for**
 - 12: Repeat above steps for remaining iterations of 5×5 cross-validation.
 - 13: Calculate average classification accuracy over test set
-

3.4 Results

This section presents the results of binary classification of hand movement directions with a detailed analysis of trial-averaged and single-trial W-PLV features. In doing so, we attempt to seek greater insight into the movement related spectro-temporal information in the various wavelet levels. As mentioned earlier in Section 3.2, the dataset used in this study comprises EEG collected from seven healthy subjects performing right hand movements in a 2D horizontal plane in four orthogonal directions. The time window chosen contains 1s of preparation and 1s of execution. This gives us the opportunity to analyse the information content of movement directions in low frequency EEG signals and in particularly the phase of low frequency EEG components. For more details on the dataset and experiment paradigm, the reader is referred to Section 3.2. Thus, we first analyse the trial-averaged W-PLV features extracted from EEG corresponding to the different hand movement directions, as described in Section 3.3. Next, we present the results of binary classification of all combinations of hand movement directions using single-trial W-PLV features. Lastly, we investigate the results of the different stages of the binary classification algorithm to gain better understanding of the working of the algorithm. We also try to provide possible interpretations of the associated neurological phenomena, wherever possible.

3.4.1 W-PLV Plots

3.4.1.1 Temporal Variation of Windowed trial-averaged W-PLS

We would like to visualize the temporal variation of trial-averaged W-PLS values over the 2 seconds of data per trial we use in this study. The motivation behind such inspection is to investigate the presence of any temporal markers that could give us some movement-related information. For this purpose, we divide the entire duration of 500 samples (2 seconds) into time-windows of 100 samples each wherein each window would correspond to an interval of 0.4 seconds. Next, we compute the mean of the trial-averaged W-PLS values computed above over all the samples within that window as in equation (3.19).

$$\bar{S}_{w_{d,l}}(x, y) = \frac{1}{100} \sum_{t \in w} S_{d,l}(x, y, t) \quad (3.19)$$

where $\bar{S}_{w,d,l}$ is the windowed-trial averaged W-PLS value for a channel pair (x, y) and direction d , at wavelet level l and time-window w . Thus, there are a total of 5 windows, each of duration 0.4 seconds.

Figure 3.3(a) shows the number of statistically significantly phase-locked channel-pairs in each time window (TW1 to TW5) for each direction averaged over all subjects for wavelet level 3. It can be seen that for all directions, TW3 and TW4 contain the maximum number of significantly phase-locked channel-pairs than all other TWs. For all directions except direction $d3$, TW3 has maximum number of significantly phase-locked channel-pairs. For direction $d3$, TW4 has maximum number of significantly phase-locked channel-pairs. Figure 3.3(b) has been plotted as an example to visualize the temporal patterns of W-PLS values. For this, we use the `imagesc` function of MATLAB and plot the channel $\times$ channel matrix for direction $d2$ of Subject 1. As the channel $\times$ channel matrices are symmetric, only the upper triangles have been plotted in Figure 3.3 for better comprehension. We can observe the build-up of phase-locking patterns starting from TW1, peaking at TW3 and reducing again in TW5, following the temporal sequence observed for all subjects in Figure 3.3(a). TW3 corresponds to -0.2 to 0.2 seconds, that includes the cue for the onset of movement at time $t = 0$. In this particular time window, it is observed that channels C6, CP5 and CP2 (corresponding to columns 21, 22 and 26) have maximum number of peaks in W-PLS values with other channels. A possible interpretation of this observation is that the activity in this time window as measured on the scalp through EEG might be centered around C6, CP5 and CP2. As this time window corresponds to the visual cue for onset of movement, the increased synchrony observed on these channels may indicate the increased interaction at the somatosensory cortex. This observation, though expected, will have to be verified using source-imaging techniques. The same channels also show huge temporal variation in the estimated synchrony and depict a build-up of synchrony starting with almost none in the first time window, peaking at the third time window and reducing to negligible synchrony again in the fifth time window. Thus, the number of peaks in the windowed, trial-averaged W-PLS values may help in isolating period of onset of motor execution.

FIGURE 3.3: Analysis of the temporal variation of windowed W-PLS values. (a) Plot of the number of significantly phase-locked channel-pairs for each direction in each time window averaged over all subjects for wavelet level 3 (0.375–0.75 Hz). (b) Example of significantly phase-locked channels plotted using direction $d2$, subject S1. The 35 channels in each channel $\times$ channel subplot are arranged as F5, F3, F1, Fz, F2, F4, F6, FC5, FC3, FC1, FCz, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P5, P3, P1, Pz, P2, P4 and P6 from top to bottom and from left to right (1 to 35, respectively). As each channel $\times$ channel matrix is symmetric, only the upper triangle has been plotted for better comprehension. TW refers to the time window. The 5 time windows (from TW1 to TW5) correspond to time durations -1 to -0.6 , -0.6 to -0.2 , -0.2 to 0.2 , 0.2 to 0.6 and 0.6 to 1 seconds, respectively. Time window TW3 shows maximum interaction centred around channels C6, CP5 and CP2 which are directly over the somatosensory cortex.

3.4.2 Spatial Contour Maps

W-PLV values averaged and normalized over all subjects are next analysed in order to identify some common trends in phase-locking patterns for the different directions. For this purpose, Figure 3.4 is plotted which presents the spatial contour maps of the mean W-PLV values over all subjects, using EEGLAB in MATLAB [170]. These spatial contour maps are plotted using W-PLV values computed for all channels with respect to the common “seed” channel Cz. After calculating the mean W-PLV values over all the subjects for each direction and wavelet level, values are then normalized such that the minimum and maximum W-PLV values take 0 and 1 respectively.

From Figure 3.4, it can be seen that the lowest wavelet levels have distinctly most variation in W-PLV patterns as compared to the higher levels. Peaks on these plots imply increased interaction between the respective channels and seed channel Cz. The high variation in the normalized W-PLV patterns seen could imply direction-dependent information extracted from EEG which would help our channel-pair selection technique select the most discriminative channel-pairs as will be seen in Section 3.4.4. In wavelet level 1, denoted by $l1$, the plots for all the four directions show common peaks at C2 while the peaks on the channels on the left hemisphere (contralateral to the moving arm) show varying patterns. The opposite trend is observed for wavelet level 2 wherein peaks can be seen on C1 and FC1 (left hemisphere) but varying patterns are seen on the channels of the right hemisphere (ipsilateral to the moving arm). There are differences in the contours for the higher wavelet levels as well but the peaks are most distinctly different for the different directions in the lower wavelet levels. For wavelet levels 5 and 6, as shown in Figure 3.4, the peaks seem to be localised at channels around C1 and C2. On changing the seed channel, different phase-locking patterns and contours are observed. However, irrespective of the choice of seed channel, the contrast in the visually discriminative information in the lower and upper wavelet levels, as shown in Figure 3.4 is consistent for all such figures.

FIGURE 3.4: Spatial contour maps plotted using W-PLV values, averaged over all trials and all subjects with seed channel at Cz. Wavelet levels $l1$, $l2$, $l5$ and $l6$ correspond to frequency bands 0.05-0.375 Hz, 0.375-0.75 Hz, 3-6 Hz and 6-12 Hz, respectively. The spatial maps in levels $l1$ and $l2$ seem to have most direction-dependent W-PLV patterns while those in $l5$ and $l6$ seem to have peaks localized around C1 and C2 and direction-dependent contours. The peaks on the left hemisphere (contralateral to the moving arm) in $l1$ and on the right hemisphere (ipsilateral to the moving arm) in level $l2$ seem to be distinctly direction-dependent. Identification of such peaks can help to increase the classification accuracy of the different hand movement directions.

TABLE 3.1: Results of Binary Classification for subjects S1 to S7 using our proposed W-PLV method with Naïve Bayesian Parzen Window classifier after 5×5 nested cross-validation. Mean accuracies reported below in percentages.

Subjects	Binary Classes						Mean
	$d1-d2$	$d1-d3$	$d1-d4$	$d2-d3$	$d2-d4$	$d3-d4$	
S1	91.75	81.00	89.25	81.25	91.00	82.00	86.04
S2	71.25	68.00	69.00	67.75	78.50	78.25	72.12
S3	69.75	71.25	78.00	75.25	95.25	72.75	77.04
S4	79.00	69.75	79.25	77.75	74.75	89.75	78.37
S5	82.25	64.00	71.25	76.75	74.00	77.25	74.25
S6	76.00	84.25	80.25	76.25	78.75	79.50	79.17
S7	67.43	76.86	72.29	65.71	68.86	74.57	70.95
Mean	76.78	73.59	77.04	74.39	80.16	79.15	76.85

TABLE 3.2: Comparison of Results of our proposed W-PLV method with other methods that have been used previously on the same dataset. Accuracies are reported below in percentages.

Methods	Mean Accuracy
Proposed W-PLV Method	76.85
Modified W-CSP [117]	71.25
W-PLV [169]	65.78

3.4.3 Binary Classification Results

Single-trial binary classification of hand movement directions is conducted for all 6 combinations of binary classes of the 4 hand movement directions. These results are tabulated for all 7 subjects using our proposed method in Table 3.1. The mean accuracy achieved after 5×5 nested cross-validation over all 7 subjects is 76.85%. The 95% confidence interval for the mean classification accuracy is (72.13%, 81.57%) which is statistically significantly above chance level, as computed using Student’s One-Sample t-test ($p < 0.00001$). The amount of discriminative information present in very low EEG frequency bands (< 1 Hz) corresponding to the first 2 wavelet levels is also compared to those including the mu band (≤ 12 Hz), i.e., wavelet levels 1 to 6. We see empirically that including more wavelet levels increases the performance of binary classification to 76.85% as compared to the case where only the lowest 2 wavelet levels have been used and a mean classification accuracy of 65.7% is achieved, as shown in Table 3.2. Moreover, in Table 3.2, the classification performance of our W-PLV method is compared with the state-of-the-art modified wavelet CSP method in [117] for binary classification and is seen to give better results. Next, we used Student’s paired t-test to compare the performance of our proposed method with the methods mentioned in Table 2. We found that although the mean accuracy of our proposed method is higher than WCSP, this difference is not statistically significant ($p > 0.05$). The 95% confidence interval of WCSP in [117] is (61.11%, 81.37%). Thus, our proposed method results in a much narrower confidence interval indicating its robustness.

The trend of classification performance over the 7 subjects is different in W-PLV and WCSP [117] methods which are based on phase-synchrony and amplitude of EEG signals, respectively. This could mean that there is complementary information in these different feature extraction methods. An effective combination of

TABLE 3.3: Classification performance for different number of wavelet levels and features. Individual columns of the first row signify (number of wavelet levels, total number of features).

Subject	6, 120	4, 80	4, 120
S1	86.04	85.42	88.17
S2	72.12	67.46	68.08
S3	77.04	76	77.71
S4	78.37	72.87	74.25
S5	74.25	68.42	69.5
S6	79.17	72.75	73.12
S7	70.95	72.95	74.24
Mean	76.85	73.70	75.01

these features could help to further increase the classification accuracy.

Effect of Wavelet Levels and Number of Features

The number and choice of wavelet levels and features selected are important parameters of the proposed algorithm. Therefore, the number of wavelet levels and features were varied to analyse the classification performance of the proposed WPLV method. First, the number of features selected were fixed at 20 channel-pairs per level, as described above. The number of wavelet levels were reduced from six to four resulting in a total number of features of 80. Next, the number of features selected per level was then increased to 15 resulting in the original number of features of 120. Results have been tabulated in Table 3.3.

It can be seen that reducing the number of wavelet levels from six to four while maintaining the same number of features selected per wavelet level results in approximately 3% drop in classification accuracy. Increasing the number of selected features to match the 120 features originally, increases the classification performance. However, even with a fixed number of 120 features, including higher wavelet levels helps to obtain a slightly better classification accuracy. Therefore, for the same number of features, increasing the number of wavelet levels spanned by the algorithm is seen to offer better performance.

Effect of Length of Time Window

The effect of the length and choice of time window on the classification accuracy performance has next been analysed. Two of the best subjects, S1 and S3, were chosen for this analysis. The proposed time window of $[-1,1]$ with respect to onset of movement was compared against smaller 1s time windows which either consisted

TABLE 3.4: Effect of time window on the classification accuracy of subject S1.

Time Window	Classification Accuracy
$[-1, 1]$	86.04
$[-1, 0]$	74.21
$[0, 1]$	78

TABLE 3.5: Effect of time window on the classification accuracy of subject S3.

Time Window	Classification Accuracy
$[-1, 1]$	77.04
$[-1, 0]$	69.58
$[0, 1]$	74.17

of the preparation phase ($[-1,1]$) or the movement execution phase ($[0,1]$). The results have been tabulated in 3.4 and 3.5. It can be clearly seen that reducing the length of the time window results in substantially lower classification accuracy for both subjects. Between the shorter time windows, the classification accuracies were higher for the execution window compared to the preparation window for both subjects. However, combining the data from the preparation and execution stages resulted in the highest accuracies.

3.4.4 Channel-Pair Selection using Pearson's Correlation Coefficient

We would like to analyse the working of our correlation-based channel-pair selection technique. For this purpose we plot Figure 3.5 for Subject S1 for channel-pairs that show highest positive correlation and highest negative correlation for wavelet level 1 and directions $d1$ and $d2$. In this figure, the graph in (a) shows the correlation coefficients sorted in decreasing order for all the 595 channel-pairs with the respect to directions $d1$ and $d2$. The higher positive PCC values correspond to those channel-pairs that show increased phase-locking for direction $d1$ and low phase-locking for direction $d2$. Channel-pair C5-CP6 has the highest positive PCC value of 0.933 and the trial averaged W-PLV values for both the directions have been plotted in Figure 3.5 showing consistently higher values for direction $d1$ as compared to direction $d2$. The opposite trend can be seen for channel-pair C1-C6 which have highest negative correlation with PCC value of -0.9743 with the class

FIGURE 3.5: Example of PCC based channel-pair selection on trial-averaged W-PLV values with the correlation coefficients sorted in descending order in (a). This figure has been plotted for Subject S1 and wavelet level 1 for the binary class of directions $d1$ and $d2$. The channel-pairs corresponding to the correlation values enclosed in the green boxes on either side of the sorted PCC values show most discriminative information between the 2 classes and are hence selected for feature selection for binary classification. The plots in (b) and (c) are two examples of the selected channel-pairs at each end of the sorted correlation values, with maximum positive correlation and maximum negative correlation respectively, which are selected for feature selection for binary classification. In these figures, the plots in black correspond to the trial-averaged W-PLV for direction $d1$ and blue to direction $d2$. PCC for each set of signals are mentioned in red for each figure.

labels as mentioned in (3.14). The channel-pairs corresponding to the PCC values in the region enclosed in the green boxes on either side of the sorted PCC values, which include the channel-pairs in (b) and (c) are selected for feature selection for binary classification.

3.4.5 Time-frequency Contour Plots of Most Frequently Selected Channel-Pairs

It is seen that including higher wavelet levels has helped to increase the classification accuracy of our W-PLV based method significantly from 65.7% in [169] to 76.85%. We would now like to investigate the contribution of the higher wavelet levels included to the increase in binary classification accuracy. Our hypothesis is that single-trial features from the higher wavelet levels containing direction-dependent information should contain consistent peaks in trial-averaged W-PLV values. We test this hypothesis by plotting time-frequency contour maps of frequently chosen features chosen across all wavelet levels. Presence and location of such peaks would provide relevant movement related information.

Figure 3.6 has been plotted using some features that are most often selected for binary classification for Subject S1 as an example. The channel-pairs most often selected to identify movement directions are used to compute the trial-averaged W-PLV values for each time sample between $[-1, 1]$. The lower 6 wavelet levels are then plotted using the `contourf()` function in MATLAB which automatically draws the contour lines that serve to identify the peaks and troughs in trial-averaged W-PLV values. From this figure we see that W-PLV peaks can be seen across all wavelet levels. In the lower levels (levels 1 to 3 corresponding to $\text{EEG} < 1 \text{ Hz}$), there are peaks in C4-CP6, from time -0.4 to 0.4 seconds in direction $d1$ and in Cz-P4 in direction $d2$ from time -0.8 to -0.4 seconds of Figure 3.6(a). In Figure 3.6(b), W-PLV peaks in levels 2 to 3 can be clearly seen in FC1-C2, direction $d3$. Due to the higher temporal resolution of the lower levels, these peaks appear to be very prominent. Due to the nature of the temporal resolution of wavelets, the peaks in the higher levels are much narrower as compared to those in the lower levels. However, we can still spot them clearly in levels 5 and 6 (corresponding to EEG between 3 - 12 Hz) in Cz-P4 in Figure 3.6(a) in time -0.5 to -0.2 seconds and 0 to 0.2 seconds. In C2-CPz in Figure 3.6(b) W-PLV peaks in the levels 5

FIGURE 3.6: Time-frequency plot of some of the most often selected channel-pairs whose W-PLV values are used for binary classification for subject S1, showing the presence of direction-dependent W-PLV peaks across various wavelet levels. (a) and (b) have been plotted for features selected most often for binary-classes $d1$ vs. $d2$ and $d1$ vs. $d3$, respectively. In (a), channel-pair C4-CP6 is chosen most often for $d1$ and Cz-P4 is chosen most often for $d2$ across all wavelet levels. In (b), channel-pair C2-CPz is chosen most often for $d1$ and FC1-C2 is chosen most often for $d3$. Peaks in both (a) and (b) can be seen spread out across all the wavelet levels from 1 to 6. Lower wavelet levels correspond to lower frequency bands.

to 6 can be seen in time -0.4 to -0.2 seconds and 0 to 0.12 seconds; in FC1-C2 in time -0.6 to -0.4 seconds and 0 to 0.2 seconds. The same observation can be made from similar figures plotted for other subjects and direction-pairs. The presence of such direction-dependent peaks in higher wavelet levels explains why including more wavelet levels adds discriminative information to the feature matrix that is used by the classifier and results in higher classification performance. Thus, they seem to have contributed to the increase in classification accuracy. Moreover, even though $d1$ is common in (a) and (b), the features selected most often for $d1$ in both cases are different as they depend on the other class. This is because the feature selected should contain most discriminative information that would help in single trial classification. Hence, our proposed method is capable of intelligently identifying discriminative features for binary classification.

3.5 Discussion

This chapter began with a literature review on the various methods that have been used to extract hand movement-related information. After that, a novel W-PLV-based feature extraction method was proposed to analyse right hand movement in 4 orthogonal directions in a horizontal 2-dimensional plane. The analyses on the proposed feature extraction method utilizing wavelet phase-locking values from EEG demonstrate the ability of the proposed method in identifying task-dependent synchronous channel-pairs. The discriminative ability of our proposed method is verified in the binary classification of hand movement directions which yields higher classification performance than other methods reported in literature.

3.5.1 Discriminative patterns of hand movement directions in W-PLV

The aim of this study was to test the hypothesis that different patterns of brain functional connections can be found in EEG to occur during unilateral hand movements in different directions. Literature suggests that the phase of low frequency electrophysiological data is informative about movement directions. While this had been reported in other electrophysiological modalities such as multi-unit recordings, ECoG and intracranial EEG, EEG-based studies on the same had rarely been reported. Therefore, using the proposed WPLV algorithm, features extracted are a measure of phase-based functional relationships between different EEG channels. If the hypothesis is true, i.e., if there are direction-induced patterns in the estimated functional connections, then we should be able to use them to predict the direction of hand movements. Since the classification accuracy achieved is significantly above chance level, we can safely conclude that there is credible evidence in support of the above hypothesis.

The wavelet phase-locking patterns extracted have the advantage of being visualized effectively which helps reveal discriminative patterns. Spatial contour maps plotted from trial-averaged W-PLV values show that the lower wavelet levels (< 1 Hz) contain the most movement-related information. However, there are also visible differences in contours in higher wavelet levels as seen in Figure 3.4. Figure 3.3 depicts the temporal variation of statistically significant phase-locking in various

channel-pairs. Inspection of this figure shows the presence of relevant movement related information such as the markedly increased phase-locking in channel-pairs centred over the somatosensory cortex during the period of onset of movement. Thus, it may be possible to use such timing information to enhance the efficiency of a movement detector which can then be used for asynchronous classification using EEG. Studies have shown the ability of using PLV-based techniques to identify actual movement and motor imagery from rest [125, 171]. Moreover, it might be possible to develop a strategy to use such information to fine-tune a detector which identifies the best time-period for classification. It is important to note that identical cues were used for movement onset for all directions and therefore contained no discriminative information.

3.5.2 Effect of various parameters on classification performance

Various parameters such as the number of features selected, number of wavelet levels included, the choice and length time window are seen to affect the classification performance. For a fixed 2s time window, it was seen that for the same number of features, including higher wavelet levels helped to slightly increase the classification accuracy. However, it is to be noted that these performance differences are only marginal and that including the lower 4 wavelet levels, which correspond to < 3 Hz or the EEG delta band, already achieved comparable performance with the WCSP method. This may point to the fact that while higher wavelet levels do provide some discriminative information about movement direction, the bulk of this information possibly lies in low frequency EEG data. This is in line with previous studies which have shown that the phase of low frequency electrophysiological signals are informative about movement directions [141, 143–145].

The parameter which had the greatest effect on classification performance was the time window chosen. The performance of the proposed algorithm was analysed using smaller time windows of 1s containing either the preparation or the execution stage. Results of the two best subjects in this study show that the longer 2s time window containing both the stages resulted in the best accuracy. However, besides the duration of time window it is also to be noted that data from strictly the preparation stage for both these subjects was still much higher than chance level.

This shows that direction-dependent transient phase-locked functional networks already begin to form during the preparation of movement in a particular direction. These results are in line with previous studies that show that PLV-based methods can track the trajectory of the formation of such direction-dependent long-range phase-synchrony. In [145], it was shown that phase-based functional connections in lower frequencies form slightly before the event-related spectral perturbations in higher frequencies. This may be a reason why discriminative information could also be found strictly in the preparation phase. Also, in ECoG studies, decoding accuracy has been shown to peak at a time closer to onset of movement [143]. Thus, the longer 2s time window containing this period may therefore be a better choice of time window as well and has been shown to result in best classification performance. Evidence of larger number of phase-locked channels in Figure 3.3 during the time windows closer to movement onset are also in line with this interpretation.

In this chapter, we have conducted a thorough analysis on the results of various steps used in the proposed W-PLV based binary classification method and empirical evidence is presented to corroborate the improvement in classification performance. Even though the trial-averaged W-PLV patterns in Figure 3.4 are distinctly more discriminative for the lowest wavelet levels than the higher ones, Figure 3.6 shows the presence of movement related peaks in W-PLV values in higher wavelet levels as well. Thus, inclusion of single-trial features extracted from higher wavelet levels adds discriminative information that can be used by the classifier.

3.6 Summary

This chapter demonstrates how an nBCI can be effectively used to decode finer movements within the same hand. The working principle of the decoder used in an nBCI is very different from that used in typical SMR-BCI systems. While existing methods such as CSP-based algorithms use spatio-spectral filtering of EEG data to derive discriminative patterns of activations on the scalp, the proposed networks-based approach estimates the phase-based interactions between different regions on the scalp (EEG channels). The classifier is then trained to identify different patterns of phase-synchrony accompanying different types of hand movements. The mean accuracy of 76.85% obtained was not only significantly above chance level but the

proposed method also provided insight into the discriminative spatio-spectral interactions between different EEG channels for the purpose of identifying different hand movement directions. Time-frequency representations of the phase-locking spectra showed peaks in phase-synchrony between different channel-pairs at multiple wavelet levels. For the lower wavelet levels (lower frequency bands), the patterns of phase-synchrony seemed to vary drastically between different movement directions. In the higher wavelet levels, the peaks in phase-synchrony were seen to be more strictly localized.

Thus, it is safe to conclude that the proposed phase-based feature extraction algorithm carries evidence of different patterns of neural (phase) synchrony for carrying out different finer motor tasks. An nBCI is shown to work effectively in decoding motor activity in spite of having a totally different working principle as compared to traditionally used SMR-BCIs. In the next chapter, we use a networks-based approach to demonstrate the involvement of regions spread out across the whole brain to motor planning and execution.

Chapter 4

Modelling Dynamic Neural Interactions during Hand Movements in Different Directions - Moving From Sensor to Source Space

4.1 Introduction

In the previous chapter, we presented a networks-approach to motor decoding for identifying different hand movement directions in the 2D plane in an SMR-BCI. Patterns of task-induced phase-synchrony showed formation of large-scale interactions between EEG channels at various wavelet levels (frequency bands). In this chapter, we demonstrate the potential sources of the observed large-scale integration seen on the scalp EEG. Specifically, we use a data-driven process to identify the involvement of different brain regions during the planning and execution of hand movements in four centre-out orthogonal directions. Results clearly indicate a web of interactions between the motor and non-motor regions such as the parietal and frontal regions. Moreover, evaluation of the dynamic connections between

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these areas shows greater dominant information flow between these regions during the planning of the movement task compared to execution of the same task. The next section presents an overview of past studies investigating the functional roles of different cortical sources to planning and execution of movements.

4.2 Background

Numerous studies in the past, using intracranial, single unit and neuroimaging modalities have shown that different parts of the brain encode different parameters of movement kinematics. As mentioned in the previous chapters, voluntary movements are goal-oriented tasks which require an internal representation of a motor program to achieve the desired movement [70]. This includes strategic planning of movements in order to optimize the completion of a certain task. It has been reported that the actual initiation of movement is preceded by the integration of sensory information and cognitive processes to develop the above mentioned motor program [172]. This motor program then includes the sequence of corticomuscular and neural interactions and activations in order to achieve the desired movement. This is said to involve interactions between multiple cortical and subcortical regions [172–175]. The dorsal premotor cortex in monkeys has been found to encode motor programming of hand movements in different directions, as determined using intracranial electrophysiological recordings [172]. When the trajectory of the hand movements included obstacles, the dorsal premotor cortex was found to encode strategic direction encoding of different directions. Moreover, within the premotor cortex, different neurons were seen to preferentially encode different movement directions. This heterogeneous distribution of movement kinematics encoding is believed to form the basis of complex limb movements. Moreover, the movement preparatory period was found to be modulated by top-down cognitive processes.

Another study on local field potentials from recordings of single unit activity from the monkey motor cortex showed encoding of different movement targets and velocity [176]. In humans, neurons in the supplementary motor area (SMA) have been shown to encode the movement velocity and direction and is said to play an important role in the planning and execution of movements [177]. Another study reported that neurons in the motor cortex not only showed preferential direction encoding but also showed dynamically evolving trajectories of movements [178].

Neuroimaging studies have also been conducted in the past to study the areas of the brain involved in the planning and execution of hand movements in different directions. In one study, fMRI scans of hand movements in different directions in healthy human subjects showed spatially disjoint foci of activations within the primary motor cortex corresponding to different directions [179]. Thus, different regions within the motor cortex were said to preferentially encode different hand movement directions. In another study, adapting patterns of activations of the primary motor cortex, premotor cortex, SMA and cerebellum were found for repeated hand movements in the same direction as compared to when repeated movements were made in different directions [180]. This also indicates the modulating effect of different hand movement directions on the activation patterns over a larger set of cortical and subcortical regions.

Another region found to be inherently involved in the planning and execution of hand movements in different directions is the posterior parietal cortex (PPC). Reviews collating the results of multiple studies have found that the PPC plays a crucial role in movement planning by integration of the visual and sensorimotor inputs and forming representations of the required motor commands to achieve the desired movement [181]. This putative functional role of goal-directed development of movement strategies of the PPC has also been corroborated using fMRI [182].

Therefore, in this chapter we aim to use EEG to identify different brain regions, as reported in other brain data modalities, including the motor and non-motor regions that are said to form a distributed network of sources with transient dynamic information flow between these regions during the planning and execution of different movements. In Chapter 2, we described a cross-scale web of interactions between neural events across multiple spatiotemporal scales. Since prior studies have shown the involvement and varied preferential encoding of different movement directions within the motor area, we expect to find neural correlates of this phenomena in EEG as well. More importantly, we would like to demonstrate the interaction among the frontoparietal regions and the sensorimotor cortex during the planning stage of a hand movements.

4.3 Experiment Design

EEG data used for this chapter is taken from the same experimental protocol as in Section 3.2 in Chapter 3. The experimental protocol used to investigate hand movements in different orthogonal directions included a small time window for motor planning after a visual depiction of the target direction. In brief, EEG data was collected from 7 healthy subjects performing right-hand centre out movements in 4 orthogonal directions in the 2D plane. The subjects performed right hand movements holding an MIT MANUS robot that recorded various hand movement parameters such as direction and trajectory. A computer randomized and controlled the sequence of trials (hand movement directions) performed by the subjects. The subjects were informed about the movement direction about 3 seconds before they were given the cue for onset of movement. They were instructed to perform the hand movements as soon as they received the cue. In this chapter, we use the same duration of 2 seconds as in the previous chapter which started one second prior to onset of movement ($t = -1s$) to one second after movement onset ($t = 1s$). EEG was recorded using a Neuroscan Synamps amplifier using 118 channels with a sampling frequency of 250 Hz. For the purpose of this study, we use a subset of 75 channels that were spread out across the scalp. The channels that were not used were those which were at the sides of the head and showed high levels of artefacts. Subjects S1 to S6 performed 40 trials per direction (total of 160 trials) and subject S7 performed 35 trials per direction. More details about the dataset can be found in the previous chapter and in [94].

4.4 Proposed Methodology

In this section, we describe the methodology used to identify different brain regions possibly involved in the planning and execution of hand movements in different directions. The steps adopted in this study have been summarised in Figure 4.1.

4.4.1 Preprocessing

The EEG data acquisition system had a lower cut off frequency of 0.05 Hz and the raw EEG data was low pass filtered at 40 Hz in preprocessed in EEGLAB

FIGURE 4.1: Summary of the methodology used in this work

[183]. This was followed by baseline removal using the mean of the 1 second time window from $t = -1$ to $t = 0$. This data was then re-referenced using Common Average Referencing (CAR). Independent Component Analysis (ICA) based artifact removal was then carried out with the help of the ADJUST plugin in EEGLAB [170, 183–185].

4.4.2 Group Analysis of Distributed IC Clusters

The aim of this method is to demonstrate the involvement of different brain regions in the planning and execution of unilateral movements in different directions. For this purpose, we used a data-driven method using an ICA as a blind source separation technique (BSS) to identify brain regions which could be interacting synchronously during the different visuomotor tasks. A similar ICA-based data-driven method has been used earlier to demonstrate the involvement of different brain regions in a visuo-motor task [186]. All analyses were performed using the STUDY module in EEGLAB. The subset of ICA components, hereafter referred to as ICs, after rejection of artefactual components above, were fit to their equivalent dipoles using the “dipfit” structure in EEGLAB using the MNI Colin 27 Boundary Element Method (BEM) head model [187] and a maximum residual variance of 15%. ICs were then grouped together across all task conditions and subjects for K-means clustering. The parameters used for clustering were the 3D coordinates, component spectra of each IC between 0.05 to 40 Hz and the actual EEG channel

values. This was done to cluster ICs which were both spatially as well as functionally related. Group level analysis was done after clustering the dipoles using K-means ($k = 15$ and $k = 30$) clustering using the STUDY module in EEGLAB. Since ‘ k ’ is a hyperparameter, two values of k were tested to find a better fit for the clustering of ICs. These particular values were chosen empirically to provide a meaningful clustering of ICs with reasonably tight spatial fitness and functional homogeneity [186]. Various properties of the clusters were then visualised such as the average spectra of the components of each cluster and movement direction and the event-related spectral perturbation.

4.4.3 Modelling Dynamic Functional Connections During Movement Planning and Execution

Next, we aimed to demonstrate that active information flow takes place between these regions during the planning and execution phases of the motor task. Thus, the EEG data of an exemplary subject (S1) corresponding to movements in the “West” direction were selected. The above STUDY module was invoked to cluster the IC components in EEGLAB. For this purpose, $k = 5$ was selected for k-means clustering. After clustering of ICs, a representative component was chosen from every cluster to model the interactions between all pairwise ICs using the Adaptive Multivariate Vector Autoregressive (AMVAR) models and analysed using the Source Information Flow Toolbox (SIFT) [183, 186, 188]. As mentioned earlier, a lower value of ‘ k ’ is selected for the individual subject as compared to the group analysis because ultimately the ICs in the clusters would be used in an AMVAR model to estimate the connectivity between different regions of the brain. Since there are much fewer trials on an individual level than for the entire group, the number of variables that can be fit using the data is even more limited. Empirically, it was observed that on an individual level, using $k = 5$ for clustering, followed by AMVAR based modelling led to satisfactory fitting of the model to the data. However, this was not the case when higher values of ‘ k ’ were used. A poorly fit model would result in misleading estimates of connectivity. The order of the model was determined by multiple criteria such as the Schwarz-Bayes criterion, Akaike Information Criterion, Akaike’s Final Prediction Error and the Hannan-Quinn Criterion. The model order chosen was the nearest integer of the average of model orders that minimized the above criteria. An AMVAR model was then fit to the

data using a shifting time-window of width 0.25 second, shifted by 0.03 second. Finally, time-varying connectivity between all pairwise ICs was quantified using direct Directed Transfer Function (dDTF) using the coefficients of the model fit to the data. Thus, if the model fit to the data is described by the transfer function $H(f)$ in the frequency domain, as per equation (2.23), the following equations describe the computation of dDTF $\delta^2(f)$ [189]. Using the transfer function $H(f)$, first $\eta_{ij}^2(f)$ is computed which is similar to normalized DTF computed in equation (2.24) normalized over all frequencies. Thus, using DTF which is a ratio between information inflow from channel j to channel i to information inflow from all channels at a given frequency, equation (4.1) further normalizes this measure over all frequencies.

$$\eta_{ij}^2(f) = \frac{|H_{ij}(f)|^2}{\sum_f \sum_{k=1}^M |H_{ik}(f)|^2} \quad (4.1)$$

Lastly, dDTF is obtained by multiplying the frequency normalized DTF function in equation (4.1) with PDC obtained in equation (2.25).

$$\delta_{ij}^2(f) = \eta_{ij}^2(f) P_{ij}^2(f) \quad (4.2)$$

where $P_{ij}^2(f)$ is the square of PDC and $\delta_{ij}^2(f)$ is the measure of dDTF. This helps dDTF result in non-zero values only when there is direct information flow between channels i to j .

Thus, the above equations are used to quantify the time-varying functional connections between all pairwise combinations of ICs at frequencies 1 to 40 Hz at each of the above time windows. For connectivity estimates at every time-frequency point, a surrogate distribution was then generated to identify time-frequency windows of statistically significant connectivity values by using phase randomization in SIFT. For this purpose, the phase of the original time series of the ICs, computed using short time Fourier transforms, were replaced by a uniform random matrix in the frequency domain. The surrogate time series was then computed using inverse Fourier transform and pairwise dDTF was recomputed. This process was repeated 400 times in order to generate the null distribution. Original connectivity values at every time-frequency bin was then compared to the null distribution and p-values were estimated as the proportion of the connectivity estimates that were less than the original connectivity value. P-values less than 0.001 were then accepted as significant and all other connectivity values were nullified.

4.5 Results

This section describes the results of the aforementioned group analysis of the IC clusters derived from EEG data corresponding to the planning and execution of hand movements in different directions. As described earlier, subjects performed right hand movements in the 2D horizontal plane in four orthogonal directions. All subjects were males and right-handed. A randomised cued protocol was used to inform the subjects about the direction in which movement is to be performed in every trial. The protocol allowed a preparation stage followed by execution stage of the movement to the subjects. Thus, it was possible to use the EEG data to identify the involvement of various brain regions in the preparation and execution of these unilateral movements. Furthermore, it provided an opportunity to analyse the transient functional networks that were established in the brain alongside the different movement directions.

The IC clusters were seen to be spread out across different brain regions across the whole cortex. With $k = 30$, clusters of ICs were much better localized as compared to $k = 15$ (not shown). Therefore, we used $k = 30$ for the rest of our analysis. The equivalent source dipole projections of these ICs were visually inspected by projecting them onto the Colin 27 template MRI provided in EEGLAB. A few clusters depicted artefactual activity as the centroids of these clusters lay in non-cortical areas such as outside the skull or behind the eyes. These clusters were excluded from further analysis. Moreover, some clusters were found to lie in deeper brain areas. Since the contribution of these areas to scalp EEG is questionable, these regions were also excluded.

Figure 4.2 shows the result of IC clustering using $k = 30$ after artefactual and deeper lying clusters are removed. From this figure, it becomes immediately apparent that brain regions involved in generating significant components of the EEG signals relevant to motor execution of a single hand in different orthogonal directions are not limited to the motor and somatosensory cortices. A number of IC clusters lie in regions outside the latter areas. Figure 4.3 and Figure 4.4 show dipoles from Cls 5 and Cls 9 plotted on a template MRI, respectively, in which ICs are found to lie in the parieto-occipital and frontal regions. As mentioned earlier, the participation of these areas to movements in different directions has been reported in prior studies and can now be derived from EEG data as well.

FIGURE 4.2: Location of clustered ICs after removing the artefactual and deep brain clusters. Red dots denote centroids of each cluster.

FIGURE 4.3: IC cluster (Cls 5) located in the parieto-occipital region. Blue spheres represent ICs across various subjects and movement directions. Red sphere represents the centroid of the IC cluster. The circumscribing mesh shows the anatomical head model used.

Several clusters are also found in the central region, towards the medial plane. Interestingly, these clusters located in the central region which includes the motor and somatosensory regions seem to participate differently to different hand movement directions. Figure 4.5 shows the spectra of Cls 1, Cls 4 and Cls 7 between 0.05 to 40 Hz, which are seen to be centrally located. While Cls 1 shows larger higher frequency power spectra for “East” than all other movement directions, Cls 4 shows highest spectral power in higher frequencies for “West”. Moreover, the spectra for horizontal directions “East” and “West” are seen to be of much higher power between the whole range of 0.05-40 Hz than the vertical directions “North” and “South”. Cls 1 shows typical alpha band peaks around 11-12 Hz for “East” and “West”, the spectra for “South” and “North” do not seem to contain these

FIGURE 4.4: IC cluster (Cls 9) located in the frontal region. Blue spheres represent ICs across various subjects and movement directions. Red sphere represents the centroid of the IC cluster (anatomical head model mesh is turned off for better visibility of the ICs).

peaks. The spectra for Cls 7 contains an alpha band peak for "South" whose entire spectrum is seen to contain much higher power than all other movement directions. Lastly, almost all components show the typical $1/f$ spectrum distribution expected from EEG signals.

Figure 4.6 further investigates the time-frequency representation in the alpha (μ) and beta bands 8-30 Hz of some of the clusters located in the central regions by computing the event-related spectrum perturbation (ERSP). This figure was plotted using EEGLAB wherein Morlet wavelets were used to derive the time-frequency spectra with 3 cycles for the lowest frequency, increasing to 25 cycles at the highest frequency and averaged across all the components in that cluster.

FIGURE 4.5: Spectra of different IC clusters located in the central region towards the medial plane.

FIGURE 4.6: Event related spectral perturbation of different IC clusters located in the central region.

This provided the time windows centred at 200 points between -442 ms to 438 ms. The time windows before movement onset were considered as baseline and used to compute the average baseline spectrum. The time windows between 0ms and above were then normalized using this baseline. Cls 4 shows a peak in both bands just after the cue for movement execution for “East”. A slight increase in the beta band can be seen for “South” after onset of movement while “West” shows a slight power suppression in the mu band. One-way ANOVA assessing the effect of movement direction on the spectral plot at every time-frequency point shows that regions in the beta band after movement onset seem to show significant differences in at least one or more movement directions ($p < 0.05$). Cls 7 shows beta band power suppression after movement onset for “East” and a slight power increase in the lower beta band after movement onset for “North” and in the mu and lower beta for “West”. Movement direction “South” shows power suppression in the mu band. However, these power amplifications and suppression were not found to be statistically significant ($p < 0.05$). Cls 16, on the other hand, showed huge areas in the time-frequency spectrum to contain significant differences in at least one or more movement directions. “South” movement direction is seen to show simultaneous power increase and decrease in the beta and mu bands, respectively.

Next, to demonstrate the presence of large-scale interactions between the IC clusters identified above, we use a similar methodology as described in Section 4.4.2, to derive the the IC clusters from one subject as an example. We investigated the spectro-temporal characteristics of the functional connections modelled using the subject-specific clusters of ICs, determined using k-means clustering ($k = 5$). Our observations on one exemplary subject for the “West” movement direction are presented here. One representative IC from each cluster was chosen. ICs were seen to be located on motor cortex, including the supplementary motor area, parieto-occipital and frontal regions. Dipoles projected from the five ICs selected have been visualized in Figure 4.7.

Time-frequency representation of the statistically significant dynamic functional connectivity computed between all pairs of ICs using dDTF is shown in Figure 4.8. Most of the significant interactions are seen to take place before movement, during the planning stage of the task. Moreover, majority of the significant connections are seen to occur in lower frequency bands, delta, theta and lower mu / alpha. Thus, significant information flow are seen to take place between the motor and

FIGURE 4.7: Representative ICs from clusters of $k = 5$ in S1 during hand movements in the “West” direction.

cognitive regions of the brain during the planning of motor activity. Figure 4.9 further visualizes this web of information flow between the motor and cognitive regions during different stages of a task. The time-varying functional connections are plotted on a template headmodel using SIFT in EEGLAB between -0.86 to 0.86s. Each IC is represented by a sphere whose size is proportional to the net outflow of information from that node to other nodes (ICs) in the network. The colours and sizes of the connections are mapped to the net outflow of information connecting two nodes, as presented in the colourmaps in the figure. It can be seen that around -0.56s, IC3 located in the parieto-occipital region becomes a source of large outflow of information to the central and frontal regions. This is followed by an increase in information interchange (large functional connectivity) within the fronto-central and frontal regions resulting in a large outflow of information between IC2 in the frontal region to other ICs at -0.232s and IC1 in the fronto-central region at -0.036s. Soon after movement initiation, at 0.356s, the central region (IC4) is seen to show large information outflow, especially to the frontal region (IC5) which is again followed by a dominant information exchange between the

fronto-central and frontal regions at around 0.524s. Thus, dynamically changing functional connections are seen to form during the planning and execution of the hand movement.

4.6 Discussion

The aim of this chapter was to demonstrate the involvement of large-scale interactions between multiple cortical regions spread out throughout the brain in the planning and execution of hand movements in different directions. A simple ICA-based method was used to identify different regions possibly involved during various stages of preparation and execution of motor activity. From the results presented in this chapter, a number of observations can be made about the contributions of different brain regions to the planning and execution of movements in different directions. From the group analysis, it can be seen that EEG signals corresponding to planning and execution of motor activity, when decomposed using ICA, originate from spatially widespread regions in the brain. Clustering of these ICs found some clusters within the central region and others spread out across the brain, in the frontal, parietal and occipital regions.

Voluntary or goal-oriented movements are known to involve dominant top-down processes which includes planning of movement and a mental strategy or motor program of reaching the target. Therefore, brain areas such as the parietal and prefrontal cortex, attributed to encode movement directions and goal-directed planning of cognitive strategies are expected to be involved. Various regions of the visual cortex are expected to be involved as well since the subject follows visual cues of the targeted direction in each trial as well as the instant of movement initiation. Therefore, in order to execute a complete motor task, it is expected that multiple brain regions coordinate in order to integrate different sensory information with motor planning which would involve the participation of higher association areas. It has been reported in literature that the prefrontal cortex serves to integrate higher order information coming from different brain regions and has therefore been shown to be involved in the planning of reaching movement tasks [148]. Moreover, the prefrontal cortex has been said to enable important systems of top-down processing in goal-oriented tasks. Thus, the presence of ICs and clusters in the frontal and prefrontal regions as shown in this chapter is in accordance with prior literature.

FIGURE 4.8: Time-frequency representation of the dynamic functional connectivity between the aforementioned 5 ICs computed using dDTF, keeping only the statistically significant connections ($p < 0.001$).

FIGURE 4.9: Dynamic changes in functional brain networks during hand movements in the “West” direction from one exemplary subject, shown during various time instances between $[-0.86, 0.86]$ with respect to the cue for movement onset at $t = 0$.

Moreover, the clusters located within the central regions showed different power spectra for different hand movement directions. As mentioned in a number of prior studies, neuronal masses within the motor cortex have been shown to encode different directions [172, 179]. Therefore, contributions of large masses of such neurons in the sensorimotor and motor cortices, that preferentially encode different hand movement directions could lead to the different power spectra and ERSF observed. Various studies have shown the involvement of multiple brain regions in reaching tasks in different directions. Cortical regions reported to be involved include premotor region [147], primary motor region [144, 146, 149], frontal region [143], prefrontal cortex [147], posterior parietal region [150], anterior cingulate cortex [143] and the precentral gyrus [147]. Thus, results presented in this work

are in line with evidence from literature. However, the ERS/ERSP results of every cluster are to be treated with caution, given the low spatial resolution of EEG and the ICA-based method used to locate the various dipoles. Each dipole may therefore correspond to the activity of a much larger region. Moreover, the spectra seen are obtained after averaging over many trials and may therefore not account for the inter-trial variability. Nonetheless, it can be concluded that the present results show the participation of multiple non-motor regions in the encoding of different movement directions. This observation from the current results are in line with literature. More specific source localization methods may be applied in the future to increase the spatial precision of the various cortical sources and highlight the areas involved in different movement directions.

On inspecting the time-course of interactions between these widespread regions in one exemplary subject, we observed evidence of a series of neural events formed by different patterns of information interchange between different regions. During the planning stage, we saw a large information outflow from parieto-occipital region to frontal and central regions. Involvement of the occipital cortex and connectivity between the latter and the motor cortex during the preparation of movement as measured through EEG has also been reported in another prior study [145]. Interestingly, prior studies have attributed movement planning and integration of visual and sensorimotor information for carrying out goal-directed movements to the parietal cortex [181]. Moreover, fronto-parietal networks have been attributed to be crucial for movement planning and visual and somatosensory integration [148, 190]. Active information interchange is also seen to occur between the fronto-central and frontal regions during the planning phase as well as execution of the movement task. This interaction could denote the processing and updating of cognitive strategies or motor command for accomplishing the movement from the centre to the given target. Thus, using a simple ICA-based technique, it is possible to uncover the underlying information interchange between widespread brain regions which facilitate carrying out a targeted movement. Our results and interpretations of the possible underlying strategies to accomplish such a visuomotor task are supported by prior studies using other brain modalities.

4.7 Summary

This chapter demonstrates a large web of interactions amongst sources spread across different regions of the brain corresponding to a motor task. IC clusters were derived from a simple ICA-based technique to identify the involvement of different brain regions to motor planning and execution. Clusters of ICs were found in both hemispheres and in all four lobes. Multiple clusters were found within the central region containing the motor and somatosensory cortices. Difference in their spectra seem to indicate preferential direction encoding within the motor cortex. To verify the interaction between different identified regions, the functional interactions between five such clusters were estimated using dDTF for an exemplary subject. Clusters were found to be located in the motor, somatosensory, frontal and occipital regions. Results indicated greater dominant interaction during the planning of the motor than during execution. The temporal precision afforded by EEG was utilised to visualize the interactions between these regions at various time instants during movement planning and execution, thus demonstrating their relevance to the movement task.

In the next chapter, a networks-based approach is applied to passive BCIs to evaluate the dynamic brain networks underlying a complex facial emotion recognition task. We also investigate group differences in the ability of brain networks to process local and global information between an autistic and a typically developing group.

Chapter 5

Moving from Reactive to Passive BCIs - Evaluating Dynamic Reorganization of Functional Brain Networks in Autism Spectrum Disorder (ASD)

5.1 Introduction

In the previous chapters, a networks-based approach to active / reactive BCIs was demonstrated to decode and analyze different hand movement directions. This approach is radically different from usual SMR-BCI systems which typically use brain activation-based feature extraction methods to classify different motor activity. In this chapter, we now demonstrate a networks-based approach in a passive BCI. As mentioned in Chapter 2, passive BCIs are another class of BCI systems in which brain signals recorded from the subject are sent to a computer, typically for monitoring the neural correlates of their cognitive performance, while they perform a certain task. In this chapter, a networks-based approach is proposed to investigate the group differences in the dynamic reorganization of neural resources during

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a complex facial emotion recognition task between a typically developing (TD) and an autistic group. Emotion recognition is known to involve dynamic transient connections between various parts of the brain. However, the exact nature of the dynamic reorganization of neural resources, as measured using EEG, remain poorly understood. Therefore, a dynamic functional networks-based approach is proposed in this chapter to investigate the underlying neuromechanisms of complex facial emotion recognition using a passive BCI.

5.1.1 Autism as an Empathy Disorder

Autism Spectrum Disorder (ASD) includes a diverse range of disorders which are typically associated to a triad of behaviours, namely, social development, communication and obsessive and repetitive behaviours [191, 192]. A number of individuals on the autism spectrum are also known to suffer from a lack of emotional processing ability [193–195]. Individuals suffering from such a disorder find it difficult to perceive emotions and therefore are often unable to respond in a socially appropriate way. A number of theories in psychology and cognitive neuroscience attempt to explain the reduced empathizing ability of such individuals [191, 193, 196–198].

According to the Central-Coherence Theory [191], a lack of empathizing ability can be seen as an individual’s preference for local processing and superior attention to detail and segmentation skills at the cost of global information integration. Perhaps one of the most widely accepted theories to explain cognitive deficits in ASD, the Theory of Mind [197, 199, 200] explains that individuals on the spectrum are unable to take another person’s perspective by putting themselves in their positions and trying to imagine what that would be like. Similar to the Central-Coherence theory, the Empathising-Systemizing (E-S) Theory [191, 196] says that besides a compromised empathizing ability in ASD, individuals show normal or superior systemizing ability. Systemizing is defined as the drive to analyse systems to reveal their “underlying lawful regularities”, to understand and predict the behaviour of such systems using these governing laws [194].

5.2 Quantifying Dynamic Cognitive Processing with Network Neuroscience

The brain is known to dynamically reorganize its resources to carry out various cognitive processes instead of having a fixed topology of neural subcircuits. This means that the flexibility in reorganizing neural resources results in not only varied weights of functional connections between regions but also a changing network architecture in response to cognitive demands and disease. The following techniques have been used in literature to quantify features of dynamic brain network topology using graph theory.

5.2.1 Graph-Theoretic Measures of Brain Topology

Functional brain networks are known to be dynamic in nature such that they change and adapt to carry out cognitive tasks [201]. Two important properties of complex brain networks are functional segregation and functional integration. Functional segregation refers to specialized areas or networks in the brain which are attributed to specific functions and show high connectivity within these networks. Functional integration refers to the ability of the brain to form large-scale connections to integrate information from various regions. It is believed that a healthy brain functions through a balance between functional segregation and integration [202].

Many graph-theoretical measures have been proposed in literature to quantify the aforementioned properties. Clustering coefficient (CC) is a measure of functional segregation and is equivalent to the fraction of triangles surrounding a node [203]. In other words, it is the fraction of the number of nodes that are connected to each other surrounding a particular node that are also connected to it. Clustering coefficient of a binary undirected graph can be computed using the following equation [203, 204].

$$C = \frac{1}{n} \sum_{i \in N} \frac{2t_i}{k_i(k_i - 1)} \quad (5.1)$$

$$\text{where } t_i = \frac{1}{2} \sum_{j, h \in N} a_{ij} a_{ih} a_{jh} \quad (5.2)$$

where N and L are the sets of all the nodes and edges, respectively, in the network, $n = |N|$, $l = |L|$, $ij = (i, j)$ corresponds to the link between the nodes i and j whose value is a_{ij} . Since we are dealing with binary undirected graphs, $a_{ij} = a_{ji}$. k_i refers to the degree of a node i . t_i in (5.2) corresponds to the number of triangles around node i and C is therefore the clustering coefficient of a given network.

Characteristic path length (CPL) is a measure of functional integration and is defined as the average shortest path length between any two nodes in a network [203]. It is computed using the following equations.

$$L = \frac{1}{n} \sum_{i \in N} \frac{\sum_{j \in N, j \neq i} d_{ij}}{n - 1} \quad (5.3)$$

$$\text{where } d_{ij} = \sum a_{uv}, \text{ such that } a_{uv} \in g_{ij} \quad (5.4)$$

where d_{ij} refers to the shortest path length between nodes i and j , g_{ij} is the shortest geodesic path between nodes i and j . If there are no connections between nodes i and j , $d_{ij} = \infty$, L is then the characteristic path length of a given binary undirected network.

Together, these parameters are often called “Small World” parameters and functional brain networks typically show dense connections within groups (also called communities) and sparse connections between groups. In order to draw inferences about the differences in brain network topology using the above parameters, a reference of multiple random null models are typically used to derive a surrogate distribution of the above values in randomized graphs. The original values are then normalized using those derived from randomized null models. As compared to random networks, functional brain networks showing small world characteristics show high normalized clustering coefficients ($\gg 1$) but similar normalized characteristic path lengths (≈ 1) [202].

5.2.2 Dynamic Reorganization of Functional Brain Networks during Cognitive Processing and Mental Disorders for Passive BCIs

The study in [205] reported increasing small world parameters, characteristic path lengths and clustering coefficients in the theta band during cognitive and perceptual processing in healthy subjects performing a visual oddball task. A greater increase in these parameters was seen during the cognitive processing of targets compared to that during distractors. There was also a decrease in the modularity observed in the theta and beta bands at various stages of processing. The study also invoked the Global Workspace Theory which proposes that the holistic network topology of the brain, beyond pairwise connections, is responsible for perception, cognition and consciousness [206]. Another study [207] reported dynamically adaptive modular structure of the brain network topology in a study of 344 healthy subjects performing a working memory and executive functioning task. Their results showed increased functional integration in the frontal regions during working-memory tasks with increased flexibility in the network modules. In [208], the authors found evolving brain network topology estimated on time-varying functional connectivity in the EEG source space during a visual task and delineated the putative functional roles of various EEG frequency bands. They concluded that a dynamic networks analysis of the brain helped to achieve a more comprehensive insight into neural dynamics than the usual activations-based analysis of EEG. The authors in [209] found flexible hubs as essential components of changing and adapting brain networks to task demands.

Studies have also found reduced small worldness in disorders such as schizophrenia [210, 211] and Alzheimer's Disease [212, 213]. Moreover, studies such as [214–216] have also reported loss of small world properties in autistic individuals using resting state EEG and fMRI. In [217], the authors found loss of small world properties in schizophrenia which they postulated was the result of an increase in global efficiency at the cost of a disproportionate reduction in local efficiency. This would then disturb the balance between functional segregation and integration which is crucial for normal information and cognitive processing.

Most studies in the past have used photos as visual stimuli which could confound the results of emotional processing as it has been conjectured that the emotional

content of static stimuli can be assessed by mental strategies and neural events that are different from dynamic real life social scenarios [218]. In that respect, video stimuli offer a more accurate means to stimulate emotional processing which are closer to lifelike events and involve dynamic information processing. It has also been found that differences between emotion recognition capacities of Autistic and TD individuals also depended on the intensity of the emotional stimuli used in the study [219]. Simpler high-intensity emotions did not show any difference between the groups whereas more subtle and complex emotions at lower intensities showed reduced emotion recognition capability in Autism.

To the best of our knowledge, a comprehensive evaluation of EEG-based large-scale, dynamically reorganizing functional segregation and integration properties of functional brain networks during complex FER tasks comparing an autistic group with a TD group has rarely been reported in literature. Thus, we now attempt to reveal more information about the underlying neurodynamics of emotion recognition deficits in ASD using a passive BCI paradigm. This chapter presents an analysis of the temporal dynamics of CC and CPL values derived from the functional brain networks within multiple EEG frequency bands while the subjects watched video stimuli to get possible insights into aberrant brain mechanisms that could potentially explain the observed differences in emotion recognition accuracies of Autistic individuals compared to TD controls. We hypothesized that emotion processing being a dynamic cognitive task would elicit dynamic reconfiguration of functional brain networks according to different stages of emotion recognition, from local facial feature extraction to identifying the complex emotion. This would manifest in rapidly adapting functional segregation and integration qualities of the network within a task. Differences in emotion recognition accuracy between autistic and TD controls would also elicit corresponding patterns in the aforementioned segregation and integration properties of the subjects' functional brain networks.

5.3 Experiment Design & Dataset Description

The data were collected at Curtin University, Perth, Western Australia, Australia, and was supported by the Cooperative Research Centre for Living with Autism (Autism CRC), Long Pocket, Brisbane, Queensland, Australia. A passive BCI system was set up in which the subject sat in front of a computer screen which was

FIGURE 5.1: Experimental protocol used for this study

used to display instructions and stimuli while EEG was collected using a 40-channel Compumedics Neuroscan EEG Quik Cap with Ag/AgCl electrodes at 1000 Hz. Electrooculogram (EOG) was collected using four electrodes to record horizontal and vertical eye movements. Each trial consisted of a fixation cross presented in the centre of the screen for 1s. A stimulus video was then displayed for 5s. Video stimuli from the Cambridge Mind Reading Face-Voice Battery [220] of actors expressing complex emotions were used in this study to evaluate FER. Participants were shown the video stimuli for a total of 5 seconds per stimuli. A total of 15 complex emotions were shown to each participant which consisted of nine negative (resentful, stern, grave, subservient, insincere and mortified), four positive (exonerated, empathic, vibrant and intimate) and two neutral emotions (lured and appealing). Following presentation of the stimuli, four word options were presented with participants required to select the emotion portrayed from one of the four options by pressing the corresponding key on the keyboard. The experimental design is the same as that mentioned elsewhere [221, 222]. In this study, only positive and negative emotions were analyzed.

5.4 Participants

Participants examined in this current sample were derived from a larger sample which recruited a total of 33 autistic adults and 35 TD adults. Autistic adults were required to have a self-reported clinical diagnosis of ASD according to the

Diagnostic and Statistical Manual for Mental Disorders 5th Edition[223] or equivalent diagnosis of ASD, Asperger Syndrome or Pervasive Developmental Disorder according to the DSM-IV-TR [224]. TD adults had no reported psychiatric conditions and were required to score below the cut-off score of score 67 (T score 60) on the Social Responsiveness Scale-2 (SRS-2)[225, 226]. The SRS-2 scale is self-reported metric of autistic traits in which participants are required to rate statements corresponding to social communication and reciprocity on a 4-point Likeart scale.

Data from 11 TD participants were subsequently excluded due to comorbidities ($n = 2$), high autistic-like traits as measured by the SRS-2 ($n = 5$) or incomplete data ($n = 2$), while data from 8 autistic participants were also excluded due to having no formal ASD diagnosis ($n = 4$), significant inattention during trial ($n = 1$), and incomplete data ($n = 3$). This resulted in a total sample of 24 TD and 25 autistic adults. Eye tracking and EEG data from sub-samples of this larger sample have been reported elsewhere[221, 222]. An additional 5 TD and 6 autistic adults were excluded due to insufficient EEG quality for the analytic methods employed in this study. Therefore, 19 autistic and 19 TD adults were used both for the EEG as well as behavioural analysis.

Autistic and TD adults were matched on age, gender, Verbal Comprehension Index (VCI), Perceptual Reasoning Index (PRI) and Full-Scale IQ (FSIQ) as measured by the Wechsler Abbreviated Scale of Intelligence [226]. Two subtests (map search and visual elevator) of the Test of Everyday Attention (TEA)[227] were also used to characterise the sample and provide a measure of visual selective attention and attention switching. The TEA, consisting of the Map Search and Elevator Counting subtests provided a measure of selective and sustained attention from the subjects.

Groups differed significantly on the two-minute map search and visual elevator subtests indicating autistic adults had poorer visual selective attention and attention switching. Groups also differed on the SRS-2, indicating that autistic adults had higher autistic-like traits. Demographic information for the sample used in this study are displayed in Table 5.1.

TABLE 5.1: Participant Demographics

	<i>NT</i>		<i>ASD</i>		<i>Test of Significance</i>
	<i>(n=19)</i>		<i>(n=19)</i>		
	Mean	SD	Mean	SD	
<i>Age (years)</i>	25.76	1.48	25.56	2.49	0.06
<i>Gender (Male:Female)</i>	13:6		16:3		0.25
<i>WASI-2</i>					
<i>VCI</i>	103.53	2.76	101.88	3.21	0.61
<i>PRI</i>	113.06	3.41	111.19	3.56	0.63
<i>FSIQ</i>	109.06	2.36	107.06	2.52	0.46
<i>TEA</i>					
<i>Map Search 1 minute</i>	9.88	0.73	7.31	0.77	0.02
<i>Map Search 2 minute</i>	8.82	0.79	5.88	0.88	0.21
<i>Visual Elevator</i>	12.29	0.59	11	0.77	0.18
<i>Timed Visual Elevator</i>	10.71	0.92	9.19	1.19	0.05
<i>SRS-2</i>	48.47	1.41	66.13	2.4	0.00

5.5 Proposed Methodology

5.5.1 Demographic Statistical Analysis

All statistical analyses presented in this chapter were carried out using SPSS Version 26. The aforementioned demographic variables were evaluated to determine if groups were comparable. Continuous demographic variables (age, IQ, TEA scores) were assessed for normality by employing Kolmogorov Smirnov tests and where subsequently submitted to Mann-Whitney U or Independent samples t-tests. Categorical data (gender) were evaluated using the Chi Square tests. Accuracy of responses was calculated as a proportion of correct responses, with each participant receiving a total accuracy score. A Repeated Measures ANOVA (RmANOVA) was conducted to investigate differences between groups based on emotion recognition accuracy. The RmANOVA included GROUP (ASD, TD) as a between subjects factor, with VALENCE (Positive, Negative) specified as a within-subjects factor.

5.5.2 EEG Pre-processing and Source Localization

All pre-processing steps were performed using EEGLAB toolbox in MATLAB [170]. EEG data was down-sampled to 250 Hz, bandpass filtered between 0.1 to 40 Hz and

referenced to the common average of all EEG channels. Data were epoched from -1 to 5 seconds with respect to onset of video stimulus. Entire noisy trials, if found, were discarded. Noisy channels, such as those which were highly contaminated with muscle artifacts, were identified after visual inspection and reinterpolated. Lastly, Independent Component Analysis (ICA) using the Infomax criterion was employed for ocular and muscle artefact removal followed by detrending of each epoch [184]. Cleaned EEG data were then used to estimate cortical source signals as a means to reduce the effect of volume conduction and spatial smearing which affect the reliability of connectivity estimates. The forward model for source localization was built using International Consortium for Brain Mapping (ICBM-152) template, co-registered in the MNI (Montreal Neurological Institute) space and a 3-layer boundary element method (BEM) model using the OpenMEEG toolbox [228]. Cortical current densities were then computed from EEG at 15002 tessellated vertices using standardized low-resolution brain electromagnetic tomography (sLORETA) [120] using standard protocols in the Brainstorm toolbox [229] in MATLAB, following earlier studies to investigate cortical dynamics [230].

5.5.3 Quantification and Analysis of Small World Parameters

Next, the task-induced, transient functional brain networks were estimated. EEG data of only the trials corresponding to correct emotion recognition responses by the participants were used. EEG epochs from each participant were grouped into two conditions of positive and negative valence and averaged. To mitigate localization errors, the Desikan-Killiany (DK) atlas [231] was used to define 68 cortical regions of interest (ROIs) which served as nodes for subsequent graph-theoretical analyses as done in prior studies [232–235]. The mean time series of all the voxels within an ROI was used to estimate its representative signal in non-overlapping windows of 1 second each, starting from 1 second of pre-stimulus rest period, resulting in six time windows. Signals from each node were filtered using a zero-phase Type II Chebyshev FIR filter into the classical EEG frequency bands of delta (0.1–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz) and gamma (31–40 Hz). In addition, signals were also filtered into narrower beta sub-bands, namely, lower beta (13–18 Hz), middle beta (19–24 Hz) and upper beta (25–30 Hz). Functional

connectivity was then estimated using the time-domain (zero lag) amplitude covariation between all pairwise signals using Pearson's correlation coefficient which has been used in prior studies to analyse group differences in functional connectivity in the EEG source space and are commonly used in fMRI [236–239]. Binary graph-theoretical techniques were then used to extract indicators of functional segregation and integration for of all participants. The conversion of weighted to binary graphs requires thresholding the edges. However, the same threshold when applied to both groups would typically result in different levels of sparsity which might then bias the results of graph-theoretical measures [214]. Therefore small world parameters, CC and CPL [203, 204], were estimated for the same sparsity level across all subjects from 0.05 to 0.85 with increments of 0.05 [214]. Since the absolute values of the above metrics can be quite arbitrary and difficult compare across individuals, each value obtained was then normalized with those computed from randomized surrogate models using the iterative Maslov-Sneppen rewiring algorithm [240] with $10^4 \times N_n(N_n - 1)/2 \approx 2.27 \times 10^7$ iterations for every graph. Using this technique, an ensemble of 100 randomized surrogate models were computed for every binary graph obtained above and used to normalize CC and CPL values. The above steps were performed using Brain Connectivity Toolbox in MATLAB [204]. Lastly, the CC and CPL values were integrated over all levels of sparsity to get a single representative statistic.

5.5.4 Statistical Analysis

Integrated and normalized CC and CPL values were analysed using a series of RmANOVAs using SPSS Version 26. As different frequency bands are hypothesised to serve different functions as described in Chapter 2, separate RmANOVAs were conducted within each frequency band (Delta, Theta, Alpha, Beta, Gamma, lower Beta, middle Beta and upper Beta). Each RmANOVA included GROUP as the between-subjects factor with levels ASD and TD. Within-subjects factors included VALENCE with levels Positive and Negative and TIME WINDOW with levels time windows one through six. Repeated measures were conducted on the latter two factors with GROUP specified as the between-subject factor. For all RmANOVA analyses, Mauchly's Test of Sphericity of was conducted to test for assumptions of sphericity. Where assumptions of sphericity were violated Greenhouse-Geisser (GG) (when ϵ is less than 0.75) or Huyhn-Feldt (HF) (when ϵ is greater than

TABLE 5.2: Results of testing between subjects factor GROUP using repeated ANOVA on FER accuracies

Tests of Between-Subjects Effects					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	409508.854	1	409508.854	1275.699	0.000
Group	1288.216	1	1288.216	4.013	0.053
Error	11556.265	36	321.007		

TABLE 5.3: Results of test of Sphericity for within subjects factor VALENCE on FER accuracies.

Mauchly's Test of Sphericity							
Within Subjects Effect	Mauchly's W	Approx. χ^2	df	Sig.	ϵ		
					GG	HF	LB
Valence	1.000	0.000	0		1.000	1.000	1.000

TABLE 5.4: Results of testing within subjects factors using repeated measures ANOVA on FER accuracies.

Tests of Within-Subjects Effects					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Valence	3229.702	1	3229.702	11.269	0.002
Valence * Group	962.315	1	962.315	3.358	0.075
Error(Valence)	10317.404	36	286.595		

0.75) corrections were applied. Thus, along with the results of the RmANOVA, we also report the results of the test of Sphreicity. Where effects were significant, Bonferroni corrected pairwise comparisons were conducted.

5.6 Results

5.6.1 Behavioural Analysis

Using RmANOVA on the FER task accuracies, autistic adults showed a trend to be less accurate than TD adults at the FER task, ($F(1, 43) = 4.013$, $p = 0.053$), as shown in Table 5.2. Though the interaction between GROUP and VALENCE was not significant ($F(1, 26) = 3.358$, $p = 0.075$) in Table 5.4, visualisation of the estimated marginal means, as shown in Figure 5.2, and univariate analysis using independent samples t-tests, showed autistic adults had lower accuracy to positive

FIGURE 5.2: Estimated marginal means of FER accuracies of complex positive and negative emotions for TD and ASD groups.

TABLE 5.5: Results of test of Sphericity for within subjects factors of VALENCE and TIME WINDOW on CPL values in the upper beta band.

Mauchly's Test of Sphericity							
Within Subjects Effect	Mauchly's W	Approx. χ^2	df	Sig.	ϵ		
					GG	HF	LB
Valence	1.000	0.000	0		1.000	1.000	1.000
Time Window	0.575	18.860	14	0.171	0.802	0.941	0.200
Valence * Time Window	0.760	9.361	14	0.808	0.914	1.000	0.200

emotions ($t(44) = 2.929$, $p = 0.005$), but not negative emotions ($t(44) = 0.524$, $p = 0.603$).

5.6.2 Dynamic Reorganization of Functional Brain Networks Topology

For characteristic path length (CPL) values, quantifying functional integration, normalised using random null networks and integrated across link densities 0.05 to 0.85, using repeated measures ANOVA, there was no effect of VALENCE for delta, theta, alpha, beta, gamma, lower beta or middle beta frequency bands. However, a significant effect of VALENCE was observed in the upper beta band ($F(1, 36) = 4.349$, $p = 0.044$), as shown in Table 5.6, which indicated that regardless of group or time window, CPL values were higher for positive emotions compared to negative emotions in the upper beta band.

Main effects of TIME WINDOW were observed for delta band ($F(5, 180) = 11.242$, $p < 0.001$) shown in Table 5.8, middle beta band ($F(5, 180) = 2.771$, $p = 0.019$)

TABLE 5.6: Results of testing within subjects Factors using repeated measures ANOVA on CPL values in the upper beta band.

Tests of Within-Subjects Effects					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Valence	0.000	1	0.000	4.349	0.044
Valence * Group	2.159E-06	1	2.159E-06	0.035	0.853
Error(Valence)	0.002	36	6.204E-05		
Time Window	0.001	5	0.000	2.901	0.015
Time Window * Group	0.001	5	0.000	1.597	0.163
Error(Time Window)	0.015	180	8.508E-05		
Valence * Time Window	0.001	5	0.000	1.397	0.227
Valence * Time Window * Group	0.001	5	0.000	1.381	0.234
Error(Valence*Time Window)	0.014	180	7.880E-05		

TABLE 5.7: Results of test of Sphericity for within subjects factors of VALENCE and TIME WINDOW on CPL values in the delta band.

Mauchly's Test of Sphericity							
Within Subjects Effect	Mauchly's W	Approx. χ^2	df	Sig.	ϵ		
					GG	HF	LB
Valence	1.000	0.000	0		1.000	1.000	1.000
Time Window	0.684	12.935	14	0.533	0.884	1.000	0.200
Valence * Time Window	0.610	16.858	14	0.265	0.852	1.000	0.200

TABLE 5.8: Results of testing within subjects factors using repeated measures ANOVA on CPL values in the delta band.

Tests of Within-Subjects Effects					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Valence	1.688E-05	1	1.688E-05	0.078	0.782
Valence * Group	0.000	1	0.000	1.719	0.198
Error(Valence)	0.008	36	0.000		
Time Window	0.011	5	0.002	11.242	0.000
Time Window * Group	0.001	5	0.000	0.876	0.498
Error(Time Window)	0.035	180	0.000		
Valence * Time Window	0.001	5	0.000	0.948	0.451
Valence * Time Window * Group	0.001	5	0.000	0.592	0.706
Error(Valence*Time Window)	0.041	180	0.000		

TABLE 5.9: Results of test of Sphericity for within subjects factors of VALENCE and TIME WINDOW on CPL values in the middle beta band.

Mauchly's Test of Sphericity							
Within Subjects Effect	Mauchly's W	Approx. χ^2	df	Sig.	ϵ		
					GG	HF	LB
Valence	1.000	0.000	0		1.000	1.000	1.000
Time Window	0.717	11.365	14	0.658	0.896	1.000	0.200
Valence * Time Window	0.518	22.411	14	0.071	0.801	0.939	0.200

TABLE 5.10: Results of testing within subjects factors using repeated measures ANOVA on CPL values in the middle beta band.

Tests of Within-Subjects Effects					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Valence	0.000	1	0.000	1.102	0.301
Valence * Group	8.734E-06	1	8.734E-06	0.059	0.810
Error(Valence)	0.005	36	0.000		
Time Window	0.001	5	0.000	2.771	0.019
Time Window * Group	0.001	5	0.000	2.067	0.072
Error(Time Window)	0.016	180	8.691E-05		
Valence * Time Window	0.000	5	4.692E-05	0.563	0.728
Valence * Time Window * Group	0.000	5	9.577E-05	1.150	0.336
Error(Valence*Time Window)	0.015	180	8.330E-05

FIGURE 5.3: Estimated marginal means with standard errors of the integrated normalized CPL values in the delta band

shown in Table 5.10 and upper beta band ($F(5, 180) = 2.901$, $p = 0.015$) shown in Table 5.6. Figure 5.3 shows the CPL values for the delta frequency band in which Bonferroni corrected pairwise comparisons showed significantly varying CPL values across time windows during FER. Figure 5.4 shows the significant main effect of TIME WINDOW on CPL values in the middle beta band, while for upper beta, Bonferroni corrected pairwise comparisons showed only a trend ($p = 0.070$) for CPL values to be higher for time window 4 compared to time window 2.

A main effect of GROUP was found for the lower beta band ($F(1, 36) = 5.603$, $p = 0.023$) shown in Table 5.11, which indicated that autistic adults had significantly lower normalised CPL values than TD adults. Similarly, a near significant trend for the main effect of group was also observed in the theta band ($F(1, 36) = 3.836$, $p = 0.058$) indicating that autistic adults had lower CPL values than TD adults,

FIGURE 5.4: Estimated marginal means with standard errors of the integrated normalized CPL values in the middle beta band. Horizontal bars with * indicate statistically significant pairwise differences.

TABLE 5.11: Results of testing between subjects factor using repeated measures ANOVA on CPL values in the lower beta

Tests of Between-Subjects Effects					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	323.392	1	323.392	1189503.934	0.000
Group	0.002	1	0.002	5.603	0.023
Error	0.010	36	0.000		

TABLE 5.12: Results of testing between subjects factor using repeated measures ANOVA on CPL values in the theta band

Tests of Between-Subjects Effects					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	327.426	1	327.426	649012.095	0.000
Group	0.002	1	0.002	3.836	0.058
Error	0.018	36	0.001		

as shown in Table 5.12. Figure 5.5 and Figure 5.6 show the group differences for the lower beta and theta bands.

A trend for an interaction between TIME WINDOW $\times$ GROUP ($F(5, 180) = 2.067$, $p = 0.072$) indicated that autistic adults had lower CPL values at time window 1 (pre-stimulus rest), compared to TD adults ($p = 0.032$).

For CC values, quantifying functional segregation, normalised and integrated similar to CPL values, a main effect of TIME WINDOW was observed in the delta band ($F(5, 180) = 3.512$, $p = 0.005$), which indicated that CC values for time window

FIGURE 5.5: Estimated marginal means of integrated CPL values showing the significant effect of GROUP with statistical significance in the lower beta band.

FIGURE 5.6: Estimated marginal means of integrated CPL values showing the near significant effect of GROUP in the theta band.

TABLE 5.13: Results of testing within subjects factors VALENCE and TIME WINDOW on CPL values in the theta band.

Tests of Within-Subjects Effects					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Valence	5.006E-05	1	5.006E-05	0.321	0.575
Valence * Group	9.672E-06	1	9.672E-06	0.062	0.805
Error(Valence)	0.006	36	0.000		
Time Window	0.001	5	0.000	1.737	0.128
Time Window * Group	0.000	5	7.994E-05	0.517	0.763
Error(Time Window)	0.028	180	0.000		
Valence * Time Window	0.001	5	0.000	1.961	0.087
Valence * Time Window * Group	0.001	5	0.000	0.885	0.492
Error(Valence*Time Window)	0.022	180	0.000		

TABLE 5.14: Results of test of Sphericity for within subjects factors VALENCE and TIME WINDOW on CC values in the delta band.

Mauchly's Test of Sphericity							
Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilonb		
					GG	HF	LB
Valence	1.000	0.000	0		1.000	1.000	1.000
Time Window	0.798	7.695	14	0.905	0.919	1.000	0.200
Valence * Time Window	0.632	15.655	14	0.336	0.879	1.000	0.200

TABLE 5.15: Results of testing within subjects factors VALENCE and TIME WINDOW on CC values in the delta band.

Tests of Within-Subjects Effects					
Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Valence	0.001	1	0.001	0.084	0.774
Valence * Group	0.112	1	0.112	6.418	0.016
Error(Valence)	0.631	36	0.018		
Time Window	0.326	5	0.065	3.512	0.005
Time Window * Group	0.024	5	0.005	0.258	0.935
Error(Time Window)	3.342	180	0.019		
Valence * Time Window	0.064	5	0.013	0.588	0.709
Valence * Time Window * Group	0.003	5	0.001	0.031	1.000
Error(Valence*Time Window)	3.928	180	0.022

FIGURE 5.7: Estimated marginal means of CC values for the interaction between GROUP $\times$ VALENCE in the delta band. TD individuals show greater difference in CC values between the positive and negative emotions. This is not the case for ASD subjects.

1 were higher than for time window 6 ($p = 0.004$). An interaction between VALENCE $\times$ GROUP was also significant for the delta band ($F(1, 36) = 6.418, p = 0.016$), as listed in Table 5.15. Bonferroni corrected comparisons for this interaction showed a near significant trend indicating that autistic adults had significantly lower CC values than TD adults when viewing positive emotions ($p = 0.057$), it also showed a near significant trend indicating that TD adults had higher CC values for negative emotions compared to positive emotions ($p = 0.054$), whereas this same effect was not observed for autistic adults. This trend has been visualized in Figure 5.7. A near significant interaction between TIME WINDOW $\times$ GROUP was also observed in the middle beta band ($F(5, 180) = 2.193, p = 0.057$), however Bonferroni corrected comparisons showed no significant results.

No other main effects or interactions apart from those mentioned above were found for CPL and CC values.

5.7 Discussion

Human brain networks have been reported to exhibit small world properties which encode a balance between functional segregation and integration. In this chapter, the entire 5-second trial of video stimulus was divided into shorter one-second windows starting from one-second pre-stimulus rest to five seconds of video input for investigating the dynamics of small world dynamics during FER.

5.7.1 Complex facial emotion recognition entails a dynamic reorganization of functional brain network topology

The aim of this chapter was to test the hypothesis that a complete complex FER task that is known to require the dynamic evolution of brain states for forming higher-order and abstract relationships from different types of information, would elicit corresponding neural signatures in EEG-based functional brain networks. Since complex FER is known to be a dynamic cognitive process, we expected to find evidence of dynamic reorganization of neural resources for the dynamic integration of information from multiple brain areas.

Correspondingly, a statistically significant trend of varying functional integration parameters (CPL) was seen across multiple EEG frequency bands such as the delta, middle and upper beta bands. In both these EEG frequency bands, the CPL values seemed to first decrease starting from pre-stimulus rest and then increase rapidly towards the end of the trial. The delta band also showed significant temporal changes in functional segregation, wherein the CC values showed a decreasing trend starting from pre-stimulus rest to the end of the trial. We postulate that this encodes a natural process of complex FER that would require forming higher order and abstract relationships from multiple types of lower level facial features and past personal experiences. The involvement of the delta band in significant dynamic topological reconfiguration is not surprising because it has been

reported in other studies that lower frequencies encode goal-directed top-down cognitive processing which is said to be an important process for emotional processing and emotion recognition. The above significant changes in quantifiers of functional segregation and integration show that FER is a dynamic cognitive task involving rapidly changing functional brain network attributes.

5.7.2 Group differences in valence-specific FER

The ability to recognize complex positive and negative emotions were contrasted between the two groups. It was found that while both groups performed at par in recognizing complex negative facial emotions, they differed significantly in recognizing complex positive facial emotions. The autistic individuals were seen to perform significantly poorly compared to their TD counterparts.

5.7.3 Differences between autistic and typically developing individuals in the dynamic reconfiguration of functional brain networks

After EEG-based functional networks were seen to show dynamic reorganization of their segregation and integration properties, we next investigated the group differences in this dynamic reorganization ability of the brain which could provide insights into the observed behavioural differences between the two groups. Therefore, we hypothesized that signatures of dynamically changing functional integration and segregation in EEG-based networks would show altered patterns in the autistic group as compared to their TD controls.

Although both groups showed evidence of dynamically adapting brain networks to the complex FER task, multiple EEG frequency bands showed statistically significant group differences. The lower beta and theta bands showed clear group differences in CPL values suggesting a closer inclination of the neural resources in autistic individuals to random networks in terms of their integrating ability [241]. Some earlier studies have shown reduced CC and increased CPL in autistic individuals, contrary to our study [242]. A possible reason for this observation could be that we maintained the same edge densities before estimating small world parameters instead of maintaining a common threshold which typically results in different

edge densities across participants. Indeed, our results then align with other studies comparing autistic versus TD individuals maintaining the same edge densities [214–216].

The above mentioned group differences in small world parameters could indicate differences in the ability of the two groups to perceive complex facial emotions. A recent meta-analysis of the altered patterns of local and global processing reported that autistic individuals showed an altered temporal structure of the balance between local and global information processing [243] such that autistic individuals tend to show slower global processing compared to TD individuals. In this study, a closer inclination of the brain to integrate information to random networks in autistic adults compared to TD individuals was found which may point towards a sub-optimal temporal evolution of brain network architecture which could lead to longer processing times required for large-scale information integration required for a complex FER task. Thus, the results obtained in this chapter using a networks approach to investigate underlying neuromechanisms seem to explain the observation from other cognitive frameworks.

5.8 Summary

This chapter evaluated the neural correlates of complex positive and negative facial emotion recognition in autistic individuals compared to TD individuals using a dynamic functional networks-perspective in the EEG source space. Statistical analysis of the behavioural outcome of the study showed that autistic individuals performed significantly poorly in recognising complex positive emotions compared to TD individuals. This chapter demonstrated the use of graph-theoretic indicators of functional segregation and integration through a networks-based approach to passive BCIs to investigate the dynamically varying functional network topology in response to a demanding cognitive task. To the best of our knowledge, this is the first study showing altered small world dynamics during a complex FER task in autistic individuals using video stimuli which are more ecologically valid and more likely reflect the everyday events requiring dynamic responses, compared to static photos[218]. This was achieved by applying established tools and techniques to the current work to reinforce technical rigor. Results indicate that the properties of

functional segregation and integration, as quantified by CC and CPL values, respectively, vary significantly with time starting from pre-stimulus rest to the end of the trial. More importantly, the autistic group showed significant group differences compared to the TD group indicating potential loss of small world properties to random networks. This was particularly seen for the lower EEG frequency bands. Since lower EEG frequency bands are known to encode large-scale integration of information, results obtained in this chapter could indicate slower global processing of information in the autistic group. Future work may focus on extracting novel features that are more suited to study biomarkers of dynamic emotion and cognitive processing in autism in order to best contrast it with TD controls. Lastly, results obtained in this work should be treated with caution as it is known that EEG signals are prone to noise and artifacts, which might influence the results obtained. Although methodical preprocessing steps have been carried out to reduce noise and improve data quality, future works may focus on further enhancing quality of data recording and preprocessing steps. Lastly, results obtained in this chapter, although in line with literature, should be taken with caution since the subject-specific MRI scans were not included. Thus, this work relied on standardised MRI template to build the forward model. Future work may consider including subject-specific MRI scans as a part of the experimental protocol which would help in increasing the accuracy of source localization estimates.

In summary, results of this chapter seem to indicate altered functional brain networks in autistic individuals compared to the TD individuals. In the next chapter, we use a sophisticated coarse-grained connectomic approach to investigate the nature of any underlying aberrations in the functional brain network architecture of autistic individuals compared to TD controls. This is also targeted to help address some methodological limitations in the current global temporal scale.

Chapter 6

Aberrant Dynamic Functional Brain Networks in Autism Spectrum Disorder (ASD) during Complex Facial Emotion Recognition - A Coarse-Grained Connectomic Perspective

6.1 Introduction

In the previous chapters, a networks-based approach was used to decode motor kinematics in a reactive BCI and assess dynamic changes in task-induced functional brain networks in a passive BCI. In Chapter 5, we saw evidence of altered neuromechanisms in autistic individuals compared to typically developing (TD) individuals in response to a complex facial emotion recognition task. In this chapter, we use a sophisticated coarse-grained EEG-based connectomic approach to further investigate the nature of aberrant functional connectivity in autistic adults compared to TD controls.

Contributions made to this chapter have been submitted as a full paper for review: T. Chouhan et al., Dynamic Functional Brain Networks of Autism Spectrum Disorder. Human Brain Mapping. (*in Revision*)

Autism is a spectrum disorder and patients show a wide range of social and behavioural deficits. Classical EEG frequency bands are attributed to various functional roles and are seen to be modulated by the behaviour and task performed by the subject. It is often conjectured whether autism involves increased or decreased connectivity with mixed evidence in literature, especially for EEG. Instead, we hypothesize that the observation of increased or decreased connectivity in EEG would depend on the EEG frequency band under investigation as well as the behavioural profile of the patient. Thus, the exact nature of aberrant functional connectivity would then be subjective and depict the cognitive style of the patient under a certain task. Thus, in this chapter we propose a brain networks perspective of the deficits in dynamic emotion recognition in ASD using a coarse-grained connectomic approach in the EEG source space.

6.2 Aberrant Brain Connectivity in ASD

Aberrant patterns of brain connectivity have been found in autistic individuals showing deficits in emotional processing. Neuroimaging modalities like fMRI and positron emission tomography (PET) offer precise information about abnormal activation patterns and neuroanatomy of subcortical structures in high spatial resolution but low temporal resolution that are commonly found in autism [244–247]. Emotional processing has been shown to activate a network of brain regions [248]. The autistic brain is typically associated with high local connectivity in tandem with low long-range connectivity, which may be attributed to widespread aberrant pruning of synapses [245]. Such a brain would then result in impaired higher-order cognitive functions such as those which are typically observed in ASD, along with impaired motor coordination and perceptual abnormalities. Prior studies on autistic individuals vs TD controls using videos of actors expressing happy or angry emotions found abnormal patterns of connectivity in the prefrontal and posterior regions along with altered connectivity between the amygdala and the dorsomedial prefrontal cortex [246]. Based on their findings, the authors postulated that inability to perceive others’ emotional states in autistic individuals may cause them to resort to an abnormal seeking strategy, driving the need to look at the emotional stimulus in different ways compared to TD controls. This could then result in the abnormal pattern of activations that they observed.

6.2.1 Functional roles of different EEG frequency bands to emotional processing

Since emotion recognition is expected to involve complex cognitive strategies, various classical EEG frequency bands have been investigated to evaluate their corresponding functional roles. In past studies, the importance of lower frequency bands has been attributed to typical emotion recognition. In [249] the theta band showed greater left ERD for subjects with greater emotional intelligence scores (EIQ) than those with average EIQ. In another study, delta and theta band were found to contain emotion-related information processing whereas the gamma band was found to contain specific responses to high arousal stimuli [250]. While the delta band was shown to correspond to emotional novelty, the theta band was shown to encode emotional significance of the face. A recent review of delta oscillations showed that it is seen to be involved in a number of cognitive and emotional processing [251] while various mental disorders such as Alzheimer's Disease and Schizophrenia showed reduced delta responses compared to healthy controls. Moreover, the review also noted that past studies on the delta band, showed increased delta band to emotional familiarity (for example, increased response to the stimulus of a loved one as compared to an unknown person) [252, 253]. In another study, delta band coherence has been attributed to decision making [254]. The lower frequency bands - delta and theta - have also been shown to encode conscious emotional processing and contain correlates emotional intelligence and sensitivity [255].

Gamma band oscillations are said to reflect processing of local neural circuits and occur in short time windows, typically concurring with neuronal excitation and inhibition [256]. Studies have found the gamma band to encode preferential processing of faces as compared to non-face stimuli [257, 258]. Higher induced gamma band activations are typically found in EEG when subjects are shown stimuli of human faces as compared to other types of stimuli such as ape faces, human hands, buildings and watches [259]. This difference in induced gamma band activations has been postulated to be associated with human expertise in distinguishing human faces compared to other types of stimuli [259]. Multimodal neuroimaging studies have also identified that the inferior occipital gyrus (IOG) and fusiform gyrus (FG) are involved in the perception of faces with preferential higher activations in the gamma-band for face stimuli as compared to non-face stimuli [260]. Thus, a number of studies suggest that the gamma band is seen to encode face detection strategies

which are especially pronounced in tasks like detection of upright versus inverted faces [261, 262]. A review study noted that besides face detection and perception, the gamma band is also involved in detecting stimuli with higher arousal [263].

Recent studies such as [214] show that theta and alpha band brain networks that are known to be involved in integration of information from different parts of the brain are disrupted in autistic children. In an event-related potentials (ERP) analysis of emotional processing of coloured photographs of expressive faces, [264] found aberrant properties of various ERP components at various source dipole locations including the occipital, temporal, frontal and parietal regions. They also found larger right-hemisphere P2 amplitudes in autism in response to happy faces compared to neutral or angry faces. The authors thus postulated that this could denote that autistic individuals rely relatively more on emotional perception instead of emotional experience. This evidence also recognizes the importance of studying possible aberrant patterns of emotional lateralization in autism. Another ERP study found that early stage social processing differentiated ASD from healthy controls [265].

6.3 A networks persepctive of cognitive and psychological frameworks of emotional processing

Various cognitive theories and frameworks have been postulated in literature to explain the observations in those afflicted with ASD. The author of the Social Brain Theory [198], based on a number of independent lesion and neurological studies, predicted that certain subcortical structures like the amygdala, the orbito-frontal cortex and the superior temporal gyrus were responsible for eliciting social response and intelligence. This prediction was confirmed in later studies such as [266] by examining autistic individuals using functional magnetic resonance imaging (fMRI) who were known to have compromised social intelligence. Patients showed abnormal activation patterns of these regions while performing a task to identify the emotions of people by looking at the photographs of their eyes. A number of other studies have also validated the abnormal functioning of the “social brain” regions

as well as other regions such as the anterior insula and anterior cingulate cortex (ACC) resulting in abnormal social responses in autistic individuals [244, 267–269].

Recently, there has been a paradigm shift in the way neural correlates of altered emotional processing in disorders like autism are studied, from abnormal activation patterns of various cortical and subcortical structures to abnormal connectivity patterns between these regions. This is because of the realization that brain regions do not work in isolation. Higher cognitive functions such as empathy require integration of high-dimensional information from multiple areas in the brain [218, 270]. Moreover, it has been mentioned that brain connectivity is especially relevant to study aberrant neural processing in autism as it can serve to unify neuroanatomy, neurophysiology and behavioural attributes within one common framework [245].

Baron-Cohen and Wheelwright present an excellent essay on empathy, a core component of emotion recognition, defined as a behavioural attribute and how the empathy quotient varies in TD controls depending on gender and contrasts with Asperger’s Syndrome and autism [194]. While they present a number of perspectives and definitions of empathy, the important points to takeaway were that empathy required a person to be able to take another person’s perspective, put oneself in the other’s shoes, predict how he might feel being in the same situation and using that prediction to model one’s response in an appropriate way in the given social scenario. Therefore, empathy requires an individual to form high-order abstract associations from the integration of multiple types of information. This must then require the “normal” functioning of both, being able to process and decode the different types of information as well as the ability to form higher-order associations among such multi-dimensional information. Aberrant processing of either type of brain function could then result in altered and compromised empathizing ability. Recent studies continue to corroborate deficits in emotion recognition in autism [271].

6.4 Emotional Lateralization

Emotional lateralization has been well documented in literature. There are various theories proposed in literature that expound on emotional processing from various contexts. On a basic level, they associate commonly observed patterns in

hemispheric asymmetries to different types and stages of processing emotions. The Valence Hypothesis proposed that the left hemisphere was responsible for processing positive emotions and right hemisphere for processing negative emotions [272]. The Right Hemisphere Hypothesis states that the right hemisphere plays a crucial role for emotional processing irrespective of the type of emotional valence [273]. A recent study used EEG-based connectivity analysis on a unilateral and bilateral positive/negative emotion task to demonstrate valence-specific specialization of either hemisphere (left/right hemisphere for positive/negative emotion, respectively) [274]. Another study, in the form of a systematic review, reported that the right hemisphere is seen to play an important role in unconscious emotional processing and left hemisphere in conscious emotional processing [275]. In another study, using intracranial electrocorticography (ECoG), it was found that the right hemisphere showed superior decoding of face processing as compared to the left hemisphere [276].

Investigating the effect of gender on emotional lateralization, authors in [277] found that males showed stronger lateralization than females although both sexes performed at par in an emotion recognition task. Similar results were found in other studies with a large number of subjects ($N = 276$) [278] and ($N = 122$) [279]. Understanding such basic differences between the two genders is important since autism is known to affect males much more than females [277, 280–283]. While understanding the reason behind this has proven to be a challenging and elusive topic in research, the implications of this observations are important to understand the altered processing of emotions in autism compared to TD controls. For instance, theories such as the Extreme Male Theory of Autism state that autistic brains can be viewed as an extreme case of the male brain from the perspective of altered emotion processing in autism [284]. Some studies have also carried out experiments on patients in various settings to test the contrasting right hemispheric and valence hypotheses [285–287]. The authors in [285] studied healthy subjects and an anterior callosotomized patient and postulated that the two hypotheses were actually not independent but mutually exclusive. In another study, the authors found that healthy controls performed significantly better at facial emotional recognition than patients with left or right hemisphere damage [286]. Patients with left-hemisphere injury performed better than those with right-hemisphere injury patients in the recognition of negative non-aroused and aroused expressions. Interestingly, there was no significant difference seen in the recognition of positive emotions in [286].

In [287], however, it was found that both hemispheres are involved in perception of both positive and negative emotions.

Not surprisingly, atypical emotional lateralization patterns have been found in Autism [288, 289]. In an imitation task of emotional stimuli, TD children showed typical increased activation of the right hemisphere, as expected, while Autistic children showed reduced right hemisphere lateralization comparatively [290]. Similarly, the authors in [291] found reduced laterality in Autistic children in response to a chimeric faces task, however another study [292] found that non-autistic adult males with above normal autistic-traits showed increased lateralisation. The authors in another study [293] then conjectured that the contrasting difference in observations in [291] and [292] could be attributed to age of the participants with older participants having increased emotional processing ability.

6.5 Experimental Paradigm

The experiment and data used in this chapter are identical to the one used in Chapter 5. In brief, a passive BCI was used to collect EEG data from two groups of autistic and TD adults while they viewed video stimuli of actors expressing complex facial emotions for 5 seconds. A total of nine negative, four positive and two neutral emotions were used in this experiment from the Cambridge Mind Reading Face-Voice Battery [220]. After each video stimulus, they were shown 4 words corresponding to 4 choices for the emotion depicted by the actor in the video and were asked to identify the correct emotion with a key press. EEG data was recorded using a 40 channel EEG headset which included 4 EOG electrodes.

6.6 Proposed Methodology

The methods used in this work have been adopted from prior studies which have used them effectively to identify and analyse contrasting biomarkers of neurodevelopmental and neurodegenerative disorders compared to controls. Thus, the methods used have already been proven in their technical rigor. Moreover, a connectivity-based estimator of emotional lateralization has been proposed and used in this chapter which uses the contrasting sub-networks identified between

the two groups to assess the nature of alterations in complex emotion processing in autism compared to controls.

6.6.1 EEG Preprocessing and Source Localization

EEG data was preprocessed exactly the same way as mentioned in Chapter 5 in EEGLAB. In brief, EEG data were band-passed filtered between 0.1 to 40 Hz, rereferenced according to the common average of all channels and subjected to baseline removal. Finally, ICA-based artefact removal was carried out. The cleaned epochs were then detrended and used for source localization. The sequence of steps for carrying out source localization of the cleaned epochs using sLORETA in Brainstorm were also exactly the same as those mentioned in Chapter 5. A forward model using a tessellation of 15002 vertices was created. A three-layer BEM model was created using OpenMEEG. Finally, sLORETA-based minimum norm imaging was used to solve the inverse problem and estimated the source signals. Unlike the previous chapter, the vertices were directly used to estimate voxel $\times$ voxel connectivity to follow a coarse-grained connectomic approach. To control for computational requirements, EEG source space of 15002 voxels was down-sampled to 500 voxels spread across the cortex.

6.6.2 Multi-temporal-scale Connectome Study

To further investigate the underlying neuromechanisms and dynamic network re-configuration under FER in ASD in greater spatial and temporal detail, a coarse-grained connectome analysis was carried out using time-varying functional connectivity at the voxel level in each frequency band mentioned previously at three temporal scales. Since different EEG frequency bands need different lengths of time windows for identifying significant differences in functional connectivity and at the same time also be able to get a holistic view of the multiscale nature of neural interactions, three different lengths of time windows were used: non-overlapping windows of 0.5s and 1s as well as one over-lapping time window of length 2s with 50% overlap. Voxel $\times$ voxel functional connectivity was estimated using Pearson's correlation coefficient between the pairwise voxel mean time series mentioned previously. Furthermore, to mitigate spurious interactions at the voxel level, all

connections between pairs of voxels 40 millimetres apart as done in prior studies using the same statistical model on EEG-based dynamic functional connectivity used in this study [239, 294]. This helps to protect against over-estimating the spatial resolution that is typically expected from EEG. Next, statistical analyses of case versus controls were carried out separately at each time scale mentioned above.

6.6.3 Network-based Statistic (NBS) Connectome Analysis

Network-based statistic (NBS) was proposed to study group differences in connectivity estimates and has gained wide popularity [295]. Significant differences in functional connections between groups were evaluated while controlling for multiple comparisons, based on the assumption that any significant treatment effect (experimental conditions under study or effect of disorders) would manifest in terms of significantly connected components in brain topology instead of randomly oriented significant links. First, a mass univariate statistic was fit to each connection to assess the difference of the edge weight of that connection between the two groups, endowing each connection with a test statistic. A hyperparameter in terms of a statistical threshold was then applied to all the edges. The edges with suprathreshold test-statistics were then submitted to a permutation-based testing to control for family-wise error rate (FWER). Permutations were repeated 5000 times and at each permutation the size of a connected component was estimated. P-values were then estimated as the proportion of randomly permuted components that were larger than the original component in favour of the null hypothesis and checked for a significance level of 0.05. One-sided Student's t-tests were used to create two types of mass-univariate models testing for significantly decreased ($TD > ASD$) and increased ($ASD > TD$) connectivity in the ASD group compared to TD. Each model was evaluated at every time window for all three temporal scales mentioned earlier. The only hyperparameter in this method was the statistical threshold. It is therefore recommended that different levels of statistical threshold be tested. In this study, both models were evaluated at three thresholds, namely, $T=2.5$, 3.1 and 3.5 .

6.6.4 Quantification of Laterality within Altered Networks

Asymmetry in the significantly altered (lower or higher connectivity) networks identified above was then estimated using the equations below.

$$L_{r_i} = \frac{N_{r_i}/A_r}{N_i/A} \quad (6.1)$$

$$L_{l_i} = \frac{N_{l_i}/A_l}{N_i/A} \quad (6.2)$$

where L_{r_i} and L_{l_i} are the connectivity-based laterality indices of the right and left hemispheres of the i^{th} significant component, respectively; N_{r_i} and N_{l_i} are the number of strictly right and left edges (edges between nodes strictly within the same hemisphere); A_r and A_l are the total number of all permissible edges within the right and left hemispheres, respectively in the original connectivity matrix after removing all edges between nodes ≤ 40 mm apart; N_i is the total number of significant edges in the identified altered network and A is the total number of permissible edges in the original connectivity matrix. Finally, the above laterality indices of the identified altered networks were aggregated over all threshold values and temporal scales in each model. Lateral dominance of one hemisphere over another within the identified statistically significant networks was then statistically tested. For this purpose, the list of laterality indices over all thresholds and temporal scales were submitted to one-sided Mann Whitney U tests and p-values were checked against a significance level of $p = 0.05$. The latter statistical tests were run on MATLAB using the Statistical and Machine Learning toolbox.

6.7 Results

Literature contains mixed evidence for decreased and increased connectivity in autistic individuals compared to TD individuals in EEG [296–298]. We hypothesized that the pattern and type of aberrant connectivity would depend on the behavioural profile of autistic individuals and putative functional roles of the EEG frequency band being analyzed. Indeed, components with significantly decreased and increased connectivity in autistic individuals compared to TD individuals during the FER task were found across multiple EEG frequency bands

TABLE 6.1: Emotional laterality summary statistics.

	Valence	TD > ASD		TD < ASD	
Delta (0.1 - 4 Hz)	Positive	L > R	R > L	No components found	
		p = 7.73e-4	p = 0.9993		
	Negative	No components found		No components found	
	Valence	TD > ASD		TD < ASD	
Theta (4 - 7 Hz)	Positive	L > R	R > L	No components found	
		p = 0.8712	p = 0.1342		
	Negative	L > R	R > L	No components found	
		p = 9.13e-5	p = 0.9999		
	Valence	TD > ASD		TD < ASD	
Alpha (8 - 12 Hz)	Positive	L > R	R > L	No components found	
		p = 0.1911	p = 0.8359		
	Negative	L > R	R > L	No components found	
		p = 0.0143	p = 1		
	Valence	TD > ASD		TD < ASD	
Beta (13 - 30 Hz)	Positive	L > R	R > L	No components found	
		p = 0.9999	p = 9.13e-5		
	Negative	L > R	R > L	No components found	
		p = 1	p = 0.0143		
	Valence	TD > ASD		TD < ASD	
Gamma (31 - 40 Hz)	Positive	No components found		L > R	R > L
				p = 0.1641	p = 0.8607
	Negative	L > R	R > L	L > R	R > L
		p = 0.1667	p = 1	p = 1	p = 0.1667
	Valence	TD > ASD		TD < ASD	
Lower Beta (13 - 18 Hz)	Positive	L > R	R > L	L > R	R > L
		p = 1	p = 0.5000	p = 1	p = 0.1667
	Negative	L > R	R > L	No components found	
		p = 1	p = 0.05		
	Valence	TD > ASD		TD < ASD	
Middle Beta (19 - 24 Hz)	Positive	L > R	R > L	No components found	
		p = 0.9998	p = 2.91e-4		
	Negative	L > R	R > L	L > R	R > L
		p = 1	p = 0.5000	p = 0.2429	p = 0.8286
	Valence	TD > ASD		TD < ASD	
Upper Beta (25 - 30 Hz)	Positive	L > R	R > L	No components found	
		p = 1	p = 0.05		
	Negative	L > R	R > L	L > R	R > L
		p = 0.1667	p = 1	p = 1	p = 0.05

using the permutation-based Network-based Statistic (NBS) Connectome statistical tool [295]. These significantly altered sub-networks in autistic adults compared to TD adults often showed dominant laterality in their intra-hemispheric connections. Typical emotional laterality is a well-documented occurrence in TD individuals. Aberrant functional connectivity patterns may alter the way emotions are processed in ASD which might then manifest in the form of atypical laterality patterns. Indeed, brain connectivity has been reported to be a major factor in shaping the observed asymmetries during various tasks [299].

Results of the hemispherical laterality of aberrantly connected sub-networks during FER in the autistic group, compared to TD, were aggregated across three statistical threshold levels and three temporal scales. The delta band was seen to have significantly lower connectivity in autistic adults compared to TD adults only for positive emotions. No significant group differences in connectivity strengths were seen for negative emotions. As listed in Table 6.1, emotional laterality indices showed that sub-networks within autistic adults had lower connectivity from the baseline of TD adults during positive emotions, the left hemisphere showed a significantly greater number of edges with lower connectivity than the right hemisphere (one-sided Mann Whitney U test, left > right, $p = 7.7303e - 4$). Figure 6.1 shows a plot comparing the laterality indices of the models with lower and higher connectivity in autistic individuals compared to TD individuals, normalised by the total number of components found to be significant across all time windows and temporal scales within the same emotion. For the delta band, only the positive emotions are seen to result in significantly lower connectivity in autistic adults compared to the TD adults.

The theta band showed significantly reduced connectivity for both types of emotions, as listed in Table 6.1 and visualized in Figure 6.2 (normalized, as explained above). While positive emotions did not show any significant difference in laterality patterns of the altered components, negative emotions showed significantly lower connectivity in the left hemisphere than the right in autistic adults compared to TD adults (one-sided Mann Whitney U test, left > right, $p = 9.1336e - 5$).

The alpha band was also seen to have significantly lower connectivity for both emotions in autistic compared to TD adults. As seen in Table 6.1 and Figure 6.3, there was significantly lower connectivity in the autistic group compared to the TD group, in the left hemisphere compared to the right, for negative emotions

FIGURE 6.1: Aggregated emotional lateralization in the delta band (0.1 – 4 Hz) and an exemplary plot of a component with decreased connectivity in the autistic group compared to the TD group during a positive emotion in time window 0 – 2s, $p = 0.019$.

FIGURE 6.2: Aggregated emotional lateralization in the theta band (4 – 7 Hz) and an exemplary plot of a component with decreased connectivity in the autistic group compared to the TD group during a positive emotion in time window 1 – 3s, $p = 0.049$.

(one-sided Mann Whitney U test, left > right, $p = 0.0143$). For positive emotions, no significant differences were found between the two hemispheres within the sub-networks with lower connectivity in autistic adults compared to TD group.

The classical beta band was seen to have significantly lower connectivity in autistic adults compared to the TD adults for both emotions. As shown in Table 6.1 and Figure 6.4, the right hemisphere had significantly lower connectivity than the left for both emotions (negative emotions, one-sided Mann Whitney U test, right >

FIGURE 6.3: Aggregated emotional lateralization in the alpha band (8 – 12 Hz) and an exemplary plot of a component with decreased connectivity in the autistic group compared to the TD group during a positive emotion in time window 4 – 5s, $p = 0.040$.

FIGURE 6.4: Aggregated emotional lateralization in the beta band (13 – 30 Hz) and an exemplary plot of a component with decreased connectivity in the autistic group compared to the TD group during a positive emotion in time window 1 – 2s, $p = 0.043$.

left, $p = 9.1336e - 5$; positive emotions, one-sided Mann Whitney U test, right > left, $p = 0.0143$).

Among the narrower beta sub-bands, the lower beta band, shown in Figure 6.5 and Table 6.1, was seen to contain sub-networks which were both significantly lower and higher in connectivity for the positive emotions, in autistic adults from the baseline of the TD adults. However, lower connectivity was only shown to be significant in autistic compared to TD adults for negative emotions. For positive emotions, neither hemisphere was seen to be significantly more dominant in the

FIGURE 6.5: Aggregated emotional lateralization in the lower beta band (13–18 Hz) and an exemplary plot of a component with decreased connectivity in the autistic group compared to the TD group in time window 2.0 – 2.5s, $p = 0.019$.

sub-networks which had lower and higher connectivity. However, for the negative emotions, the right hemisphere was seen to contain significantly greater number of edges with lower connectivity than the left (one-sided Mann Whitney U test, right $>$ left, $p = 0.0500$).

The middle beta band, shown in Figure 6.6 and Table 6.1, was seen to contain sub-networks with significantly lower connectivity for the positive emotions while sub-networks for the negative emotions were seen to have both lower and higher connectivity in the autistic group compared to TD individuals. While the sub-networks which had lower and higher connectivity during the negative emotions did not show any significant differences in laterality indices of either hemisphere, the positive emotions showed significantly greater number of edges in the right hemisphere within the networks that had lower connectivity in the autistic adults (one-sided Mann Whitney U test, right $>$ left, $p = 2.9142e - 4$).

The upper beta sub-band, shown in Table 6.1 and Figure 6.7, showed significantly lower connectivity during the positive emotions while sub-networks which had both higher and lower connectivity were found for the negative emotions in the autistic adults compared to the TD adults. There were significantly greater number of edges in the right hemisphere than the left within the sub-network with lower connectivity in autistic adults compared to the TD adults during positive emotions (one-sided Mann Whitney U test, right $>$ left, $p = 0.0500$) while those for the negative emotions did not show any significant differences between either hemisphere.

FIGURE 6.6: Aggregated emotional lateralization in the middle beta band (19–24 Hz) and an exemplary plot of a component with decreased connectivity in the autistic group compared to the TD group during a positive emotion in time window 1–2s, $p = 0.026$.

FIGURE 6.7: Aggregated emotional lateralization in the upper beta band (25–30 Hz) and an exemplary plot of a component with decreased connectivity in the autistic group compared to the TD group during a positive emotion in time window 3.5–4.0s, $p = 0.030$.

However, the sub-network with higher connectivity during negative emotions in autistic compared to the TD adults showed significantly greater number of edges in the right hemisphere than the left (one-sided Mann Whitney U test, right > left, $p = 0.0500$).

The gamma band, as shown in Table 6.1 and Figure 6.8, had significantly greater connectivity for autistic individuals compared to the TD individuals during positive

FIGURE 6.8: Aggregated emotional lateralization in the gamma band (31 – 40 Hz) and an exemplary plot of a component with decreased connectivity in the autistic group compared to the TD group during a positive emotion in time window 1 – 2s, $p = 0.026$.

emotions and had simultaneously lower and higher connectivity during negative emotions. However, neither emotion showed significantly greater number of intra-hemispherical edges.

6.7.1 Temporal Variation of Emotional Lateralization

The temporal variations in the classical EEG frequency bands have been summarized in Figure 6.9. For each emotion, the emotional lateralization indices computed for each hemisphere using the sub-networks with significantly reduced and increased connectivity identified using the NBS connectome method have been indicated at the highest level of ‘T’ found. Sub-networks with significantly reduced connectivity in ASD compared to TD have been indicated with blue and those with significantly increased connectivity have been shown in red. A number of interesting observations can be made from this figure.

Firstly, positive emotions show predominantly reduced connectivity in ASD compared to TD throughout the length of the trial, especially in the lower EEG frequency bands. The negative emotions also show a few time windows with reduced connectivity in ASD compared to TD but the number of these windows is much smaller compared to positive emotions. Moreover, the delta band shows much higher laterality indices for left than right hemisphere during most of the duration

FIGURE 6.9: Summary of the temporal variation in emotional lateralization over all the temporal scales for the classical EEG frequency bands. The values of emotional lateralization reported are for the highest levels of T for which significant components were found using the NBS connectome analysis. ‘Lr’ and ‘LI’ stand for right and left laterality indices, respectively. The side showing higher index is shown in bold. Components with reduced connectivity in ASD compared to TD are shown in red text, components with increased connectivity in ASD compared to TD are shown in blue text.

of the trial in the sub-networks with reduced connectivity in ASD compared to TD for positive emotions. Thus, it can be said that much of the sub-networks with reduced connectivity found in ASD in the delta are located within the left hemisphere and retain their weaker connections for most of the duration of the trial.

The theta band is also seen to contain sub-networks with significantly reduced connectivity in ASD compared to TD for most of the duration of the trial for positive emotions. However, unlike the delta band, laterality of the weaker connected sub-networks in the theta band in ASD seems to change throughout the duration of the trial. Interestingly, during negative emotions, the theta band showed sub-networks with significantly reduced connectivity mostly in the middle of the trials. The laterality indices computed show that these components are found to be mostly in the left hemisphere. Thus, it can be said that for the positive emotions, the theta band shows dynamically changing topologies of reduced connectivity during the entire duration of the trial. For negative emotions, on the other hand, majority of the components with reduced connectivity in the theta band in ASD are located within the left hemisphere that only appear in the middle of the trial.

The alpha band showed significantly reduced connectivity in ASD compared to TD during both emotions mostly just after the commencement of the trials. In most of these sub-networks with weaker connections in ASD, the laterality indices for both emotions indicate greater contribution of the weaker connections in the left hemisphere than the right. Interestingly, a few time windows during positive emotions also showed reduced connectivity in the alpha band towards the end of the trial. However, the laterality indices here show the opposite trend compared to sub-networks found after the start of the trial.

The beta band showed significantly reduced connectivity in ASD compared to TD during both emotions mostly during the first half of the trial. The laterality indices computed showed greater contribution of the right hemisphere to the weaker connections. Interestingly, this trend in laterality is opposite to that in the alpha band during the first half of the trials even though both bands showed reduced connectivity in both emotions.

Lastly, the gamma band shows dominantly increased connectivity in ASD compared to TD, only during the first half of the trials. While this observation was

found across all temporal scales in the positive emotion, only one time window simultaneously showed sub-networks with reduced and increased connectivity in the negative emotions. Therefore, overall, it can be said that the gamma band showed preferentially increased connectivity during the first half of the trial for positive emotions. Moreover, apart from one time window, all other time windows showing increased connectivity in the gamma band showed greater contribution of the left hemisphere than the right to the sub-networks with stronger connections in ASD compared to TD.

6.8 Discussion

6.8.1 Shift in emotional processing to higher frequency bands in ASD

From the results of the coarse-grained connectome study as well as the significant group differences in small world parameters in the lower frequency bands, we postulate that there is a shift in emotional processing in autistic individuals from lower to higher frequency bands. The results of the coarse-grained connectomes are aggregated and visualized in Figure 6.10 showing the spectrum of significantly decreased and increased connectivity in autistic compared to TD individuals in each frequency band normalized over all EEG frequency bands. It can be seen that this spectral shift showing preferential processing to the gamma band is particularly more drastic for positive emotions with dominant lower-connectivity in all of the lower EEG frequency bands and higher connectivity in the gamma band. There are components with both lower and higher connectivity in the lower and higher frequency bands, respectively, during negative emotions as well, but these seem to show a stronger preference to the beta sub-bands, than the gamma band, where they simultaneously coexist alongside components with lower connectivity within the same band. For positive emotions, however, the gamma band had predominantly higher connectivity with no simultaneously coexisting component with lower connectivity.

We propose an explanation for this observation by drawing from recent developments in cognitive frameworks in ASD. Cognitive alterations regarding what has

(a) Both Emotions Combined

(b) Negative Emotions

(c) Positive Emotions

FIGURE 6.10: Trends in spectral shift of functional brain networks in autistic individuals compared to TD individuals during complex FER task.

been called weak central coherence [300], local processing bias, or enhanced perceptual functioning [301] are today rather understood as a cognitive style, possibly being associated with impairment, but surely being associated with strengths. This cognitive style entails a privileged access to parts and details through hypersensitivity, and a default for enhanced local processing of stimuli. It has been observed that while TD individuals show a default top-down or global processing mechanism [302], the balance between local and global visual processing seems to be different for autistic individuals, i.e., autistic individuals show preference to local information processing and typically slower global processing [243]. Another approach to cognitive style in autism that overlaps with local processing bias is hypersystemizing[303]. It proposes that the human mind possesses a systemizing mechanism to identify lawful and often causal regularities in collectable, mechanical, numerical, abstract natural, social and motoric systems, and that autistic individuals tend to have a default to search regularities in any data that is systemizable more strongly than TD individuals. The gamma band has been shown to encode the perception of facial features and facial orientation as well as emotional perception [257, 261, 262]. Thus, it is reasonable to argue that the observed shift indicates that the autistic group probably relied more on emotional perception using lower-level features instead of more abstract emotional experience which seems to be a property of lower frequency bands.

Decreased connectivity in the lower EEG frequency bands was also reported earlier on a similar sample using imaginary part of coherency [222]. In one study, autistic children performed on par with TD children during a face recognition task although they showed a preference for high-pass frequency features more than TD controls [304]. In another, absence of the modulation of theta-band coherence during emotion recognition task in autistic children compared to TD children was found [305]. The severity of social impairment, as measured through Autistic Diagnostic Interview-Revised scores, was found to be related to the absence of such emotional modulation of theta cortical connectivity. Another study comparing autistic and TD individuals found that facial emotion processing in ASD contained a preference for high-spatial frequency features along with other studies which have also reported detail-oriented visual perception in autistic individuals [306]. This observation is known to be associated with weaker central coherence in autistic individuals [300]. A recent review found that over a number of independent EEG studies, lower connectivity seemed to be dominant in the lower frequencies

while higher and lower connectivity appeared to be dominant in the higher frequency bands [297]. Thus, prior studies on individual frequency bands also seem to support our hypothesis of an aberrant and altered shift in FER in ASD. If this is true, then at least at the group level, we can find evidence to support theories in clinical psychology in the brain's dynamic task-based reconfiguration of neural resources using EEG source space. To the best of our knowledge, such comprehensive insight into task-induced brain dynamics underlying complex FER in ASD has not been reported before.

6.8.2 Spatial shift in intra-hemispherical emotional processing in ASD

There was not only a spectral but also a spatial shift in the FER-induced aberrant functional connections for both emotion valences. The lower frequency bands had significantly lower connectivity in the left hemisphere than the right (delta – positive, theta and alpha – negative). However, the classical beta and the beta sub-bands had significantly lower connectivity in the right hemisphere (beta – positive and negative, lower beta – negative, middle beta – positive, upper beta positive). The upper beta band showed significantly lower connectivity for positive emotions and higher connectivity for negative emotions in the right hemisphere than the left. The gamma band did not show any significantly greater laterality in components with higher connectivity for either emotion type. As mentioned above, lower frequency bands seem to play a crucial role in integrating higher-level abstractions and since they seem to have significantly lower connectivity in the left rather than the right, processing of positive emotions would tend to get more affected as compared to the negative emotions, as per the valence hypothesis. It would be intriguing to see whether a cohort of autistic individuals showing significantly poorer behavioural outcome for the negative emotions rather than the positive showed the opposite trend in the above laterality patterns of components with lower connectivity compared to TD controls.

Although the above seems to support the valence hypothesis, we also find simultaneously coexisting observations in support of the right hemisphere hypothesis, as summarized in Table 6.2. Thus, we postulate that no one theory is sufficient to explain the emotional difficulties observed in ASD. While there seems to be an

TABLE 6.2: Evidence showing (atypical) laterality patterns in components with significantly decreased and increased connectivity in ASD compared to TD for supporting either emotional laterality hypothesis

In support of the right hemisphere hypothesis “right hemisphere is crucial for all emotions”	In support of the valence hypothesis “left hemisphere is responsible for positive and right for negative emotions.”
Delta band showed dominantly decreased connectivity in autistic individuals, compared to TD individuals, for positive emotions but significantly lesser decreased connectivity in the right hemisphere compared the left, indicating relatively greater involvement of the right hemisphere than the left.	In the theta and alpha bands, for positive emotions, where autistic individuals performed significantly poorly compared to TD individuals, the subnetworks with decreased connectivity in autistic individuals showed no clear laterality where we would have expected to find more involvement of the left hemisphere, i.e., reduced sense of decreased connectivity in the left hemisphere compared to the right. The delta band, instead, shows significantly more reduced connectivity in the left than the right hemisphere for autistic individuals compared to TD individuals for positive emotions which may have been a contributing factor to the observed poorer FER accuracy for positive emotions.
Irrespective of the emotion valence, the beta band showed reduced connectivity for both negative and positive emotions. If solely the valence hypothesis were true, then the negative emotions should also have been impacted for autistic individuals as it predicts that negative emotions are processed in the right hemisphere.	For negative emotions, the theta and alpha bands, showed lesser decreased connectivity in autistic individuals compared to TD individuals in the right hemisphere than the left while behavioural outcome of autistic individuals was at par with TD for negative emotions.
The gamma band showed increased connectivity in the right hemisphere in autistic individuals compared to TD individuals for both positive and negative emotions.	The gamma band showed a trend for greater increased connectivity in the left hemisphere during positive emotions than negative emotions for autistic individuals compared to TD individuals.
The lower beta band showed a trend for simultaneous greater increased and decreased connectivity in the right hemisphere than the left for positive emotions. This might indicate a compensation mechanism for neural abnormality in the right hemisphere showing its importance for complex FER.	Compared to TD individuals, the upper beta sub-band in autistic individuals showed significantly lesser decreased connectivity in the left hemisphere than the right for positive emotions.

overall reduction in the number of intra-hemispheric connections in the right hemisphere, there does seem to be some modulating influence of emotional valence on the aberrantly connected components. Thus, similar to recent studies [285, 307], we propose that the two theories do not account for opposing but instead complementary neuromechanisms that are important for emotional processing and only then can all the observations in this study be accounted for.

6.9 Summary

The main aim of this chapter was to find possible explanations of the observed significantly different behavioural profile seen in the autistic individuals compared to typically developing individuals from a functional brain networks perspective. A coarse-grained connectomic approach was undertaken to compare group differences in functional brain networks across multiple temporal scales across the whole duration of the trial. Results showed statistically significant decrease in connectivity in the lower EEG frequency bands. While the autistic group during both emotions showed an apparent shift in connectivity strengths from lower to higher frequency bands compared to typically developing individuals, this relative shift in spectrum was much more drastic in positive emotions. The gamma band is known to encode sensory integration and binding of features while the lower EEG frequency bands are known to contain correlates of emotional intelligence and experience. Thus, our results seem to indicate that the autistic group shows greater tendency for bottom-up processing of facial features as means to identify different complex positive emotions compared to typically developing individuals. Emotional laterality patterns were assessed within the altered sub-networks across all temporal scales. Results showed that when the valence hypotheses and right hemisphere hypotheses were considered to encode complementary neural mechanisms of emotion recognition, almost all the observations in this chapter could be accounted for. Like recent studies, these results seem to indicate that these theories do not seem to be opposing but instead complementary. Future studies may build on the results obtained in this work to carry out more sophisticated analyses to improve our knowledge of autism. For instance, individuals on the autism spectrum are known to have diverse symptomatic and behavioural profiles which makes it difficult to generalize the conclusions from different studies. Thus, appropriate matching techniques may

be used in the future to delineate the autistic cohort into smaller samples to study the individual differences amongst them. This would also require much more data to be collected on an individual level.

In the next section, the summary of the research work presented in this thesis are discussed with specific focus on the significance of the contributions. Future research directions are also discussed that can be explored to reveal greater insights into the working of the human brain and decode various movement and mental states from EEG using BCIs.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

The conclusions of the contributions of this thesis to BCI research and some potential future directions are presented in this chapter. The major objectives of this thesis were to present a networks-based approach to BCIs to decode motor kinematics such as hand movements in different directions and investigate the underlying large-scale functional brain networks enabling motor execution and dynamic cognitive processes such as facial emotion recognition. Thus, the research presented in this thesis support a networks-approach to decode motor activity in EEG-based SMR-BCIs as well as reveal the dynamic large-scale interactions between different brain regions accompanying different motor actions. In passive BCIs, a networks-perspective was shown to reveal dynamically reorganizing properties of information processing which have been shown to be crucial to important social and cognitive processes. Thus, the ultimate conclusion of the research presented in this thesis indicates the need for a holistic view and assessment of neural interactions as key to revealing important insights into the underlying mechanisms of motion and emotion, especially in EEG-based systems.

In this thesis, various signal processing techniques and algorithms were detailed for evaluating the functional interactions between different areas of the brain, befitting the hypotheses and research questions in the various chapters.

A networks-approach to SMR-BCIs was proposed to decode motor activity as an alternate strategy to traditional BCI systems. A phase-locking based estimator of neural synchrony was proposed to estimate task-induced functional connections in the EEG sensor space to decode patterns of different large-scale brain interactions accompanying different types of motor actions. To verify this working principle, binary classification of hand movements in different orthogonal directions was carried out using EEG data acquired from seven subjects. The proposed algorithm, called Wavelet-Phase Locking Values (W-PLV) achieved a mean binary classification accuracy of 76.85% which was shown to be significantly greater than chance level as well as perform at par with a popular CSP-based algorithm which had been used to decode hand movement directions in literature. Further investigation of the features used for identifying different hand movement directions showed presence of discriminative patterns of phase-synchrony in multiple wavelet levels. Thus, different patterns of large-scale functional connections were seen to accompany different motor actions.

Next, a simple data-driven technique was used to identify potential cortical regions involved in the planning and execution of motor activity. An ICA-based technique was used to demonstrate the involvement of brain areas typically associated with visuomotor planning and cognitive processes alongside the motor and somatosensory cortices. Different patterns of spectra from the different clusters of ICs from within the central region of the brain showed potential direction-specificity of regions within the motor and somatosensory cortices. Lastly, EEG data during a particular hand movement direction was used to identify potential cortical regions involved in the planning and execution of that motor task. The interactions amongst the identified clusters in the parieto-occipital, frontal, motor and somatosensory areas were modelled using AMVAR-based dDTF to assess the dynamic flow of information amongst these regions. Greater statistically significant functional interaction was found during the planning stage of the task compared to actual movement execution. This confirmed our hypothesis of finding a network of large-scale brain regions accompanying motor activity. Therefore, dynamically varying functional interrelationships between different brain regions were found to occur alongside movement planning and execution.

In the next contribution, a networks-perspective was undertaken to investigate the dynamic neural correlates of complex emotion recognition. EEG data collected

from subjects watching videos of actors expressing complex facial emotions was used to investigate the temporal evolution of information processing in the brain. It was hypothesized that functional brain networks showed signatures of dynamic neural reorganization to accomplish a demanding cognitive task like complex facial emotion recognition. For this purpose, properties of functional integration and functional segregation were quantified within multiple EEG frequency bands using CPL and CC values over various time instants of watching the expressive video stimuli. Rigorous statistical analyses showed dynamically changing patterns of these values indicating reorganization of neural resources for emotional processing. Furthermore, group differences in the properties of functional segregation and integration between a TD and an autistic group were tested. Results showed statistically significant group differences in these properties in the lower EEG frequency bands. Emerging patterns of group differences indicated a preference to random-networks for information integration in the autistic brain, potentially alluding to sub-optimal or slower global processing compared to TD individuals. Hence, evidence of dynamic changes in the functional network architecture of the brain were seen to underlie emotion recognition, wherein a deviation of such reorganizing properties were seen to accompany a neurodevelopmental disorder, such as ASD.

Finally, the nature of group differences in functional brain networks between an autistic and a TD group was investigated. For this purpose, a coarse-grained connectomic approach was undertaken in the EEG source space to investigate the putative functional roles of different classical EEG frequency bands to altered emotion recognition capabilities in autism. Results showed significantly decreased large-scale connections in lower frequency bands in autistic individuals compared to TD individuals. The autistic individuals were found to perform significantly poorly than the TD individuals for positive emotions. Correspondingly, the shift in large-scale functional connections from the lower frequencies to increased connectivity in the gamma band in the autistic individuals compared to TD individuals were seen to be more drastic for positive rather than negative emotions. Results indicate a greater tendency for bottom-up processing, enabled by sensory integration, of complex positive emotions in the autistic group which support widely purported cognitive theories in autism. Thus, aberrant functional networks were seen to contribute to altered emotion recognition capabilities.

The research presented in this thesis used a networks-based approach to decode and

investigate the neurodynamics of different types of motor and cognitive processes. Using this approach, we were able to identify different motor actions with satisfactory accuracy and identify group differences in the underlying neuromechanisms between TD and autism individuals. Moreover, we were also able to identify rapidly changing associations between different regions during a task. This indicates that a complete functional meaningful task involves a number of stages of different fundamental cognitive sub-processes. The latter would involve dynamically evolving participation of different brain regions which seem to have corresponding neural signatures in EEG signals. Thus, a BCI system could potentially be developed to extract information from these rapidly evolving patterns of functional interrelationships as an alternate strategy to decode mental states, motor intentions and monitor cognitive processes.

7.2 Significance of the key contributions of this thesis

The primary objective of this thesis was to develop a networks-based approach that could be used in active / reactive or passive EEG-based BCIs to accomplish a variety of tasks. The exact mathematical formulation of modelling different neural interactions would depend on various factors such as the nature of task to be decoded or investigated, the properties of EEG signals of interest, the experimental protocol used to analyse a given task and so on. However, the objective of using a networks-based approach is a central theme of all the chapters presented in this thesis. The key considerations and significance of using a networks-based approach in BCIs are described below.

Validating an alternate working principle for motor decoding in SMR-BCIs: Firstly, we wanted to investigate the hypothesis that like other complex cognitive processes, even motor activity is seen to occur alongside transient large-scale neural interactions which possibly integrate multiple types of information. Voluntary movements are said to be goal-oriented top-down processes which involves the representation of a motor program. Moreover, past studies especially from invasive modalities like ECoG have reported large-scale phase-synchrony in the primate motor cortex accompanying visuomotor activity. Thus, we aimed to verify whether an EEG-based

SMR-BCI could be used to estimate and identify different patterns of large-scale phase-synchrony to classify different types of motor actions. Therefore, a single-trial measure of phase-synchrony was proposed based on prior estimators of phase-locking values and used to decode different hand movement directions. In doing so, we were able to achieve satisfactory classification accuracy which supported the idea of using a networks-based approach to motor decoding.

Studying distributed whole-brain functional networks underlying motor activity: Traditional BCI systems use various strategies to decode hand kinematics in the EEG sensor space. Studies in the recent years have demonstrated the advantage of richer spatial and anatomical information in the EEG source space [118, 230]. However, identifying regions of interests in the EEG source space is still an open-ended problem, given the manifold increase in the number of variables (number of sources $\gg$ EEG channels). Commonly used strategies to select regions of interest in literature include using *a priori* knowledge to select potential regions of interest based on the task to be investigated. For motor decoding, some studies limit their investigation to the motor and somatosensory cortices. However, insufficient regions used in a model may lead to incomplete or erroneous interpretations of the source space network or sub-optimal performance of motor decoding. In Chapter 4, we showed the involvement of multiple brain regions beyond the motor and somatosensory cortices in a fairly complex unilateral motor task using a simple ICA-based method. Thus, we aimed to demonstrate the possibility of guiding the cortical region selection process using a simple method. More importantly, we demonstrated that motor, cognitive and sensory cortices form a web of interactions which enable different types of movements.

Investigating the networks-basis of human behaviour and neurodevelopmental disorders: Cognitive processes are said to have a basis in the ability of the brain to strike a balance between functional integration and segregation. Moreover, the brain is expected to be flexible in reorganizing its resources to accomplish various stages of a larger and complex cognitive process. However, to the best of our knowledge, signatures of such functional reorganizations of neural resources have rarely been reported in EEG-based studies of complex facial emotion recognition. We showed that task-induced EEG functional networks do not maintain a constant topology throughout the task but instead show significant temporal variations. Difficulties to perceive emotions or evaluate everyday social scenarios may thus be affected if

the brain's ability to flexibly reorganize its resources to integrate different types of information is compromised.

Finding a neurophysiological basis for widely purported cognitive theories in autism:

Recent advances in our understanding of autism comes from studies assessing different cognitive styles in autistic individuals. The weaker central coherence theory, for example, states that autistic individuals have a different cognitive style of perceiving social cues than TD individuals. The former seem to have a preference to enhanced bottom-up processing, directed by sensory integration over and above TD individuals, who instead perceive the external environment in wholesome and semantically meaningful groups. The latter requires a stronger top-down component. Our results from Chapters 5 and 6 together seem to provide neurophysiological evidence to support this theory. Lower frequency bands are said to encode top-down processes through large-scale integration of information from different brain regions. Higher frequency bands show greater spatial localization and enable more precise temporal processing of local sensory features. We saw a preference to random networks in the lower EEG frequency bands seen in Chapter 5 and relative shift in functional networks from the lower to higher EEG frequency bands in Chapter 6 in the autistic group compared to TD group. These observations directly indicate possibility of enhanced attention to lower-level detail and a sub-optimal integration of higher-level abstract information, as predicted by weaker central coherence. Such a comprehensive account has only been made possible by using a dynamic networks-approach to EEG investigation.

7.3 Future Work

7.3.1 Short-term goals

The research presented in this thesis presented a novel, networks-based approach to BCIs. While the same central theme can be extended to investigate and decode different types of motor and cognitive processes, a few methodological limitations provide room for future improvement.

- *Decoding of different movement kinematic variables* - When used in active / reactive SMR-BCIs, the W-PLV method can be extended to decode different

types of movement kinematic variables such as hand orientation, position, velocity, etc. The working principle of the presented algorithm involves identifying different patterns of phase-synchrony in the wavelet domain which is supposed to accompany different types of motor activity. In its current form, it is more suitable for binary classification than multi-class classification due to the use of correlation-based feature selection. However, with appropriate modifications to the feature selection module, the same algorithm can be used to explore multi-class scenarios.

- *Accurate cortical region selection in the EEG source space* - As mentioned earlier, the aim of ICA-based approach was to demonstrate the involvement of non-motor cortical regions in a web of interconnections with motor regions during the planning and execution of a motor task. However, it is only meant as a guide to indicate potential cortical regions of interest to a certain task. Given that each IC represents a large area of cortical activations, it is not accurate in determining the spatial boundaries of a particular region of interest. Thus, more sophisticated methods like information-theoretic clustering [308] with appropriate regularization may be used as extensions of this method to identify whole-brain regions of interest to a certain task with greater spatial precision. Moreover, this thesis one of the first studies to examine the trajectory of small-worldness in dynamic emotion recognition in autistic individuals compared to TD controls, a few methodological limitations can be addressed in future studies. The standard Desikan-Killiany (DK) atlas was employed in this work in line with other studies investigating connectivity in the EEG source space. However, there might be other atlases that may be more appropriate to study Autistic individuals as compared to the DK atlas. Future studies may therefore conduct a systematic quantitative analysis of the variation in the estimates of small-world parameters with varying atlases. It is postulated that the qualitative conclusions of the analyses may still be consistent with the present study and those reported in literature across various atlases. This hypothesis will be investigated in future studies.
- *Investigating eye-tracking with EEG in facial emotion recognition in autism* - Using a networks-based approach provides rich information about the dynamically changing brain network topology in response to a demanding cognitive task. With eye-tracking data, researchers can further gain multi-modal information about the visual cues being used by subjects at different instances of

the task. This would then provide greater insights into the kinds of features being processed, the preferred cognitive style of emotion perception and the accompanying changes in brain networks in different EEG frequency bands in response to specific visual input. The current dataset used had limited EEG trials which limited the estimation of functional connections to simpler temporal correlation-based estimators. With greater number of trials and runs, more specific phase-lag based and model-based estimators of functional connectivity could then be used to extract precise timing information as well as direction of information flow, respectively, within the estimated EEG-based networks. Higher level of temporal precision and directed interactions between different brain regions could give more comprehensive insights into the underlying neuromechanisms of autism.

7.3.2 Long-term goals

In addition to the above short-term goals, a few long-term research goals for future work based on this thesis are also mentioned below.

- *SMR-BCIs for Distal Upper Limbs* - To the best of our knowledge, very few EEG-based BCI studies have reported decoding of motor kinematics of finer finger and wrist movements. A traditional EEG-based SMR-BCI may not have the required power to identify such fine movements and movement imagination. There could be several reasons for this. When movements become more complex, they are shown to have increasingly complex and overlapping patterns of activations. While powerful neuroimaging tools like fMRI may be able to localize the exact correlates of finer finger movements, EEG-based methods typically do not have the capability to achieve such spatial precision, even after cortical source imaging. Thus, in an EEG-based BCI which is the preferred data modality for important rehabilitative applications such as Stroke rehabilitation, a different working principle may be required to decode such fine finger movements. It is known that different types of hand and finger movements are generated by different configurations of the same set of muscles in the arm and wrist. Therefore, a networks-based BCI may be useful in identifying different patterns of interactions with different corticomuscular nervous pathways.

- *Deep Learning in the EEG Source Space* - While other areas such as computer vision, speech recognition and robotics have seen a huge paradigm shift in AI-based techniques to Deep Learning (DL), the BCI research community has only recently awakened to the idea of using Deep Learning for motor and mental state decoding. However, existing DL techniques have mostly been carried out in the EEG sensor space [97]. The latter is known to suffer from volume conduction and spatial smearing of signals making it extremely challenging to interpret interactions between different brain regions. EEG-based source imaging offers richer spatial information with greater unmixing of signals from different cortical regions. The power of DL is known to come from its ability to extract exceedingly higher-order and abstract relationships from raw data. Such techniques when applied to EEG source space could offer rich information and higher decoding accuracies than existing techniques, including DL-based methods in the EEG sensor space. Thus, one of the future efforts can seek to develop Deep Learning techniques for decoding movement kinematic variables from the EEG source space.
- *Asynchronous decoding of kinematic variables from EEG* - For real-time SMR-BCI applications, multiple kinematic variables will have to be decoded simultaneously in order to recreate the intended movement more accurately. Deep Learning in the EEG source space may be able to achieve this in future. However, developing an asynchronous SMR-BCI with control over multiple degrees of freedom is still a challenge. Moreover, simultaneous asynchronous decoding of multiple movement kinematic variables would also entail a more fundamental neuroscientific investigation. It is known that not only do different regions of the motor, somatosensory and parietal cortices show preferential tuning to different kinematic variables, the information profile of these different variables are shown to peak at different instances. A possible reason for this is known to be that the expression of one kinematic variable may have an inhibiting effect on that of other variables. This may render it difficult to decode such kinematic variables simultaneously. Therefore, future efforts will also be made to develop effective asynchronous SMR-BCI systems.

Thus, in future, more comprehensive BCI techniques will be developed to contribute to the various research areas discussed above. The ultimate goal of BCIs

would be to use high accuracy decoders of different kinds of mental states in real-time scenarios.

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