Neural signal processing techniques to analyse motor functions in EEG-based brain-computer interfaces

Vikram, Shenoy Handiru

2018

Vikram, S. H. (2018). Neural signal processing techniques to analyse motor functions in eeg-based brain-computer interfaces. Doctoral thesis, Nanyang Technological University, Singapore.

<http://hdl.handle.net/10356/73334>

<https://doi.org/10.32657/10356/73334>

**NEURAL SIGNAL PROCESSING TECHNIQUES
TO ANALYSE MOTOR FUNCTIONS IN
EEG-BASED BRAIN-COMPUTER INTERFACES**

VIKRAM SHENOY HANDIRU

INTERDISCIPLINARY GRADUATE SCHOOL
Nanyang Institute for Health Technologies

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2017

Acknowledgments

I am extremely grateful to Prof. Vinod Prasad for giving me the opportunity to pursue my Ph.D. under his guidance. It has been a great learning experience with his supervision. I would like to consider Prof Vinod for being my “doctor father” in every meaning of this term. Not only did he teach me the ‘art’ of research but also imparted the wisdom of how to be humble and stay grounded to become a better person. He always gave me the freedom to think and explore new research ideas. I am truly grateful to his support all these years. He has certainly been a source of inspiration for me.

I am also deeply thankful to Prof Guan Cuntai who co-supervised my Ph.D. research. As his co-supervised student, I have been affiliated to the Institute for Infocomm Research (I2R) at Agency for Science, Technology, and Research (A*STAR) since 2014. Without the support of Prof Guan, this thesis would not have been possible. He pushed me from my comfort zone and taught me how to think beyond the traditional approaches to solve a given problem. He has always been approachable whenever I wanted to discuss my research ideas.

I would like to thank the Nanyang Institute for Health technologies (HealthTech), Interdisciplinary Graduate School, NTU, for the financial support of my Ph.D. study. I also thank the Hardware and Embedded Systems Lab (erstwhile Center of High-Performance Embedded System (CHiPES)), School of Computer Science and Engineering for providing me the workspace for research, and also super co-operative lab executive Mr. Jeremiah for his technical support.

I am also grateful to my co-supervisor Dr. Ser Wee and clinician mentor Dr Ng Yee Sien. I highly appreciate their wisdom and attitude towards research as well as life, which has inspired me a lot. I am also very appreciative of Dr. Kavitha whose help was indispensable when I wrote my first paper as a Ph.D. student. Dr. Neethu

Robinson is another great mentor whose works on the BCI for movement decoding have laid foundation for latter half of my thesis. I really admire how approachable both Dr. Kavitha and Dr. Neethu are. I am also deeply thankful to Dr. Kai Keng for his valuable suggestions during the regular lab meetings at I2R; not to forget the inquisitive nature of Dr. Atieh and Siavash whose questions during the lab meetings at I2R propelled me to think about the challenges.

I am also grateful to IEEE Computational Society for granting me the Graduate Research Award because of which I got a wonderful opportunity to work under Dr. Moritz Grosse-Wentrup at Max Planck Institute for Intelligent Systems, Tuebingen as a visiting research student. I gained an interesting experience in terms of exposure to a very different work environment and meeting with a lot of brilliant minds.

I would like to thank my lunch group friends at NTU - Abhishek, Sumedh, Tushar, Supriya, Kaushik, Sheetal, Nishanth, Raja, Saurabh, Areetha, Nikitha for the most sociable moments during my Ph.D. which I cherish forever. Also, I would like to thank IGS student club members - Sheetal, Abhijit, Ashish, Andrew, Betty, Aravind, Prasanna, Calvin, Bingjie, Zhang Xin, Hongxin, Arun, Akshay, Shuhan, Tam, Minh Sang, Santiago, Ishara, and many more! with whom I had a great time organizing fun events.

Last but not the least, nothing could have been possible without the wishes and support of my parents. It is my parents' unconditional support that acted as a strong pillar for me to lean.

I would like to dedicate this thesis to my parents.

Thesis Abstract

The electroencephalogram (EEG)-based Brain-Computer Interface (BCI) provides an alternative pathway to transmit neural information to a computer. Nowadays, EEG-based Brain-Computer Interfaces are becoming popular due to the cost-effectiveness, portability, and the high temporal resolution of EEG. Also, there have been substantial progress in the EEG-based BCI during the past two decades. However, there are still several shortcomings that need to be addressed such as - poor spatial resolution, non-stationary nature of cortical signals, and high variability of BCI performance across subjects. As the recorded EEG signals are usually noisy, special approaches for signal processing need to be used to extract useful information from highly non-stationary EEG signals. To this end, several research challenges concerned with the spatial filtering algorithms are addressed in this thesis by developing a computationally efficient channel selection algorithm to improve the scalp-spatial resolution and also by robustifying the covariance estimation to handle nonstationarities in a small-sample BCI setup. As the EEG sensor-space recordings are affected by the linear mixing of cortical sources and the volume conduction effect, the latter half of the thesis is devoted to the EEG source localization to extract underlying features relevant to motor tasks. The research presented in this thesis explored different datasets related to motor-imagery and motor-execution tasks in a BCI setup and investigated the robustness of spatial filtering algorithms in terms of cross-subject generalization, source-space analysis and also the clinical stroke data. A novel supervised factor analytic approach for EEG source-space feature extraction was also developed that allows for a better interpretation of task-related cortical sources and particularly useful in multi-class BCIs. After evaluating on several types of datasets, it is demonstrated that the EEG source-space features not only helps in obtaining better performance in classifying the multi-class motor tasks but also helps in the better

interpretation of neural correlates. Continuing further, the EEG source-space analysis is extended to study the causal effects of transcranial direct current stimulation on the Motor-Imagery BCI performance of stroke patients. With the increasing number of source imaging approaches extending beyond BCI applications to clinical diagnosis, this thesis suggest that the EEG source-space studies will have a significant attention in the coming years.

Contents

Abstract	iii
List of Figures	xv
List of Tables	xvii
List of Abbreviations	xviii
1 Introduction	2
1.1 Brain-Computer Interfaces (BCI)	2
1.2 Motivation	3
1.3 Research Objectives	6
1.4 Contributions of the Thesis	8
1.5 Thesis Structure	9
List of Author's Publications	11
1.5.1 Journal articles	11
1.5.2 Conference Articles	11
2 Brain-Computer Interfaces for movement decoding: Background	13
2.1 Brain-Computer Interface: System Components	14
2.1.1 Signal Acquisition	15
2.1.1.1 Types of Data Acquisition Modalities	15
2.1.1.2 Neurophysiology Behind the EEG Data Acquisition	18
2.1.2 Event-Related Desynchronization: Neurophysiological Interpretation	19
2.1.3 EEG Preprocessing	22
2.1.4 Feature Extraction	23
2.1.5 Feature Selection	25
2.1.6 Feature Classification	26

2.2	Sensor-space BCI	27
2.2.1	Spatial Filtering in the Sensor-space EEG	27
2.2.2	State-of-the-art Feature Extraction Methods for Scalp EEG-based Movement Decoding	28
2.2.2.1	Common Spatial Pattern: General Framework	28
2.2.2.2	Variants of the Common Spatial Patterns	29
2.2.2.3	Handling the Nonstationarities of EEG	30
2.3	Source Imaging	33
2.3.1	Forward modeling	33
2.3.2	Inverse Modeling	34
2.4	BCI for Movement Decoding	36
2.4.1	Directional decoding	36
2.4.2	Decoding of movement kinematic parameters	38
2.4.3	Interpretational caveats with the regression-based studies for move- ment decoding	39
2.4.4	Localized arm movement decoding	39
2.5	Limitations of the State-of-the-art Methods in Movement Decoding . . .	42
2.6	Summary	43
	List of Author's Publications	13

3	Spatial Filtering for Cross-Subject Generalization of EEG Sensor Se- lection in BCI	44
3.1	Introduction	44
3.1.1	Literature Review	45
3.2	Formal Background	47
3.3	Methodology	49
3.3.1	Iterative Multi-Objective Channel Selection (IMOCS)	50
3.3.2	Intra-trial Task related Desynchronization (ITTRD)	52
3.3.3	Termination Criteria for the Iterative Update of Channel Weights	52
3.3.4	Feature Extraction Using Modified Filter Bank Common Spatial pattern (MFBCSP)	53

3.3.5	Feature Selection and Classification	55
3.4	Evaluation Dataset	56
3.4.1	Datasets used in this study	56
3.4.1.1	Dataset IVa, BCI Competition III [136] “Dataset 1” . .	56
3.4.1.2	Dataset 2a from BCI competition IV [137]-“Dataset 2” .	56
3.4.1.3	Wadsworth Data - “Dataset 3”	56
3.4.2	Data Analysis	57
3.5	Results	59
3.5.1	Performance Evaluation based on the Motor-imagery Classification Accuracy	59
3.5.2	Cross-subject generalization of EEG channel selection	62
3.6	Discussion	67
3.6.1	Effect of Channel Selection on the Classification Accuracy	67
3.6.2	Statistical Analysis	68
3.6.3	Computational Complexity	68
3.6.4	Effect of Channel Selection on the Cross-Subject generalization .	69
3.7	Summary	70
4	Spatial filtering: Moving from Sensor- to Source-space EEG	72
4.1	Introduction	72
4.2	Shrinkage Regularization based Covariance Estimation for Spatial Filtering	73
4.2.1	Shrinkage-Regularized Common Spatial Pattern (SR-CSP)	73
4.2.2	Methods	75
4.2.3	Results and Discussion	76
4.3	Spatiotemporal EEG Source Localization for Movement Decoding	80
4.3.1	Methodology	81
4.3.1.1	Data Preprocessing	81
4.3.1.2	Source Localization	82
4.3.1.3	Region of Interest (ROI) for functional modeling	84
4.3.2	Results and Discussion	84
4.4	Comparative Study of Spatial Filtering in the Sensor- and Source -space EEG for Multi-direction Movement Decoding	88

4.4.1	Methodology	88
4.4.1.1	Participants	88
4.4.1.2	Data Acquisition	88
4.4.1.3	Experimental Setup	89
4.4.1.4	Preprocessing	90
4.4.2	EEG source Imaging	92
4.4.3	Feature extraction	93
4.4.4	Results and Discussion	95
4.5	Summary	97

5 Supervised Factor Analysis for classifying the Multi-directional Arm Movement using Source-EEG 98

5.1	Introduction	98
5.2	Materials and Methods	100
5.2.1	Data description	100
5.2.2	EEG Source Imaging	101
5.2.2.1	Forward Modeling.	101
5.2.2.2	Inverse Modeling.	103
5.2.2.3	Region of Interest (ROI).	103
5.2.3	Factor Analysis based EEG modeling	103
5.2.3.1	Supervised Factor Analysis for Feature Extraction.	106
5.2.4	Benchmarking Algorithms	109
5.2.5	Statistical Analysis	109
5.3	Results	109
5.3.1	Classification Performance of Source Space Features	109
5.3.2	Source Activation of Hand Movement in Different Directions	110
5.3.3	Source Dipoles Corresponding to Hand Movement in Different Directions	112
5.3.4	Spectral-temporal Characteristics of Multidirectional Movement Decoding	112
5.4	Discussion	116

5.4.1	Comparison of Feature Extraction Techniques	116
5.4.2	Contribution of Supervised Factor Analytic Approach for Source-space Feature Extraction	117
5.4.3	Cortical Source Activation of Hand Movement in Different Directions	117
5.4.4	Spectral Characteristics of Cortical activation corresponding to different directions	118
5.4.5	Contribution of Source Dipoles for a Given Task	118
5.4.6	Limitations	119
5.5	Summary	120
6	EEG Source-space study of Brain Stimulation in Stroke Patients	122
6.1	Introduction	122
6.2	Experimental Setup	124
6.2.1	Participants	124
6.2.2	Transcranial Direct Current Stimulation	124
6.2.3	Experimental Procedure	125
6.2.4	EEG Data Acquisition and Preprocessing	125
6.3	Methodology	127
6.3.1	EEG Source Imaging	127
6.3.2	Dimension Reduction	127
6.3.3	An Ensemble Feature Extraction Method using Shrinkage-regularized Filter Bank Common Spatial Patterns (SR-FBCSP)	128
6.3.4	Functional Connectivity	129
6.3.5	Effective Connectivity	130
6.3.5.1	Dynamic Causal Modeling (DCM)	131
6.3.5.2	Bayesian Model Selection (BMS)	133
6.4	Results and Discussions	134
6.4.1	Classification Performance	134
6.4.2	Spectral Source Power Analysis	136
6.4.3	Connectivity Analysis using Imaginary Coherence	140
6.4.4	Effects of tDCS on the Modulation of Motor Networks	141
6.4.5	Limitations	146
6.5	Summary	147

7	Conclusion and Future Works	148
7.1	Conclusion	148
7.2	Future Research Directions	151
7.2.1	Improved feature extraction for an Asynchronous BCI	152
7.2.2	Source Localization: Pitfalls and Challenges	153
7.2.3	EEG Source Imaging for Clinical Applications	153
A	Appendix	156
A.1	Dimension reduction techniques used for the benchmarking in Chapter 3	156
A.1.1	Principal Component Analysis (PCA)	156
A.1.2	Gaussian Process Latent Variable Model (GPLVM)	157
A.1.3	Isomaps	157
A.1.4	Locally Linear Embedding (LLE)	158
A.1.5	Laplacian Eigenmaps	158
A.1.6	Locality Preserving Projection (LPP)	159
A.1.7	Neighborhood Preserving Embedding (NPE)	159
A.1.8	Locally Linear Tangent Space Alignment (LLTSA)	160
A.1.9	Fisher's Criteria (FC)	160
A.1.10	Support Vector Machine- Recursive Feature Elimination (SVM-RFE)	161
A.1.11	Common Spatial Pattern-Channel Selection (CSP-CS)	161
A.1.12	Particle Swarm Optimization (PSO)	162
	References	163

List of Figures

1.1	A brief highlight of the research challenges and the methods addressed in this thesis	6
2.1	Block diagram of the Brain-Computer Interface system [19]	14
2.2	Illustration of non-invasive BCI modalities and their source of recordings [22]	17
2.3	Illustration of Mu ERD and beta ERS [4]	21
3.1	Block diagram of an Iterative Multi-objective Optimization for EEG Channel Selection.	49
3.2	Illustrative CSP plots of 5 subjects (<i>aa, al, av, aw, ay</i>) in dataset 1 based on the reduced number of channels.	62
3.3	Performance comparison of using different number of features in the classifier on <i>Dataset-1</i>	63
3.4	Average classification accuracy of 85 subjects in <i>Dataset-3</i> as a function of the number of EEG channels.	63
3.5	Performance plots of different channel selection techniques evaluated on the best performing 35 subjects of <i>Dataset-3</i>	64
3.6	Effects of the channel selection and feature reduction on the classification accuracy in <i>Dataset-3</i>	64
3.7	Histogram plot for statistical estimation of most frequently selected channels across 9 subjects of <i>Dataset-2</i>	65
3.8	Absolute frequency mapping of EEG channel occurrence in the subset of most relevant channels in <i>Dataset-3</i>	65

3.9	Histogram count based channel subset selection for cross-subject performance evaluation in <i>Dataset-3</i>	67
4.1	Boxplot of 10×10 cross validation accuracies obtained on <i>Dataset-3</i> using variants of CSP and FBCSP with and without regularization	77
4.2	Boxplot of 10×10 cross validation accuracies obtained on <i>Dataset 2</i> using variants of CSP and FBCSP with and without regularization	78
4.3	Visualization of regularized filter bank Common Spatial patterns in some representative subjects of Dataset-1	79
4.4	Example result of artifact detection using ADJUST algorithm	85
4.5	Forward head modeling based on 3 layered nested concentric sphere. (a) 64 electrodes registered on the scalp, (b) Mesh-based Boundary element method (BEM) for co-registration	86
4.6	(a) Temporal slicing of EEG source localization results during a left hand movement imagination task. (b) Single trial ERS averaged over the cortical region of interest (ROI) in contralateral motor cortex (RH) for left hand MI task	87
4.7	Experiment setup and task timeline (a) Direction cues for 2D center-out movements are shown with the dark filled circle at the centre referred to as initial ‘Home’, and the target circle (blank circle on the circumference) indicating the final position (b) Experimental setup including the reaching apparatus -MIT MANUS robot; (c) Task timeline for direction cue ‘NORTH’. EEG recorded during the ‘Analysis Timeline’ has been used for further processing.	89
4.8	Block diagram of the proposed methodology illustrating the use of sensor- and source-space EEG to compute features for classifying the hand movement in 4 directions	91
4.9	Mean amplitude variation response of Left and right premotor cortex for hand movement in 4 directions	96
4.10	(a) Statistically significant activation ($p < 0.01$) shown at the cortical surface, (b) Morlet Wavelets decomposition corresponding to the averaged response in Brodmann Area 6	96

5.1	Procedural block diagram describing the proposed source space feature extraction. Raw EEG extracted from 118 electrodes are pre-processed as shown, followed by source-space feature extraction. Expanded view of the source-space feature extraction (sub-block) is shown in the right half of this figure. Schematic shows the inverse modeling using sLORETA technique followed by the selection of anatomical ROI in the Brodmann atlas (BA4, BA6). Forward modeling of EEG is shown in the top pipeline of source imaging block. It involves the EEG sensor montage and ICBM152 template anatomy and a three-layer realistic-geometry head model. Cortical time-series information is down sampled into designated ROI (BA4 and BA6) for further feature extraction and classification.	102
5.2	Performance assessment of different feature extraction algorithms in-terms of 5×5 cross-validation accuracy of classifying the EEG corresponding to hand movement in 4-directions. X-axis indicates different feature extraction algorithms with feature space (sensor/source) highlighted in braces. Y-axis indicates the average 5×5 cross-validation percentage accuracy. Jittered points indicate the decoding accuracy of individual subject. . . .	111
5.3	Trial-averaged response of Subject ‘S01’ to 4 different directional cues in (a) East (b) West (c) North and (d) South directions respectively. Legends indicate stereotactic coordinates corresponding to centroid of different Brodmann areas. These coordinates are further shown in Table I. Shaded error indicates the deviation from the mean response. X-axis denotes the experimental timeline in seconds. Y-axis denotes the normalized amplitude resulted from sLORETA.	113
5.4	Group average cortical source maps of all subjects ($n = 7$, right handed). sLORETA source activation patterns resulted from hand movements in different directions as (a) East (b) West (c) North and (d) South. Cortical activation are shown in three orientations (from left towards right): left lateral, dorsal and right lateral view of cortex.	114
5.5	Left lateral view of group average sLORETA-based source activation maps corresponding to different frequency bands ranging from Delta (0.5-4 Hz) to High Gamma (60-90 Hz).	115

5.6	Subject-specific source dipoles selected using our proposed factor analytic method. FDR ($p < 0.01$) corrected sources are shown in the form of spherical nodes corresponding to different directions (a) East (b) West (c) North, and (d) South respectively. Different sizes of these spherical nodes suggest their relative proportion of variance in factor loading. . . .	116
6.1	Experimental timeline of the evaluation portion in each MI-BCI rehabilitation session	126
6.2	Overview of the procedural block diagram of EEG data processing in this study.	126
6.3	Illustrative example of an endogenous DCM Model used to study the causal effects of tDCS on stroke recovery. Different regions shown inside the circles are associated with the functions of motor imagery and execution task after observing a visual cue.	134
6.4	Models used for comparison in the DCM- BMS in Subject N001. Task-dependent modulations of connectivity for motor imagery after giving anodal (excitatory) stimulation to the ipsilesional M1 (Right hemisphere) and cathodal (inhibitory) stimulation to the contralesional M1 (left hemisphere).	134
6.5	Group-average session wise 5×5 crossvalidation based binary classification accuracies of MI vs. Idle state using different types of features	135
6.6	An illustrative example of comparison between post-tDCS intervention and pre-tDCS intervention spectral source power - (a) delta frequency band (0.5-4Hz) (b) alpha frequency band (8-12Hz). The time-series information corresponds to the source activation in the predefined ROI (BA4 and BA6).139	139
6.7	Group-averaged sLORETA activation results during the MI trials in (a) tDCS and (b) Sham group	140
6.8	Group-averaged Functional Connectivity measured using Imaginary Coherence in different spectral bands for (a) tDCS and (b) Sham group before tDCS intervention	142

6.9	Group-averaged Functional Connectivity measured using Imaginary Coherence in different spectral bands for (a) tDCS and (b) Sham group after the 10th session of tDCS intervention	143
6.10	Results of Subject-level inference of Bayesian model selection showing the Log-evidence and Model Posterior Probability for different models.	144
6.11	Endogenous coupling of the winner model after performing Bayesian Model Selection	145
7.1	A consolidated view of the objectives and scientific contributions presented in this thesis.	151

List of Tables

2.1	Summary of different BCI modalities	19
2.2	Overview of the characteristic EEG rhythms	20
2.3	Overview of Various Artifact Removal Methods	24
2.4	Overview of the State-of-the-art Spatial Filtering Algorithms used in the Sensor-space EEG-based BCI	31
2.5	Overview of Feature Extraction Methods in the Spectral domain	32
2.6	Overview of the State-of-the-art methods in EEG Source Analysis of Move- ment Type Classification	37
2.7	Overview of the State-of-the-art methods in EEG-based Localized Arm Movement and Kinematics	40
3.1	Comparison of Percentage (%) Classification Accuracies of different meth- ods on Dataset-1 with 118 channels	60
3.2	Comparison of Percentage (%) Classification Accuracies of different meth- ods on Dataset-2 with 22 channels	61
3.3	Comparison of classification accuracies of subject-independent channels and subject-specific channel selection for the <i>Dataset-2</i>	66
3.4	Cross-validation results of cross-subject generalization performance on <i>Dataset-</i> <i>3</i>	67
3.5	Comparison of the computational complexity of various channel selection techniques used in this study	69
4.1	Percentage Classification accuracies obtained for each subject of <i>Dataset</i> <i>2</i> for the standard CSP and its regularized variants	77

4.2	Average Percentage Classification Accuracy using Fisher’s Linear Discriminant Classifier (5×5 Cross-validation)	95
5.1	Percentage Classification Accuracies for 4-class classification resulted from different benchmarking algorithms	111
5.2	Stereotactic Coordinates of significant cortical activation	112
6.1	5×5 Cross validation accuracies of Sensor-space SR-FBCSP algorithm to classify MI vs Idle states across sessions 1-10 (T1-T10) in the tDCS group	136
6.2	5x5 Cross validation accuracies of Source-space SR-FBCSP algorithm to classify MI vs Idle states across sessions 1-10 (T1-T10) in the tDCS group	137
6.3	5x5 Cross validation accuracies of Sensor-space SR-FBCSP algorithm to classify MI vs Idle states across sessions 1-10 in the sham group	137
6.4	5x5 Cross validation accuracies of Source-space SR-FBCSP algorithm to classify MI vs Idle states across sessions 1-10 in the sham group	138
6.5	Weighted Node Degree (WND) values of connectivity matrices estimated in different frequency bands across both the groups (tDCS and Sham) and sessions (week-0 and week-2)	141
7.1	Recent works (Year: 2013 onwards-) on EEG-based Cortical Biomarker Systems for Clinical Applications	155

List of Abbreviations

ACC	Anterior Cingulate Cortex
ADJUST	Artifact Detection based on Joint Use of Spatial and Temporal features
AD	Alzheimer’s Disease
ANOVA	Analysis of Variance
BBF	Block-based Adaptive BeamFormer
BCI	Brain-Computer Interface
BESA	Brain Electrical Source Analysis
BP	Bereitschaftspotential
CA	Classification Accuracy
CART-SVM	Classification and Regression tree- Support Vector Machine
CCA	Canonical Correlation Analysis
CCD	Cortical Current Density
CSP	Common Spatial Pattern
CSF	CerebroSpinal Fluid
CT	Contour Integration Task
DCM	Dynamic Causal Modeling
DSP	Discriminative Spatial Pattern
ECD	Equivalent Current Dipole
EDA	Equivalent Dipole Analysis
EEG	Electroencephalography
EEMD	Ensemble Empirical Mode Decomposition
EOG	Electrooculography
ERSP	Event-related Power Spectral Perturbation
ERD/S	Event Related (De)Synchronization
ErrP	Error Potential
HD	Huntington’s Disease
fMRI	Functional Magnetic Resonance Imaging
fNIRS	Functional Near-InfraRed Spectroscopy
GPLVM	Gaussian Process Latent Variable Model
ICA	Independent Component Analysis
IIR	Infinite Impulse Response
IMOCs	Iterative Multi-Objective Channel Selection
ITTRD	Intra-Trial Task Related De-synchronization

LAURA	Local Auto-Regressive Average
LDA	Linear Discriminant Analysis
LLE	Locally Linear Embedding
LLTSA	Locally Linear Tangent Space Alignment
LPP	Locality Preserving Projections
LPS	Lagged Phase Synchronization
LPC	Lateral Prefrontal Cortex
LOO-SVM	Leave One Out Support Vector Machine
MD	Mahalanobis Distance
ME	Motor Execution
MI	Motor Imagery
MMSE	Mini-mental State Exam
MNE	Minimum Norm Estimate
MRCP	Movement-Related Cortical Potentials
MTBI	Mild Traumatic Brain Injury
NFT	Neurofeedback training
NPE	Neighborhood Preserving Embedding
OVR-SVM	One-versus-Rest Support Vector Machine
PCA	Principal Component Analysis
PLS	Partial Least Squares
PSD	Power Spectral Density
PSO	Particle Swarm Optimization
pre-SMA	Pre-supplementary Motor Cortex
SBF	Static Beamformer
SCSP	Sparse Common Spatial Patterns
sLORETA	Standardized Low-Resolution Brain Electromagnetic Tomography
SPT	Self-paced tapping
SRLDA	Shrinkage-Regularized LDA
STS	Superior Temporal Sulcus
TDCS	Transcranial Direct Current Stimulation
TRCSP	Tikhonov Regularized CSP
TR-MNE	Tikhonov Regularized MNE
wMNE	Weighted MNE
WCSP	Wavelet CSP

Chapter 1

Introduction

“If the human brain were so simple that we could understand it, we would be so simple that we couldn’t”

- Emerson M. Pugh

1.1 Brain-Computer Interfaces (BCI)

It is estimated that each year, there are about 15 million new stroke victims worldwide, with 30% of stroke survivors needing various rehabilitations [1, 2]. Hence, it is evident that there is a need for better technology which can bypass the conventional neuro-motor pathway between the brain and limbs. In the first International meeting of Brain Computer Interface (BCI), pioneering researchers Wolpaw et.al shaped the definition of BCI which states that “Brain-Computer Interface is a communication system that does not depend on the brain’s normal output pathways of peripheral nerves and muscles” [3]. Research in the area of brain computer interfaces have been attracting a lot of researchers around the world due to its potential applications not only limited to stroke rehabilitation, neuroprosthesis and diagnosis of neurophysiological disorders but also neurogaming, criminal investigation, memory retrieval, and cognitive enhancement. There are ample data acquisition techniques for Brain computer interface, like EEG (Electroencephalography), fMRI (functional Magnetic Resonance Imaging), fNIRS (functional Near-Infra-red Spectroscopy), PET (Positron Emission Topography), MEG (Magnetic encephalography), ECoG (Electrocorticography) and Intracortical recordings.

Some of these techniques are invasive, which means the signal acquisition is done through the implanted electrodes inside the brain whereas non-invasive techniques rely only on the sensors placed outside the scalp. The non-invasive techniques however, instill an interest in most of the researchers because there is no fear of possible neural damage or requirement of surgical implantation of electrodes as in the case of invasive BCIs. Also, recent studies have shown that non-invasive BCI techniques are capable of decoding the neural activity in the brain. Research in the area of machine learning, signal processing, and neuroscience have reported the significance of brain computer interface technology in understanding the inherent neuronal activity that trigger human actions and behaviour. However, state-of-the-art non-invasive BCI technologies are still not promising enough for practical use in neurorehabilitation as there is a need for further improvement in various factors such as decoding accuracy, interpretability of neural features and robustness in terms of cross-subject generalizability which forms the crux of challenges addressed in this thesis.

1.2 Motivation

A significant amount of research in the non-invasive BCI in the past decade rely on EEG (Electroencephalography) since it has the best temporal resolution, cost-effectiveness and portability factor. Recent studies on EEG based BCI have reported the successful decoding of right- v/s left-hand movement by analysing the sensory motor rhythms [4]. Furthermore, it has been shown that the motor tasks often involve mental planning (termed as Motor Imagery) before the actual execution of movement tasks, which are based on synchronization and de-synchronization of neural population in the motor cortex. These findings encourage us to explore further in the domain of neurorehabilitation by studying how EEG features can be deciphered further to gather more information about the type and kinematics of movement. Although preliminary results show that it is possible to classify right- vs. left-hand movement by analysing the EEG signals from motor cortex, it is very important to understand the observed neural correlates involved in decoding the EEG recordings while performing dexterous arm movements. Realizing complex tasks like reaching out to grasp a cup of tea or lifting and opening the water

bottle with the help of a robotic arm through brain translated signals requires significant understanding of source localization of brain activities. However, EEG has an inherent disadvantage of poor spatial resolution because of the significant noise contributed by the volume conduction effect which is nothing but the signal degradation from the source of neural activation (cortex) towards the region of signal acquisition (scalp). This ultimately inhibits the understanding of source localization which results in poor feature extraction required for achieving high accuracy in decoding the movement of different arm parts. Therefore, this key issue of spatial enhancement needs to be addressed thoroughly by developing signal processing algorithms. However, the investigation of spatial filtering algorithms in studying the neural correlates of motor functions has not been done so far, which is a key motivation for this thesis topic - “Neural Signal Processing Techniques to Analyse Motor Functions in EEG-based Brain Computer Interfaces”.

As traditional EEG-based studies typically focus on the brain activity at the scalp level, it is difficult to obtain the information regarding the neuronal activity in localized cortical regions. With the recent advances in state-of-the-art cortical source localization algorithms [5, 6], it is possible to use EEG as a useful neuroimaging modality that provides a clear picture of the neuronal activation at cortical sources. The major challenge, however, is concerned with the precise localization of task-related cortical sources as the recordings are usually done using a fewer number (<100) of channels. Fewer number of EEG channels would result in an ill-posed problem as there are far higher number of cortical sources. Furthermore, to classify complex motor imagery tasks such as shoulder abduction, elbow flexion, wrist pronation and supination and other related ones, we need to know more about the underlying neurophysiological phenomenon that concerns the activation of these complex tasks. Therefore, it is necessary to use a priori information to solve this ill-posed problem by employing a head model, a noise model, and cortical region of interest. Even then, the inverse modeling alone may not provide any discriminative information about a given task. The set of relevant cortical sources determined by a prior neural correlate should also be discriminative for a better classification performance. This motivates to develop an algorithm that can provide discriminative information in the cortical subspace while still justifying the neurophysiological phenomenon.

With regard to the practical significance of BCI application, stroke rehabilitation seems to be the obvious choice. Stroke is considered to be one of the top 5 leading causes

of death around the world [7]. Further, the statistics of 85-90% of stroke survivors with severe upper-limb impairment never regaining full use of their arms are quite alarming and thus there has been significant attention for stroke rehabilitation therapies in the past decade. As the Motor Imagery-based Brain-Computer Interface (MI-BCI) technology can circumvent nerves and muscles for the movement control, MI-BCI is seen as a promising technology in assisting partially locked-in stroke patients. Also, the stroke is a neurological disorder that occurs due to the lack of blood supply (ischemic stroke) or internal bleeding (hemorrhagic stroke), it is important to understand which part of the brain is affected. Functional Magnetic Resonance Imaging (fMRI) is one of the most widely used neuroimaging technologies which helps us to locate the impaired brain region. However, fMRI has several disadvantages such as high cost, non-portability (which necessitates frequent visits to hospitals), complicated setup (which requires specialized room and technically skilled operator, and the acoustic noise needed to obtain scans, to which the brain inevitably reacts). Moreover, during fMRI scanning, the subject must be restrained from any movement, and hence it is not feasible to obtain cortical activation maps when the subject is undergoing a rehabilitation therapy. On the contrary, Electroencephalography (EEG) is inexpensive, portable, and safe and can be operated by minimally trained personnel. Therefore, EEG is the most attractive neural signal recording modality which can be quickly set up even in a non-clinical environment. EEG-based studies typically focus on the brain activity at the scalp level and, therefore, fail to obtain the information regarding the neuronal activity at specific localized cortical regions, which is vital for efficient stroke rehabilitation therapy. To this end, the research in EEG-based neuroimaging for diagnosing the cortical plasticity during stroke rehabilitation is gaining momentum [8, 9, 10].

Although MI-BCI can facilitate the user to modulate his/her sensorimotor rhythms, there are no changes in the cortical excitation. Since the motor recovery is crucial in stroke rehabilitation, the behavioral effects of noninvasive brain stimulation techniques (eg. Transcranial Direct Current Stimulation (tDCS) and Transcranial Magnetic Stimulation (TMS)) are being investigated to observe if the stimulation alters the motor performance by exciting the motor regions in stroke patients [11, 12, 13, 14]. As these stimulation techniques are still in their nascent stages, there is no strong consensus in the

Figure 1.1: A brief highlight of the research challenges and the methods addressed in this thesis

literature whether the stroke recovery is due to the stimulation or due to the confounding factors. This is a motivation for this thesis work to investigate the causal interpretation of tDCS intervention to improve Motor-Imagery BCI performance in the stroke patients by observing the neural correlates using EEG source localization.

The research challenges and the methods are summarized as shown in Fig. 1.1.

1.3 Research Objectives

Develop robust signal processing algorithms for-

(i) **Computationally Efficient Optimal Channel Selection**

Spatial enhancement of EEG depends mainly on 2 factors - number of scalp EEG channels (or electrode) and the volume conduction effect. The inter-electrode distance plays a crucial role in contributing to the spatial resolution of EEG. However,

high-resolution EEG in terms of higher number of electrodes has its own disadvantages because of redundancy and longer preparation time. Therefore, the objective is to develop a computationally efficient EEG channel selection algorithm which can address this issue by selecting an optimal number of channels without compromising on decoding accuracy. This will have potential applications in reducing the clinical preparation time as well as to address subject variability issues.

(ii) **Spatial filtering algorithms in sensor- and source-space EEG**

To improve the spatial resolution of EEG, reducing the volume conduction effect is quite important. The signal that is originated in the cortical region degrades in its signal-to-noise ratio because of the noisy artifacts during the signal propagation from cortex to scalp EEG electrodes. One of the key objectives of this thesis is to decode the movement direction using cortical potentials. Although scalp EEG has been used for the direction decoding, it limits the visual interpretation of neural correlates. It is also envisaged by the author that an effective source localization algorithm could reduce the dependence on expensive fMRI, a modality with high spatial resolution.

(iii) **Source-space feature extraction and interpretation of neural correlates**

As there is a linear mixing of hidden cortical sources that results in an observable scalp EEG recordings, there is a need to study the latent variables that are responsible for motor functions. A desirable algorithm to study this latent space of cortical EEG should be able to,

- Handle non-stationarity due to the biological noise
- Explain the collective behavior of neural population
- Explain the variability within the neural population
- Justify the neurophysiological phenomenon of a given task
- Provide discriminative features for the robust classification of complex tasks

(iv) **Functional and Effective Connectivity Analysis Using the Source-space EEG to Prognosticate Stroke Recovery**

In recent years, there are studies which report that the brain stimulation could aid in the recovery of stroke patients by improving the motor learning [14, 11, 12]. However, there is a lack of causal inference studies that explain the observed correlates of motor recovery in stroke patients. Therefore, the objective is to-

- Estimate the functional and effective connectivity measures in stroke patients' EEG
- To study the effects of noninvasive brain stimulation on the stroke recovery as well as their MI-BCI performance using the source space EEG

1.4 Contributions of the Thesis

The main contributions of this thesis directly related to the above-mentioned research objectives can be summarized as follows.

- Computationally Efficient EEG Channel Selection Algorithm based on Bi-objective Optimization
 - A bi-objective optimization technique to optimize the motor imagery classification performance and the neurophysiological relevance of selected EEG channels
 - Investigate the robustness of the proposed channel selection algorithm on cross-subject generalization by evaluating different types of datasets with varying number of subjects and EEG channels
- Spatial Filtering Framework in Sensor- and Source-space EEG
 - A novel shrinkage regularization framework for an EEG spatial filtering algorithm to robustify against small sample settings like single trial EEG.
 - Single-trial spatiotemporal localization of motor imagery using the inverse mapping of EEG onto the cortical source space
 - A comparative study of state-of-the-art spatial filtering algorithms in sensor- and source-space EEG

- Novel Supervised Factor Analysis algorithm for EEG Source-space Feature Extraction
 - Factor analysis as a basic framework to explain the heteroscedasticity of EEG
 - A supervised framework to factor analysis by exploiting a priori information of neurophysiological regions-of-interest.
 - A novel way to visually interpret the task-relevant cortical sources based on their contribution to the trial-averaged variance
- Functional and Effective Connectivity Analysis to study the effects of noninvasive brain stimulation in stroke patients
 - Use of ensemble source-space EEG features to study the MI-BCI performance across tDCS and sham group
 - Usability and practicability of EEG source-imaging in prognosticating the stroke recovery after transcranial direct current stimulation
 - Causal interpretation of the stroke recovery using the source-space EEG in effective connectivity measures

1.5 Thesis Structure

Chapter 2 provides the background information on the basic principles of Brain-Computer Interface technology (BCI) followed by various stages of BCI system including the signal recording, pre-processing, feature extraction, feature selection, and feature classification. As the main focus of this thesis is on the spatial filtering techniques for EEG feature extraction, a brief account of the existing spatial filtering algorithms is provided. Latter half of the chapter provides an overview of state-of-the-art in BCI for movement decoding applications. Chapter 3 introduces the first contribution of this thesis i.e. an EEG channel selection algorithm called ‘IMOCS’ based on a bi-objective optimization technique that is evaluated on multiple datasets with a variable number of subjects and channels to test robustness. Following this, a novel shrinkage regularization framework is introduced in Chapter 4 to robustify against small sample settings, followed by an introduction to EEG

source imaging for spatio-temporal localization of MI tasks, and a comparative study of spatial filtering algorithms in sensor- and source-space EEG features for movement direction classification. Chapter 5 is devoted to a novel supervised factor analysis algorithm for EEG source-space feature extraction to classify multi-directional hand movement. The final contribution in Chapter 6 presents an EEG source-space study of non-invasive brain stimulation in stroke patients. It is a first-of-its-kind study which presents source-space functional and effective connectivity measures to evaluate the neural correlates and explains the causal behavior of different regions-of-interest after stroke patients are provided with non-invasive transcranial direct current stimulation. This chapter presents the clinical applications of EEG source imaging to evaluate BCI-based stroke rehabilitation. This thesis is concluded in the Chapter 7 in which the contributions of this thesis are summarized, and the future research direction is highlighted.

List of Author's Publications

The work presented in this thesis serves as a basis for manuscripts that are published (or under review) in peer-reviewed journals and conference proceedings listed below.

1.5.1 Journal articles

- (i) **H. V. Shenoy**, A. P. Vinod, and C. Guan, “EEG Source Space Analysis of Supervised Factor Analytic Approach for the Classification of Multi-directional Arm Movement,” *Journal of Neural Engineering* , 14(4) p. 46008 (**I.F: 3.464**)
- (ii) **H. V. Shenoy**, and A. P. Vinod, “Optimized Bi-Objective EEG Channel Selection and Cross-Subject Generalization With Brain-Computer Interfaces,” *IEEE Trans. on Human-Machine Syst.* 46, 777-786. doi:10.1109/THMS.2016.2573827, (**I.F: 2.493**)
- (iii) **H. V. Shenoy**, A. P. Vinod, and C. Guan, “EEG Source Imaging of Movement Decoding: The State-of-the-art and Future Guidelines,” *Review article : IEEE SMC Magazine (Accepted)*
- (iv) **H. V. Shenoy**, A. P. Vinod, C. Guan, K. K. Ang, and E. Chew, “EEG Source-space study of Functional and Effective Connectivity Measures in tDCS-based Stroke Rehabilitation” *in preparation*

1.5.2 Conference Articles

- (v) **H. V. Shenoy**, A. P. Vinod, C. Guan, K. K. Ang, and E. Chew, “Effects of Transcranial Direct Current Stimulation on the Motor-Imagery Brain-Computer

- Interface for stroke recovery: An EEG Source-space Study,” in (*2017 Intl. Conf. on Systems, Man, & Cybernetics* (SMC)). IEEE (accepted)
- (vi) **H. V. Shenoy**, A. P. Vinod, and C. Guan, 2016. “A Novel Supervised Locality Sensitive Factor analysis to Classify Voluntary Hand Movement in Multi-direction using EEG Source Space,” in *2016 IEEE Intl. Conf. on Systems, Man, and Cybernetics* (SMC). IEEE, pp. 2795-2800.
 - (vii) **H. V. Shenoy**, A. P. Vinod, and C. Guan, “Multi-direction Hand Movement Classification using EEG-based Source-space Analysis,” in *2016 38th Annl. Intl. Conf. of the IEEE Engg in Med. and Bio. Society* (EMBC). IEEE, pp. 4551-4554.
 - (viii) **H. V. Shenoy**, A. P. Vinod, and C. Guan, “Shrinkage Estimator Based Regularization for EEG Motor Imagery Classification,” in *Intl. Conf. on Information, Communication and Signal Processing* (ICICS), 2015
 - (ix) **H. V. Shenoy**, A. P. Vinod, and C. Guan, “Cortical Source Localization for Analysing Single-Trial Motor Imagery EEG,” in *2015 IEEE Intl. Conf. on Syst., Man, and Cybernetics* (SMC), pp. 3146-3151.
 - (x) **H. V. Shenoy**, and A. P. Vinod, “An Iterative Optimization Technique for Robust Channel Selection in Motor Imagery based Brain-Computer Interface,” in *2014 IEEE Intl. Conf. on Syst., Man, and Cybernetics* (SMC), pp. 1858-1863 (**best student paper award**)

Chapter 2

Brain-Computer Interfaces for movement decoding: Background

“The similarities between humans and computers are far more numerous than the differences”

- P.A.Scott

Intrigued by the intricacies of neuroscience, Eduard Hitzig and Gustav Frisch conducted the neurostimulation experiment on a dog’s brain and demonstrated for the first time in 1870 that the brain is indeed excitable by an electrical stimulus [15]. Their research on localized study of the brain in 19th century opened the new door for neuroscientists to explore different parts of the brain and their functional behaviour. During the same period as of Hitzig and Frisch, Dr. Richard Canton demonstrated the electrical nature of the brain by measuring the electrical impulses from a rabbit and monkey’s brain using a galvanometer [16]. Motivated by this, a German scientist named Hans Berger measured the human brain activity for the first time, which he called ‘*Elektrenkephalogramm*’ [17]. Although Berger’s findings were received with much skepticism in the beginning, the neuroscience community eventually accepted the seminal contribution of Berger when Dr. Eduard Douglas Adrian (Nobel Awardee 1932) confirmed the observations by reproducing the EEG recordings in 1934. Since then, EEG received widespread attention, especially in the clinical practice. Much later in 1973, Jacques Vidal coined the term ‘Brain-Computer Interface’ in his paper [18] where he demonstrated the computer processing and classification of evoked EEG response. Over the last 3 decades, the BCI

research has come a long way owing to the diverse seminal technological advances in the computing, material sciences, and neuroscience.

Here onwards, this thesis will focus on the BCI for movement decoding which has promising applications in the field of neurorehabilitation.

The remainder of this chapter is as follows: Section 2.1 will highlight the essential components of a BCI system, Section 2.2 will provide an overview of scalp EEG processing followed by an introduction to the cortical source-space EEG in Section 2.3. Following this, Section 2.4 will present the state-of-the-art in BCI-based movement decoding. Section 2.6 will conclude the chapter.

2.1 Brain-Computer Interface: System Components

A typical BCI system comprises of various components such as data acquisition, artifact removal, feature extraction and classification, and the feedback to the user. BCI system components as shown in Fig. 2.1 encompass data acquisition, signal pre-processing (noise removal), signal processing for feature extraction, classification, translation into action commands and a closed-loop feedback to the user.

Figure 2.1: Block diagram of the Brain-Computer Interface system [19]

BCI systems are broadly categorized into two major types i.e. (i) Stimulus-based and (ii) Neurofeedback-based [20]. In a stimulus based BCI paradigm, subjects are given a

visual/audio stimulus, and the corresponding neuronal activity is recorded. The visual stimulus could be an on-screen cue; audio stimulus could be a beep sound - either of them indicating the start of an experimental task that evokes a neural response. In Neurofeedback based BCI paradigm, after performing the task, a feedback is given to the subjects to enable them to learn how to control (increase/decrease) the change in neural behaviour. In the following sections, different system components of the stimulus based BCI are described.

2.1.1 Signal Acquisition

2.1.1.1 Types of Data Acquisition Modalities

Signal acquisition is the foremost functional unit of BCI which is responsible for recording the brain signals either from the scalp or cortical regions. The mode with which signal acquisition is done also categorizes the BCI into two major types: Invasive BCI and Non-Invasive BCI. Former one taps the brain signals from cortical regions by placing the electrodes deep inside the brain and hence termed as “Invasive” whereas, the latter non-invasively records the neural activity either from the scalp electrodes(EEG) or by using imaging technologies. The properties of different data acquisition modalities are listed in Table 2.1.

Invasive BCI: Invasive signal acquisition technique depends on the sensors/electrodes placed inside the scalp. It is quite promising in terms of the signal quality and information transfer rate. However, it is prone to clinical risks even for the patients, and not permissible for healthy individuals. Multiple risks such as surgical implantation of electrodes, periodic replacement of electrodes and repeated surgeries deters the usage of invasive BCIs. It is exercised for only those people who suffer from neurophysiological disorders and are left with no other alternative means of treatment. The origin of BCI - Hans Berger’s famous experiment of intracranial EEG for identifying the oscillatory activity is, in fact, an invasive BCI [17]. Breakthrough in the sensor technology made it possible to record the brain activity in a non-invasive fashion.

Some of the prominent invasive BCI techniques are:

(i) **Microelectrode array based intracranial recording:** In this technique, the electrodes are implanted deep inside the cortex. BrainGate is one of the successful invasive BCI techniques used for controlling the robotic arm in 3D by imagining the movement

[21]. It involved placing the BrainGate chip inside the precentral gyrus (portion of the brain responsible for complex motor actions). Although microelectrode array used in the chip provides a very good signal quality, it is quite risky as it involves implanting the electrodes deep inside the skull.

(ii) **ElectroCorticography**: This technique is not strictly invasive as it does not break the blood-brain barrier, albeit it does involve placing the electrodes directly under the skull. Therefore this technique is a semi-invasive/partially-invasive modality with a high temporal resolution (order of milliseconds) as well as high spatial resolution (order of few millimeters), which means the precision of measurement with respect to time and space (in terms of source localization) is better compared to any of the non-invasive recordings. The only downside is this modality requires placing the electrodes beneath the skull which requires expensive surgery as well as poses safety issues for healthy individuals.

Non-invasive BCI: To avoid the above issues related to clinical risks and economic feasibility, research in the sensor technologies have led to the invention of what we now call as “Non-invasive BCI” technique. Fig. 2.2 illustrates the non-invasive brain signal acquisition modalities. Some of the important non-invasive signal acquisition techniques are explained below.

(i) **Functional Magnetic Resonance Imaging (fMRI)**: A popular non-invasive signal acquisition technique wherein the brain activity is measured in terms of hemodynamic response called as BOLD (Blood Oxygen Level Dependent). It has been observed that whenever a neural population becomes active, there is an increase in the blood flow to that region. This blood flow is an inflow of oxygen rich blood which replaces the oxygen-depleted active region. Oxygen-rich blood is diamagnetic (virtually no effects due to magnetic field), and oxygen-depleted blood is paramagnetic (strong attraction towards the magnetic field) and this comparative change in magnetization between oxygen-rich and oxygen-poor blood is used for measuring BOLD. This technique has a very good spatial resolution as it can discriminate two regions which are few millimeters apart based on the type of activity. However, fMRI suffers from poor temporal resolution (several seconds), non-portability and also expensive set-up which imposes constraints in its use in real-time BCI applications.

Figure 2.2: Illustration of non-invasive BCI modalities and their source of recordings [22]

(ii) Functional Near-Infrared Spectroscopy (fNIRS): This technique is a spectroscopic method for recording the brain activity. It uses the near-infrared region of electromagnetic spectrum to analyze the hemodynamic response through the level of Infrared (IR) light absorption in the scalp optodes. The level of IR light absorption is different for oxygen-rich (oxygenated) blood and the oxygen-depleted (de-oxygenated) blood. This difference of absorption is considered as a change in hemodynamic response of a brain activity. fNIRS has a better spatial resolution compared to EEG as it can detect the hemodynamic response upto sub-centimeter scale on the cortex, but the temporal resolution of fNIRS is few seconds. The application of fNIRS-based BCI mostly depends on the type of application in consideration. Considering how quickly the human brain responds in most of the daily activities, fNIRS-based BCI may not be suitable for most of the practical applications as of now.

(iii) Magnetoencephalography (MEG): This is the recent non-invasive data acquisition technique built on the principles of magnetic field produced by the electrical currents in the brain. MEG uses an array of SQUID (Superconducting Quantum Interference Devices) as magnetometer to measure the magnetic field. As there is a very high magnetic noise in a traditional setup, MEG measurements require magnetically shielded room to avoid such noise. MEG is very promising neuroimaging modality because of

its very high temporal resolution ($\sim 1\text{ms}$) as well as high spatial resolution ($< 5\text{mm}$). However, MEG is very expensive and non-portable like fMRI, which is why it is only limited to research purposes to study the neural correlates of various tasks.

(iv) Electroencephalography (EEG): This is the oldest and one of the most widely used non-invasive BCI techniques. EEG involves placing the sensors on the scalp to record the neural activity in terms of electrical potentials. This technique is the most cost-effective and portable modality for recording brain activity. Among all other non-invasive modalities, EEG has the best temporal resolution (few milliseconds) and thus, most suitable for event-related studies. As a tradeoff, EEG suffers from poor spatial resolution (several centimeters) which makes it difficult for fine visualization of the brain regions that are active. The main contribution in this thesis is the spatial filtering of EEG to understand the neural correlates of BCI. Here onwards, this thesis will focus on the EEG-based Brain Computer Interfaces.

2.1.1.2 Neurophysiology Behind the EEG Data Acquisition

To understand how the brain signals are recorded using EEG, a little background on the neurotransmission is essential. The human brain is composed of a highly complex network of about 86 billion neurons [23]. A typical neuron comprises of the cell body, an axon, and the dendrites. A cell body carries out the metabolic activities of the cell, and the dendrites receive signals from neighboring neurons. An axon sends out the signal to other neurons via synapse (gaps between an axon and the receptor dendrites). Neuronal cell membranes are built like ionic pump houses that contain transmembrane proteins actively transporting the molecules through the membrane. Due to the activity of these ionic pumps, a high concentration of potassium (K^+) is maintained inside the neural cells whereas the calcium (Ca^{2+}) and Sodium (Na^+) ions are more concentrated outside the cell. In the resting state of the cell, such concentrations lead to a voltage difference of approximately -70mV across the membrane - which we call '*Resting Potential*.' Depending on the stimulus (either electrical or sensory), the resting potential of neurons after crossing a certain threshold (typically -55mV) leads to the inflow of sodium ions into the cell thus triggering the rapid rise and fall in the membrane potential termed as '*action potential*'. These action potentials are carried via axons and trigger action

Table 2.1: Summary of different BCI modalities

BCI modalities	Measured Activity	Invasiveness	Portability	Spatial Resolution	Temporal Resolution	Cost-effectiveness
Intra-cortical recordings	Electrical	Invasive	Portable	$\sim 0.1\text{mm}$	$\sim 0.003s$	Expensive
ElectroCorticography (ECoG)	Electrical	Partially Invasive	Portable	$\sim 0.1\text{mm}$	$\sim 0.003s$	Expensive
Functional Magnetic Resonance Imaging (fMRI)	Metabolic	Non-Invasive	Non-Portable	$\sim 1\text{mm}$	$\sim 1s$	Expensive
Functional Near Infrared Spectroscopy (fNIRS)	Metabolic	Non-Invasive	limited Portability	$\sim 5\text{mm}$	$\sim 1s$	Medium-Expensive
Magnetoencephalography (MEG)	Magnetic	Non-invasive	Non-portable	$\sim 5\text{mm}$	$< 0.02s$	Expensive
Electroencephalography (EEG)	Electrical	Non-Invasive	Portable	$\sim 10\text{mm}$	$< 0.05s$	Inexpensive

potentials in the neighboring neurons. With regard to the overall membrane potential, excitatory postsynaptic potential (EPSP) is resulted when there is a flow of positively charged ions towards the postsynaptic cell, causing a momentary depolarization [24]. Similarly, inhibitory postsynaptic potential (IPSP) occurs when there is a flow of negatively charged ions towards the postsynaptic cellm causing a hyperpolarization. These postsynaptic potentials are graded, which means that the potentials can have a range of values. However, action potentials are all-or-none responses that are triggered only when there is a sufficient depolarization.

In the context of non-invasive EEG, these intracellular and intercellular currents accumulated over a region of millions of neurons allow for a measurable voltage. EEG signals are generally produced by the EPSP generated at apical dendrites of pyramidal cells (cells that are oriented vertical to the soma radiating lateral outward) in the cortex. Some of the characteristic EEG rhythms are listed in Table 2.2.

2.1.2 Event-Related Desynchronization: Neurophysiological Interpretation

Event-related Desynchronization (ERD) is a phenomenon widely known in the BCI community because of the distinguishable pattern of movement imagination and execution encoded in the motor cortex. Event-related Desynchronization (ERD) corresponds to

Table 2.2: Overview of the characteristic EEG rhythms

Name	Frequency range	Region of Interest	Characteristic	Illustration
Delta (δ)	<4Hz	frontal and posterior regions	sleep, drowsiness
Theta (θ)	4-8 Hz	various locations	drowsiness
Alpha (α)	8-13 Hz	Occipital and parietal regions	attention and relaxed state
Mu (μ)	8-13 Hz	primary motor cortex	Event-related desynchronization during the movement imagination (MI)
Beta (β)	13-30 Hz	Somatosensory cortex and Frontoparietal regions	Event-related Synchronization during the movement execution
Gamma (γ)	> 30 Hz	various locations	Cognitive tasks and Consciousness

the decrease in power level of Mu rhythm (8-12Hz) contralateral to the task performed, i.e. ERD is witnessed in the left motor cortex whenever there is a movement in the right arm/limb and vice versa. On the contrary, Event-related Synchronization (ERS) is contributed by beta rhythm (12-30 Hz) that is characterized by increase in the power level of ipsilateral cortical region. Fig. 2.3 illustrates the ERD/S pattern with respect to the movement onset and execution [4]. In this figure, we can notice that during the movement onset, there is a power decrease in 10-12 Hz (Mu band) corresponding to ERD followed by post-movement ERS in early beta band (14-18Hz).

Four major factors that affect the neuronal oscillations and their synchrony responsible for ERD/S are [25]:

Figure 2.3: Illustration of Mu ERD and beta ERS [4]

(i) Intrinsic neural membrane properties:

Membrane potential and the frequency of oscillation are the properties associated with the neuron membrane. Depending on the input, the neural population tend to oscillate at a specific frequency (For ex: neurons tend to oscillate at 10Hz if the membrane potential is hyperpolarized than at the rest).

(ii) Interconnectivity between the neural elements:

It is observed that for a given input (or any driving force), different sets of neuron population behave differently. This behavioural adaptation could be influenced by other neuronal elements within the local network and/or that of the distant neurons. For instance, visual stimulus given during a motor task could affect the synchronization between neuronal population within the occipital region and also the motor cortex, but not necessarily in a same manner.

(iii) Synaptic processes:

As previously mentioned, the neural elements behave differently depending on the modulating synaptic inputs and the interconnection between neuronal populations via synaptic transmission. Also, the feedforward and feedback loop dynamics of synaptic interaction are important in understanding the synchronization between the local neuronal networks.

(iv) Influence from neurotransmitter:

Neuromodulation is a physiological process where multiple neurons are affected by a small group of neurons as opposed to synaptic transmission which is a process between two neurons. Acetylcholine and Dopamine are the important neurotransmitters that influences the motor behavior.

2.1.3 EEG Preprocessing

As mentioned in the Section 2.1.1.2, the scalp EEG measures the cortical activity of millions of neurons. Unfortunately, the scalp EEG is often contaminated by various biological artifacts (undesired noise in the signal) in addition to the cerebral activity. These non-cerebral artifacts include eyeball movements, eye blinks, jaw movement, muscular activity, and cardiac activity which affect the signal of interest. Also, the external factors such as hair thickness, the type of conductive gel used (liquid vs. viscous, clear vs. abrasive, etc.) could affect the EEG measurement. Although the artifact removal is a necessary preprocessing step, there is no consensus on the most optimal way of noise removal. Some of the established techniques for artifact removal involve blind source separation (BSS) [26, 27, 28], regression methods [29, 30], filtering methods [31, 32, 33], and decomposition methods [34, 35].

Regression-based methods are one of the oldest methods which were in practice until early 90s because of simpler computational demand and reliable removal of ocular artifacts. Regression methods mostly use Linear Regression model (LRM) that assumes each EEG channel is the sum of the non-noisy source signal and a fraction of the source artifact that is available through a reference channel (eg. EOG or EMG). However, the regression-based methods do not work if there is no reference channel.

Other class of artifact removal methods are ‘Filtering methods’ such as Adaptive filtering [31], Weiner filtering [33], and Bayesian filtering [36]. Similar to the regression-based approach, it is crucial to use a reference channel (EOG or EMG) for adaptive filtering wherein a new signal correlated with the artifacts is generated using a reference channel and it is subtracted by the acquired EEG. This is followed by iterative weight adaptation using the least mean square method which is linear in time-complexity and therefore, it is computationally faster. As opposed to Adaptive Filters, Weiner filter

doesn't need a reference channel as it minimizes the error between the acquired EEG and its estimate using a time-invariant filter, but it takes a lot of time for calibration of filter weights and thus, inoperable in online BCI experiments.

Contrary to the above methods that operate on an individual EEG channel in a sequential manner and estimate artifact-corrected channels, BSS methods transform the EEG signal space into a different subspace wherein each individual channel would be transformed into a '*component*'. Independent Component Analysis (ICA) is still the most widely used BSS method that identifies the artifacts that are not originated in the brain. [26].

Another approach for artifact removal is to decompose the input EEG signal into basic waveforms called as '*Intrinsic Mode Functions*' that takes various forms in different techniques such as Ensemble Empirical Mode Decomposition (EEMD) [34] and Nonlinear Mode Decomposition (NMD) [35]. The basic principle is to decompose the incoming signal into zero-mean Amplitude and frequency modulated signals and a non-zero-mean polynomial reminder in the case of EEMD whereas, the signals are decomposed into nonlinear modes which are basically the oscillatory components and its harmonics. As of today, ICA is the most widely used pre-processing algorithm.

All the above artifact removal methods are summarized in Table 2.3.

2.1.4 Feature Extraction

According to the popular machine learning principle 'garbage-in-garbage-out,' the classifiers will produce nonsensical results if the input itself is noisy. Therefore, it is crucial to extract task-relevant features for further classification and translation, while rejecting undesirable signals. In the context of EEG, there are various approaches to extract features from temporal, spectral, and spatial domains. Amongst these, temporal features such as peak amplitude and latency of EEG are often the simplest ones as they are readily observable. Since EEG is non-stationary, temporal features provide useful and interpretable information when the neural events are phase-locked [25, 39, 40, 41]. For instance, the motor cortex gets activated (or involved in movement planning) few hundred milliseconds before the movement execution. Spectral features correspond to the frequency domain, as some of the EEG-based experiments involve phase-locked features (evoked potential

Table 2.3: Overview of Various Artifact Removal Methods

Type of denoising methods	Techniques	Advantages	Limitations
Filtering-based	Adaptive filtering [31, 32]	Performs better than regression-based methods	Artifact reference is essential; does not work very well if there are no additional modalities like EOG and EMG
	Wiener Filtering [33]	Can work independent of the reference signal	Needs calibration of the parameters; unsuitable for real-time BCI
	Bayes Filtering [36]	Can work independent of the reference signal	Algorithm needs calibration for better SNR
Regression-based	Linear regression [29]	Computationally faster; still the ‘gold standard’ of removing the ocular artifacts if EOG is recorded	Does not work if there are no reference channels
Blind Source Separation	Principal Component Analysis (PCA) [37, 38]	Effective at removing ocular artifacts without the need of EOG	Assumes the orthogonality between the artifacts and the brain signal which does not hold
	Independent Component Analysis (ICA) [26, 27]	Most popular artifact removal technique; robust identification of brain sources and the artifacts	Iterative procedure; does not perform reliably well when there is less data
	Canonical correlation Analysis (CCA) [28]	Computationally faster than ICA (suitable for real-time BCI); effective in removing the muscle artifacts	CCA doesn’t outperform ICA
Source decomposition methods	Ensemble Empirical Mode Decomposition (EEMD) [34]	Well-separation of signals and artifacts; Can also be used with BSS methods	Computationally complex; lack strong mathematical framework (empirical)
	Non-linear Mode decomposition (NMD) [35]	Strong mathematical framework; Performs better than EEMD	Not well-reproduced in any other literature

studies) or the features in a specific frequency band [42]. As mentioned in section 2.1.2, ERD is a phenomenon that is observable in Mu band (8-13Hz) and ERS is observable in 13-30Hz and these signify the neurophysiological phenomena of motor planning and execution. In the context of BCI, other spectral feature methods such as Power Spectral Density estimation, Short-time Fourier Transform, Quadratic Energy Distributions (variants of Wigner-Ville Distribution), Wavelet approaches, and Autoregressive models etc. are quantitatively compared in [43].

As the traditional feature extraction approaches do not discard information from time domain, the features would be referred to as ‘*spatio-temporal*’ features if the spatial features (either sensor- or source-space) correspond to the time domain [44, 45, 46, 47, 48, 49, 50] and ‘*spatio-spectral*’ features if the spatial features correspond to frequency domain [51, 52, 53, 54, 42]. Similarly, if the features are computed using both time and frequency domain, they would be simply referred to ‘TF’ features or spectral-temporal features [43]. Nevertheless, most of the popular approaches belong to the class of spatio-temporal and spatio-spectral features. Since the focus of this thesis is more towards the spatial filtering of movement-related tasks, the emphasis is on the review of state-of-the-art in spatiotemporal feature extraction in MI-BCI as given in the subsection 2.2.2.

2.1.5 Feature Selection

Depending upon the type of feature extraction algorithm, the feature matrices could be very large, and often contain redundant features. It is reported that the use of redundant features in addition to the discriminative ones could result in the degraded performance. In BCI paradigms, there have been several studies which use feature selection as a mandatory processing stage before sending the features for classification. Most of the current state-of-the-art feature selection methods generally compute the statistical dependency between the class label and the features of a given trial to rank different features. Some of the popular feature selection algorithms used in BCI studies are Recursive Feature Elimination (RFE) [55], genetic algorithm based feature selection [56], minimum-redundancy maximum-relevancy (mRMR) [57], Mutual-information Based Best-Individual Feature (MIBIF) [58] and also, Sequential Floating Forward Selection (SFFS) [59]. Amongst these methods, mRMR and MIBIF approaches are called filter-based feature selection

methods that do not depend on the specific classifier; thus, they are generalizable across classifiers and robust to overfitting. MIBIF uses mutual information as a statistical measure to evaluate the dependency between the feature columns and class labels in a BCI experiment (e.g., left vs. right hand MI). In comparison to MIBIF, mRMR also computes the mutual information between different features and penalizes the redundant features with an objective of maintaining maximum dependency between the features and class labels. The relevance of a feature set S for the class ' c ' is defined by the average value of all mutual information values between the individual feature f_i and the class ' c ' and redundancy of a feature set S is defined by the average value of all mutual information values between the individual feature f_i and f_j . Subsequently, a predetermined number of features ranked according to the mutual information values are used for further classification.

Another class of feature selection methods called 'wrapper approach' attempts to maximize the classification accuracy by searching for an optimal number of features and thus, the feature selection depends upon the specific classifier algorithm used. SFFS does this by sequentially adding a feature to an empty set thereby trying to search for the number of features that gives maximum classification accuracy, whereas RFE recursively removes each feature from the original set until the classification accuracy is maximized. RFE-based feature selection is used as EEG channel selection strategy in was used in [60]. Genetic algorithm was used as a meta-heuristic search strategy to optimize the number of features and classification accuracy [56] on a BCI dataset with 5 different mental tasks. The limitations of wrapper-based approaches are - the bias of the classifier algorithm used and the computationally slower execution as it requires to train the classifier for each feature subset.

2.1.6 Feature Classification

For an effective BCI control, the features obtained using a subject's EEG must be distinguishable to be able to translate into control commands. To this end, the feature classification algorithms play a crucial role. Since the past two decades, there has been a considerable interest in EEG-based BCI by the machine learning community who have extensively investigated the use of classification algorithms to classify EEG features; a

comprehensive review of the same is provided in [61]. In summary, two of the most widely used classification algorithms are Linear Discriminant Analysis (LDA) [56, 62] and Support Vector Machine (SVM) [56, 63]. LDA is a linear classifier as it projects (or transforms) the feature space such that the resultant hyperplane maximizes the inter-class separation and minimizes the intra-class separation. Also, LDA is computationally efficient as it has analytical solution and thus, it is suitable for online BCI. Although SVM also classifies the feature space using a discriminant hyperplane, it does not project the feature space into a different subspace as LDA does. Instead, SVM finds an optimal hyperplane that separates the features from different classes with maximum separation. SVM has the advantage of classifying non-linear EEG data as there are ‘kernel tricks’ that uses the different types of kernels to create nonlinear decision boundaries. Both of these algorithms are extensively used in motor imagery BCI applications, in addition to their regularized variants [64].

2.2 Sensor-space BCI

The conventional methods for EEG-based BCI involve sensor-space features. An overview of different spatial filtering algorithms for sensor-space EEG feature extraction is provided in the following subsection.

2.2.1 Spatial Filtering in the Sensor-space EEG

The analysis of EEG signals for motor tasks involve event-related potentials (time and phase locked) and/or ERD/S (time locked but not phase locked) because it represents the cumulative effect of electric potentials appearing at the dendritic end of several neurons that cause the rhythmic behavior. EEG signals capture not only the voltage fluctuations underneath the scalp electrodes but also capture the distant current sources due to the volume conduction effect. Therefore, the scalp EEG recordings $X \in \mathbb{R}^{N \times t}$ is generally modeled as a linear mixture of underlying neural sources and the noise as shown in Eq. (5.1) [5],

$$X = \Theta_f J + \varepsilon \quad (2.1)$$

where, X is the sensor-space EEG recorded from ‘ N ’ channels, Θ_f is the lead field matrix (LFM) of size $N \times m$ ($m \gg N$). Θ_f describes the propagation of current from source

dipoles (m) to each scalp electrode (N). J is an $m \times t$ matrix of source dipole time series. ε is the noise perturbation matrix with covariance matrix Ψ .

The columns of Θ_f corresponds to the spatial patterns of underlying neural activity. Since most of the BCI studies for motor task classification focus on the discriminative spatial patterns, the next subsection will describe the general framework of the most widely used spatial filtering algorithm called ‘*Common Spatial Pattern*’. Following this, a brief overview of different variants of CSP is provided.

2.2.2 State-of-the-art Feature Extraction Methods for Scalp EEG-based Movement Decoding

2.2.2.1 Common Spatial Pattern: General Framework

CSP is the most widely used algorithm in BCI experiments because of its capability in discriminating two classes very effectively [25]. CSP does a linear transformation of EEG signal (N channels $\times$ T samples per trial) into a low-dimensional subspace. The rows of resultant projection matrix $\mathbb{W}$ consist of channel weights. This transformation basically maximizes the inter-class variance and minimizes the intra-class variance of 2 classes and by simultaneously diagonalizing the covariance matrices and which are expressed as shown in Eq. (2.2) [44],

$$C_{\chi_i} = \frac{E_i E_i^T}{\text{trace}(E_i E_i^T)} \quad (2.2)$$

where, E_i denotes the scalp EEG $E \in \mathbb{R}^{N \times T}$ for class ‘ i ’. $\text{Trace}(\chi)$ gives the summation of all the diagonal elements in the matrix χ . These spatial covariance matrices C_{χ_i} are averaged over all the trials to result in $\hat{C}_{\chi_i}$ and which are denoted as Eq. (2.3),

$$\bar{C}_{\chi_i} = \frac{1}{N_i} \sum_{j=1}^{j=N_i} C_{\chi_i}(j) \quad (2.3)$$

where, N_i represents the number of trials in class ‘ $i = 1, 2$ ’. The composite spatial covariance matrix $C_c = \bar{C}_{\chi_1} + \bar{C}_{\chi_2}$ can be modelled as a generalized eigenvalue problem $C_C = U_c \lambda_c U_c^T$ where, U_c is the matrix of eigenvectors and λ_c is the diagonal matrix of eigenvalues. This singular value decomposition problem can be solved using a whitening transformation $P = \sqrt{\lambda_c^{-1}} U_c^T$, resulting in new matrices $S_i = P \bar{C}_{\chi_i} P^T$ ($i = [1, 2]$) sharing

the common eigenvectors. This can be alternatively represented as $S_i = E\Lambda_i E^T$. With the condition that the sum of common eigenvectors ($\sum_{i=1}^{i=2} \Lambda_i$) is always an identity matrix, the maximum eigenvalue of S_1 corresponds to the minimum eigenvalue of S_2 . This constrained property makes the eigenvectors to discriminate two classes more effectively. Now the EEG data E is projected into a new spatial-subspace Z with $\mathbb{W}$ being the projection matrix, which is written as,

$$\mathbb{W} = (U_c^T P)^T \quad (2.4)$$

$$Z = \mathbb{W} \times E \quad (2.5)$$

$$(2.6)$$

The columns of $\mathbb{W}^{-1}$ represent the common spatial patterns.

Traditionally the EEG-based motor imagery (MI) classification models have been built on the variants of CSP algorithm.

2.2.2.2 Variants of the Common Spatial Patterns

In this subsection, an overview of different variants of the CSP algorithm will be provided. In [45], Discriminative Spatial Pattern (DSP) and Common Spatial Patterns (CSP) were used to extract the discriminative brain component analysis. Essentially, DSP is a spatially regularized variant of CSP but transforms the ERD time-series as opposed to the filtered EEG time-series in the case of CSP. A new approach of incorporating filter-banks to the CSP was proposed by [65] in which the EEG signals were filtered in different frequency bands, and a subset of features were selected using Mutual Information based Best Individual Feature (MIBIF) algorithm. Developing further, [66] proposed a discriminative filter bank CSP (DFB-CSP) which selects subject-specific frequency bands, and the results showed that the discriminative filter bank approach significantly reduced the error rate of classifying motor imagery tasks.

Another technique called Common Spatial Frequency Pattern (CSFP) was proposed in [67] which overcomes the issue of non-discriminative brain rhythm in CSP. In another study [68], sparsity was induced in the spatial filters (sparse-CSP) to perform channel selection.

Since the CSP computation involves the estimation of covariance matrices, different approaches have been proposed in the literature to improve the same. M -estimator based covariance estimation for CSP is proposed in [69], whereas the regularized framework for estimating the covariance is proposed in [70].

Another way to robustify the CSP is to adopt a regularization framework in the CSP objective function. An example of the same is to exploit Tikhonov Regularization in the objective function as proposed in [71]. In the same paper, the authors proposed spatially regularized CSP where the objective function was regularized by using the spatial information provided by the EEG sensors. An extension of this spatial regularization framework was proposed in [72] in which the spatially regularized Wavelet-CSP was used to improve the classification accuracies of multiclass EEG.

2.2.2.3 Handling the Nonstationarities of EEG

It is to be noted that the EEG signals are highly nonstationary in nature as there are between-subject variabilities (across subjects) as well as within-subject variabilities (across sessions). To address this challenge, various approaches were developed to compensating the non-stationarities either by regularizing the CSP towards stationary solution or by robustifying the spatial filters against the inter-session and inter-subject variabilities. To this end, [50] proposed EEG data space adaptation technique based on Kullback-Leibler divergence criteria to reduce the intersession non-stationarities. Subject-to-subject information transfer based on Bayesian approach was proposed in [73]. Similar study was carried out by [48] in which multitask CSP was proposed to learn new spatial filters for a given subject based on the previous data from other subjects. Stationary Subspace CSP was proposed by [49] in which the principal nonstationary directions common to most subjects were removed using stationary subspace CSP algorithm. A summary of various types of CSP algorithm is presented in Table 2.4.

More recent study on the EEG-based BCI [74] revealed that the transfer learning approach can minimize the inter-session and inter-subject variabilities. Learning from these studies, a cross-subject generalization based on optimized EEG channel selection is proposed in this thesis and presented in Chapter 3.

Table 2.4: Overview of the State-of-the-art Spatial Filtering Algorithms used in the Sensor-space EEG-based BCI

Method	Objective function	Covariance estimation	Remarks
CSP [44]	$J(w) = \frac{w^T C_1 w}{w^T C_2 w}$	Sample covariance $C_i = \frac{E_i E_i^T}{\text{trace}(E_i E_i^T)}$	maximizes inter-class variance and minimizes the intra-class variance; Resultant subspace $Z_i = W^T X_i$
DSP [45]	$J(w) = \frac{w^T S_B w}{w^T S_W w}$	$C_i = \frac{E_i E_i^T}{\text{trace}(E_i E_i^T)}$	Similar to CSP in the objective function, but differs in the transformed subspace : $Z_i = W^T X_i \omega_o$
TRCSP [71]	$J(w) = \frac{w^T S_B w}{w^T S_W w + \alpha P(w)}$	$C_i = \frac{E_i E_i^T}{\text{trace}(E_i E_i^T)}$	Regularized parameter α in the objective function
R-CSP [70]	$J(w) = \frac{w^T S_B w}{w^T S_W w + \alpha P(w)}$	$\Sigma_C(\beta, \gamma) =$ $(1\gamma)\hat{\Omega}_c(\beta) + \frac{\gamma}{N} \text{tr}[\hat{\Omega}_c(\beta)] \cdot \mathbf{I}$	Regularized parameter Ω in the covariance estimation.
multitask CSP [48]	$\arg\max_{\mathbf{w}} \frac{\mathbf{w}^T (\Sigma_{1,1} + \Sigma_{1,2}) \mathbf{w}_1 + \lambda_1 \ \mathbf{w}_0\ ^2 + \lambda_2 \ \mathbf{v}_1\ ^2}{\mathbf{w}^T \Sigma_{1,c} \mathbf{w}}$	$\hat{\Sigma}_{i,C} = (1 - \lambda) \Sigma_{i,C} + \lambda \frac{1}{n-1} \sum_{i=1}^{n-1} \Sigma_{i,C}$	Global solution is not guaranteed due to the non-convex optimization technique
Stationary CSP [49]	$\arg\max_{\mathbf{w}} \frac{\mathbf{w}^T C_1 \mathbf{w}}{\mathbf{w}^T (C_1 + C_2) + \lambda (\Delta_1 + \Delta_2) \mathbf{w}}$	C_i with a penalty Δ_i $\Delta_i = \frac{1}{K} \sum_{k=1}^K F(C_k - \bar{C})$	Regularization in the objective function penalizes the spatial filters extracting non-stationary features
Sparse CSP [68]	$\min_{\mathbf{w}_i} (1 - r) \left(\sum_{i=1}^{i=m} w_i C_2 w^T + \sum_{i=2m}^{i=2m} w_i C_1 w^T \right) + r \sum_{i=1}^{i=2m} \frac{\ w_i\ _1}{\ w_i\ _2}$	condition: $w_i (C_1 + C_2) w_i^T = 1$; $\forall i = 1, 2, \dots, 2m$ $w_i (C_1 + C_2) w_i^T = 1$; $\forall i, j = 1, 2, \dots, 2m; i \neq j$	Regularization parameter $r \in [0, 1]$ controls the sparsity and classification accuracy
Spatially Reg. CSP [75]	$J(w) = \frac{w^T C_1 w}{w^T (C_2 w + \alpha K) w}$	$C_i = \frac{E_i E_i^T}{\text{trace}(E_i E_i^T)}$	K is the Laplacian ($K = D - G$) and G is a Gaussian Kernel, α is the user-defined constant
Composite CSP [73]	$J(w) = \frac{w^T C_1 w}{w^T C_2 w}$	$\hat{C}_c^k = (1 - \lambda) C_c^k + \lambda \sum_{j \neq k} a_{jk} C_c^j$	$\lambda \in (0, 1)$ is a tuning parameter and a_{jk} is computed using Kullback-Leibler divergence; Suitable for subjects with fewer training samples

Table 2.5: Overview of Feature Extraction Methods in the Spectral domain

Methods	Techniques	Principle	Remarks
Spectral Features	Power Spectral Density (PSD) [43]	Parametric spectral estimation based on Yule-Walker method	good generalizability in session-to-session performance
	Morlet wavelets and Probabilistic models [76]	Integrative features using Morlet-wavelets for individual EEG spectra followed by Probabilistic models for each class of MI task	requires crossvalidation based tuning of hyperparameters
	Common Sparse Spectral Spatial Patterns (CSSSP) [52]	Simultaneously optimizes the spatial and spectral filters by allowing for an extended delay in the FIR filter response	Allows for interpretable spatial and temporal filters
	Spectrally Weighted CSP (SPEC-CSP) [51]	generalization of CSP with non-homogenous weights for cross-spectrum matrices	modular filters open up possibility to extend to non-cortical signals as well
	Iterative Spatio-Spectral Patterns Learning (ISSPL) [53]	Simultaneous parameterization of spectral filters and the classifier; statistical learning theory to perform automatic learning of spatial-spectral filters	Requires fine tuned parameters based on crossvalidation for superior performance
Spatio-Spectral methods	Adaptively Weighted Spectral-Spatial Patterns (AWSSP) [42]	tracks the variation in subject-specific discriminative frequency components over time and adaptively updates the weights of frequency bands	Discriminative weights of frequency bands needs supervised updating and therefore, the classifier needs retraining every session.
	Optimum Spatio-Spectral Filtering Network (OSSFN) [54]	Learning of spatial-spectral filters by maximizing the mutual information between filters	Extension of OSSFN to a multiclass problem is very challenging

2.3 Source Imaging

Although EEG has an advantage of high temporal resolution, its inherent limitation of poor spatial resolution makes it very challenging to gather cortical information. Traditional approaches focused on increasing the number of scalp electrodes to improve the scalp spatial resolution, which unfortunately do not address the problem of volume conduction effect. EEG source localization addresses this issue of volume conduction to some extent; EEG source imaging is essentially a model-based neuroimaging technique that uses anatomical constraints to solve the ill-posed problem of identifying the cortical sources that generate electrical potentials recorded on the scalp. Although there have been several multimodal neuroimaging methods (EEG and MRI) in the literature [77] that incorporate high temporal resolution of EEG and high spatial resolution of MRI to complement each others limitations, there are serious practical limitations concerning the monetary cost and the lack of portability.

It is to be noted that the scalp EEG is affected by the volume conduction, which refers to the transmission of electric or magnetic fields from a primary electric current source through the tissues in the brain towards scalp electrodes. Fortunately, as the characteristic EEG signals belong to the frequency bands $< 1000\text{Hz}$, quasi-static approximation of Maxwell equations is valid, and thus, we can neglect the capacitive component of the tissue impedance. Therefore, the propagation of the electrical and magnetic fields inside the human brain can be approximated by using a four layered spherical model made of skull, scalp, cortex, and grey matter. In principle, electrophysiological neuroimaging is achieved in two stages: Forward modeling and Inverse modeling. In forward modeling problem, scalp potentials are calculated by assuming the dipole positions as described by the head model. Later, these scalp potentials are analyzed together with recorded EEG observation by solving the inverse modeling problem to best fit the dipole sources.

2.3.1 Forward modeling

Forward modeling is a critical stage in EEG-based source imaging as it affects the accuracy of source localization results substantially. Forward model relates the cortical sources to the sensor-space EEG recordings by a simple transformation using the lead

field matrix. Two of the common ways to obtain the forward model are by either- (1) Using the multimodal EEG-fMRI where an individual MRI provides the subject-specific head anatomy to which EEG can be co-registered. Or (2) Using the template anatomy such as Colin 27 (single-subject, multiple MRI scans[78]) or ICBM-152 (a non-linear average of MRI obtained from 152 subjects [79] when there is no subject-specific MRI available. To this end, the head model is created using Boundary Element Method (BEM) or Finite Element Method based on the requirements of computational vs accurate head modeling.

2.3.2 Inverse Modeling

As EEG source imaging is an ill-posed problem, several morphological and anatomical constraints are used to reduce the number of unknowns. There are different techniques to solve the inverse problem: parametric methods like equivalent current dipole (ECD) and non-parametric methods (distributed solution) such as current density methods and Beamformer-based methods. Minimum Norm Estimation (MNE), standardized Low-Resolution Electromagnetic Tomography (sLORETA) and Local Autoregressive Average (LAURA) are some of the popular current density methods, and Linearly Constrained Minimum Variance (LCMV), Dynamic Imaging of Coherent Sources (DICS) are beamformer approaches. A detailed literature review of various methods to solve the inverse modeling can be read here [5]. There are several open source toolboxes to implement ESI are available such as Brainstorm toolbox [80], MNE [81], Fieldtrip [82], Statistical Parametric Mapping [83], MobilLab plug-in extension to EEGLAB, and so on. The consistency of different inverse methods using different toolboxes is reported in [6]. Since the research presented in this thesis revolves around the current density methods for EEG source localization, a brief mathematical background is provided below.

The principle equation of EEG source imaging is of the form Eq. (2.7) [5],

$$\phi = L_f J + \varepsilon \quad (2.7)$$

where, $\phi \in \mathbb{R}^{N_E \times 1}$ is the EEG recorded from N_E channels, L_f corresponds to the Lead-field matrix that transforms the source-space EEG into scalp recordings, J denotes the current density matrix, and ε denotes the noise perturbation term.

The primary current density matrix $J \in \mathbb{R}^{3N_v \times 1}$ corresponds to the dipole moments of N_v number of voxels in 3 directions (x, y, z). L_f is a matrix $L_f \in \mathbb{R}^{N_E \times 3N_v}$, describing the propagation of current density in 3 orientations (x,y,z) from N_v voxels to N_E scalp electrodes. The inverse modeling methods such as MNE, sLORETA, LAURA aims at estimating the matrix J .

As the name suggests, MNE tries to find the closed form solution by minimizing the L_2 -norm ($\|\cdot\|^2$) with the help of a regularization parameter α as shown in Eq. (2.8),

$$\hat{J} = \underset{J}{\operatorname{argmin}} \{ \|\phi - L_f J\|^2 + \alpha \|J\|^2 \} \quad (2.8)$$

The resultant MN solution is shown below,

$$\hat{J}_{MNE} = L_f^T (L_f L_f^T + \alpha \Sigma_\varepsilon)^{-1} \phi \quad (2.9)$$

Sensor-space variance Σ_ϕ is a function of covariances $(\Sigma_J, \Sigma_\varepsilon)$ of source-space EEG and the noise perturbation term and is represented as,

$$\Sigma_\phi = L_f \Sigma_J L_f^T + \Sigma_\varepsilon \quad (2.10)$$

The covariance of the estimated current density distribution $\Sigma_{\hat{J}}$ is written as,

$$\Sigma_{\hat{J}} = L_f^T (L_f L_f^T + \alpha \Sigma_\varepsilon)^{-1} L_f \quad (2.11)$$

MNE does not result in the zero-localization error although the noise is negligible. Therefore, sLORETA uses a standardization approach where the variance of the noise perturbation term is also estimated along with the variance of actual cortical sources, which is not the case with MNE. As sLORETA accounts for the variance of noisy measurements, it is reported to achieve zero-localization error even in the presence of noise. The variance of the estimated $J_{sLORETA}$ would be just the product of J and the resolution matrix $\Sigma_{\hat{J}}$.

The standardized current density solution of sLORETA corresponds to $\hat{J}^T [\Sigma_{\hat{J}}]_{ll} \hat{J}$. Here, $[\Sigma_J]_{ll} \in \mathbb{R}^{3 \times 3}$ is the l^{th} diagonal block of $\Sigma_{\hat{J}}$.

2.4 BCI for Movement Decoding

With some background on different methods to estimate the EEG features in sensor- and source-space, let us study the applications of EEG-based BCI for movement decoding. An ideal BCI mediated control should be similar to that of a natural arm control in terms of the motor function. With an advent of the robotic arm and prosthetics with higher degrees of freedom (DoF), the current assistive technologies (or effectors) are capable of mimicking some of the basic arm movements like holding a bottle, grabbing an object and placing it at a target position and so on. However, the decoding of neural signals with such a high degree of precision is difficult as the cortical regions responsible for finer movements are located very close to each other in the motor cortex. Classification of these closely located cortical sources is not a trivial task, especially by using the sensor EEG. Therefore, researchers have investigated various modalities to observe the neural correlates of movement kinematics. A review of BCI techniques (mostly invasive) focusing on decoding the movement direction and continuous movement trajectories (until 2009) is presented in [84]. Since then, there have been an increasing number of non-invasive BCI studies in this direction. In the following subsections, a brief overview of current state-of-the-art methods in the BCI for movement decoding is provided. Table 2.6 summarizes the contributions toward the EEG-based movement decoding.

2.4.1 Directional decoding

In [94], it is shown that the hand movement direction decoding is possible using non-invasive MEG and EEG with a significant power modulation in the frequency range of $<7\text{Hz}$ and high gamma ($62\text{-}87\text{Hz}$). In another high-density EEG study (128-channels), Wang et.al [95] reported the MI classification of left vs. right arm movement direction intention using the equivalent dipole approach for source localization. Both [94, 95] have reported the features from the parietal reach region (PRR) to provide good decoding accuracy, partially due to the fact the PRR receives a visual cue regarding the movement direction. In another BCI-based cursor-direction control paradigm, [93], Bradberry et.al. demonstrated that the motor-imagery (MI) based cursor control is possible with just a single training and calibration session of 20 minutes. Also, they used sLORETA inverse

Table 2.6: Overview of the State-of-the-art methods in EEG Source Analysis of Movement Type Classification

Study	Type of experiment	N_{ch}	Inverse Methods	Features and Classifier	Key findings (Classification Accuracies)
[85]	Left-vs Right hand MI	59	EDA and CCD	TF features using Complex Morlet wavelets;	CA of 78.9% (EDA), 80.6% (CCD)
[86]	BCI Competition 2003 Dataset IV [51]: Self-paced Tapping (SPT)	28	sLORETA	Data driven spatial-filter + SLORETA source power in left and Right ROIs, classification based on a simple decision tree	CA of 83% (sLORETA +spatial filter), 78% (sLORETA, no spatial filter)
[47]	Dataset IV [51]: SPT; Dataset IIIa [53]	60	sLORETA	FuRIA (Fuzzy Region of Interest Activity) based features, Classification using OVR-SVM	CA of 84% (Dataset IV), CA of 82.4% (Dataset IIIa)
[87]	BCI Comp. 2003 Dataset IV [51]: SPT; Extended dataset (SPT) 4 subjects	28	LORETA	Change in power Spectral density (1-40Hz) and BP followed by Mutual Information based feature selection	CA of 84.25% (Identity and Central sulcus prior before feature extraction)
[88]	Left-hand vs Left Foot MI with an Error-potential paradigm	64	sLORETA	PSD features from sensor-space are classified using a simple Gaussian Classifier. sLORETA used as a localization tool.	CA of 81.8% (Correct trials) and 76.2% (error trials). Significant activation in pre-SMA and ACC
[89]	MI-based Cursor control in L vs. R (Graz approach)	128	Beamformer	Log-bandpower of 20 frequency bands; spatial filters obtained using CSP, SBF, BBF, LP	Mean CA of 79.8% achieved using SBF
[90]	Left- vs. right index finger tapping (ME)	128	LAURA	Single-trial discriminative power features classified using LOO-SVM crossvalidation	Average CA of 97% over 12 subjects
[91]	Left- vs Right hand MI	64	MNE	Morlet-wavelets based TF selection (6-30Hz) followed by ERD/S,	Source R > Scalp R
[92]	Self-initiated movement to one of the 8 directions	128	sLORETA	Linear decoding model to fit the 3D coordinates of hand movement with EEG	Continuous decoding of hand velocity from EEG is demonstrated
[93]	MI-based Cursor control in up, down, left, & right	128	sLORETA	Regression weights of the linear decoding model multiplied by time-series of voxels	Continuous decoding of hand MI with minimal calibration

modeling to show the neural sources that encoded the cursor movement. Specifically, the cortical areas such as precentral- and postcentral gyrus, lateral premotor (LPM) cortex, superior temporal sulcus (STS) and lateral prefrontal cortex (LPC) were reported to have played a large role in the encoding of observed cursor velocity. Similar to the above paradigm of cursor control, but a right arm MI in 2D plane (horizontal and vertical plane) was presented in [96]. Here, sLORETA based source-space contributions were calculated using Partial Least Squares (PLS) regression instead of multiple linear regression (MLR) as the weights of an MLS model are not interpretable. Interestingly, the central subareas of SMA contained the predominant sources which were consistent across subjects. Another study on the multi-directional hand movement decoding revealed promising results [72]. In this study, regularized Wavelet-CSP was used for feature extraction in time-frequency domain followed by mutual information based feature selection.

2.4.2 Decoding of movement kinematic parameters

In addition to the directional decoding, kinematic movement parameter like speed is also vital for neuroprosthetics control. An EEG sensor-space study was carried out by a work on 2D hand movement velocity decoding from EEG during a drawing task was carried out by [97]. Another interesting experiment of filling a cup from water bottle is designed by Heger et.al [98] for continuous decoding of 3D hand movement. In an EEG-fMRI multimodal study [99], different finger-tapping speeds were found to be associated with the activation of different parts of the M1 and PMc. In an MEG-based visuomotor adaptation study [100], sLORETA-based source imaging identified the cortical network that encodes hand velocity. Contralateral precentral gyrus (PrG), postcentral gyrus (PoG), ipsilateral superior parietal lobule (SPL), and precuneus (PCu) involved in encoding of the hand velocity in all phases. Although [100] is MEG-based study, the same source localization method can also be extended to EEG. On the similar task of hand movement pace decoding, Robinson et.al [101] performed an experiment using MIT-MANUS robot to classify the EEG signal corresponding to hand movement speed (fast vs. slow). Wavelet Common Spatial Pattern (W-CSP) was used as a feature extraction technique, wherein the wavelet reconstructed signal $X_W(i)$ is projected instead of filtered EEG signal $X(i)$.

2.4.3 Interpretational caveats with the regression-based studies for movement decoding

Noninvasive EEG based movement trajectory reconstruction is pioneered by Bradberry et.al [92]. However, the positive correlation results of linear regression based sensor-space studies may not essentially be a good indicator of successful trajectory reconstruction based on neural correlates. The main reason behind this is the fact that the correlations of limb kinematics reconstruction were not significantly above the chance level when computed between the recorded EEG-recorded velocity profiles vs. shuffled EEG-recorded velocity and compared against the synthetic generated EEG to compute the correlation with the velocity profile. To investigate the veracity of the claims in [92], source localization based on sLORETA was used in [102] to see if there are any neural correlates. It turns out that there were no neural sources in the motor region of chance-level decoding models. Since the real-EEG model did not significantly outperform chance-level decoding models in terms of normalized root mean square error, such linear-regression-based results must be interpreted carefully by considering the neurophysiological plausibility.

2.4.4 Localized arm movement decoding

For a more realistic and practical neuroprosthesis, it is important to decode the movement of localized arm parts such as finger, wrist, elbow, and shoulder. However, the localization of cortical sources responsible for the movement of these arm parts is not trivial as these neural sources overlap in the cytoarchitectural maps of the brain. Motivated by this challenge, researchers have explored the non-invasive EEG-based movement decoding of localized arm parts. In a sequential finger-tapping movement imagery vs. execution study [109], sLORETA-based inverse model was used to localize the sources. SLORETA showed significant differences between MI and ME in Brodmann Areas 2 and 3. However, the Lateralized Readiness Potential (LRP) which is a negative potential observed after the cue is presented in different time periods (between 50-250ms and 350-600ms) were shown to reveal differences between MI and ME of localized arm movement tasks. It was hypothesized that the neuronal sources involved in localized arm movement imagery would be restricted to the selection of arm part and additional set of neurons would engage in parameters such as direction, speed, and force. As this study was conducted

Table 2.7: Overview of the State-of-the-art methods in EEG-based Localized Arm Movement and Kinematics

Study	Type of experiment	Features and Classifier	Key findings (Classification Accuracies)
[103]	lower limb extension/flexion (ME)	Task-related bandpower (TRP1/TRPD)	BA6 and Cingulate cortex (BA23, 24, 31) involved in the gait-movement relative to resting period
[104]	Radial-ulnar wrist MI and ME	Time-frequency bins classified using Bayes-Linear Classifier	Strong activity in the Precentral, Postcentral, and premotor areas
[105]	Radial-ulnar wrist ME of right hand	Low pass filtered (1.6Hz) and band-pass filtered (4-6Hz) signals from sensorimotor regions	EEG Source-space features could classify 4 types of wrist movement with an accuracy of 79.8%
[106]	RH-MI of Flexion, Extension, Pronation and Supination	Morlet TF features from selected ROIs followed by MD-based One-versus-rest classification	Contralateral activity (M1,S1) during hand-opening, bilateral activity during hand-closing
[107]	Hand opening and closing (ME)	Time-Frequency synthesized spatial patterns (TFSP)	Source-space EEG can distinguish goal-directed and non-goal directed movements with the same kinematics
[108]	Right hand ME (goal-directed vs non-goal directed)	MRCF features classified using SRLDA followed by DSP analysis of brain sources	cortical source-space results revealed few sources would be involved in the selection of arm part, but more sources for kinematic parameters
[109]	Sequential finger tapping movement imagery and execution	sLORETA based inverse modeling followed by Lateralized Readiness Potential (LRP) -based features	Faster wrist movements are associated with greater rebound rate and vice versa for slower wrist movement
[110]	Wrist movement type (extension vs. rotation) and speed (fast vs. slow) decoding	features used are Bereitschaftspotential and rebound-rate of Movement-related Cortical Potential (MRCF)	Mean single-trial classification accuracy of 80% with a bit rate of 10 bits/min
[111]	Left vs. Right Finger Tapping	Fourier Transform features followed by Kolmogorov test-based feature selection	Significant correlation observed between the predicted and observed trajectory
[112]	Finger movement decoding	Genetic algorithm based channel selection followed by finger movement trajectory reconstruction using a linear decoder model	Mean accuracy of 92.9 % of classifying shoulder abduction vs. elbow flexion
[113]	Shoulder vs. torque	Time-Frequency synthesized spatial patterns (TFSP) followed by CART-SVM classifier	

using only 28 EEG-channels with no MRI co-registration, the results interpreted in [109] need further validation.

The study on discrimination of wrist movement type (extension and rotation) and speed (fast and slow) is carried out in [110]. Their experiment involved classifying 4 different tasks of wrist movement like Fast Extension (FE), Slow Extension (SE), Fast Rotation (FR), and Slow Rotation (SR). In this work, Bereitschaftspotential (surface negativity observed approximately 2s before the movement onset) and rebound rate of Movement-related cortical potential (MRCP) are recorded. The experimental results show that the faster wrist movements are associated with greater rebound rate and vice versa for slower movements. However, the discrimination between Fast Rotation (FR) and Fast Extension (FE) is poor compared to *fast* vs. *slow* tasks which leaves rotation v/s extension discrimination based on neural correlation unanswered. Online classification of single-trial EEG for finger movements is presented in [111]. This subject-specific work, however, does not involve classification from the perspective of motor imagery but depend on the Kolmogorov test statistics for classifying two random variables. Another novel method of representing finger kinematics in terms of scalp EEG recordings is presented in [112]. Multiple kinematic parameters like finger tapping speed, extension angle, and the range of motion are computed for metacarpal-phalangeal joint of index finger trajectory. This work involved Genetic algorithm for optimal channel selection which could not answer the variability issues among different subjects. Zhou et.al. conducted an experiment for decoding elbow vs. shoulder torque intentions [113]. Time-frequency synthesized spatial pattern was used for power spectral distribution in various time and frequency bands i.e. and finally a single time-frequency decomposition is modelled which is followed by CART-SVM (Classification and Regression Tree-Support Vector Machine) classifier. This work [113] however do not describe the kinematic background between differentiating the shoulder abduction and elbow flexion. The paper did not justify exactly how such a good accuracy could be achieved where the spatial distance between the shoulder and elbow activity is as small as 10 mm.

A summary of the methods described above is listed in Table 2.7.

Nevertheless, all these studies have instilled an interest in numerous researchers in this area which is still an open challenge.

2.5 Limitations of the State-of-the-art Methods in Movement Decoding

In this chapter, the comprehensive review of the state-of-the-art methods in EEG-based motor task decoding is provided. Various aspects of signal processing and feature extraction methods for movement decoding in the sensor as well as source-space EEG have been discussed, and it is noted that there are still several challenges to be addressed. One can easily notice how the feature extraction methods have evolved over the years from simple features such as peak amplitude of EEG to the complex ones such as subspace transformation and optimization problems. Nevertheless, even with the advent of remarkable feature extraction techniques, noninvasive EEG-based practical BCI for movement decoding is still a challenge due to the inherent limitations of EEG. Two major reasons that contribute to this challenge are nonstationary nature of EEG and the poor spatial resolution of EEG that limits our understanding of a highly complex neural circuitry of the brain region that is associated with the dexterous movement of arms and limbs.

Most of the existing algorithms that report superior performance in classifying the motor tasks using the EEG rely on regularization techniques that attempts to address the nonstationarity. However, most of these regularization requires fine tuning of hyperparameters based on crossvalidation. Although this is not a concern in an offline analysis, it is not advisable for online BCI wherein the features need to be extracted from the incoming signal and thus, limits the use of crossvalidation based regularization techniques. Therefore, the spatial filtering algorithms with an analytical solution for the regularization parameter are preferred. Further, the sensor-space EEG is prone to the lack of interpretability of underlying neural correlates of a movement task. With the recent advances in source-space transformation of the recorded EEG, various studies have shown growing interest in using the source-space EEG for movement decoding (refer to Table 2.7 and Table 2.6.) However, most of these source-space studies lack sophisticated data modeling algorithms which not only extracts useful features for classification and/or trajectory decoding but also explain the neurophysiological modeling. Unlike the exploration of various machine learning algorithms in the sensor-space EEG, the source-space EEG still remains relatively unexplored. There needs to be top-down approaches driven

by the data (i.e. EEG), as well as bottom-up approaches driven by neurophysiological models (a prior information about the regions of interest) to understand the cortical function during movement-related tasks. Further, the cortical activation observed using source-space EEG needs causal explanation which is still a challenge in EEG-based studies. In the subsequent chapters, an attempt is made to address most of the aforementioned challenges in the EEG source imaging of movement decoding.

2.6 Summary

This chapter reported the overview of the BCI systems and components and the use of BCI in motor imagery tasks. After highlighting the advantages and limitations of different brain signal acquisition modalities, a detailed description of EEG is provided. An extensive literature review of the current state of the art techniques for EEG preprocessing and feature extraction is provided. Followed by the limitations of sensor-space EEG, an introduction to cortical source EEG is also presented. State of the art in EEG-based BCI technology for movement decoding is described in detail.

Chapter 3

Spatial Filtering for Cross-Subject Generalization of EEG Sensor Selection in BCI

3.1 Introduction

The practicality of any BCI paradigm depends on how much effort is involved with the BCI preparation set-up. This factor motivates methods to minimize the preparation efforts using a minimal yet relevant set of channels. EEG channel selection can also be seen as complementary to the regular spatial filtering methods.

The human brain consists of different portions that are associated with different tasks such as the motor cortex with motor tasks, occipital cortex with visual processing, and the fronto-parietal regions with decision-making. Thus, the selection of task-related signal recording position can reduce the preparation time as well as improve the comfort level in non-clinical BCI applications. With an optimal set of channels, it could be possible not only to achieve a better classification of experimental tasks but also to reduce the computational cost involved in processing high-dimensional data. In this chapter, multichannel EEG signal processing for motor imagery (MI) is presented as a multidimensional classification problem. A channel selection algorithm can be used to alleviate the curse of dimensionality associated with multichannel signal information and corresponding time-varying features. Although having prior knowledge of the neural correlate helps in selecting the relevant channels, it may not be true for all individuals [114]. There exists inter-subject variability for a given BCI experiment wherein the best-performing

channels for one user may not be the same for another user. Therefore, manual sensor selection may not be the best way to improve the performance. Furthermore, there have not been many approaches which examine the generalization of task-relevant channels across subjects. To this end, a multi-objective optimization based EEG channel selection algorithm is presented in this chapter to study its contribution to the improvement in the classification accuracy as well as cross-subject generalization.

3.1.1 Literature Review

As mentioned in Chapter 2, the literature survey on EEG based localized arm movement suggested that it is quite difficult to classify the MI tasks that are associated with high degrees of freedom because of the poor spatial resolution of EEG. There is another challenge of subject variability issue where the electrode locations for a desired arm movement task (especially, localized arm movement) are not universal, instead they are subjective. Large number of electrodes also demand longer preparation time which is tedious for not only clinical applications but also non-clinical ones. Another issue with the large number of electrodes is an increased computational complexity in spatial filtering. EEG headsets have a standard size which might not fit-in perfectly for all the subjects because of different head-sizes. This causes slight mismatch in the electrode placement due to which it is not advisable to consider any specific channel as a reference (eg: C3 and C4) for analysing motor task. Higher the number of channels, higher the redundancy leading to overfitting. These are the motivating factors to study the selection of EEG channels having the highest correlation with the performed proximal arm movement.

There exists several methods which try to address the EEG channel selection that target experiments based on movement and cognitive tasks. An analysis of channel selection algorithms for event-related potentials was presented in [115]. It discussed the intra- and inter-session channel transfer to observe the performance variation across the subjects. Similarly, the significance of channel parameters was elucidated in [116]. In the context of MI, several techniques have been proposed focusing on the suitable sensor space. The most widely used feature extraction technique called common spatial pattern (CSP) was presented as a channel selection algorithm in [117], which considers the coefficients of the projection matrix for ranking the channels. Although CSP is

capable of discriminating two classes, it is often affected by artifacts in the EEG signal [44]. Another channel selection strategy uses support vector machine (SVM) as its base classifier [60]. In their study, recursive feature elimination (RFE) was used for eliminating the irrelevant channels in a given experimental task useful for BCI experiments without requiring the explicit knowledge of neural substrates. Several other channel selection methods, such as artificial neural networks-genetic algorithm (ANN-GA) [118] and sparse common spatial pattern (SCSP) [68], are computationally intensive and are unsuited for online experiments.

Evolutionary algorithms have also been explored for the EEG channel selection paradigm as an optimization problem. A GA-based evolutionary approach is presented in [118] for selecting the most discriminative channels. However, GA requires careful selection of parameters that might otherwise affect the classification accuracy. Particle swarm optimization (PSO) is another popular nature-inspired algorithm that has been used for channel selection in BCI [119]. To select the best channel set, CSP and PSO are wrapped together in [120]. In their work, the trade-off coefficients need to be adjusted to select the best channel set that might not be advisable for real-time online BCI experiments. Another study based on GA and binary PSO (BPSO) is presented in [121]. BPSO is a discrete variant of PSO with slightly modified velocity and position update.

Interactive approaches to multi-objective optimization problems rely on the decision maker to find the Pareto-optimal solution. The reference point-based approach is relatively computationally inexpensive, as the solution search space can be minimized based on the reference point [122]. However, this requires some a priori information about the optimization problem and an idea of the criterion vector. Because most of the EEG-based MI or execution experiments involve tasks whose spatial activation regions are limited to the motor cortex, a reference point approach for solving multi-objective optimization seems valid. Although the signal information obtained from the channels in the motor cortex is said to contribute more to the classification accuracy of movement-related tasks, the channels in the visual cortex area are also reported to have contributed to the improvement in accuracy [123]. Therefore, whether most frequently selected channels are necessarily located in the motor cortex or the visual cortex is unknown.

Another interesting approach is to explore subject-independent models for channel selection. Subject-independent BCI (SI-BCI) models have been reported to reduce the

calibration time for training [75] and also different methods have been compared to subject transfer models where linear classifiers perform better [47]. Findings suggested that subject-specific BCI (SS-BCI) outperforms the SI-BCI model. Although the subject-independent channels may not outclass the subject-specific channels, the subject-to-subject transfer has to be conducted for a large number of subjects over several sessions. If the subject transfer with fewer channels can perform as well as use all the channels for each individual subject, more efficient studies can be executed.

In this chapter, a method called iterative bi-objective optimization for channel selection (IMOCS) is proposed to choose the best set of EEG channels.

3.2 Formal Background

In this study, an MI task classification problem is posed as a bi-objective optimization problem wherein the set of relevant EEG channels determined by a prior neural correlate and the set of EEG channels that contribute towards the classification accuracy could conflict with each other. This conflict can be seen as a *bi-objective optimization problem* where there can be more than one solution satisfying both the criteria or there can be a solution that can satisfy at least one criterion (optimal number of channels) without worsening the other (classification accuracy). A single dominant solution may not exist in this case; rather, multiple solutions exist, which are Pareto dominant (more than 1 channel).

Let $x_i \in \mathbb{R}^{D \times N} \{i = 1, 2, 3, \dots, N\}$ represent a training sample space, where N is the number of MI training trials and D is the total number of EEG channels. The product $D \times N$ defines the total dimension, which is directly proportional to the number of EEG channels. Let the solution space be represented as $Y_i \in \{Y_1(\mathbf{x}), Y_2(\mathbf{x}), \dots, Y_D(\mathbf{x})\}$, where $\mathbf{x} \in X$. A solution $\tilde{x} \in X$ is said to be a Pareto Optimal Solution, if there exists no other solution $\mathbf{x} \in X$ such that $Y_i(\tilde{x}) \geq Y_i(x)$.

Based on the neural correlate, the solution space is assumed to be constrained within the region of interest (ROI), which in this case is the motor cortex. However, the set of channels within the motor cortex that contributes to the better performance is not known. Therefore, the motor cortex is considered as an ROI wherein the Pareto channels

are to be determined based on the MI task-related characteristics. In the context of mathematical optimization, this ROI is referred to as bounded feasible set that contains all possible candidate solutions or channels. The radial basis function (RBF) kernel is used as a distance metric to specify the criterion space or an ROI. The advantage of the reference point approach is that the neighborhood can be easily defined in terms of a distance metric, which helps in reducing the solution search space. Capturing the preference information regarding the location of a solution helps to significantly reduce the computation time.

To further understand the bi-objective optimization framework, the terminology of certain key terms is explained below.

A multi-objective optimization problem involving M conflicting objectives with x as a decision variable is defined as in Eq. (3.1), [124],

$$\begin{aligned} & \underset{\text{subject } x \in S}{\text{minimize}} \{f_1(x), f_2(x), \dots, f_n(x)\} \end{aligned} \quad (3.1)$$

where $S \subset \mathbb{R}^n$ is a Pareto-optimal set or a set of solutions, which provides a trade-off between the conflicting objectives. The present study involves finding an optimal solution for two conflicting objectives; therefore, the problem addressed henceforth is a bi-objective optimization problem ($m=2$).

For a bi-objective optimization problem, a dominant solution is defined as follows:

Definition 1: A decision vector $\mathcal{H}_1$ is said to *dominate* another decision vector $\mathcal{H}_2$, where $\mathcal{H}_1$ and $\mathcal{H}_2$ correspond to $\mathcal{F} \subseteq \{f_1, f_2\}$ and we write $\mathcal{H}_1 \preceq_{\mathcal{F}} \mathcal{H}_2$. Here, the function of a decision vector $\mathcal{H}_2$ should be greater than that of $\mathcal{H}_1$ in at least one objective.

A given multi-objective optimization problem may not have a strictly dominant solution. Therefore, a non-dominated set is defined as S' which contains the solutions that are not dominated by any solution in S . A Pareto-optimal set can also contain non-dominant solutions. Most multi-objective optimization problems involve solving for the non-dominant solutions. Often, it is required to find a solution that is no worse than other solutions in one or more conflicting objectives.

Definition 2: A decision vector $\mathcal{H}_1$ and its corresponding objective vector $f(\mathcal{H}_1)$ is defined as *Pareto-Optimal* if there is no other decision vector that dominates $\mathcal{H}_1$.

Figure 3.1: Block diagram of an Iterative Multi-objective Optimization for EEG Channel Selection.

Henceforth, the solution space of interest is Pareto optimal. While solving such multi-objective problems, we come across *utopian objective vector* and *nadir objective vector*, which are defined as follows:

Definition 3: A vector $z^{utopian}$ is called a utopian objective vector whose components correspond to the minimum function value of an m th objective. Mathematically, the utopian objective vector is defined as the constrained minimum of the problem,

$$\underset{\text{subject to } \mathbf{x} \in \wp}{\operatorname{argmin}} f_m(\mathbf{x}) \text{ where, } \wp \text{ is a Pareto-Optimal set.}$$

Definition 4: A vector z^{nadir} is called a nadir objective vector whose components correspond to the maximum function value of an m th objective. Mathematically, the nadir objective vector is defined as constrained maximum of the problem, $\underset{\text{subject to } \mathbf{x} \in \wp}{\operatorname{argmax}} f_m(\mathbf{x})$. It is to be noted that the nadir objective vector corresponds to the best solution of an m th objective and not for all objectives.

3.3 Methodology

The data processing procedure is highlighted in Fig. 3.1.

3.3.1 Iterative Multi-Objective Channel Selection (IMOCS)

In the context of EEG sensor selection, the optimal solution refers to that particular sensor (or channel) that has the highest relevance for the experimental task involved. In this study, EEG channel selection is posed as a multi-objective (or bi-objective) optimization problem, where the first objective is to get the candidate solution (channel) in the vicinity of the known neurophysiological activation region and the other objective is to obtain a channel whose contribution to the experimental task classification accuracy is higher. Therefore, the objective function concerned with both these parameters (ROI and the contribution for classification accuracy) is solved for an optimal solution using an iterative approach to multi-objective optimization problem. This approach uses a reference point-based iterative method to determine the optimal solution. In this procedure, the channel weights and the objective function are updated in every iteration. With a reference point-based approach, it is easier to find a Pareto-optimal solution using a local search [125]. Reference point-based approach for MI considers the channels C3 and C4 as the initial candidate solution for left-hand versus right-hand MI classification. This assumption is based on previous studies that demonstrate the usefulness of channels in the motor cortex. An inverse relationship between the weight and the distance [126] support rapid convergence and excellent fitness values.

While defining channel selection as a bi-objective optimization problem, we introduce a generalization of the relation between the two objectives. ROI is expressed by channel weight vector $f_1 = \{\mu^{(1)}, \mu^{(2)}, \mu^{(3)}, \dots, \mu^{(N)}\}$, and the intra-trial task-related desynchronization (ITTRD) vector is specified by $f_2 = \{\beta(x^{(1)}), \beta(x^{(2)}), \beta(x^{(3)}), \dots, \beta(x^{(N)})\}$. A weak dominance relationship is introduced between the decision vectors $\mathcal{H}_1$ and $\mathcal{H}_2$ corresponding to $\mathcal{F} \subseteq \{f_1, f_2\}$ iff $\forall f \in \mathcal{F} : f(\mathcal{H}_1) \leq f(\mathcal{H}_2)$. Here, $\mathcal{H}_1 \preceq_{\mathcal{F}} \mathcal{H}_2$ represents the preferential relationship between $\mathcal{H}_1$ and $\mathcal{H}_2$ in the domain F . In the context of channel selection, the contribution of a channel to the classification accuracy is expected to be at least weakly dominant compared to its spatial location within the ROI.

The objective function is normalized in the domain of Pareto-optimal region. In this study, the Gaussian kernel defining the neighbourhood around initial reference channel specifies the Pareto-optimal region. It is expressed as Eq. (3.2),

$$\phi(c_{ref}, c_k) = \exp\left(-\frac{\|c_{ref} - c_k\|^2}{2\sigma^2}\right) \quad (3.2)$$

In Eq. (3.2), $\phi(c_{ref}, c_k)$ defines the Gaussian kernel to specify the distance between reference channel c_{ref} and the neighboring channel c_k . The neighborhood is defined by the kernel radius as parameterized by σ . For the sake of simplicity, the parameter σ is set as $\sigma=1$. The channel weights are initialized according to the exponential decay relationship with respect to the distance between the reference channel and the neighboring channel. Basically, the rule of thumb is that the reference channel gets the highest weight during the initialization and the neighboring channels get smaller weights as they are farther from the reference channel. In this study, the channel weight initialization is expressed as Eq. (3.3).

$$\mu^{(k)} = \phi(c_{ref}, c_k) \quad (3.3)$$

Some of the multi-criteria optimization problems involve weighted aggregation of multiple objectives to be optimized and some involve a slightly more complicated single objective function [127]. A simpler single objective function $\Theta(\mu^{(k)}, \beta(x^{(k)}))$ for optimizing both criteria ($\mu^{(k)}$ and $\beta(x^{(k)})$) is used in this study. It is used as an “achievement function” [128], thereby focusing on the maximization of the objective function $\Theta(\mu^{(k)}, \beta(x^{(k)}))$,

$$\Theta(\mu^{(k)}, \beta(x^{(k)})) = \frac{f(\mu_i^k, \beta(x_i^k)) - \mathbf{z}^{\text{utopian}}(\mu_i^k, \beta(x_i^k))}{\mathbf{z}^{\text{nadir}}(\mu_i^k, \beta(x_i^k)) - \mathbf{z}^{\text{utopian}}(\mu_i^k, \beta(x_i^k))} \quad (3.4)$$

In this iterative method for updating the channel weights, the channel weight vector is updated in the i th iteration as shown in Eq. (3.5).

$$\mu_{i+1}^{(k)} = \mu_i^{(k)} + \Theta(\mu_i^{(k)}, \beta(x_i^{(k)})) \quad (3.5)$$

Essentially, the maximization of an objective $\mathbf{f}$ is equivalent to the minimization of $-\mathbf{f}$, where $\mathbf{f}(\mu^{(k)}, \beta(x^{(k)}))$ is $\mu^{(k)} \times \beta(x^{(k)})$. $\mathbf{z}^{\text{utopian}}(\mu_i^k, \beta(x_i^k))$ is a utopian objective vector which defines the lower bound of the Pareto-optimal solution [128] i.e., $\mathbf{z}^{\text{utopian}} = \arg \min_{\forall k} f(\mu_i^{(k)}, \beta(x_i^{(k)}))$. Similarly, $\mathbf{z}^{\text{nadir}}(\mu_i^k, \beta(x_i^k))$ is a nadir objective vector that defines an upper bound of the Pareto-optimal solution, i.e. $\mathbf{z}^{\text{nadir}} = \arg \max_{\forall k} f(\mu_i^{(k)}, \beta(x_i^{(k)}))$. The current bi-objective optimization problem is viewed as a channel selection problem wherein the number of channels (sensors) is reduced from its original sensor space (N) to a smaller sensor space (M).

3.3.2 Intra-trial Task related Desynchronization (ITTRD)

Event-related desynchronization (ERD) and event-related synchronization (ERS) are important characteristics associated with an EEG-based MI. ERD is related to the desynchronization or decrease in the power level of contralateral neural ensemble involved in MI task whenever a movement is imagined. Similarly, ERS is associated with the increase in neural activity shown in the contralateral motor cortex after the movement is performed [25]. Conventional techniques for ERD and ERS computation involve bandpass filtering in μ -band (813 Hz) and/or β -band (1330 Hz) followed by signal power averaging over all the recorded trials. However, this might not be the best way to quantify ERD. Several factors such as the extent of the subject's involvement in a given trial, the time delay in imagining and/or executing the movement suggested by the cue, and the intrinsic variability of an underlying neuronal activity could affect the averaging of ERD over all trials [129]. To address this issue, ERD quantification within a single trial recording [130] referred to as an intra-trial task-related Desynchronization (ITTRD) is employed in the current study. It is expressed as Eq. (3.6),

$$\beta(x_i^k) = \left(\frac{\hat{P}_{activation} - \hat{P}_{baseline}}{\hat{P}_{baseline}} \right) \times 100 \quad (3.6)$$

where $\hat{P}_{activation}$ is the signal power during the activation period (post-cue) and $\hat{P}_{baseline}$ is the signal power computed for pre-cue indicating the baseline for each trial. This power computation is based on the modified periodogram with a moving hamming window $w_R[n]$ and it is computed as Eq. (3.7) [131],

$$\hat{P}_{XX}(e^{i\omega}) = \frac{1}{N} \left| \sum_{n=0}^{N-1} w_R[n] x[n] e^{-i\omega n} \right|^2 \quad (3.7)$$

3.3.3 Termination Criteria for the Iterative Update of Channel Weights

Most of the interactive approaches for solving multi-objective optimization problems do not always involve mathematical convergence. Some rely on manual convergence as decided by the human decision-maker. In this study, a convergence metric based

on inter-trial deviation-based conditional upper bound is used. In iterative methods for multi-objective problems, iteration termination criteria based on deviation between variable vectors in successive iterations have been suggested [125]. Similarly, an iterative method for spatio-spectral learning has a termination criteria specified by the relative change in the eigenvalues resulted by CSP computation in two successive iterations [53].

Considering the reduction in the channel vector length from N to L , the vector corresponding to the reduced channel set is used for sum-of-squared deviation (SSD) computation. This SSD-based deviation weight has been used for minimum distance approximation and to analyze asymptotic error rate [132]. The SSD $m^{(i)}$ for a reduced channel vector $r^{(i)} = [r_1^{(i)}, r_2^{(i)}, r_3^{(i)}, \dots, r_L^{(i)}]$ in the i^{th} iteration [132] is,

$$m^{(i)} = \frac{(\sum_{j=1}^L \mu_j^{(i)} r_j^{(i)})^2}{\sum_{j=1}^L (\mu_j^{(i)} r_j^{(i)})^2} \times \frac{1}{L} \quad (3.8)$$

where, L is the number of selected channels. The whole iterative procedure terminates when the difference of SSD between successive iterations (i.e., $m^{(i+1)} - m^{(i)}$) reaches the relative termination criteria specified by $\epsilon < 10e - 4$. The proposed channel selection approach (IMOCS) is summarized in Algorithm 1.

3.3.4 Feature Extraction Using Modified Filter Bank Common Spatial pattern (MFBCSP)

The channels selected in the previous stage are used for Common Spatial Pattern (CSP) computation to help reduce the noise due to irrelevant channels. CSP has been shown to discriminate between two classes very effectively in BCI experiments [44]. A brief mathematical introduction to CSP is provided in Section 2.2.2 of Chapter 2. Linear transformation of EEG signal $X_i \in \mathbb{R}^{L \times T}$ (L channels $\times$ T time samples in i^{th} trial) creates a spatially filtered subspace $\mathbf{Z}$ as, $\mathbf{Z} = \mathbf{W} \times \mathbf{X}$ where $\mathbf{W}$ is the projection matrix. The conventional method of CSP computation does not consider the brain signal as decomposed into different filter bands. However, a non-decomposed signal does not reveal much of the spectral information. Therefore, a modified Filter bank CSP (FBCSP) is proposed in [66]. Motivated by the findings in [66], the overlapping filter bands are employed in this current work for better discriminative features. Another advantage of

modified FBCSP is that it captures more information about the frequency portion in the bandpass edge frequencies. Although the same information can be obtained using a higher-order Chebyshev type-II IIR filter, it increases the computational complexity compared to overlapping filter bands with lower filter order. The resultant signal after projecting into new spatial subspace $Z_{M,i}$ is expressed as shown in Eq. (3.9),

$$Z_{M,i} = W_M^T X_{M,i} \quad (3.9)$$

where, M corresponds to the filter band number for a single trial EEG signal $X_{M,i}$.

Algorithm 1 Proposed Channel selection method - IMOCS

Input: Filtered signal $X \in \mathbb{R}^{N \times T}$ (N channels, T samples)

Output: $\hat{c}_{res} \leftarrow [c_1^*, c_2^*, \dots, c_L^*]$ (L selected channels)

1: INITIALIZE

Reference Channel $c_{ref} = \{\hat{c}_1 \forall y_i = 1; \hat{c}_2 \forall y_i = 0\}$

Neighborhood: $c_k \in \eta$ if $Euclidean(c_{ref}, c_k) < \rho$

Channel Weights: $\varphi(c_{ref}, c_k) = \exp(-\frac{(c_{ref} - c_k)^2}{2\sigma^2})$
 $\forall c_k \in \eta$

2: **for** $i=1, \dots, \text{numIter}$ **do**

3: $\beta(x_i^{(k)}) \leftarrow (\frac{\hat{P}_{activation} - \hat{P}_{baseline}}{\hat{P}_{baseline}}) \times 100$

4: $f(\mu_i^{(k)}, \beta(x_i^{(k)})) \leftarrow \mu_i^{(k)} \beta(x_i^{(k)})$

5: $z^{nadir} \leftarrow \arg \max_{\forall k} f(\mu_i^{(k)}, \beta(x_i^{(k)}))$
 $z^{utopian} \leftarrow \arg \min_{\forall k} f(\mu_i^{(k)}, \beta(x_i^{(k)}))$

6: $\Theta(\mu_i^{(k)}, \beta(x_i^{(k)})) \leftarrow \frac{f(\mu_i^{(k)}, \beta(x_i^{(k)})) - z^{utopian}}{z^{nadir} - z^{utopian}}$

7: $\mu_{i+1}^{(k)} \leftarrow \mu_i^{(k)} + \Theta_i(\mu^{(k)}, \beta(x^{(k)}))$

8: $m^{(i)} \leftarrow \frac{(\sum_{j=1}^N \mu_j^{(i)} r_j^{(i)})^2}{\sum_{j=1}^N (\mu_j^{(i)} r_j^{(i)})^2} \times \frac{1}{N}$

9: **if** $m^{(i+1)} - m^{(i)} < \varepsilon$ **then**

10: terminate

11: **end if**

12: **end for**

13: **return** $\hat{c}_{res}$

$W_{M,i}$ is computed by solving singular eigenvalue decomposition problem. The rows of resultant projection matrix $W_{M,i}$ consists of weights for each channel which are referred to as spatial filters and the columns of $W_{M,i}^{-1}$ correspond to the common spatial patterns. The extracted feature set is basically the log-transformation of normalized $Z_{M,i}$. The features are calculated as Eq. (3.10),

$$v_{M,i} = \log\left(\frac{\text{diag}(\widehat{W}_M^T X_{M,i} X_{M,i}^T \widehat{W}_M)}{\text{trace}(\widehat{W}_M^T X_{M,i} X_{M,i}^T \widehat{W}_M)}\right) \quad (3.10)$$

The resultant feature vector is $v_i = [v_{1,i}, v_{2,i}, \dots, v_{M,i}]$, where $v_i \in \mathbb{R}^{1 \times (M \times 2m)}$ represents the first and last ‘ m ’ spatial filters of W_M . For N trials, the feature matrix is $\overline{\mathbf{v}}_N \in \mathbb{R}^{N \times (M \times 2m)}$.

3.3.5 Feature Selection and Classification

FBCSP results in larger feature space because of the decomposition of EEG signal from selected channels into nine different bands. This results in a feature space of size N filter bands $\times M$ CSP spatial filters $\times T$ classes. In the current study, the feature space is of size 9 filter bands $\times 2$ CSP spatial filters $\times 2$ classes, which totals 36. To achieve better classification accuracy, it is necessary to have only those features that actually contribute towards the classification and are relevant to the task. A feature selection algorithm called minimum redundancy maximum relevancy (mRMR) used in classification studies based on non-invasive recordings [133],[134] is employed. This technique takes into account the mutual information between the class labels c_i and individual features x_i and ranks them accordingly. In a given feature space, it is possible for some features to have a dependency on each other and their combination could be redundant, and it is necessary to have only those features that are relevant. The selected features are then classified using an SVM classifier for which LIBSVM toolbox is used [135].

3.4 Evaluation Dataset

3.4.1 Datasets used in this study

3.4.1.1 Dataset IVa, BCI Competition III [136] “Dataset 1”

This dataset consists of signal recordings from 5 subjects (*‘aa’*, *‘al’*, *‘av’*, *‘aw’* and *‘ay’*) using 118 EEG channels in a single session. Subjects were instructed to imagine the movement of one of the following three classes namely, left hand, right hand and right foot. In the competition dataset, cues for the right hand (RH) and right foot (RF) imagery were provided, so in this study, the proposed method aims at classifying right hand and foot trials. Training and testing data together comprised of 280 trials. The downsampled (100 Hz) version of the EEG data provided in the dataset, which is originally sampled at 1000 Hz, is used in this study.

3.4.1.2 Dataset 2a from BCI competition IV [137]-“Dataset 2”

This dataset comprises EEG signals of 9 subjects using 22 channels. Dataset is obtained from a cue-based BCI experiment which has four different MI tasks, i.e., imagining the movement of the left hand, right hand, both feet and tongue. However, in this current study, only two class MI tasks of left and right hand are considered. The EEG data was sampled at 250 Hz and pre-filtered in the pass band 0.5-100 Hz. There were two sessions held, out of which each session had 72 trials for each motor imagery task.

3.4.1.3 Wadsworth Data - “Dataset 3”

The data set is obtained from the experiment conducted by the Wadsworth Center. Physiobank toolkit [138, 139] data set obtained from 109 healthy volunteers is used. EEG recordings acquired from 64 channels with the help of BCI2000 toolkit (<http://www.bci2000.org>) are used in this study. Data are sampled at a frequency of 160 Hz and the EEG signals are referenced to earlobe electrodes. This dataset is publicly available at <http://www.physionet.org/pn4/eegmmidb/>.

There were 14 experimental runs conducted on each subject. Out of these 14 experimental runs, 2 were considered as the baseline; one run with eyes open and another run with eyes closed for 1 minute each. The whole experiment conducted in the Wadsworth

Center consisted of tasks such as the real movement of a right fist or left fist, imagining the movement of either right fist or left fist, the real movement of either both fists or both feet, and the imaginary movement of either both fists or both feet. In our current study, MI task classification of right fist and left fist is considered. Out of 14 runs, only run numbers 4, 8, and 12 corresponding to right fist and left fist MI are evaluated, with eyes closed during the rest considered as a baseline for pre-processing. Each of the MI experimental runs has 15 trials, thus making it 45 MI trials per subject. Each trial would last for 4.1s followed by a rest period of 4s.

Due to the different trial recording parameters and annotations in certain subjects, the proposed approach IMOCS and the benchmarking algorithms are evaluated on 85 subjects where consistency is maintained out of 109 subjects. In this study, the independent variables included are the proposed channel selection technique (IMOCS) and the feature reduction method (mRMR). The dependent variable is the percentage accuracy results of MI task classification.

3.4.2 Data Analysis

The data sets are bandpass filtered between 4 and 40 Hz, as this frequency range carries valuable information related to movement-related tasks in BCI. For this purpose, a fifth-order Butterworth bandpass filter is used. Baseline correction is accomplished by subtracting the mean of signal amplitudes obtained during the trials when eyes were kept open. This time-series information is fed as an input to the channel selection stage wherein the most relevant channels are determined. For any classification problem, it is necessary to have a set of features that are discriminative. However, in some of the real-world applications, the dimensionality of the data is too high for feature extraction because of the redundancy. Thus, dimensionality reduction techniques [64] reduce the number of EEG channels.

After the preprocessing, channel selection algorithm followed by MFBCSP is applied for feature extraction. Several channel selection algorithms are compared to the proposed IMOCS for benchmarking. Especially, principal component analysis (PCA), locality preserving projection (LPP), Fisher discriminant analysis (FDA), and local FDA have been used earlier for dimensionality reduction of EEG features [140]. Motivated by their

findings, this study focuses on the study of eight dimensionality reduction and four other feature selection techniques for choosing the relevant EEG channels. The algorithms considered in this study are traditional dimensionality reduction techniques such as PCA [141], LPP [142], locally linear embedding (LLE) [143], Gaussian process latent variable model (GPLVM) [144], Linear local tangent space alignment (LLTSA) [145], Isomap [146], Neighborhood preserving embedding (NPE) [147], Laplacian Eigenmap [148] and some of the state-of-the-art channel selection algorithms like Fisher Score [60], [149], SVM-Recursive feature elimination (SVM-RFE)[150], CSP channel selection (CSP-CS) [117] and particle swarm optimization (PSO) [151].

PCA has been used in the area of MI BCI for feature reduction [141]. Certain benchmarking algorithms, such as Isomaps and Laplacian Eigenmaps, serve as justification for the weight function used in the proposed method (IMOCS). They define the relationship between the source node (a reference channel) and the target node (a given channel), which justifies our intuition for initializing the channel weights based on their distance. Cost minimization function used in techniques such as LLE, and LLTSA supports our intuition behind the optimization of channels based on smaller weights for bad channels and larger weights for good channels. Most of these techniques are based on the neighborhood initialization followed by the transformation of input feature space into low-dimensional embedding. A brief mathematical description of all the benchmarking algorithms is given in A.

Features extracted from the reduced set of EEG channels followed by MFBCSP (3.3.4) are then classified using an SVM classifier with the help of LIBSVM toolbox [152]. A 5×5 cross-validation is performed to evaluate the performance of the proposed IMOCS as well as the benchmarking algorithms by randomly selecting 80% of all trials for training and the rest 20% for testing and repeating this by randomizing five more times.

Furthermore, to perform the statistical analysis of the proposed approach, SPSS Statistical Modeling Software (SPSS 22.0 IBM Corp., Chicago, IL) is used. We perform one-way analysis of variance (ANOVA) to observe the significant differences among various channel selection algorithms and 2×2 ANOVA to find the interaction effects between two independent variables (proposed channel selection method IMOCS and the feature reduction technique mRMR) on the classification accuracy, which is a dependent variable.

3.5 Results

3.5.1 Performance Evaluation based on the Motor-imagery Classification Accuracy

The results obtained on different datasets will be explained in this subsection. Performance evaluation in terms of classifying the left-hand and right-hand MI tasks is carried out in this study. With this evaluation criteria, we investigated what would be the optimum number of EEG channels that would result in the best performance.

In Table 3.1, the results of the proposed method evaluated on dataset 1 are compared with Filter bank CSP [65], Sparse Common Spatial Pattern -1 (SCSP1) and Sparse Common Spatial Pattern 2 (SCSP2) [68]. SCSP1 and SCSP2 differ in terms of the regularization norm being used. SCSP 1 uses l_1/l_2 norm and SCSP2 uses l_2 norm for the regularization parameter. FBCSP (in the column 3 of Table 3.1) uses pre-selected 25 channels. Column 4 and Column 5 of Table 3.1 represent the performance evaluation of SCSP1 and SCSP2 respectively, uses fewer channels (around 22) as compared to 118 channels. Our proposed method selectively picks 10 most relevant channels for each subject. The results in Table 3.1 clearly suggests that there is a significant improvement in the classification accuracy of at least 8% over the existing method SCSP which itself is proven to be better than Regularized CSP and SVM [68]. Further, the proposed method resulted in a slightly higher accuracy compared to the state-of-the-art FBCSP algorithm (Column 3 of Table 3.1) using just 10 channels as opposed to 25 channels in the case of FBCSP.

During the evaluation of CSP algorithm, the parameter ‘m’ (which decides the spatial filters used in the feature extraction) was set at 2. Thus, the number of features obtained is 36 (2 classes $\times$ 9 filter bands $\times$ 2 spatial filters). The CSP plots for dataset 1 are shown in Fig. 3.2. It can be observed that the spatial filters corresponding to right and foot MI tasks are located in their respective topographic locations of motor cortex.

In our study, the optimal number of features required for achieving good accuracy is estimated using mRMR feature selection algorithm. Since the feature matrix of our method has 36 features, we attempted to minimize the redundancy in feature space that

does not contribute towards the accuracy. Therefore, the accuracy of 10×10 cross validation is estimated with different number of features $f_1 = 2, f_2 = 4, f_3 = 6, \dots, f_9 = 18$. The graph plot of a number of features vs. accuracy is shown in Fig. 3.3. From this observation, it can be concluded that the average accuracy is the highest at $f=10$ features. Further increment in the number of features does not improve the accuracy. Hence, the same feature selection criterion is used for the dataset 2 as well.

The results obtained on dataset-2 are shown in Table 3.2. This dataset employs 22 channels of which 10 prominent channels are being chosen in our proposed method. Column 3 corresponds to the results obtained using all 22 channels. It is to be noted that the classification accuracy of SCSP1 is slightly better (by 0.42%) compared to our method. However, it can be noted that SCSP method with either regularization terms (SCSP1 with l_1/l_2 norm and SCSP2 with l_2 norm) may have feasibility constraints for practical applications of online BCI due to the high computational expense involved in solving sequential quadratic programming [68].

The classification results obtained on dataset-3 are plotted as shown in Fig. 3.4. Here, the x-axis represents the number of EEG channels selected and the y-axis displays the corresponding percentage classification accuracies of classifying left- versus right hand MI averaged over 85 subjects.

For further comparison of the proposed method (IMOCS) to other channel selection algorithms, 35 best-performing subjects were considered. Classification accuracies averaged over these 35 subjects are shown in Fig. 3.5. An average classification accuracy of 79.9% is achieved using the proposed IMOCS method with at least 7% improvement in

Table 3.1: Comparison of Percentage (%) Classification Accuracies of different methods on Dataset-1 with 118 channels

Subject	Proposed method	FBCSP [65]	SCSP1 [68]	SCSP2 [68]
aa	90.68	93.97	80.71	71.42
al	98.39	99.03	97.14	95.71
av	74.93	69.0	57.14	57.14
aw	94.80	95.1	85.0	77.85
ay	95.18	93.82	91.42	94.28
Mean	90.77	90.01	82.28	79.28

Table 3.2: Comparison of Percentage (%) Classification Accuracies of different methods on Dataset-2 with 22 channels

Subject	Proposed method (%)	All Ch [68] (%)	SCSP1 [68] (%)	SCSP2 [68] (%)
A01	89.65	90.97	91.66	91.66
A02	62.96	56.25	67.36	60.41
A03	95.81	96.25	97.91	97.14
A04	75.03	72.91	72.22	70.83
A05	87.80	63.88	65.27	63.19
A06	66.29	63.88	66.27	61.11
A07	89.06	79.86	84.72	78.47
A08	94.53	97.22	97.22	95.13
A09	69.76	91.66	91.66	93.75
Mean	81.21	79.23	81.63*	79.07

the accuracy compared to the next best method, which is, Fisher score-based channel selection. Further, one-way ANOVA was performed to evaluate the statistical significance of channel selection algorithms. In this analysis, the dependent (or response) variable is the classification accuracy, and the independent variables are different channel selection algorithms. Analysis revealed an F ratio, $F(1,85)=6.1$, $p=2.67 \times 10^{-7}$. Although one-way ANOVA gives us an idea of whether there is, at least, a single group mean that is significant compared to the rest, it does not suggest which group mean it is. Therefore, post-hoc analysis using Bonferroni correction is performed. Because there are 13 independent hypotheses (channel selection algorithms), the Bonferroni-adjusted significant value is $p=0.05/13$ (i.e., 0.0038).

Because the overall classification accuracy could be influenced by another confounding factor, which is the number of features selected, we performed two-way factorial ANOVA. It is important to analyze the contribution of both factors, channel selection and feature reduction in terms of main effect (within a factor) and interaction effect (between the factors). This hypothesis testing revealed that the main effect of IMOCs yielded an F ratio of $F(1,136)=14.797$, $p=0.0002$. However, the main effect of feature reduction is not significant as it yielded an F ratio of $F(1,136)=0.649$, $p>0.05$. For better visualization, the interaction plot is shown in Fig. 3.6.

The channel selection is based on the histogram count or the frequency of channel

Figure 3.2: Illustrative CSP plots of 5 subjects (*aa*, *al*, *av*, *aw*, *ay*) in dataset 1 based on the reduced number of channels.

appearing in the Pareto set. For a better visualization, the absolute frequency of appearance of a channel is mapped to the montage of 64 channels, where each channel is assigned a weight corresponding to its frequency. The grayscale image shown in Fig. 3.8 indicates the concentration of channels. The color bar shown in Fig. 3.8 is normalized for better representation. Regions (or channels) filled with black show a high frequency of being selected; similarly, the ones filled with white imply a lesser relevance.

3.5.2 Cross-subject generalization of EEG channel selection

Another study to investigate the effect of channel selection on cross-subject generalization has been carried out to examine whether the subject-independent channels can outperform the results obtained using all channels. The viability of subject-to-subject

Figure 3.3: Performance comparison of using different number of features in the classifier on *Dataset-1*.

transfer could prove beneficial in exploring within the subject or intra-subject variability. As a preliminary investigation, 3×1 cross validation of the pooled data of dataset-2 was performed. As part of this, three different combinations of 6 subjects are used as a

Figure 3.4: Average classification accuracy of 85 subjects in *Dataset-3* as a function of the number of EEG channels.

Figure 3.5: Performance plots of different channel selection techniques evaluated on the best performing 35 subjects of *Dataset-3*.

training set to get the most relevant channels appearing across all training sets. Based on the histogram plot, most frequently selected channels were used for testing the other

Figure 3.6: Effects of the channel selection and feature reduction on the classification accuracy in *Dataset-3*.

Figure 3.7: Histogram plot for statistical estimation of most frequently selected channels across 9 subjects of *Dataset-2*.

Figure 3.8: Absolute frequency mapping of EEG channel occurrence in the subset of most relevant channels in *Dataset-3*.

3 subjects. The histogram for this statistical analysis is shown in Fig. 3.7.

Extension of subject specific channel selection to subject independent channel selection is carried out. The results of subject independent channel selection for MI task are

Table 3.3: Comparison of classification accuracies of subject-independent channels and subject-specific channel selection for the *Dataset-2*

Subject	Subject-Independent Channels	Subject-specific Channels (%)	Channels used
A01	87.26	89.65	'FC3','FC2','FC4','C1','C2','C3','C4', 'C5', 'C6', 'CP3' (6 subjects A04, A05,A09)
A02	59.86	62.96	
A03	93.84	95.81	
A04	73.29	75.03	'FC3','FC2', 'FC4','C1','C2','C3','C6','CP3','CP1' (6 subjects A01, A02, A03, A07, A08 and A09)
A05	86.14	87.80	
A06	60.69	66.29	
A07	93.14	89.06	'FC3','FC4', 'C1', 'C2','C3','C4', 'C5','C6', 'CP3','CP4' (6 subjects A01, A02,A06)
A08	94.13	94.53	
A09	70.45	69.76	
Mean	79.86	81.21	

shown in Table 3.3 . Columns 2 and 3 of Table 3.3 refer to the classification accuracies of subject independent channels and subject specific channels respectively. It can be noted that the deterioration of accuracy obtained from subject independent channels compared to that of subject specific channels is minimal. Column 4 of Table 3.3 corresponds to the most relevant channels used on the test dataset. Motivated by these findings, the cross-subject generalization in the dataset-3 (Wadsworth Data) was evaluated using 5×5 fold cross-validation wherein 68 out of 85 (80%) subjects are considered for training. Based on the histogram count, most frequently appearing channels across these training subjects are used as subject-independent channels for the rest of the 17 test subjects. This random partitioning is done five times to ensure each subset is used for validation exactly once. An example of the histogram count of choosing a set of subject-independent channels is shown in Fig. 3.9, where the x-axis indicates a number assigned to each channel according to the montage specification given in the database and y-axis indicates the normalized frequency of appearance of each channel. The top 16 channels are selected as a set of subject-independent channels for test subjects. Classification accuracies of subject-independent and subject-dependent channels are reported in Table 3.4.

Table 3.4: Cross-validation results of cross-subject generalization performance on *Dataset-3*.

5×5 cross-validation	Mean Classification Accuracy(%)	
	IMOCS	Fisher Score based Channel Selection
Subject-Specific Channels	63.62±6.98	60.07±6.78
Subject-Independent Channels	60.80±1.94	56.57±5.40
Using all 64 channels	61.0141 ± 2.063	

3.6 Discussion

3.6.1 Effect of Channel Selection on the Classification Accuracy

It can be observed from Fig. 3.4 that higher classification accuracy is achieved when the number of channels is neither very few nor very large. This observation is in agreement with the findings reported in [60]. Out of all the number of channels used, best performance is obtained when either 16 or 20 channels are used. For 16 channels, the

Figure 3.9: Histogram count based channel subset selection for cross-subject performance evaluation in *Dataset-3*.

average classification accuracy of 63% was obtained for 85 subjects. An improvement in classification accuracy of more than 2% is shown by 16 channels when compared to using all 64 channels. Therefore, we decided to retain 16 as the sub-space dimension for further comparison with benchmarking algorithms. Also, the number of neighbors employed in the benchmarking algorithms is 12 [153]. We can observe from Fig. 3.5 that, for the same number of channels, IMOCS performed better than all other methods.

3.6.2 Statistical Analysis

Furthermore, the statistical significance tests revealed that there is a significantly different mean classification accuracy. It is observed that the pairwise comparison results obtained from IMOCS are significantly different ($p < 0.05$) from all other channel selection approaches, except Fisher score and SVM-RFE. It is to be noted that, as the number of hypotheses increases, Bonferroni correction becomes more conservative. One has to be careful while reporting the results because, quite more than often, the experimental results are influenced by several confounding factors. In our study, there are two variables (channel selection and feature reduction) to be considered, which might have influenced the overall classification accuracy. Therefore, two-way factorial ANOVA is performed as mentioned in Section 3.5 where channel selection and feature reduction are the factors under consideration. From Fig. 3.6, ordinal interaction behavior can be noticed as the lines are not intersecting. A difference in level for both lines between IMOCS and all channels indicates the main effect of channel selection, which is clearly visible in Fig. 3.6. Therefore, it can be concluded that IMOCS by itself plays a significant role in the better classification accuracy. Although feature reduction combined with IMOCS helps to achieve even higher classification accuracy compared to that without feature reduction, the effect is not statistically significant.

3.6.3 Computational Complexity

Another aspect of computational complexity is also studied, and the comparison is shown in Table 3.5. From this comparison, it can be observed that the proposed approach IMOCS outperforms other methods such as PCA, GPLVM, NPE, and LPP ($\mathcal{O}(D^3)$) that involve eigenvalue decomposition for ranking the channels. It is to be noted that

Table 3.5: Comparison of the computational complexity of various channel selection techniques used in this study

Techniques	Overall Computational Complexity (D : Input Dimension, N : Input training samples, k : number of nearest neighbours, d : output dimension, M : number of Iterations, K : number of particles)
PCA	$\mathcal{O}(D^3 + D^2N)$
GPLVM	$\mathcal{O}[D^3N^3]$
Isomaps	$\mathcal{O}[D \log(k) N \log(N)] + \mathcal{O}[N^2(k + \log(N))] + \mathcal{O}[dN^2]$
LLE	$\mathcal{O}[D \log(k) N \log(N + \mathcal{O}[DNk^3] + \mathcal{O}[dN^2])]$
Laplacian	$\mathcal{O}[D \log(k) N \log(N + \mathcal{O}[DNk^3] + \mathcal{O}[dN^2])]$
LPP	$\mathcal{O}[D^2N + dN^3]$
NPE	$\mathcal{O}[D^3 + dN^3]$
LLTSA	$\mathcal{O}[D \log(k) N \log(N)] + \mathcal{O}[k^2d] + \mathcal{O}[DNk^3] + \mathcal{O}[dN^2]$
PSO	$\mathcal{O}[D^2KM]$
CSP	$\mathcal{O}[D^2N]$
SVM-RFE	$\mathcal{O}[Max(D, N) N^2]$
SCSP	$\mathcal{O}[D^3N^2]$
IMOCS	$\mathcal{O}[DN + N \log_2(N)]$

some of the algorithms have $\mathcal{O}(D)$ similar to IMOCS. However, those algorithms having $\mathcal{O}(D)$ complexity suffer from additional computations due to $\mathcal{O}(N^2)$, whereas IMOCS has a computational complexity of $\mathcal{O}(N)$. Here, the overall computational complexity is represented by the product $N^n D^m$ (where, $n, m > 1$), which is smaller in the case of IMOCS; thus, IMOCS outperforms most of the benchmarking techniques.

3.6.4 Effect of Channel Selection on the Cross-Subject generalization

The use of subject independent channels serve two main purposes of (1) reducing the preparation time in multiple session EEG experiments and (2) obtaining more relevant EEG signals from fewer channels so that redundancy and artifacts/noise due to all the channels would be minimized. The results in Table 3.3 support our hypothesis that the subject independent channel selection can be used to reduce the preparation time without compromising much on classification accuracy. Furthermore, the results shown in Table 3.4 indicate the superior performance of subject-specific channels for classification compared to either using subject-independent channels or using all the channels.

It is noteworthy that the subject-independent selected channels performed as good as using all the channels. The proposed IMOCS method is also compared to the next best channel selection algorithm (i.e., Fisher score-based channel selection for cross-subject generalization). From the results shown in Table 3.4, it can be noted that the Fisher score-based channel selection performed poorly compared to IMOCS in deciding a good set of subject-independent channels. It is also noteworthy that the subject-independent channels obtained using Fisher score did not give higher classification accuracy compared to all the 64 channels. This indicates that the Fisher score-based channel selection is highly subject specific, whereas IMOCS has an added advantage of better results, if not statistically significant. The advantage of IMOCS can be attributed to the fact that it selects a set of channels that are task relevant across different subjects.

Besides, the Fisher score method selects the optimal channels based on a trial (class) label, making it very subject specific. As these subject-independent channels are selected based on the histogram count, there are some channels that have a higher frequency of appearance across subjects. Interestingly, in Fig. 3.8, it can be observed that certain channels such as *Fp1*, *Po1*, and *Po3* are represented darker compared to even some of the channels in the motor cortex. This could be due to the activation of visual cortex while focusing on the screen for observing the cue. Although we do not have the brain mapping results obtained from techniques such as fMRI to support the hypothesis, the possibility of visual cortex activation during an MI task cannot be ruled out. Nevertheless, using these subject-independent channels obtained from IMOCS still assist in minimizing the redundancy due to noisy artifacts. The statistical significance test is carried out pairwise for three methods, and the analysis revealed an F ratio, $F(1,25)=13.62$, $p=0.001$, for subject-specific channels versus subject-independent channels, thus rejecting the null hypothesis.

3.7 Summary

The key objective of the study presented in this chapter was to investigate the effects of EEG channel selection as a spatial filtering method to evaluate the classification accuracy and also its implications for cross-subject generalization. Recording from all the EEG

electrodes is an arduous task, especially during multi-session experiments and clinical scenarios. Therefore, an extensive study was carried out to evaluate various channel selection techniques for MI task classification. The results suggested that the classification accuracy of the proposed method is substantially higher than all other benchmarking algorithms used in this study. Also, the proposed method has lower computational complexity compared to other benchmarking algorithms. Furthermore, different datasets with variable number of subjects gave a prospect to investigate cross-subject generalization. The proposed method IMOCS outperformed the next best benchmarking algorithm (i.e., Fisher score-based channel selection by selecting a subset of channels for subject-independent analysis). Findings from the assessment of subject-independent channels for untrained test subjects indicate the improvement in classification accuracy when compared to using all the channels. A wide range of subjects provided us a good estimate of whether a cross-subject generalization can be significant or not. It would be interesting in the future to employ the current method for real-time online BCI experiments, as it is computationally less expensive compared to other channel selection methods. With the emphasis of EEG channel selection as a type of spatial filtering technique, the thesis will focus on the new types of spatial filtering algorithms in the next chapter where a novel regularization framework is presented to handle small-sample non-stationarities.

Chapter 4

Spatial filtering: Moving from Sensor- to Source-space EEG

4.1 Introduction

As we have seen in the previous chapters, the spatial filtering algorithms like CSP can be used to classify motor imagery tasks in a BCI experiment. However, CSPs are not very robust when the training sample size is not big enough. Therefore, some form of a regularization approach is required which can handle small sample settings as well as noisy outliers. Furthermore, it is essential to address the inter-trial variability and low signal-to-noise ratio (SNR) in a single-trial EEG [154]. In addition to this, there are still certain challenges with respect to the temporal dynamics, as the background EEG activity is correlated not only in spatial but also the temporal domain. As we can recall from chapter 2, accurate information of spatial and temporal characteristics is required for the precise localization of cortical sources. We should note that the background neural activity at the cortical level contribute to the ‘noise’ in the sensor-space EEG as there is a linear mixing of these various background neural signals. Therefore, a robust spatial filtering algorithm should handle noisy between-sensor covariances. Since the covariance estimation plays a crucial role in the spatial filtering, this chapter explicates the significance of robust covariance estimators to improve the classification accuracies in MI-BCI experiments.

4.2 Shrinkage Regularization based Covariance Estimation for Spatial Filtering

Although there have been some studies which regularize the covariance matrix based on weighted approach, most of them depend on either hand-picked constant or cross-validation [71]. However, in an online setting it is important to find a computationally efficient analytical solution for the regularization parameter. The objective of this approach is to handle trial-to-trial variability that is inherent in most of the EEG based BCI experiments. In the context of EEG covariance matrix estimation, shrinkage parameter has been used to compute normalized distance to true covariance matrix [155]. The initial contribution in this chapter is to use shrinkage estimator as a regularization technique for CSP to classify motor imagery EEG. It also has the advantage of an analytical solution for the regularization parameter and does not require heuristic evaluation, thus very useful in an online BCI. This estimator regularizes the sample-to-sample variation in the empirical covariance matrix resulting in a more robust estimation.

4.2.1 Shrinkage-Regularized Common Spatial Pattern (SR-CSP)

As described in the previous chapters, CSP is one of the most widely used algorithms in BCI experiments because of its capability in discriminating two classes very effectively [44]. However, the CSP has its limitations of being highly sensitive to spatio-temporal noise and severely over-fits in the cases where the training set is small [156]. CSP does a linear transformation of EEG signal (N channels $\times$ T samples per trial) into a low-dimensional subspace. We can recall that the conventional covariance matrices for CSP computation are expressed as Eq. (4.1) [44],

$$C_{E_i} = \frac{E_i E_i^T}{\text{trace}(E_i E_i^T)} \quad \forall i = \{1, 2\} \quad (4.1)$$

where, E_i denotes $E \in \mathbb{R}^{N \times T}$ for class ' i '. $\text{Trace}(E)$ gives the sum of all the diagonal elements in the matrix ' E '. Usually these spatial covariance matrices C_{E_1} and C_{E_2} are averaged over the trials to result in the sample covariance matrices S_1 and S_2 which are denoted as Eq. (4.2),

$$S_1 = \frac{1}{N_1} \sum_{j=1}^{j=N_1} C_{E_1}(j) \quad S_2 = \frac{1}{N_2} \sum_{j=1}^{j=N_2} C_{E_2}(j) \quad (4.2)$$

where, N_1 and N_2 represent the number of class 1 and class 2 trials respectively.

Most of the conventional techniques for covariance estimation employ sample covariance estimator. However, it is to be noted that an estimator which is both well-conditioned and more accurate than sample covariance matrix is needed to achieve robust performance in small-sample settings [157, 158]. This estimator is the weighted average of sample covariance matrix and the structured estimator.

$$\hat{\Omega}_S = \alpha_\Omega T_\Omega + (1 - \alpha_\Omega) S_\Omega \quad (4.3)$$

Eq. (4.3) represents a linear combination of two types of covariance estimators with high-variance-low-bias (S_Ω) and low-variance-high-bias (T_Ω). Considering the *Omega* as an unknown true covariance to be estimated, we need a structured estimator ($\hat{\Omega}$) that minimizes the least square error i.e., $LSE(\hat{\Omega}_S) = \min(E\{\|\hat{\Omega}_S - \Omega\|_F^2\})$, (where $\|\cdot\|_F$ is the Frobenius norm). The shrinkage estimator allows us to find the optimal shrinkage parameter (α_Ω). The idea is to use shrinkage estimator instead of the sample covariance matrix (S_Ω) for eigenvalue decomposition in Common spatial pattern algorithm.

There are already studies in which structured estimator has been used to regularize the CSP [46, 70]. However, these studies involve choosing the regularization parameter by cross-validation. As this is a tedious process and applicable for offline BCI, an analytical solution for regularization parameter is preferred in an online BCI setup. It can be computed by minimizing the least square error as follows in Eq. (4.4),

$$\begin{aligned} LSE(\hat{\Omega}_S) &= \mathbb{E}\{\|\hat{\Omega}_S - \Omega\|_F^2\} \\ &= \mathbb{E}\{\|\alpha_\Omega(T_\Omega - S_\Omega) + (S_\Omega - \Omega)\|_F^2\} \\ &= \alpha_\Omega^2 \mathbb{E}\{\|T_\Omega - S_\Omega\|_F^2\} + \mathbb{E}\{\|S_\Omega - \Omega\|_F^2\} \\ &\quad + 2\alpha_\Omega \mathbb{E}\{tr\{(T_\Omega - S_\Omega)(S_\Omega - \Omega)^T\}\} \end{aligned} \quad (4.4)$$

Here, the relation $\|A + B\|_F^2 = \|A\|_F^2 + \|B\|_F^2 + 2tr\{AB^T\}$ for square matrices is used. Shrinkage parameter α_Ω is derived by equating the first order differential of $LSE(\hat{\Omega}_S)$ to zero.

$$\hat{\alpha}_\Omega = \frac{\mathbb{E}\{tr\{(T_\Omega - S_\Omega)(S_\Omega - \Omega)^T\}\}}{\mathbb{E}\{\|(T_\Omega - S_\Omega)\|_F^2\}} \quad (4.5)$$

The numerator can be decomposed into ,

$$\begin{aligned}
 & \mathbb{E}\{tr\{(S_\Omega - T_\Omega)(S_\Omega - \Omega)^T\}\} \\
 &= \mathbb{E}\{\|S_\Omega\|_F^2\} - tr\{\mathbb{E}\{T_\Omega S_\Omega^T\}\} \\
 &\quad - tr\{\mathbb{E}\{S_\Omega - T_\Omega\}\Omega^T\} \\
 &= \mathbb{E}\{\|S_\Omega\|_F^2\} - tr\{\mathbb{E}\{T_\Omega S_\Omega^T\}\} \\
 &\quad - tr\{\mathbb{E}\{S_\Omega - T_\Omega\}\mathbb{E}\{\Omega^T\}\} \\
 &\quad + tr\{\mathbb{E}\{S_\Omega - T_\Omega\}\mathbb{B}\{\Omega^T\}\} \\
 &= \underbrace{\mathbb{E}\{\|S_\Omega\|_F^2\} - \|\mathbb{E}\{S_\Omega\}\|_F^2}_{\mathbb{V}\{S_\Omega\}} \\
 &\quad - \underbrace{tr\{\mathbb{E}\{T_\Omega S_\Omega^T\}\} - \mathbb{E}\{T_\Omega\}\mathbb{E}\{S_\Omega^T\}}_{\mathbb{C}\{S_\Omega, T_\Omega\}} \\
 &\quad + tr\{\mathbb{E}\{S_\Omega - T_\Omega\}\{\Omega^T\}\}
 \end{aligned} \tag{4.6}$$

where, $\mathbb{B}\{S_\Omega\}$ is a biased matrix of S_Ω written as $\mathbb{E}\{S_\Omega\} - \Omega$. If we consider S_Ω as an unbiased estimator of Ω , then $\mathbb{B}\{\Omega^T\}$ in the above expression becomes zero. Therefore, the analytical expression for α_Ω is given as,

$$\hat{\alpha}_\Omega = \frac{\mathbb{V}\{S_\Omega\} - \mathbb{C}\{S_\Omega, T_\Omega\}}{\mathbb{E}\{\|(T_\Omega - S_\Omega)\|_F^2\}} \tag{4.7}$$

here, $\mathbb{V}\{S_\Omega\}$ corresponds to the Frobenius norm variance of S_Ω , and $\mathbb{C}\{S_\Omega, T_\Omega\}$ corresponds to the covariance between the S_Ω and T_Ω . Now the composite spatial covariance matrix C_c expressed as shown in Eq. (4.8),

$$C_C = \bar{\Omega}_{S_1} + \bar{\Omega}_{S_2} \tag{4.8}$$

Once the analytical solution for α is computed using Eq. (4.7), the subsequent stages of CSP computation follow as described in section 2.2.2.

Filter bank variant of SR-CSP (SR-FBCSP) is similar to that of SR-CSP, but differs in terms of number of output features. It follows the exact same procedure to compute FBCSP, only differs in the way in which the covariance matrices are estimated.

4.2.2 Methods

Two datasets (*Dataset 2* and *Dataset 3*) of considerably different number of subjects, channels and trials are evaluated in this study. *Dataset-2* consists of 9 subjects' EEG

recorded over 144 trials of 2 classes, and *Dataset 3* consists of 109 subjects' MI EEG data with 45 trials per subject. These datasets are described in the previous chapter 3.4.1.

The data processing involves zero-phase bandpass filtering of raw EEG signal between 4-40Hz using 5th order Butterworth filter. After estimating the covariances using shrinkage regularization, the FBCSP approach is used in which the input EEG is filtered in 9 different filter banks of 4 Hz bandwidth each i.e. 4-8 Hz, 8-12 Hz, 12-16 Hz,..., 36-40 Hz. The filter bank approach is preferred due to the discriminative subject-specific frequency range, which helps in improving the classification accuracy [159, 66]. Filtered signals are then segmented into epochs based on the trial label and duration. Subsequently, these filtered signals are projected into a different subspace using shrinkage regularized Common Spatial pattern. New feature space is minimized using a feature selection algorithm called minimum redundancy maximum relevancy (mRMR) [57]. For further feature classification, Support Vector Machine Classifier based on LIBSVM package is used [152]. 10×10 cross validation is performed to ensure robustness.

4.2.3 Results and Discussion

The performance of the proposed method is evaluated based on the classification accuracy as resulted by 10 fold cross validation using the SVM classifier. Since the *Dataset 3* used in this study has 85 subjects, subject-wise accuracy is difficult to interpret. Therefore, a jittered boxplot is shown in Fig. 4.1 in which the jittered data points show the distribution of classification accuracies of various subjects and the boxplot itself highlights information regarding the mean and median classification accuracies. From Fig. 4.1, it can be observed that SR-FBCSP and SR-CSP outperforms FBCSP and CSP by at least 3%. Also, SR-FBCSP performs better compared to SR-CSP due to discriminative information from multiple frequency bands. These results are in agreement with [65], which presents superiority of FBCSP compared to CSP. In [65], FBCSP is integrated with Mutual Information based Best Individual feature (MIBIF) as its feature selection algorithm and Naive Bayesian Parsen Window (NBPW) as its classification technique. In the current work, FBCSP is integrated with mRMR and SVM for feature selection and classification. It can be observed that the results for Dataset-2 shows slightly improved accuracy compared to [65].

Figure 4.1: Boxplot of 10×10 cross validation accuracies obtained on *Dataset-3* using variants of CSP and FBCSP with and without regularization

Table 4.1: Percentage Classification accuracies obtained for each subject of *Dataset 2* for the standard CSP and its regularized variants

Subjects	CSP(%)	SR-CSP (%)	FBCSP (%)	SR-FBCSP(%)
A01	56.38	58.75	87.51	89.24
A02	68.21	66.99	63.41	59.36
A03	79.75	80.17	96.87	95.81
A04	54.79	55.84	72.34	70.73
A05	65.42	64.87	79.34	78.1
A06	56.25	60.02	65.64	69.98
A07	74.88	75.27	85.26	88.24
A08	95.77	94.11	94.8	95.32
A09	88.33	87.36	89.39	91.92
Mean	71.0867	71.4867	81.6178	82.0656

It is to be noted that the number of training trials is very less in *Dataset 3* compared

to that of *Dataset 2*. Therefore, 10×10 cross validation is performed to ensure the same training to testing ratio. From the results shown in Fig. 4.1 and Fig. 4.2, it can be observed that regularized approach (SR-CSP and SR-FBCSP) performs much better than CSP and FBCSP in *Dataset 3*, however it is not so significant in *Dataset 2*. Reason for this can be attributed to the fact that shrinkage regularized approach makes a difference when the training set is small. Otherwise the shrinkage parameter (α_Ω) in Eq. (4.3) approaches zero, thus reducing the whole expression Ω_S into S_Ω which is essentially the sample covariance matrix. Apart from the classification performance distribution shown in Fig. 4.2, subject-specific classification accuracies for Dataset 2 is shown in Table 4.1. From this table, an improvement of slightly more than 10% can be observed when the filter bank approach is used. Also, the proposed SR-FBCSP method results in better accuracy, if not statistically significant compared to the regularized approaches presented in [160]. In addition to this, it is interesting to observe the spatial patterns confirming

Figure 4.2: Boxplot of 10×10 cross validation accuracies obtained on *Dataset 2* using variants of CSP and FBCSP with and without regularization

Figure 4.3: Visualization of regularized filter bank Common Spatial patterns in some representative subjects of Dataset-1

the neurophysiological correlation of left and right hand motor imagery in Fig. 4.3. In this figure, the topographical plot of SR-FBCSP is shown for few representative subjects from *Dataset 3*. It can be observed that there is a clear discrimination between left and right hand motor imagery in its contralateral brain region, thus validating the neurophysiological plausibility of the proposed method.

Summary: In this section, a shrinkage parameter based regularized approach for Filter bank Common Spatial Pattern (SR-FBCSP) was presented. The proposed method

was evaluated on the EEG data from 2 publicly available datasets. Overall, Shrinkage Regularized Filter Bank Common Spatial Pattern (SR-FBCSP) gave better results compared to other variants of CSP. For a bigger dataset, shrinkage parameter approaches zero, thus resulting in a similar performance as that of a non-regularized approach. On the contrary, SR-FBCSP gives better results when the number of training trials is very less. This is validated from the results obtained on *Dataset 3* with less than 25 trials per class for a given subject. Furthermore, this shrinkage approach for covariance estimation plays an important role in the EEG source localization. It would be interesting to observe the effect of regularized spatial covariance matrix on inverse modeling for EEG source localization to analyse single-trial EEG, which will be discussed in the next section.

4.3 Spatiotemporal EEG Source Localization for Movement Decoding

Although there are non-invasive EEG based BCI studies which demonstrate the contralateral motor cortex activation during movement planning and execution, they are often limited to a time-averaged response in a given trial. In order to temporally locate the motor intention within a single trial, it is necessary to know which part of the brain is more active at a given instant. To this end, the information given by the cytoarchitectural maps (e.g., Brodmann Atlas) of the human brain can be leveraged that labels different parts of the brain associated with different functionalities [161].

As mentioned earlier, EEG does not provide much information regarding the specific cortical source responsible for a given task. In this regard, inverse modeling can help us to localize the active sources from the obtained scalp EEG signal. Since the number of cortical sources outweigh the number of EEG channels, this inverse problem becomes ill-posed. Therefore, apriori information about the number of dipoles, volume conductivity, region of interest (ROI) and other regularization parameters are used to minimize the unknown variables. In [162], electrophysiological imaging is illustrated by reviewing various methods. Minimum Norm estimate (MNE) is one such optimization method which uses L2 norm for source estimation by applying certain physical and physiological constraints [163]. Several variants of MNE are presented in the literature which are

extensively used for Source localization of EEG and MEG [5]. There are some studies which have focused on source localization to analyze motor imagery tasks. In [164], motor task classification using source analysis based on Cortical Current Density (CCD) is performed. The results demonstrate that the equivalent dipole analysis and CCD can localize the sources better than spatial filtering using the Surface Laplacian.

Similar approach for classifying left and right hand MI is used in [165]. However, the classification based on source localization features is not trivial to justify, if there is no ground truth from a neuroimaging modality. In [96], EEG based MI direction classification is performed, where the source analysis is used to demonstrate the focal activation in sensorimotor area (SMA). Another study with multimodal EEG-fMRI approach is presented for higher gamma-band activation during motor imagery tasks, and also the co-localization of EEG with that of fMRI Blood Oxygenation Level Dependence (BOLD) is clearly presented [166]. Although these studies provide compelling evidence for using EEG to locate the cortical sources, seldom they confine the temporal window of activation. It is necessary not only to analyse “which” part of the brain is activated during a task, but also to analyse “when” the activity triggered in a specific cortical region. Therefore, in this section, a method to analyse the spatiotemporal localization of single trial EEG is proposed, and it is evaluated on the publicly available Wadsworth dataset.

It is to be noted that while evaluating the source localization results, an fMRI ground truth is required as a validation tool. Since the dataset used for evaluation is EEG-only, it is difficult to justify whether the source localization results are accurate. As an alternative metric to validate the results, it is desirable to select those subjects which are known to have performed well. In this regard, the subjects in Dataset 3 whose MI-BCI classification accuracies based on SR-FBCSP features (previous section 4.2.3) were higher than 95% are considered. The aim is to validate further in which time window one can observe the ERS/D for a given trial.

4.3.1 Methodology

4.3.1.1 Data Preprocessing

The data used for this study is *Dataset 3*. The data description is provided in the previous chapter 3.4.1. Altogether, 45 trials segmented from 3 runs per subject are evaluated for further processing.

Preprocessing is performed to minimize the effect of eye and muscle related artifact to improve the signal quality when performing movement imagination tasks. Before the artifact removal, EEG recordings from all 64 channels are segmented based on the time markers. Continuous signal recording is bandpass filtered from 0.5Hz to 40Hz using 4th order zero-phase Butterworth filters. Furthermore, the time segment of 2 seconds before the cue ('T1' or 'T2') is considered for baseline correction and the time series information for 3 seconds after the cue is extracted for task specific information. This epoched data is further spatially filtered using Common Average Referencing (CAR) [25]. This spatial smoothing method calculates the mean of all EEG channels and then subtracts it from each channel, thereby minimizing the effect of noise common to all the EEG channels.

Independent Component Analysis (ICA) denoising ICA has been quite popular in identifying the independent components of the signal by transforming the data into different subspace [167]. It allows us to identify those artifact not related to brain activity such as eye blink, neck muscle movement, and others. For this purpose, extended Infomax Independent Component Analysis (ICA) in EEGLAB toolbox is used [168]. However, it requires visual inspection by an expert to identify and reject those independent components (ICs) which makes it a subjective decision dependent and time-consuming procedure. Therefore, ADJUST plugin [169] for EEGLAB toolbox is used for automatic detection and removal of artifact components after running ICA on spatially filtered epoched data. ADJUST is an automated algorithm which identifies eye blinks (EB), horizontal eye movement (HEM), vertical eye movement (VEM) and generic discontinuities (GD) based on statistical computation methods like spatial average difference (SAD), Maximum Epoch Variance (MEV) and Temporal Kurtosis (TK).

4.3.1.2 Source Localization

The mathematical framework for the EEG source localization has already been discussed in the earlier chapter 2.3. In this subsection, I shall discuss the practical aspect of implementing the EEG source localization.

Forward Head Modeling The accuracy of EEG source localization depends on the forward head modeling. The dataset under study is not a multimodal (EEG-fMRI) integrated data and therefore, subject specific fMRI scans are not available. Thus, this study requires the use of a template anatomy for which the Talairach human brain atlas as registered in International Consortium of Brain Mapping (ICBM) template [170] is used. ICBM 152 template anatomy is a nonlinear average of MRI scans of 152 healthy subjects that can be used for co-registration of an individual subject anatomy to develop a head model. Although the requirement of subject-specific head model based on individual fMRI seems intuitive, studies suggest that the template scan can still provide comparable results in the case of group analysis [171]. Head model is assumed as a 3 layered spherical model warped to template anatomy. Conductivity values of 1 S/m, 1 S/m, and 0.0125 S/m is used for brain, scalp and the skull [172]. Symmetric Boundary Element method (sBEM) in OpenMEEG [81] is used for the purpose of interpolating triangular meshes.

Inverse Source Modeling In this study, Standardized Low-Resolution Electromagnetic Tomography (sLORETA) is used as a nonparametric inverse modeling [173]. Brainstorm toolbox is used to implement this source modelling with 15002 voxels. As we can recall from the mathematical model of EEG source imaging (Eq. 4.9), the sensor space recordings are due to the linear mixing of cortical source time series in addition to the noise perturbation term (ε).

$$\phi_{sensor} = \mathbb{L}_f J_{sLORETA} + \varepsilon \quad (4.9)$$

Here, the covariance of ε is estimated trial wise using the automatic shrinkage regularization method. Subsequently, the source kernel matrix is multiplied with the observed sensor recordings ϕ_{sensor} to obtain the time-series information in the source space ($J_{sLORETA}$).

Once the source-space EEG time series information is obtained after inverse modeling, then Intra-trial Task Related Desynchronization is computed as explained in Section 3.3.2 in Chapter 3.

4.3.1.3 Region of Interest (ROI) for functional modeling

The aim of creating a region of interest is to group the voxels which belong to functionally similar cortical region. In this study, Brodmann atlas is used to create an ROI as it allows us to map different regions in the brain associated with a similar functional behaviour. Brodmann areas namely BA4, BA6 which covers sensorimotor association cortex (SMA), premotor cortex (A6) and some part of postcentral gyrus are largely associated with movement related functions. The source activation values are constrained to this region.

4.3.2 Results and Discussion

Data pre-processing involves ICA denoising and the automatic detection of artifacts using ADJUST algorithm. One of the examples of affected components is shown in Fig 4.4. It can be observed that the vertical eye movement is detected as an artifact owing to large amplitude fluctuations in frontal region. The data should be free from artifacts to achieve an accurate source modelling as otherwise it could affect the results of source localization. Since the fundamental assumption in EEG is the synchronization between surrounding channels that are associated with similar neural functionality, those components can be discarded as artifacts which show sudden discontinuity in comparison with a neighbouring component. Other possible artifact detection is related to an eye blink, where there is a sudden increase in the amplitude of channels located in frontal region.

Once the pre-processing is done, source localization is carried out as per the method mentioned in section 4.3.1.2. Forward modelling is independent of the signal information as it requires only the EEG electrode positions and the conductivity values of brain, scalp, and skull. Therefore, forward modelling can be done even before the pre-processing. OpenMEEG plugin with Brainstorm toolbox is used to model subject's head with the conductivity values as mentioned in the Section 4.3.1.2. The results of forward head modelling are shown in Fig. 4.5. In this figure, (a) depicts the electrode registration on the template head model, while (b) shows Boundary Element method (BEM) based characterization of head surface. BEM uses triangular meshes as seen in Fig. 4.5(b)) which are parcelled into equal sized patches.

Source localization results based on sLORETA is shown in Fig. 4.6. It is a representative figure of one of the left hand MI trials of a subject S034. Although the results shown

Figure 4.4: Example result of artifact detection using ADJUST algorithm

in this image is for only 1 trial, it is reproducible for other trials as well. In Fig. 4.6a, there are 40 images of cortex surface representing the brain source contribution. Each cortical image is a volume temporally sliced at every 125ms. The brain source activation is shown on absolute scale (magnitude values only) since for a given voxel, its activation can be best represented if it is significant compared to other voxel.

A threshold of 50% is set, which means those voxels are shown to be ‘activated’, if their activation values are more than 50% of the highest voxel activation. In Fig. 4.6b, the time-course average of ITTRD over the region of interest is shown. It can be noticed in the figure that the ITTRD is not negative, as only the magnitude is considered. The interesting part of the image is the temporal localization of this ITTRD activity in the

Figure 4.5: Forward head modeling based on 3 layered nested concentric sphere. (a) 64 electrodes registered on the scalp, (b) Mesh-based Boundary element method (BEM) for co-registration

region of interest defined over the right motor cortex. Visibly discriminative peak can be observed at around 0.5s after the onset, marking the moment of movement imagination in a given trial. The peak around -1.75s can be attributed to the possible motor imagery during the rest trial. However, the focus is to locate the time instant after the stimulus is presented. Thus, significant activation in ROI at 0.5s post-onset is considered to be the key finding.

In this section, a novel approach to analyse the single-trial EEG is proposed. Conventional methods to analyse EEG based motor imagery tasks do not give sufficient information about the ‘moment’ of movement imagination within a single trial. However, this can be tackled by using source localization approach to detect the activation of cortical sources that are responsible for the movement imagination. Since EEG in itself is not a neuroimaging modality, a 3D head geometry is modelled using template anatomy and inverse problem to find the cortical sources is solved using sLORETA. This section gives a proof-of-concept of an idea which could be extended to real-time BCI experiments for spatiotemporal localization of complex movement imagination of arm, shoulder, and wrist, etc. Also, this section bridges the subsequent chapters from now on, as the following sections and chapters will involve a comprehensive study of the neural correlates of movement decoding.

(a)

(b)

Figure 4.6: (a) Temporal slicing of EEG source localization results during a left hand movement imagination task. (b) Single trial ERS averaged over the cortical region of interest (ROI) in contralateral motor cortex (RH) for left hand MI task

4.4 Comparative Study of Spatial Filtering in the Sensor- and Source -space EEG for Multi-direction Movement Decoding

In the previous section, the spatiotemporal localization of movement imagery was presented using an EEG source imaging approach exploiting simple band power features. Extending further, the state-of-the-art spatial filtering algorithms in the EEG source domain will be explored in this section. There are no EEG source-space studies investigating the use of discriminative cortical patterns to classify the challenging tasks such as Multi-direction arm movement. It is necessary to have spatial information much more than just the scalp topography to achieve higher classification accuracy in multi-class movement related tasks. We can recall from the concept of motor homunculus that the cortical activation regions corresponding to complex motor tasks are often overlapping or located very close to each other inside the cortex [174]. Now, the CSP variants in both sensor- and source-domain will be presented to classify the EEG of 4-direction hand movement.

4.4.1 Methodology

4.4.1.1 Participants

Seven healthy right-handed healthy participants (all male, age range: 25 - 36, mean 31 ± 4.4 (SD)) took part in this experiment. All participants gave a written informed consent before participation. The experimental protocol was approved by the local Institutional Review Board of Neural Signal Processing Laboratory at Institute for Infocomm Research (I2R), Singapore.

4.4.1.2 Data Acquisition

EEG was continuously recorded from 118 electrodes out of a 128-channel Quickcap placed on subject's head, according to the extended International 10-20 system. Neuroscan SynAmps2 amplifier was used to record the EEG data during the experiment conducted at Brain-Computer Interface Laboratory at Institute for Infocomm Research, Singapore. Continuous EEG data were sampled at 250 Hz, followed by band-pass filtering between

Figure 4.7: Experiment setup and task timeline (a) Direction cues for 2D center-out movements are shown with the dark filled circle at the centre referred to as initial ‘Home’, and the target circle (blank circle on the circumference) indicating the final position (b) Experimental setup including the reaching apparatus -MIT MANUS robot; (c) Task timeline for direction cue ‘NORTH’. EEG recorded during the ‘Analysis Timeline’ has been used for further processing.

0.5 Hz and 100 Hz. Subsequent data analysis was performed offline using custom written MATLAB[®] code.

4.4.1.3 Experimental Setup

The experimental setup involved center-out right hand movement in 4 directions (North, South, East, and West) using the MIT-MANUS robotic arm [175] as indicated in Fig. 4.7. “North” indicates the movement of the subject’s hand outward and away from the body, “South” indicates the subject’s hand movement inward and toward the body. Similarly, “West” and “East” corresponds to the movement towards left and right respectively. In this experiment, subjects were seated in front of a monitor, and they were instructed to hold the MIT-MANUS robot arm with their right hand, while the left hand was rested on the table. The display monitor was placed at a comfortable viewing distance

of about 60 cm in front of the subject. The cursor was shown in the form of a plus sign. The target was a circle of 1 cm radius displayed on the screen, initially positioned at the center. Every trial began with a rest period of 4s, after which visual cues were shown on the screen as a cursor and a target circle. Based on a randomized stimulus, the target circle shifted from the center of the screen to another position on the screen corresponding to the direction cue, allowing the subject to plan his hand movement in the direction instructed. The target circle remained at its new position for 2s after which the ‘home’ circle disappeared, thus signaling the subject to move his hand. Center-to-target distance is about 15cm. Subjects performed a task of center-out movement by moving the robot arm to match a cursor with a target circle shown on the screen during one of the four conditions. The robot recorded different kinematic parameters such as position, velocity, and force applied. Subjects were instructed to finish their movement from center-to-target (distance 15cm) within 0.5s to avoid confusion regarding the duration of the reach. Moreover, the movement accuracy was not very critical as the task required only coarse movement to target direction. None of the trials were rejected based on the movement trajectory information. The position of the target circle was continuously presented throughout the experiment. Electrooculography (EOG) was also recorded to monitor eye-movement. A total of 40 trials for each direction was recorded for each subject, thus resulting in 160 trials in 4-directions.

An overall block diagram of the proposed method to use spatial features from sensor- and source-space EEG is illustrated in Fig. 4.8.

4.4.1.4 Preprocessing

EEG recorded from all 118 channels is used for the analysis. Since the objective is to use the cortical time series information for better feature extraction, a dense EEG headset is used to record the data as suggested in [176]. Trial segmentation is based on randomized trial codes corresponding to the hand movement in ‘East,’ ‘West,’ ‘North,’ and ‘South’ direction that is also analogous to ‘right,’ ‘left,’ ‘forward’ and ‘backward’ direction respectively. Continuous EEG was segmented into uniform epochs of 2 seconds each, with a baseline of 1 second (-1 to 0 s) and movement for 1 second (0 to 1s), thus covering the movement preparation and execution. It is to be noted that the subjects were instructed

Figure 4.8: Block diagram of the proposed methodology illustrating the use of sensor- and source-space EEG to compute features for classifying the hand movement in 4 directions

to finish their movement within 0.5s, therefore the EEG corresponding to 0.5s-1s gives us the post-movement information. Raw EEG from all 118 channels is band-pass filtered between 0.5-100 Hz using a 14th order Chebyshev Type-2 filter. Artifacts correction was done using Independent Component Analysis (ICA) with the help of EEGLAB toolbox [168]. ICA was implemented using an extended infomax algorithm applied to all 118 EEG channels across 160 concatenated trials corresponding to 4 different classes, where each trial epoch was of duration 2s. Artifact removal involves visual inspection of every ICs, which is a tedious process. ADJUST (Automatic Detector- Joint Use of Spatial and Temporal Features) plug-in extension to the EEGLAB toolbox was used [169] to avoid the time-consuming process of manual inspection of all independent components (ICs). ADJUST is an automated artifact detection algorithm that uses various statisti-

cal measures such as Spatial Average Difference (SAD) score, Maximum Epoch Variance (MEV) and Temporal Kurtosis (TK) to identify eye related artifacts such as eye blinks, horizontal and vertical eye movements, and other generic discontinuities. Independent components that were identified as artifacts by the ADJUST plugin were then removed, followed by interpolation of removed components. EOG artifacts were also removed by finding the artifact components that are highly correlated with the recorded EOG. The rest of the data were then back-projected into the sensor space. Subsequently, the local Surface Laplacian filter was applied to the data as it is found to be robust in separating out muscle artifacts [177].

4.4.2 EEG source Imaging

The proposed approach involves regularized variants of a traditional spatial filtering algorithm CSP in the cortical source space. Since EEG source space information is not directly observable from the scalp recordings, it requires inverse modeling to find the cortical source activation. We use the weighted minimum norm estimation (wMNE) for inverse modeling [5] and also it has been used in [106] for multi-class arm motor imagery classification. wMNE, a compensated form of minimum norm estimate also accounts for the activation of dipoles at the cortical surface in addition to the deeper ones. wMNE is mathematically represented as Eq. (4.10),

$$D_{wMNE} = (L_f^T L_f + \alpha W^T W)^{-1} L_f^T \phi \quad (4.10)$$

where, L_f is the lead field matrix, α is a regularization parameter, W is the weight matrix computed by taking the norm of columns of the lead field matrix L_f .

Brodmann area BA6, which covers the dorsal premotor cortex in both the hemispheres, is chosen as the region of interest since it is shown to be associated with the direction of voluntary arm movement [178, 179]. Out of 15002 voxels resulted in the source kernel, only 296 voxels corresponding to the left and right premotor cortex are used for further feature extraction. These voxels can be considered analogous to the channels in the source space. Time series information from these voxels is further used in the feature extraction stage.

4.4.3 Feature extraction

Since traditional approaches use different variants of the popular CSP algorithm for feature extraction, CSP with- and without regularization method is evaluated in the sensor- as well as source-space. Overall, three different techniques namely CSP, Tikhonov regularized CSP (TRCSP), and Shrinkage Regularized CSP (SRCSP) are compared in both domains. CSP is a spatial filtering algorithm which learns the spatial filters by maximizing the variance of EEG signals from one class while minimizing the variance from other class. We can recall that the CSP can be formulated as a generalized Rayleigh quotient shown in Eq. (4.11) [44],

$$J(w) = \frac{w^T C_1 w}{w^T C_2 w} \quad (4.11)$$

where, C_i is the covariance matrix of class ‘ i ’, and ‘ w ’ are the spatial filters. However, CSP is sensitive to overfitting, and thus, it requires some form of regularization. There are several approaches which add regularization term to an objective function $J(w)$ or the covariance matrix (C_i) as shown in Eq. (4.12) and Eq. (4.13) respectively [71]. For this purpose, TRCSP and SRCSP are chosen.

$$\hat{J}(w) = \frac{w^T C_1 w}{w^T C_2 w + \alpha P(w)} \quad (4.12)$$

$$C_c = (1 - \gamma)C_i + \gamma I \quad (4.13)$$

Here, α is the regularization parameter used in the Tikhonov regularization and γ is a parameter employed in the shrinkage regularization which regularizes the covariance matrices. Tikhonov regularization is a classical approach in most of the regularization problems in which the solution with larger weights is penalized. TRCSP regularizes the objective function $J(w)$ with quadratic penalties $P(w)$, and the results show that TRCSP is very efficient compared to CSP among in comparison with other regularization approaches [71]. In addition to this, Shrinkage regularized CSP is also considered that regularizes class-wise covariance matrix in which the shrinkage parameter in Eq. (4.13) can be analytically solved using Ledoit and Wolf’s method [157]. SRCSP approach has been well described throughout this chapter. We can recall that the SRCSP

approach performs better especially when the training sets are small. For TRCSP, the regularization parameter α is chosen empirically as $10e-4$ instead of finding it using the cross-validation. Although it is a heuristic approach to choosing a regularization parameter, it saves a lot of computation time. However, there is no such need to select a regularization parameter for SRCSP as it has a closed form solution for the shrinkage parameter. Wavelet CSP with feature selection (WCSP-FS) is another variant of CSP examined in this study, as it is the same approach used in [72]. Wavelet CSP aims at maximizing the objective function $J(w_b)$ as in Eq. (4.14),

$$J(w_b) = \frac{w_b^T C_1 w_b}{w_b^T C_2 w_b} \quad (4.14)$$

Here, w_b corresponds to the spatial filter for a sub-band ‘ b ’ of the wavelet decomposition of the EEG signal.

Since the traditional CSP can solve for the objective function by optimizing the Rayleigh quotient for only two classes (C_1 and C_2), one-versus-rest approach is used to extract the features from four classes. For each class ‘ i ’, covariance matrix C_1 is calculated for trials corresponding to class i , while C_2 is computed for trials corresponding to $j \neq i$. Once the spatial pattern matrix W is obtained after solving the Eigendecomposition problem, features F_p ($p = 1, \dots, 2m$) are calculated as Eq. (4.16),

$$Z = W \times E \quad (4.15)$$

$$F_p = \log\left(\frac{\text{var}(Z_p)}{\sum_{i=1}^{2m} \text{var}(Z_p)}\right) \quad (4.16)$$

where, E corresponds to the time series data (source space or sensor space), and Z is the resultant subspace obtained by projecting E using the spatial pattern matrix W . Only first, and last two spatial filters ($m=2$) of W are used for feature computation. Subsequently, these multiclass features are classified using the Fisher’s Linear Discriminant (FLD) classifier with the one-versus-rest (OVR) approach. FLD classifier aims at maximizing the between-class scatter matrix S_B and minimizing the in-class scatter S_W [62].

Table 4.2: Average Percentage Classification Accuracy using Fisher’s Linear Discriminant Classifier (5×5 Cross-validation)

Subjects	Source Space				Sensor Space			
	CSP	TRCSP	SRCSP	WCSP-FS (k=13)	CSP	TRCSP	SRCSP	WCSP-FS (k=13)
<i>S01</i>	67.87	70.87	53.5	91	36.87	56.12	54.37	87.87
<i>S02</i>	36	48.25	63.12	73.25	34.12	30.87	49.25	73.25
<i>S03</i>	56	59.5	67.62	67.5	35.75	51.37	57.37	68.25
<i>S04</i>	30.87	63	67.25	69.87	29	34.75	47	71.87
<i>S05</i>	38.12	51.5	56.5	61.37	33	35.75	47	60.87
<i>S06</i>	49	67.12	59.87	79.25	38.37	51.12	44	77.62
<i>S07</i>	51.71	62.71	71.28	54.43	37.25	45.28	66.42	55.85
Mean	47.8	60.42	64.98	70.95	34.9	43.61	52.2	70.8

4.4.4 Results and Discussion

The average classification accuracies of 4-direction (North, South, East, and West) classification for 7 subjects (*S01*, *S02*, *S03*, *S04*, *S05*, *S06*, and *S07*) using the proposed method are shown in Table 4.2 and compared with the existing methods in the sensor space. It can be observed that the classification accuracies are statistically significant compared to the chance level accuracy of 25%. We observed that the classification accuracies are much higher compared to that of sensor space for a given feature extraction technique. The highest mean classification accuracy of 70.95% for seven subjects was obtained using WCSP features in the source domain. Overall, there was at least 10% improvement in the classification accuracy when source space features are used as compared to sensor space features. We believe that the increase in classification accuracy in source space is due to the additive information of underlying neuronal activity. It is in agreement with the findings reported in [106]. However, when the W-CSP is used with the cross-validated feature selection parameters as proposed in [72], one can only observe a marginal improvement in the source space compared to sensor space. This could be due to the careful parameter selection (k) in the WCSP-FS in the sensor space. The number of features responsible for highest training accuracy in the sensor space may not be the same as in the source space, which is worth investigating in the future.

Figure 4.9: Mean amplitude variation response of Left and right premotor cortex for hand movement in 4 directions

In Fig. 4.9, amplitude variation of the left premotor cortex and the right premotor cortex averaged over trials corresponding to different arm movement directions is shown. It is to be noted that the pre-cue signal is attenuated because of the dynamic Z -score normalization which suppresses the baseline. It gives an indication of the post-cue signal

Figure 4.10: (a) Statistically significant activation ($p < 0.01$) shown at the cortical surface, (b) Morlet Wavelets decomposition corresponding to the averaged response in Brodmann Area 6

relative to the baseline. Furthermore, the amplitude variation responses shown in Fig. 4.9 are the average response of all the voxels corresponding to scouts BA 6L (left premotor cortex) and BA 6R (right premotor cortex) respectively. Also, the wavelet features were investigated to find which frequency bands that provide the most discriminative information. Based on the cortical activation averaged over all the dipoles within the ROI, it was found out that the delta band ($<4\text{Hz}$) is discriminative, as shown in Fig. 4.10. It concurs with the findings reported in [94].

4.5 Summary

In this chapter, a shrinkage parameter based regularization approach for Filter bank Common Spatial Pattern is presented as a spatial filtering algorithm. Subsequently, EEG source imaging based spatiotemporal localization of movement intention is presented. Motivated by the findings, the cortical source space features are used to analyze complex arm movement parameters like direction classification. The traditional sensor space approaches were compared with the corresponding features in the source space, and the source space features were shown to provide better classification accuracy especially for the challenging classification tasks of voluntary arm movement in different directions. In addition to the better classification performance, it was presented that the source space can make use of the underlying neurophysiological phenomenon as a priori for better data modeling. Instead of a data-driven approach to finding the region of interest, the functional information of dorsal premotor cortex is used to guide towards the direction decoding. Different approaches involving regularization of an objective function and the covariance matrix are compared in this study to evaluate the robustness of the source- and sensor-space features. Certainly there is a scope for further improvement in the classification accuracy using feature selection, with lesser emphasis on cross-validated parameters. In the next chapter, the neural correlates of multi-direction hand movement classification are studied.

Chapter 5

Supervised Factor Analysis for classifying the Multi-directional Arm Movement using Source-EEG

5.1 Introduction

In previous chapters we observed how EEG-based electrophysiological imaging can be achieved and also we noticed that the CSP features from source-space EEG can result in improved classification accuracies as compared to sensor-space CSP features in classifying the hand movement in 4 directions. The inherent nature of CSP as a binary classification problem is suited for tasks like left-versus-right hand motor imagery or execution. Although it was noticed in the previous chapter that the regularized variants of CSP can be used for 4-class classification problem, the neural correlates of this classification are still unknown. Furthermore, there have not been significant studies in decoding fine arm movement related parameters such as type, direction, and speed using the source-space EEG. In contrast, there are sensor-space based studies reporting the decoding of parameters such as type [110, 180, 181, 182], speed [110, 183, 101], direction [72, 184], and force [185]. As the sensor-space EEG can only reveal limited neurophysiological interpretation, this chapter intends to explore the role of source-space EEG in interpreting the neural correlates of multidirectional hand movement.

As a preliminary study, we reported in the previous chapter that by defining an anatomical region of interest (ROI), the analysis of different functional clusters becomes easier as there are fewer number of voxels to be processed. In the case of motor task

analysis, it is a well-established fact that the primary motor cortex is involved in motor functions. There are other fMRI-based studies which report that the neuronal clusters in the primary motor cortex (also known as *M1*) are directionally tuned, and they are spatially segregated along the cortical surface [186, 187]. Task priors from the relevant ROIs have found to result in improved classification accuracy [89].

Even though the source localization and anatomical ROI can help us appreciate an underlying neural activity of a given task, they are not sufficient as a priori for data modeling. As there are several unknown (or rather, unobservable) cortical sources that contribute towards a given task to varying degrees, it is very difficult to model any neural observation solely based on the observable recordings irrespective of the data acquisition modality [188]. Since the scalp EEG is observable as a two-dimensional signal (electrodes $\times$ time samples) in the continuous raw data, we can refer to these observable recordings as “manifest variable.” As the actual cortical sources are not observable directly from the scalp EEG, we refer to these cortical sources as “latent variables.” There is a need to contemplate the behavior of underlying neurophysiological phenomena of multidirectional hand movement in terms of manifest variables and latent variables corresponding to scalp electrodes and cortical sources respectively. Factor analysis [189] is one such algorithm that extracts the information embedded in the latent space. Santhanam et. al. has used traditional factor analysis based approach for neural prosthesis [188]. In this study conducted on monkeys, they tried to explain the variability of the neural population when reach-out movement tasks are performed. This variability shown by a set of neurons is categorized into “shared” and “independent” variability. Shared variability is the variability that is common for different neurons for a given task, whereas the independent variability corresponds to the unique neural response shown by a neuron. However, the method presented in [188] cannot leverage the class labels as it is unsupervised. Therefore, a supervised approach is proposed in this study to learn the factor representation across classes by leveraging the spatial information of source dipoles. The hypothesis is based on the concept of motor homunculus which highlights that the cortical sources involved in complex movement tasks are located closely [174].

Further, the spectral characteristics of movement related tasks are not conclusive, as there have been studies that report different frequency bands of interest ranging from

Delta (or Slow cortical potentials $< 4\text{Hz}$) [92] till high gamma ($> 60\text{ Hz}$) [190, 94]. One should be cautious while analyzing time-frequency maps due to the power-law dynamics (spectral power decreases with increasing frequencies). Some of the other related studies involving spectral characteristics of EEG cortical space features can be found in [191]. Thus, there is a need to analyze the role of different frequency bands in the multi direction hand movement task without a lot of prior assumptions.

The primary goal of this study is to investigate the effectiveness of the source space EEG in extracting useful features to discriminate arm movement directions. Further, instead of relying on the traditional feature extraction methods, a novel supervised factor analytic approach is proposed in this study for better data interpretation. Also, the proposed approach can help visualize the cortical source features that are more relevant to a given movement direction stimulus. To the best of our knowledge, there are very few studies that use cortical source space information to extract discriminative features to decode the direction of arm movement from EEG. The main contribution in this chapter is to extract discriminating features by modifying the classical unsupervised factor analysis to a supervised approach by embedding class-wise label information.

5.2 Materials and Methods

5.2.1 Data description

The data used in this study is described in Chapter 4 Section 4.4.1.1. A total of 160 trials of EEG were recorded from seven healthy subjects during a synchronized BCI experiment of hand movement execution in four directions. Trials corresponding to the hand movement in right, left, forward, and backward directions are denoted as ‘East,’ ‘West,’ ‘North,’ and ‘South’ respectively. A detailed description of the experimental setup is given in Section 4.4.1.3. Continuous EEG segmented into uniform epochs of 2 seconds each for the baseline (-1 to 0 s) and the movement (0 to 1s) are studied. Temporal window of 0.5s-1s post onset gives us the movement information and the EEG neural correlates are also studied using these time segments. The preprocessing pipeline is also described previously in Section 4.4.1.4. After band pass filtering the EEG within the frequencies of interest, ADJUST plug-in for ICA is used for an automatic detection and removal of noisy artifacts.

5.2.2 EEG Source Imaging

EEG Source Localization requires transforming the sensor domain into the source domain, albeit the number of cortical sources vastly outnumber the number of scalp electrodes. This ill-posed problem has to be solved using several constraints and a priori information about the cortical region of interest. To convert EEG data from the sensor domain to the source domain, a forward head model and a subsequent inverse solution is needed. A block diagram of the proposed method is illustrated in Fig. 5.1.

5.2.2.1 Forward Modeling.

Forward modeling is a critical stage in source imaging as it affects the accuracy of EEG source localization results substantially. The forward model is the subjects' head model that can determine the scalp measurements, provided the locations of cortical sources are known. Various physical properties such as geometrical shape, conductivity values of different layers of the brain and also the number of voxels (3D volumetric pixels) are considered in the forward model. To achieve good source localization accuracy, local anisotropies in different layers of the brain are considered with the following conductivity values of 0.018 S/m, 0.44 S/m and 0.25 S/m for the skull, scalp, and the cortex respectively [176]. A template anatomy of the International Consortium for Brain Mapping (ICBM-152) co-registered in MNI (Montreal Neurological Institute) space is used for the forward model [170]. After that, the template head model is warped to fit the template MNI anatomy of a subject using the Neuroscan template 3D digitized locations of all 118 channels used in this study. It is suggested that when a subject's MRI is not available, EEG source localization should include multilayer Boundary Element Model (BEM) model with a realistic estimate of conductivity values and warped to co-registered electrode positions [192]. Previous studies have shown that the template anatomy can still provide comparable results in the case of group analysis [193, 171]. Following this, the cortical surface is tessellated into a triangular mesh composed of 15002 vertices. Boundary Element Method (BEM) is computed to achieve this tessellation using an OpenMEEG toolbox [81], that is reported to be reasonably accurate and also easier and faster to compute than Finite Element method [194]. Solving this forward model result in a lead field matrix (Θ_f) that is essentially a subspace transformation matrix that transforms

Figure 5.1: Procedural block diagram describing the proposed source space feature extraction. Raw EEG extracted from 118 electrodes are pre-processed as shown, followed by source-space feature extraction. Expanded view of the source-space feature extraction (sub-block) is shown in the right half of this figure. Schematic shows the inverse modeling using sLORETA technique followed by the selection of anatomical ROI in the Brodmann atlas (BA4, BA6). Forward modeling of EEG is shown in the top pipeline of source imaging block. It involves the EEG sensor montage and ICBM152 template anatomy and a three-layer realistic-geometry head model. Cortical time-series information is down sampled into designated ROI (BA4 and BA6) for further feature extraction and classification.

the sensor space EEG into cortical source space. Mathematically, EEG source imaging can be modeled as Eq. (5.1),

$$\Omega = \Theta_f J + \varepsilon \quad (5.1)$$

where, Ω is the sensor-space EEG recorded from ‘ N ’ channels, Θ_f is the lead field matrix (LFM) of size $N \times m$ ($m \gg N$). Θ_f describes the propagation of current from

source dipoles (m) to each scalp electrode (N). J is an $m \times t$ matrix of source dipole time series. ε is the noise perturbation matrix with covariance matrix Ψ . Task-independent signal information from the pre-stimulus baseline period (-1 to 0s) is used to compute the noise covariance matrix.

5.2.2.2 Inverse Modeling.

Standardized low-resolution electromagnetic tomography (sLORETA) based current density estimation technique using the BrainStorm Toolbox [80] is used for inverse modeling. sLORETA is a variant of weighted minimum norm estimation technique for an inverse solution [195].

5.2.2.3 Region of Interest (ROI).

For a balanced run-time complexity and memory demand, a cortical ROI is defined that contains source dipoles mostly correlated with movement related parameter like direction. For this purpose, an ROI is chosen from the anterior and posterior primary motor cortex (M1) spatially segregated in the Brodmann atlas referred to as BA4a and BA4p respectively. Also, the voxels belonging to Brodmann Area 6 (BA6) that comprises of premotor cortex (PMC) and a part of the supplementary motor area (SMA) are also selected as they are reported to be associated with the movement involving spatial target [179, 178]. From a warped cortical surface obtained after performing forward modeling, a total of 410 voxels corresponding to the ROI mentioned above is chosen for further analysis. It has been reported that the motor area specific to arm movement execution and imagery (also known as hand knob region) is located near the precentral gyrus [106, 196].

5.2.3 Factor Analysis based EEG modeling

It is known that many cortical sources synchronize/desynchronize during certain tasks. A certain degree of correlation exists between cortical sources belonging to a region associated with similar functionality. However, each of these source dipoles is unique to some extent, thus resulting in a complex neural mechanism for every task. Therefore, a mathematical model is needed that can describe this distinction between the commonality

and the uniqueness of each source dipole. Factor analysis is one such method that is rarely investigated in the context of non-invasive EEG source space analysis. Factor analysis is useful to extract the behavioral information that is common across source dipoles of a similar ROI and also to get some insight into the unique behavior within the source dipoles of interest. Especially for a relatively challenging task of classifying different directions of arm movement, it is critical to understand which neuronal cluster contributes towards the movement in a particular direction. Hereafter, the mathematical framework of factor analysis is provided to understand it as an unsupervised approach followed by the contribution of this chapter i.e. embedding a supervised approach for the same.

Consider an EEG trial ‘ i ’ recorded from N sensors for ‘ t ’ time samples. After inverse modeling, there are m source dipoles as random variables: $x_1, x_2, x_3, \dots, x_m$ with respective means $\mu_1, \mu_2, \mu_3, \dots, \mu_m$. Mathematical model of factor analysis is expressed as Eq. (5.2),

$$x_i^t - \mu_i^t = \lambda_{i1}\xi_1^t + \lambda_{i2}\xi_2^t + \dots \lambda_{ik}\xi_k^t + \varepsilon_i^t \quad (5.2)$$

Here, ξ denote common factors signifying the non-zero correlation between factors and λ_{ij} ($j = 1, 2, \dots, k$) denotes factor loading. Note that there are certain assumptions as natural consequences of the objectives of factor analysis. ε_i refers to the unique factor independently distributed with zero mean ($E(\varepsilon_i)=0$) with a finite variance ψ , thus resulting in $Cov(\varepsilon) = Diag(\psi_1, \psi_2, \psi_3, \dots, \psi_P)$. The diagonal covariance $Cov(\varepsilon) = \Psi$ signifies the heteroscedastic noise that relatively better explains the biological noise model as it does not make any assumption of identical noise variance for all sources. As the noise model is crucial in source imaging [158], it is desirable to select a model that can explain the data reasonably well. Both common factors and unique factors are important in factor analysis as they explain the shared behavior and the unique behavior of cortical sources. Unlike Maximum Likelihood Estimation (MLE) based factor extraction, Principal Axis Method (PAM) is chosen as there is no need to assume a normal distribution in the noise model [197].

In matrix form, the factor analysis can be modeled as shown in Eq. (5.3),

$$\bar{x} = \lambda\xi + \varepsilon \quad (5.3)$$

Computing the covariance of both sides,

$$\begin{aligned} \Sigma &= \text{cov}(\lambda\xi) + \text{cov}(\varepsilon) \\ \Sigma &= \Lambda \text{cov}(\xi) \Lambda' + \Psi \\ \Sigma &= \Lambda \Lambda' + \Psi \\ \Sigma &= \Lambda \Lambda' + \Psi \end{aligned} \quad (5.4)$$

Since λ_{ij} is the $(ij)^{th}$ element of Λ , Eq. (5.4) can be algebraically represented as $\text{cov}(\bar{x}_i, \xi_i) = \Lambda$, that follows that the correlation of $\bar{x}_i$ and Ψ_i as $\text{corr}(\bar{x}_i, \xi_i = \lambda_{ij}) \forall i \in 1, 2, 3, \dots, m, j \in 1, 2, 3, \dots, p$.

$$\begin{aligned} \sigma_{ii} = \text{var}(x_i) &= (\lambda_{i1}^2 + \lambda_{i2}^2 + \lambda_{i3}^2 + \dots \lambda_{im}^2) + \psi_i \\ &= h_i^2 + \psi_i \end{aligned} \quad (5.5)$$

Further, Eq. (5.5) can be partitioned into two components: first component representing common factors (h_i^2) termed as “communality” and second component unique to ψ_i called as “specific variance.” Note that the covariance matrix Σ cannot be expressed exactly as shown in Eq. (5.4) i.e. Ψ as a diagonal matrix. Factor analysis involves the correlation matrix R modeled as an estimated Σ . Therefore, an estimator is used that will best approximate Eq. (5.4) as Eq. (5.6),

$$R \cong \hat{\Lambda} \hat{\Lambda}' + \hat{\Psi} \quad (5.6)$$

By applying singular value decomposition on $R - \hat{\Psi}$, Λ is decomposed into CDC' (spectral decomposition) where the normalized eigenvectors of $R(c_i'c_i = 1)$ form an orthogonal matrix C and a diagonal matrix D with eigenvalues $\theta_1, \theta_2, \theta_3, \dots, \theta_p$ as its diagonal entries. This matrix D can be decomposed into $D^{1/2}D^{1/2}$, and therefore the spectrally decomposed product CDC' (or $CD^{1/2}D^{1/2}C'$) can be factored in the form of $\hat{\Lambda}\hat{\Lambda}'$ as $(CD^{1/2})(CD^{1/2})'$. As Λ is of the form $p \times m$ ($m < p$), only top ‘m eigenvalues of $D(\theta_1, \theta_2, \theta_3, \dots, \theta_p)$, and their corresponding eigenvectors $C_1 = (c_1, c_2, c_3 \dots c_m)$ are considered. Therefore, $\hat{\Lambda}$ can be written as $c_1\sqrt{\theta_1}, c_2\sqrt{\theta_2}, \dots, c_m\sqrt{\theta_m}$. Now, R can be represented as Eq. (5.7) [198],

$$\hat{\Psi}_{ii} \cong R_{ii} - \sum_{j=1}^m \hat{\lambda}_{ij}^2 \quad (5.7)$$

Following the extraction of factors, they are sorted in a descending fashion indicating their relative contribution towards the variance in a given trial. This means that the subset of factors that explain most of the variance (for, e.g., 90%) in a given trial will be considered for further analysis. Since these subsets of factors correspond to the source dipoles within the ROI, they preserve the neurophysiological relevance of the experimental task.

5.2.3.1 Supervised Factor Analysis for Feature Extraction.

As the approach used so far is unsupervised, a model is trained to cluster a group of source dipoles $x_i (i = 1, 2, \dots, j \dots P)$ as indexed by factors and class labels. The spatial information of a given dipole x_i in terms of its coordinates $S(x_i) = x_i(x, y, z)$ is used to compute the Euclidean distance. Thereafter, the class-wise label for every training trial ‘ t ,’ as $l(t) = 1, 2, 3, 4$ is used, corresponding to the directional cues - ‘North,’ ‘South,’ ‘East,’ and ‘West’ respectively. The within-class graph (G_w) and between-class graph (G_b) are defined to study the local neighborhood of nodes (source dipoles), where each node is assigned a weight as per the kernel function shown in Eq. (5.8) and Eq. (5.9) [199],

$$W_{w,ij} = \begin{cases} (1 + \exp(-\frac{\|x_i - x_j\|^2}{\beta})) & \text{if } x_i \in N(x_j) \text{ and } l(x_i) = l(x_j) \\ 0 & \text{otherwise} \end{cases} \quad (5.8)$$

$$W_{b,ij} = \begin{cases} (1 - \exp(-\frac{\|x_i - x_j\|^2}{\beta})) & \text{if } x_i \in N(x_j) \text{ and } l(x_i) \neq l(x_j) \\ 0 & \text{otherwise} \end{cases} \quad (5.9)$$

where, $W_{w,ij}$ denotes the weight of within-class graph and similarly, $W_{b,ij}$ denotes the weight of between-class graph. β is a Gaussian kernel parameter ($0 < \beta < 1$) that controls the rate of decay. If ‘ x_i ’ and ‘ x_j ’ are neighboring dipoles and belong to the same class, then within class graph (G_w) will be assigned a non-zero weight. Similarly,

a non-zero weight will be assigned to the neighboring nodes in the between-class graph (G_b) if those nodes belong to a different class.

The source space EEG can be represented as $y_i = A^T x_i + \epsilon$, where the optimization problem to solve for the maximization of inter-class and minimization of intra-class separation can be defined as Eq. (5.10), Eq. (5.11), and Eq. (5.12),

$$\min \frac{1}{2} \sum_{ij} (y_i - y_j)^2 W_{w,ij} \quad (5.10)$$

$$\max \frac{1}{2} \sum_{ij} (y_i - y_j)^2 W_{b,ij} \quad (5.11)$$

$$\min \sum_{c=1}^C \sum_{j=1}^{n_c} (y_j^c - \mu_c)^2 \quad (5.12)$$

The combined expression can be derived by optimizing the objective functions in Eq. (5.10), Eq. (5.11), and Eq. (5.12),

$$\begin{aligned} \min \frac{1}{2} \sum_{ij} (y_i - y_j)^2 W_{w,ij} \\ &= \min \frac{1}{2} \sum_{ij} ((A^T x_i + \epsilon) - (A^T x_j + \epsilon))^2 W_{w,ij} \\ &= \min \sum_i A^T x_i D_{w,ii} x_i^T A - \min \sum_{ij} A^T x_i W_{w,ij} x_j^T A \\ &= \min A^T X (D_w - W_w) X^T A \\ &= \min A^T X L_W X^T A \end{aligned} \quad (5.13)$$

$$\begin{aligned} \max \frac{1}{2} \sum_{ij} (y_i - y_j)^2 W_{b,ij} \\ &= \max \frac{1}{2} \sum_{ij} ((A^T x_i + \epsilon) - (A^T x_j + \epsilon))^2 W_{b,ij} \\ &= \max \sum_i A^T x_i D_{b,ii} x_i^T A - \max \sum_{ij} A^T x_i W_{b,ij} x_j^T A \\ &= \max A^T X (D_b - W_b) X^T A \\ &= \min A^T X L_b X^T A \end{aligned} \quad (5.14)$$

From Eq. (5.12), we have

$$\begin{aligned}
& \min \sum_{c=1}^C \sum_{j=1}^{n_c} (y_j^c - \mu_c)^2 \\
&= \min \sum_{c=1}^C \left(\sum_{j=1}^{n_c} (y_j^c - \mu_c)(y_j^c - \mu_c)^T \right) \\
&= \min \sum_{c=1}^C \left(\sum_{j=1}^{n_c} (y_j^c y_j^{cT} - \mu_c y_j^{cT} - y_j^{cT} \mu_c + \mu_c \mu_c^T) \right) \\
&= \min \sum_{c=1}^C \left(\sum_{j=1}^{n_c} (y_j^c y_j^{cT} - n_c \mu_c \mu_c^T) \right) \\
&= \min \sum_{c=1}^C \left(\sum_{j=1}^{n_c} (y_j^c y_j^{cT} - \frac{1}{n_c} (y_1^c + \dots y_{n_c}^c)(y_1^c + \dots y_{n_c}^c)^T) \right) \\
&= \min \sum_{c=1}^C \left(\sum_{j=1}^{n_c} (A x_j^c)(A x_j^c)^T - \frac{1}{n_c} (A^T x_1^c + \dots A^T x_{n_c}^c)(A^T x_1^c + \dots A^T x_{n_c}^c)^T \right) \\
&= \min A^T \sum_{c=1}^C \left(X_c \left(I - \frac{1}{n_c} e_c e_c^T \right) X_c^T A \right)
\end{aligned} \tag{5.15}$$

Combined optimization problem of Eq. (5.13), Eq. (5.14), and Eq. (5.15) can be defined as shown in Eq. (5.16) [200],

$$\begin{aligned}
& \arg \max A^T (P - \alpha S_w) A \\
& \text{s.t. } A^T A = I
\end{aligned} \tag{5.16}$$

where, α is a shrinkage regularization parameter with analytical solution [201], The diagonal matrix corresponding to the column sums of W_w and W_b is denoted as D_w and D_b . L_b is the Laplacian matrix computed as $D_b - W_b$, and $P = X (L_b - L_w) X^T$, $S_w = \sum_{c=1}^C X_c \left(I - \frac{1}{n_c} e_c e_c^T \right) X_c^T$ and e_c is a n -dimensional identity vector. A Lagrangian multiplier is applied on the objective function Eq. (5.16) to obtain the optimal transformation matrix A as Eq. (5.17),

$$\frac{\partial}{\partial A} (A^T (P - \alpha S_w) A - \lambda (A^T A - I)) = 0 \tag{5.17}$$

Further, Eq. (5.16) is converted into an eigenvalue problem as,

$$(P - \alpha S_w) A = \lambda A \tag{5.18}$$

The eigenvalue problem in Eq. (5.18) is solved for the eigenvectors that are sorted in a descending order to give us the features. These features corresponding to the eigenvector $[a_1, a_2, \dots, a_d]$ are classified using Fisher's Linear Discriminant Classifier (FLD) [62].

5.2.4 Benchmarking Algorithms

To compare the proposed approach with the existing methods, different regularized variants of CSP (TR-CSP and SR-CSP) are evaluated as benchmarking algorithms. These variants of CSP have already been explained previously in Chapter 4 Section 4.4.3. Just to recall, Tikhonov Regularized CSP (TRCSP) and Shrinkage Regularized CSP (SRCSP) are used that regularizes the objective function and covariance estimation of CSP respectively.

Since the traditional CSP is well-suited for two-class problem, one-versus-rest (OVR) approach is used to extract multi-class features corresponding to 4 directions.

Subsequently, these multi-class features are classified using the Fisher's Linear Discriminant (FLD) classifier [62] with the one-versus-rest (OVR) approach.

5.2.5 Statistical Analysis

The classification performance of the proposed method was assessed using one-way repeated measures ANOVA. The type of feature space (sensor or source) is considered as a between-subjects factor (condition) with different regularization methods (CSP, TRCSP, SRCSP) as 'levels'. Further, one-way ANOVA corrected for multiple comparisons is also performed to observe the significance across feature extraction methods considering the decoding accuracy as a dependent variable. Post-hoc tests were done using a Tukey Honest Significance Difference (HSD) test. To establish the statistical significance of the proposed method, the significance level is set at $p < 0.05$. All statistical tests are performed using the SPSS[®] Software.

5.3 Results

5.3.1 Classification Performance of Source Space Features

To assess the performance of the proposed method in classifying different directions, the cross-validation performance is compared with other traditional sensor-space techniques.

As mentioned previously in Section 5.2.4, FLD classifier is used while not rejecting any of the trials. To ensure robustness, a cross validation of the whole dataset is performed by randomly taking 80% of the trials as a training set and the rest 20% of the trials as test set, that was then repeated 5 times by randomizing the order of trials. This 5×5 cross-validation percentage accuracy is used as the performance criteria to evaluate different methods that are tabulated in Table 5.1, and a box plot of the same is shown in Fig. 5.2.

Individual subject-wise decoding accuracy is shown as a small jitter next to each box-plot. The legends in Fig. 5.2 show different feature extraction techniques. All the feature extraction methods used in this study could classify with the decoding accuracy higher than the chance level (25%) for 4-class classification. One-way ANOVA of classification accuracies resulted from various feature extraction methods revealed the $F(1, 7) = 14.1541$ with a p -value = $9.7e9$ suggesting that the one or more treatments are significantly different. However, these results overestimate the significance, and therefore, Tukey-HSD tests for multiple comparisons were performed. Tukey-HSD tests revealed that at least one or more pairs of treatments (feature extraction methods) are significantly different. Pairwise comparisons of the proposed proposed method and the rest showed statistically significant results except the SRCSP in the source space ($F = 3.305; p > 0.05$). Furthermore, 2-way repeated measures ANOVA with within-subject effects (Sensor and Source space), and three levels (CSP, TRCSP, and SRCSP) revealed a significant difference ($F = 54.683; p < 0.001$) between the two effects. Tests of between-subject effects of 3 feature extraction methods with Bonferroni correction for multiple comparisons showed significant differences ($F = 8.654, p = 0.002$).

5.3.2 Source Activation of Hand Movement in Different Directions

The results of sLORETA source localization showed cortical activation of right hand movement in different directions. A prior knowledge of anatomical ROI is an advantage as it can be used to validate our results. To illustrate this, the trial-averaged response of subject (S01) from the source dipoles confined to Brodmann Areas BA4aL, BA4pL, and BA6L is presented in Fig. 5.3. The stereotaxic coordinates to plot this time-series

Table 5.1: Percentage Classification Accuracies for 4-class classification resulted from different benchmarking algorithms

	CSP (Sensor)	TR-CSP (Sensor)	SR-CSP (Sensor)	WCSP (Sensor)	CSP (Source)	TR-CSP (Source)	SR-CSP (Source)	WCSP (Source)	SFA (Source)
S01	36.87	56.12	54.37	77.87	67.87	70.87	53.5	89.81	88.3
S02	34.12	30.87	49.25	73.25	36	48.25	63.12	72.5	73.67
S03	35.75	51.37	57.37	58.25	56	59.5	67.62	65.54	68.67
S04	29	34.75	47	61.87	30.87	63	67.25	68.08	72.37
S05	33	35.75	47	50.87	38.12	51.5	56.5	58.78	61.31
S06	38.37	51.12	44	77.62	49	67.12	59.87	76.41	78.06
S07	37.25	45.28	66.42	55.85	51.71	62.71	71.28	55.41	58.29
Mean	34.91	43.61	52.20	65.08	47.08	60.42	62.73	69.504	71.52

Figure 5.2: Performance assessment of different feature extraction algorithms in-terms of 5×5 cross-validation accuracy of classifying the EEG corresponding to hand movement in 4-directions. X-axis indicates different feature extraction algorithms with feature space (sensor/source) highlighted in braces. Y-axis indicates the average 5×5 cross-validation percentage accuracy. Jittered points indicate the decoding accuracy of individual subject.

are shown in Table 5.2. The most representative source dipole of these ROIs (BA4aL, BA4pL, and BA6L) is shown as 3D-stereotaxic coordinates used in the forward model. Furthermore, to avoid the bias of prior neurophysiological information about the motor task to reflect the cortical functioning, the full-brain activation on the cortex surface is shown in Fig. 5.4.

Table 5.2: Stereotactic Coordinates of significant cortical activation

Anatomical Region of Interest (ROI)	Brodmann Area (BA) nomenclature	Coordinates		
		x	y	z
Left anterior Primary Motor cortex (M1)	BA4a	80	107	138
Left posterior Primary Motor cortex (M1)	BA4p	62	117	123
Left preSMA	BA6	74	134	133

5.3.3 Source Dipoles Corresponding to Hand Movement in Different Directions

In this subsection, the usage of factor analytic approach to visualize the source dipoles influencing the task is presented. Although there are 410 dipoles chosen from the Brodmann areas BA4a, BA4p and BA6 from both hemispheres, very few dipoles would essentially result in a significant variance. In this study, the false discovery rate (FDR) of $p < 0.01$ is set as the criteria to select the dipoles based on the factor loading obtained from the supervised factor analysis. FDR of $p < 0.01$ allows us to limit the number of false positive source dipoles corresponding to a given directional cue. During different cross validation runs for each subject, the number of dipoles selected after applying the statistical criterion is not constant. It was observed that on an average around ten dipoles would remain after FDR based criterion is applied. For the purpose of illustration, the dipoles corresponding to hand movement in different directions of one of the subjects (S01) in the form of colored nodes are shown in Fig. 5.6 using the BrainNet software [202].

5.3.4 Spectral-temporal Characteristics of Multidirectional Movement Decoding

EEG Source activations exhibited direction-specific movement related modulation. To illustrate this, the time series information of ROIs (Brodmann Areas BA4aL, BA4pL, and BA6L) is shown in Fig. 5.3. One can observe a clear peak in at least one of the Brodmann areas (BA4aL, BA4pL, and BA6L) at around 0.3-0.5s after onset, which also shows that the anatomical ROIs have a temporal correlation with the actual movement duration of 0.5s. To investigate the spectral characteristics of source imaging, cortical time series were bandpass filtered in different frequency bands ranging from Delta ($< 4\text{Hz}$) to high Gamma (60-90Hz). The spectral-domain responses are shown in Fig. 5.5 after

computing the band power averaged over trials. In the Fig. 5.5, each column indicates different movement direction and each row indicates a characteristic frequency band.

Figure 5.3: Trial-averaged response of Subject ‘S01’ to 4 different directional cues in (a) East (b) West (c) North and (d) South directions respectively. Legends indicate stereotactic coordinates corresponding to centroid of different Brodmann areas. These coordinates are further shown in Table I. Shaded error indicates the deviation from the mean response. X-axis denotes the experimental timeline in seconds. Y-axis denotes the normalized amplitude resulted from sLORETA.

Figure 5.4: Group average cortical source maps of all subjects ($n = 7$, right handed). sLORETA source activation patterns resulted from hand movements in different directions as (a) East (b) West (c) North and (d) South. Cortical activation are shown in three orientations (from left towards right): left lateral, dorsal and right lateral view of cortex.

Figure 5.5: Left lateral view of group average sLORETA-based source activation maps corresponding to different frequency bands ranging from Delta (0.5-4 Hz) to High Gamma (60-90 Hz).

Figure 5.6: Subject-specific source dipoles selected using our proposed factor analytic method. FDR ($p < 0.01$) corrected sources are shown in the form of spherical nodes corresponding to different directions (a) East (b) West (c) North, and (d) South respectively. Different sizes of these spherical nodes suggest their relative proportion of variance in factor loading.

5.4 Discussion

5.4.1 Comparison of Feature Extraction Techniques

In this study, a supervised factor analytic approach is proposed to extract the cortical source space features for multi direction hand movement classification. Extending the results obtained in sensor space, it was found that the cortical source space features could be modeled in such a way that explain the variability as well as similarity of source dipoles related to a given task. Regarding classification performance, the proposed method outperforms traditional sensor-space spatial filter techniques such as regularized variants of CSP. The improvement in the classification accuracy compared to regularized variants of CSP could be attributed to the discriminating spatial features extracted by the proposed algorithm. The weights assigned to different source dipoles according to their relevance to the task label and neural anatomy add to the discriminability as compared to the spatial filters obtained from the traditional CSP approach. This method is different from the CSP-based approach in the sense that CSP (and its regularized variants) maximizes the variance between 2 classes by solving the eigenvalue problem, whereas the proposed approach finds the most optimal eigenvalue corresponding to a given class (or task). As

one can recall from Eq. (5.7), the eigenvectors are extracted by sorting in a descending fashion corresponding to their relative contribution towards the variance. In hindsight, CSP based approaches derive the spatial filters based on the difference between the 2 classes as compared to task-specific neural correlates identified by the proposed SFA approach. Further, the weights assigned to each source node based on its neighborhood and the class label explains the task-specific feature extraction of the proposed method.

5.4.2 Contribution of Supervised Factor Analytic Approach for Source-space Feature Extraction

In this study, a factor analytic framework is used to construct a generative model that could reasonably describe how the human cortical sources relate to the experimental task. Although Principal axis factor analysis based approach is used to model the data that does not require Gaussian prior, there is a caveat that the factor analytic approach is iterative. Despite this caveat of iterative procedure, one can notice that the proposed supervised factor analytic approach improves the classification performance quite significantly compared to the traditional feature extraction method. The future approach would involve training an online adaptive classifier that learns the convergence parameters from previous sessions and subjects.

5.4.3 Cortical Source Activation of Hand Movement in Different Directions

The current study indicates that the cortical activation related to hand movement in 4 orthogonal directions is spatially segregated within the motor area, primarily in the hand region of M1. The findings concur with the previous studies that report spatial segregation of populations of neurons that are directional tuned [186, 203, 204]. Time-series information provided by brain scouts (BA4aL, BA4pL, and BA6L) in Fig. 5.3 reveal that the neuronal regions responsible for movement in different directions are indeed spatially segregated. It can be seen that the activation of the contralateral posterior primary motor cortex (BA4aL) is higher for the movement in ‘East’ direction, whereas contralateral anterior primary motor cortex (BA4pL) is more active during ‘West’ directional movement. Similarly, the contralateral presupplementary motor area (BA6L) is significant

while moving the arm in ‘South’ direction, in contrast to anterior primary motor cortex (BA4L) in the case of ‘North’ direction. Of course, this is not indicative of how every trial should look like. It merely adds to our knowledge that spatial segregation of a relatively complex arm movement is indeed interpretable. Visualization of full-brain inverse modeling in Fig. 5.4 illustrates that the grand average results show significant activation in the cortical areas spanning over premotor cortex, primary motor cortex and superior frontal gyrus in the contralateral hemisphere of the brain. Even without any priors of specific anatomical regions, the observations are in line with the neurophysiological behavior of sensorimotor functions to validate the results obtained.

5.4.4 Spectral Characteristics of Cortical activation corresponding to different directions

Spectral characteristics of movement-related tasks are always a subject of debate. Many researchers have shown the variations in the ERD/S spanning over a wide range of frequencies. Although it is well-documented in the literature that the Mu-rhythms are the frequencies of interest, there are also studies that report beta-band activity to be more consistent as compared to Mu-band [205]. Although the experimental paradigms are not the same, it is still possible that beta and gamma rhythms might play an important role in the multidirectional movement task. Therefore, a group analysis ($n = 7$) of broad spectrum cortical activation (normalized amplitude of sLORETA) was performed to investigate the spectral characteristics of source activation in terms of different characteristic frequency bands of EEG. Similar to the analysis done in Section 5.3, the full brain sLORETA maps were used to analyze the spectral characteristics. In Fig. 5.5, the contralateral view of grand average cortical activation across subjects in different frequency bands ranging from Delta (0.5-4Hz) to High Gamma (60-90Hz) is shown. From Fig. 5.5, it is evident that motor areas show higher activation in the Delta, Alpha, and Beta frequency range.

5.4.5 Contribution of Source Dipoles for a Given Task

From Fig. 5.6 one can observe that the spherical nodes are of different sizes that indicate their relative proportion of variance. In simpler terms- bigger the source node, more

significant is its contribution to a given task. The significant source nodes are located along the precentral gyrus, although the anatomical region covers a much larger cortical surface. This visual illustration is subject-specific, and the location of significant source nodes varies across subjects, albeit they conform to the same anatomical ROI. Another interesting observation is that the significant nodes corresponding to the movement in ‘NORTH’ and ‘SOUTH’ directions are relatively more concentrated towards the central region. From a neurophysiological perspective, there are more muscles and joints involved while moving ones arm in ‘NORTH’ and ‘SOUTH’ direction that signifies the neural activation corresponding to the elbow and shoulder. According to the concept of the motor homunculus, elbow and shoulder have distinct neuronal activation regions in the central part of the brain, albeit they occupy a relatively smaller overlapping area of the cortex. Further, it would be interesting to go beyond the neural correlates and observe the causal interpretation of stimulus (direction-cue) on the cortical activation in different frequency band aka effects.

5.4.6 Limitations

In this study, a subject-independent template anatomy is used as the subject-specific MRI was not available. Although there are studies that have reported robust forward modeling results from the template anatomy, it would be worth investigating the effect of the data-driven forward model proposed by [206]. Furthermore, the current study involved pre-defined ROIs based on the well-documented literature concerning the motor tasks. Note that the process is not completely automatic as it still requires manual intervention. Although the manual ROI selection tends to give a better justification of source space results and also saves computation time due to the reduced feature dimension, it is not robust when a given experimental paradigm does not have a specific ROI concerned with the task. Especially for studies involving functional interference across neural regions during a complex cognitive task, ROI-based feature extraction would not be very helpful. Fig. 5.4 illustrates that the full-brain cortical map point towards the active regions is nearly overlapping the predefined cortical ROI, which implies that the source localization is not sensitive to pre-defined regions. Further, it would be interesting to see how the features from data-driven ROI selection would affect the performance of the current

method. The proposed method involved a novel supervised learning for factor analysis that did not take into account any regularization of weights. There is a scope to regularize the objective functions that could lead to higher classification accuracies.

5.5 Summary

We have proposed a novel feature extraction method based on supervised factor analysis that considers the somatotopic organization of hand movement in 4 orthogonal directions. A mathematical framework based on supervised factor analysis is used to classify 4-direction movement. In scenarios where decoding the motor actions with higher degrees of freedom is of paramount importance, prior knowledge of neurophysiology can aid in translating brain signal into control commands for effectors. Although it is difficult for current state-of-the-art brain-controlled devices to perfectly mimic real human arm functionalities, the development of more robust movement decoding algorithms in the future will certainly push the boundaries of traditional neurorehabilitation practices based on BCI. The present work on the multi-directional arm movement classification using cortical EEG features is a contribution in this direction. As compared to conventional methods that use sensor-space features, the source-space features resulted in more than 10% improvement in the classification accuracy. Previous work from our group [72] emphasized on improving the classification accuracy of 4-direction movement classification by using different regularized approaches in Wavelet-Common Spatial patterns in the EEG sensor space. In contrast, the current method (SFA) emphasizes on the cortical source distribution inferred from sLORETA inverse modeling. As a result, SFA provides more information about the neurophysiological aspects of right hand movement in 4 orthogonal directions. As a spatial filtering algorithm, SFA preserves the local information of anatomical ROIs. The confinement of the ROI to motor regions helps not only to reduce the computation time significantly but also to achieve substantially higher classification accuracy than that of the sensor-space features. Different statistical tests revealed that source space features enhance the classification accuracy of multidirectional hand movement.

In the next section, the EEG source-space study will be extended to clinical applications to investigate the effects of noninvasive brain stimulation on the motor-imagery

brain-computer interface performance of stroke patients. Different types of connectivity measures using the source-space EEG will be discussed in detail in the next chapter to explain the neural correlates of stroke recovery.

Chapter 6

EEG Source-space study of Brain Stimulation in Stroke Patients

6.1 Introduction

The Motor-Imagery (MI) BCI paradigms are extensively explored in healthy as well as stroke subjects with varying types of movement imagination [104, 207]. Although MI-BCI can facilitate the user to modulate his/her sensorimotor rhythms, there are no changes in the cortical excitation. Since the motor recovery is crucial in stroke rehabilitation, the behavioral effects of noninvasive brain stimulation on stroke subjects are studied recently [11, 12, 13, 208] to see if the stimulation alters the motor performance by exciting the motor regions. Most widely known noninvasive brain stimulation methods are transcranial direct current stimulation (tDCS) and transcranial magnetic stimulation (TMS) [11, 13, 209]. Both tDCS and TMS-based studies conventionally use direct current impulses and magnetic impulses respectively to stimulate certain areas of the brain. In this chapter, the effects of tDCS on the MI-BCI performance of stroke subjects in a randomized control trial (RCT) setting is studied. Here, the subjects are randomly allocated into two groups: One group received the treatment, whereas another group is considered to be a control group (or sham). In the present context of tDCS intervention for stroke recovery, the group receiving the brain stimulation is called ‘tDCS’ group, and the control group is ‘sham.’ To describe briefly, sham stimulation remains off for the remainder of the stimulation period after emitting a brief current for a very short period (typically, few seconds). When using the sham stimulation, the person does not have the knowledge

that they are not receiving prolonged stimulation. Therefore, one can see how much of an effect is caused by the current stimulation as the results in subjects exposed to tDCS are compared with that of subjects exposed to sham. Therefore, this research aims to validate the effects of tDCS on the MI-BCI performance by using cortical source EEG features to classify MI and Idle states. The hypothesis is, anodal tDCS as an excitatory stimulus will result in better cortical excitation in the motor region, thus facilitating better discrimination between MI and idle state. The previous studies in this thesis have shown that the EEG source space can result in more discriminating features [210, 199] in movement-related tasks. However, there have not been many studies investigating the use of cortical source features in stroke patients. Since the stroke patients have a very limited movement, the goal is to provide useful features that can classify movement intentions with a high accuracy and understand the functional implications of the tDCS on MI-BCI performance. To this end, the spatiotemporal features are extracted from the sensor space as well as the cortical source space and compared them by evaluating the crossvalidation accuracies across experimental sessions. In the previous study on the current dataset [208], Ang et.al performed online classification of MI-BCI using Filter Bank Common Spatial Pattern (FBCSP) features based on session-to-session transfer learning. Since this dataset was not studied from the cortical source perspective, the objective of this chapter is to investigate the neural correlates of differences between the tDCS and sham group and the causal interpretation of stroke recovery due to the brain stimulation.

To study the functional aspects of neuronal changes, connectivity measures between the cortical region of interests are investigated to observe how the tDCS stimulation affects the brain modulation in different regions. As the stroke patients' cortical activity undergoes substantial changes in terms of inter hemispheric connection strength, it would be worthwhile exploring how the tDCS-BCI rehabilitation could assist in stroke recovery by altering the cortical networks. Traditional methods for connectivity analysis use fMRI due to the improved spatial resolution, however there is a significant loss of temporal information. As connectivity measures inherently depend on the temporal correlation, EEG is very promising as it has high temporal resolution.

To the best of our knowledge, there are no studies which have used source-space EEG features to study the MI-BCI for stroke recovery with tDCS intervention. In this chapter, the efficacy of MI vs. Idle classification in the tDCS and sham subjects is evaluated using source-space EEG features. The remainder of this chapter is as follows: Section 6.2 describes the Participants, tDCS setup, Experimental procedure, and EEG data acquisition and preprocessing. Section 6.3 describes the EEG source imaging and dimension reduction for computationally efficient feature extraction followed by the connectivity measures (functional and effective). Section 6.4 exemplifies the results and discussion. Section 6.5 will conclude the chapter and highlight possible future research directions.

6.2 Experimental Setup

6.2.1 Participants

A randomized control trial (RCT) was conducted at National University Hospital (Singapore) in which a total of 42 chronic stroke patients were recruited for this study. Five subjects did not meet the inclusion criteria of at least nine months post stroke onset. Out of the 37 subjects who went BCI screening, 11 subjects did not meet the BCI performance criteria (above chance-level performance), and seven subjects declined to participate further. So, the remaining 19 subjects were randomized into two groups: ‘tDCS’ and ‘sham.’ Fugl-Meyer Assessment (FMA) upper extremity scores of these subjects ranged from 11 to 45 (out of the maximum points of 66). Higher FMA scores indicate better motor functioning. An informed consent from all the subjects was obtained as per the principles of the National Healthcare Group Domain Specific Review Board of Singapore.

6.2.2 Transcranial Direct Current Stimulation

The stroke patients in the ‘tDCS’ group were subjected to the direct current stimulation for 20 minutes before beginning the MI-BCI experiment. For the ‘sham’ group, the current was applied only for 30 seconds, as it has been reported not to alter the cortical source excitability and also the duration is enough to blind the subjects from knowing whether they are in the ‘tDCS’ or ‘sham’ group. For specific details of the tDCS procedure, please refer to [208].

6.2.3 Experimental Procedure

A total of 10 rehabilitation sessions were conducted over a period of 2 weeks (1st week: 1-5 sessions; 2nd week: 6-10 sessions). Before the rehabilitation session, a calibration session was conducted wherein the EEG data were used to train a model for an online MI-BCI with a robotic feedback [208]. Each rehabilitation session comprised of therapy and evaluation portion wherein the therapy portion had repetitive trials of MI task, and the evaluation portion had randomized order of ‘MI’ and ‘Idle’ tasks. During the ‘MI’ task, subjects were instructed to imagine the movement of their stroke-affected hand toward the target indicated on the 8-point clock-face game [211] while their affected hand was strapped to the MIT-MANUS robotic exoskeleton, that restricted the volitional movements of the stroke-affected hand. Since the MIT-MANUS robot was programmed to give a feedback based on the output of MI task, subjects were instructed to keep repeating the MI until they saw the visual feedback on whether the trial was successful or a failure. If a trial was correctly classified as MI, then the MANUS robot would move from the center towards a predefined target. In this study, the data from the evaluation portion is used as it had trials corresponding to both the classes for evaluating the binary classification. In each session, evaluation portion had 20 trials of ‘MI’ and 20 trials of ‘idle’ task, totaling to 200 trials of each class in 10 sessions per subject. An experimental timeline of an evaluation portion is shown in Fig. 6.1. After the rest period, a visual cue was shown to indicate the preparation for the trial, after which another visual cue appeared corresponding to a randomized order of MI or Idle task. EEG data corresponding to 1s before the stimulus-onset until 3.5s after the onset were used for the offline analysis .

6.2.4 EEG Data Acquisition and Preprocessing

Continuous EEG data were recorded from 27 channels using the Neuroscan Nuamps EEG amplifier. Sampling frequency was 250Hz. EEG trials were bandpass filtered between 0.5-40Hz, followed by common-average referencing. Independent component analysis was performed using an extended infomax algorithm in the EEGLAB toolbox [168], followed by automatic artifact removal using the MARA(Multiple Artifact Removal Algorithm) plugin of EEGLAB [212].

Figure 6.1: Experimental timeline of the evaluation portion in each MI-BCI rehabilitation session

Figure 6.2: Overview of the procedural block diagram of EEG data processing in this study.

6.3 Methodology

6.3.1 EEG Source Imaging

One of the main objectives of this chapter is to observe the cortical features in the stroke subjects after tDCS vs. sham intervention. As emphasized in the previous chapter, the EEG source localization is used to study the neural correlates. The detailed description of EEG source imaging has been given in Chapter 2 Section 2.3 and Chapter 5 Section 5.2.2.1.

6.3.2 Dimension Reduction

Since the cortical source-space EEG is of very high dimension ($15002 \text{ voxels} \times 1126 \text{ time samples} \times 20 \text{ trials} \times 2 \text{ classes}$) per session; feature extraction would be computationally prohibitive. Therefore, a priori information of the regions of interest (ROI) is used along with the state-of-the-art dimensionality reduction method that preserves the local information in a low-dimensional subspace.

Region of Interest (ROI) It has been well-established in the literature that the neural population in sensorimotor cortex is responsible for MI and ME tasks. Therefore, the spatial information is down-sampled by picking the voxels that belong to Brodmann Areas BA4 and BA6 that covers the primary motor cortex (M1), premotor cortex, (PMc) and supplementary motor areas (SMA).

Locality Preserving Projections Even after selecting an ROI, the number of voxels belonging to these ROIs is more than 1000. Therefore, the number of dimensions is further reduced to have much more tractable computation in the feature extraction stage. Locality Preserving Projection (LPP) is used as a dimension reduction technique that is insensitive to outliers and other noise as compared to traditional method like Principal Component Analysis [142]. It preserves the neighborhood of data as the nearest neighbor search in a low-dimensional subspace will fetch similar results to that of high dimensional data [142]. In the current study, the number of reduced dimension is set at 30 which is comparable to the dimensions ($N=27$) of the sensor-space EEG.

6.3.3 An Ensemble Feature Extraction Method using Shrinkage-regularized Filter Bank Common Spatial Patterns (SR-FBCSP)

To evaluate the MI-BCI binary classification performance, a regularized version of a popular (CSP) algorithm is used [213]. Extending the traditional approach of computing CSP using the sensor-space EEG, we propose to use ensemble features by concatenating the features from both sensor, and source space EEG. In principle, CSP maximizes the inter-class (between-class) variance and minimizes the intra-class (or within-class) variance. The objective function of conventional CSP algorithm $J(w)$ is as shown in Eq. (6.1) [71],

$$J(w) = \frac{w^T C_1 w}{w^T C_2 w} \quad (6.1)$$

where, w denotes the spatial filters, C_i denotes the covariance matrix computed for all the trials belonging to class i . Traditionally, an empirical covariance is used as the covariance matrix. Although it is unbiased and usually works well, it leads to imprecise estimation when the sample size (in this context, number of trials) is small [214]. Therefore, the shrinkage regularized CSP (SR-CSP) is used that computes a structured estimator (C_c) instead of an empirical covariance matrix C_i as shown in Eq. (6.2),

$$C_c = (1 - \gamma)C_i + \gamma I \quad (6.2)$$

where, γ is the shrinkage regularization parameter that has analytical solution [214], I is the identity matrix. As the traditional CSP computation in a single frequency band does not reveal spectral information as much, a filter bank CSP (FBCSP) was proposed in [65]. Based on this approach, we filter the EEG in 10 non-overlapping filter bands ranging from 0.5Hz to 40Hz (0.5-4Hz, 4-8Hz,...,36-40Hz) using a Chebyshev type-II Infinite Impulse Response (IIR) filter with zero-phase. Extending the resultant multiband filtered EEG, we apply SRCSP- now called as SR-FBCSP. It projects the input $X_i(t) = R^{N \times T}$ (N channels $\times T$ time samples in an i^{th} trial) into a spatially filtered subspace Z as, $Z = W \times X$ where the columns of W' corresponds to the spatial filters. In the case of source-space EEG, the input would be $X'_i(t) = R^{N' \times T}$, where N' is the number

of low-dimensional cortical sources. The features are computed by log-normalizing the top and bottom ‘ m ’ rows of Z as shown in Eq. (6.3),

$$F_p = \log \left[\text{var}(\mathbf{Z}_p) / \sum_{i=1}^{i=2m} \text{var}(\mathbf{Z}_p) \right] \quad (6.3)$$

Once these features are computed, the classification accuracies are evaluated using Fishers Linear Discriminant Classifier (FLD) [62]. The performance was evaluated in terms of mean classification accuracy using 5×5 cross validation where the data were split into 80% training and 20% testing repeated five times.

6.3.4 Functional Connectivity

In addition to observing the classification performance of the motor-imagery BCI, it is also essential to study the neuronal aspects of cortical functions in stroke patients. In this regard, connectivity measures help us to study the involvement of different cortical regions while performing a task. Functional connectivity is one such measure that explains how different regions share similar functional properties based on the temporal correlation between the signals from different cortical sources (or scalp sensors). Especially in the clinical studies, it has been a standard practice to study the functional connectivity as it helps the clinicians to understand the brain plasticity over a period of neurorehabilitation. In the case of stroke research, the neuroimaging studies on the stroke recovery have confirmed the sequence of 3 main hypotheses such as - (1) Due to an ischemic stroke, the functional connectivity gets affected not only at the site of lesion but also cortical regions that are remote to the lesion area (2) Post-stroke residual functional connectivity reveals the behavioral consequences (3) Post-stroke reorganization of cortical connectivity is possible and it is essential for motor recovery [215]. Although these hypothesis have been confirmed with several independent neuroimaging studies, there are no EEG-based BCI studies that evaluate the changes in functional connectivity after tDCS intervention. Therefore, in this section, the functional connectivity measure will be emphasized to study the inter-hemispheric differences after tDCS intervention.

In the literature, it has been shown that the imaginary part of coherence (iCOH) explains the phase synchrony between two signals and thus it can be used to explain the

functional relation between two sources [216]. Furthermore, imaginary coherence (iCOH) has been proven to be robust against the source mixing (or volume conduction effect) as it has non-zero values only for non-zero delays. In other words, the non-zero iCOH ($Im(Coh_{X,Y}(j))$) cannot be due to source-mixing as it only implies that the sources have time-lagged interaction between them.

Let us consider the k^{th} segment of i^{th} time course as $x_{i,k}$ and its corresponding Fourier Transform as $X_{i,k}(f)$. The cross-spectral matrix is then computed as Eq. (6.4) [216],

$$S_{i,j}(f) = \frac{1}{K} \sum_{K=1}^K X_{i,k}^*(f) X_{j,k}(f) \quad (6.4)$$

$$Coh_{i,j}(f) = \frac{S_{i,j}(f)}{(S_{i,i}(f) S_{j,j}(f))^{1/2}} \quad (6.5)$$

In this study, the imaginary coherence is computed between the seed voxels of different ROIs as it is computationally intractable to compute all combinations of 15000 voxels. Therefore, the iCOH values is computed for different frequency bands ($\delta = < 4Hz$, $\theta = 4 - 8Hz$, $\alpha = 8 - 13Hz$, $\beta = 13 - 30Hz$) by using a moving window approach (bin width=1 Hz) within each frequency band.

Once the iCOH values are computed, the weighted node degree (WND) is computed at each representative voxel from different regions of interest as shown in Eq. (6.6).

$$K_i = \sum_j Coh_{i,j}(f) \quad (6.6)$$

The hypothesis of computing WND values is that the higher WND would be associated with the stroke recovery in terms of improvement in the Fugl-Meyer Scores.

The iCOH values are computed at group-level (tDCS and sham) for different spectral bands followed by the WND values for each ROI.

6.3.5 Effective Connectivity

In addition to studying the functional implications aka neural correlates, it is also essential to study the underlying causal explanation of the observed neural correlates. Traditionally, there are model-based as well as data-driven causal inference algorithms

such as Dynamic Causal Modeling (DCM) and Mixed Effect Recovery in Linear Networks (MERLIN) respectively. Functional connectivity does not explain the influence of a cortical region on the other, instead it only reveals whether there is a statistical dependency between time course of two ROIs. Effective connectivity addresses this issue by giving a causal interpretation of connectivity between 2 regions; in other words effective connectivity explains which cortical region modulates the activity in other cortical regions upon giving a stimulus. Therefore, one of the key differences between functional and effective connectivity is that the latter one depends on the stimulus as it is used to explain the causal effects of a given stimulus on the cortical activity whereas the former (FC) is used to just explain the resting-state cortical connections.

In the following subsection, a brief introduction of DCM is provided.

6.3.5.1 Dynamic Causal Modeling (DCM)

DCM is a measure of effective connectivity that also describes the causal structure. DCM is modelled using a dynamic input-state-output-system with multiple inputs and outputs. The main underlying principle of DCM for EEG is that the DCM considers EEG as a measured response to an experimental stimulus in a dynamic input-output system. To this end, DCM is modelled using a neural mass model at different cortical layers of neural population such as an excitatory subpopulation in the granular layer, inhibitory sub-population in the supra-granular layer, and a population of pyramidal cells in the infra-granular layer. The network dynamics and interactions between these sources are specified using first-order bilinear differential equations. It is to be noted that the DCM is a hypothesis-driven approach that requires the user to specify several plausible models that could explain the behavior, and therefore, DCM is not meant for exploratory purposes.

To describe briefly, the mathematical framework for DCM is based on state-space equations that describe the average synaptic dynamics in terms of spike-rate dependent cortical current and voltage changes as shown in Eq. (6.8),

$$\begin{aligned}\dot{x} &= f(x, u, \theta) \\ h &= g(x, \theta)\end{aligned}\tag{6.7}$$

Here, x describes the neuronal states of the cortical sources, θ quantifies the parameters of the state and the observer equations, and u describes the exogenous inputs.

Output equation couples specific states (average depolarization of pyramidal cells in each source), using a forward model i.e. $y = L(\theta)x_\theta + \varepsilon$ similar to the one used in EEG source-imaging.

In addition to the neuronal mass model, DCM requires an estimation of 3 types of parameters that are: (i) Task-independent endogenous coupling matrix (DCM-A) (ii) Task-dependent input-sensitive coupling matrix (DCM-B) to explain the effective connectivity between the cortical regions caused to the experimental stimulus, and (iii) an exogenous influence of inputs that drive the neural activity (DCM-C). As DCM is a hypothesis-driven model mentioned earlier, all the matrices (DCM-A, DCM-B, and DCM-C) need to be specified in terms of cortical regions of interest (ROI). Each of the ROI can be represented by a single-node or in other words- a representative voxel. Traditional methods use either the centroid of all the voxels within an ROI or extract the first eigenvariate (or first principal component) using a singular value decomposition of time-series matrix composed of all the voxels of a given ROI. Since the current study is based on motor imagery task, ROIs are chosen based on the neurophysiological relevance; thus, contralesional and ipsilesional primary motor cortex ($lM1$, $rM1$), supplementary motor area ($lSMA$, $rSMA$), and premotor cortex ($lPMC$, $rPMC$) are chosen as the task-relevant ROIs whereas the visual cue as an experimental stimulus input is assumed to drive the primary visual cortex ($lV1$, $rV1$) [217, 218]. In order to select the most representative voxel for each ROI, Mahalanobis distance (MD) based measure as shown in Eq. (6.8) was used where the voxel with the least MD to the average time series of all the voxels was selected.

$$d = \sqrt{(\mu_1 - \mu_2)\Sigma^{-1}(\mu_1 - \mu_2)^T} \quad (6.8)$$

Although there are numerous combinations of interregional connections, not all of them are necessarily affected by the condition-specific modulation (like motor imagery vs. idle state) [219]. Therefore, for the sake of computational simplicity, 4 different models based on an endogenous connectivity matrix (DCM-A shown in Fig. 6.3) are set up in this study that represent neurophysiological plausible interregional coupling during

the motor imagery task. The visual stimulus indicating whether the task is MI or Idle was provided on the screen in front of the subjects, and therefore the primary visual cortex is believed to drive the task-dependent influence that is reflected in DCM-C matrix. With regard to DCM-B matrix, the models are constructed based on several combinations such as the presence (vs. absence) of inter-hemispheric connections, presence (vs. absence) of heterotopic inter-hemispheric connections, and presence (vs. absence) of homotopic inter-hemispheric connections. An illustrative example of the models used for comparison in Subject N001 is shown in Fig. 6.4. The DCM-B models shown in Fig. 6.4 illustrate the how different ROIs modulate the activity of others. Since the anodal stimulation is given to the ipsilesional M1, it is hypothesized that the M1 will causally drive the activity in interconnected regions. Once these model priors are specified, random-effects Bayesian Model selection (BMS) is performed to select the most plausible model out of all the models for comparison. The details of BMS are given below.

6.3.5.2 Bayesian Model Selection (BMS)

As the DCM requires several models for comparison, a Bayesian Model Selection (BMS) is used to select the most plausible model that can account for the generalization ability.

A given DCM ‘ m ’ is inverted to approximate its posterior probability on a set of parameters using Bayes rule as shown in Eq. (6.9),

$$p(\theta|y, m) = \frac{p(y|\theta, m)p(\theta|m)}{p(y|m)} \quad (6.9)$$

Further, the statistical inference is done on the best model i.e. a model with a highest log-evidence (i.e. the smallest free-energy) $\log[p(y|m)]$.

Bayes-factor at the group-level can be simply calculated by adding the log-evidences from each subject as shown in Eq. (6.10),

$$\log p(y_1, \dots, y_n|m_i) = \sum_{j=1}^n \log p(y_j|m_i) \quad (6.10)$$

Detailed description of the estimation procedure employed in DCM is given in [220].

Figure 6.3: Illustrative example of an endogenous DCM Model used to study the causal effects of tDCS on stroke recovery. Different regions shown inside the circles are associated with the functions of motor imagery and execution task after observing a visual cue.

Figure 6.4: Models used for comparison in the DCM- BMS in Subject N001. Task-dependent modulations of connectivity for motor imagery after giving anodal (excitatory) stimulation to the ipsilesional M1 (Right hemisphere) and cathodal (inhibitory) stimulation to the contralesional M1 (left hemisphere).

6.4 Results and Discussions

6.4.1 Classification Performance

In this study, we proposed an ensemble feature method that uses spatial features from both sensor and source domain to classify MI vs. Idle state. The plot shown in Fig. 6.5

illustrates session-wise 5×5 cross validation accuracies of all the subjects across the two groups evaluated using different types of features.

Figure 6.5: Group-average session wise 5×5 crossvalidation based binary classification accuracies of MI vs. Idle state using different types of features

In particular, the session-wise 5×5 cross-validation classification accuracies were evaluated for each session consisting 40 trials (20 MI, 20 Idle). Session-wise group results for sensor- and source-space feature classification of MI-BCI in tDCS subjects are shown in Table 6.1 and Table 6.2 respectively. Similarly, the session-wise group results for sensor- and source-space feature classification of MI-BCI in sham subjects are shown in Table 6.3 and Table 6.4 respectively. For group-level comparison, the subject-specific accuracies for each session are averaged across all the subjects from the same group (tDCS or sham) and is plotted in Fig 6.5. For both groups (tDCS and sham), the SR-FBCSP features from the sensor and the source space individually were compared with the combined features. In this figure, x-axis indicates the session index (1-10), and y-axis corresponds to percentage classification accuracies averaged over the group of subjects.

The ensemble features resulted in a higher classification accuracy (64.42%) in tDCS group as compared to using either sensor (58.47%) or source space features (61.48%)

alone. Similar is the observation in the sham group, although the improvement in the classification accuracy using ensemble features (58.67%) is not significant compared to either sensor (58.04%) or source-space (58.04%) features in sham group subjects. The performance of tDCS group was better than that of sham group. Irrespective of the type of subjects or feature space, there is no clear trend in the classification accuracy over a period of 10 rehabilitation sessions, although the grand-average classification accuracies across different types of features were significantly higher than chance level accuracy. Post-hoc analysis (paired sample t-test) was conducted to observe the efficacy of the proposed method. The ensemble features resulted in a statistically significant ($p < 0.001$) improvement compared to the features from both sensor and source space EEG in the tDCS group, but not in the sham group ($p = 0.343$). Similarly, the groupwise comparison revealed that the MI vs. Idle classification accuracies in the tDCS group are significantly higher compared to the sham group ($p < 0.001$).

Table 6.1: 5×5 Cross validation accuracies of Sensor-space SR-FBCSP algorithm to classify MI vs Idle states across sessions 1-10 (T1-T10) in the tDCS group

tDCS Subjects	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	Session average
N001	0.87	0.612	0.512	0.62	0.637	0.7375	0.6125	0.5375	0.8125	0.5	0.64
N005	0.6	0.55	0.5125	0.588	0.588	0.438	0.5625	0.475	0.5625	0.45	0.53
N006	0.587	0.537	0.625	0.65	0.55	0.575	0.65	0.675	0.6125	0.45	0.591
N010	0.613	0.662	0.55	0.588	0.575	0.5625	0.5375	0.4625	0.5	0.6375	0.569
N015	0.66	0.55	0.65	0.675	0.6125	0.55	0.788	0.5125	0.8375	0.7375	0.657
N025	0.77	0.75	0.475	0.5625	0.6375	0.5125	0.5	0.5125	0.5	0.4625	0.568
N027	0.55	0.625	0.5375	0.538	0.5125	0.6	0.488	0.688	0.6375	0.6125	0.578
N029	0.563	0.45	0.3875	0.5625	0.5125	0.55	0.4875	0.425	0.4875	0.525	0.495
N035	0.52	0.55	0.5375	0.6125	0.675	0.6875	0.65	0.85	0.725	0.875	0.668
N037	0.488	0.55	0.575	0.5125	0.525	0.5125	0.475	0.625	0.525	0.4875	0.528
Group- average	0.636	0.583	0.536	0.591	0.582	0.572	0.575	0.576	0.62	0.573	0.584

6.4.2 Spectral Source Power Analysis

The cortical source activation patterns across tDCS and sham groups in different frequency bands were also studied. Since we defined ROIs earlier, trial-averaged band power of time series information in these ROIs were computed corresponding to the calibration session that was commenced before the tDCS intervention and the 10th session

Table 6.2: 5x5 Cross validation accuracies of Source-space SR-FBCSP algorithm to classify MI vs Idle states across sessions 1-10 (T1-T10) in the tDCS group

tDCS Subjects	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	Session average
N001	0.935	0.605	0.59	0.765	0.62	0.735	0.73	0.63	0.795	0.575	0.698
N005	0.57	0.485	0.5	0.525	0.53	0.445	0.435	0.52	0.495	0.455	0.496
N006	0.61	0.6	0.52	0.705	0.565	0.65	0.575	0.61	0.625	0.475	0.5935
N010	0.51	0.695	0.6	0.56	0.7	0.535	0.565	0.57	0.52	0.695	0.595
N015	0.79	0.48	0.74	0.67	0.765	0.755	0.845	0.6	0.855	0.84	0.734
N025	0.8	0.83	0.55	0.635	0.66	0.7	0.495	0.51	0.465	0.475	0.612
N027	0.635	0.69	0.635	0.515	0.5	0.52	0.57	0.71	0.725	0.65	0.615
N029	0.48	0.52	0.54	0.545	0.505	0.515	0.52	0.49	0.49	0.56	0.5165
N035	0.595	0.69	0.635	0.805	0.72	0.81	0.66	0.74	0.74	0.925	0.732
N037	0.47	0.615	0.435	0.685	0.54	0.54	0.52	0.57	0.6	0.52	0.5495
Group- average	0.60	0.62	0.560	0.598	0.628	0.636	0.608	0.586	0.606	0.63	0.615

Table 6.3: 5x5 Cross validation accuracies of Sensor-space SR-FBCSP algorithm to classify MI vs Idle states across sessions 1-10 in the sham group

Sham Subjects	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	Session average
N007	0.58	0.535	0.525	0.495	0.535	0.575	0.685	0.54	0.495	0.49	0.545
N009	0.685	0.66	0.485	0.605	0.695	0.565	0.78	0.875	0.88	0.685	0.691
N011	0.545	0.575	0.645	0.575	0.63	0.535	0.615	0.575	0.44	0.565	0.57
N018	0.55	0.525	0.585	0.53	0.57	0.51	0.445	0.653	0.515	0.5	0.538
N019	0.545	0.475	0.56	0.5	0.42	0.555	0.515	0.49	0.49	0.46	0.501
N021	0.61	0.54	0.465	0.64	0.5	0.505	0.48	0.6	0.455	0.445	0.524
N030	0.66	0.53	0.565	0.535	0.56	0.5	0.685	0.67	0.53	0.64	0.5875
N031	0.695	0.625	0.665	0.825	0.795	0.655	0.7	0.6	0.585	0.715	0.686
N032	0.535	0.48	0.515	0.535	0.44	0.515	0.475	0.565	0.47	0.565	0.5095
Group- average	0.60	0.55	0.557	0.582	0.572	0.546	0.598	0.618	0.54	0.563	0.573

Table 6.4: 5x5 Cross validation accuracies of Source-space SR-FBCSP algorithm to classify MI vs Idle states across sessions 1-10 in the sham group

Sham Subjects	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	Session average
N007	0.42	0.51	0.575	0.505	0.51	0.475	0.52	0.59	0.525	0.575	0.5205
N009	0.77	0.66	0.58	0.75	0.765	0.71	0.82	0.91	0.855	0.69	0.751
N011	0.58	0.53	0.705	0.59	0.62	0.495	0.54	0.495	0.505	0.535	0.5595
N018	0.585	0.685	0.685	0.655	0.475	0.48	0.55	0.621905	0.65	0.48	0.58669
N019	0.465	0.45	0.395	0.615	0.505	0.44	0.42	0.505	0.605	0.54	0.494
N021	0.595	0.555	0.535	0.69	0.6	0.515	0.57	0.58	0.41	0.485	0.5535
N030	0.615	0.62	0.5	0.47	0.41	0.39	0.69	0.605	0.535	0.58	0.5415
N031	0.765	0.61	0.74	0.825	0.75	0.58	0.695	0.575	0.72	0.745	0.7005
N032	0.46	0.56	0.58	0.575	0.49	0.505	0.51	0.525	0.52	0.435	0.516
Group- average	0.584	0.575	0.588	0.630	0.57	0.51	0.590	0.600	0.591	0.563	0.58

which is at the end of 2 weeks of tDCS intervention. As a case proof, the source-space EEG data of one of the subjects was studied whose MI-BCI classification performance and the FMA scores were improved during the intervention. It was observed that the average band power of Delta ($< 4\text{Hz}$) and Alpha ($8\text{-}12\text{Hz}$) frequency bands were significantly higher during the post-intervention as compared to pre-intervention, based on the number of voxels that are significantly different compared to the baseline. The results are shown in Fig. 6.6 in which the thick line and shaded portion represent the mean and standard deviation of source power of all the dipoles belonging to an ROI determined earlier. Post-hoc two sample t -tests revealed that the tDCS stimulation was associated with significant band power increase ($p < 0.001$) in both delta and alpha frequencies as compared to before the intervention, which concur with the findings in [221].

Extending further, we studied the group-level neural patterns by averaging the source activation across all sessions and subjects in each group. In Fig. 6.7, we have shown the group-averaged significant source activation based on the paired t -test results at a significance level of 0.05.

We found that the number of significant voxels was higher in the tDCS group as compared to the sham group. Interestingly, the significant source dipoles are located in the central region of Brodmann areas BA4 and BA6 which are associated with motor functions. It is to be noted that the subjects received anodal tDCS (or sham) stimulation

(a)

(b)

Figure 6.6: An illustrative example of comparison between post-tDCS intervention and pre-tDCS intervention spectral source power - (a) delta frequency band (0.5-4Hz) (b) alpha frequency band (8-12Hz). The time-series information corresponds to the source activation in the predefined ROI (BA4 and BA6).

Figure 6.7: Group-averaged sLORETA activation results during the MI trials in (a) tDCS and (b) Sham group

only in the ipsilesional motor region. Since there were almost equal number of subjects with either right or left-hand stroke-affected, the group average did not reveal any significant cortical excitation in either of the hemispheres. Nevertheless, there is no conclusive causal interpretation of whether the relatively stronger source activation in tDCS group has implications on the MI-BCI performance as well as FMA scores during the therapy.

6.4.3 Connectivity Analysis using Imaginary Coherence

The imaginary coherence measures (iCOH) corresponding to the calibration session were computed in different frequency bands across subjects within the tDCS and sham groups, and the results are plotted in Fig. 6.8. Similarly, the iCOH values corresponding to the closing session (10th rehab session) are plotted in Fig. 6.9. Between-group analysis of WND measures in the Delta, Theta, and Beta frequency bands using paired t -tests revealed significant differences ($p < 0.01$) between tDCS and sham subjects during week-0 (calibration session), but not in the Alpha band ($p > 0.05$). However, after the end of week-2 (10th session), there was also significant difference in the Alpha-band coherence ($p < 0.01$) along with the Delta-band coherence, but not in Theta and Beta coherence.

Table 6.5: Weighted Node Degree (WND) values of connectivity matrices estimated in different frequency bands across both the groups (tDCS and Sham) and sessions (week-0 and week-2)

	Wk0-tDCS	Wk2-tDCS	Wk0-Sham	Wk2-sham
Delta iCOH	1.43	2.06	3.63	3.82
Theta iCOH	2.31	1.64	2.15	1.84
Alpha iCOH	1.32	1.65	1.50	2.19
Beta iCOH	1.56	3.13	1.23	1.94

This intriguing results motivated to investigate the within-group WND comparison across sessions (week 0 and week 2) and the results are shown in Table 6.5.

6.4.4 Effects of tDCS on the Modulation of Motor Networks

DCM was implemented using SPM 12 toolbox where the regions of interest were selected a prior. After estimating the DCM using the endogenous matrix (DCM-A) shown in Fig. 6.3 and each of the model priors shown in Fig. 6.4, Bayesian model selection was performed using SPM12 toolbox [222]. A Fixed-effect analysis in Bayesian Model Selection was used for subject-level model selection. The model posterior probability and the log-evidence values for different models under comparison is shown in Fig. 6.10. It can be seen that the Model-1 has the highest model posterior probability and it is considered as the most plausible model. It further justifies that the modulatory effects of ipsilesional M1 is not just limited to homotopic, but extends to interhemispheric heterotopic connections. The endogenous coupling of winning model is shown in Fig. 6.11.

The analysis of subject-specific coupling revealed that there is a strong bidirectional coupling between the ipsilesional SMA and PMC, as well as contralesional M1 and PMC. Anodal excitatory stimulation given to ipsilesional M1 and cathodal inhibitory stimulation given to contralesional M1 revealed that the unidirectional coupling from ipsi-M1 is not very significant, however there is a strong unidirectional coupling from contra-M1 to contra-SMA and contra-PMC. This is an interesting aspect to be studied in the future with respect to the increased coupling after ipsilesional inhibition.

Figure 6.8: Group-averaged Functional Connectivity measured using Imaginary Coherence in different spectral bands for (a) tDCS and (b) Sham group before tDCS intervention

Figure 6.9: Group-averaged Functional Connectivity measured using Imaginary Coherence in different spectral bands for (a) tDCS and (b) Sham group after the 10th session of tDCS intervention

Figure 6.10: Results of Subject-level inference of Bayesian model selection showing the Log-evidence and Model Posterior Probability for different models.

Figure 6.11: Endogenous coupling of the winner model after performing Bayesian Model Selection

6.4.5 Limitations

As is the case with any BCI study, there is a lot of both intra-subject and inter-subject variability in this study as well. Within each subject, there is a high variability in the MI vs. Idle classification results performance across sessions. Further, both the groups (tDCS and sham) showed a high variability in the session-averaged classification results across subjects. In the previous study [208], the model trained using the calibration session data was transferred to each online session. Although the session-to-session transfer may result in relatively lesser variability as compared to cross-validation study, the classification results may not be necessarily better in the case of session-to-session transfer. Since the classification accuracies were computed session-wise, we suspect the training sample size is not enough to obtain good classification accuracies. It would be interesting to investigate robust transfer learning algorithms in the future studies with multiple subjects and sessions.

Also, a subject-independent template anatomy for the head model digitized based on a fewer number of scalp EEG electrodes was used in this study which is not ideal for accurate source localization. Nonetheless, this study is not as critical from an EEG source localization perspective as is the case with epileptic studies where it is very crucial to achieve a very high localization accuracy of detecting the seizure locations. Further, the study is limited to a relatively fewer subjects and therefore, there is a need to validate the findings from longitudinal studies in the future. Although it was observed that the tDCS-intervention resulted in increase in the bandpower of delta and alpha frequencies in the motor regions, the results must be carefully analyzed regarding its implication on the prognosis of stroke recovery.

Further, the stroke subjects did not have many follow-up sessions which limited the access to information of their cortical structural changes. With more number of sessions, it would have been possible to observe the correlation of stroke recovery in terms of FMA scores with the connectivity strengths in terms of WND values in different spectral bands. Concerning the DCM studies, this chapter only briefly illustrated the use of effective connectivity in one of the subjects in tDCS group. More elaborative study is required in terms of group-level analysis and also the findings of DCM for EEG would need further validation using fMRI in the future.

6.5 Summary

In this chapter, different aspects of EEG source-space features are studied in stroke patients who underwent tDCS intervention for rehabilitation. Furthermore, the motor-imagery brain-computer interface performance is also studied in terms of MI vs. Idle two-class classification accuracy. It was observed that an ensemble of features resulting from concatenated spatial features computed using sensor-space and sLORETA-based source EEG resulted in a higher classification accuracy as compared to using either sensor or source-space features alone. The spectral analysis in the Brodmann Areas BA4 and BA6 showed significant increase in the band power of Delta ($<4\text{Hz}$) and Alpha bands (8-12 Hz) during the tDCS intervention. At the end of 2 weeks of tDCS intervention, the tDCS group showed stronger cortical activation as compared to the sham group.

Another key aspect of connectivity measures is also investigated in this chapter in terms of imaginary coherence as a functional connectivity measure and Dynamic causal modeling as an effective connectivity measure. It was observed that the WND values in different frequency bands showed significant differences across tDCS and sham group of subjects. Dynamic Causal Modeling as an effective connectivity measure revealed that there is a significant cross-region modulation due to the tDCS stimulation.

In the future work, the current dataset of stroke patients needs to be studied from the perspective of data-driven causal inference algorithms such as stimulus-based causal inference (SCI) proposed in [223] as opposed to a model-driven approach like DCM. Furthermore, the neural correlates of stroke recovery needs to be studied subject-wise as the current chapter highlights only group-level analysis. Since the stroke recovery is highly subject-specific, there is a need to understand the structural and functional changes in the brain over a period of rehabilitation. With the current dataset, the future research direction would be generalize the connectivity changes for each subject, but across all 10 sessions as the number of MI trials per subject across all the therapy portions of rehabilitation sessions ($N=1600$ trials) constitutes relatively a large dataset.

Chapter 7

Conclusion and Future Works

7.1 Conclusion

The objectives laid earlier in this thesis were aimed at improved spatial filtering algorithms and an easier interpretation of observed scalp EEG-based BCI for movement decoding. Therefore, the emphasis is laid on developing machine learning and signal processing algorithms to improve the accuracy, computational efficiency, and interpretability of EEG-based BCI.

To summarize the contributions of this thesis, different signal processing and machine learning algorithms have been presented to improve the performance of BCI system. To this end, an EEG channel selection algorithm called *IMOCS* was presented as a dimension reduction technique to better classify the Motor-Imagery Brain-Computer Interfaces in Chapter 3. The approach is based on a multi-objective optimization technique, which tries to optimize both the classification accuracy as well as computational efficiency. The channel selection algorithm (IMOCS) followed by Filter bank Common Spatial Patterns (FBCSP) as a feature extraction method was evaluated using several datasets. An average classification accuracy of 90.77% (right hand vs. right foot MI) was obtained on Dataset-1 with 5 subjects using as few as 10 channels out of 118 channels. Similarly, an average classification accuracy of 81.21% was obtained on Dataset-2 with 9 subjects. In both these datasets, the classification performance of the proposed channel selection algorithm is at par or even better than that of the state-of-the-art methods published in the literature and it is worthwhile to note that the proposed method is computationally much faster than the convex optimization methods which were the benchmarking

algorithms. IMOCS was also evaluated on dataset-3 with 85 subjects whose EEG was recorded using 64 channels. An average classification accuracy of 64% was obtained where over 80% accuracy was obtained on the top 35 subjects. Considering the state-of-the-art BCI studies, this is relatively a larger pool of subjects. Further, the robustness of the proposed IMOCS algorithm was evaluated in terms of cross-subject generalizability or in other words ‘subject-to-subject transfer learning.’ It was noted that the channels selected across a group of subjects resulted in almost similar classification results as compared to using all the channels, further validating the author’s hypothesis that not all EEG channels are necessary for computing the features for classification. Alongside the classification performance, the reduced number of channels would aid in shortening the preparation time especially in the multiple-session BCI experiments.

After addressing the scalp-spatial filtering in terms of EEG channel selection, the research further delved into robustifying the feature computation as the traditional CSP algorithm is not robust to small sample setting (or fewer number of trials per class). A shrinkage regularized framework with an analytical solution (SR-CSP) was proposed in Chapter 4 to robustify the CSP algorithm and the evaluations on dataset-2 and dataset-3 revealed that the SR-FBCSP performed better than the FBCSP algorithm, a winner algorithm of BCI competition IV [159]. With an objective of understanding more about the neuronal correlates of MI-BCI performance, the research direction pivoted to EEG source localization as the cortical sources are not explored in traditional feature extraction methods. To this end, EEG inverse mapping of scalp sensors onto the cortical source-space was investigated and interestingly, EEG source imaging provided an improved spatiotemporal localization of MI tasks which is hard to interpret if we just use sensor-space features. The proposed approach of EEG source localization to compute single-trial task-related synchronization could identify the time-trigger of a motor imagery task. The preliminary findings suggested that it is possible to achieve real-time spatio-temporal localization of motor imagery using source-space EEG. Intrigued by this, further research was carried out in the cortical-source EEG by extending the traditional sensor-space feature techniques to the source-space EEG for a comparative study of the multi-directional (4-class) hand movement classification. An improvement of classification accuracy over 10% was obtained using the source-space CSP features as compared to sensor-space features.

Neural correlates of multi-directional hand movement are poorly understood if one uses CSP algorithm, as the CSP algorithm is a binary classification problem and the spatial patterns can identify the differences across 2 classes only. Therefore, a novel supervised factor analytic approach was presented in Chapter 5 where the traditional factor analysis was modeled similar to the EEG source localization that could also explain the heteroscedastic noise (unequal variance across cortical sources) in the brain. Using the region-of-interests as a priori knowledge, class labels were embedded to otherwise unsupervised factor analysis. Inspired by the Locality Sensitive Analysis (LSA) algorithm in graph theory for dimension reduction, the proposed supervised factor analysis algorithm used the local coordinates of source dipoles (or nodes) to assign them weights depending on whether the source dipole belongs to the neighborhood of predefined ROIs and also contributes to trial variance for a given movement direction. This approach preserves the neurophysiological relevance as well as allows for discriminative features. In addition to the improved 5×5 crossvalidation classification performance of (71%) across 4-classes, the proposed method also allowed for better interpretation of the movement direction-dependent neural correlates by localizing the significant source dipoles.

With the growing interest in brain stimulation for stroke recovery, this thesis also aimed to study more about the neural correlates of the brain stimulation in stroke patients and their MI-BCI performance. Preliminary findings on the source-space analysis of MI-BCI performance of two groups of stroke patients (tDCS and sham) suggested that the effects of tDCS on the stroke recovery are more pronounced in subjects whose delta ($<4\text{Hz}$) and alpha (8-12Hz) band power during the post-intervention is significantly higher as compared to pre-intervention. Also, the significant differences in inter-regional connection strengths evaluated based on imaginary coherence are observed across tDCS and sham group of subjects. Dynamic Causal Modeling as an effective connectivity measure revealed that there is a significant cross-region modulation due to the tDCS stimulation.

A consolidated view of the objective and the scientific contributions of this thesis is presented in Fig. 7.1.

Figure 7.1: A consolidated view of the objectives and scientific contributions presented in this thesis.

7.2 Future Research Directions

The work presented in this thesis has left some questions unanswered which throw light on some possible future works.

Concerning the spatial filtering algorithms, it would be interesting to study the effect of different types of regularization framework that can not only handle small sample settings but also session-to-session and subject-to-subject variability. It would be interesting to see if there is a unified feature extraction method that can address different types of variabilities. There is a need for much more explorative studies on EEG source localization as there are increasing number of inverse modeling methods that are evolving. Some of the possible interpretational pitfalls associated with EEG source-space studies are explicated in the later subsection. Concerning the work on supervised factor analysis algorithm, future work should investigate regularized variants of factor analysis to improve the classification accuracies in a multi-class BCI paradigm. Also, a robust feature classifier should be developed for localized arm movement such as individual finger tapping, elbow flexion, shoulder abduction, wrist pronation, supination and so on. We can recall that some of the studies focusing on EEG-based upper-limb movement decoding have already been described in Chapter 2 Section 2.4.2. However, the challenges are concerned with the real-time MI decoding of localized arm parts. Anatomical information

of ROIs can be leveraged to extract task-relevant features for fast classification. Finally, concerning the clinical application, future works on EEG source-space are dedicated to the prognosis of different neuromuscular disorders.

7.2.1 Improved feature extraction for an Asynchronous BCI

A truly practical Brain-Computer interface is an asynchronous system as the user does not have to wait for a ‘timed-experiment’ to mentally execute his tasks. In the long run, one would envisage a plug-and-play BCI system that can be interfaced quickly, and requires minimal calibration time. Although this is a desirable system, there is a multitude of challenges due to the non-stationarity and noisy recordings of EEG. In the literature review presented in Chapter 2, most of the popular signal processing algorithms for preprocessing and feature extraction have been emphasized. As the observed EEG recordings can be very noisy, there is a need for online automated artifact removal that not only picks up the obvious muscle and eye artifacts but also detects non-cortical signals. Further, the state-of-the-art feature extraction methods in synchronous BCI experiments have an advantage of choosing the temporal window (stimulus onset - until few seconds after the stimulus), thus significantly reducing the required feature computations. However, this would be a challenge in the case of asynchronous BCI as there is a need to track the pattern changes continuously without any stimulus. Therefore, EEG source-space studies can be extended to asynchronous BCI in the future as the current state-of-the-art is limited to synchronous BCI.

Extending further, the future research should aim at developing robust algorithms to address non-stationary EEG while adapting and calibrating itself according to the user’s past EEG data. With the upcoming advances in the computationally efficient deep neural networks [224], it is possible to achieve the subject-specific adaptation of EEG. Also, the key contribution of this thesis in the field of source-space EEG features can be extended to real-time application as recently several real-time EEG source localization toolboxes are made open-source [225, 226] and we can expect that in the coming decade there will be increasing number of real-time online BCI systems that can extract source-space EEG features as well.

7.2.2 Source Localization: Pitfalls and Challenges

There exist some practical concerns regarding the accuracy of source imaging, for which it is recommended to have subject-specific MRI scans, which is crucial for more accurate forward modeling. Although MRI is expensive, only one scan would ever be needed for a subject-specific anatomy as it can be reused again. Further, it is advisable to perform the digitization of EEG electrode positions to create a coordinate transformation between the subject-specific head model and the electrode location in a 3D geophysical space. Although it is obvious that the higher the number of EEG electrodes, better is the spatial resolution, the improvement in the source localization accuracy is minimal beyond a certain number of channels [176]. If there is no subject-specific MRI scan available, then the next suggested approach is to use a template anatomy of ICBM 152 and co-registering the positions of EEG electrodes with the help of a digitizer like Polhemus or ANT-Xensor. In the absence of both (MRI and a 3D digitizer), the last resort would be to use a template anatomy as it is, at the cost of less reliable source localization accuracy. Recently, Yu et.al proposed the New York head, a precise, standardized head model that can be used for the head model in the absence of MRI [227]. Since the New York head is a highly detailed anatomical model developed using Finite Element Method (FEM), the source localization accuracy is higher than what one would get by using a BEM of ICBM152 [227]. With the improvements in the forward modeling algorithms, the researchers should make use of the state-of-the-art forward models to improve the source localization accuracy.

7.2.3 EEG Source Imaging for Clinical Applications

In this subsection, we shall review the literature concerning the EEG source imaging in other neurological disorders. Nowadays, the use of brain connectivity measures as a potential biomarker is being examined in stroke, Amyotrophic Lateral Sclerosis (ALS), Alzheimers disease (AD), Parkinsons disease (PD) and Huntingtons disease (HD). Cortical connectivity measures give an idea of the statistical dependencies between the time-series data of different brain regions (functional connectivity) or the causal interactions of different ROIs (effective connectivity). Alpha- and beta-band coherence based FC measures were reported in a group of Ischemic stroke patients [8, 10]. Alpha-band synchrony

was used as a prognostic indicator of post-stroke cortical plasticity; the findings were also concurred with that of a similar MEG-based study [228]. Connectivity analyses are studied in neurodegenerative diseases like ALS and Parkinsons disease (PD). In one such study on the PD-related Dementia and Alzheimers, EEG-based sensor-connectivity analysis revealed that the relative wavelet energy could be used as an indication of healthy vs. dementia-affected people, while the wavelet coherence values could be used to differentiate Parkinsons related Dementia and Alzheimers disease [229]. In a cognitive impairment study, a source-level connectivity measure named Lagged Phase Synchronization (LPS) [230] showed a negative correlation with the Mini-Mental State Exam (MMSE) scores, signifying the cognitive decline. In another study conducted on Huntingtons disease (HD) patients, EEG connectivity analysis using eLORETA-based inverse solution revealed that there was an increased inter-hemispheric coupling between the motor areas during the wake state in HD patients as compared to healthy controls.

Traditionally, the connectivity measures are computed using the sensor-space EEG which is not robust against volume conduction effect [235]. Despite this, many studies compute the connectivity measures using scalp EEG for ease-of-computation and report the findings based on the statistical correlation observed. Since the correlation does not imply causation, the results reported that way must be carefully interpreted by accounting for the confounding factors. Especially when it comes to clinical diagnosis, it is recommended to use EEG-based biomarkers only as a secondary measure. FMRI-based neuroimaging studies have reported the causal interpretation of brain connectivity using Dynamic Causal Modeling (DCM), Granger causality (GC) and other related techniques. However, fMRI is limited by poor temporal resolution which is not ideal for effective connectivity analysis where the temporal information plays a crucial role. Therefore, the readers are recommended to weigh-in the advantage of either multimodal EEG-fMRI or EEG-based source imaging before interpreting the sensor-space connectivity measures.

Based on the observation of current research trend as shown in Table 7.1, EEG-based cortical biomarker studies are gaining momentum in diagnosing various movement-related disorders. However, it is to be noted that the fewer number of channels (eg. $N=19$) are used in non-stroke related clinical studies that could lead to poor localization accuracy. Although there are few sensor-space studies [236, 237], to the best of our knowledge,

Table 7.1: Recent works (Year: 2013 onwards-) on EEG-based Cortical Biomarker Systems for Clinical Applications

Study	Type of disorder	N_{ch}	Inverse Methods	Main Connectivity findings	Clinical Correlates
[9]	Chronic stroke	128	Beamformer	Resting-state alpha-band coherence with NFT can induce region- and band-specific enhancement of neural synchrony	motor deficit
[8]	Ischemic stroke	128	Beamformer	↓ alpha band iCOH (imaginary component of Coherence) between lesion-affected and rest of the brain	Cognitive and Motor deficit
[10]	Ischemic Stroke	128	Beamformer	↑ beta-band WND (graph-theoretic measure) at ipsilesional M1↑ motor improvement within 2-3 weeks after stroke onset	motor and cognitive deficit
[231]	MTBI	19	sLORETA	↑ short-distance connectivity in occipital and parietal areas; ↓ in long-distance connectivity	MTBI
[232]	AD	19	eLORETA	↓ CSF beta-amyloid (Ab42) concentration ↑ in CSD (right temporal area)	AD pathophysiology
[233]	AD and MCI	19	sLORETA	↑ Lagged Linear Coherence (graph parameter: characteristic path length) ↓ MMSE scores	Cognitive decline
[234]	HD	19	eLORETA	↑ LPS in delta (BA 6-8) , theta and alpha (BA1-2-3)	Cognitive decline

EEG source imaging for connectivity analysis has not been explored in ALS patients. It is a potential venue to explore EEG source-level connectivity as a cortical biomarker. Further, the readers can refer to [238] for a list of some of the ongoing clinical trials that use EEG-based BCI for neurorehabilitation.

To conclude, we believe that the trend of EEG source imaging based studies will thrive until there is a significant disruption in the BCI modalities (eg. Low-cost portable fMRI or optical imaging modalities). Further progress in the robust machine learning and signal processing techniques for EEG-based BCI can result in more visible impact on our day-to-day lives.

Appendix A

Appendix

A.1 Dimension reduction techniques used for the benchmarking in Chapter 3

A.1.1 Principal Component Analysis (PCA)

PCA is a well-known unsupervised dimensionality reduction technique which transforms the data into a different subspace of lower dimensionality. PCA has also been used in the area of BCI for feature reduction [141]. To express mathematically, PCA attempts to reduce the dimensionality by maximizing the cost function as shown in Eq. A.1,

$$C_{PCA} = \text{trace}(C^T \text{cov}(X)C) \quad (\text{A.1})$$

where, $\text{cov}(X)$ is covariance of the data matrix X . The linear transformation is preserved because of the principal eigenvectors of the covariance matrix. These eigenvalues are computed by solving the Eigen problem as shown in Eq. A.2,

$$\text{cov}(X)C = \lambda C \quad (\text{A.2})$$

PCA can be computationally intensive especially when it is applied on very large number of dimensions. To alleviate the effects of scaling, it is recommended to normalize the data. Based on the ranking of eigenvectors, channels are selected according to the indices of eigenvectors.

A.1.2 Gaussian Process Latent Variable Model (GPLVM)

Latent variable model (LVM) transforms the input dataspace where the original variables are converted to latent variables. The aggregation of large number of variables to form meaningful latent variables makes it a dimension reduction technique [144]. Gaussian Process latent Variable Model (GP-LVM) is a LVM technique which implements non-linear mapping of latent variables and helps to infer the hidden variables by providing a Bayesian framework. Unlike PCA where the original data space is transformed into a different linear subspace, in GPLVM it is transformed from latent space to the original space. Since the latent space is unknown, it is estimated by PCA and then marginalization of latent variables is performed.

A.1.3 Isomaps

Isomap is an extension of Multidimensional scaling (MDS), a non-linear dimensionality reduction technique [146]. A graph based method is used to define the neighborhood for data points (or nodes). Initially, the data points are clustered based on the K-nearest neighbor method. Subsequently, every edge connected between the neighboring nodes is assigned a weight as shown in Eq. A.3, corresponding to the Euclidean distance between them.

$$W_{ij} = d(x_i, x_j) \quad (\text{A.3})$$

For this connected graph, the shortest path distance is calculated using dijkstras algorithm. A positive semi-definite matrix D is constructed such that $D_{i,j} = d_{ij}^2$. A centering matrix H is defined as Eq. A.4 [239],

$$H = I - \frac{1}{2}e_n e_n^T \quad (\text{A.4})$$

where, e_n is $[1, 1, \dots, 1]^T$ of length n . Now the eigenvalue problem is solved for B , such that $B = 0.5HDH^T$ is decomposed into $B = U\theta U^T$. Top ' l ' eigenvectors are considered as the embedding coordinates in the Isomap and thus, the relevant EEG Channels.

A.1.4 Locally Linear Embedding (LLE)

Locally Linear Embedding is a nonlinear technique which came to light about the same time as that of Isomap. The advantage of LLE compared to Isomap is that the former is computationally faster [143]. In LLE, the input data points are assigned to its neighbors based on K-nearest neighbor technique. Minimization of cost function defined as shown in Eq. A.5,

$$\min \left\| \sum_i (\mathbf{x}_i - \sum_j W_{ij} \mathbf{x}_j) \right\|^2 \quad (\text{A.5})$$

Here, x_i corresponds to the input data point and x_j is its j^{th} neighbor. The reconstruction error is the cost function where, the reconstruction of original datapoints is done only from the neighboring points. Once the best reconstruction of X is achieved by solving constrained linear squares problem, the embedding vector Y is calculated by minimizing the quadratic function. Here, W_{ih} is fixed and the embedding data points Y_i are solved as constrained linear squares problem in Eq. A.6,

$$\min \Phi(Y) = \left\| \sum_i (Y_i - \sum_j W_{ij} Y_j) \right\|^2 \quad (\text{A.6})$$

A.1.5 Laplacian Eigenmaps

Laplacian Eigenmaps is another approach for visualizing the high-dimensional data [148]. It has an underlying assumption that, the high dimensional data lies in a low-dimensional manifold M . The concept of neighborhood is defined based on the adjacency graph, where node i and j are considered to be closer if $\|\mathbf{x}_i - \mathbf{x}_j\|^2 < \epsilon$. The weights assigned to these connected nodes i and j are based on Gaussian kernel, which is expressed as in Eq. A.7,

$$W_{ij} = e^{-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{t}} \quad (\text{A.7})$$

For non-connected nodes, the weight will be assigned 0, which makes W , a sparse symmetric matrix. For the sake of simplicity, W_{ij} is 1 if the nodes i and j are connected (i.e., $t = \infty$). The column entries of W are summed together resulting in a diagonal matrix D . The matrix L is defined as $D - W$, which is a laplacian matrix. The data points mentioned

as x_i are the column entries of the data matrix X , which is used in the eigenvalue problem as Eq. A.8,

$$L\mathbf{f} = \lambda D\mathbf{f} \quad (\text{A.8})$$

where, $\mathbf{f}$ is a solution vector which is sorted according to the eigenvalues and this sorted vector constitutes the set of relevant EEG channels. It is also interesting to note that the weight assignment function is similar to that of the proposed method.

A.1.6 Locality Preserving Projection (LPP)

Locality linear projection is insensitive to outliers and other noise compared to PCA. It preserves the neighborhood of data as the nearest neighbor search in a low-dimensional subspace will fetch the same results as that of a high dimensional data [142]. The mathematical framework of LPP follows the similar principles of Laplacian Eigenmaps but differs in the formulation of generalized eigenvalue problem. Unlike Laplacian Eigenmaps, which is a non-linear dimensionality reduction technique, LPP preserves the local neighborhood as it is a linear technique. Also, LPP can also be evaluated on test data points unlike PCA and Laplacian Eigenmaps. The eigenvalue problem is expressed as Eq. A.9,

$$XLX^T\phi = \lambda XDX^T\phi \quad (\text{A.9})$$

where, input data $X = [x_1, x_2, x_3, \dots, x_m]$ in $\mathbb{R}^n$, L is a Laplacian matrix. The solution vector ϕ is sorted according to the eigenvalues, thus resulting in reduced dimensions based on ranking of eigenvalues. The resulting transformation $Y = \phi^T X$ is of a lower dimension as $\phi = [\phi_1, \phi_2, \dots, \phi_l]$, ($l < n$).

A.1.7 Neighborhood Preserving Embedding (NPE)

Neighborhood Preserving Embedding is a linear approximation to the Locally Linear Embedding [143]. NPE computation method is quite similar to that of LPP. The same concept of neighborhood based on connected nodes is defined as in LPP and also the similar generalized eigenvalue problem.

$$XMX^T\phi = \lambda XX^T\phi \quad (\text{A.10})$$

In Eq. A.10, it can be seen that the eigenvalue problem to solve for ϕ involves M , which is computed as Eq. A.11,

$$M = (I - W)^T(I - W) \quad (\text{A.11})$$

where, I is an Identity matrix and W is the weight matrix as computed in LLE.

Instead of computing a laplacian matrix L as in the case of LPP, a semi definite positive matrix M is used in NPE. Essentially, NPE and LPP are different ways of approximating the Laplace Beltrami Operator. The solution vector ϕ is sorted in a descending order according to the eigenvalues.

A.1.8 Locally Linear Tangent Space Alignment (LLTSA)

LLTSA is an extension of Local Tangent Space Alignment. LTSA, unlike aforementioned methods, does not define a neighborhood. Instead, it uses the concept of Local Tangent Space to preserve the local properties of high dimensional data [145]. LLTSA is a linear approximation of LTSA, and it performs the local tangent space computation for the data points x_i . It is known that linear mapping L_i exists between the high-dimensional data and the local tangent space Θ_i of the same. The same linear mapping exists between the local tangent space that resulted above and the low-dimensional data. The solution vector is resulted from minimization of the following Eq. A.12[153],

$$\min_{\mathbf{Y}_i, \mathbf{L}_i} \sum_i \|\mathbf{Y}_i \mathbf{J}_k - \mathbf{L}_i \Theta_i\|^2 \quad (\text{A.12})$$

where, $\mathbf{J}_k$ is the centering matrix. The minimization for finding $\mathbf{Y}_i$ involves eigenvalue decomposition where, the top ‘ d ’ eigenvectors correspond to the set of most relevant EEG dimensions.

A.1.9 Fisher’s Criteria (FC)

Unlike aforementioned benchmarking algorithms, Fishers criteria (FC) is not a dimensionality reduction technique. FC is a feature selection technique which describes the relationship between a feature and its label. A score $F_j(X)$ of feature ‘ j ’ is used to define the Fishers criteria as in Eq. A.13 [60],

$$F_j(X) = \frac{(\mu_j(X^+) - \mu_j(X^-))^2}{V_j(X^+) + V_j(X^-)} \quad (\text{A.13})$$

In Eq. A.13, X^+ and X^- denote the set of trials corresponding to class 1 and class 2 respectively. μ_j and V_j denote the mean and variance of j^{th} feature respectively. The rank of a channel is simply set to the mean score of the corresponding features. Based on the ranking, channels are selected in a simple sorting procedure.

A.1.10 Support Vector Machine- Recursive Feature Elimination (SVM-RFE)

Support Vector Machine (SVM) is one of the most widely used classifier. SVM works on the principle of maximizing the separation between the two classes of data $X \subset \mathbb{R}^d$ and corresponding class labels Y by finding a hyperplane H with weight $w \in \mathbb{R}^d$ and an offset $b \in \mathbb{R}$. This hyperplane also has the largest distance to the nearest datapoints of both classes. It is expressed as in Eq. A.14,

$$\begin{aligned} H : \mathbb{R}^d &\rightarrow \{-1, 1\} \\ x &\rightarrow \text{sign}(w \cdot x + b) \end{aligned} \quad (\text{A.14})$$

Recursive feature elimination is a feature selection technique influenced by SVM [150]. In this channel selection paradigm, a given channel's significance is determined by its influence on the margin of a trained SVM [60]. Let us consider W as the inverse of margin of hyperplane, which can be expressed as Eq. A.15,

$$W(X, Y, C) = (\gamma(X, Y, C))^{-1} \quad (\text{A.15})$$

In every SVM training iteration, dimension k that minimizes $|W(X, Y, C) - W(X^{-k}, Y^{-k}, C)|$ is removed. In the context of channel selection, it is the k^{th} channel which is eliminated after each iteration because of its low score.

A.1.11 Common Spatial Pattern-Channel Selection (CSP-CS)

Common Spatial Pattern is a popular algorithm to distinguish 2 classes of EEG data. The signal subspace transformation is already described in the 3.3.4. CSP is proposed as a channel selection algorithm by Wang et.al [117]. It can be recalled from 3.3.4, that the columns of W^{-1} form the spatial patterns. The optimal channels (CH_1 and CH_2) for

a given task classification problem involving classes $T1$ and $T2$, can be determined by searching the maximum of absolute value of spatial patterns SP_1 and SP_2 corresponding to $T1$ and $T2$ respectively.

$$\begin{aligned} CH_1 &= find(|SP_1| == \max(|SP_1|)) \\ CH_2 &= find(|SP_2| == \max(|SP_2|)) \end{aligned} \quad (A.16)$$

To select more channels, the spatial pattern values can be sorted in descending order. These resulting channels are further used for feature extraction and classification procedure.

A.1.12 Particle Swarm Optimization (PSO)

Particle swarm optimization is an algorithm inspired by the social behavior of bird flock while searching for food. In the context of a given optimization problem, food is nothing but the solution. Each particle flies in search of solution in an N -dimensional search space with an adaptive velocity based on its previously acquired knowledge. Accordingly, the current position (x_{t+1}) of an i^{th} particle is updated with respect to its previous position x_t and current velocity (v_{t+1}). Mathematically, this behavior is represented as Eq. A.17 and Eq. A.18,

$$v_i^{t+1} = wv_i^t + c_1r_1(p_{best}^t - x_i^t) + c_2r_2(g_{best} - x_i^t) \quad (A.17)$$

$$x_i^{t+1} = x_i^t + v_i^t \quad (A.18)$$

In the above equation, v_i^{t+1} is the velocity of an i^{th} particle in $(t+1)^{th}$ iteration. w is the inertia weight which represents the relationship of the particle to its current position x_i [151]. c_1, c_2 are the cognitive learning factors whose values are random numbers in $[0,1]$. Initialization of all these parameters are according to the literature [151]. Binary PSO is a variant of PSO where a particle can have position values x_i of either 0 or 1. Each particle is of the dimension $N \times 1$, where N is the number of EEG channels. Therefore, a channel is said to be selected if its value is 1 and not selected if its value is 0. Position of the d^{th} bit of a particle is updated as Eq. A.19,

$$x_{id}^{t+1} = \begin{cases} 1 & \text{if } rand < (1 + e^{-v_{id}^t})^{-1} \\ 0 & \text{otherwise} \end{cases} \quad (A.19)$$

Bibliography

- [1] M. M. Ouellette, N. K. LeBrasseur, J. F. Bean, E. Phillips, J. Stein, W. R. Frontera, and R. A. Fielding, “High-intensity resistance training improves muscle strength, self-reported function, and disability in long-term stroke survivors.,” *Stroke; a journal of cerebral circulation*, vol. 35, pp. 1404–9, Jun 2004.
- [2] P. A. Lapchak, “Translational stroke research using a rabbit embolic stroke model: a correlative analysis hypothesis for novel therapy development.,” *Translational stroke research*, vol. 1, pp. 96–107, Jun 2010.
- [3] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, “Brain-computer interface technology: A review of the first international meeting.,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 164–73, Jun 2000.
- [4] G. Pfurtscheller, C. Brunner, A. Schlögl, and F. H. Lopes da Silva, “Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks,” *NeuroImage*, vol. 31, pp. 153–159, May 2006.
- [5] R. Grech, T. Cassar, J. Muscat, K. P. Camilleri, S. G. Fabri, M. Zervakis, P. Xanthopoulos, V. Sakkalis, and B. Vanrumste, “Review on solving the inverse problem in EEG source analysis.,” *Journal of neuroengineering and rehabilitation*, vol. 5, p. 25, Jan 2008.
- [6] K. Mahjoory, V. V. Nikulin, L. Botrel, K. Linkenkaer-Hansen, M. M. Fato, and S. Haufe, “Consistency of eeg source localization and connectivity estimates,” *NeuroImage*, vol. 152, pp. 590–601, May 2017.

- [7] N. Venketasubramanian, H. M. Chang, B. P. L. Chan, S. H. Young, K. H. Kong, K. F. Tang, Y. H. Ang, A. Ahmad, and K. Y. Chow, “Countrywide stroke incidence, subtypes, management and outcome in a multiethnic Asian population: the Singapore Stroke Registry–methodology,” *International journal of stroke : official journal of the International Stroke Society*, vol. 10, pp. 767–9, Jul 2015.
- [8] S. Dubovik, R. Ptak, T. Aboulafia, C. Magnin, N. Gillabert, L. Allet, J. M. Pignat, A. Schnider, and A. G. Guggisberg, “EEG alpha band synchrony predicts cognitive and motor performance in patients with ischemic stroke,” *Behavioural Neurology*, vol. 26, pp. 187–189, May 2013.
- [9] A. Mottaz, M. Solcà, C. Magnin, T. Corbet, A. Schnider, and A. G. Guggisberg, “Neurofeedback training of alpha-band coherence enhances motor performance,” *Clinical Neurophysiology*, vol. 126, pp. 1754–1760, Sept 2015.
- [10] P. Nicolo, S. Rizk, C. Magnin, M. D. Pietro, A. Schnider, and A. G. Guggisberg, “Coherent neural oscillations predict future motor and language improvement after stroke,” *Brain*, vol. 138, pp. 3048–3060, Jul 2015.
- [11] A. J. Butler, M. Shuster, E. O’Hara, K. Hurley, D. Middlebrooks, and K. Guilkey *Journal of Hand Therapy*, vol. 26, pp. 162–171, Sept 2013.
- [12] J. Marquez, P. van Vliet, P. Mcelduff, J. Lagopoulos, and M. Parsons, “Transcranial direct current stimulation (tDCS): Does it have merit in stroke rehabilitation? A systematic review,” *International Journal of Stroke*, vol. 10, pp. 306–316, Apr 2015.
- [13] A. Saimpont, C. Mercier, F. Malouin, A. Guillot, C. Collet, J. Doyon, and P. L. Jackson, “Anodal transcranial direct current stimulation enhances the effects of motor imagery training in a finger tapping task,” *European Journal of Neuroscience*, vol. 43, pp. 113–119, Jan 2016.
- [14] K. K. Ang, C. Guan, K. S. Phua, C. Wang, L. Zhao, W. P. Teo, C. Chen, Y. S. Ng, and E. Chew, “Facilitating effects of transcranial direct current stimulation on motor imagery brain-computer interface with robotic feedback for stroke rehabilitation,” *Archives of Physical Medicine and Rehabilitation*, vol. 96, pp. S79–S87, Mar 2015.

BIBLIOGRAPHY

- [15] G. Fritsch and E. Hitzig, “Ueber die elektrische Erregbarkeit des Grosshirns,” *Archiv für Anatomie, Physiologie und wissenschaftliche Medicin*, vol. 37, pp. 300–332, 1870.
- [16] R. Caton, “The Electric Currents of the Brain,” *British Medical Journal*, vol. 2, p. 278, 1875.
- [17] H. Berger, “Über das Elektroenkephalogramm des Menschen,” *Archiv für Psychiatrie*, vol. 87, pp. 527–570, 1929.
- [18] J. J. Vidal, “Toward Direct Brain-Computer Communication,” *Annual Review of Biophysics and Bioengineering*, vol. 2, pp. 157–180, Jun 1973.
- [19] J. R. Wolpaw, *Brain-Computer Interfaces: Principles and Practice*. 2012.
- [20] G. Dornhege, J. del R. Millán, T. Hinterberger, D. McFarland, and K. Müller, “Single-Trial Analysis of EEG during Rapid Visual Discrimination: Enabling Cortically Coupled Computer Vision,” *Towards Brain-Computer Interfacing*, pp. 423–439, 2007.
- [21] V. A. Zerris, J. D. Donoghue, L. R. Hochberg, D. K. O’Rourke, and E. A. Chiocca, “Braingate: Turning Thought into Action-First Experience with a Human Neuro-motor Prosthesis: 885,” *Neurosurgery*, vol. 57, p. 425, Aug 2005.
- [22] B. K. Min, M. J. Marzelli, and S. S. Yoo, “Neuroimaging-based approaches in the brain-computer interface,” *Trends in Biotechnology*, vol. 28, pp. 552–560, Nov 2010.
- [23] S. Herculano-Houzel, “The human brain in numbers: a linearly scaled-up primate brain.,” *Frontiers in human neuroscience*, vol. 3, no. Nov, p. 31, 2009.
- [24] A. S. Blum and S. B. Rutkove, *The clinical neurophysiology primer*. Springer Science and Business Media, Sept 2007.
- [25] G. Pfurtscheller and F. H. Lopes da Silva, “Event-related EEG/MEG synchronization and desynchronization: basic principles,” *Clinical neurophysiology*, vol. 110, pp. 1842–57, Nov 1999.

- [26] A. Delorme, J. Palmer, J. Onton, R. Oostenveld, and S. Makeig, “Independent eeg sources are dipolar,” *PloS one*, vol. 7, p. e30135, Feb 2012.
- [27] T. W. Lee, M. Girolami, and T. J. Sejnowski, “Independent component analysis using an extended infomax algorithm for mixed subgaussian and supergaussian sources,” *Neural computation*, vol. 11, pp. 417–441, Feb 1999.
- [28] W. De Clercq, A. Vergult, B. Vanrumste, W. Van Paesschen, and S. Van Huffel, “Canonical correlation analysis applied to remove muscle artifacts from the electroencephalogram,” *IEEE Transactions on Biomedical Engineering*, vol. 53, pp. 2583–2587, Nov 2006.
- [29] R. J. Croft and R. J. Barry, “Removal of ocular artifact from the EEG: A review,” *Neurophysiologie Clinique*, vol. 30, pp. 5–19, Feb 2000.
- [30] G. Gratton, M. G. H. Coles, and E. Donchin, “A new method for off-line removal of ocular artifact,” *Electroencephalography and Clinical Neurophysiology*, vol. 55, pp. 468–484, Apr 1983.
- [31] S. V. Vaseghi, *Advanced Digital Signal Processing and Noise Reduction*. Wiley, 2009.
- [32] S. Romero, M. A. Mañanas, and M. J. Barbanoj, “Ocular reduction in EEG signals based on adaptive filtering, regression and blind source separation,” *Annals of Biomedical Engineering*, vol. 37, pp. 176–191, Jan 2009.
- [33] K. T. Sweeney, H. Ayaz, T. E. Ward, M. Izzetoglu, S. F. McLoone, and B. Onaral, “A methodology for validating artifact removal techniques for physiological signals,” *IEEE Transactions on Information Technology in Biomedicine*, vol. 16, pp. 918–926, Sept 2012.
- [34] Z. Wu and N. E. Huang, “Ensemble Empirical Mode Decomposition: a Noise-Assisted Data Analysis Method,” *Advances in Adaptive Data Analysis*, vol. 01, pp. 1–41, Jan 2009.

- [35] D. Iatsenko, P. V. E. McClintock, and A. Stefanovska, “Nonlinear mode decomposition: A noise-robust, adaptive decomposition method,” *Physical Review E*, vol. 92, p. 032916, Sep 2015.
- [36] F. Morbidi, A. Garulli, D. Prattichizzo, C. Rizzo, and S. Rossi, “Application of Kalman filter to remove TMS-induced artifacts from EEG recordings,” *IEEE Transactions on Control Systems Technology*, vol. 16, pp. 1360–1366, Nov 2008.
- [37] N. Ille, P. Berg, and M. Scherg, “Artifact correction of the ongoing EEG using spatial filters based on artifact and brain signal topographies,” *Clinical Neurophysiology*, vol. 19, pp. 113–24, Mar 2002.
- [38] G. L. Wallstrom, R. E. Kass, A. Miller, J. F. Cohn, and N. A. Fox, “Automatic correction of ocular artifacts in the EEG: A comparison of regression-based and component-based methods,” *International Journal of Psychophysiology*, vol. 53, pp. 105–119, Jul 2004.
- [39] B. Obermaier, C. Guger, C. Neuper, and G. Pfurtscheller, “Hidden Markov models for online classification of single trial EEG data,” *Pattern Recognition Letters*, vol. 22, pp. 1299–1309, Oct 2001.
- [40] C. Vidaurre, N. Krämer, B. Blankertz, and A. Schlögl, “Time Domain Parameters as a feature for EEG-based Brain-Computer Interfaces,” *Neural Networks*, vol. 22, pp. 1313–1319, Nov 2009.
- [41] A. Khorshidtalab, M. J. E. Salami, and M. Hamed, “Robust classification of motor imagery EEG signals using statistical timedomain features,” *Physiological Measurement*, vol. 34, pp. 1563–1579, Nov 2013.
- [42] K. P. Thomas, C. Guan, C. T. Lau, A. P. Vinod, and K. K. Ang, “Adaptive tracking of discriminative frequency components in electroencephalograms for a robust brain-computer interface,” *Journal of neural engineering*, vol. 8, p. 036007, Apr 2011.

- [43] P. Herman, G. Prasad, T. M. McGinnity, and D. Coyle, “Comparative analysis of spectral approaches to feature extraction for EEG-based motor imagery classification,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 16, pp. 317–326, Aug 2008.
- [44] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, “Optimal spatial filtering of single trial EEG during imagined hand movement.,” *IEEE Trans. on Rehab. Engg*, vol. 8, pp. 441–6, Dec 2000.
- [45] X. Liao, D. Yao, D. Wu, and C. Li, “Combining spatial filters for the classification of single-trial EEG in a finger movement task,” *IEEE Transactions on Biomedical Engineering*, vol. 54, pp. 821–831, May 2007.
- [46] H. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos, “Regularized common spatial patterns with generic learning for eeg signal classification,” in *31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, (Minneapolis), pp. 6599–6602, IEEE, Sept 2009.
- [47] F. Lotte, C. Guan, and K. K. Ang, “Comparison of designs towards a subject-independent brain-computer interface based on motor imagery,” in *31st Ann. Intl. Conf. of the IEEE Engg. in Med. and Bio. Soc.*, (Minnesota, USA), pp. 4543–4546, Sept 2009.
- [48] D. Devlaminck, B. Wyns, M. Grosse-Wentrup, G. Otte, and P. Santens, “Multisubject learning for common spatial patterns in motor-imagery BCI,” *Computational Intelligence and Neuroscience*, vol. 2011, Jan 2011.
- [49] W. Samek, F. C. Meinecke, and K. R. Muller, “Transferring subspaces between subjects in Brain - Computer interfacing,” *IEEE Transactions on Biomedical Engineering*, vol. 60, pp. 2289–2298, Aug 2013.
- [50] M. Arvaneh, C. T. Guan, K. K. Ang, and C. Quek, “EEG Data Space Adaptation to Reduce Intersession Nonstationarity in Brain-Computer Interface,” *Neural Computation*, vol. 25, pp. 2146–2171, Aug 2013.

- [51] R. Tomioka, G. Dornhege, G. Nolte, B. Blankertz, K. Aihara, and K.-R. Müller, “Spectrally weighted Common Spatial Pattern algorithm for single trial EEG classification,” *Dept Math Eng, Univ Tokyo, Japan Tech Rep*, vol. 40, no. July, p. 25, 2006.
- [52] G. Dornhege, B. Blankertz, M. Krauledat, F. Losch, G. Curio, and K.-R. Müller, “Combined optimization of spatial and temporal filters for improving brain-computer interfacing,” *IEEE Transactions on Biomedical Engineering*, vol. 53, pp. 2274–81, Nov 2006.
- [53] W. Wu, X. Gao, B. Hong, and S. Gao, “Classifying single-trial EEG during motor imagery by iterative spatio-spectral patterns learning (ISSPL),” *IEEE Trans. on Biomed. Engg.*, vol. 55, pp. 1733–43, June 2008.
- [54] H. Zhang, Z. Y. Chin, K. K. Ang, C. Guan, and C. Wang, “Optimum spatio-spectral filtering network for brain-computer interface,” *IEEE Transactions on Neural Networks*, vol. 22, pp. 52–63, Jan 2011.
- [55] K. Q. Shen, C. J. Ong, X. P. Li, Z. Hui, and E. P. Wilder-Smith, “A feature selection method for multilevel mental fatigue EEG classification,” *IEEE Trans Biomed Eng*, vol. 54, pp. 1231–1237, Jul 2007.
- [56] D. Garrett, D. Peterson, C. Anderson, and M. Thaut, “Comparison of linear, non-linear, and feature selection methods for EEG signal classification,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, pp. 141–144, Jun 2003.
- [57] H. Peng, F. Long, and C. Ding, “Feature selection based on mutual information: criteria of max-dependency, max-relevance, and min-redundancy,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, pp. 1226–38, Aug 2005.
- [58] K. K. Ang, Z. Y. Chin, H. Zhang, and C. Guan, “Mutual information-based selection of optimal spatialtemporal patterns for single-trial EEG-based BCIs,” *Pattern Recognition*, vol. 45, pp. 2137–2144, Jun 2012.

- [59] J. F. D. Saa and M. Çetin, “Discriminative Methods for Classification of Asynchronous Imaginary Motor Tasks From EEG Data,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 21, pp. 716–724, Sept 2013.
- [60] T. N. Lal, M. Schröder, T. Hinterberger, J. Weston, M. Bogdan, N. Birbaumer, and B. Schölkopf, “Support vector channel selection in BCI,” *IEEE Trans. on Biomed. Engg.*, vol. 51, pp. 1003–10, Jun 2004.
- [61] F. Lotte, M. Congedo, a. Lécuyer, F. Lamarche, and B. Arnaldi, “A review of classification algorithms for EEG-based brain-computer interfaces.,” *J Neural Eng*, vol. 4, pp. R1–R13, Jan 2007.
- [62] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*. John Wiley and Sons, Nov 2000.
- [63] B. Blankertz, G. Curio, and K.-R. Müller, “Classifying single trial EEG: Towards brain computer interfacing,” *Advances in Neural Information Processing Systems*, vol. 1, pp. 157–164, 2002.
- [64] K. Müller, M. Krauledat, G. Dornhege, G. Curio, and B. Blankertz, “Machine learning techniques for brain-computer interfaces,” *Biomedical Engineering*, pp. 11–22, 2004.
- [65] Kai Keng Ang, Zheng Yang Chin, Haihong Zhang, and Cuntai Guan, “Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface,” in *2008 IEEE International Joint Conference on Neural Networks (IJCNN)*, pp. 2390–2397, IEEE, jun 2008.
- [66] K. P. Thomas, C. Guan, C. T. Lau, A. P. Vinod, and K. K. Ang, “A new discriminative common spatial pattern method for motor imagery brain-computer interfaces.,” *IEEE Trans. on Biomed. Engg.*, vol. 56, pp. 2730–33, Nov 2009.
- [67] Q. Zhao, L. Zhang, and A. Cichocki, “EEG-based asynchronous BCI control of a car in 3D virtual reality environments,” *Chinese Science Bulletin*, vol. 54, pp. 78–87, Jan 2009.

- [68] M. Arvaneh, C. Guan, K. K. Ang, and C. Quek, “Optimizing the channel selection and classification accuracy in EEG-based BCI,” *IEEE Transactions on Biomedical Engineering*, vol. 58, pp. 1865–73, Jun 2011.
- [69] X. Yong, R. K. Ward, and G. E. Birch, “Robust Common Spatial Patterns for EEG signal preprocessing,” in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, (Vancouver), pp. 2087–2090, Aug 2008.
- [70] H. Lu, H. L. Eng, C. Guan, K. N. Plataniotis, and A. N. Venetsanopoulos, “Regularized common spatial pattern with aggregation for EEG Classification in small-sample setting,” *IEEE Transactions on Biomedical Engineering*, vol. 57, pp. 2936–2946, Dec 2010.
- [71] F. Lotte and C. Guan, “Regularizing common spatial patterns to improve BCI designs: Unified theory and new algorithms,” *IEEE Transactions on Biomedical Engineering*, vol. 58, pp. 355–362, Feb 2011.
- [72] N. Robinson, C. Guan, A. P. Vinod, K. K. Ang, and K. P. Tee, “Multi-class EEG classification of voluntary hand movement directions,” *Journal of neural engineering*, vol. 10, pp. 01–11, Oct. 2013.
- [73] H. Kang, Y. Nam, and S. Choi, “Composite common spatial pattern for subject-to-subject transfer,” *IEEE Signal Processing Letters*, vol. 16, pp. 683–686, Aug 2009.
- [74] V. Jayaram, M. Alamgir, Y. Altun, B. Scholkopf, and M. Grosse-Wentrup, “Transfer Learning in Brain-Computer Interfaces,” *IEEE Computational Intelligence Magazine*, vol. 11, pp. 20–31, Feb 2016.
- [75] F. Lotte and C. Guan, “Spatially regularized common spatial patterns for eeg classification,” in *20th International Conference on Pattern Recognition (ICPR)*, (Istanbul), pp. 3712–3715, IEEE, 2010.
- [76] S. Lemm, C. Schafer, and G. Curio, “BCI competition 2003-data set III: probabilistic modeling of sensorimotor/spl mu/rhythms for classification of imaginary hand

BIBLIOGRAPHY

- movements,” *IEEE Transactions on Biomedical Engineering*, vol. 51, pp. 1077–1080, Jun 2004.
- [77] A. M. Dale and M. I. Sereno, “Improved Localization of Cortical Activity by Combining EEG and MEG with MRI Cortical Surface Reconstruction: A Linear Approach,” *Journal of Cognitive Neuroscience*, vol. 5, no. 2, pp. 162–176, 1993.
- [78] C. J. Holmes, R. Hoge, L. Collins, R. Woods, a. W. Toga, and a. C. Evans, “Enhancement of MR images using registration for signal averaging,” *Journal of computer assisted tomography*, vol. 22, pp. 324–333, Mar 2015.
- [79] J. C. Mazziotta, A. W. Toga, A. Evans, P. Fox, and J. Lancaster, “A probabilistic atlas of the human brain: Theory and rationale for its development: The international consortium for brain mapping (icbm),” *Neuroimage*, vol. 2, pp. 89–101, Jun 1995.
- [80] F. Tadel, S. Baillet, J. C. Mosher, D. Pantazis, and R. M. Leahy, “Brainstorm: A user-friendly application for MEG/EEG analysis,” *Computational Intelligence and Neuroscience*, vol. 2011, 2011.
- [81] A. Gramfort, T. Papadopoulos, E. Olivi, and M. Clerc, “OpenMEEG: open-source software for quasistatic bioelectromagnetics,” *Biomedical engineering online*, vol. 9, p. 45, Sept 2010.
- [82] R. Oostenveld, P. Fries, E. Maris, and J. M. Schoffelen, “FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data,” *Computational Intelligence and Neuroscience*, vol. 2011, Jan 2011.
- [83] K. J. Friston, A. P. Holmes, K. J. Worsley, J.-P. Poline, C. D. Frith, and R. S. J. Frackowiak, “Statistical parametric maps in functional imaging: A general linear approach,” *Human Brain Mapping*, vol. 2, pp. 189–210, Oct 1994.
- [84] S. Waldert, T. Pistohl, C. Braun, T. Ball, A. Aertsen, and C. Mehring, “A review on directional information in neural signals for brain-machine interfaces,” *Journal of Physiology Paris*, vol. 103, pp. 244–254, Sept 2009.

- [85] L. Qin, L. Ding, and B. He, “Motor Imagery Classification by Means of Source Analysis for Brain Computer Interface Applications,” *Journal of neural engineering*, vol. 2, pp. 65–72, Aug 2005.
- [86] M. Congedo, F. Lotte, and A. Lecuyer, “Classification of movement intention by spatially filtered electromagnetic inverse solutions.,” *Physics in medicine and biology*, vol. 51, pp. 1971–1989, Mar 2006.
- [87] Q. Noirhomme, R. I. Kitney, and B. Macq, “Single-trial EEG source reconstruction for brain-computer interface,” *IEEE Transactions on Biomedical Engineering*, vol. 55, pp. 1592–1601, May 2008.
- [88] P. W. Ferrez and J. del R Millan, “EEG-Based Brain-Computer Interaction: Improved Accuracy by Automatic Single-Trial Error Detection,” *Neural Information Processing Systems Conference*, pp. 441–448, 2008.
- [89] M. Grosse-Wentrup, C. Liefhold, K. Gramann, and M. Buss, “Beamforming in Noninvasive BrainComputer Interfaces,” *IEEE Transactions on Biomedical Engineering*, vol. 56, pp. 1209–1219, Apr 2009.
- [90] R. Grave de Peralta, T. Landis, and S. Gonzalez Andino, “Electrical neuroimaging of single trials to identify laterality and brain regions involved in finger movements,” *Journal of Physiology Paris*, vol. 103, pp. 324–332, Nov 2009.
- [91] Han Yuan, A. Doud, A. Gururajan, and Bin He, “Cortical Imaging of Event-Related (de)Synchronization During Online Control of Brain-Computer Interface Using Minimum-Norm Estimates in Frequency Domain,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 16, pp. 425–431, Oct 2008.
- [92] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, “Reconstructing three-dimensional hand movements from noninvasive electroencephalographic signals.,” *Journal of neuroscience*, vol. 30, pp. 3432–7, Mar 2010.
- [93] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, “Fast attainment of computer cursor control with noninvasively acquired brain signals.,” *Journal of neural engineering*, vol. 8, p. 036010, Apr 2011.

- [94] S. Waldert, H. Preissl, E. Demandt, C. Braun, N. Birbaumer, A. Aertsen, and C. Mehring, “Hand movement direction decoded from MEG and EEG.,” *Journal of neuroscience*, vol. 28, pp. 1000–8, Jan 2008.
- [95] Y. Wang and S. Makeig, “Predicting intended movement direction using EEG from human posterior parietal cortex,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 5638 LNAI, pp. 437–446, 2009.
- [96] P. Ofner and G. R. Muller-Putz, “Using a Non-Invasive Decoding Method to Classify Rhythmic Movement Imaginations of the Arm in Two Planes.,” *IEEE transactions on bio-medical engineering*, vol. 9294, pp. 1–10, Dec 2014.
- [97] J. Lv, Y. Li, and Z. Gu, “Decoding hand movement velocity from electroencephalogram signals during a drawing task,” *BioMedical Engineering Online*, vol. 9, p. 64, Oct 2010.
- [98] D. Heger, R. Jäkel, F. Putze, M. Lösch, and T. Schultz, “Filling a glass of water: continuously decoding the speed of 3D hand movements from EEG signals.,” in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society.*, (San Diego, USA), pp. 4095–98, Jan 2012.
- [99] L. Jäncke, K. Lutz, and S. Koeneke, “Converging evidence of ERD/ERS and BOLD responses in motor control research.,” *Progress in brain research*, vol. 159, pp. 261–71, Jan 2006.
- [100] T. J. Bradberry, F. Rong, and J. L. Contreras-Vidal, “Decoding center-out hand velocity from MEG signals during visuomotor adaptation,” *NeuroImage*, vol. 47, pp. 1691–1700, Oct 2009.
- [101] N. Robinson, A. P. Vinod, K. K. Ang, K. P. Tee, and C. T. Guan, “EEG-based classification of fast and slow hand movements using Wavelet-CSP algorithm.,” *IEEE Trans. on Biomed. Engg.*, vol. 60, pp. 2123–32, Aug. 2013.

BIBLIOGRAPHY

- [102] J. M. Antelis, L. Montesano, A. Ramos-Murguialday, N. Birbaumer, and J. Minguez, “On the usage of linear regression models to reconstruct limb kinematics from low frequency EEG signals.,” *PloS one*, vol. 8, p. e61976, Jan 2013.
- [103] M. Wieser, J. Haefeli, L. Büttler, L. Jäncke, R. Riener, and S. Koeneke, “Temporal and spatial patterns of cortical activation during assisted lower limb movement,” *Experimental Brain Research*, vol. 203, pp. 181–191, May 2010.
- [104] F. Galán, M. R. Baker, K. Alter, and S. N. Baker, “Degraded EEG decoding of wrist movements in absence of kinaesthetic feedback.,” *Human brain mapping*, vol. 36, pp. 643–654, Oct 2014.
- [105] M. Witte, F. Galán, S. Waldert, C. Braun, and C. Mehring, “Concurrent stable and unstable cortical correlates of human wrist movements.,” *Human brain mapping*, vol. 35, pp. 3867–79, Aug 2014.
- [106] B. J. Edelman, B. Baxter, and B. He, “EEG Source Imaging Enhances the Decoding of Complex Right-Hand Motor Imagery Tasks.,” *IEEE Transactions on Biomedical Engineering*, vol. 63, pp. 4–14, Jan 2016.
- [107] J. Yao, C. Sheaff, C. Carmona, and J. P. Dewald, “Impact of Shoulder Abduction Loading on Brain-Machine Interface in Predicting Hand Opening and Closing in Individuals With Chronic Stroke,” *Neurorehabilitation and Neural Repair*, vol. 30, pp. 363–372, May 2016.
- [108] J. Pereira, P. Ofner, A. Schwarz, A. Ioana Sburlea, and G. R. Müller-Putz, “EEG neural correlates of goal-directed movement intention,” *NeuroImage*, vol. 149, pp. 129–140, Jan 2017.
- [109] M. T. Carrillo-de-la Peña, S. Galdo-Álvarez, and C. Lastra-Barreira, “Equivalent is not equal: Primary motor cortex (MI) activation during motor imagery and execution of sequential movements,” *Brain Research*, vol. 1226, pp. 134–143, Aug 2008.

- [110] Y. Gu, K. Dremstrup, and D. Farina, “Single-trial discrimination of type and speed of wrist movements from EEG recordings,” *Clinical neurophysiology*, vol. 120, pp. 1596–600, Aug 2009.
- [111] J. Lehtonen, P. Jylänki, L. Kauhanen, and M. Sams, “Online classification of single EEG trials during finger movements,” *IEEE Transactions on Biomedical Engineering*, vol. 55, pp. 713–720, Feb 2008.
- [112] A. Y. Paek, *Decoding Repetitive finger movements with Brain signals acquired via noninvasive Electroencephalography*. PhD thesis, University of Maryland, College Park, 2011.
- [113] J. Zhou, J. Yao, J. Deng, and J. Dewald, “EEG-based Discrimination of Elbow/Shoulder Torques using Brain Computer Interface Algorithms: Implications for Rehabilitation,” *International Conference of IEEE Engineering in Medicine and Biology Society*, vol. 4, pp. 4134–4137, Sept 2005.
- [114] B. Blankertz, F. Losch, M. Krauledat, G. Dornhege, G. Curio, and K.-R. Müller, “The Berlin Brain–Computer Interface: accurate performance from first-session in BCI-naïve subjects,” *IEEE Trans. on Biomedical Engineering*, vol. 55, pp. 2452–62, Oct 2008.
- [115] D. Feess, M. M. Krell, and J. H. Metzen, “Comparison of Sensor Selection Mechanisms for an ERP-Based Brain-Computer Interface,” *PLoS ONE*, vol. 8, Jul 2013.
- [116] Y. Li, A. Cichocki, and S.-I. Amari, “Blind estimation of channel parameters and source components for EEG signals: a sparse factorization approach,” *IEEE Trans. on Neural Networks*, vol. 17, pp. 419–31, Mar. 2006.
- [117] Y. Wang, S. Gao, and X. Gao, “Common Spatial Pattern Method for Channel Selection in Motor Imagery Based Brain-computer Interface,” in *27th Annl. Intl. Conf. of the IEEE Engg. in Med. and Bio. Soc.*, vol. 5, (Shanghai), pp. 5392–5395, Sept 2005.

- [118] J. Yang, H. Singh, E. L. Hines, F. Schlaghecken, D. D. Iliescu, M. S. Leeson, and N. G. Stocks, “Channel selection and classification of electroencephalogram signals: an artificial neural network and genetic algorithm-based approach,” *Artificial intelligence in medicine*, vol. 55, pp. 117–26, Jun 2012.
- [119] J. Jin, B. Z. Allison, C. Brunner, B. Wang, X. Wang, J. Zhang, C. Neuper, and G. Pfurtscheller, “P300 Chinese input system based on Bayesian LDA,” *Biomedizinische Technik*, vol. 55, pp. 5–18, 2010.
- [120] J. Lv and M. Liu, “Common Spatial Pattern and Particle Swarm Optimization for Channel Selection in BCI,” in *3rd Intl. Conf.on Innovative Computing Information and Control*, (Dalian), p. 457, Jun 2008.
- [121] J.-y. Kim, S.-m. Park, K.-e. Ko, and K.-b. Sim, “Optimal EEG Channel Selection for Motor Imagery BCI System Using BPSO and GA,” *Robot Intelligence Technol. & Appl*, vol. 208, pp. 231–239, 2013.
- [122] K. Klamroth and K. Miettinen, “Integrating approximation and interactive decision making in multicriteria optimization,” *Operations Research*, vol. 56, pp. 222–234, Feb 2008.
- [123] H. Yang, C. Guan, K. K. Ang, K. S. Phua, and C. Wang, “Selection of effective EEG channels in brain computer interfaces based on inconsistencies of classifiers,” in *36th Ann. Intl. Conf. of the IEEE Engineering in Medicine and Biology Society*, pp. 672–675, Aug. 2014.
- [124] K. Deb, *Multi-Objective Optimization Using Evolutionary Algorithms*. John Wiley & Sons, Inc., 2001.
- [125] K. Deb, K. Miettinen, and S. Chaudhuri, “Toward an estimation of nadir objective vector using a hybrid of evolutionary and local search approaches,” *IEEE Trans. on Evolutionary Computation*, vol. 14, pp. 821–841, Dec 2010.
- [126] S. J. Simske, *Meta-algorithmics: Patterns for robust, low cost, high quality systems*. John Wiley & Sons, 2013.

- [127] R. C. Purshouse and P. J. Fleming, “Conflict, harmony and independence: Relationships in evolutionary multi-criterion optimisation,” in *Proc. of the 2nd Intl Conf. on Evolutionary Multi-Criterion Optimization*, (Faro, Portugal), pp. 16–30, Apr 2003.
- [128] K. Miettinen, F. Ruiz, and A. P. Wierzbicki, “Introduction to multiobjective optimization: Interactive approaches,” in *Lecture Notes in Computer Science*, vol. 5252 LNCS, pp. 27–57, 2008.
- [129] P. Sajda, A. D. Gerson, M. G. Philiastides, and L. C. Parra, “Single-trial analysis of EEG during rapid visual discrimination: Enabling cortically-coupled computer vision,” *Towards brain-computer interfacing*, pp. 423–44, 2007.
- [130] H. Tan, N. Jenkinson, and P. Brown, “Dynamic neural correlates of motor error monitoring and adaptation during trial-to-trial learning,” *Journal of neuroscience*, vol. 34, pp. 5678–88, Apr. 2014.
- [131] P. Welch, “The use of fast fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms,” *IEEE Trans. on Audio and Electroacoustics*, pp. 70–73, Jun 1967.
- [132] E. T. Psota, J. Kowalczyk, and L. C. Perez, “A deviation-based conditional upper bound on the error floor performance for min-sum decoding of short ldpc codes,” *IEEE Trans. on Comm.*, vol. 60, pp. 3567–3578, Dec 2012.
- [133] F. Oveisi and A. Erfanian, “A Minimax Mutual Information Scheme for Supervised Feature Extraction and Its Application to EEG-Based Brain-Computer Interfacing,” *EURASIP Journal on Advances in Signal Processing*, vol. 2008, p. 673040, July 2008.
- [134] M. Sabeti, S. Katebi, R. Boostani, and G. Price, “A new approach for EEG signal classification of schizophrenic and control participants,” *Expert Systems with Applications*, vol. 38, pp. 2063–2071, Mar. 2011.
- [135] C.-C. Chang and C.-J. Lin, “Libsvm: a library for support vector machines,” *ACM Trans. on Intelligent Systems and Technology (TIST)*, vol. 2, no. 3, p. 27, 2011.

BIBLIOGRAPHY

- [136] G. Dornhege, B. Blankertz, G. Curio, and K.-R. Muller, “Boosting bit rates in noninvasive eeg single-trial classifications by feature combination and multiclass paradigms,” *IEEE Transactions on Biomedical Engineering*, vol. 51, pp. 993–1002, Jun 2004.
- [137] M. Naeem, C. Brunner, R. Leeb, B. Graimann, and G. Pfurtscheller, “Seperability of four-class motor imagery data using independent components analysis,” *Journal of Neural Engineering*, vol. 3, pp. 208–16, Sep 2006.
- [138] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, “BCI2000: A general-purpose brain-computer interface (BCI) system,” *IEEE Trans. on Biomed. Engg.*, vol. 51, pp. 1034–1043, Jun 2004.
- [139] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, “Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals,” *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.
- [140] P. J. García-Laencina, G. Rodríguez-Bermudez, and J. Roca-Dorda, “Exploring dimensionality reduction of EEG features in motor imagery task classification,” *Expert Systems with Applications*, vol. 41, pp. 5285–5295, Sept. 2014.
- [141] X. Yu, P. Chum, and K.-B. Sim, “Analysis the effect of PCA for feature reduction in non-stationary EEG based motor imagery of BCI system,” *Optik - International Journal for Light and Electron Optics*, vol. 125, pp. 1498–1502, Feb. 2014.
- [142] X. He and P. Niyogi, “Locality preserving projections,” *Advances in Neural information processing systems*, vol. 16, p. 153, 2004.
- [143] S. T. Roweis and L. K. Saul, “Nonlinear dimensionality reduction by locally linear embedding,” *Science (New York, N.Y.)*, vol. 290, pp. 2323–6, Dec. 2000.
- [144] N. D. Lawrence, “Gaussian process latent variable models for visualisation of high dimensional data,” *Advances in neural information processing systems*, vol. 16, no. 3, pp. 329–336, 2004.

- [145] T. Zhang, J. Yang, D. Zhao, and X. Ge, “Linear local tangent space alignment and application to face recognition,” *Neurocomputing*, vol. 70, pp. 1547–1553, Mar. 2007.
- [146] J. B. Tenenbaum, V. De Silva, and J. C. Langford, “A global geometric framework for nonlinear dimensionality reduction,” *Science*, vol. 290, pp. 2319–2323, Dec 2000.
- [147] X. He, D. Cai, S. Yan, and H.-J. Zhang, “Neighborhood preserving embedding,” in *Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on*, vol. 2, (Beijing), pp. 1208–1213, IEEE, Oct 2005.
- [148] M. Belkin and P. Niyogi, “Laplacian Eigenmaps for Dimensionality Reduction and Data Representation,” *Neural Computation*, vol. 15, pp. 1373–1396, June 2003.
- [149] J. Long, Z. Gu, Y. Li, T. Yu, F. Li, and M. Fu, “Semi-supervised joint spatio-temporal feature selection for P300-based BCI speller,” *Cognitive neurodynamics*, vol. 5, pp. 387–98, Nov. 2011.
- [150] I. Guyon, J. Weston, S. Barnhill, and V. Vapnik, “Gene selection for cancer classification using support vector machines,” *Machine learning*, vol. 46, pp. 389–422, Jan 2002.
- [151] J. Y. Kim, S. M. Park, K. E. Ko, and K. B. Sim, “A binary PSO-based optimal EEG channel selection method for a motor imagery based BCI system,” in *Communications in Computer and Information Science*, vol. 310 CCIS, pp. 245–252, Springer Berlin Heidelberg, 2012.
- [152] C.-C. Chang and C.-J. Lin, “LIBSVM: A Library for Support Vector Machines,” *ACM Transactions on Intelligent Systems and Technology*, vol. 2, pp. 1–27, Apr 2011.
- [153] L. J. P. Van Der Maaten, E. O. Postma, and H. J. Van Den Herik, “Dimensionality Reduction: A Comparative Review,” *Journal of Machine Learning Research*, vol. 10, pp. 1–41, Oct 2009.

- [154] B. Blankertz, S. Lemm, M. Treder, S. Haufe, and K.-R. Müller, “Single-trial analysis and classification of ERP components—a tutorial,” *NeuroImage*, vol. 56, pp. 814–25, May 2011.
- [155] L. Beltrachini, N. von Ellenrieder, and C. H. Muravchik, “Shrinkage Approach for Spatiotemporal EEG Covariance Matrix Estimation,” *IEEE Transactions on Signal Processing*, vol. 61, pp. 1797–1808, Apr 2013.
- [156] M. Grosse-Wentrup, C. Liefhold, K. Gramann, and M. Buss, “Beamforming in noninvasive brain-computer interfaces,” *IEEE Transactions on Biomedical Engineering*, vol. 56, pp. 1209–1219, Apr 2009.
- [157] O. Ledoit and M. Wolf, “A well-conditioned estimator for large-dimensional covariance matrices,” *Journal of Multivariate Analysis*, vol. 88, pp. 365–411, Feb 2004.
- [158] D. A. Engemann and A. Gramfort, “Automated model selection in covariance estimation and spatial whitening of MEG and EEG signals,” *NeuroImage*, vol. 108, pp. 328–42, Mar 2015.
- [159] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, “Filter Bank Common Spatial Pattern Algorithm on BCI Competition IV Datasets 2a and 2b,” *Frontiers in neuroscience*, vol. 6, p. 39, Jan 2012.
- [160] H. Vikram Shenoy and A. P. Vinod, “An iterative optimization technique for robust channel selection in motor imagery based Brain Computer Interface,” in *2014 IEEE Intl. Conf. on Systems, Man, and Cybernetics (SMC)*, pp. 1858–1863, Oct. 2014.
- [161] K. Zilles and K. Amunts, “Centenary of Brodmann’s map—conception and fate,” *Nature reviews. Neuroscience*, vol. 11, pp. 139–45, Feb. 2010.
- [162] B. He, L. Yang, C. Wilke, and H. Yuan, “Electrophysiological imaging of brain activity and connectivity- challenges and opportunities,” *IEEE Transactions on Biomedical Engineering*, vol. 58, pp. 1918–1931, Jul 2011.

- [163] M. S. Hämäläinen and R. J. Ilmoniemi, “Interpreting magnetic fields of the brain: minimum norm estimates.,” *Medical & biological engineering & computing*, vol. 32, pp. 35–42, Jan 1994.
- [164] L. Qin, L. Ding, and B. He, “Motor imagery classification by means of source analysis for brain-computer interface applications.,” *Journal of neural engineering*, vol. 1, pp. 135–41, Sep 2004.
- [165] B. Kamousi, Z. Liu, and B. He, “Classification of motor imagery tasks for brain-computer interface applications by means of two equivalent dipoles analysis,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 13, pp. 166–171, Jun 2005.
- [166] M. M. Smith, K. E. Weaver, T. J. Grabowski, R. P. N. Rao, and F. Darvas, “Non-invasive detection of high gamma band activity during motor imagery.,” *Frontiers in Human Neuroscience*, vol. 8, p. 817, Jan. 2014.
- [167] P. Comon, “Independent component analysis, A new concept?,” *Signal Processing*, vol. 36, pp. 287–314, Apr 1994.
- [168] A. Delorme and S. Makeig, “EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis,” *Journal of Neuroscience Methods*, vol. 134, pp. 9–21, Mar 2004.
- [169] A. Mognon, J. Jovicich, L. Bruzzone, and M. Buiatti, “ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features.,” *Psychophysiology*, vol. 48, pp. 229–240, Feb 2010.
- [170] D. L. Collins, P. Neelin, T. M. Peters, and A. C. Evans, “Automatic 3D intersubject registration of MR volumetric data in standardized Talairach space.,” *Journal of computer assisted tomography*, vol. 18, pp. 192–205, Jan 1994.
- [171] O. Steinstraeter, I. K. Teismann, A. Wollbrink, S. Suntrup, K. Stoeckigt, R. Dziewas, and C. Pantev, “Local sphere-based co-registration for SAM group analysis in subjects without individual MRI,” *Experimental Brain Research*, vol. 193, pp. 387–396, Mar 2009.

BIBLIOGRAPHY

- [172] B. N. Cuffin, D. L. Schomer, J. R. Ives, and H. Blume, “Experimental tests of EEG source localization accuracy in spherical head models,” *Clinical neurophysiology*, vol. 112, pp. 46–51, Jan. 2001.
- [173] R. D. Pascual-Marqui, C. Michel, and D. Lehmann, “Low resolution electromagnetic tomography: a new method for localizing electrical activity in the brain,” *International Journal of Psychophysiology*, vol. 18, pp. 49–65, Oct 1994.
- [174] G. D. Schott, “Penfield’s homunculus: a note on cerebral cartography,” *Journal of neurology, neurosurgery, and psychiatry*, vol. 56, no. 4, pp. 329–33, 1993.
- [175] H. Igo Krebs, N. Hogan, M. L. Aisen, and B. T. Volpe, “Robot-aided neurorehabilitation,” *IEEE Transactions on Rehabilitation Engineering*, vol. 6, pp. 75–87, Mar 1998.
- [176] J. Song, C. Davey, C. Poulsen, P. Luu, S. Turovets, E. Anderson, K. Li, and D. Tucker, “EEG source localization: Sensor density and head surface coverage,” *Journal of Neuroscience Methods*, vol. 256, pp. 9–21, Dec 2015.
- [177] S. P. Fitzgibbon, T. W. Lewis, D. M. W. Powers, E. W. Whitham, J. O. Willoughby, and K. J. Pope, “Surface laplacian of central scalp electrical signals is insensitive to muscle contamination,” *IEEE Transactions on Biomedical Engineering*, vol. 60, pp. 4–9, Jan 2013.
- [178] I. Kermadi and D. Boussaoud, “Role of the primate striatum in attention and sensorimotor processes: comparison with premotor cortex,” *Neuroreport*, vol. 6, pp. 1177–81, May 1995.
- [179] R. Caminiti, P. B. Johnson, C. Galli, S. Ferraina, and Y. Burnod, “Making arm movements within different parts of space: the premotor and motor cortical representation of a coordinate system for reaching to visual targets,” *The Journal of neuroscience*, vol. 11, pp. 1182–97, May 1991.
- [180] K. Liao, R. Xiao, J. Gonzalez, L. Ding, and Z. Zhang, “Decoding Individual Finger Movements from One Hand Using Human EEG Signals,” *PLoS ONE*, vol. 9, p. e85192, Jan 2014.

BIBLIOGRAPHY

- [181] X. Yong, C. Menon, B. Wessel, M. Hallet, L. Cohen, and B. He, “EEG Classification of Different Imaginary Movements within the Same Limb,” *PLOS ONE*, vol. 10, p. e0121896, Apr 2015.
- [182] R. Xiao and L. Ding, “EEG resolutions in detecting and decoding finger movements from spectral analysis.,” *Frontiers in neuroscience*, vol. 9, p. 308, Sept 2015.
- [183] J. Hammer, T. Pistohl, J. Fischer, P. Kršek, M. Tomášek, P. Marusič, A. Schulze-Bonhage, A. Aertsen, and T. Ball, “Predominance of Movement Speed Over Direction in Neuronal Population Signals of Motor Cortex: Intracranial EEG Data and A Simple Explanatory Model,” *Cerebral Cortex*, vol. 26, pp. 2863–81, Mar 2016.
- [184] H. Yuan, C. Perdoni, and B. He, “Relationship between speed and EEG activity during imagined and executed hand movements.,” *Journal of Neural Engineering*, vol. 7, p. 26001, Feb 2010.
- [185] M. Zaepffel, R. Trachel, B. E. Kilavik, and T. Brochier, “Modulations of EEG Beta Power during Planning and Execution of Grasping Movements,” *PLoS ONE*, vol. 8, Mar 2013.
- [186] C. D. Cowper-Smith, E. Y. Lau, C. A. Helmick, G. A. Eskes, and D. A. Westwood, “Neural coding of movement direction in the healthy human brain,” *PLoS ONE*, vol. 5, p. e13330, Oct 2010.
- [187] M. Eisenberg, L. Shmuelof, E. Vaadia, and E. Zohary, “Functional organization of human motor cortex: directional selectivity for movement,” *J Neurosci*, vol. 30, pp. 8897–8905, Jun 2010.
- [188] G. Santhanam, B. M. Yu, V. Gilja, S. Ryu, A. Afshar, M. Sahani, and K. V. Shenoy, “Factor-analysis methods for higher-performance neural prostheses.,” *Journal of neurophysiology*, vol. 102, pp. 1315–1330, Aug 2009.
- [189] H. H. Harman, *Modern Factor Analysis*. University of Chicago Press, 1976.

BIBLIOGRAPHY

- [190] C. A. Chestek, V. Gilja, C. H. Blabe, B. L. Foster, K. V. Shenoy, J. Parvizi, and J. M. Henderson, “Hand posture classification using electrocorticography signals in the gamma band over human sensorimotor brain areas.,” *Journal of neural engineering*, vol. 10, p. 026002, Jan 2013.
- [191] M. Seeber, R. Scherer, J. Wagner, T. Solis-Escalante, and G. R. Müller-Putz, “High and low gamma EEG oscillations in central sensorimotor areas are conversely modulated during the human gait cycle,” *NeuroImage*, vol. 112, pp. 318–326, May 2015.
- [192] Z. Akalin Acar and S. Makeig, “Effects of forward model errors on EEG source localization.,” *Brain topography*, vol. 26, pp. 378–96, Jul 2013.
- [193] D. Eytan, E. W. Pang, S. M. Doesburg, V. Nenadovic, B. Gavrilovic, P. Laussen, and A.-M. Guerguerian, “Bedside functional brain imaging in critically-ill children using high-density EEG source modeling and multi-modal sensory stimulation,” *NeuroImage: Clinical*, vol. 12, pp. 198–211, Dec 2016.
- [194] X. Lei, T. Wu, and P. A. Valdes-Sosa, “Incorporating priors for EEG source imaging and connectivity analysis.,” *Frontiers in neuroscience*, vol. 9, p. 284, Aug 2015.
- [195] R. D. Pascual-Marqui, “Standardized low resolution brain electromagnetic tomography,” *Methods and findings in experimental and clinical pharmacology*, vol. 24 Suppl D, pp. 5–12, Jan 2002.
- [196] A. J. Szameitat, S. Shen, and A. Sterr, “Motor imagery of complex everyday movements. An fMRI study.,” *NeuroImage*, vol. 34, pp. 702–13, Jan 2007.
- [197] A. C. Rencher, *Methods of Multivariate Analysis*. John Wiley & Sons, 2003.
- [198] S. A. Mulaik, *Foundations of factor analysis*. CRC press, 2009.
- [199] H. V. Shenoy, A. P. Vinod, and C. Guan, “Multi-direction hand movement classification using EEG-based source space analysis,” in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 4551–4554, IEEE, Aug 2016.

- [200] Y. Yi, B. Zhang, J. Kong, and J. Wang, “An improved locality sensitive discriminant analysis approach for feature extraction,” *Multimedia Tools and Applications*, vol. 74, pp. 85–104, Jan 2013.
- [201] H. Vikram Shenoy, A. P. Vinod, and C. Guan, “Shrinkage estimator based regularization for EEG motor imagery classification,” in *2015 10th International Conference on Information, Communications and Signal Processing (ICICS)*, (Singapore), pp. 1–5, IEEE, Dec 2015.
- [202] M. Xia, J. Wang, and Y. He, “BrainNet Viewer: A Network Visualization Tool for Human Brain Connectomics,” *PLoS ONE*, vol. 8, Jul 2013.
- [203] M. Eisenberg, L. Shmuelof, E. Vaadia, and E. Zohary, “Functional organization of human motor cortex: directional selectivity for movement.,” *Journal of neuroscience*, vol. 30, no. 26, pp. 8897–905, 2010.
- [204] C. M. Toxopeus, B. M. de Jong, G. Valsan, B. A. Conway, K. L. Leenders, and N. M. Maurits, “Direction of movement is encoded in the human primary motor cortex.,” *PloS one*, vol. 6, p. e27838, Nov 2011.
- [205] M. Seeber, R. Scherer, J. Wagner, T. Solis-Escalante, and G. R. Muller-Putz, “EEG beta suppression and low gamma modulation are different elements of human upright walking,” *Frontiers in Human Neuroscience*, vol. 8, pp. 1–9, July 2014.
- [206] S. T. Hansen, S. Hauberg, and L. K. Hansen, “Data-driven forward model inference for EEG brain imaging,” *NeuroImage*, vol. 139, pp. 249–258, Oct 2016.
- [207] K. K. Ang, K. S. G. Chua, K. S. Phua, C. Wang, Z. Y. Chin, C. W. K. Kuah, W. Low, and C. Guan, “A Randomized Controlled Trial of EEG-Based Motor Imagery Brain-Computer Interface Robotic Rehabilitation for Stroke.,” *Clinical EEG and neuroscience*, vol. 46, pp. 310–20, Oct 2014.
- [208] K. K. Ang and C. Guan, “Brain-Computer Interface for Neurorehabilitation of Upper Limb After Stroke,” *Proceedings of the IEEE*, vol. 103, pp. 944–953, Jun 2015.

BIBLIOGRAPHY

- [209] J. Reis, E. M. Robertson, J. W. Krakauer, and R. et Al., “Consensus: Can transcranial direct current stimulation and transcranial magnetic stimulation enhance motor learning and memory formation?,” *Brain Stimulation*, vol. 1, pp. 363–369, Oct 2008.
- [210] H. V. Shenoy, A. P. Vinod, and C. Guan, “Multi-direction hand movement classification using EEG-based source space analysis,” in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 4551–4554, IEEE, Aug 2016.
- [211] H. I. Krebs, B. T. Volpe, D. Williams, J. Celestino, S. K. Charles, D. Lynch, and N. Hogan, “Robot-aided neurorehabilitation: A robot for wrist rehabilitation,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 15, pp. 327–335, Sept 2007.
- [212] I. Winkler, S. Brandl, F. Horn, E. Waldburger, C. Allefeld, and M. Tangermann, “Robust artifactual independent component classification for BCI practitioners,” *Journal of Neural Engineering*, vol. 11, p. 035013, Jun 2014.
- [213] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, “Optimal spatial filtering of single trial EEG during imagined hand movement,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 441–446, Dec 2000.
- [214] H. Vikram Shenoy, A. P. Vinod, and C. Guan, “Shrinkage estimator based regularization for EEG motor imagery classification,” in *2015 10th IEEE International Conference on Information, Communications and Signal Processing (ICICS)*, (Singapore), pp. 1–5, IEEE, Dec 2015.
- [215] K. P. Westlake and S. S. Nagarajan, “Functional Connectivity in Relation to Motor Performance and Recovery After Stroke,” *Frontiers in Systems Neuroscience*, vol. 5, pp. 1–12, March 2011.
- [216] G. Nolte, O. Bai, L. Wheaton, Z. Mari, S. Vorbach, and M. Hallett, “Identifying true brain interaction from EEG data using the imaginary part of coherency,” *Clinical Neurophysiology*, vol. 115, pp. 2292–2307, Oct 2004.

- [217] C. Grefkes, D. A. Nowak, L. E. Wang, M. Dafotakis, S. B. Eickhoff, and G. R. Fink, “Modulating cortical connectivity in stroke patients by rTMS assessed with fMRI and dynamic causal modeling,” *NeuroImage*, vol. 50, pp. 233–242, Mar 2010.
- [218] A. K. Rehme, S. B. Eickhoff, L. E. Wang, G. R. Fink, and C. Grefkes, “Dynamic causal modeling of cortical activity from the acute to the chronic stage after stroke,” *NeuroImage*, vol. 55, pp. 1147–1158, Apr 2011.
- [219] K. E. Stephan, W. D. Penny, J. Daunizeau, R. J. Moran, and K. J. Friston, “Bayesian model selection for group studies,” *NeuroImage*, vol. 46, pp. 1004–1017, Jul 2009.
- [220] K. Friston, L. Harrison, and W. Penny, “Dynamic causal modelling,” *NeuroImage*, vol. 19, pp. 1273–1302, Aug 2003.
- [221] S. R. Soekadar, M. Witkowski, E. G. Cossio, N. Birbaumer, and L. G. Cohen, “Learned EEG-based brain self-regulation of motor-related oscillations during application of transcranial electric brain stimulation: feasibility and limitations,” *Frontiers in Behavioral Neuroscience*, vol. 8, p. 93, Mar 2014.
- [222] J. Ashburner, G. Barnes, C. Chen, J. Daunizeau, G. Flandin, K. Friston, S. Kiebel, J. Kilner, V. Litvak, R. Moran, *et al.*, “SPM12 Manual,” *Wellcome Trust Centre for Neuroimaging, London (UK)*, 2014.
- [223] M. Grosse-Wentrup, D. Janzing, M. Siegel, and B. Schölkopf, “Identification of causal relations in neuroimaging data with latent confounders: An instrumental variable approach,” *NeuroImage*, vol. 125, pp. 825–833, Jan 2016.
- [224] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell, “Caffe: Convolutional architecture for fast feature embedding,” in *Proceedings of the 22nd ACM Intl. Conf. on Multimedia*, pp. 675–678, ACM, Nov 2014.
- [225] C. Dinh, M. Luessi, L. Sun, J. Haueisen, and M. S. Hamalainen, “Mne-X: MEG/EEG Real-Time Acquisition, Real-Time Processing, and Real-Time Source

- Localization Framework,” *Biomedical Engineering / Biomedizinische Technik*, Jan 2013.
- [226] L. Pion-Tonachini, S.-H. Sheng-Hsiou Hsu, S. Makeig, T.-P. Tzyy-Ping Jung, and G. Cauwenberghs, “Real-time EEG Source-mapping Toolbox (REST): Online ICA and source localization,” in *2015 37th Annl. Intl. Conf. of the IEEE Engg. in Med. and Bio. Society (EMBC)*, vol. 2015, (Milan), pp. 4114–4117, IEEE, Aug 2015.
 - [227] Y. Huang, L. C. Parra, and S. Haufe, “The New York Head - A precise standardized volume conductor model for EEG source localization and tES targeting,” *NeuroImage*, vol. 140, pp. 150–162, Oct 2016.
 - [228] T. W. Wilson, A. Fleischer, D. Archer, S. Hayasaka, and L. Sawaki, “Oscillatory MEG motor activity reflects therapy-related plasticity in stroke patients.,” *Neurorehabilitation and neural repair*, vol. 25, pp. 188–193, Feb 2011.
 - [229] D.-H. Jeong, Y.-D. Kim, I.-U. Song, Y.-A. Chung, and J. Jeong, “Wavelet Energy and Wavelet Coherence as EEG Biomarkers for the Diagnosis of Parkinson’s Disease-Related Dementia and Alzheimer’s Disease,” *Entropy*, vol. 18, p. 8, Dec 2015.
 - [230] D. V. Moretti, G. B. Frisoni, C. Fracassi, M. Pievani, C. Geroldi, G. Binetti, P. M. Rossini, and O. Zanetti, “MCI patients’ EEGs show group differences between those who progress and those who do not progress to AD,” *Neurobiology of Aging*, vol. 32, pp. 563–571, Apr 2011.
 - [231] C. Cao and S. Slobounov, “Alteration of cortical functional connectivity as a result of traumatic brain injury revealed by graph theory, ICA, and sLORETA analyses of EEG signals,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, pp. 11–19, Feb 2010.
 - [232] M. Hata, T. Tanaka, H. Kazui, R. Ishii, L. Canuet, R. D. Pascual-Marqui, Y. Aoki, S. Ikeda, S. Sato, Y. Suzuki, H. Kanemoto, K. Yoshiyama, and M. Iwase, “Cerebrospinal Fluid Biomarkers of Alzheimers Disease Correlate With Electroencephalography Parameters Assessed by Exact Low-Resolution Electromagnetic Tomography (eLORETA),” *Clinical EEG and Neuroscience*, Aug 2016.

- [233] F. Vecchio, F. Miraglia, C. Marra, D. Quaranta, M. G. Vita, P. Bramanti, and P. M. Rossini, “Human brain networks in cognitive decline: A graph theoretical analysis of cortical connectivity from EEG data,” *Journal of Alzheimer’s Disease*, vol. 41, pp. 113–127, Jan 2014.
- [234] C. Piano, C. Imperatori, A. Losurdo, A. Rita Bentivoglio, P. Cortelli, and G. Della Marca, “Sleep-related modifications of EEG connectivity in the sensory-motor networks in Huntington Disease: An eLORETA Study and Review of the Literature,” *Clinical Neurophysiology*, Jul 2016.
- [235] C. Brunner, M. Billinger, M. Seeber, T. R. Mullen, and S. Makeig, “Volume Conduction Influences Scalp-Based Connectivity Estimates,” *Frontiers in Computational Neuroscience*, vol. 10, p. 121, Nov 2016.
- [236] N. Bizovičar, J. Dreo, B. Koritnik, and J. Zidar, “Decreased movement-related beta desynchronization and impaired post-movement beta rebound in amyotrophic lateral sclerosis,” *Clinical Neurophysiology*, vol. 125, pp. 1689–1699, Aug 2014.
- [237] P. M. Iyer, C. Egan, M. Pinto-Grau, T. Burke, M. Elamin, B. Nasserroleslami, N. Pender, E. C. Lalor, and O. Hardiman, “Functional Connectivity Changes in Resting-State EEG as Potential Biomarker for Amyotrophic Lateral Sclerosis,” *Plos One*, vol. 10, p. e0128682, Jun 2015.
- [238] U. Chaudhary, N. Birbaumer, and A. Ramos-murguialday, “Brain-computer interfaces for communication and rehabilitation,” *Nature Publishing Group*, vol. 12, pp. 513–525, Sept 2016.
- [239] J. I. Marden, *Analyzing and Modeling Rank Data*. CRC Press, 1996.