Efficient EEG frequency band selection techniques for a robust motor imagery based brain-computer interface

Kavitha P. Thomas

2011

Kavitha, P. T. (2011). Efficient EEG frequency band selection techniques for a robust motor imagery based brain-computer interface. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/46231>

<https://doi.org/10.32657/10356/46231>

Efficient EEG Frequency Band Selection Techniques for a Robust Motor Imagery based Brain-Computer Interface

Kavitha P Thomas

School of Computer Engineering
Nanyang Technological University

2011

Nanyang Technological University

Efficient EEG Frequency Band Selection Techniques for a Robust Motor Imagery based Brain-Computer Interface

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

by

Kavitha P Thomas

School of Computer Engineering

2011

ORIGINALITY STATEMENT

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at Nanyang Technological University, Singapore or any other educational institution, except where due acknowledgment is made in the thesis. Any contribution made to the research by others, with whom I have worked at the university or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

Signed: Kavitha P Thomas

Date: 13-07-2011

Abstract

Recently, Electroencephalogram (EEG)-based Brain-Computer Interfaces (BCIs) have become a hot topic in the study of neural engineering, rehabilitation and brain science. BCIs translate human intentions into control signals to establish a direct communication channel between the human brain and output devices bypassing brain's normal output pathway of nerves and muscles. This new approach is a promising communication channel for paralyzed patients to interact with the external world and a new direction in entertainment through BCI games in healthy people as well. In order to decipher the intentions accurately, it is important to obtain distinguishable EEG features. At present, event-related de/synchronization (ERD/ERS) patterns during imagination of motor movements or motor imagery have been extensively applied to design BCI. These patterns are the attenuation and enhancement of EEG rhythmic power during motor imagery. One of the critical elements in the design of any BCI is the extraction of reliable and discriminative features that represent the intended task by the user.

The work presented in this thesis focuses on improving the discrimination between features extracted during various motor imagery tasks. More specifically, techniques towards a robust motor imagery based BCI by selecting the relevant frequency components carrying the discriminative information are proposed.

The first proposed algorithm in the work is a discriminative filter bank (DFB) based approach to distinguish between motor imagery patterns. The algorithm named as Discriminative Filter bank Common Spatial Pattern (DFBCSP) employs a parent filter bank of twelve bandpass filters to filter the EEG recorded from sensory motor cortex. The Fisher ratio values computed at each filter output determine the discriminative capability of the respective bands. A set of four bandpass filters offering highest Fisher ratio values are selected from the parent filter bank to form DFB. Common Spatial Pattern (CSP) features extracted from the DFB output are used for distinguishing the various motor imagery tasks.

Experimental results show that the classification performance of DFBCSP is better than the existing filter bank based method.

In order to avoid the multi-band filtering present in the band selection process of DFBCSP, a time-frequency Fisher ratio pattern approach is then proposed for estimating the discriminative frequency bands. By automatically detecting the discriminative frequency bands from the Fisher ratio pattern, subject-specific filter bank can be designed effectively. Using this time-frequency approach, variation of the subject-specific discriminative bands over time is also investigated and considerable inter-session and intra-session frequency band variations are found in the analysis. In order to demonstrate the effect of this spectral variability on BCI performance, two BCI approaches named as Static Spectral Features (SSF) and Variable Spectral Features (VSF) are proposed. The VSF method addresses the spectral variability issue by updating the bandpass filters over time whereas SSF method employs fixed parameters always. Experimental analysis shows that the VSF method provides better classification accuracies than the SSF method which employs fixed bands over time.

In order to further improve the spectral variability tracking process, an Adaptively Weighted Spectral-Spatial Pattern (AWSSP) is proposed. The AWSSP effectively tracks the informative bands by estimating the varying discriminative weight values of frequency components over time. Whenever the deviation of weight values is greater than a threshold, frequency bands are re-computed and the bandpass filters are re-configured accordingly. In the online and offline experiments, AWSSP provides significant improvement in the classification accuracy of motor imagery patterns compared to the BCI approach employing fixed frequency bands.

The significance of subject-specific band selection during motor imagery, the effect of frequency selection on BCI performance and the importance of tracking the variation of these bands over time are investigated using the online and offline evaluation of motor imagery patterns. The proposed methods outperform the state-of-art method in terms of classification accuracy, highlighting the necessity of efficient frequency band selection techniques in real time motor imagery based BCI applications.

Contents

Abstract	iii
Table of Contents	v
List of Figures	ix
List of Tables	xii
Acknowledgments	xv
Dedication	xvi
1 Introduction	1
1.1 Motivation	2
1.2 Objectives	3
1.3 Organization of the thesis	5
2 Literature Review	6
2.1 BCI: An overview	6
2.1.1 Core components of a Brain-Computer Interface	7
2.1.2 Techniques for measuring brain activity	9
2.1.3 Neural features in EEG used to drive BCIs	15
2.2 ERD/ERS based BCI	18
2.2.1 Characteristics of ERD/ERS patterns	19
2.2.2 Applications of ERD/ERS based BCIs	22
2.3 Techniques to extract ERD/ERS features during motor imagery	25

2.3.1	Frequency related features	26
2.3.2	Time-domain features	26
2.3.3	Time-frequency patterns	27
2.3.4	Autoregressive model	28
2.3.5	Common Spatial Pattern	28
2.4	Frequency Optimization for ERD/ERS patterns	32
2.4.1	Neurophysiological background	32
2.4.2	Significance	33
2.4.3	Existing algorithms	34
	Common Spatio-Spectral filters	34
	Common Sparse Spectral Spatial Pattern	35
	Subband Common Spatial Pattern	35
	Iterative Spatio-Spectral Patterns Learning Algorithm	36
	Filter bank Common Spatial Pattern	37
2.5	Conclusion	38
3	Discriminative Filter Bank for Motor Imagery based BCI	39
3.1	Proposed Method: DFBCSP	40
3.1.1	Coefficient Decimation technique for bandpass filtering	41
3.1.2	Generation of Discriminative Filter bank and bandpass filtering	45
3.1.3	Feature extraction using Common Spatial Pattern	46
3.1.4	Classification using Support Vector Machine	47
3.2	Results and discussions	47
3.2.1	Using BCI Competition III dataset IVa	48
3.2.2	Using BCI Competition IV dataset IIb	52
3.3	Conclusion	56

4	Impact of EEG spectral variability on BCI performance	58
4.1	New BCI approaches: SSF and VSF	59
4.2	Calibration procedure in SSF and VSF approaches	59
4.2.1	Stage 1: Band selection process	60
4.2.2	Stage 2: Bandpass filtering	65
4.2.3	Stage 3: Feature extraction using CSP	65
4.2.4	Stage 4: Classification	65
4.3	Evaluation procedures	66
4.3.1	SSF evaluation	66
4.3.2	VSF evaluation	67
4.4	Experiments and analyses	68
4.4.1	EEG data used	68
4.4.2	Band selection	70
4.4.3	Analysis of discriminative spectral variability over sessions	71
	Inter-session variability of frequency bands	73
	Intra-session variability of frequency bands	74
4.4.4	Calibration and evaluation using SSF and VSF methods	75
4.5	Results and discussions	76
4.6	Conclusion	80
5	An Adaptively Weighted Spectral-Spatial Pattern Algorithm	82
5.1	New methodology	83
5.1.1	BCI system during calibration	85
	Stage 1: Estimation of bands based on discriminative weights	85
	Stage 2: Bandpass filtering using Coefficient Decimation approach	89
	Stages 3 and 4: Feature extraction using CSP and classification	89
5.1.2	AWSSP evaluation	90

5.2	Experiments and analysis	93
5.2.1	Offline experiments using BCI competition IV dataset IIb	93
5.2.2	Online experiments	94
	Session-1 experiments	95
	Session-2 experiments	96
	Session-3 experiments	96
5.3	Results and discussions	97
5.3.1	Results of BCI Competition IV dataset IIb	97
5.3.2	Results of online data	101
	Results of session-1 and session-2	101
	Results of session-3: Effect of feedback on DDW	104
5.4	Conclusion	106
6	Conclusions and future work	108
6.1	Conclusions	108
6.2	Directions of future work	110
	Bibliography	113
	A Publication list	125

List of Figures

2.1	Block diagram of a conventional BCI system [1, 6, 7].	7
2.2	The functional units in the brain [22]	11
2.3	Electrode positions according to the 10-20 international system of electrode placement [23].	12
2.4	Electrode positions according to the extended 10-20 international system of electrode placement and respective brain areas [25].	13
2.5	ERD/ERS patterns during the right finger movement task and the recorded EEG signals [39, 41].	17
2.6	Geometrical mapping between brain and body.	19
2.7	Time courses of ERD/ERS observed in left and right hand motor imagery in two subjects from channels C3 and C4 [56].	21
2.8	The time-frequency pattern and topographical distribution of band power during motor imagery [37].	22
2.9	Effect of CSP filtering. CSP analysis has been performed to obtain four spatial filters that discriminate left from right hand motor imagery. The graph shows continuous bandpass filtered EEG after applying CSP. The resulting signals in filters CSP:L1 and CSP:L2 have larger variance during right hand imagery (segments shaded in green) while signals in filters CSP:R1 and CSP:R2 have larger variance during left hand imagery (segment shaded red) [114].	30
2.10	SBCSP approach.	36
2.11	FBCSP approach.	37
3.1	Schematic of proposed DFBCSP.	40
3.2	Basic steps in the design of bandpass filter using CD technique.	43

3.3	Fig. 3.3(a) shows the average validation accuracy and standard deviation over five subjects in BCI Competition III dataset IVa with Laplacian C3, Group of channel around C3, C3 and Cz. Fig. 3.3(b) represents the average validation accuracy vs. bandwidth of filters and 3.3(c) shows the average validation accuracy and standard deviation over five subjects vs. number of filters used in DFB.	48
3.4	Parent filter bank and discriminative frequency bands chosen for the subjects <i>aa</i> , <i>al</i> , <i>av</i> , <i>aw</i> and <i>ay</i> in BCI Competition III dataset IVa using DFBCSP. The shaded portions stand for DFB for each subject. The four frequency bands in DFB are ranked according the Fisher ratio values.	49
3.5	Average Power Spectral Density plots of right hand and foot trials for subject <i>av</i> in BCI Competition III dataset IVa. Bands chosen by Fisher analysis in proposed DFBCSP and feature selection algorithm in FBCSP are shaded accordingly.	50
3.6	Classification accuracy for BCI Competition III dataset IVa.	51
3.7	The timing protocol for data recording in BCI Competition IV dataset IIb.	52
3.8	Power spectral density estimates of left hand and right hand motor imagery from C3, Cz and C4.	54
3.9	The 10×10 -fold cross-validation accuracies for all subjects in BCI Competition IV dataset IIb using FBCSP and DFBCSP in session-3.	55
4.1	The proposed BCI system during calibration.	60
4.2	The proposed band selection process using the time-frequency Fisher ratio pattern. In step 2, the energy values are estimated according to eqn. (4.4). Step 3 selects the optimum frequency location using eqn. (4.5) for all bandwidths and step 4 computes the delta values according to eqn. (4.6).	62
4.3	Comparison of delta values for estimating the discriminative band.	63
4.4	Evaluation process in SSF method.	66
4.5	Evaluation process in VSF method. If there are N_1 complete single-trials in side the buffer, time-frequency Fisher ratio pattern is computed using the completed tasks. Frequency bands are estimated from the pattern and bandpass filters are updated accordingly. The updated parameters are used for processing $N_1 + 1^{th}$ trial onwards.	67
4.6	Time-frequency Fisher ratio patterns of nine subjects from session-3 of BCI Competition IV dataset IIb. The x-axis corresponds to the time segments obtained during the STFT estimation of 5 sec of EEG data and y-axis represents the frequency in Hz. The scale of the plot is shown on the right side of each pattern.	69

4.7	Average classification accuracy over nine subjects in the BCI Competition IV dataset I Ib for different number of bands.	71
4.8	Variation of discriminative frequency bands in 5 sessions for nine subjects. The black and red plots represent the first and second most discriminative bands respectively for the corresponding session. The x-axis represents the sessions 1, 2, 3, 4 and 5. The y-axis represents the frequency in Hz.	72
4.9	The variation of discriminative frequency bands in session-2 of subject 1 to subject 9.	75
4.10	Variation of accuracy vs. channel selection for band estimation and variation of accuracy vs. number of tasks in the VSF method.	77
4.11	Comparison of classification accuracies of test trials using the proposed SSF and VSF methods in the evaluation sessions. The number of trials in each of the evaluation session are given in Table 3.2.	78
4.12	Comparison of classification accuracies using DFBCSP and VSF method.	79
5.1	The framework for adaptively weighted spectral-spatial pattern algorithm during calibration.	83
5.2	The framework for AWSSP algorithm during evaluation.	84
5.3	The band selection procedure.	85
5.4	DW values for session-1 in nine subjects of BCI Competition IV dataset I Ib.	87
5.5	Variation of Discriminative Weight values over sessions for subjects 1, 6 and 9.	92
5.6	The timing protocol for online experiments.	94
5.7	Effect of threshold chosen on the performance of AWSSP _{sup}	97
5.8	Comparison of classification accuracies using SWSSP, AWSSP and FBCSP.	99
5.9	Average sensitivity and specificity measures of nine subjects in BCI Competition IV dataset I Ib using AWSSP _{sup} algorithm.	101
5.10	Percentage DDW values for subjects SG, SM and SS with and without feedback.	105
5.11	For adaptive evaluation.	106
5.12	For static evaluation.	106

List of Tables

2.1	Cortical areas of the brain and their functions[22]	12
3.1	Classification accuracy of motor imagery patterns in BCI Competition III dataset IVa	50
3.2	Number of motor imagery trials in BCI Competition IV dataset IIb	53
4.1	Computational complexity of band selection algorithm	63
5.1	The selected frequency bands for the nine subjects	88
5.2	Average classification accuracy in 9 subjects over 4 sessions with channel used for band selection.	98
5.3	Classification accuracy of online experiments	102
5.4	Details of the online updates in subject SM in session-1	102
5.5	Details of the online updates in subject SG in session-1	103
5.6	Details of the online updates in subject SS in session-1	103
5.7	Details of the online updates in subject SM in session-2	103
5.8	Details of the online updates in subject SG in session-2	103
5.9	Details of the online updates in subject SS in session-2	103

List of Abbreviations

AWSSP	Adaptively Weighted Spectral Spatial Pattern
BCI	Brain-Computer Interface
CD	Coefficient Decimation
CDM-1	Coefficient Decimation Method-1
CDM-2	Coefficient Decimation Method-2
CSP	Common Spatial Pattern
CSSP	Common Spatio Spectral Pattern
CSSSP	Common Sparse Spectral Spatial Pattern
DDW	Deviation in Discriminative Weight
DFB	Discriminative Filter Bank
DFBCSP	Discriminative Filter Bank Common Spatial Pattern
DW	Discriminative Weight
EEG	Electroencephalogram
ERD/ERS	Event-related desynchronization/synchronization
FBCSP	Filter Bank Common Spatial Pattern
FIR	Finite Impulse Response
fMRI	functional Magnetic Resonance Imaging
IIR	Infinite Impulse Response
ISSPL	Iterative Spatio Spectral Patterns Learning
MEG	Magnetoencephalography
PET	Positron Emission Tomography
PSD	Power Spectral Density
SBCSP	Subband Common Spatial Pattern
SCP	Slow Cortical Potential
SSF	Static Spectral Feature
SSVEP	Steady State Visually Evoked Potential

STFT	Short Time Fourier Transform
SVM	Support Vector Machine
SWSSP	Static Weighted Spectral Spatial Pattern
VEP	Visually Evoked Potential
VSF	Variable Spectral Feature

Acknowledgments

At this place, I would like to express my sincere thanks to my supervisor Dr. Lau Chiew Tong for giving me this opportunity to do research and, for the valuable guidance.

My deepest gratitude to my co-supervisor Dr. Cuntai Guan, for his inspiring ideas and consistent support. It was Dr. Cuntai's unlimited encouragement, patience and availability to answer my questions that kept me focused and enthusiastic throughout the course of this work.

Very special thanks to my co-supervisor Dr. A. P. Vinod for all the discussions, advices and guidance. Without his great support and concern, this thesis would not have been possible.

I thank all the staffs in the Neural Signal processing Lab of Institute for Infocomm Research, especially Dr. Ang Kai Keng, Mr. Wang Chuanchu, Dr. Fabien Lotte, Mr. Chin Zheng Yang and Mr. Rong Sheng for their friendly and skilled assistance in this work.

I wish to express my sincere gratitude to Dr. Raveendranatha Panicker Mahesh for the inspiration and concern.

My sincere thanks to all my friends and family members.

And above all, I am here only because of the merciful blessings from my Lord Jesus. It was His amazing love and great miracles that protected me in the time of struggles throughout this work.

Dedicated to my parents

And

To my husband

Chapter 1

Introduction

Electroencephalogram (EEG), one of the most popular non-invasive methods of obtaining brain activity, is widely used for clinical diagnoses and interpreting human intentions. Recently, establishing a new communication channel between brain and computer has been receiving great attention in neuro-science research through the neural features extracted from EEG. This new mode of communication, dubbed as Brain-Computer Interface (BCI) which bypasses the brain's normal output pathway of nerves and muscles has been employed successfully to control external devices such as a word processing program, the cursor on a computer screen, a wheel chair etc. through the brain signals. It is a promising technology for paralyzed patients to express their intentions to the external world. In addition, it is a new direction in communication and games that can be explored for the healthy people too. Although, recent years have featured a rapid growth in BCI research, numerous challenges exist in the development of a commercial BCI. The key research challenges exist in the signal acquisition methods, development of pre-processing and feature extraction techniques, classification and translation algorithms, operational protocols and user training strategies. This project aims to address the signal processing aspects of EEG-based BCI including pre-processing and feature extraction methods.

1.1 Motivation

Various neurological phenomena present in EEG have been employed as communication strategies for developing a BCI system. In contrast to the invasive techniques of brain activity measurement, the non-invasive techniques provide low signal to noise ratio, which is one of the major issues in the design of EEG-based BCIs. In order to achieve efficient human computer interaction in an EEG-based BCI, robust feature extraction techniques are necessary. Among the various neurological signals explored in EEG-based BCIs, the event-related desynchronization and event-related synchronization (ERD/ERS) patterns during motor imagery have been used to interpret human intentions in BCI applications successfully. These ERD/ERS patterns are defined as the attenuation and enhancement in EEG rhythms respectively occurring in specific frequency bands when the brain is activated either by execution or imagination of motor movements.

The work in this thesis focuses on the BCI approaches based on the ERD/ERS patterns occurring during the mental imagination of motor movements or motor imagery. It is reported that the frequency bands for discriminating 2 types of motor imagery are subject-specific. Due to this inter-subject variability in discriminative frequency bands, the pre-selection of subject-specific bands is significant for reliable feature extraction and obtaining better classification accuracy of ERD/ERS based BCIs. Besides, these bands may not be stable over time for the same subject due to the non-stationary nature of the EEG signals and the presence of oscillating ERD/ERS patterns. This results in a considerable intra-subject variability of the discriminative frequency bands also. Therefore, both inter-subject and intra-subject variability of discriminative frequency bands during motor imagery must be addressed to develop a robust BCI based on ERD/ERS patterns. This thesis aims at improving the feature extraction techniques in a motor imagery based BCI, presenting new band selection techniques and BCI approaches tackling both inter-subject and intra-subject variability of discriminative frequency bands effectively. The robustness of the proposed methods is demonstrated by using offline and online experiments. The main criterion used for frequency band selection in this work is the Fisher ratio values of the EEG signals recorded from the motor cortex of brain.

The analysis and results presented in this thesis are based on the experiments done on two publicly available datasets and an online dataset recorded in the Neural Signal processing

Lab of Institute for Infocomm Research, Agency for Science, Technology and Research, Singapore. The two publicly available datasets are (i) BCI Competition III dataset IVa consisting of right hand and foot motor imagery trials and (ii) BCI Competition IV Dataset IIb having left hand and right hand motor imagery trials. The online dataset consists of left and right hand motor imagery trials. The various motor imagery patterns available in these datasets are analyzed and three new methods to optimize the frequency band selection procedure are presented in order to enhance the BCI performance. The proposed frequency selection methods are based on the discriminative capability of EEG signals recorded from the sensorimotor cortex.

1.2 Objectives

It is reported that imagination of motor movements or motor imagery induces patterns in the rhythmic components of EEG in the form of short lasting amplitude attenuation and enhancement named as ERD/ERS patterns. In order to identify patterns generated by different motor imagery activities, Common Spatial Pattern (CSP) is found to be an effective technique. As the ERD/ERS patterns occur in subject-specific frequency bands, the success of CSP algorithm greatly depends upon the pre-selection of informative bands. The work in this thesis uses CSP technique for feature extraction and propose new methods to find the subject-specific discriminative bands for improving the BCI performance. The main objectives of this thesis are as follows:

- Propose effective methods to estimate the subject-specific discriminative frequency bands during motor imagery.
- Study the variability of the estimated discriminate frequency bands of a single subject over time.
- Propose methods to track the variation of discriminative bands over time and investigate the effect of tracking the spectral variability on the performance of motor imagery based BCI.
- Investigate the feasibility of proposed methods using offline and online experiments.

At first, a new Discriminative Filter Bank Common Spatial Pattern (DFBCSP) algorithm is proposed which employs Fisher ratio values to estimate the discriminative filter bank for each subject. The DFBCSP system uses a parent filter bank of twelve Finite Impulse Response (FIR) filters in the frequency range of 6-40 Hz for bandpass filtering the raw EEG recorded from motor cortex. The Fisher ratio values computed at each filter output decide the subject-specific discriminative filters. A set of four filters with the highest Fisher ratio values form the subject-specific discriminative filter bank and are used for bandpass filtering the EEG from all the electrodes. Features are extracted from the filtered EEG for classification. Experimental analysis shows that DFBCSP performs better than the existing filter bank based method in terms of classification accuracy.

The DFBCSP requires multi-band filtering for band selection. Hence, a time-frequency Fisher ratio pattern approach is proposed for band selection in order to reduce the complexity of DFBCSP. Using this time-frequency approach, discriminative frequency bands over various sessions of EEG during motor imagery are investigated. The variation of discriminative frequency bands between subjects is discussed in literature, but its variation over time is hardly addressed. Considerable inter-session and intra-session frequency band variations are found in the analysis for most of the subjects. In order to investigate the effect of tracking this spectral variability on BCI performance, two BCI approaches are proposed named as the Static Spectral Features (SSF) and Variable Spectral Features (VSF). SSF method processes EEG with fixed model parameters whereas VSF method addresses the variability of bands over time. In the experimental results, VSF method outperforms SSF showing the requirement of tracking the spectral variability of motor imagery patterns over time.

Later, in order to further improve the spectral variability tracking process, an Adaptively Weighted Spectral-Spatial Pattern (AWSSP) algorithm is proposed. In order to estimate the bands, the VSF method uses discriminative power of frequency components held in time-frequency domain whereas the AWSSP uses the discrete discriminative weight values of frequency components. Whenever the deviation in discriminative weights computed exceeds the threshold defined in the AWSSP algorithm, the bandpass filters and the classifier are updated. The AWSSP algorithm is evaluated using offline and online experiments and it is found that the adaptive weighting and selection of discriminative frequency bands do provide significant improvement in the BCI performance in terms of classification accuracy.

1.3 Organization of the thesis

The organization of this thesis is as follows:

In Chapter 2, an overview of current EEG-based BCI approaches is given. It provides brief discussions about the basic building blocks of BCI, various techniques for measuring brain activity, neural features driving EEG-based BCI, characteristics of ERD/ERS patterns, existing BCI applications and feature extraction techniques. This chapter also presents the necessity of discriminative frequency band selection algorithms for enhancing the performance of motor imagery based BCIs.

In Chapter 3, the Discriminative Filter Bank Common Spatial Pattern (DFBCSP) algorithm is presented which employs Fisher ratio values to estimate the discriminative filter bank for each subject.

In Chapter 4, the process of estimating discriminative frequency components using time-frequency Fisher ratio pattern is proposed. This chapter also presents the variation of subject-specific discriminative frequency bands over time and BCI approaches to address this spectral variability.

In Chapter 5, a new adaptive method for tracking the frequency band variations over time is proposed. The proposed BCI approach named as Adaptively Weighted Spectral-Spatial Pattern (AWSSP) algorithm tracks the variation of discriminative weights of frequency components over time and is evaluated using offline and online experiments.

In Chapter 6, conclusion of the thesis and future directions of research are presented.

Chapter 2

Literature Review

Over the last three decades, Brain-Computer Interface (BCI) has attracted much attention in cognitive neuro-science research, triggered by new scientific progress in understanding brain functions and by impressive applications. BCI is an alternative communication and control channel from brain to the external world. This approach allows direct control of a computer application or a neuroprosthesis, solely by human intentions extracted from suitable brain signals [1]. The patients suffering from neuro-muscular diseases such as amyotrophic lateral sclerosis, brain-stem stroke, spinal cord injury etc. are having very poor communication capability and they can be even in “completely locked-in stage” without being able to control their muscle movements. As this new approach bypasses the conventional motor output pathway of human nerves and muscles, it is a promising communication tool for the disabled people [2, 3]. BCI technology has great potential not only in the betterment of disabled people but also in the development of brain related games for healthy people or in the constant monitoring of attentional states in working environments with high risks [4].

2.1 BCI: An overview

In a BCI system, the messages or commands that an individual sends to the external world do not pass through the brain’s normal output pathways of nerves and muscles. Instead, the system directly reads out the user’s intent and translates it into physical commands that

control the output devices. According to the first international meeting of BCI research held in 1999, BCI is defined as: *a communication system which does not depend on the brain's normal communication pathway of peripheral nerves and muscles* [3]. A cognitively intact brain in highly paralyzed patients enables them to generate movement plans even though they are not able to realize such actions. If such movement intentions can be identified successfully using brain signals, BCI can be an efficient tool for patients to express their wishes to the external world [5, 6].

Before the BCI technology can reach to its full potential, there are many critical issues that have to be addressed. The main challenges include selection of signal acquisition methods, development of feature extraction methods and translation algorithms, design of output devices, formulation of operational protocols and definition of user training strategies. In order to address all these challenges, many BCI approaches have been proposed. Even though there is no standard design that represents a BCI, the basic building units, the techniques for measuring the brain activity and the neurophysiological signals used to drive them are similar and they are briefly described here.

2.1.1 Core components of a Brain-Computer Interface

Figure 2.1: Block diagram of a conventional BCI system [1, 6, 7].

Like any communication and control system, the BCI system also has an input, an output, and a translation algorithm that converts the former to the latter. The block diagram of

a BCI system is shown in Fig. 2.1 [1, 6, 7]. The BCI input is the brain signal carrying informative neural features. BCI outputs can be letter or icon selection on computer screen, a wheel chair control, neuroprosthesis etc. [6]. Each BCI uses specific algorithms to translate its input into command signals to control some output devices such as linear or nonlinear equations, a neural network, or other methods. The core components of a BCI are as follows:

- 1. Data acquisition unit:** This part is responsible for recording brain activity using various types of sensors. After amplification and digitization, the recorded brain signals serve as BCI inputs.
- 2. Preprocessing unit:** This unit eliminates noise or artifacts present in the brain signals in order to enhance the relevant information hidden in the input signal.
- 3. Feature extraction:** The feature extractor transforms the amplified signals into feature values that correspond to the underlying neurological mechanism. These features are employed by BCI for controlling the output device.
- 4. Classification unit:** This part is responsible for identifying the intention of the user.
- 5. Translation unit:** The classifier output is transformed into a device dependent control signal by translation unit.
- 6. Output device:** Output device can be a computer screen and output is a selection of targets.
- 7. Feedback:** Ideally, BCI should be a closed loop system such that the system shows the output (the identified mental state) to the user after processing the brain activity. It helps the user to control his brain activity and adapt accordingly to enhance the overall performance of BCI.
- 8. Operating protocol:** Protocol guides the operation of BCI, i.e. it determines the on-set, the offset and the timing of its operation, type and extent of user training required etc. A sufficient amount of calibration work is necessary which develops informative sensors, the optimum features and classification algorithm, before operating any BCI as shown in Fig. 2.1. The brain signals vary from subject to subject and each user has to undergo a certain amount of training before applying BCI [8].

All the above units are highly important in the development of an efficient BCI and affect the BCI performance in terms of accuracy, speed and information transfer rate. BCI must be designed such that it is comfortably carried out without any harm to the user's health. The choice of brain signal measurement technique is of great importance regarding the

health, safety and comfort of BCI users. The following section presents a few non-invasive brain signal recording techniques exploited in BCI applications.

2.1.2 Techniques for measuring brain activity

The brain activity is the outcome of firing of millions neurons inside the cerebral cortex. Numerous techniques have been used to measure brain activity. These techniques fall into two groups: invasive and non-invasive [9]. If the measurement sensors are within the brain, the technique is said to be invasive. It is non-invasive, if the measurement sensors are outside the head, on the scalp for instance. The invasive techniques record data directly from the skull and they require surgical interventions to implant the electrodes. Implanted electrodes gives better signal quality and spatial resolution than non-invasive methods. Most of the BCI researches using the invasive techniques were done for primates [10]. Recent studies have shown the feasibility of invasive BCIs in humans [11, 12]. But, the main drawback of the invasive BCI is that the implanted electrodes have limited lifetime which necessitates regular surgery operations for electrode replacement. They might be harmful to the health of subject and the implantation of electrodes raises some ethic issues too. Therefore, the non-invasive methods are preferred in BCI systems than invasive measurement techniques [13, 14].

These non-invasive methods acquire data through electrodes placed on the surface of the head. A number of non-invasive methods explored in BCI applications are briefly described here including functional Magnetic Resonance Imaging (fMRI), Positron Emission Tomography (PET), Magnetoencephalography (MEG) and Electroencephalogram (EEG).

Positron Emission Tomography

During brain activity measurement using the PET scans, radio-active tracer isotopes with a short decay period are incorporated into metabolically active molecules (for instance sugar). When these molecules are injected into the blood flow, the decay can be measured especially at locations where high metabolic activity is performed [15]. The measurement of decay can detect the regions of high neuronal activity. This type of brain activity measurement takes a long time and has risks connected to the dosage of ionizing radiation. Also PET scanners are expensive and bulky which hinders its applications in portable BCI.

Functional Magnetic Resonance Imaging

The neural activity of brain is related to the changes in the blood flow and oxygenation of blood in the brain. The nerve cells consume oxygen in the active state. The magnetic properties of de-oxygenated hemoglobin are different from oxygenated hemoglobin (oxygen carrier protein in the blood). By applying strong magnetic resonance pulses to the brain, the Blood Oxygenation Level Dependent (BOLD) changes can be recorded in fMRI [16]. The spatial resolution of this method is high, but the temporal resolution is low because significant BOLD changes can be detected after some seconds of neural activity only. The fMRI devices are also large, expensive, and require magnetic fields during data recording.

Magnetoencephalography

MEG measures the magnetic fields generated by electric currents flowing through the dendrites of neurons in the brain. Due to the orthogonality of magnetic field and electric current, MEG can measure the response of large neuron populations with dendrites oriented tangentially to the scalp surface. It has high spatial and temporal resolution and has been used in BCI experiments [17-19]. But, the demerit of this measurement technique is its huge size and the requirement of magnetically shielded environment for signal recording.

Electroencephalography

EEG is a non-invasive and relatively small size brain signal recording device. EEG records brain potentials by placing electrodes on the scalp. These electrodes are small metallic plates with sufficient conductivity. During signal recording, the application of gel on the electrodes lowers the impedance between electrodes and scalp. EEG measurements are also effective in diagnosing diseases such as epilepsy, states of altered consciousness, head trauma and coma, cerebral infections, sleep disorders, etc.

EEG as well as MEG are functional imaging techniques that directly detect neuronal activity with millisecond temporal resolution. EEG measures brain signal from scalp using electrodes whereas MEG is contact less and practically insensitive to tissue conductivity differences of head. Due to its insensitivity to the conductivity profile of the head tissues, MEG has the ability to accurately locate the tangential components of neuronal sources [17]. When EEG can detect both the tangential and radial components of the source, MEG cannot reliably detect the radial component of the neuronal current that is perpendicular to inner skull

surface. But, EEG's localization accuracy depends on the estimated conductivity profile of the head. Therefore, MEG and EEG are considered as complementary rather than competing modalities recently, and most MEG protocols routinely include simultaneous acquisition of multichannel EEG data [19].

MEG instrumentation typically requires the use of superconducting magnetometers housed in a magnetically shielded room. As EEG is easily recordable with a less expensive equipment compared to MEG, most of the current BCI systems use EEG for recording brain activity [20, 13]. Therefore, work in this thesis focuses on EEG-based BCI systems.

The voltage fluctuations recorded by EEG are summations of ongoing electrical activity of large populations of cortical neurons [21]. Basically, the brain is divided into 5 structures: cerebral cortex, cerebellum, brain-stem, hypothalamus, and thalamus. For BCI, the most relevant part is cerebral cortex. The functional units in the brain are shown in Fig. 2.2. Various units of cerebral cortex responsible for specific functions are shown in Table 2.1 [22]. Knowledge of specific brain parts excited by different actions is relevant in the development of every BCI application.

Figure 2.2: The functional units in the brain [22]

For electrode placement in EEG measurements, brain is divided as shown in Fig. 2.3 [22-24]. It is according to the 10-20 international system [23] for electrode placement where the electrodes are named based on their scalp location. The cortex is divided into two hemispheres where each hemisphere is divided into four lobes named as frontal, parietal, occipital and temporal lobes. Electrodes in the left hemisphere are odd numbered and even numbered electrodes are on the right hemisphere. Z (or zero) refers to the electrodes placed in the middle line. Typically, the reference electrodes for EEG recording are attached to

Table 2.1: Cortical areas of the brain and their functions[22]

Cortical Area	Function
Auditory Association area	Complex processing of auditory information
Auditory cortex	Detection of sound quality
Speech Center (Broca's area)	Speech production and articulation
Prefrontal cortex	Problem solving, emotion, complex thought
Motor association area	Coordination of complex movement
Primary motor cortex	Initiation of voluntary movement
Primary Somatosensory cortex	Receives tactile information from the body
Sensory Association area	Processing multi sensory information
Visual Association area	Complex processing of visual information
Wernicke's area	Language comprehension

the nasion or to mastoids. Alternatively, scalp electrodes such as Cz or Fz can be used as the ground.

Figure 2.3: Electrode positions according to the 10-20 international system of electrode placement [23].

The arrangement of EEG electrodes shown in Fig. 2.4 (a) is an extension of the 10-20 international system of electrode placement [25]. In this figure, the head is viewed from above and the small triangle on top of the circle marks the nose. The frontal scalp electrodes are represented in white, central in blue, parietal in yellow, occipital in red and temporal in green colour. Fig. 2.4(b) shows the major lobes of the brain, as viewed from the temporal perspective, inside the head. The color coding has been synchronized with the electrode montage in 2.4(a) [24, 25].

(a)

(b)

Figure 2.4: Electrode positions according to the extended 10-20 international system of electrode placement and respective brain areas [25].

The brain activity measured by these electrode plates is the sum of the post-synaptic potentials generated by thousands of neurons having the same the orientation with respect to the scalp. Conventionally, EEG signals are composed of various oscillations named as “rhythms” [20, 26]. The important brain rhythms present in EEG are:

- *Delta* rhythm: EEG waves below 4 Hz (usually 0.1-4 Hz) belong to the *delta* waves. Infants (around the age of two months) show irregular *delta* activity of 2-3.5 Hz (amplitudes 50-100 μ V) in the waking state. In adults *delta* waves are only seen in deep sleep.
- *Theta* rhythm: *Theta* waves are between 4 Hz and 8 Hz. *Theta* rhythm plays an important role in infancy and childhood. In normal adults *theta* waves are seen mostly in states of drowsiness and sleep. During waking hours, the EEG contains only a small amount of *theta* activity and no organized *theta* rhythm.
- *Alpha* rhythm: Rhythm at 8-13 Hz occurring during wakefulness over the posterior regions of the head, generally with higher voltage over the occipital areas. Best seen with eyes closed and under conditions of physical relaxation and relative mental inactivity.
- *Mu* rhythm: *Mu* rhythm frequency is around 10 Hz. Although the frequency and the amplitude of the *mu* rhythm are similar to those of the *alpha* rhythm, the *mu* rhythm is topographically and physiologically different from the *alpha* rhythm. The *mu* rhythm is strongly related to the functions of the motor cortex and the adjacent somatosensory cortex. The thoughts about performing movements and readiness are related to the *mu* rhythm and this rhythm has been employed effectively in BCI applications.
- *Beta* rhythms: Any rhythmical activity in the frequency band of 13-30 Hz may be regarded as a *beta* rhythm. *Beta* rhythms can mainly be found over the frontal and central regions. It can be blocked by motor activity and tactile stimulation.
- *Gamma* rhythm: Gamma rhythm concerns mainly frequencies above 30 Hz. This rhythm is usually has a maximal frequency around 80 Hz or 100 Hz. It is associated associated with attention, perception, and cognition.

2.1.3 Neural features in EEG used to drive BCIs

Until now, EEG-based BCIs have been applied various neural features present in EEG for developing communication devices [27] and a number of commonly used neural features are listed here.

1. **Slow cortical potentials (SCPs):** SCPs are slow potential shifts generated at the cortex, reflecting changes in the cortical polarization of the EEG, lasting from hundreds of milliseconds up to several seconds. Positive shifts in SCPs are associated with cortical relaxation and slow negative shifts are associated with cortical activation while evoked either by the movement execution or by a mental task [28]. SCPs had been exploited to develop BCIs. In a thought translation device developed in [8], SCPs are used to control the movements of an object on a computer screen. However, a user learns to control SCPs, generally after a very long training period [27].
2. **P300:** The P300 component of the EEG is a positive potential that occurs in response to an “oddball” paradigm, where a series of standard stimuli is randomly interleaved with a rare stimuli, termed as deviants [29, 30]. If the deviant is relevant to the user, a large positive potential occurs with a relative latency of approximately 300ms to the stimulus, named as P300. This positive component which is not present in response to the standard stimuli is predominantly found in parietal areas of the scalp. The use of the P300 has been demonstrated in BCI context to develop effective communication devices. A speller in [29] uses a matrix of with 6 rows and 6 columns containing 26 alphabet letters and 10 digits. When the subject is instructed to attend a single letter, the rows and columns are highlighted randomly. The correct letter was decoded by averaging over the rows and columns separately and by selecting the row/column pair to which the subject responded with the largest P300 component. Although P300 has been studied extensively, it can be an exhausting experience for the users to concentrate on the flickering symbols.
3. **Visually evoked potentials(VEPs):** VEP is an evoked potential caused by a visual stimulus, such as an alternating checkerboard pattern on a computer screen. These responses usually originate from the occipital cortex, the area of the brain involved in the reception and interpretation of visual signals. VEPs reflect the visual information-processing mechanism in the brain. VEPs corresponding to low stimulus rates are

categorized as transient VEP. The Steady State Visual Evoked Potential (SSVEP) is defined as periodic evoked potentials, induced by rapidly repetitive visual stimulation, typically at frequencies greater than 6 Hz. Transient VEP as well as SSVEP have been employed to drive BCIs [31].

The transient VEP is a true transient response to a stimulus when the relevant brain mechanisms are in resting states and it does not depend on any previous trial. If the visual stimulation is rapidly repeated, an SSVEP is generated. In this circumstance, the brain is considered in a steady state of excitability. The frequency range associated with the SSVEPs normally consists of the fundamental frequency of the visual stimulus as well as its harmonics [32]. The main part of the SSVEP based BCI system was an LED panel, where each LED flickers at a specific frequency representing a specific command. The user would be able to express the specific command just by gazing at the corresponding LED. In such applications, the user should draw his continuous attention on the button he wants to activate. Many SSVEP based BCIs have been already proposed and the one in [33] reports a high information transfer rate of 60-90 bits per min. Information transfer rate is a standard measure of a communication system usually expressed in bit rate in BCI context. It takes into account of accuracy, the number of possible selections, and the time required for making each selection. The number of bits transmitted per trial B is estimated as [7]:

$$B = \log_2 N + p \log_2 p + (1 - p) \log_2 \frac{1 - p}{N - 1} \quad (2.1)$$

where N is the number of targets and p is the probability that the BCI selects what the user intends. Bits/min is obtained by dividing B by the duration of each trial. Higher the information transfer rate, the better the BCI performance.

4. **ERD/ERS patterns:** Event-related desynchronization and event-related synchronization (ERD/ERS) patterns are one of the most commonly used neural features in EEG based BCIs. In awake people, primary sensory or motor cortical areas often display 8-12 Hz EEG activity when they are not engaged in processing sensory input or producing motor output [26]. This idling activity, called *mu* rhythm is focused over somatosensory or motor cortex. The *mu*-rhythm activity comprises a variety of different 8-12 Hz rhythms, distinguished from each other by location, frequency, and relationship to concurrent sensory input or motor output [2]. These *mu* rhythms are

usually associated with 18-26 Hz *beta* rhythms. While some *beta* rhythms are harmonics of *mu* rhythms, some are separable from them by topography and/or timing, and thus are independent EEG features [2, 34].

Movement or preparation for movement is typically accompanied by a decrease in *mu* and *beta* rhythms, particularly contralateral to the movement. This decrease has been labeled “event-related desynchronization” or ERD [20, 26, 34-38]. Its opposite, an ipsilateral rhythm increase, or “event-related synchronization” (ERS) occurs after movement and with relaxation. These ERD/ERS patterns are firstly reported as the amplitude suppression and enhancement of the *mu* and *beta* rhythms respectively in the motor cortex related to the planning and execution of self paced-hand movements. Later, it is found that similar patterns are observed during the mental imagination of motor movements too and can serve as a communication feature in EEG-based BCI systems [39]. These oscillations in EEG might be due to the modulating influences of neuro-chemical brain systems, changes in the strength of synaptic interactions, or changes in the intrinsic membrane properties of the local neurons [40]. The sensory

Figure 2.5: ERD/ERS patterns during the right finger movement task and the recorded EEG signals [39, 41].

and cognitive processing and the motor behavior generate complex spatio temporal patterns because of the related dynamics in brain oscillations. Fig. 2.5 shows the superimposed band power courses during right index finger lifting, computed for 3 different frequency bands 10-12 Hz, 14-18 Hz and 36-40 Hz respectively for EEG trials recorded from the electrode position C3 according to the 10-20 international system of

electrode placement. The vertical line given in the upper panel shows the beginning of the movement trigger. At 2.5 sec prior to the movement-offset, the *mu* ERD is found and a *gamma* (36-40 Hz) ERS is noted immediately prior to the movement offset. And a *beta* ERS is observed just after the movement offset. The lower panel shows the EEG recorded during the right finger movement. The amplitude reduction or ERD is observed prior to the movement offset in the central electrode positions and enhanced EEG activity in the posterior region [39, 41]. It is observed that in a single scalp location, synchronization of higher frequency components and desynchronization of lower frequency components do happen during the execution of motor movements. Also, these power decrease and increase are observed in other locations other than central electrodes.

Many EEG studies confirm that primary sensorimotor areas are similarly activated either by execution or mental imagination of motor movements [36, 41-51]. And now, one of the most commonly used neural features to drive EEG-based BCI is ERD/ERS patterns during motor imagery. In this thesis, a number of signal processing issues to improve the classification accuracy of EEG signals during the performance of motor imagery task have been addressed. They include discriminative frequency band selection algorithms during motor imagery, feature extraction techniques and techniques to track inter-subject and intra-subject variability of discriminative bands.

2.2 ERD/ERS based BCI

Quantification of ERD and ERS in the *alpha* and *beta* bands during the execution of hand or foot motor movement had been reported in [42-44] using brain signal analysis. In 1997, it was found that the brain regions and functions involved in the mental imagination of motor movements are similar to those activated during the execution and preparation of motor movements [45]. Motor imagery is the mental rehearsal of a motor movement without any overt motor output. According to a study using PET techniques, the main difference between motor imagery and execution is that the former case is blocked at some cortico-spinal level [46]. The primary cortex activation by motor imagery is also reported using fMRI studies [47]. The primary motor cortex is activated during motor imagery and their neural responses reflected in EEG are similar to that obtained during execution. From 1997 onwards, BCI research community has been focusing on ERD/ERS during motor imagery

[36, 39]. Currently, most of the EEG based BCI applications rely on motor imagery since it requires no real motor movement, but imagination only [37].

2.2.1 Characteristics of ERD/ERS patterns

Figure 2.6: Geometrical mapping between brain and body.

During the imagination of motor movements, significant changes occur in brain rhythms of the motor cortex. Motor movements refer to the up, down, left or right movements of motor parts of body usually, hand or leg. Depending on the BCI paradigm they can be either actual or imagination. Example of hand motor imagery can be thoughts about squeezing a ball and, for foot motor imagery, pulling a brake in vehicle can also be imagined. According to the concept known as homunculus [38], for each part of the human body there exists a respective region in the motor and somatosensory area of the neurocortex. The functional units of the brain are shown in Fig. 2.2. The “mapping” from the body to the respective brain areas preserves topography as given in Fig. 2.6, i.e. neighboring parts of the body are represented in neighboring parts of the cortex. The figure shows the two sections of the brain, viewed from a dorsal perspective. The left half of motor cortex is shown on the left

and right half of the somato-sensorimotor cortex is given on the right side of Fig. 2.6. Each body part has a corresponding region in the motor cortex as shown [52, 53].

While the region of the feet is at the center of the vertex, the left hand is represented lateralized on the right hemisphere and the right hand on the left hemisphere. When a subject is not engaged with one of his limbs (movements, tactile senses, or just mental introspection), large populations of neurons in the respective cortex are firing in rhythmical synchrony. These idle rhythms are attenuated when engagement with the respective limb takes place and that can be measured at the scalp in the EEG as a brain rhythm around 10 Hz or 20 Hz. This neurophysiologic observation is a possible feature of brain activity that can be exploited for BCIs. As the attenuation effect is due to loss of synchrony in the neural populations, it is termed as ERD. The dual effect of this enhanced rhythmic activity is termed as ERS. Thus preparation for a real movement or imagination of a movement is accompanied by a contralateral decrease (ERD) or ipsilateral increase (ERS) of alpha or *beta* band power of EEG signal in primary sensory motor area [54, 55].

In [56], the separability of signal recorded during left and right hand motor imagery is analyzed and found that the ERD and ERS patterns clearly exist in subject-specific frequency bands. The study was done using four subjects and the cursor on a computer screen was controlled by ERD/ERS patterns during motor imagery. Fig. 2.7 shows the ERD/ERS time courses of two subjects in selected frequency bands 9-13 Hz and 10-12 Hz respectively during imagined movement of the right (black line) and left hand (gray line), recorded from the left and right sensorimotor areas using EEG channels C3 and C4. The study in [51] reports the activation of neurons in the vertex during foot movement imagination which was clearly recorded in Cz channel.

Fig. 2.8 shows the quantification of ERD reported in [37]. The band power estimates of each single trial EEG are computed by band pass filtering, squaring the samples and subsequent averaging over trials and sample points. The time-frequency maps are plotted using these band power estimates and based on this, the most informative bands are selected for the electrodes C3, Cz and C4. The ERD/ERS is estimated as percentage power decrease and increase with respect to a 1 sec interval before the warning tone to the start motor imagery. It is found that the left and right hand actions are focused on the left and right motor cortex, giving excitement in the channel C4 or C3. For the foot imagery, the respective part is vertex and the ERD/ERS was significantly found in Cz channel.

Figure 2.7: Time courses of ERD/ERS observed in left and right hand motor imagery in two subjects from channels C3 and C4 [56].

Thus, the studies showed that during the imagination of left hand movement there will be observable power changes in the region related to hand area on the right hemisphere and in the left hemisphere ERD will be seen during right hand movement imagination. These distinct spatio-temporal patterns in sensorimotor cortex generated by motor imagery make the ERD/ERS an appropriate candidature for BCI task development [56-60].

Several factors suggest that ERD/ERS patterns could be good signal features for EEG-based communication. They are associated with cortical areas that are directly connected to the brain's normal motor output channels. Furthermore, and most relevant for BCI use, the ERD and ERS during motor imagery do not require actual movement, they occur also with motor imagery, i.e imagination of motor movements [2, 35, 36]. The applications of SSVEP, VEP or P300 in BCI, require a stimuli and it may cause user fatigue in continuous applications. Motor imagery generates cortical changes rather than spinal excitability changes. Hence, activation of the primary motor cortex is not only found in healthy subjects, but also in paralyzed patients suffering from locked-in syndrome. They retain their ability to generate neural signals for motor control, although their motor pathway may be severely interrupted. Reports in [5] show that specific training in motor imagery tasks may

produce physiologic changes in sensorimotor cortex. This plasticity of sensorimotor cortex will help to regain the motor control of paralyzed patients and has a great impact in BCI based rehabilitation procedures.

ERD/ERS patterns during the imagination of hand, foot, and tongue movements have been reported to be effective in the development of BCIs and a few applications are listed here.

(a) Time-frequency maps displaying ERD and ERS in C3, Cz and C4 during left hand, right hand and foot motor imagery. Red indicates ERD and blue shows ERS.

(b) Topographical distribution of averaged band power in the upper alpha band of 10-12 Hz. The scale of the pattern is as given.

Figure 2.8: The time-frequency pattern and topographical distribution of band power during motor imagery [37].

2.2.2 Applications of ERD/ERS based BCIs

The similarity of ERD/ERS patterns occurring during the mental imagination and execution of motor movements was confirmed in 1997 [36]. Until then, the sensorimotor rhythms during the preparation or execution of motor movements have been used to drive BCIs [59-63]. The band power changes of *mu* and *beta* bands during execution of motor movements

have been successfully employed to develop various BCI applications [61-67]. Likewise, ERD/ERS during motor imagery have also been applied as command signals for: controlling the cursor movement or selecting targets on computer screen, robotic applications, wheel chair control, neuroprosthesis etc. A few previously published applications are briefly presented in the following section.

1. Cursor movement and target selection

The scalp-recorded EEG signals have been actively modulated to move a cursor on a video screen in a continuous fashion in one, two or four dimensions. For this application, the users are trained to modulate amplitudes of sensory motor rhythms in the *mu* or *beta* frequency bands over left and/or right sensorimotor cortex [68, 69]. Band power estimates from two hemispherical channels controlling cursor movement independently in two dimensions to hit targets along the periphery of the monitor is reported in [70]. The employment of autoregressive model parameters for feature extraction gives significant improvement in user performance in [71, 72].

The cursor movement performance is further improved in [73] using a new feature other than the left or right hand motor imagery. The two dimensional movement of the cursor towards the target is controlled by ERD/ERS patterns obtained from left or right hemisphere and the target can be selected and rejected by performing or withholding hand-grasp imagery. This imagery evokes a transient response that can be detected and used to improve the overall accuracy by reducing unintended target selections. The study in [74] reports the improvement in BCI performance accomplished by autoregressive spectral analysis.

It is reported that the sensorimotor beta rhythm of EEG associated with human natural motor behavior can be used for a reliable and high performance BCI for both healthy subjects and patients with neurological disorders [75]. A recent study in [60] develops user friendly BCI requiring minimal training and less mental load in paralyzed patients. The ALS and PLS patients controls four-dimensional cursor movement by mental imagination of motor movements achieving an accuracy of around 50-60%.

2. Spelling devices

Using the band power features extracted from the ERD/ERS patterns, verbal communication is accomplished in a patient with cerebral palsy. This study makes use of bio-feedback, claims an average accuracy of 70% with a communication rate of 1 letter per min [76].

Another study in [77] presents an asynchronously controlled three-class BCI based spelling device, operated by spontaneous EEG and modulated by motor imagery. Considering three able-bodied subjects operating the virtual keyboard, two are successful, showing an improvement of the average spelling rate (the number of correctly spelled letters per min) of 1.99.

Motor imagery based mental typewriter and communication devices are also proposed in [78, 79]. The study in [80] reports the implementation of a prototype assistive communication platform which improves the mobility and communication of 14 patients with the surrounding environment. These patients of severe motor disabilities due to progressive neurodegenerative disorders control the system by voluntary modulations of EEG sensorimotor rhythms recorded on the scalp. This skill is learnt by all subjects even though the subjects have not had control over their limbs for a long time.

3. Wheel Chair control

The study in [81] uses brain waves during the imagination of movements of paralyzed feet by a tetraplegic patient to control movements of his wheelchair in virtual reality (VR). In this case study, the spinal cord injured subject is able to induce centrally localized *beta* oscillations in the EEG by imagination of feet movement and he had a feeling of virtual walk.

4. Robotic applications

A pioneering application of motor imagery based BCI is attaining control of a small mobile robot through the rooms of a model house, by mental imagination [82]. The after-stroke rehabilitation exercises reported in [83] analyzes 8 stroke patients, by combining the BCI and robotic arm operated by motor imagery. The results show that most BCI-naive hemiparetic stroke patients are capable of operating the BCI effectively, hence motivates further clinical studies towards BCI-based robotic rehabilitation [83, 84].

5. Other applications

The study in [85] investigates whether the self-induced brain potential can be used to help a severely disabled 22 year old tetraplegic patient who had a limited muscle activity. The subject could control an electrical driven hand orthosis fitting his left hand by the band power estimates of reactive frequency bands during the motor imagery after a few months of training.

The grasp-function of a 28 year old highly paralyzed patient could be restored using EEG and a functional electrical stimulation device in [86]. The *beta* burst activity of foot movement imagination is successfully translated as command signal to control the device.

A practical motor imagery-based brain-controlled switch functioning as a real world switch is introduced in [87]. Four healthy volunteers were instructed to perform an intended motor imagery task following an external sync signal in order to turn on a virtual switch provided on a computer screen. This device is convenient for users because the switch does not need subject's attention when he/she does not need to activate it. Also the device is reported to have a low false positive operation rate [87].

Considering the currently available EEG-based BCI systems, most of the applications work in synchronous mode, and a few in the asynchronous mode. In synchronous mode, the subject is allowed to respond only when the system displays the stimulus. In asynchronous BCIs, the subject is free to intend a specific thought and control the operation of the system. In other words, synchronous BCI is system-initiated and asynchronous BCI is user-initiated. The user has full control on the operation of asynchronous BCI which makes its design more challenging than that of synchronous BCI. BCI community is trying to address all the issues related to both modes of operation [59, 60, 88, 89]. This thesis will be focusing about synchronous BCI applications.

Each of these listed BCI approaches differ in the way they extract features during motor imagery. A number of successful feature extraction techniques are described in the next section.

2.3 Techniques to extract ERD/ERS features during motor imagery

During mental imagination of motor movements, neurons in the motor cortex are activated generating ERD/ERS patterns. The foot, tongue or hand movement imaginations generate distinguishable spatio-temporal patterns in motor cortex. In order to identify the performed motor imagery, the informative feature in the recorded EEG signals have to be extracted properly. Therefore, feature extraction is an important step in the development of any BCI. Feature extraction process is responsible for forming the discriminative set of features, for

each mental task. If the distribution of feature set is distinct enough, the mental tasks can be accurately identified. A number of effective techniques reported in literature, to extract features accompanied with ERD/ERS are briefly explained here [90-95]. As this thesis is focusing on one of the most effective feature extraction techniques using the Common Spatial Pattern (CSP), it is presented in detail and other methods are also briefly explained.

2.3.1 Frequency related features

As the ERD/ERS patterns are occurring in subject-specific reactive frequency bands, the power of the signal filtered in that range is taken as the band power feature for classifying motor imagery patterns [92]. Conventionally, band power estimates of 1 or 2 frequency bands are used in BCI researches, to avoid the dimensionality problem. Band power estimates of *mu* and *beta* rhythms have been used in BCI applications to control cursor movement on computer screen and to control numerous external devices [68-70]. The complex band power features as well as Power Spectral Density (PSD) features have also been employed in [96-98] to extract informative features during motor imagery. These techniques are relatively simple, but require prior knowledge of subject-specific frequency bands and ignores the information outside these frequency ranges.

2.3.2 Time-domain features

Time domain parameters related to ERD/ERS are also exploited as BCI features in [95, 99]. The time-domain parameters were introduced by Hjorth in the 1970s. These parameters describe the temporal dynamics of a signal $X(t)$, by using three measures named as the activity, the mobility and the complexity. Activity is the wide band filtered signal power, mobility is the mean frequency and complexity is the change in frequency. These features for a signal $X(t)$ are computed using the following equations [13]:

$$\text{Activity}(X(t)) = \text{Var}(X(t)) \quad (2.2)$$

$$\text{Mobility}(X(t)) = \sqrt{\frac{\text{activity}\left(\frac{dX(t)}{dt}\right)}{\text{activity}(X(t))}} \quad (2.3)$$

$$\text{Complexity}(X(t)) = \frac{\text{Mobility}\left(\frac{dX(t)}{dt}\right)}{\text{Mobility}(X(t))} \quad (2.4)$$

Band power feature is similar to the time-domain feature activity at some specific frequency bands. Time domain parameters extracted from the derivatives of signal are also explored in motor imagery research and found to be effective [95]. For this method, the spectral information is not required in advance. Therefore, the representation in the time domain must be sufficient enough to represent the distinctive features of data.

2.3.3 Time-frequency patterns

The complexity of motor imagery feature is that it spans over time, frequency, and spatial domains. Expressing motor imagery features in one (or two) domain(s) while disregarding the other(s) may result in loss of information. Hence, the time-frequency estimates of ERD/ERS have been explored in BCI applications and reported as more effective [100-103].

Short time Fourier transform (STFT) have also been employed to find the frequency spectra and to extract reliable features from EEG signals altered by right/left hand movement imagination [104]. Then, the features are estimated by calculating the norm of the power in predetermined subject-specific frequency bands.

Efficacy of wavelets in BCI is also demonstrated in [105] which employs a subject-based feature extraction method using wavelet packet best basis decomposition (WPBBD) in BCIs. The idea is to employ the wavelet packet best basis algorithm to adapt to each subject separately. This method consists of the decomposition of EEG to a given level in time-frequency domain by wavelet packet transform and finding the best-adapted basis for that particular subject. The subband energies contained in the best basis are taken as features for discriminating different mental tasks.

The main advantage of these time-frequency representations is that they can catch relatively sudden temporal variations of the signals, while still keeping frequential informations. On the contrary, pure frequency-domain methods are assuming that the EEG signal is in a stationary state.

2.3.4 Autoregressive model

Adaptive and non-adaptive autoregressive parameters have been investigated to express the features related to motor imagery [56, 74, 93, 106, 107]. In the autoregressive modeling method, the amplitude of a signal at a given period is obtained by summing up the amplitudes of previous samples, and adding an estimation error. The amplitude rates are represented by autoregressive model coefficients and they account for differentiating signals from different mental tasks. The order of autoregressive model depends on the number of autoregressive coefficients and decides the number of features extracted. The autoregressive model helps to reduce the dimension of selected features as 3 - 9 per channel [108] depending on the model order. This approach has an advantage that no reactive frequency bands must be specified as *a priori*. But this method is sensitive to artifacts [108, 109].

2.3.5 Common Spatial Pattern

The method of common spatial patterns was first applied to EEG for the detection of abnormalities [110] and later used to discriminate movement-related patterns [111]. Now, it is one of the most effective methods used in motor imagery based BCIs [96, 112]. The method of CSP is based on a decomposition of the raw EEG signals into spatial patterns, which are extracted from two populations of single trial EEG [113-119].

The CSP algorithm is found to be effective in computing the subject-specific discriminative spatial filters for detecting ERD/ERS effects with respect to their topographic patterns. Given two distributions in a high dimensional feature space, the CSP algorithm estimates directions or spatial filters such that they maximize the variance of one class and minimizing the variance of other classes. The design of such spatial filters is based on the simultaneous diagonalization of two covariance matrices. The procedure to design spatial filters and computation of CSP based features from a set of two classes of EEG signals, recorded during left hand and right hand motor imagery have been reported in [113] and is as follows:

For the analysis, the raw EEG data of a single trial is represented by a matrix $\mathbf{E}$ of size $N \times T$, where N is the number of electrodes or channels and T is the number of samples per

channel. The normalized spatial covariance of $\mathbf{E}$ is given as:

$$C = \frac{\mathbf{E}\mathbf{E}'}{\text{trace}(\mathbf{E}\mathbf{E}')} \quad (2.5)$$

where $\mathbf{E}'$ is the transpose of $\mathbf{E}$ and $\text{trace}(\mathbf{E}\mathbf{E}')$ is the sum of diagonal elements of $\mathbf{E}\mathbf{E}'$. For each of the distributions of motor imagery, the spatial covariance matrix is estimated by averaging over the trials of each group. The composite spatial covariance matrix $\mathbf{C}_c$ is computed as:

$$\mathbf{C}_c = \overline{\mathbf{C}}_l + \overline{\mathbf{C}}_r \quad (2.6)$$

where $\overline{\mathbf{C}}_l$ and $\overline{\mathbf{C}}_r$ are the covariance matrices for left hand and right hand motor imagery respectively. The composite covariance $\mathbf{C}_c$ can be factored as:

$$\mathbf{C}_c = \mathbf{U}_c \mathbf{\Lambda}_c \mathbf{U}_c' \quad (2.7)$$

where $\mathbf{U}_c$ is the matrix of eigenvectors and $\mathbf{\Lambda}_c$ is the diagonal matrix of eigenvalues. In $\mathbf{\Lambda}_c$, eigenvalues are assumed to be stored in the descending order. The whitening matrix $\mathbf{P}$ is computed as:

$$\mathbf{P} = \sqrt{\mathbf{\Lambda}_c^{-1}} \mathbf{U}_c^{-1} \quad (2.8)$$

This whitening matrix equalizes the variances in space spanned by $\mathbf{U}_c$ and all eigenvalues of $\mathbf{P}\mathbf{C}_c\mathbf{P}'$ are equal to one. If $\overline{\mathbf{C}}_l$ and $\overline{\mathbf{C}}_r$ are transformed as:

$$\mathbf{S}_l = \mathbf{P}\overline{\mathbf{C}}_l\mathbf{P}', \mathbf{S}_r = \mathbf{P}\overline{\mathbf{C}}_r\mathbf{P}' \quad (2.9)$$

$\mathbf{S}_l$ and $\mathbf{S}_r$ share common eigenvectors such that if $\mathbf{S}_l = \mathbf{B}\mathbf{\Lambda}_l\mathbf{B}'$ then, $\mathbf{S}_r = \mathbf{B}\mathbf{\Lambda}_r\mathbf{B}'$ and $\mathbf{\Lambda}_l + \mathbf{\Lambda}_r = \mathbf{I}$ where $\mathbf{I}$ is the identity matrix. As the sum of two corresponding eigenvalues is always one, the eigenvector with largest eigenvalue for $\mathbf{S}_l$ has the smallest eigenvalue for $\mathbf{S}_r$ and vice versa. This property makes the eigenvector $\mathbf{B}$ useful for classification of two distributions. The projections of whitened EEG into first and last eigenvectors in $\mathbf{B}$ (i.e. eigenvectors corresponding to the largest $\mathbf{\Lambda}_l$ and $\mathbf{\Lambda}_r$) will give feature vectors that are optimal for discriminating two populations of EEG in least squares sense. Then, the CSP projection matrix $\mathbf{W} = \mathbf{B}'\mathbf{P}$ can be used to decompose the EEG signal $\mathbf{E}$. The rows of $\mathbf{W}$ are the spatial filters and columns of $\mathbf{W}^{-1}$ are the common spatial patterns. The spatially

filtered signal $\mathbf{Z}$ is computed as:

$$\mathbf{Z} = \mathbf{W}\mathbf{E} \quad (2.10)$$

The spatially filtered EEG signal maximizes the differences in the variance of the two classes of EEG measurements. However, the variances of only a small number m of the spatial filtered signal are most suitable for discrimination and are generally used as features for classification. The signals Z_p ($p = 1, \dots, 2m$) that maximize the difference in variance of left versus right motor imagery EEG are the ones associated with largest eigenvalues of $\mathbf{\Lambda}_l$ and $\mathbf{\Lambda}_r$. These signals are first and last m rows of $\mathbf{Z}$. The feature vectors $\mathbf{F}_p$ for left and right hand trials are as follows [113]:

$$F_p = \log \left[\frac{\text{var}(Z_p)}{\sum_{i=1}^{2m} \text{var}(Z_i)} \right] \quad (2.11)$$

The log-transformation serves to approximate the normal distribution of the data.

Figure 2.9: Effect of CSP filtering. CSP analysis has been performed to obtain four spatial filters that discriminate left from right hand motor imagery. The graph shows continuous bandpass filtered EEG after applying CSP. The resulting signals in filters CSP:L1 and CSP:L2 have larger variance during right hand imagery (segments shaded in green) while signals in filters CSP:R1 and CSP:R2 have larger variance during left hand imagery (segment shaded red) [114].

The optimization criterion in CSP is to determine the decomposition matrix $\mathbf{W}$ such that the CSP filters (each row of $\mathbf{W}$) maximize the variance of the spatially filtered signal under one condition while minimizing it for the other condition. Since variance of bandpass filtered signals is equal to band power, CSP analysis is applied to bandpass filtered signals in order

to obtain an effective discrimination of mental states that are characterized by ERD/ERS effects. A high variance reflects a stronger rhythm whereas low variance a weak rhythm. Fig. 2.9 shows the result of applying CSP filters to continuous bandpass filtered EEG data recorded during the performance of left hand and right hand motor imagery. Four spatial filters with highest discrimination between two types of signals have been shown named as CSP:L1, CSP:L2, CSP:R1 and CSP:R2. Intervals of right motor imagery and left motor imagery are shaded green and red respectively in the figure. During right hand imagery, projections of CSP:L1 and CSP:L2 filters show larger variance whereas CSP:R1 and CSP:R2 filters provide larger variance during left hand motor imagery [114]. Coefficients in spatial filter are spatial weights assigned to EEG channels. Thus, CSP finds optimum spatial weights for EEG channels such that projection of raw EEG using spatial filters gives maximum discrimination between two types of motor imagery tasks.

Motor imagery activates motor cortex, but the most active areas in cortex depend on the imagined body part [94, 107, 113]. Left hand imagery results signal power attenuation in right motor cortex and right imagery causes signal attenuation on left cortex [37, 38]. Because of this topographical distribution of the signal power during motor imagery, the CSP technique is a good candidature of extracting features related to ERD/ERS patterns [114]. CSP can find spatial locations of highest discriminative energy and signal energy (or variance) from the selected locations can be employed as the features for classifying different motor imagery patterns effectively.

In general, motor imagery evokes neural activation in multiple brain regions, including primary motor area, supplementary motor area, premotor area, and pre-frontal area. CSP based feature extraction is effective in achieving the spatial information hidden in the features, whereas separate algorithms are necessary to achieve the spectral information [120-123]. Conventionally, the frequency bands at which the CSP algorithm operates were either selected manually or a broad band filter is used [114]. As presented in Section 2.2, the precise timing and frequency of ERD/ERS vary among subjects resulting in high inter-subject and intra-subject variability in frequency bands. Therefore, the subject-specific discriminative frequency bands have to be optimized along with the spatial filter due to the variability in ERD based BCIs. The next section will highlight the significance of frequency selection and a number of recent frequency optimization methods along with the CSP technique.

2.4 Frequency Optimization for ERD/ERS patterns

2.4.1 Neurophysiological background

During preparation or execution of motor movement, significant ERD/ERS in EEG occur over the primary sensorimotor area. These oscillations are due to a decrease or increase in the synchrony of underlying neuronal populations. Populations of neurons form complex networks in which feedback loops are responsible for the generation of oscillatory activity [124-126]. Sensory stimulation, motor behavior, and mental imagery can change the functional connectivity within the cortex and results in an amplitude suppression (ERD) or in an amplitude enhancement (ERS) of *mu* and central *beta* rhythms. These changes can be due to modulating influences of neuro-chemical brain systems, changes in the strength of synaptic interactions and/or changes of intrinsic membrane properties of the local neurons [40, 124]. The interplay between thalamic relay cells and the thalamic reticular nucleus also control the cortical dynamics of brain oscillations. The dynamics of brain oscillations associated with sensory and cognitive processing and motor behavior can form complex spatio-temporal patterns. A synchronization of higher frequency components embedded in a desynchronization of lower frequency components can be found on a specific electrode location at the same moment of time. Also, simultaneous desynchronization and synchronization of frequency components are possible on different scalp locations too [39, 125].

According to the study in [36], a desynchronized EEG indicates excited cell assemblies ready or prepared for sensory, motor and cognitive processing and a synchronization can be interpreted as a correlate of a deactivated or actively inhibited motor area neurons. Reports in [124] state that the activity of local interactions between main neurons and inter neurons control the frequency components of EEG during ERD/ERS and a large variability is found in dominant frequencies. During a finger movement task, [124] reports induced oscillations of three different bands (10-12 Hz, 14-18 Hz and 36-40 Hz) at same electrode of one subject. Motor imagery is associated with similar neuronal structures as that of motor planning and execution [36]. Hence, activations of alpha, beta and gamma components of EEG are possible during motor imagery too. During preparation and execution of motor movements, EEG spectrum undergoes a sequence of changes, but the underlying physiological mechanisms and functional units are yet to be discovered clearly [126]. The dominant frequencies for ERD/ERS can vary from subject to subject [125, 127] and therefore, it becomes necessary

to specify the frequency bands when referring to ERD/ERS of EEG signals.

2.4.2 Significance

The signals resulting from the motor imagery performance have very specific temporal, spectral and spatial features [37]. Therefore, the feature extraction process should be done in such a way that the output features contain the most relevant information in time, frequency and spatial domains, at a reduced complexity and dimensionality. High resolution studies using the spatio temporal patterns of EEG during mental imagination of motor movement report that the ERD/ERS are subject-specific and the most active frequency bands vary with subjects. In [36], three subjects were analyzed while performing motor imagery and the most active subject-specific frequency bands were found to be 9-13 Hz, 10-12 Hz and 22-29 Hz respectively. Both the *alpha* and *beta* bands are engaged in motor imagery and important changes were available in the primary sensorimotor areas. In order to distinguish different motor imagery tasks effectively, it is important to find out the frequency bands for each subject.

The significance of subject-specific band selection in the performance of a motor imagery based BCI has been initially demonstrated in [107] and [65]. They report improvements in classification accuracy of motor imagery patterns achieved on account of automatic selection of subject-specific frequency components, rather than expending fixed *alpha* or *beta* band filtering for all subjects. A distinction sensitive learning vector quantization (DSLQ) [120, 121] classifier was employed in [65] and [107] to determine the subject-specific frequency components. DSLQ uses a weighted distance function and adjusts the influence of different input features through supervised learning. The influence of a single feature is modified according to its contribution to correct or incorrect classifications of the system. Further studies also emphasize on the careful selection of relevant frequency components in motor imagery based BCIs. A few recently proposed techniques to optimize the temporal filters along with spatial filters in CSP are presented in the following section.

2.4.3 Existing algorithms

As CSP is one of the most effective feature extraction techniques available [27, 114], the work in this thesis adopts the CSP method and also reviews a few existing algorithms which optimize frequency bands along with spatial filter optimization through CSP.

Common Spatio-Spectral filters

In [115], Common Spatio-Spectral filters (CSSP) algorithm is proposed where frequency filters for each channel are optimized together with spatial-filters. It suggests an extension of CSP to the state space, which utilizes the method of time delay embedding. In order to extract robust features, equation (2.10) is extended by one delayed co-ordinate to form the following equation [115].

$$\mathbf{Z} = \mathbf{W}^0 \mathbf{E} + \mathbf{W}^\tau \delta^\tau \mathbf{E} \quad (2.12)$$

where $\delta^\tau \mathbf{E}$ denotes the signal $\mathbf{E}$ delayed by time τ , $\mathbf{W}^0$ and $\mathbf{W}^\tau$ represent the projection matrices related to $\mathbf{E}$ and $\delta^\tau \mathbf{E}$ respectively. Appending the delayed vectors $\delta^\tau \mathbf{E}$ as the additional channels to $\mathbf{E}$, the new EEG matrix $\hat{\mathbf{E}}$ is obtained as:

$$\hat{\mathbf{E}} = \begin{pmatrix} \mathbf{E} \\ \delta^\tau \mathbf{E} \end{pmatrix} \quad (2.13)$$

The optimization criterion is to find projections of $\mathbf{W}^0$ and $\mathbf{W}^\tau$ (given in equation (2.12)) such that signal variance of different $\mathbf{Z}$ best discriminates two given classes, i.e. maximizing the variance for one class while minimizing it for the opposite class. The equations (2.12) and (2.13) can be re-arranged as:

$$\widehat{\mathbf{W}} \hat{\mathbf{E}} = (\widehat{\mathbf{W}}^0 \widehat{\mathbf{W}}^\tau) \hat{\mathbf{E}} \quad (2.14)$$

The columns of $\widehat{\mathbf{W}}$ are two sub matrices $\widehat{\mathbf{W}}^0$ that applies to $\mathbf{E}$ and $\widehat{\mathbf{W}}^\tau$ that applies to the delayed channels $\delta^\tau \mathbf{E}$ as given in equation (2.12). The optimum solution for the decomposition matrix $\widehat{\mathbf{W}}$ in [115] includes interpretations of both spatial and spectral filters. In other words, each row of the optimum decomposition matrix contains coefficients of a spatial filter along with a Finite Impulse Response (FIR) filter that focuses on the frequency band of

interest at each electrode. Thus, the CSSP performs spatial and spectral optimization to discriminate between two populations of EEG and offers better classification results than CSP. In CSSP, the original CSP approach is applied to the concatenation of $\mathbf{E}$ and $\delta^\tau \mathbf{E}$ in the channel dimension as in (2.12). The delayed signals $\delta^\tau \mathbf{E}$ are treated as new channels and therefore, its computational demands are doubled compared to the original CSP.

Common Sparse Spectral Spatial Pattern

In the CSSP algorithm, frequency filters for each channel are optimized along with the spatial filters. The concatenation step in CSSP algorithm (as in eqn. (2.12)) can provide better flexibility of frequency filters, but it is computationally demanding. The flexibility of frequency filter is still limited even though the CSSP results showed improvement over CSP. The highly subject-specific discriminative frequency bands were better addressed by the CSSSP algorithm proposed in [116] which optimizes an arbitrary FIR filter within the CSP analysis itself. The signal processing technique done in CSSSP could reveal the discriminating parts in the spectrum and thus helps to understand the mechanisms a subject uses for his/her imagination task. The spatial and temporal filter are learned from data itself and on average, this algorithm outperforms CSP and CSSP. Even though CSSSP offers better classification results than the CSP algorithm, the solution of filter coefficients in CSSSP algorithm is restricted by the choice of the initial parameters.

Subband Common Spatial Pattern

As the solution of filter coefficients in CSSSP greatly depends on the initial parameter settings, an alternative approach called Subband Common Spatial Pattern (SBCSP) is proposed in [117]. The SBCSP algorithm tried to avoid the fine tuning process of accurately finding the subject-specific frequency band, which is one of the most challenging issues in motor imagery based BCI. Instead of optimizing a single arbitrary FIR filter within the CSP algorithm, SBCSP used a filter bank that decomposes the EEG measurements into multiple subbands. The filter bank uses 24 Gabor filters of bandwidth 4 Hz in range of 8-40 Hz. Spatial filters that use the CSP algorithm were then employed on each of these sub-bands. After obtaining subband scores using a Linear Discriminant Analysis (LDA), recursive band elimination or a classification algorithm was employed to fuse the sub-band

score. The score values computed from the SBCSP features determines the classification capabilities of each frequency bands. The SBCSP outperformed the CSSP and CSSSP algorithms and the system flow-chart is given in Fig. 2.10.

Figure 2.10: SBCSP approach.

Although SBCSP can use different sub-band score fusion techniques and classification algorithms, only the results from the use of the Support Vector Machine (SVM) to fuse the sub-band score as well as to perform classification are presented in [117]. Hence, a comparative study of using different sub-band score fusion techniques and classification algorithms is not available.

Iterative Spatio-Spectral Patterns Learning Algorithm

The Iterative Spatio-Spectral Patterns Learning Algorithm (ISSPL) [118], focuses on the automatic learning of spatial filters along with optimization of parameters for temporal filters. ISSPL replaces the time-consuming manual tuning of subject-specific frequency bands by a statistical learning theory where the spectral filters and the classifier are parameterized for optimization to achieve good generalization performance. ISSPL uses band power estimates in the selected discriminative bands as the features for classifying motor imagery tasks. This is based on the neurophysiological studies showing the short-lasting decrease or increase in the EEG power in specific frequency bands on sensorimotor cortex.

Conventionally, feature extractor in a motor imagery based BCI maximizes the discrimination of band power features between two classes and is having multiple pairs of spatio-

temporal filters. The temporal and spatial filters are designed such that they capture the useful information in the frequency domain and spatial domain respectively reducing the dimensionality of the data. This ISSPL algorithm learned the spatio-spectral filters and the classifier sequentially from the labeled multichannel EEG data in an iterative fashion. In each iteration, the spatial filters are firstly learned based on the spectral filters optimized in the preceding iteration. Then, both the spectral filters and classifier were learned simultaneously via a maximal margin hyperplane. The alternating optimization repeats until a certain number of iterations or the stopping criteria set by the user is reached. Authors of ISSPL claim that the computational complexity of algorithm is such that ISSPL is applicable in real time BCI systems [118].

Filter bank Common Spatial Pattern

A new machine learning approach Filter bank Common Spatial Patterns (FBCSP) is presented in [119] for processing EEG measurements in motor imagery-based BCI. FBCSP comprises of 4 stages: frequency filtering, spatial filtering, feature selection, and classification as shown in Figure 2.11.

Figure 2.11: FBCSP approach.

The first stage employs a filter bank of nine bandpass filters of bandwidth 4 Hz to split up the multichannel EEG signals (4-8 Hz, 8-12 Hz, 12-16 Hz, 16-20 Hz, 20-24 Hz, 24-28Hz, 28-32 Hz, 32-36 Hz and 36-40Hz). The second stage performs spatial filtering on each of these bands using the CSP algorithm and extracts CSP features. Thus, each pair of

bandpass and spatial filter yields CSP features that are specific to the frequency range of the bandpass filter. The third stage employed a feature selection algorithm to automatically select discriminative pairs of frequency bands and corresponding CSP features. In the fourth stage, a classification algorithm was used to classify the selected CSP features to obtain the class label. Experimental results [119] showed that the proposed FBCSP yields superior classification accuracy compared with SBCSP and CSP with manually selected operational frequency bands. Extensive experimental results on various feature selection and classification algorithms are reported in [119].

2.5 Conclusion

In this chapter, the existing methods for developing BCIs were reviewed, as well as the existing BCI applications. At first, the basic building units of a BCI including brain signal measuring unit, pre-processing and feature extraction units, classification/translational algorithms, experimental protocols etc. were presented. The non-invasive techniques for brain signal acquisition were also discussed, along with the most popular non-invasive brain signal recording technique using EEG. Then, various features in EEG used to drive BCIs were presented, from which the focus was on the ERD/ERS patterns accompanied with the mental imagination of motor movements. Thus, this chapter mainly contributes a brief review of BCI technology, existing algorithms to develop a BCI framework and major issues to be addressed for improving its performance and efficacy.

A large number of studies related to the BCI research aimed at addressing various issues in the development of BCI are highlighted in this chapter. Motor imagery has been extensively explored in developing BCIs operated by healthy as well as paralyzed patients in order to achieve control on the movement of cursor on computer screen, wheel chair movement, robots, neuroprosthesis, etc. Despite this large number of BCI studies, the appropriate signal processing, classification, and translational algorithms are yet to be developed so that BCI could be available in market [2,13]. One of the main signal processing issues in motor imagery based BCIs is the optimization of subject-specific temporal and spatial filters to distinguish various ERD/ERS patterns [122, 123]. In the next 3 chapters, the issue of frequency band optimization towards the development of a robust BCI is addressed.

Chapter 3

Discriminative Filter Bank for Motor Imagery based BCI

Event-related De/Synchronization (ERD/ERS) patterns during right/left motor imagery have been reported as effective features for an EEG-based BCI. As discussed in Chapter 2, the motor imagery tasks are subject-specific and selection of subject-specific discriminative frequency components play a vital role in distinguishing these patterns. One of the most effective feature extraction techniques for motor imagery based BCI is CSP. The success of CSP in BCI application greatly depends on the proper selection of subject-specific frequency bands. In Chapter 2, the algorithms optimizing frequency bands along with CSP such as CSSSP, SBCSP and FBCSP were discussed. The FBCSP [119], which won dataset IIa and IIb in BCI Competition IV held in 2008 [128], uses CSP features from a set of nine fixed bandpass filters and a feature selection algorithm based on mutual information to effectively choose the subject-specific features. Eventually, this selection process selects features from the relevant frequency components.

As the subject-specific frequency components carry distinct features, this chapter presents a Discriminative Filter Bank Common Spatial Pattern (DFBCSP) algorithm which employs a subject-specific filter bank selection before feature extraction to enhance the accuracy of the FBCSP framework. This new method employs subject-specific Discriminative Filter bank (DFB) instead of using fixed filter bank for all subjects. The following sections present

the steps in the design of proposed DFBCSP algorithm including generation of DFB, feature extraction and classification algorithms. The classification performance of DFBCSP is analyzed using two datasets: the BCI Competition III dataset IVa [129, 130] and BCI Competition IV dataset IIb [128].

3.1 Proposed Method: DFBCSP

The new DFBCSP system extracts subject-specific discriminative frequency bands from a set of filters, named as parent filter bank in the following parts of this method. The parent filter bank is designed using a coefficient decimation technique [131] and the filter bank covers all frequency components in the range of 6-40 Hz. As it has been shown that EEG signals from sensorimotor cortex have the highest discriminating power between various motor imagery tasks, the EEG channels C3 and C4 are selected in order to determine the subject-specific discriminative frequency components. Fig. 3.1 shows the schematic of DFBCSP. In the band selection procedure, the parent filter bank filters EEG from C3 or C4 and Fisher ratio of filtered EEG is used to determine the subject-specific discriminative frequency bands. Once the subject-specific frequency bands are selected, the EEG from all channels is filtered using these discriminative bands for further CSP processing. A Support Vector machine (SVM) classifier is used to predict the output. Each of the EEG processing steps in the proposed method is explained in the following subsections:

Figure 3.1: Schematic of proposed DFBCSP.

3.1.1 Coefficient Decimation technique for bandpass filtering

The frequency bands associated with motor imagery vary between subjects and the Coefficient Decimation (CD) technique has the ability to obtain subbands with desired center frequencies. For the subject-specific filter design, current work uses a CD based approach proposed in [131] to implement low complexity reconfigurable Finite Impulse Response (FIR) filters. Linear phase FIR filters are widely employed in many filtering applications because of the advantages such as guaranteed stability and low coefficient sensitivity. However, the main problem of FIR filters lies in its high implementation complexity due to the requirement of higher order compared to its Infinite Impulse Response (IIR) counterpart. CD technique is a computationally efficient approach to realize FIR filters that have flexible frequency responses. The basic philosophy of CD is as follows: If every M^{th} coefficient of an FIR filter $\mathbf{h}(\mathbf{n})$ (called modal filter) is kept unchanged and all other coefficients are replaced by zeros, a decimated filter $\mathbf{h}'(\mathbf{n})$ is obtained, that has a multi-band frequency response [131, 132]:

$$h'(n) = h(n) \cdot c_M(n) \quad (3.1)$$

$$\text{where } c_M(n) = \begin{cases} 1, & \text{for } n = kM, k = 0, 1, 2, \dots, M-1 \\ 0, & \text{Otherwise} \end{cases}$$

The function $\mathbf{c}_M(\mathbf{n})$ is periodic with period M , and hence its Fourier series expansion is given by:

$$c_M(n) = \frac{1}{M} \sum_{k=0}^{M-1} c(k) e^{\frac{j2\pi kn}{M}} \quad (3.2)$$

where $\mathbf{c}(\mathbf{k})$ are complex valued Fourier series coefficients defined by:

$$c(k) = \sum_{n=0}^{M-1} c_M(n) e^{-\frac{j2\pi kn}{M}} \quad (3.3)$$

It is clear from eqn. (3.1) that value of $\mathbf{c}_M(\mathbf{n})$ is non zero only at integer multiples of M . In the computation of $\mathbf{c}(\mathbf{k})$ according to eqn. (3.3), $\mathbf{c}_M(\mathbf{n}) = 1$ only at $n = 0$. $e^{\frac{j2\pi kn}{M}}$ equals 1 only at $n = 0$ and therefore, $C(k)$ becomes 1 for every k . Substituting $c(k)$ in eqn. (3.2):

$$c_M(n) = \frac{1}{M} \sum_{k=0}^{M-1} e^{\frac{j2\pi kn}{M}} \quad (3.4)$$

Now the Fourier transform of the modified coefficients, $\mathbf{h}'(\mathbf{n})$ is obtained as given in equations (3.5) to (3.7):

$$H'(e^{jw}) = \sum_{n=-\infty}^{\infty} h'(n)e^{-jwn} \quad (3.5)$$

$$= \sum_{n=-\infty}^{\infty} h(n)C_M(n)e^{-jwn} \quad (3.6)$$

$$= \sum_{n=-\infty}^{\infty} h(n) \left[\frac{1}{M} \sum_{k=0}^{M-1} e^{\frac{j2\pi kn}{M}} \right] e^{-jwn} \quad (3.7)$$

By inter changing the sums in (3.5):

$$H'(e^{jw}) = \frac{1}{M} \sum_{k=0}^{M-1} \sum_{n=-\infty}^{\infty} h(n)e^{-jn(w-\frac{2\pi k}{M})} \quad (3.8)$$

$$= \frac{1}{M} \sum_{k=0}^{M-1} H \left(e^{j(w-\frac{2\pi k}{M})} \right) \quad (3.9)$$

From equation (3.9), it is found that the frequency response of $\mathbf{h}'(\mathbf{n})$ is scaled by M with respect to that of $\mathbf{h}(\mathbf{n})$ and the replicas of the frequency spectrum are introduced at integer multiples of $2\pi/M$. By changing the value of M , different numbers of frequency response replicas located at different center frequencies can be obtained. In the following text, this CD method is named as CDM-1. The passbands of the multi-band response obtained using CDM-1 will have identical widths as that of the modal filter. If all the coefficients of the coefficient decimated filter obtained using CDM-1 are grouped together after discarding the in-between zeros, a decimated version of the original frequency response is obtained whose passband width is M times that of the original modal filter and this method is termed as CDM-2. If the multi-band frequency responses obtained using CDM-2 are selectively masked using inherently low complex wide transition-band frequency response masking filters, different lowpass, highpass, bandpass, and bandstop filters can be obtained. This can be illustrated using the following example.

The following steps explain the design of a (23-27 Hz) bandpass filter from a low pass modal filter of width 0.5 Hz.

(a) Frequency response of modal filter H_0 .

(b) Frequency responses of decimated filters H_1 and H_2 .

(c) Frequency responses of H_3 and masking filter.

(d) Frequency response of the final filter output.

Figure 3.2: Basic steps in the design of bandpass filter using CD technique.

Step 1 : Let $\mathbf{H}_0$ be the modal filter whose passband and stopband edges are 0.5 Hz and 0.8 Hz as in Fig. 3.2(a). Enlarged view of $\mathbf{H}_0$ is provided on the right side to clarify the passband and stopband edges. The selected sampling frequency is 100 Hz and spectrum shown is in $0-\pi$ (corresponding to 0-50 Hz) range.

Step 2 : Employing CDM-1 for $M_1=4$ in $\mathbf{H}_0$, $\mathbf{H}_1$ is obtained as shown in 3.2(b). It is by replacing all coefficients in $\mathbf{H}_0$ by zero other than every 4^{th} coefficient. $\mathbf{H}_1$ has passband frequency responses at center frequencies of $\frac{2\pi k}{4}$, for $k=0, 1, 2$.

Step 3 : Applying CDM-2 on $\mathbf{H}_1$ will increase the pass-band width of $\mathbf{H}_0$ by 4 times as in $\mathbf{H}_2$. The plots are provided in 3.2(b). It is obtained by grouping only every 4^{th} coefficient of $\mathbf{H}_0$.

Step 4 : If CDM-1 is applied on $\mathbf{H}_2$ for $M_2=4$, a multi-band response $\mathbf{H}_3$ is obtained (Fig. 3.2(c)). The desired pass-band can be extracted from the multi-band filter $\mathbf{H}_2$ using a suitable low order masking filter as plotted in 3.2(c). Frequency responses of $\mathbf{H}_3$ are at $\frac{2\pi k}{4}$, for $k=0, 1, 2$. For $k=1$, the center frequency equals $\frac{2\pi}{4}$. The sampling frequency is 100 Hz and therefore, the center frequency of passband at $k=1$ in $\mathbf{H}_3$ equals 25 Hz.

Step 5: Convolution of $\mathbf{H}_3$ with low order masking filter will result the final frequency response of 23-27 Hz bandpass filter as given in 3.2(d).

As given in step. 2, width of passband in $\mathbf{H}_1$ is 1 Hz. It is obtained by decimating a lowpass modal filter $\mathbf{H}_0$ having a passband edge of 0.5 Hz by $M_1=4$. Grouping of nonzero coefficients in $\mathbf{H}_1$ gives $\mathbf{H}_2$, and $\mathbf{H}_2$ has passband width 2 Hz which is M_1 times that of $\mathbf{H}_0$. Thus the bandwidth can be controlled by decimation factor M_1 . Then, further decimation of $\mathbf{H}_2$ by $M_2=4$ gives three passbands in $\mathbf{H}_3$ as explained in step. 4. The bandwidth of passband at $k=1$ for $\mathbf{H}_3$ is 4 Hz. Thus for a fixed M_1 , uniform bandwidth filters at different center frequencies can be generated by varying M_2 . In general, by decimating a lowpass filter by a decimation factor M , frequency responses are obtained at center frequencies of $\frac{2\pi k}{M}$ for $k=0$ to $M-1$. In this work, appropriate values of M_1 and M_2 are chosen in order to obtain different bandwidths and center frequencies in the filter bank. Various bandwidths can be obtained by changing M_1 whereas M_2 is varied to get different center frequencies. The settings explained in Fig. 3.2 correspond to design of a 23-27 Hz bandpass filter. Depending on the center frequency and bandwidth of required filter, appropriate decimation factors have to be computed according to the procedure explained above.

Thus the CD technique has good control over the locations of center frequencies and pass-

band widths. Based on the requirement of desired bandpass filters in the BCI system, different center frequencies and passband widths can be obtained by choosing appropriate decimation factors. More details of CD technique can be found in [128, 129]. In the DF-BCSP algorithm presented in this chapter, the required bandpass filters are designed using the CD technique to perform multi-band filtering.

3.1.2 Generation of Discriminative Filter bank and bandpass filtering

The parent filter bank covers frequency components from 6 Hz to 40 Hz. However, the most discriminative bands during motor imagery vary between subjects. The FBCSP algorithm extracts CSP features from a fixed filter bank consisting of nine Chebyshev type II bandpass filters and a feature selection process is done before classifying the signals. Instead of using a fixed filter bank for all subjects, the proposed method uses a subject-specific filter bank to enhance the classification accuracy. In order to obtain the subject-specific Discriminative Filter bank (DFB) from the original set of bands, a discriminative spectral estimation of signals from motor cortex is used. Once the DFB is obtained from the training data for each subject, it is fixed during evaluation of new EEG signals.

Fisher ratio (a measure of discrimination between two classes of motor imagery tasks of spectral power from channels C3 or C4) is used to determine the most discriminative frequency bands for all subjects. For EEG patterns of right hand and foot motor imagery, channel C3 on the contralateral hemisphere or Cz should give better discrimination. Therefore, the effectiveness of different channel selection possibilities are tested in this work (i) Single channel-C3, (ii) GC3- group of channels surrounding C3 (iii) LC3-Laplacian filtered C3 and (iv) Cz. Also for patterns from right and left hand motor imagery, the efficacy of channels C3 and C4 are also tested. The parent filter bank processes these signals and an estimate of spectral power associated with each subband is calculated using the following equation to obtain subject-specific DFB.

$$P(i, t) = \frac{1}{T} \sum_{n=1}^T (x_i^t(n))^2 \quad (3.10)$$

In (3.10), $P(i, t)$ is the spectral power estimated for the filtered EEG in i^{th} band output for the t^{th} trial. T is the number of samples in filtered EEG signal and $x_i^t(n)$ is the n^{th} sample

of the filtered EEG of the t^{th} trial in the i^{th} band. Thus, a $N_f \times N_t$ matrix corresponding to spectral power is obtained where N_f is the number of bands and N_t is total number of trials. Thus, each trial is associated with an estimated $\mathbf{P}$ value in all the frequency bands. In order to select the best informative filters, the Fisher ratio $\mathbf{F_R}$ is calculated from all filter outputs from parent filter bank. The Fisher ratio at i^{th} band output is obtained as:

$$F_R(i) = \frac{S_B(i)}{S_W(i)} \quad (3.11)$$

where $\mathbf{S_W}$ and $\mathbf{S_B}$ are respectively the within-class variance and between-class variance obtained according to following equations.

$$S_W(i) = \sum_{k=1}^C \sum_{t=1}^{n_k} (P(i, t) - m_{i,k})^2 \quad (3.12)$$

$$S_B(i) = \sum_{k=1}^C n_k (m_i - m_{i,k})^2 \quad (3.13)$$

where m_i is the total average for i^{th} band, $m_{i,k}$ is the average for class k in i^{th} band, ($k = 1, 2$), C is the number of classes and n_k denotes the number of trials for class k . Then, filters giving highest Fisher ratio values possess better discriminating power and are used for further data processing.

3.1.3 Feature extraction using Common Spatial Pattern

After bandpass filtering using the DFB, EEG signal from each frequency band is applied with a CSP transformation to obtain the features to be classified. CSP is an effective technique for discriminating motor imagery tasks [113, 114]. The decomposition of EEG using CSP or spatial filtering leads to a new time series, whose variances are optimal for the discrimination of two populations. The spatially filtered signal $\mathbf{Z}$ of a single trial EEG is given by $\mathbf{Z} = \mathbf{W}\mathbf{E}$ (refer to equation (2.10)) where $\mathbf{E}$ is an $N \times T$ matrix representing the raw EEG measurement data of a single trial, N is the number of channels, and T is the number of samples, and $\mathbf{W}$ is the CSP projection matrix. The rows of $\mathbf{W}$ or spatial filters are designed such that the variances of first and last rows of $\mathbf{Z}$ give the maximum discrimination between two classes of motor imagery tasks. Therefore, the feature vector $\mathbf{F_p}$ is formed from $\mathbf{Z_p}$ according to equation (2.11), where $\mathbf{Z_p}$ is the first and last m rows

of $\mathbf{Z}$. The value of m is taken as one in the proposed DFBCSP framework.

3.1.4 Classification using Support Vector Machine

SVM is a linear discriminant that maximizes the separation between the two classes of motor imagery task based on the assumption that it improves classifier's generalization ability. The CSP features extracted from DFB are used to train the SVM classifier. The SVM model developed from the training data is used to evaluate the new EEG samples or test EEG [119].

3.2 Results and discussions

As the DFBCSP addresses the separability of two-class motor imagery patterns, two publicly available datasets: BCI competition III dataset IVa [129, 130] and BCI Competition IV dataset IIB [128] are explored in the analysis. The BCI competition III dataset IVa is of right hand and foot motor imagery and BCI Competition IV dataset IIB is of right hand and left hand motor imagery tasks. Comparison of classification accuracies in both datasets by the proposed DFBCSP algorithm with existing FBCSP algorithm is presented.

The classification performance is evaluated in FBCSP and DFBCSP using a 10×10 -fold cross-validation procedure. This validation procedure mixes the data set in a trial based manner and divides it into ten equally sized distinct partitions. Single-trials in each partition are then used for testing; while other partitions are used for training the model. This results in ten different error rates or accuracy, which are averaged. This is the accuracy value of 10-fold cross validation. To further improve the estimate, the procedure is repeated ten times and all accuracies over these ten runs are again averaged. The average accuracy or error rate over ten runs obtained for the test data is taken as the performance evaluation criterion which is named as validation accuracy or validation error rate of one subject. During the training phase, a subject-specific DFB and an SVM classifier model are learned from the training data and this DFB is fixed for evaluating the test data. No further frequency tuning is performed in the test data. For the classification purpose, the SVM algorithm in Bioinformatics Matlab toolbox is used with default parameters.

3.2.1 Using BCI Competition III dataset IVa

The BCI Competition III dataset IVa is of right hand and foot motor imagery tasks recorded from five subjects named *aa*, *al*, *av*, *aw* and *ay* from 118 electrodes. As the training data in the BCI competition III dataset IVa is small, its training and test data are merged together such that the resulting dataset consists of 280 trials of EEG measurements, 140 trials from each class of motor imagery. Then, a 10×10 -fold cross-validation is done to analyze the performance. The data are extracted from a number of selected electrode positions, starting from 0.5 to 2.5 sec after the visual cue.

As the patterns are of right hand and foot motor imagery tasks, signals from the contralateral channel C3, vertex channel Cz and its surrounding channels are filtered to estimate the Fisher ratio associated with each subband as explained in 3.1.2. The single channel C3 alone offers better performance for selecting DFB, compared with a set of channels around C3, Laplacian filtered C3 and Cz. Thus, the frequency selection channel is fixed as C3 for all the five subjects. After getting DFB, CSP features extracted from filtered EEG signals are given to an SVM classifier.

Figure 3.3: Fig. 3.3(a) shows the average validation accuracy and standard deviation over five subjects in BCI Competition III dataset IVa with Laplacian C3, Group of channel around C3, C3 and Cz. Fig. 3.3(b) represents the average validation accuracy vs. bandwidth of filters and 3.3(c) shows the average validation accuracy and standard deviation over five subjects vs. number of filters used in DFB.

The average validation accuracy across five subjects vs. various channel selection possibilities and bandwidth of the filters are plotted in Figs. 3.3(a) and 3.3(b) respectively. The bandwidth of the filters is varied from 2 to 6 Hz and best results in the proposed DFBCSP scheme correspond to a bandwidth of 4 Hz. Therefore, parent filter bank is fixed as a set of twelve bandpass filters with a bandwidth of 4 Hz, covering frequency components from 6 to 40 Hz. In addition, the variation of average validation accuracies and standard deviation for 10×10 -fold cross-validation corresponding to different number of filter pass bands are shown in Fig. 3.3(c). Among various numbers of bands from two to eight, a selection of four bands in DFB gives a fair performance in the proposed DFBCSP scheme. The classification accuracy corresponding to six bands is slightly higher than that of four bands. As the deterioration in classification accuracy of four bands is small with respect to the accuracy of six bands, the number of bands is fixed as four taking advantage of reduced complexity that can be achieved using four bands compared to six bands.

6-10Hz	8-12Hz	12-16Hz	14-18Hz	18-22Hz	20-24Hz	23-27Hz	26-30Hz	28-32Hz	31-35Hz	32-36Hz	36-40Hz	
1	2	3	4	5	6	7	8	9	10	11	12	Parent FB
		1			4	2	3					'aa'
		1	4		3	2						'al'
	4		3	2	1							'av'
			2	1	3						4	'aw'
	2	4				1			3			'ay'

Figure 3.4: Parent filter bank and discriminative frequency bands chosen for the subjects *aa*, *al*, *av*, *aw* and *ay* in BCI Competition III dataset IVa using DFBCSP. The shaded portions stand for DFB for each subject. The four frequency bands in DFB are ranked according the Fisher ratio values.

The twelve frequency bands in the parent filter bank and subject-specific bands selected for five subjects are shown in Fig. 3.4. The parent filter bank is composed of twelve frequency bands with a uniform bandwidth of 4 Hz which is obtained by applying the CD technique to a prototype low pass filter with a bandwidth of 2 Hz. The locations of the center frequencies depend on the decimation values as explained in Section 3.1.1. The frequency ranges of twelve bandpass filters are : 6-10 Hz, 8-12 Hz, 12-16 Hz, 14-18 Hz, 18-22 Hz, 20-24 Hz, 23-27 Hz, 26-30 Hz, 28-32 Hz, 31-35 Hz, 32-36 Hz and 36-40 Hz respectively. The four frequency bands in the DFB are ranked 1 to 4 according to the descending order of

Table 3.1: Classification accuracy of motor imagery patterns in BCI Competition III dataset IVa

Subject	FBCSP [119]	DFBCSP
<i>aa</i>	93.07 ± 0.58	90.21 ± 0.56
<i>al</i>	99.03 ± 0.24	98.68 ± 0.29
<i>av</i>	69.00 ± 1.42	77.79 ± 0.99
<i>aw</i>	95.10 ± 0.89	97.86 ± 0.37
<i>ay</i>	93.82 ± 0.97	94.21 ± 0.53
Average	90.01 ± 0.82	91.75 ± 0.54

Fisher ratio values obtained i.e. rank 1 is assigned to the band with the highest Fisher ratio value and the band with rank 4 has the lowest Fisher ratio. The inter-subject variability of discriminative frequency components is shown in Fig. 3.4. The plots in Fig. 3.4 correspond to the DFB obtained from training data during the first fold of 10×10 -fold cross-validation for the given three subjects.

Figure 3.5: Average Power Spectral Density plots of right hand and foot trials for subject *av* in BCI Competition III dataset IVa. Bands chosen by Fisher analysis in proposed DFBCSP and feature selection algorithm in FBCSP are shaded accordingly.

In addition, the average PSD of two-class EEG signals recorded from C3 for subject *av* is plotted in Fig. 3.5. The discrimination frequency components are observed in the ranges of 8-12 Hz and 15-25 Hz. In the FBCSP algorithm, EEG signals are bandpass filtered using a fixed filter bank of nine bandpass filters. CSP features are then extracted from filtered EEG and a feature selection algorithm based on a mutual information criterion selects the best features for classification. Observing the selected features, the bands from which those features are extracted can be obtained. From this analysis, it is found that the feature selection stage in FBCSP selects features from bands 8-12 Hz and 20-24 Hz and DFB

Figure 3.6: Classification accuracy for BCI Competition III dataset IVa.

selection technique in DFBCSP selects four bands; 8-12 Hz, 14-18 Hz, 18-22 Hz and 20-24Hz. In the DFBCSP, bands are selected based on the Fisher ratio criterion. Therefore, DFBCSP efficiently identifies the discriminative frequency components and offers better results. The classification accuracies for five subjects are given in Table 3.1, where columns two and three tabulate the validation results of FBCSP [119] and DFBCSP algorithm presented in this chapter respectively. These experimental results show the proposed DFBCSP gives an error rate reduction of 17.42% compared to the FBCSP algorithm. The percentage of error rate reduction is computed using the following equation.

$$\%Error\ rate\ reduction = \frac{Initial\ error\ rate - Final\ error\ rate}{Initial\ error\ rate} \times 100 \quad (3.14)$$

Fig. 3.6 shows the average classification accuracy of five subjects in the 10×10 -fold cross-validation using DFBCSP and FBCSP. As observed in the figure, the performances of subjects *aa* and *al* are lower with DFBCSP compared to FBCSP. This is probably due to the higher effectiveness of selecting best features in FBCSP in the respective datasets compared to the efficacy of selecting DFB in DFBCSP. The DFBCSP performs better in the other three subjects *av*, *aw* and *ay*. Even though, DFBCSP offers slightly higher average classification accuracy, the robustness of the technique has to be further enhanced to obtain significantly better performance improvements.

3.2.2 Using BCI Competition IV dataset I Ib

The BCI competition IV dataset I Ib consists of EEG data from nine healthy right-handed subjects of a study published in [128]. The nine subjects are named as S_1 , S_2 , S_3 , S_4 , S_5 , S_6 , S_7 , S_8 and S_9 respectively. The recorded EEG was bandpass filtered between 0.5 Hz and 100 Hz and a 50 Hz notch filter was utilized. Since this dataset is used in the subsequent chapters also, a detailed explanation of data recording is provided here. During the recording of EEG, the electrode position Fz served as the EEG ground.

All the nine subjects attended two training (or screening) sessions and three online feedback sessions. During the initial training sessions twenty two EEG electrodes were recorded sampled at 250 Hz whereas in all feedback sessions the number was reduced to three bipolar electrodes C3, Cz and C4 in order to improve the comfort of users. For each of the three electrode positions, three bipolar derivations were generated, two of them with a small distance between the bipolar electrodes (anterior-central, central-posterior) and one with a large distance (anterior-posterior). Hence there are nine possible channel combinations. They are analyzed separately and an optimization procedure was performed on the training data [128]. The combination with the best performance was chosen for further feedback experiments in each subject and EEG measurements from the respective bipolar arrangements are used in this work.

Figure 3.7: The timing protocol for data recording in BCI Competition IV dataset I Ib.

The cue-based screening paradigm (see Fig. 3.7(a)) consisted two classes, namely the motor

Table 3.2: Number of motor imagery trials in BCI Competition IV dataset IIB

Session	Total	Left hand	Right hand
1, 2	120	60	60
3, 4, 5	160	80	80

imagery of left hand (class 1) and right hand (class 2). Each subject participated in two screening sessions without feedback recorded on two different days within two weeks. Each session consisted of six runs with ten trials each and two classes of imagery. This resulted in twenty trials per run and 120 trials per session. Data of 120 repetitions of each motor imagery class were available for each person in total. Prior to the first motor imagery training, the subject executed and imagined different movements for each body part and selected the one which they could imagine best (e. g. squeezing a ball or pulling a brake). Each trial started with a fixation cross and an additional short acoustic warning tone (1 kHz, 70 ms). Some seconds later a visual cue (an arrow pointing either to the left or right, according to the requested class) was presented for 1.25 sec. Afterwards the subjects had to imagine the corresponding hand movement over a period of 4 sec. Each trial was followed by a short break of at least 1.5 sec. A randomized time of up to 1 sec was added to the break to avoid adaptation.

For the three online feedback sessions four runs with smiley feedback were recorded (see Fig. 3.7(b)), whereby each run consisted of 20 trials for each type of motor imagery. At the beginning of each trial (second 0) the feedback (a gray smiley) was centered on the screen. At second 2, a short warning beep (1 kHz, 70 ms) was given. The cue was presented from second 3 to 7.5. Depending on the cue, the subjects were required to move the smiley towards the left or right side by imagining left or right hand movements, respectively. During the feedback period, the smiley changed to green when moved in the correct direction, otherwise it became red. The distance of the smiley from the origin was set according to the integrated classification output over the past 2 sec. Furthermore, the classifier output was also mapped to the curvature of the mouth causing the smiley to be happy (corners of the mouth upwards) or sad (corners of the mouth downwards). At second 7.5, the screen went blank and a random interval between 1.0 and 2.0 sec was added to the trial. The subject was instructed to keep the smiley on the correct side for as long as possible and therefore to perform the motor imagery as long as possible [128].

The details regarding the number of trials in the dataset are given in Table 3.2. For all the

nine subjects, the number of trials in all sessions is the same as those given in Table 3.2. The exceptions are the session-4 of subject 2 with 120 trials, session-2 of subject 4 with 140 trials and session-2 of subject 4 with 140 trials.

Figure 3.8: Power spectral density estimates of left hand and right hand motor imagery from C3, Cz and C4.

Using this BCI Competition III dataset IVa, the effectiveness of 3 channel selection possibilities in frequency estimation are evaluated by using C3, Cz and C4 in order to discriminate right hand and left hand motor imagery tasks. The frequency spectra plotted in Fig. 3.8(a)-c) represent the PSD estimates of left hand and right hand motor imagery patterns from channels C3, Cz and C4 respectively for subject S_6 . It is the average power estimated over all the left and right hand trials separately in session-3. As expected, the channels C3 and C4 are more informative about the discriminative spectrum estimation than Cz. The most discriminative frequency components from channels C3 and C4 are in the range of 8-13 Hz as given in Fig. 3.8(a) and (c) respectively, whereas the power estimates of those frequency components from Cz are not distinct enough as observed in Fig. 3.8(b). Another discriminative band of around 19-23 Hz is also detected in C4. While analyzing the PSD

Figure 3.9: The 10×10 -fold cross-validation accuracies for all subjects in BCI Competition IV dataset IIb using FBCSP and DFBCSP in session-3.

of EEG signals during left hand and right hand motor imagery, certain discriminative frequency components could be estimated even from channel Cz for a few subjects. But this information was not consistent in all subjects. From the experiments done for all the nine subjects, the informative frequency components to discriminate between left hand and right hand motor imagery patterns are mostly found in channel C4.

Experimental results show that the DFB selection from C4 yields better validation accuracy than using C3 in the proposed DFBCSP framework for most of the subjects. The classification performance of DFBCSP and FBCSP in all the sessions in the dataset and comparison of classification accuracies using FBCSP [119] and proposed DFBCSP algorithms are analyzed for all the nine subjects in the first feedback session of the dataset is given in Fig. 3.9. The new DFBCSP algorithm provides an error rate reduction of 8.9% over the existing FBCSP algorithm. The reason for choosing FBCSP is that it is the winning algorithm of BCI Competition IV held in 2008 for the discussed dataset.

Comparing the classification results of DFBCSP and FBCSP in both datasets, it is found that ten out of fourteen subjects perform better by employing DFBCSP algorithm whereas four subjects yield better accuracy in FBCSP algorithm. The reason for this higher performance achieved by FBCSP in the case of four subjects could be explained as follows. FBCSP enables efficient selection of best features from a bigger set a CSP features obtained after bandpass filtering the multi-channel EEG, using a fixed set of nine bandpass filters.

As the feature selection is performed after bandpass filtering and CSP transformation, the FBCSP algorithm is able to optimize the spectral and spatial separability of features simultaneously before classification. But in DFBCSP, subject-specific discriminative bands are estimated from single channel C4 and it is used for bandpass filtering all EEG channels prior to the spatial filtering stage. Thus, the spectral optimization is done before spatial filtering and the CSP features available for classification are restricted by DFB. It is possible that the selected DFB is not equally optimum for all channels. In a BCI system, classification results depend on the spatial as well as spectral separability of features.

3.3 Conclusion

Contribution of this chapter is the proposal of DFBCSP algorithm which is a new method to find out subject-specific DFB and to extract features from the DFB for signal classification. The classification performance of DFBCSP is slightly better than the state-of-art method: FBCSP which uses a fixed filter bank for all subjects. The DFBCSP method successfully replaces the feature extraction from nine filter outputs followed by a feature selection procedure in FBCSP, by DFB selection and feature extraction processes. The DFBCSP selects the subject-specific discriminative frequency bands using Fisher ratio of filtered EEG signal from channels C3 or C4. The discriminative spectral estimation from C3 and C4 provided higher accuracies in the experimental analysis for classifying ERD/ERS patterns during motor imagery. This observation is in line with the studies reported in [2], [35] and [114].

The DFBCSP enhances the classification accuracy of BCI Competition III dataset IVa and BCI competition IV dataset IIb yielding an average error rate reductions of 17.42% and 8.9% respectively compared to the state-of-art. Even though, the classification results are not significantly better than the FBCSP algorithm, DFBCSP effectively selects the informative frequency components and generates useful features for classification. Out of fourteen subjects analyzed, ten subjects yield better accuracy with DFBCSP whereas four subjects offer slightly lower results than FBCSP. Therefore, robustness of the proposed DFBCSP has to be further improved to obtain significant performance enhancement. Regarding the computational cost, FBCSP filters EEG from all channels using nine filters whereas DFBCSP requires filtering of single channel EEG using twelve filters (parent filter bank) for frequency estimation. In FBCSP, CSP has to be estimated for nine filters whereas it is to

be estimated only for four filters in DFBCSP. DFBCSP has reduced computational cost in bandpass filtering and CSP computation, but it has to perform an additional task of frequency selection using Fisher ratio. Therefore, DFBCSP enables us to highlight the importance of selecting proper frequency components in motor imagery based BCIs.

Preliminary results of optimizing frequency bands using Fisher ratio in BCI are promising and the next chapter present a new frequency optimization method in motor imagery based BCIs.

Chapter 4

Impact of EEG spectral variability on BCI performance

In EEG based BCIs, motor imagery is one of the mental activities which can be effectively detected and used in practical applications. Yet, the discriminative frequency bands in EEG during motor imagery are known to be subject-specific. Moreover, such subject-specific discriminative frequency bands vary over time. The DFBCSP algorithm presented in Chapter 3 addressed the inter-subject variation of discriminative frequency bands. In the subject-specific discriminative filter bank (DFB) selection process, DFBCSP algorithm filters the EEG using the parent filter bank of twelve bandpass filters. In this chapter, a new approach based on the time-frequency Fisher ratio pattern is presented to estimate the subject-specific bands in order to avoid this multi-band filtering process. The variation of the subject-specific bands over time (intra-subject variability) is also investigated in this chapter, along with inter-subject variability.

In order to demonstrate the effect of this spectral variability on the performance of EEG-based BCI, two BCI approaches named as Static Spectral Features (SSF) method and Variable Spectral Features (VSF) method are presented. Both the SSF and VSF learn a subject-specific model using the fixed calibration procedure and evaluate the new EEG samples using fixed frequency and variable frequency bands respectively. Most of the methods in literature estimate the optimal frequency bands during calibration and then keep them

fixed for the new sessions of EEG, without addressing their variability over time. A robust BCI should incorporate not only the variations of frequency bands between subjects but also their variations within subjects.

Motivated by this fact, the variation of the discriminative frequency bands over sessions and its impact on the classification accuracy of motor imagery tasks is analyzed in this chapter using SSF and VSF approaches. Specifically, this chapter investigates how to track the changes in the discriminative frequency bands over time and make use of it, in order to improve the BCI performance.

4.1 New BCI approaches: SSF and VSF

The procedure for calibrating the subject-specific model is fixed for both SSF and VSF methods. After developing a subject-specific model from the training data, the SSF evaluates new signals without any model updates over time whereas VSF method updates the model parameters addressing the spectral variability over time. The subject-specific model parameters consist of the discriminative frequency bands, the CSP projection matrix for spatial filtering and the classifier model. Then, the subject-specific model is evaluated on new EEG signals using SSF and VSF methods employing fixed and variable frequency bands respectively. All the experiments and analysis in the work were performed using Matlab. The fixed calibration procedure of VSF and SSF is presented in Section 4.2 and evaluation phases are given in Section 4.3.

4.2 Calibration procedure in SSF and VSF approaches

The proposed discriminative frequency bands based BCI system during calibration is composed of 4 stages as shown in Fig. 4.1. The 4 stages including the band selection process, the bandpass filtering, feature extraction, and classification procedure are described here in subsections 1, 2, 3 and 4.

Figure 4.1: The proposed BCI system during calibration.

4.2.1 Stage 1: Band selection process

In the analysis of motor imagery tasks, Fisher ratio values are effectively used to determine the subject-specific discriminative frequency bands in DFBCSP algorithm presented in Chapter 3. Fisher ratio is known as a measure of discrimination between two classes of data [133-135]. Therefore, the proposed technique uses a time-frequency Fisher ratio pattern of EEG signal in order to determine the discriminative frequency bands. The PSD in shifting time windows using Short-Time Fourier Transform (STFT) is computed, for every single trial EEG. A single trial EEG is the multi-channel EEG signal recorded for a certain length of time when the subject is performing motor imagery tasks in response to a visual cue. In this context, two types of motor imagery are analyzed; the imagination of right hand and left hand movements for a period of about 4 sec. In the STFT estimation for each single trial EEG, a 256 point FFT is used with a window of length 500 ms and an overlap of 200 ms. Thus, each trial is associated with a discrete time-frequency density pattern $I_n(f, t)$. Then, the Fisher ratio $F_R(f, t)$ is calculated to measure the discriminative power of each time-frequency point across trials and classes [133, 134].

$$S_W(f, t) = \sum_{k=1}^C \sum_{n=1}^{n_k} (I_n(f, t) - m_k(f, t))(I_n(f, t) - m_k(f, t))^T \quad (4.1)$$

$$S_B(f, t) = \sum_{k=1}^C n_k (m(f, t) - m_k(f, t))(m(f, t) - m_k(f, t))^T \quad (4.2)$$

$$F_R(f, t) = \frac{S_B(f, t)}{S_W(f, t)} \quad (4.3)$$

In the equations (4.1) to (4.3), the S_W , S_B , m_k , m and F_R are two dimensional matrices where $S_W(f, t)$ and $S_B(f, t)$ represent the within-class and between-class variances respectively, $m_k(f, t)$ is the average time-frequency density pattern for class k , $m(f, t)$ is the average time-frequency density pattern over k classes where $k = \{1, 2, \dots, C\}$ and n_k denotes the number of trials for class k .

Then, after getting the time-frequency Fisher ratio pattern, the band selection algorithm automatically locates the discriminative bands. To select the first discriminative frequency band, the maximum energy for a given bandwidth and center frequency is determined and compared with that of other frequency locations. This band selection procedure is shown in Fig. 4.2 and described here in steps of 1 to 5.

Step 1: A series of rectangular windows of width 3 Hz covers the frequency range of 6-40 Hz. The value of bandwidth is varied from 3 Hz to 9 Hz in steps of 1 Hz as shown in Fig. 4.2. In total, there are seven bandwidth specifications denoted generally as BW_j where $\{j = 1, 2, \dots, 7\}$. In other words, BW_1 equals 3 Hz and BW_7 equals 9 Hz.

Step 2: Determine the energy distribution α :

$$\alpha(F_i, BW_j) = \sum_{f=F_i-\frac{BW_j}{2}}^{F_i+\frac{BW_j}{2}} \sum_{t=1}^{T_s} F_R^2(f, t) \quad (4.4)$$

This value is computed for every location obtained when sliding the rectangular window along the frequency axis of Fisher ratio pattern. In equation (4.4), T_s represents the number of time segments in the Fisher ratio pattern.

Step 3: Estimate the location F_j^{opt} among all locations F_i which provides maximum energy values α according to the following equation.

$$F_j^{opt} = \underset{i}{\operatorname{argmax}} \alpha(F_i, BW_j) \quad (4.5)$$

This computation is repeated for every BW_j . Thus, for each j , optimum energy measures α_j^{opt} related to center frequencies F_j^{opt} are obtained.

Step 4: Compute the relative change of consecutive α^{opt} values in order to compare the

Figure 4.2: The proposed band selection process using the time-frequency Fisher ratio pattern. In step 2, the energy values are estimated according to eqn. (4.4). Step 3 selects the optimum frequency location using eqn. (4.5) for all bandwidths and step 4 computes the delta values according to eqn. (4.6).

discriminative capability of various BW_j . The relative change δ_j is estimated as:

$$\delta_j = \frac{\alpha_j^{opt} - \alpha_{j-1}^{opt}}{\alpha_j^{opt}} \times 100 \quad (4.6)$$

delta_j is computed for $j = \{2, 3, \dots, 7\}$. For instance, initially the value of **delta₂** is calculated using values of α_2^{opt} and α_1^{opt} as shown in Fig. 4.2.

Step 5: After estimating **delta_j** values, its values are compared with a threshold δ_{min} . For example, the value of **delta₂** is compared with δ_{min} to check whether the increase of bandwidth from $BW_1 = 3$ Hz to $BW_2 = 4$ Hz contains frequency components that contribute to the discriminative power. If **delta₂** $\leq \delta_{min}$, the contribution from the next higher bandwidth is checked by δ_3 and so on. The threshold δ_{min} is selected from the experimental analysis and is fixed for all subjects. For various values of δ_{min} such as 10%, 20%, 30%, 40%, ..., etc., the bands estimated by the algorithm have been noted and it is found that as the threshold increases, the tendency to select only 3 Hz bandwidth is high. Hence, in order to accommodate all frequency components even with a slightly higher discriminative power, the threshold is chosen as 10%.

Table 4.1: Computational complexity of band selection algorithm

Operation	Number of multiplications	Number of additions
1) PSD estimation of n_k trials in C classes of EEG signals using N-point FFT	$n_k.T_s(N/2).log_2N$	$n_k.T_s.N.log_2N$
2) Computing $\mathbf{S}_W$ according to eqn. (4.1)	$F.T_s.C.n_k + F.T_s.C$	$F.T_s.C.n_k + F.T_s.C(n_k - 1)$
3) Computing $\mathbf{S}_B$ according to eqn. (4.2)	$F.T_s.C + F.T_s + C$	$F.T_s.C + F.T_s$
4) $\mathbf{F}_R$ computation according to eqn. (4.3)	$F.T_s$	-
5) Estimation of α values	$1393T_s$	$2583(T_s - 1)$
6) Comparison of α and δ values using equations (4.5) and (4.6)	12	206
Total	$[(N/2)log_2N]n_k.T_s + F.T_sC(n_k + 2) + 2F.T_s + C + 1393T_s + 12$	$n_k.T_s.N.log_2N + 2n_k.F.T_s.C + F.T_s + 2583(T_s - 1) + 206$

Figure 4.3: Comparison of delta values for estimating the discriminative band.

Details of step 5 are shown in Fig. 4.3. The search stops when $\delta_j \leq \delta_{min}$ and the $j - 1^{th}$ location is taken as the first discriminative band or Band-1. To estimate the second band, the search is repeated from 6 Hz to 40 Hz of the time-frequency Fisher ratio pattern avoiding the selected band (1 Hz overlap is also used). It means that if the first band selected is 8-13

Hz, the next search starts from 6 Hz to 40 Hz after replacing the Fisher values of frequency points 9- 12 Hz as zero over the whole time axis in Fisher ratio pattern. Similarly, the band search continues until a certain number of bands is reached.

The optimum number of discriminative bands is determined based on an experimental analysis presented in Section 4.4.2. Also, δ_{min} is set to ten for all subjects based on the experiments. The bands of relative change less than δ_{min} are eliminated as the corresponding frequency components do not contribute much to the energy distribution of the Fisher ratio pattern. Once the band selection algorithm has selected the subject-specific frequency bands, the EEG from all channels were filtered using these discriminative bands for further processing.

Computational complexity of this band selection procedure can be approximately estimated by computing the number of multiplications and additions in each of the steps. For the estimation of Fisher ratio pattern in band selection process, the PSD values of EEG signals are computed using STFT. Let T_s be the number of time-segments generated using an N -point FFT and F be the number of frequency points in the Fisher pattern. If there are n_k number of trials in every C classes of EEG signals, the complexity of estimating the discriminative band from the time-frequency Fisher pattern of size $F \times T_s$ can be approximately calculated as given in Table 4. 1. For simplicity, the computational cost of subtraction is taken as same as that of addition operation.

The band selection algorithm always considers frequency components in the range of 6-40 Hz using rectangular windows of bandwidths 3 Hz, 4 Hz, 5 Hz, 6 Hz, 7 Hz, 8 Hz and 9 Hz during the computation of α values. Sliding of these windows along the frequency axis of Fisher ratio pattern gives 32 bands of 3 Hz bandwidth, 31 bands of 4 Hz, 30 bands of 5 Hz, 29 bands of 6 Hz, 28 bands of 7 Hz, 27 bands of 8 Hz and 26 bands of 9 Hz respectively. Computational costs for these specific values are given in Table 4.1. After deciding the optimum α values for every the bandwidth, δ values are computed according to eqn. (4.6). Then, the δ values are compared to select the discriminative frequency band. The total computational cost increases with increase in the number of bands to be estimated.

4.2.2 Stage 2: Bandpass filtering

The discriminative bands selected by analyzing the time-frequency Fisher ratio pattern are used for the subject-specific filter bank design. Depending on the frequency band information from Fisher ratio pattern, the desired bandpass filters in the BCI system are configured by choosing appropriate decimation factors in the Coefficient Decimation technique described in Section 3.1.1. Thus, depending on the bands estimated from time-frequency Fisher ratio pattern, required bandpass filters are configured and multi-band filtering is performed.

4.2.3 Stage 3: Feature extraction using CSP

The filtered EEG signals are processed by CSP in order to extract the features. The CSP technique constructs a new time series by projecting high dimensional, spatio-temporal EEG signal onto very few spatial filters [117]. The details about feature extraction using CSP is explained in Section 2.3.5.

4.2.4 Stage 4: Classification

The classifier estimates the type of motor imagery performed from the trained model. The trained model is constructed from training data that comprises of the features and respective class labels. The naive Bayesian classifier applied in this work estimates the probability values $p(X|w)$ and $P(w)$ from the training data samples and predicts the class w with the highest posterior probability $p(w|X)$ using the Bayes rule [119]:

$$p(w|X) = \frac{p(X|w) \times P(w)}{p(X)} \quad (4.7)$$

where $X = \{X_1, X_2, \dots, X_d\}$ is the data sample with d features. The computation of $p(w|X)$ is rendered feasible by a naive assumption that all the features X are conditionally independent for a given class w and the details regarding the estimation of probability functions are available in [119].

4.3 Evaluation procedures

In the calibration phase explained in the previous section, three subject-specific models are learnt and they are:

- (i) Bandpass filters corresponding to the discriminative frequency bands selected using the time-frequency Fisher ratio pattern of the training data,
- (ii) CSP transformation matrix for feature extraction and
- (iii) Classifier model.

Each of these subject-specific models has their own set of parameters. The parameters are fixed for SSF evaluation whereas they are updated in VSF evaluation phase. SSF and VSF evaluations are explained in Sections 4.3.1 and 4.3.2 respectively.

4.3.1 SSF evaluation

Figure 4.4: Evaluation process in SSF method.

With the SSF evaluation as shown in Fig. 4.4, all the three sets of calibrated model parameters are always fixed for a particular subject. Stages in the evaluation phase of SSF are:
Stage 1: EEG signals are filtered with the bandpass filters obtained during calibration (refer to section 4.2),

Stage 2: Features are extracted by projecting the filtered EEG using CSP transformation matrix ($\mathbf{W}$) computed from the calibration data.

Stage 3: The extracted features are classified using the classifier model learned during calibration.

As the SSF method does not update the model parameters, the spectral variability is not addressed in the SSF system.

4.3.2 VSF evaluation

Due to variations of the discriminative frequency bands over time, the operational frequency bands obtained from calibration data may not be appropriate for processing new EEG signals. The effects of updating the frequency bands over time in the performance of the BCI are investigated using VSF method. With the VSF method given in Fig. 4.5, the system keeps track of variations in discriminative spectral components. In order to track this discriminative spectral variability in the VSF method, after a small number of trials, say N_1 trials in the evaluation session, the frequency bands are updated. During testing, the first N_1 trials of motor imagery tasks are evaluated using the subject-specific models learned during calibration. These models include bandpass filters, CSP transformation matrix and classifier model.

Figure 4.5: Evaluation process in VSF method. If there are N_1 complete single-trials in side the buffer, time-frequency Fisher ratio pattern is computed using the completed tasks. Frequency bands are estimated from the pattern and bandpass filters are updated accordingly. The updated parameters are used for processing $N_1 + 1^{th}$ trial onwards.

In order to track band variations over time, a time-frequency Fisher ratio pattern is obtained using the current N_1 EEG single-trials and its discriminative frequency bands are estimated. These updated frequency bands are used for bandpass filtering the next batch of N_1 tasks. Similarly, the updates are done at every N_1^{th} task. Thus, the most recent discriminative frequency information is utilized for processing the signals. The updated information is used only for processing future samples, and not for the current tasks. The buffer shown in Fig. 4.5 is used to keep the EEG signals for the purpose of updating the frequency bands. The classifier is also updated at every N_1^{th} task, using the features from the previous tasks. Since, this work focuses on the optimization of discriminative frequency components in EEG, the CSP transformation matrix is kept fixed over all sessions assuming the spatial

weights of all channels are fixed. The procedure is presented in 8 steps as shown here. The value of N_1 is fixed based on the experimental analysis given in Section 4.5.

VSF evaluation procedure:

- (1) Set $n = 1$; and select the time-frequency Fisher ratio pattern, bandpass filters, CSP matrix $\mathbf{W}$ and classifier model obtained during calibration for processing the signal.
 - (2) Filter the EEG using the selected bandpass filters, extract the CSP features and predict the task performed using the classifier.
 - (3) Save the data $\mathbf{E}$ and note the type of imagination performed.
 - (4) If n is a multiple of N_1 , go to step 5. Otherwise, go to step 7.
 - (5) Compute the new discriminative frequency bands according to equations (4.1)-(4.6) from the time-frequency Fisher ratio pattern of the saved N_1 single-trials.
 - (6) Update the bandpass filters according to the newly estimated bands and retrain the classifier using previous features.
 - (7) Wait for the next trial.
 - (8) When new EEG single-trial is received, $n = n+1$ and proceed to step 2.
-

4.4 Experiments and analyses

Various experiments were performed to validate the study. The effectiveness of band selection from the time-frequency Fisher ratio pattern and the investigation of spectral variability over sessions are given in sections 4.2.2 and 4.2.3 respectively. The experiments done using the proposed SSF and VSF methods are provided in Section 4.4.1.

4.4.1 EEG data used

The data set used in this work is the publicly available BCI competition IV dataset IIB. It consists of EEG data from nine healthy right-handed subjects of a study published in [128]. In every subject, 3 bipolar EEG measurements are available from the electrodes C3, Cz and C4, sampled at 250Hz. The recorded EEG was bandpass filtered between 0.5 Hz and 100 Hz and a 50 Hz notch filter was enabled. The details are given in Section 3.2.2.

Figure 4.6: Time-frequency Fisher ratio patterns of nine subjects from session-3 of BCI Competition IV dataset IIb. The x-axis corresponds to the time segments obtained during the STFT estimation of 5 sec of EEG data and y-axis represents the frequency in Hz. The scale of the plot is shown on the right side of each pattern.

4.4.2 Band selection

The method of estimating the frequency bands from the time-frequency Fisher ratio pattern is described in Section 4.2.1. The EEG signals recorded by electrodes on sensorimotor cortices give the highest discrimination between motor imagery tasks [36]. Therefore, the proposed algorithm in this chapter uses the Fisher ratio values of EEG channel C4 in order to find out the informative frequency bands similar to the DFBCSP algorithm in Chapter 3. Fig. 4.6(a)-(i) show the time-frequency Fisher ratio patterns obtained in session-3 of channel C4 for subjects 1, 2, 3, 4, 5, 6, 7, 8 and 9 respectively. These patterns shown in Fig. 4.6 are the contour plots of $\mathbf{F_R}$ that are obtained using equations (4.1)-(4.3). The scale for each plot is provided on the right side of the respective patterns. Applying STFT on the EEG signal of duration 5 sec, the obtained power spectral density $I_n(f, t)$ has 16 time segments as provided in Fig. 4.6. The frequency range is from 1 Hz to 40 Hz. From these patterns, the informative bands are estimated.

The search for the second band using the same Fisher ratio pattern avoids the first estimated band from the $\mathbf{F_R}$, but allowing an overlap of 1 Hz at the 2 edges of Band-1. Therefore, the selected bands overlap slightly for some subjects. To keep the consistency in the band selection and respective feature extraction processes, the number of bands is fixed at two in the study without merging the overlapping bands into one. Based on the time-frequency Fisher ratio patterns shown in Fig. 4.6(a)-(i), the discriminative bands selected are {19-23 Hz and 11-14 Hz} for Subject 1, {8-13 Hz and 24-30 Hz} for Subject 2, {15-21 Hz and 31-36 Hz} for Subject 3, {11-16 Hz and 9-12 Hz} for Subject 4, {28-32 Hz and 23-29Hz} for Subject 5, {12-15 Hz and 9-13 Hz} for Subject 6, {12-16 Hz and 11-14 Hz} for Subject 7, {10-13 Hz and 8-11 Hz} for Subject 8 and {23-27 Hz and 21-24 Hz} for Subject 9 respectively.

Fig. 4.6 clearly shows the inter-subject variability of discriminative frequency bands in ERD/ERS patterns. The characteristics of ERD/ERS patterns might depend on many factors such as subject's age, lack of concentration, attention, noise, strategy of imagination, presence of feedback etc. The study in [136] is one of the few attempts to get an insight into the relationship between the cognitive ability to imagine movements and increasing age. The study indicates that ability to generate and manipulate mental images shows a decline in elderly participants. The study also shows that with increasing age the capacity to imagine movements is not stable but shows a subtle change, in that elderly (≥ 64 yr) showed some decline in the ability to imagine movements from an internal perspective. Also, each

subject has specific physioanatomical structure and may use different imagery strategies to induce ERD and ERS patterns [127]. Visual feedback and process of learning are also responsible for changes in EEG frequency patterns [5]. The effects of other variables such as motivation, attention and learning history are not yet fully understood, and a matter of current research [137].

Figure 4.7: Average classification accuracy over nine subjects in the BCI Competition IV dataset I Ib for different number of bands.

However, the discriminative frequency points are effectively located by the proposed band selection algorithm and can be used in the automatic estimation of frequency bands in BCI applications. In order to fix the number of bands to be chosen from time-frequency Fisher ratio pattern, an experimental analysis is done using BCI Competition IV dataset I Ib. The average classification accuracies over nine subjects in four evaluation sessions for different number of bands are computed and are shown in Fig. 4.7. It is observed that increasing the number of bands beyond two does not give a noticeable performance improvement in the experimental results. Therefore, the number of subject-specific discriminative bands (N_B) is fixed as two in the proposed methods.

4.4.3 Analysis of discriminative spectral variability over sessions

In order to investigate the discriminative spectral variability during the performance of motor imagery, the discriminative bands in various sessions are analyzed separately using the Fisher ratio patterns.

Figure 4.8: Variation of discriminative frequency bands in 5 sessions for nine subjects. The black and red plots represent the first and second most discriminative bands respectively for the corresponding session. The x-axis represents the sessions 1, 2, 3, 4 and 5. The y-axis represents the frequency in Hz.

Inter-session variability of frequency bands

A 10-fold cross-validation procedure is done to analyze the discriminative spectral variability over various sessions. The 10-fold cross-validation mixes the data set randomly and divides into ten equally sized distinct partitions. Each partition is then used for testing; while other nine partitions are used for training the model. From each training set, two discriminative frequency bands are estimated which are used for bandpass filtering the EEG signals in the test set. The bands are selected using the time-frequency Fisher ratio method described in Section 4.2. From each of the training set in the 10-folds, ten sets of frequency bands (total ten bands) are estimated. Then, the fold-specific bands are noted and the number of times each band appears is computed. The first and second discriminative bands are selected based on the number of times they are selected in all folds; i.e. the most frequent band is selected as the first discriminative band.

The 10-fold cross-validation is done on all sessions individually and the two discriminative bands are noted. Fig. 4.8(a)-(i) show the selected discriminative bands in five sessions for Subject 1 to Subject 9 respectively. The black and red plots in Fig. 4.8 represent the first and second most discriminative bands respectively. After choosing the session-specific discriminative bands based on the procedure explained previously, the 10-fold cross-validation procedure is repeated by processing all the folds in these two selected frequency bands in the respective sessions for all subjects. Features from these two selected discriminative bands gave similar or higher classification accuracies in most of the sessions in all the subjects compared to fold-specific bands. Hence, the selected bands plotted in Fig. 4.8 represent the discriminative spectral information in all sessions.

Fig. 4.8 reveals the significant inter-session variation of discriminative frequency bands in all subjects. But, the degree of discriminative band variation is found to be subject-specific. For example, in Subject 1 the selected bands for sessions 1, 2, 3, 4 and 5 are: {11-14 Hz and 9-12 Hz}, {10-14 Hz and 8-11 Hz}, {19-23 Hz and 11-14 Hz}, {11-14 Hz and 22-26 Hz} and {23-29 Hz and 35-39 Hz} respectively. Similarly, in all the nine subjects, the discriminative bands vary from session to session.

The inter-subject and intra-subject variation of discriminative frequency bands are clearly visible in Fig. 4.8. It is reported that EEG spectrum undergoes a sequence of changes during preparation, execution and imagination of motor movements [126]. A number of

human EEG studies have led to a hypothesis that event-related changes in different EEG band power arise from different neurophysiological mechanisms and have different functional meanings. But, they are yet to be discovered clearly [126]. Synchronization of signals in the alpha and beta bands has been postulated to reflect an aroused but idling state of cerebral cortex and suppression of power in these bands has been postulated to reflect either inhibition of cortical activity or resetting of cortical circuits in preparation for future activation. In contrast, event related augmentation of gamma band activity has been associated with functional activation of cortex. Hence, activation of motor cortex by motor imagery can be reflected as power changes in subject-specific alpha, beta and gamma bands of EEG [124, 138].

Intra-session variability of frequency bands

In the 10-fold cross-validation, the fold-specific bands were consistent in six subjects for at least one session. For example, in the 10-fold cross-validation done in session-3 of subject 1, the bands {19-23 Hz and 11-14 Hz} have been consistently selected in all the ten0 folds as first and second discriminative bands respectively. In order to analyze the intra-session variability of frequency bands more specifically, the EEG data for each session is divided into segments of forty trials and estimated the bands from the respective time-frequency Fisher ratio patterns. The process is done for the five sessions in all the nine subjects to analyze the intra-session variability of frequency bands. Fig. 4.9 shows the variability for nine subjects in session-2 and the three segments each having 40 trials are denoted as T_1 , T_2 and T_3 . From each Fisher pattern, two frequency bands are estimated. The selected frequency components in T_1 , T_2 and T_3 are shown in black, grey and blue shades respectively. A certain percentage of overlap exists between segment-specific discriminative frequency bands in most of the subjects. From the analysis of five sessions in the nine subjects, inter-session variability of discriminative bands found to be more prominent than their intra-session variability.

In Fig 4.9, it is found that there are beta activity beyond 20 Hz for a few subjects. Motor imagery is associated with an amplitude attenuation (ERD) or enhancement (ERS) in subject-specific frequency bands of EEG. Beta ERS is based on the cooperative or synchronized behavior of large number of neurons in motor cortex. These oscillations can include

frequency components either in a single band or in multiple frequency bands, whereby each person has his own subject-specific beta frequency components [124]. It is also possible to have simultaneous occurrence of ERD and ERS in beta bands at the same electrode. These time-frequency characteristics of ERD/ERS patterns reflect circuitry and behavior of underlying neuronal networks and they are subject-specific [138].

Figure 4.9: The variation of discriminative frequency bands in session-2 of subject 1 to subject 9.

4.4.4 Calibration and evaluation using SSF and VSF methods

In both the SSF and VSF methods, the session-1 EEG of each subject is used for training the subject-specific models. To estimate the subject-specific operational frequency bands, the time-frequency Fisher ratio pattern of EEG channel C4 is employed in the experiments as the Fisher values from C4 is effectively used to choose the discriminative frequency bands in the previous work proposed in Chapter 3. Experiments presented in Section 4.4.2 show that a number of two frequency bands gives a good classification performance. Therefore, the number of discriminative bands is fixed at two in the experiments.

The two discriminative bands selected by the band selection algorithm based on the time-frequency Fisher ratio of session-1 in nine subjects are {11-14 Hz and 9-12 Hz} for Subject 1, {36-39 Hz and 15-20 Hz} for Subject 2, {7-12 Hz and 25-29 Hz} for Subject 3, {10-13 Hz and 18-22 Hz} for Subject 4, {24-30 Hz and 21-25 Hz} for Subject 5, {12-15 Hz and

22-28 Hz} for Subject 6, {10-15 Hz and 19-23 Hz} for Subject 7, {9-13 Hz and 7-10 Hz} for Subject 8 and {23-27 Hz and 36-40 Hz} for Subject 9 respectively. In the analysis presented in 4.4.3, it is observed that there exists considerable variation of discriminative frequency bands over time for all the nine subjects. Therefore, the frequency bands estimated from session-1, will not be appropriate for processing the subsequent sessions.

In order to demonstrate the effect of tracking the discriminative spectral variability on the performance of a BCI, the subject-specific model learnt from session-1 for each subject is tested on sessions 2, 3, 4 and 5 with and without incorporating spectral updates using SSF and VSF methods respectively. During evaluation, the SSF method uses the same models obtained during training whereas the VSF method keeps track of the discriminative frequency bands over time to develop a robust BCI. The VSF method updates the frequency bands and classifier model after a small number of trials (N_1) in the new session. These (N_1) trials are evaluated using the calibrated model and the remaining trials of the session are evaluated using the updated model. For example, while evaluating session-2 (with 120 trials in total), the first (N_1) trials are classified using the calibrated model and the remaining $120-(N_1)$ trials are classified by incorporating the updates as described in Section 4.3.2. The experimental analysis to fix the value of N_1 is presented in Section 4.5.

The comparison of SSF and VSF approaches is done based on the accuracy of classifying the imagery trials in the evaluation sessions. During the evaluation, every incoming single trial EEG is processed to extract the specific features and the classifier predicts the possible class (left or right hand imagery) into which the given trial belongs to. The classifier output is named as predicted label in the following part of thesis. The stimulus codes of all trials or the true class labels are already available in the dataset. The percentage of correctly classified trials over the total number of trials in one session is computed and its value serves as the percentage classification accuracy of that session.

4.5 Results and discussions

The subject-specific model trained from session-1 is evaluated in sessions 2, 3, 4 and 5 respectively using the proposed SSF and VSF methods.

In the VSF method, a few channel selection possibilities depending on the source signal

(a) Variation of classification accuracy vs. channel selected for band estimation.

(b) Variation of classification accuracy vs. number of trials (N_1).

Figure 4.10: Variation of accuracy vs. channel selection for band estimation and variation of accuracy vs. number of tasks in the VSF method.

from which bands are estimated have also been investigated and the accuracy results are plotted in Fig. 4.10(a). The PSD using STFT from the mentioned channels are utilized for getting the time-frequency Fisher ratio pattern. It is found that the single channel C4 alone gives better classification accuracy than individual EEG channels either C3 or Cz and also than a combination of C3, Cz and C4. In the combination channel model, the mean PSD of all the three channels is used for time-frequency Fisher ratio estimation.

In order to find out the optimum number of trials (N_1) required for updating the filters and classifier in the VSF method, an experimental analysis was done by varying the number of tasks. Fig. 4.10(b) shows the variation of overall accuracy (average accuracy of nine subjects over four sessions) vs. number of trials N_1 . From the analysis, a buffer of 40 trials is found to be sufficient to obtain discriminative time-frequency patterns and to update the frequency bands. Indeed, even 20 trials might have been sufficient, since average performance is not significantly lower for $N_1=20$. However, since higher number of updates are required while using $N_1=20$ compared to 40, N_1 is fixed as 40 in the experiments.

Fig. 4.11(a), 11(b), 11(c) and 11(d) show the classification accuracies for the nine subjects (S_1 to S_9) and their respective average values using SSF and VSF methods in sessions 2, 3, 4 and 5 respectively. Fig. 4.11(e) shows the average accuracy over nine subjects in four evaluation sessions. The reported results are obtained using the EEG channel C4 for band selection and a buffer of $N_1 = 40$ tasks. The results showed that the proposed VSF

(a) Session-2

(b) Session-3

(c) Session-4

(d) Session-5

(e) Sessions 2, 3 4 and 5

Figure 4.11: Comparison of classification accuracies of test trials using the proposed SSF and VSF methods in the evaluation sessions. The number of trials in each of the evaluation session are given in Table 3.2.

method performs better than SSF in most of the subjects. For example, in Subject 1, the two discriminative bands obtained by 10-fold cross-validation in session-1 are {11-14 Hz and 9-12 Hz} whereas the bands obtained in session-5 are {23-29 Hz and 35-39 Hz}. Thus, there is a significant shift in discriminative bands between sessions 1 and 5 for Subject 1. Therefore, while evaluating session-5, the VSF method which tracks the relevant spectrum over time gives an error rate of only 21% whereas the SSF method which uses features from the calibrated bands (from session-1) gives a higher error rate of 43% as seen in Fig. 4.11(c). On average, the VSF method outperforms SSF with error rate reductions of 5.41%, 4.86%, 21.01% and 14.95% in sessions 2, 3, 4 and 5 respectively. The average error rate reduction obtained by VSF method is 11.50% across all 4 sessions. The error rate reduction is computed using the equation (3.14) given in Chapter 3.

The results of the proposed VSF method are also compared with DFBCSP algorithm presented in Chapter 3 and the comparison is given in Fig. 4.12. The DFBCSP algorithm uses CSP features from a selected subject-specific discriminative filter bank and does not employ any filter updates over time. In the analysis of nine subjects, it is found that the proposed VSF gives an error rate reduction of about 10% over DFBCSP in the four test sessions.

Figure 4.12: Comparison of classification accuracies using DFBCSP and VSF method.

The discriminative spectral variations over sessions during motor imagery tasks and its effect on the classification performance of BCI have been investigated in this chapter. The inter-session discriminative spectral variability is verified using the 10-fold cross-validation procedure and the effect of discriminative spectral variability on the classification accuracy of motor imagery tasks is demonstrated by comparing the classification accuracies of the

BCI systems employing static and updated spectral features. In order to demonstrate this, the true labels are utilized for the frequency updates. But, in real time BCI applications, the true labels are not always available. Therefore, in order to extend the scope of this work to online applications, the VSF method is repeated in all subjects without using the true labels. The updates were based on the predicted class labels in order to make the procedure fully automatic. The resulting classification accuracies are found to be better than static method, even though the updates on the frequency bands and classifier are unsupervised.

The average classification accuracy over nine subjects in four sessions are 74.75% and 72.40% when using the true labels and the predicted labels respectively for the VSF method, whereas it is 71.40% in SSF with fixed frequency bands. The results of VSF method are better than those of SSF method. Also, the study could analyze the variation of frequency bands over time and the effect of tracking these variations on the performance of BCI. As the selection of relevant frequency components is very important in BCI design, the development of robust algorithms to track their variations over time is necessary in future.

In this study, the spatial filter W for feature extraction is fixed, assuming the channel weights are stable even though the filters are updated. The possibility of updating the spatial filter along with temporal filters was also explored, but it hardly helps to further improve the results in the discussed dataset. Thus, this study showed that the classification accuracy has a significant dependency on discriminative frequency bands, even though the spatial weights were fixed. Hence, the simplicity of the new system lies in the fact that the CSP transformation matrix for spatial filtering is not retrained for new EEG samples even though they are filtered in different bands.

4.6 Conclusion

This chapter proposed a new technique based on time-frequency Fisher ratio pattern for estimating subject-specific discriminative frequency bands. The mentioned technique is employed to analyze the inter-subject and intra-subject variability of discriminative bands. This chapter also contributes studies on inter-session variability of subject-specific discriminative frequency bands and the effect of this variability on the classification accuracy of motor imagery tasks in BCI. To demonstrate this effect, two BCI systems are proposed: Static Spectral Features (SSF) method and Variable Spectral Features (VSF) method. SSF

evaluation uses only the discriminative bands which were learnt during training whereas VSF method keeps track of discriminative spectral variability when motor imagery tasks are received in new sessions. In all the sessions, the results showed that VSF method outperforms SSF method, which emphasized the requirement of adaptive updates of the discriminative bands in BCI applications. In the proposed VSF method, the frequency bands and band-pass filters are updated for new EEG signals during evaluation phase whereas the spatial filters are kept the same as those obtained during calibration. The method of designing filters using coefficient decimation approach makes it easier to reconfigure the frequency bands at a reduced computational complexity for real time applications.

A few subjects in the dataset showed poor performance even though the discriminative bands were tracked. As EEG signals are non-stationary, an optimal BCI must have the ability to adapt dynamically throughout its use in time, frequency and spatial domain. The BCI performance can also be improved by employing adaptive updates on the classifier model with time [139-145]. Therefore, new adaptation techniques will be investigated in the next chapter for further improvement in the system performance and to achieve efficient on line applications.

In the next chapter, an adaptive approach is proposed to address the discriminative spectral variability, using online and offline experiments.

Chapter 5

An Adaptively Weighted Spectral-Spatial Pattern Algorithm

Motor imagery causes detectable amplitude changes in subject-specific frequency bands, dubbed as ERD/ERS patterns and such frequency bands are subject to change over various sessions. In Chapters 2, 3 and 4, it is found that the accurate estimation of subject-specific bands improves the classification accuracy of motor imagery patterns. In Chapter 4, the time-frequency Fisher ratio pattern is employed to estimate the discriminative frequency points based on Fisher ratio values. Although this method has more flexibility in finding subject-specific bands than the DFBCSP method (in which the parent filter bank in DFBCSP is fixed) presented in Chapter 3, the discriminative power is estimated using the time-frequency Fisher ratio pattern. In the Fisher ratio pattern, the discriminative information using Fisher values is expressed as a function of time and frequency as given in Fig. 4.6. In order to track the variations of discriminative frequency bands over time, the complexity will be less if the discriminative capability estimation is expressed as discrete values, rather than expressing in both time and frequency domains as done in Fisher patterns. Therefore, in this chapter, a new band selection method based on discrete discriminative weight values is presented instead of time-frequency patterns. Obviously in adaptive methods, it will be easier to compare the discrete weight values than to compare the time-frequency Fisher ratio pattern.

With the help of SSF and VSF methods presented in Chapter 4, the importance of identifying the subject-specific frequency bands for the accurate classification of motor imagery activities is verified. In this chapter, a new adaptive method is presented to track the change of discriminative frequency bands over time during motor imagery. The new Adaptively Weighted Spectral-Spatial Patterns algorithm estimates the discriminative frequency components and updates the bandpass filters adaptively based on a discriminative weight deviation. A study on the effect of feedback on the variation of discriminative bands is also performed using online experiments and it is found that presence of visual feedback results an increased variation of frequency bands.

5.1 New methodology

Figure 5.1: The framework for adaptively weighted spectral-spatial pattern algorithm during calibration.

Chapter 4 presented the discriminative spectral variability and its effect on the performance of motor imagery based BCI. The subject-specific frequency information was extracted using the time-frequency Fisher ratio pattern of the EEG signals from the sensorimotor cortex. In this chapter, a band selection technique is presented based on the discriminative weights of frequency components, which is also based on the Fisher ratio values. Using the new band selection technique, a BCI approach named as “Adaptively Weighted Spectral-Spatial Patterns” (AWSSP) is presented here which tracks the spectral variability of motor imagery patterns based on their discriminative weights. The new adaptation technique employed in this work improves the classification accuracy of most of the subjects analyzed in both offline and online experiments. The comparison of classification performance of the proposed methods with existing systems is also presented.

The proposed techniques aim to develop a BCI system using an adaptive feature extraction technique which can track the variations of discriminative frequency bands over time. The systems during calibration and evaluation are shown in Figs. 5.1 and 5.2 respectively. In

Figure 5.2: The framework for AWSSP algorithm during evaluation.

both the calibration and evaluation systems, the informative frequency bands are determined based on the Discriminative Weight (DW) values of frequency components. The separability criterion based on Fisher ratio is used for estimating the DW values. During calibration, three subject-specific model parameters are developed:

- (i) DW values, discriminative frequency bands and bandpass filters,
- (ii) CSP projection matrix (spatial filter) for feature extraction and
- (iii) Classifier model.

After developing the calibration models, new single-trial EEG signals have been evaluated by AWSSP method. Up to a certain number of trials, AWSSP keeps the calibrated subject-specific models (bandpass filters, CSP transformation matrix and classifier model) for processing the signals. After that, AWSSP compute the DW values of the newly received EEG trials and checks their deviation from the calibrated DW values. If the deviation is greater than a threshold defined in the proposed system, the frequency bands are estimated from the recently estimated DW. For each new incoming trial, the deviation of DW values is continuously estimated. If the deviation is larger than the threshold, the bandpass filters and classifier model are updated. This updated information is used for processing future EEG samples only, but not for the current trial. Illustrations of both calibration and evaluation systems are given in sections 5.1.1 and 5.1.2 respectively.

5.1.1 BCI system during calibration

The proposed BCI system using weighted spectral-spatial features has 4 stages as illustrated in Fig. 5.1.

Stage 1: Estimate the subject-specific discriminative frequency bands based on the discriminative weights of frequency components.

Stage 2: After getting the discriminative frequency bands, design the required bandpass filters using a Coefficient Decimation technique and filter the EEG.

Stage 3: Apply CSP to the bandpass filtered EEG to extract the features.

Stage 4: Classify the extracted features to predict the task performed.

The various steps are described in the following sections.

Stage 1: Estimation of bands based on discriminative weights

Figure 5.3: The band selection procedure.

Fig. 5.3 shows the various steps in the band selection procedure using DW values. In the proposed technique, the DW values are estimated from the time-frequency Fisher ratio values of EEG signal obtained from channel C4. During right or left hand motor imagery, EEG signals from motor cortex, especially channels C3 and C4 gives comparatively better discriminative information for frequency estimation and classification. Also, the Fisher ratio pattern of EEG from channel C4 has been successfully used in the previous work presented in Chapter 4, in order to determine the subject-specific discriminative frequency bands. Initially, the power spectral density in shifting time windows using Short-Time Fourier Transform (STFT) is computed for each motor imagery task with a 256 point FFT. The sampling frequency of the signal is 100 Hz. For STFT, a window length of 800 ms and overlap of 500 ms are used. Thus, a discrete time-frequency density pattern $I(f, t)$ is obtained for each trial similar to the procedure proposed in Chapter 4. Then, Fisher ratio pattern $\mathbf{F_R}$ which is the measure the discriminative power of each time-frequency point across trials and classes is computed according to equations (4.1) to (4.3) provided in

Chapter 4. Then, the Discriminative Weight $DW(f)$ is computed from F_R as:

$$DW(f) = \sum_{t=1}^T F_R(f, t) \quad (5.1)$$

where T represents the number of time segments obtained by STFT transformation. After obtaining $DW(f)$, a similar band searching method reported in Chapter 4 (refer 4.1.1) is applied to choose the informative bands. In order to automatically decide the informative frequency components, rectangular windows are shifted along the frequency axis of $DW(f)$. Initially a rectangular window of width 3 Hz slides from the initial point 6 Hz until 40 Hz of $DW(f)$. This window is shifted in steps of 1 Hz to obtain different frequency band locations of {6-9 Hz}, {7-10 Hz}, . . . until {37-40 Hz}. In the next step, the energy distribution of frequency components in each window is calculated and the frequency band corresponding to maximum energy is determined as given in the following equations.

$$\alpha(F_i, BW_j) = \sum_{f=f_j - \frac{BW_j}{2}}^{f_j + \frac{BW_j}{2}} DW(f) \quad (5.2)$$

where F_i is the center frequency of the i^{th} band location obtained while sliding the rectangular window along the frequency axis of $DW(f)$. The bandwidth of the window (BW_j) is varied from 3 Hz to 9 Hz. In other words j varies from 1 to 7 where $BW_1 = 3$ Hz, $BW_2 = 4$ Hz, . . ., $BW_7 = 9$ Hz. For a fixed bandwidth, a number of bands are obtained while sliding and the location of band possessing highest discriminative energy has to be determined. Thus, for each j , the optimum band with center frequency F_j corresponding to maximum energy is obtained using the following equation.

$$F_j^{opt} = \underset{i}{\operatorname{argmax}} \alpha(F_i, BW_j) \quad (5.3)$$

After estimating the F_j^{opt} values for all bandwidths, the most discriminative bands are chosen according to the procedure explained in section 4.1.1 of Chapter 4. Steps 4 and 5 provided in the band selection process of 4.1.1 explain how to estimate the discriminative frequency components automatically from the time-frequency Fisher ratio pattern. The same procedure is applied to estimate the informative bands from $DW(f)$ also.

(a) For Subjects 1, 2 and 3.

(b) For Subjects 4, 5 and 6.

(c) For Subjects 7, 8 and 9

Figure 5.4: DW values for session-1 in nine subjects of BCI Competition IV dataset IIb.

Table 5.1: The selected frequency bands for the nine subjects

Subject	Band-1	Band-2
S1	10-14Hz	8-11 Hz
S2	11-17Hz	34-39 Hz
S3	7-12 Hz	25-30 Hz
S4	10-13 Hz	18-22 Hz
S5	24-30 Hz	22-25Hz
S6	12-15 Hz	19-27 Hz
S7	10-15 Hz	17-25 Hz
S8	9-13 Hz	7-10 Hz
S9	23-27 Hz	36-40 Hz

Based on the observation from the experimental analysis, the criterion level δ_{min} is fixed at ten in all subjects. Alternate values of δ_{min} were also analyzed, but a value of 10 served better to select the proper bandwidth and frequency components in the experiments. The bands of relative change less than δ_{min} are eliminated because of their lower DW values. Frequency components with lower DW values have relatively lower impact in classifying different motor imagery patterns. Band search continues until a certain number of bands (N_B) is reached. In this work, the band searching process stops after selecting two bands with higher discriminative weights. Increasing the number of bands did not improve the system performance in the discussed datasets. It is also found from experiments that the frequency bands estimated from the time-frequency Fisher ratio pattern and DW values are almost the same. Therefore, DW values can be an effective measure for estimating the discriminative capability of frequency components during imagery tasks.

This band selection procedure is employed in the proposed BCI system and is presented in the following section. The plots in Fig. 5.4(a) - (c) show the variation of the DW values with frequency components for 9 subjects in the BCI Competition IV dataset IIB. The DW plots shown in Fig. 5.4 correspond to the EEG signals of 5 sec after the presentation of a visual cue. The proposed band selection algorithm effectively locates frequency components with higher DW values and the selected bands are shown in Table 5.1. Even though the frequency bands estimated for a few subjects slightly overlap, the number of bands is fixed at two without merging into single band to keep the consistency in the feature extraction process and classifier model parameters. The frequency components with larger DW are used for the subject-specific bandpass filter design.

The DW values in Fig. 5.4 show the subject-specific involvement of alpha, beta and gamma bands during ERD/ERS activity. The bands given Table 5.1 correspond to the frequency components that give maximum discrimination between left hand and right hand motor imagery based on the Fisher ratio values. In subjects 1, 4 and 8, only alpha and beta bands are counted as discriminative. For subjects 2 and 9, gamma bands also show comparatively higher DW values. Involvement of gamma bands in motor imagery reflects a stage of active information processing by the subject [124, 146]. Also the induced oscillations in alpha, beta and gamma bands are possible in the same electrode as in subject-3. According to the reports in [124], it is possible to have both ERD and ERS are in beta bands at the same electrode. For subject 5, two of the discriminative bands are in beta range. ERD/ERS is mainly controlled by the rates of oscillations in underlying neuronal networks and their rates are found to be different from subject to subject. Other physiological factors such as subject's mental state, level of attention/concentration, motivation, presence of feedback, strategy of imagination, method of learning etc. can affect the spectrum of EEG patterns. However, effects of these psychological variables are not fully understood and a matter of current research [5, 137].

Stage 2: Bandpass filtering using Coefficient Decimation approach

The discriminative bands located by analyzing the DW values are used for the subject-specific filter bank design. For the subject-specific filter design, this work uses a Coefficient Decimation (CD) based approach (refer section 3.1.1 in Chapter 3) to implement low complexity reconfigurable FIR filters. Thus, the required bandpass filters are designed using the CD technique to perform multi-band filtering.

Stages 3 and 4: Feature extraction using CSP and classification

The CSP technique allows to determine spatial filters that maximize the variance of signals of one condition and at the same time minimize the variance of signals of another condition. In the BCI Competition IV dataset IIb, the CSP features are extracted from two discriminative filter outputs and therefore each trial is accompanied with four features corresponding to $m = 1$ in the CSP algorithm. In the online experiments, the value of m is selected as two. Then, the features are classified using naive Bayesian Classifier.

5.1.2 AWSSP evaluation

Due to the non-stationarity of brain signals [5, 147, 148] and the presence of oscillating ERD/ERS patterns, the subject-specific discriminative frequency bands may vary with time during motor imagery. This inter-session variation of discriminative spectrum is explained in Chapter 4. A BCI system is said to be robust if it can keep track of the spectral non-stationarities in the EEG signals. Motivated by this fact, an adaptive method AWSSP that tracks the variations of informative bands over time is proposed. The new evaluation technique keeps estimating the DW values over time and updates the filtering process adaptively addressing the inter-subject and intra-subject variability of discriminative frequency bands. Before evaluation, a subject-specific model is learnt from calibration. The calibration develops the subject-specific bandpass filters, CSP projection matrix for spatial filtering and a classifier model as explained in Section 5.1.1. As the DW values of frequency components are not stable over time, continuous tracking of the discriminative frequency bands will improve the system performance. Hence, the new AWSSP method updates the DW values to track the frequency variations when new EEG samples are received in the evaluation sessions. The proposed AWSSP BCI system is given in Fig. 5.2.

In the beginning of the proposed evaluation process, a few motor imagery tasks are processed using the same model parameters learnt from the calibration session. The number of tasks processed in the calibrated parameters is fixed at 40 because it is found that around 40 tasks are required to give a fair estimate of DW values. Therefore, until the 40th task in evaluation sessions, the classifier model, CSP transformation matrix and the bandpass filters are fixed. After the 40th task, the DW values are re-computed from these 40 trials. Then, the deviation of these updated DW values from the calibrated DW values is determined as given in equation (5.4). The percentage Deviation in DW (DDW) for i^{th} trial is computed as follows:

$$\%DDW \text{ for } i^{th} \text{ trial} = \frac{\sum_{n=1}^{N_B} \sum_{k=-BW/2}^{BW/2} [DW_i(f_n+k) - DW_{i-1}(f_n+k)]}{\sum_{n=1}^{N_B} \sum_{k=-BW/2}^{BW/2} DW_{i-1}(f_n+k)} \times 100 \quad (5.4)$$

In equation (5.4), N_B = Number of bands estimated (here it is two), f_n is the center frequency of the n^{th} band. DW_i and DW_{i-1} represent the DW values in the i^{th} and $i-1^{th}$ trial. At the end of i^{th} trial, the deviation in the DW of current bands is estimated using the above equation. When DDW is greater than or equal to threshold, the frequency bands

are estimated from the DW_i values. Consequently the bandpass filters in the system are re-configured. The $i + 1^{th}$ trial is processed using the updated bands. If DDW is less than the threshold, current bands are used for next tasks too, without any updates. The threshold is determined from the experimental analysis and is fixed for all subjects in the dataset. The same procedure is repeated for the subsequent EEG samples. The various steps in AWSSP algorithm when a new motor imagery task is received during evaluation are summarized here in steps 1 to 10. In the illustration, n represents the index of the motor imagery task or the received EEG matrix $\mathbf{E}$ of size $C \times T$, where C is the number of channels and T is the number of time samples.

AWSSP:

- (1) Set $n = 1$; and select the DW values, bandpass filters, CSP matrix $\mathbf{W}$ and classifier model obtained during calibration for processing the signal.
 - (2) Filter the EEG using the selected bandpass filters, extract the CSP features and predict the task performed using the classifier.
 - (3) Save the power spectral density of the data $\mathbf{E}$ in the left/right power spectral density matrix depending on the predicted/true class label.
 - (4) If $n \leq 40$, go to step 9. Otherwise, go to step 5.
 - (5) Compute the new $\mathbf{DW}(\mathbf{f})$ according to equations (5.1)-(5.4) from the saved power spectral density matrix of previous 40 motor imagery tasks.
 - (6) Calculate DDW as per equation (11) by comparing the existing and new $DW(\mathbf{f})$ values.
 - (7) If the DDW is greater than the threshold, go to step 8. Otherwise, no updates are done and proceed to step 9.
 - (8) Update frequency bands from the new $\mathbf{DW}(\mathbf{f})$. Reconfigure the bandpass filters according to the updated bands and retrain the classifier using the features from the previous tasks.
 - (9) Wait for the next trial.
 - (10) When new EEG is received, $n = n+1$ and proceed to step 2.
-

In the training-evaluation procedure, session-1 is used to train the model and the model is tested on sessions 2, 3, 4 and 5. Two types of evaluation methods are proposed; using AWSSP and a Static WSSP (SWSSP), based on how the weighting and updating of frequency components are done in evaluation sessions. In SWSSP, the model parameters developed during calibration are also fixed during evaluation, without any updates. The subject-specific bandpass filters, CSP transformation matrix for spatial filtering and classifier model used for new EEG samples are the same as those developed during calibration. In AWSSP, the discriminative frequency components and classifier are updated using either the information of true labels or the predicted labels. These two evaluation methods

are termed as supervised AWSSP ($\text{AWSSP}_{\text{sup}}$) and unsupervised AWSSP ($\text{AWSSP}_{\text{unsup}}$) respectively in the following sections. These algorithms update the discriminative weights of frequency components when new EEG tasks are received. The mechanism of updating is provided in the explanation of AWSSP algorithm. Based on the DDW values, the bands from updated weight information is used for processing the new task. In both $\text{AWSSP}_{\text{unsup}}$ and $\text{AWSSP}_{\text{sup}}$, the classifier is retrained using previous 40 features whenever the bands are updated.

(a) For Subject-1.

(b) For Subject-6.

(c) For Subject-9.

Figure 5.5: Variation of Discriminative Weight values over sessions for subjects 1, 6 and 9.

5.2 Experiments and analysis

The proposed methods are analyzed using offline and online experiments. The offline analysis is done using the publicly available BCI competition IV dataset I Ib. In the online experiments, the performance of 3 subjects are analyzed, using the proposed algorithms.

5.2.1 Offline experiments using BCI competition IV dataset I Ib

BCI competition IV dataset I Ib were collected from nine normal right-handed subjects performing left and right motor imagery tasks. The cue-based data-recording paradigm consisted of two classes, namely the motor imagery of left hand and that of right hand. Three bipolar EEG measurements were recorded from electrodes C3, Cz and C4, and sampled at 250Hz. For the analysis, the EEG signal in the duration of 0.5 - 4.5 sec after the presentation of visual cue is used. Visual cue is an arrow pointing towards left or right, to represent the motor imagery to be performed. The recording set up and timing protocol have been provided in Section 3.2.2. Thus the dataset comprises of five sessions for nine subjects recorded in different days.

In order to show the inter-session variation of DW values of frequency components, Fig. 5.5 displays the DW values in different sessions in subjects 1, 6 and 9. The DW values shown here are computed by comparing the PSD of all the right hand and left hand motor imagery trials in the respective sessions. The PSD estimation, Fisher ratio estimation and DW computation are done according to the equations 4.1 to 4.3 provided in Chapter 4 and equation 5.1. Fisher ratio computation mainly involves the variance estimation of single-trial EEG PSD from the mean PSD of all the motor imagery tasks. In the analysis, it is found that the discriminative frequency components (or the DW values) vary from session to session for all the subjects. The inter-session variation of discriminative frequency bands is also presented in Section 4.4.3. The selected sessions in Fig. 5.5 provide comparatively larger inter-session deviation in their DW values. As the informative bands are observed to be unstable over sessions, the performance can be improved by updating the bands over time.

Figure 5.6: The timing protocol for online experiments.

5.2.2 Online experiments

The online experiments were done using Neuroscan NuAmps 32 channel EEG amplifier. Recorded EEG were bandpass filtered between 0.5-100 Hz and a notch filter of 50 Hz was enabled. The sampling rate was set as 250 Hz. The 25 EEG channels around the motor cortex were selected for analysis and they are: F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, CZ, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4 and P8. EEG data were taken from three subjects. For each subject, four sets of EEG were recorded each of 120 trials, consisting of 60 left and 60 right hand movement imaginations after learning the calibration model. During data collection, the subject was sitting in a comfortable armchair 150 cm in front of a computer monitor and was instructed not to move, to keep both arms and hands relaxed. The timing protocols for calibration and evaluation are shown in Fig. 5.6(a) and 5.6(b) respectively. As shown in Fig. 5.6(a), the experiment started with a display of fixation cross that was shown in the center of the monitor. After 2 sec, a warning stimulus was given in the form of a beep. From 3 to 4.5 sec, an arrow pointing left or right was shown on the monitor. The subject was instructed to imagine a left or right hand movement for 5 sec, depending on the direction of the arrow. Each trial was followed by a short break of at least 1.5 sec.

Using the calibration session a subject-specific model is learnt for each subject as explained in 5.1.1. This model was used to evaluate new EEG signals recorded in the online sessions. For the evaluation session, the subject was instructed to imagine left or right hand movement according to the cue displayed. As given in Fig. 5.6(b), the subject performed motor imagery between 3 and 8 sec depending on the cue. Between 8 sec and 9 sec, the EEG was classified online and the classification result was translated into a feed back stimulus in the form of a horizontal bar that appeared in the center of the monitor. If the person imagined a left hand movement, then the bar varying in length would extend to the left as shown in Fig. 5.6(b). In the given Fig. 5.6(b), the horizontal bars are shown towards left and right for left hand and right hand motor imagery respectively assuming correct classifications. The length of this feedback bar depends on the confidence score of classification of the corresponding task. The time interval between 2 trials was 1.5 sec. The online experiments with feedback were conducted on three different days for all the subjects. Accordingly the experiments were divided into three sessions. The part of the whole online experiments conducted in one single day is referred by the word “session”. In each session, adaptive and static evaluations of EEG signals have been performed separately. The details are as follows:

Session-1 experiments

The first online evaluation session was conducted on the same day as of calibration for each subject. After developing a subject-specific model according to the procedure explained in 5.1.1, the new trials were processed with and without incorporating spectral updates over time. In the session-1, the first set of 120 motor imagery trials (including sixty left and right hand trials) was processed and classified online using the calibration model parameters (using SWSSP). The next set of 120 motor imagery trials was evaluated by the adaptive algorithm, addressing the spectral non-stationarity over time (using AWSSP_{sup}). In AWSSP_{sup}, the first forty motor imagery tasks are processed using the calibrated model parameters itself and the following EEG samples in the evaluation session are evaluated by employing the filtering and classifier updates based on the procedure explained in Section 5.1.2.

Session-2 experiments

The second stage of experiments or session-2 was done around five weeks after the session-1 experiments. In session-2, the adaptive and non-adaptive evaluations of motor imagery trials were done using $AWSSP_{sup}$ and $SWSSP$ algorithms respectively. In order to assess the effect of subject-adaptation along with the system adaptation, the adaptive evaluation was done before the non-adaptive, in session-2. The experiments in session-2 were done under the same experimental setup as that of session-1 for each subject. The results of the experiments are discussed in Section 5.3.2.

Session-3 experiments

Both the static and adaptive evaluations in session-1 and session-2 were performed with feedback only. The study in [5] reports that the relevant frequency bands can change due to the visual feedback as the subject may try to optimize his or her strategy with feedback, leading to changes in EEG patterns. Therefore, one more online experiment session (session-3) had also been performed in order to investigate the effect of feedback on the variation of DFC. In this session, experiments were conducted with and without feedback using static and adaptive evaluation techniques. The specific aim of this session was to study the effect of feedback on the variation of DDW values of frequency components. At first, the subject was presented with a set of 120 motor imagery trials (60 left and 60 right) without providing feedback and then, another set of 120 trials along with feedback. The signals were processed and classified using the adaptive scheme. And finally, one more set of 120 trials were recorded with feedback, and classified using static scheme. During the experiment, the deviation in DW values have been computed for every new bunch of 30 single trial motor imagery EEGs according to eqn. (5.4), compared to the DW values obtained during calibration phase. This has been done for all the EEG recorded in session-3 and the experimental results are provided in Section 5.3.

(a) Variation of classification accuracy vs. threshold in DDW

(b) Variation of number of updates done vs. threshold in DDW.

Figure 5.7: Effect of threshold chosen on the performance of $\text{AWSSP}_{\text{sup}}$.

5.3 Results and discussions

5.3.1 Results of BCI Competition IV dataset IIb

Among the 5 sessions available in the Competition dataset, session-1 is used for calibration and other 4 sessions are taken for evaluation. After performing the calibration, sessions 2, 3, 4 and 5 are evaluated using SWSSP and AWSSP methods respectively. The updating process in $\text{AWSSP}_{\text{unsup}}$ and $\text{AWSSP}_{\text{sup}}$ are the same except the $\text{AWSSP}_{\text{unsup}}$ makes use of the predicted class labels whereas $\text{AWSSP}_{\text{sup}}$ uses true labels for updates. In order to study the effect of threshold value set for DDW on the classification performance of motor imagery tasks by $\text{AWSSP}_{\text{sup}}$, the classification accuracies of the algorithm are noted for various values of threshold. Fig. 5.7(a) shows the average percentage accuracy of classification for 9 subjects in the four evaluation sessions with the threshold value. In order to find the threshold setting that gives good performance with less number of updates, its value is varied from 0% to 70%. The threshold refers to the minimum value of percentage DDW allowed in the DDW values of existing frequency components. The equation (5.4) is used to compute the percentage DDW values. If percentage DDW is greater than the threshold, the bandpass filters and classifier are updated. Obviously, as the threshold value decreases, the number of updates done will increase. Fig. 5.7(b) shows the number of updates over 4

Table 5.2: Average classification accuracy in 9 subjects over 4 sessions with channel used for band selection.

Channel	C3	Cz	C4	C3,Cz and C4
Average accuracy	71.29%	69.25%	74.30%	68%

evaluation sessions per subject for various threshold values. From the analysis, the value of threshold is fixed at 30% for all the subjects in the analysis. In addition, the classification accuracies for various channel selection possibilities are also verified to find the optimal channel for band selection process. The average classification accuracies in the dataset using AWSSP_{sup} are presented in Table 5.2. As the classification accuracy obtained for C4 is better than that of other channels, we fixed C4 as the band selection channel.

Fig. 5.8(a) shows the average accuracy over four sessions for all the 9 subjects. The results show that the proposed AWSSP_{sup} method performs better than SWSSP in most of the subjects. On average, the AWSSP_{sup} method outperforms SWSSP by error rate reduction of 11.05%. Also the unsupervised testing AWSSP_{unsup} gives an error rate reduction of 6.2% compared to SWSSP. The AWSSP_{sup} outperforms SWSSP because the former tracks the variations of informative frequency components over time. Making use of the true labels, AWSSP_{sup} performs better than AWSSP_{unsup} which depends on the predicted class labels only. The classification performances using the proposed algorithms SWSSP, AWSSP_{sup} and AWSSP_{unsup} and the FBCSP [119] are presented in Fig. 5.8(b). Fig. 5.8(b) shows the average classification accuracies and standard deviation over nine subjects in four evaluation sessions. It is found that on average, the proposed AWSSP_{sup} method outperforms all the other methods listed here.

The computational complexities of the adaptive (AWSSP) and non-adaptive (SWSSP) algorithms are analyzed and the computational overhead in AWSSP is estimated. Let the incoming EEG task be $\mathbf{E}$ of order $C \times T$, (C and T are the number of channels and the number of samples respectively), N_B = number of bands selected by the band selection process and N_{tap} = number of taps in the FIR filter designed using CD technique. In the proposed evaluation process of SWSSP, the features are extracted from the bandpass filtered EEG and given to the classifier. The bandpass filters, CSP matrix and classifier are the same as those developed during calibration. Since C channels have to be filtered using N_B bands, the complexity for bandpass filtering has the order of $\mathbf{O}(\mathbf{CN}_B)$. And CSP feature extraction involves the covariance estimation of EEG signals with dimension $C \times$

T , eigen value decomposition of covariance matrix ($C \times C$) and projection of EEG using CSP transformation matrix of dimension ($C \times C$). Its complexity has the order of $\mathbf{O}(C)$. The complexity of classifier depends on the number of features. Since CSP features are extracted from N_B bands, the number of features depends on N_B .

(a) In 9 subjects

(b) In 5 sessions

Figure 5.8: Comparison of classification accuracies using SWSSP, AWSSP and FBCSP.

In AWSSP, bandpass filters have to be reconfigured based on the PSD estimation and DW computation of new EEG trials in the evaluation phase. Also, the classifier has to be retrained. Thus, in $\text{AWSSP}_{\text{sup}}$, the approximate computational overhead lies in (i) the estimation of PSD for each trial using 256-point FFT (since an N -point FFT requires $\frac{N}{2} \log_2 N$ complex multiplications and $N \log_2 N$ complex additions, this stage requires 1024 complex multiplications and 2048 complex additions per each trial), (ii) calculation of the DW values from the power spectral density of previous 40 tasks and comparison with the threshold (25810 multiplications and 49200 additions), (iii) band decision from DW values (2200 multiplications and 1860 additions), (iv) filter design and filtering (in the $\mathbf{O}(\text{CN}_B \cdot \text{N}_B \cdot \text{N}_{\text{tap}})$) and (v) finally retraining the classifier using features from previous 40 tasks. The complexity of filter design and filtering (if the percentage DDW is greater than

threshold in the evaluation phase of AWSSP) depends on the selection of N_B frequency bands to be estimated from DW values, design of corresponding N_B filters with order N_{tap} and filtering of C channels in N_B bands.

The sensitivity and specificity are also estimated in order to measure the classification performance of AWSSP_{sup}. Sensitivity and specificity are statistical measures of the performance of a binary classification test. Sensitivity (also called recall rate in some fields) measures the proportion of actual positives which are correctly identified as such (e.g. the percentage of left tasks those are correctly identified). Specificity measures the proportion of negatives which are correctly identified (e.g. the percentage of right imagery tasks those are correctly identified). A theoretical, optimal prediction can achieve 100% sensitivity (i.e. predict all left tasks from its group as left) and 100% specificity (i.e. not predict any task from the right group as left). A two-class classifier can have four outcomes: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The sensitivity and specificity measures are computed as [149]:

$$Sensitivity = \frac{TP}{TP + FN} \quad (5.5)$$

$$Specificity = \frac{TN}{TN + FP} \quad (5.6)$$

The average sensitivity and specificity of classifier outcomes of nine subjects in four evaluation sessions of BCI Competition dataset IIb is computed and plotted in Fig. 5.9. The average values of sensitivity and specificity measures over nine subjects are 0.72 and 0.75 respectively.

In order to estimate the discriminative frequency bands during motor imagery for BCI, a DFBCSP has been presented in Chapter 3 and a subject-adaptive method based on time-frequency Fisher ratio pattern in Chapter 4. In DFBCSP, the discriminative filter bank is developed by filtering the EEG from C4 using a parent filter bank consisting of twelve FIR filters, each of 4 Hz bandwidth in the range of 6-40 Hz. The Fisher ratio values calculated using the power spectral density estimated at each filter output form the basis for locating the subject-specific filter. Then, the selected four bands are used for processing the whole channel EEG signal. In the analysis, it is found that AWSSP_{sup} and AWSSP_{unsup} offer error rate reductions of around 11% and 5% respectively over DFBCSP in the BCI Competition IV dataset IIb. Eventhough AWSSP_{sup} is significantly better than DFBCSP, more robust

Figure 5.9: Average sensitivity and specificity measures of nine subjects in BCI Competition IV dataset IIb using AWSSP_{sup} algorithm.

techniques have to be developed to obtain significant performance improvement using the unsupervised method, AWSSP_{usup}.

5.3.2 Results of online data

In the online study, the thresholds in DDW and EEG channel selected for band selection are consistent with those used in the offline evaluation also. The threshold in DDW is kept as 30% and the bands are estimated from EEG channel C4.

Results of session-1 and session-2

Three subjects named as *SG*, *SM* and *SS* respectively participated in the online experiments. The subject-specific model learnt from the calibration session evaluates the EEG signals recorded in the online sessions, with and without adaptation. The classification accuracies of all the 120 trials in each online session are tabulated in Table 5.3. The session-1 and session-2 in Table 5.3 represent the experiments done on two different days, separated by around five weeks. In both sessions, 120 motor imagery trials have been evaluated adaptively as well as 120 trials non-adaptively, using AWSSP_{sup} and SWSSP respectively. In session-1 and session-2, the adaptive evaluation of all the three subjects provide higher classification accuracies than using a static method. In session-2, the adaptive evaluation offers an average accuracy of 86.11% whereas it is 80.11% without adaptation, even though

Table 5.3: Classification accuracy of online experiments

Session	Session-1		Session-2	
Subject	Static	Adaptive	Static	Adaptive
<i>SG</i>	85.83%	92.50%	84.51%	87.50%
<i>SM</i>	84.17%	87.50%	81.66%	88.33%
<i>SS</i>	79.17%	86.67%	74.17%	82.50%
Average	83.05%	88.90%	80.11%	86.11%

Table 5.4: Details of the online updates in subject SM in session-1

Index of trial	DDW	Updated bands	Processing time
40	38.50%	15-19 Hz and 10-14 Hz	250 ms
55	31.86%	10-17 Hz and 28-34 Hz	271 ms
74	32.00%	7-14 Hz and 16-20 Hz	248 ms
114	32.00%	9-13 Hz and 15-20 Hz	237 ms

the session-2 was done five weeks after the subject-specific model development. As the calibration and session-1 experiments were done on the same day, the results of static method in session-1 is better than that of session-2.

It is observed that the adaptive method consistently shows improvement in all the subjects. This shows the effectiveness of adaptive tracking of the spectrum variations over time, by the proposed method. For the adaptive method $AWSSP_{sup}$, as mentioned in Section 5.1.2, until 40th trial, the signals are processed using the calibrated model and DW values are re-computed after 40th trial. Then, the filtering and classifier updates are done based on the DDW values computed according to equation (5.6). Whenever the DDW is greater than 30%, the bandpass filters and the classifier model are updated. Comparing the performances of all subjects, the $AWSSP_{sup}$ method provides an average error rate reduction of 32.13% over $SWSSP$. The error rate reduction is computed according to the equation (3.14) provided in Chapter 3.

During calibration for subject *SM*, 9-15 Hz and 20-24 Hz were selected as the two discriminative frequency bands. When new samples were received, four updates were done in the adaptive evaluation of session-1 to track the variations of the signal and the details are shown in Table 5.4. The time taken for displaying the feedback by the algorithm after receiving the input EEG is also provided to show the feasibility of the proposed method in real time applications. The processing time mentioned in Table 5.4 is using an Intel(r)Xeon(R)

Table 5.5: Details of the online updates in subject SG in session-1

Index of trial	DDW	Updated bands	Processing time
40	59.35%	13-17 Hz and 19-25 Hz	280 ms
60	31.45%	10-17 Hz and 22-29 Hz	271 ms
84	31.03%	20-27 Hz and 9-15 Hz	242 ms
112	31.15%	8-12 Hz and 16-21 Hz	236 ms

Table 5.6: Details of the online updates in subject SS in session-1

Index of trial	DDW	Updated bands	Processing time
40	37.10%	9-12 Hz and 31-37 Hz	278 ms
85	63.03%	10-13 Hz and 15-18 Hz	264 ms
100	30.83%	9-13 Hz and 17-23 Hz	270 ms

Table 5.7: Details of the online updates in subject SM in session-2

Index of trial	DDW	Updated bands	Processing time
40	46.18%	15-20 Hz and 7-13 Hz	260 ms
61	31.86%	8-14 Hz and 16-23 Hz	256 ms
98	32.21%	9-14 Hz and 18-24 Hz	236 ms
113	30.80%	9-13 Hz and 14-21 Hz	253 ms

Table 5.8: Details of the online updates in subject SG in session-2

Index of trial	DDW	Updated bands	Processing time
40	55.38%	15-21 Hz and 9-16 Hz	265 ms
62	33.97%	9-13 Hz and 18-24 Hz	250 ms
78	32.10%	20-27 Hz and 7-12 Hz	236 ms
99	34.70%	9-14 Hz and 19-25 Hz	236 ms

Table 5.9: Details of the online updates in subject SS in session-2

Index of trial	DDW	Updated bands	Processing time
40	51.17%	9-13 Hz and 14-18 Hz	265 ms
59	31.40%	10-13 Hz and 37-40 Hz	240 ms
68	35.43%	10-13 Hz and 28-33 Hz	245 ms
98	33.17%	10-13 Hz and 6-10 Hz	254 ms

2.00 GHz processor of 3.25 GB RAM. In the session-2 of subject *SM*, the adaptation of frequency bands offers an accuracy of 88.33% whereas it is 81.66% using the static method. The online updates done for other two subjects *SG* and *SS* in session-1 are shown in Tables 5.5 and 5.6. The online updates for session-2 in subjects *SM*, *SG* and *SS* are provided in Tables 5.7, 5.8 and 5.9 respectively.

Considering the performance of all the three subjects, the average time for processing a single trial with and without updates are 250 ms and 110 ms respectively. However, the online updates are found to be effective in improving the classification accuracies. The statistical analysis of the classification accuracies obtained in the four evaluation sessions of the BCI Competition dataset using $AWSSP_{unsup}$ and $SWSSP$ gives a two tailed p value of 0.002 in a paired t-test. In a statistical t-test, if the p value is less than 0.05, the considered values are significantly different. Therefore, this test implies that the classification accuracy offered by proposed $AWSSP_{sup}$ is significantly better than $SWSSP$. Also, comparing the online adaptive and non-adaptive evaluation results of the subjects *SG*, *SM* and *SS* in two sessions, a paired t-test provides a p value of 0.03. The online and offline results reflect the significant performance improvement by the adaptive method over the static, and emphasize the importance of tracking the non-stationary EEG spectral components in real time BCI applications based on motor imagery.

During the online experiments, it is found that the additional time taken for processing a single trial by the adaptive method over the non-adaptive method is around 140 ms only using an Intel(r)Xeon(R) 2.00 GHz processor. The overall time for processing a single trial with updates in the proposed adaptive evaluation method is only 250 ms.

Results of session-3: Effect of feedback on DDW

The study on the effect of feedback on variation of DFC is performed by computing the DDW values for every new bunch of 30 motor imagery trials received in each EEG recording. After estimating DW values for every bunch, the DDW of these DW values compared to the subject-specific DW values obtained during calibration are estimated. Hence percentage DDW values are estimated at trials 30, 60, 90 and 120. This computation is repeated for all the three subjects in EEG recordings with and without feedback. Fig. 5.10 shows the percentage DDW values for subjects *SG*, *SM* and *SS* with and without feedback for EEG

signals evaluated by adaptive method. It is observed from the figure that the deviation of DDW values in EEG is higher in all subjects with feedback compared to the signals without feedback.

Figure 5.10: Percentage DDW values for subjects SG, SM and SS with and without feedback.

In order to present the variation of DDW with feedback, the average values of percentage DDW values for all subjects are computed and plotted. Fig. 5.11 and 5.12 represent the average percentage DDW values for EEG recordings with and without feedback for EEG for all the three subjects in session-3, in the adaptive and static recordings respectively.

Comparing the percentage DDW values with and without feedback given in Fig. 5.11 and Fig. 5.12, the percentage increase in average percentage DDW values over three subjects with feedback is found to be 21.88% and 12.80% in adaptive and static methods respectively. This study clearly shows that visual feedback in online experiments make subject optimize his or her strategy of thinking and results in an increased percentage DDW. As the presence of feedback influences the variation of DFC, the adaptation of these informative frequency components becomes essential in BCI experiments with feedback.

From the online and offline experimental analysis, it is observed that the classification accuracies can be improved by updating the discriminative frequency components and bandpass

Figure 5.11: For adaptive evaluation.

Figure 5.12: For static evaluation.

filters adaptively over time. During calibration, three calibration model parameters are developed that comprises the discriminative bands, CSP projection Matrix W or (spatial filter) and classifier model. The same classifier hyperplane and CSP matrix are applied throughout the evaluation sessions in the SWSSP. The frequency bands and the classifier are updated in AWSSP.

The experimental results emphasize the fact that discriminative bands play a significant role in BCI system even though the weights of channels obtained by the CSP matrix are kept fixed all throughout the analysis. Also for real time applications, filter design using CD approach can reconfigure the frequency bands at a reduced computational complexity.

5.4 Conclusion

In a motor imagery based BCI system, the ERD/ERS patterns have been successfully used to provide a direct control pathway from brain to computer. These ERD/ERS patterns occur in subject-specific frequency bands and found to be unstable over time. Therefore, during the discrimination of various motor imagery tasks in BCI systems, the selection of relevant frequency components is important. Even though the variability of these discriminative frequency components between subjects is discussed in literature, their variation over time is hardly addressed.

This chapter proposed a new adaptive method named as Adaptively Weighted Spectral-Spatial Patterns (AWSSP) in order to track the variations of subject-specific discriminative bands over time. This is carried out by updating the varying Discriminative Weight (DW) values of frequency components. The DW values are computed from Fisher ratio analysis of the brain signal recorded from EEG channel C4. In the proposed system, the subject-specific model parameters including discriminative frequency components, CSP projection matrix and classifier model are developed during calibration. When new samples are received in evaluation sessions, AWSSP addressed the variations in DW values of frequency components either by supervised or unsupervised updating strategies.

The improvement in classification accuracy offered by the proposed AWSSP is promising. By conducting offline and online experiments, the importance of addressing the spectral non-stationarities in EEG signal during motor imagery tasks is highlighted. The study on the effect of visual feedback on the DW values of frequency components also emphasizes the requirement of updating the discriminative frequency components over time. Further work is needed to optimize the unsupervised adaptation techniques. New methods that can adapt to the changing EEG environments more effectively should also be explored in future.

Chapter 6

Conclusions and future work

In this chapter, the conclusions of the works done and some possible directions of future work are provided.

6.1 Conclusions

During the mental process by which an individual rehearses or simulates a motor movement or motor imagery, *mu* and *beta* bands of EEG signals display an attenuation close to the contralateral primary motor areas and enhancement of similar frequency components in the ipsilateral hemisphere termed as ERD/ERS patterns. These patterns are suitable strategies to develop communication between brain and computer for paralyzed patients as they are generated within working memory of the brain without any real movements.

It is reported that the effects of ERD/ERS on EEG recordings are not reflected to the same degree in all frequency bands. In general, the *mu* rhythm has a frequency band 8-12 Hz and the *beta* rhythm has 13-30 Hz. But these frequency bands can vary with subjects and mental states of the subject. As the ERD/ERS occur in subject-specific frequency bands, the selection of relevant frequency bands is significant in the extraction of ERD/ERS features.

In this thesis, the significance of frequency optimization for discriminating different classes

of motor imagery in BCI is investigated and three new approaches are proposed. All the three methods use the Common Spatial Pattern (CSP) technique for feature extraction and different methods for bandpass filter selection before CSP processing.

The first method, “Discriminative Filter bank Common Spatial Pattern” (DFBCSP) algorithm determined the subject-specific discriminative filter bank for each subject by filtering EEG signals from channels C3 and C4. These sensorimotor cortex channels provide most relevant information for discriminating various motor imagery patterns. In DFBCSP, a parent filter bank filters EEG from C3 or C4. The filter bank is designed using a low complexity FIR filter design method dubbed as Coefficient Decimation technique. After filtering, the Fisher ratio values from filter outputs are computed to estimate the discriminative capability of each bandpass filter. Four filters providing highest Fisher ratio values are selected from the parent filter bank and this subset serve as Discriminative Filter Bank (DFB). Then, EEG from all channels is filtered using DFB and CSP features are extracted. These features are given as inputs to a classifier to predict the type of imagery being performed. As presented in Chapter 3, the classification accuracy of DFBCSP algorithm is slightly better than the existing filter bank based method “Filter bank Common Spatial Pattern” (FBCSP).

The subject-specific filter selection in DFBCSP required filtering the EEG by the 12 bandpass filters in parent filter bank. In order to avoid this multi-band filtering, a time-frequency method of band selection is proposed in Chapter 4. The time-frequency Fisher ratio pattern is obtained from the power spectral density estimates of motor imagery patterns. Then, the most discriminative frequency bands are selected from the Fisher ratio pattern by employing an automatic band selection algorithm. This algorithm searches and finds out the informative bands which are then used for filter design. The coefficient decimation technique allowed to generate variable bandwidth and center frequency filter responses from a single set of filter coefficients. After bandpass filtering the whole channel EEG signals, the CSP features were extracted and classified. Exploiting this band selection method, discriminative frequency bands over five sessions of EEG available in the BCI Competition IV dataset IIb are estimated. It is found that the discriminative bands vary over time for most of the subjects. In order to tackle this spectral variability, two BCI approaches named as Static Spectral features (SSF) method and Variable Spectral Features (VSF) method are proposed. After learning the subject-specific calibration model, SSF method evaluates new EEG trials using fixed frequency bands and VSF method with updated frequency bands.

VSF method addressed the spectral variability of ERD/ERS over time employing timely frequency updates and provides better results than SSF, which demonstrates the necessity of tracking the spectral variability in EEG during motor imagery.

In the time-frequency Fisher ratio pattern method employed in SSF and VSF approaches, the discriminative frequency information was carried by two domains. Therefore, in order to effectively track the variations in frequency components representing ERD/ERS patterns, a discriminative weight value from Fisher ratio pattern is computed which carries the discrete discriminative capability of frequency bands. The “Adaptively weighted Spectral-Spatial Pattern” (AWSSP) algorithm presented in Chapter 5 selected the discriminative frequency bands based on the discriminative weights of frequency components. This weight information is the basis for frequency updates in the system and the deviation in the discriminative weights are tracked by the AWSSP algorithm. Whenever this deviation is greater than a particular threshold, frequency bands are re-estimated using the previous trials and classifier model is retrained. The AWSSP algorithm is evaluated using BCI Competition IV dataset IIb and online dataset. Both these datasets have two classes of motor imagery: left hand and right hand. In the online and offline evaluation of motor imagery patterns in various subjects, adaptive tracking of discriminative frequency bands using AWSSP offered significantly better classification accuracies than static method which employs fixed bands.

6.2 Directions of future work

The work done in this thesis investigated the significance of discriminative frequency bands in motor imagery based BCI and aimed towards improving the performance of BCI in terms of classification accuracy of motor imagery trials. In future, it would be worth to focus on simple and effective novel frequency band selection techniques which can improve not only the accuracy but also the speed of the BCI operation. The ultimate aim of BCI is to help paralyzed people to communicate in a fast and accurate way to the external world, without the use of peripheral nerves and muscles. Therefore, in future the proposed methods have to be evaluated in the rehabilitation of stroke patients.

The possible future works can be summarized as follows:

- The band selection algorithms using time-frequency Fisher ratio pattern and Dis-

criminative Weight values require a minimum number of (around 40) left hand or right hand motor imagery trials to accurately estimate the discriminative frequency components. In future, more robust techniques which can compute the informative bands more effectively from a smaller number of trials have to be explored. From the experimental analysis, it is found that the vertex channel Cz also provides some information to discriminate left hand right hand motor imagery patterns. The degree of discriminative information content in different spatial location varies from subject to subject. Therefore, the study can be extended with more number of subjects and automatic selection of best subject-specific discriminative channels can be analyzed. The variation of discriminative capability of different channels over time are also to be explored. During the imagination of a unilateral motor movement, ERS occurs in the ipsilateral hemisphere of the brain, while the ERD effect occurs in the contralateral hemisphere. ERS is due to the firing of neurons in the synchronized manner whereas ERD causes them to fire in de-synchronized manner. EEG is never fully a deterministic signal. It is non-stationary in time, frequency and spatial domain. Along with the frequency optimization, new methods have to be explored to decide the subject-specific reactive time segment. Incorporating these non-stationarities from multiple domains, the overall BCI performance can be improved.

- The experiments and analysis done in this study was using EEG patterns from only two classes of motor imagery. In future, EEG signals from multi-class motor imagery have to be analyzed. Along with extending the proposed methods to multi-class paradigms, new methods have to be proposed to handle their frequency optimization issues.
- The adaptive method proposed in this thesis addresses only the variability of temporal filter. The classifier is retrained whenever the frequency bands are updated, but the spatial filter was fixed. A real time robust BCI system should be able to track the time, frequency and spatial domain non-stationarities of EEG signal adaptively. Therefore, adapting the spatial filter and classifier model along with temporal filter would offer a better BCI. In addition, the BCI operation depends on effective interaction between the 2 adaptive controllers; the user's brain and the system itself. The co-adaptation (BCI adapting to the subject, while the subject adapts to the BCI) is important to optimize the performance of a BCI. Also, the current study used only supervised adaptation technique in the online experiments. Unsupervised adaptation techniques

have to be explored in future.

- The investigations presented in this thesis were done using EEG from healthy subjects. The ultimate aim of a BCI is to bridge the gap between brain and computer in paralyzed patients. In future, it would be worth extend the study to analyze the motor imagery patterns of stroke patients. In a preliminary study of 40 stroke patients, the subjects were able to control the movement of a robotic arm by the mental imagination of disabled hand. It would be meaningful to work towards the enhancement of rehabilitation process, employing the existing and novel techniques in real time BCI applications.

Bibliography

- [1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, pp. 767-791, June 2002.
- [2] J. R. Wolpaw, D. J. McFarland and T. M. Vaughan, "Brain-computer interface research at the Wadsworth Center," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 222-226, 2000.
- [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, no. 2, pp. 164-173, June 2000.
- [4] B. Blankertz, G. Dornhege, Mathias Krauledat, K. R. Muller and G. Curio, "The non-invasive Berlin Brain-Computer interface: Fast acquisition of effective performance in untrained subjects," *NeuroImage*, vol. 37, pp. 539-550, 2007.
- [5] C. Neuper, G. R. Muller, A. Kubler, N. Birbaumer and G. Pfurtscheller, "Clinical application of an EEG-based Brain-computer interface: a case study in a patient with severe motor impairment," *Clinical Neurophysiology*, vol. 114, pp. 399-409, 2003.
- [6] G. E. Fabiani, D. J. McFarland, J. R. Wolpaw and G. Pfurtscheller, "Conversion of EEG activity into cursor movement by a Brain-computer interface (BCI)," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 12, pp. 331-338, 2004.
- [7] T. Ebrahimi, J. M. Vesin and G. Garcia, "Brain-computer interface in multimedia communication," *IEEE Signal Processing Magazine*, vol. 20, issue 1, pp. 14-24, January 2003.
- [8] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kubler, J. Perelmouter, E. Taub and H. Flor, "A spelling device for the paralysed," *Nature*, vol. 398, pp. 297-298, 1999.
- [9] J. R. Wolpaw, G. E. Loeb, B. Z. Allison, E. Donchin, O. F. do Nascimento, W. J. Heetderks, F. Nijboer, W. G. Shain and J. N. Turner, "BCI meeting 2005-workshop on signals and recording methods," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, pp. 138-141, 2006.
- [10] M. A. Lebedev and M. A. L. Nicolelis, "Brain-machine interfaces: past, present and future," *Trends in Neurosciences*, vol. 29, issue 9, pp. 536-546, 2006.

- [11] L. R. Hochberg, M. D. Serruya, G. M. Friehs, J. A. Mukand, M. Saleh, A. H. Caplan, A. Branner, D. Chen, R. D. Penn and J. P. Donoghue, "Neuronal ensemble control of prosthetic devices by a human with tetraplegia," *Nature*, vol. 442, pp. 164-171, 2006.
- [12] A. Schwartz, X. Cui, D. Weber and D. Moran, "Brain-controlled interfaces: Movement restoration with neural prosthetics," *Neuron*, vol. 52, pp. 205-220, 2006.
- [13] F. Lotte, "Study of Electroencephalographic Signal Processing and Classification Techniques towards the use of Brain-Computer Interfaces in Virtual Reality Applications," *PhD Thesis from the National Institute of Applied Sciences (INSA)*, Rennes, 2008.
- [14] J. Haynes and G. Rees, "Decoding mental states from brain activity in humans," *Nature Reviews Neuro-science*, vol. 7, pp. 523-534, 2006.
- [15] M. E. Phelps, "Emission computed tomography," *Seminars in Nuclear Medicine*, vol. 7, pp. 337-365, 1977.
- [16] R. Sitaram, A. Caria, R. Veit, K. Uludag, T. Gaber, A. Kubler and N. Birbaumer, "Functional magnetic resonance imaging based BCI for neuro-rehabilitation," *Proceedings of the 3rd International Brain-Computer Interface Workshop and Training Course*, pp. 104-106, 2006.
- [17] Editorial, "On the opposition of EEG and MEG," *Clinical Neurophysiology*, vol. 118, pp. 1658-1659, 2007.
- [18] T. N. Lal, T. Hinterberger, G. Widman, M. Schroder, N. J. Hill, W. Rosenstiel, C. E. Elger, B. Scholkopf and N. Birbaumer, "Methods towards invasive human brain-computer interfaces," In L. K. Saul, Y. Weiss and L. Bottou, editors *Advances in Neural Information Processing Systems*, vol. 17, pp. 737-744, 2005.
- [19] M. X. Huang, T. Song, D. J. Hagler, I. Podgorny, V. Jousmaki, L. Cui, K. Gaa, D. L. Harrington, A. M. Dale, R. R. Lee, J. Elman, and E. Halgren, "A novel integrated MEG and EEG analysis method for dipolar sources," *NeuroImage*, vol. 37, pp. 731-748, 2007.
- [20] N. Birbaumer, "Brain-computer-interface research: Coming of age," *Clinical Neurophysiology*, vol. 117, no. 3, pp. 479-83, 2006.
- [21] E. Niedermeyer and F. Lopes da Silva, "Electroencephalography: basic principles, clinical applications, and related fields," *Lippincott Williams and Wilkins*, ISBN-0781751268, 5th edition, 2004.
- [22] E. H. Chudler, "The functional divisions of the cerebral cortex," [http : //faculty.washington.edu/chudler/functional.html](http://faculty.washington.edu/chudler/functional.html), 2000.
- [23] H. H. Jasper, "The ten-twenty electrode system of the international federation," *Electroencephalography and Clinical Neurophysiology*, vol. 10, pp. 370-375, 1958.
- [24] H. Gray, "Anatomy of the Human Body," *Lea and Febiger*, Philadelphia, 1918.
- [25] "American electroencephalographic society: Guidelines for standard electrode position nomenclature," *Journal of Clinical Neurophysiology*, vol. 8, issue 2, pp. 200-202, 1991.

- [26] E. Niedermeyer and Lopes da Silva, "Electroencephalography," *Lippincott Williams and Wilkins*, Chapter 9, pp. 149-173, 1999.
- [27] D. Guido, J. Millan, T. Hinterberger, D. J. McFarland, K. R. Muller and J. S. Terrence, "Toward Brain-Computer Interfacing," *MIT Press*, pp. 14-55, Cambridge, MA, 2007.
- [28] N. Birbaumer, "Slow Cortical Potentials: their origin, Meaning and Clinical Use," *Brain and Behavior: Past, Present and Future*, Tilburg University press, pp. 25-39, van Boxtel GJM, Boecker KBE Editors, 1997.
- [29] E. Donchin, K. M. Spencer and R. Wijesinghe, "The mental prosthesis: Assessing the speed of a P300-based brain-computer interface," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, issue 2, pp. 174-179, June 2000.
- [30] L. Alexander, Mathias Keper and Helge J. Ritter, "An adaptive P300 based online Brain-Computer Interface," *IEEE Transactions on neural systems and Rehabilitation Engineering*, vol. 16, pp. 121-130, 2008.
- [31] X. R. Gao, D. Xu, M. Cheng and S. K. Gao, "A BCI-based environmental controller for the motion-disabled," *IEEE Transactions on neural systems and Rehabilitation Engineering*, vol. 11, no. 2, pp. 137-140, 2003.
- [32] Y. Wang, I. Gao, B. Hong, C. Jia and S. Gao, "Brain-Computer Interfaces Based on Visual Evoked Potentials," *Engineering in Medicine and Biology Magazine*, vol. 27, pp. 64-71, 2008.
- [33] M. Middendorf, G. McMillan, G. Calhoun and K. S. Jones, "Brain-computer interfaces based on steady-state visual evoked response," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 2, pp. 211-213, June 2000.
- [34] D. J. McFarland, L.A. Miner, T. M. Vaughan and J. R. Wolpaw, "Mu and beta rhythm topographies during motor imagery and actual movement," *Brain Topography*, vol. 3, pp. 177-186, 2000.
- [35] J. R. Wolpaw, D. J. McFarland, T. M. Vaughan and G. Schalk, "The wardsworth center brain-computer interface (BCI) research and development program," *IEEE Transactions on neural systems and Rehabilitation Engineering*, vol. 11, no. 2, pp. 204-207, June 2003.
- [36] G. Pfurtscheller and C. Neuper, "Motor Imagery activates primary sensorimotor area in humans," *Neuroscience Letters*, vol. 239, pp. 65-68, December 1997.
- [37] G. Pfurtscheller, C. Brunner, A. Schlogl 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, 2006.
- [38] H. H. Jasper and W. Penfield, "Electrocorticograms in man: effect of the voluntary movement upon the electrical activity of the precentral gyrus," *European Archives of Psychiatry and Clinical Neuroscience*, vol. 183, pp. 163-174, 1949.
- [39] G. Purfscheller and C. Neuper, "Motor imagery and direct Brain computer communication," *Invited paper in proceedings of IEEE*, vol. 89, pp. 1123-1134, July 2001.

- [40] F. H. Lopes da Silva, "Neural mechanisms underlying brain waves: from neural membranes to networks," *Electroencephalography and Clinical Neurophysiology*, vol. 79, pp. 81-93, 1991.
- [41] G. Pfurtscheller and F. H. Lopes da Silva, "Functional meaning of event-related desynchronization (ERD) and synchronization (ERS)," *Event-Related Desynchronization, Handbook of Electroencephalography and Clinical Neurophysiology*, G. Pfurtscheller and F. H. Lopes da Silva Editors., vol. 6, pp. 51-65, 1999.
- [42] G. Pfurtscheller and A. Aranibar, "Event-related cortical desynchronization detected by power measurements of scalp EEG," *Electroencephalography and Clinical Neurophysiology*, vol. 42, pp. 817-826, 1977.
- [43] C. Toro, G. Deuschl, R. Thatcher, S. Sato, C. Kufta and M. Hallett, "Event-related desynchronization and movement-related cortical potentials on the ECoG and EEG," *Electroencephalography and Clinical Neurophysiology*, vol. 93, pp. 380-389, 1994.
- [44] N. E. Crone, D. L. Miglioretti, B. Gordon, J. M. Sieracki, M. T. Wilson, S. Uematsu and R. P. Lesser, "Functional mapping of human sensorimotor cortex with electrocorticographic spectral analysis: Alpha and beta event-related desynchronization," *Brain*, vol. 121, pp. 2271-2299, 1998.
- [45] M. J. Jeannerod, "Mental imagery in the motor context," *Neuropsychologia*, vol. 33, no. 11, pp. 1419-1432, 1995.
- [46] J. Decety, D. Perani, M. Jeannerod, V. Bettinardi, B. Tadard, R. Woods, J. Mazziotta and F. Fazio, "Mapping motor representations with positron emission tomography," *Nature*, vol. 371, pp. 600-602, 1994.
- [47] M. Hallett, J. Fieldman, L. G. Cohen, N. Sadato and A. Pascual-Leone, "Involvement of primary motor cortex in motor imagery and mental practice," *Behavioural and Brain Science*, vol. 17, pp. 210, 1994.
- [48] R. Beisteiner, P. Hollinger, G. Lindinger, W. Lang and A. Berthoz, "Mental representations of movements, Brain potentials associated with imagination of hand movements," *Electroencephalography and Clinical Neurophysiology*, vol. 96, pp. 183-192, 1995.
- [49] W. Lang, D. Cheyne, P. Hollinger, W. Gerschlag and G. Lindinger, "Electric and magnetic fields of the brain accompanying internal simulation of movement," *Cognitive Brain Research*, vol. 3, pp. 125-129, 1996.
- [50] C. Neuper and G. Pfurtscheller, "Motor imagery and ERD," *Event-Related Desynchronization, Handbook of Electroencephalography and Clinical Neurophysiology, Revised series*, G. Pfurtscheller and F. H. L. da Silva, Editors. Amsterdam, The Netherlands: Elsevier, vol. 6, pp. 303-325, 1999.
- [51] G. Pfurtscheller, C. Neuper, C. Brunner and F. Lopes da Silva, "Beta rebound after different types of motor imagery in man," *Neuroscience letters*, vol. 378, pp. 156-159, 2005.

- [52] R. Krepki, “Brain-Computer Interfaces: Design and Implementation of an Online BCI System of the Control in Gaming Applications and Virtual Limbs,” *PhD thesis*, Technische Universitt Berlin, Fakultt IV Elektrotechnik und Informatik, 2004.
- [53] M. Krauledat, “Analysis of Nonstationarities in EEG Signals for Improving Brain-Computer Interface Performance,” *PhD thesis*, Technische Universitat Berlin, Fakultt IV – Elektrotechnik und Informatik, 2008.
- [54] K. Inow, D. Mori, K. Sugioka, G. Pfurtscheller and K. Kuaru, “Feature Extraction of EEG Signals During Right and Left Motor Imagery,” *SICE 2004 Annual Conference*, vol. 3, pp. 2183-2187, 2004.
- [55] D. Zhang, Y. Wang, X. Gao, B. Hong and S. Gao, “An algorithm for idle-state detection in motor imagery-based brain-computer interface,” *Computational Intelligence and Neuroscience*, vol. 1, pp. 5-15, 2007.
- [56] G. Pfurtscheller, C. Neuper, A. Schlogl and Klaus Lugger, “Separability of EEG Signals Recorded During Right and Left Motor Imagery using Adaptive Autoregressive Parameters,” *IEEE Transactions on Rehabilitation Engineering*, vol. 6, pp. 316-325, September 1998.
- [57] C. Neuper, Michael Wortz and G. Pfurtscheller, “ERD\ERS patterns reflecting sensorimotor activation and deactivation,” *Progress in Brain Research*, vol. 159, pp. 211-222, 2006.
- [58] G. Pfurtscheller and C. Neuper, “Future prospects of ERD\ERS in the context of brain-computer interface (BCI) developments,” *Progress in Brain Research*, vol. 159, pp. 433-437, 2006.
- [59] S. Zhou, J. Q. Han and S. Francisco, “Classifying mental tasks based on features of higher-order statistics from EEG signals in Brain-Computer interface,” *Information Sciences*, vol. 178, pp. 1629-1640, 2008.
- [60] O. Bai, P. Lin, D. Huang, D. Fei and M. K. Floeter, “Towards a user-friendly brain-computer interface: Initial tests in ALS and PLS patients,” *Clinical Neurophysiology*, vol. 121, issue 8, pp. 1293-1303, March 2010.
- [61] J. R. Wolpaw, D. J. McFarland, G. W. Neat and C. Forneris, “An EEG-based brain-computer interface for cursor control,” *Electroencephalography and Clinical Neurophysiology*, vol. 78, pp. 252-259, 1991.
- [62] D. J. McFarland, A. T. Lefkowitz and J. R. Wolpaw, “Design and operation of an EEG-based brain-computer interface with digital signal processing technology,” *Behavior Research Methods, Instruments and Computers*, vol. 29, no. 3, pp. 337-345, 1997.
- [63] J. R. Wolpaw, D. Flotzinger, G. Pfurtscheller and D. J. McFarland, “Timing of EEG-based cursor control,” *Journal of Clinical Neurophysiology*, vol. 14, no. 6, pp. 529-538, 1997.
- [64] J. Kalcher, D. Flotzinger, C. Neuper, S. Golly and G. Pfurtscheller, “Graz Brain-Computer Interface II: Toward communication between humans and computers based on online classification of three different EEG patterns,” *Medical and Biological Engineering and Computing*, vol. 34, pp. 382-388, 1996.

- [65] M. Pgegenzer and G. Pfurtscheller, "Frequency component selection for an EEG-based brain-computer interface (BCI)," *IEEE Transactions on Rehabilitation Engineering*, vol. 7, no. 4, pp. 413-419, 1999.
- [66] T. Kohonen, "The self-organizing map," *Proceedings of IEEE*, vol. 78, no. 9, pp. 1464-1480, 1990.
- [67] C. Guger, A. Schlogl, C. Neuper, D. Walterspacher, T. Strein and G. Pfurtscheller, "Rapid prototyping of an EEG-based brain-computer interface (BCI)," *IEEE Transactions on neural systems and Rehabilitation Engineering*, vol. 9, pp. 49-58, March 2001.
- [68] D. J. McFarland and J. R. Wolpaw, "EEG-based communication and control: speed-accuracy relationships," *Applied Psychophysiology and Biofeedback*, vol. 28, pp. 217-231, 2003.
- [69] D. J. McFarland, W. A. Sarnacki, T. M. Vaughan and J. R. Wolpaw, "Brain-computer interface (BCI) operation: Signal and noise during early training sessions," *Clinical Neurophysiology*, vol. 116, pp. 56-62, 2004.
- [70] J. R. Wolpaw and D. J. McFarland, "Control of a two-dimensional movement signal by a non-invasive brain-computer interface in humans," *Proceedings of National Academy of Sciences*, vol. 101, pp. 849-854, 2004.
- [71] D. J. McFarland and J. R. Wolpaw, "Sensorimotor rhythm-based Brain-computer interface (BCI): Feature selection by regression improves performance," *IEEE Transactions on neural systems and Rehabilitation Engineering*, vol. 13, pp. 372-379, 2005.
- [72] D. J. Krusienski, G. Schalk, D. J. McFarland and J. R. Wolpaw, "A mu-rhythm matched filter for continuous control of a brain-computer interface," *IEEE Transactions on Biomedical Engineering*, vol. 54, pp. 273-280, 2006.
- [73] D. J. McFarland, D. J. Krusienski, W. A. Sarnacki and J. R. Wolpaw, "Emulation of computer mouse control with a noninvasive brain-computer interface," *Journal of Neural Engineering*, vol. 5, pp. 101-110, 2008.
- [74] D. J. McFarland and J. R. Wolpaw, "Sensorimotor rhythm-based brain-computer interface (BCI): Model order selection for autoregressive spectral analysis," *Journal of Neural Engineering*, vol. 5, pp. 155-162, 2008.
- [75] O. Bai, P. Lin, S. Vorbach, M. K. Floeter, N. Hattori and M. Hallett, "A high performance sensorimotor beta rhythm-based braincomputer interface associated with human natural motor behavior," *Journal of Neural Engineering*, , vol. 5, 24, March 2008.
- [76] C. Neuper, G. R. Muller, A. Kubler, N. Birbaumer and G. Pfurtscheller, "Clinical application of an EEG-based brain-computer interface: a case study in a patient with severe motor impairment," *Clinical Neurophysiology*, vol. 114, pp. 399-409, 2003.
- [77] R. Scherer, G.R. Muller, C. Neuper, B. Graimann and G. Pfurtscheller, "An asynchronously controlled EEG-based virtual keyboard: improvement of the spelling rate," *IEEE Transactions on Biomedical Engineering*, vol. 51, pp. 979-984, 2004.

- [78] B. Blankertz, M. Krauledat, G. Dornhege, J. Williamson, R. Murray-Smith and K. R. Muller, "A note on brain actuated spelling with the Berlin Brain-Computer Interface," *In: C. Stephanidis(Ed.), Universal Access in HCI*, pp. 759-768, Part II, HCI 2007, vol. 4555 of LNCS, Springer, Berlin Heidelberg.
- [79] K. R. Muller and B. Blankertz, "Toward noninvasive brain-computer interfaces," *IEEE Signal Process Magazine*, vol. 23 pp. 125-128, September 2006.
- [80] F. Cincotti, D. Mattia, F. Aloise, S. Bufalari, G. Schalk, G. Oriolo, A. Cherubini, M. G. Marciani and F. Babiloni, "Non-invasive Brain-computer interface system: Towards its application as assistive technology," *Brain Research Bulletin*, vol. 75, pp. 796-803, 2008.
- [81] R. Leeb, D. Friedman, M. Slater and G. Pfurtscheller, "A tetraplegic patient controls a wheelchair in virtual reality," *In proceedings of BRAINPLAY 2007*, 2007.
- [82] J. del R. Millan, F. Renkens, J. Mourino and W. Gerstner, "Non-invasive brain actuated control of a mobile robot by human EEG," *IEEE Transactions on Biomedical Engineering*, vol. 51, pp. 1026-1033, June 2004.
- [83] C. Wang, K. S. Phua, K. K. Ang, C. Guan, H. Zhang, R. S. Lin, K. S. G. Chua and B. T. Ang, "A feasibility study of non-invasive motor-imagery BCI-based robotic rehabilitation for Stroke patients," *4th International IEEE Engineering in Medicine and Biology Society Conference on Neural Engineering*, pp. 271-274, May 2009.
- [84] K. K. Ang, C. Guan, K.S.G. Chua, B. T. Ang, C. Wee Keong Kuah, C. Wang, K. S. Phua, Z. Yang Chin and H. Zhang, "A clinical evaluation of non-invasive motor imagery-based brain computer interface in stroke," *30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 4178-4181, August 2008.
- [85] G. Pfurtscheller, C. Guger, G. R. Muller, G. Krausz and C. Neuper, "Brain oscillations control hand orthosis in a tetraplegic," *Neuroscience Letters*, vol. 292, pp. 211-214, 2000.
- [86] G. Pfurtscheller, G. R. Muller, G. Pfurtscheller, H. J. Gerner and R. Rupp, "Thought control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia," *Neuroscience letters*, vol. 351, pp. 33-36, 2003.
- [87] K. Qian, P. Nikolov, D. Huang, D. Y. Fei, X. Chen and O. Bai, "A motor imagery-based online interactive brain-controlled switch: Paradigm development and preliminary test," *Clinical Neurophysiology*, vol. 121, issue 8, pp. 1304-1313, March 2010.
- [88] G. R. Muller, R. Scherer, G. Pfurtscheller and Rupp R., "EEG-based neuroprosthesis control: a step towards clinical practice," *Neuroscience letters*, vol. 382, pp. 169-174, 2005.
- [89] J. J. Daly and J. R. Wolpaw, "Brain-computer interfaces in neurological rehabilitation," *The Lancet Neurology*, vol. 7, issue 11, pp. 1032-1043, November 2008.
- [90] Stefan Cososchi, Rodica Strungaru, Alexandru Ungureanu and Mihaela Ungureanu, "EEG Features Extraction for Motor Imagery," *Proceedings of the 28th IEEE EMBS Annual International Conference*, Aug 30-Sept 3, New York City, USA, 2006.

- [91] G. Pfurtscheller, C. Neuper, C. Guger, W. harken, H.Ramoser, A. Schlogl, B.Oberamaier and M. Pergenzer, "Current trends in Graz-Brain-Computer interface research," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 216-219, June 2000.
- [92] G. Pfurtscheller, C. Neuper, D. Flotzinger and M. Pergenzer, "EEG based discrimination between imagination of right and left hand movement," *Electroencephalography and Clinical Neurophysiology*, vol. 103, pp. 642-651, 1997.
- [93] A. Schlogl, D. Flotzinger and G. Pfurtscheller, "Adaptive autoregressive modeling used for single-trial EEG classification," *Biomedizinische Technik/Biomedical Engineering*, vol. 42, pp. 162-167, 1997.
- [94] D. J. McFarland, L. M. McCane, S. V. David and J. R. Wolpaw, "Spatial filter selection for EEG-based communication," *Electroencephalography and Clinical Neurophysiology*, vol. 103, pp. 386-394, 1997.
- [95] V. Carmen, N. Kramer, B. Blankertz and A. Schlogl, "Time Domain parameters as a feature for EEG-Based Brain-Computer Interface," *Neural networks*, vol. 22, pp. 1313-1319, 2009.
- [96] G. Townsend, B. Graimann and G. Pfurtscheller, "A Comparison of Common Spatial Patterns With Complex Band Power Features in a Four-Class BCI Experiment," *IEEE transactions on Biomedical Engineering*, vol. 53, pp. 642-651, April 2006.
- [97] S. Chiappa and S. Bengio, "HMM and IOHMM modeling of EEG rhythms for asynchronous BCI systems," *European Symposium on Artificial Neural Networks ESANN*, pp. 985-992, 2004.
- [98] J. R. Millan and J. Mourino, "Asynchronous BCI and local neural classifiers:an overview of the adaptive brain interface project," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, pp. 159-161, 2003.
- [99] R. Boostani and M. H. Moradi, "A new approach in the BCI research based on fractal dimension as feature and adaboost as classifier," *Journal of Neural Engineering*, vol. 1, issue 4, pp. 212-217, 2004.
- [100] T. Wang, J.Deng and B. He, "Classifying EEG-based motor imagery tasks by means of time-frequency synthesized spatial patterns," *Clinical Neurophysiology*, vol. 115, pp. 2744-53, 2004.
- [101] T. Wang and B. He, "An efficient rhythmic component expression and weighting synthesis strategy for classifying motor imagery EEG in a brain-computer interface," *Journal of Neural Engineering*, vol. 1, pp. 1-7, January 2004.
- [102] N. Yamawaki, C. Wilke, Z. Liu and B. He, "An enhanced time-frequency-spatial approach for motor imagery classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, issue 2, pp. 250-254, June 2006.
- [103] A. Vuckovic and F. Sepulveda, "Quantification and visualisation of differences between two motor tasks based on energy density maps for brain-computer interface applications," *Clinical Neurophysiology*, vol. 119, pp. 446-458, 2008.

- [104] D. Coyle, G. Prasad and T. M. McGinnity, "A Time-Frequency Approach to Feature Extraction for a Brain-Computer Interface with a Comparative Analysis of Performance Measures," *Journal on Applied Signal Processing*, vol. 19, pp. 3141-3151, 2005.
- [105] Y. B. Hua, Y. G. Zheng, Y. R. Guo and W. Ting, "Adaptive subject-based feature extraction in brain-computer interfaces using wavelet packet best basis decomposition," *Medical Engineering Physics*, vol. 29, pp. 48-53, 2007.
- [106] W. D. Penny, S. J. Roberts, E. A. Curran and M. J. Stokes, "EEG-based communication: a pattern recognition approach," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 214-215, 2000.
- [107] D. J. McFarland and J. R. Wolpaw, "Sensorimotor rhythm-based brain-computer interface (BCI): model order selection for autoregressive spectral analysis," *Journal of Neural Engineering*, vol. 5, pp. 155-162, 2008.
- [108] I. G. Ulera, M. K. Kiymikb, M. Akinc and A. Alkanb, "AR spectral analysis of EEG signals by using maximum likelihood estimation," *Computers in Biology and Medicine*, vol. 31, pp. 441-450, 2001.
- [109] A. Schlogl, F. Y. Lee, H. Bischof and G. Pfurtscheller, "Characterization of four class motor imagery EEG data for the BCI-competition 2005," *Journal of Neural Engineering*, vol. 2, issue 4, L14-L22, 2005.
- [110] Z. J. Koles, "The quantitative extraction and topographic mapping of the abnormal components in the clinical EEG," *Electroencephalography and clinical neurophysiology*, vol. 79, pp. 440-447, 1991.
- [111] J. Muller Gerking, G. Pfurtscheller and H. Flyvbjerg, "Designing optimal spatial filters for single-trial EEG classification in a movement task," *Electroencephalography and Clinical Neurophysiology*, vol. 110, issue 5, pp. 787-798, May 1999.
- [112] A. Eleanor Currana and J. Maria, "Learning to control brain activity: A review of the production and control of EEG components for driving brain-computer interface (BCI) systems," *Stoke, Brain and Cognition*, vol. 51, pp. 326-336, 2003.
- [113] H. Ramoser, J. Muller 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, December 2000.
- [114] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe and K. R. Muller, "Optimizing spatial filters for robust EEG single trial analysis," *IEEE Signal Processing Magazine*, vol. 25, pp. 41-56, 2008.
- [115] S. Lemm, B. Blankertz, G. Curio and K. R. Muller, "Spatio-spectral filters for improving the classification of single trial EEG," *IEEE transactions on Biomedical Engineering*, vol. 52, no. 9, pp. 1541-1548, 2005.
- [116] G. Dornhege, M. Krauledat, F. Losch, G. Curio and K. R. Muller, "Combined optimization of spatial and temporal filters for improving Brain-Computer interface," *IEEE Transactions on Biomedical Engineering*, vol. 53, pp. 2274-2281, 2006.

- [117] Q. Novi, C. Guan, T. H. Dat and P. Xue, "Subband common spatial pattern for brain-computer interface," *Proceedings of 3rd International Conference on neural Engineering of IEEE Engineering. in Medicine Biology Society (EMBS)*, pp. 204-207, May 2007.
- [118] W. Wu, X. Gao, B. Hong and S. Gao, "Classifying single-trial EEG during motor imagery by iterative spatio-spectral patterns learning (ISSPL)," *IEEE Transactions on Biomedical Engineering*, vol. 55, issue 6, pp. 1733-43, June 2008.
- [119] K. K. Ang, Z. Y. Chin, H. Zhang and C. Guan, "Filter bank common spatial pattern (FBCSP) in brain-computer interface," *Proceedings of IEEE International Joint Conference on Neural Networks*, pp. 2390-2397, June 2008.
- [120] M. Pregenzer, D. Flotzinger and G. Pfurtscheller, "Distinction sensitive learning vector quantization A noise insensitive classification method," *Proceedings of IEEE International Conference on Neural Networks ICNN-94*, pp. 2890-2894, Orlando, FL, 1994.
- [121] M. Pregenzer, "Distinction sensitive learning vector quantization," *Doctoral dissertation*, Univ. Technology, Graz, Austria, 1997.
- [122] G. Liua, G. Huang, J. Menga and X. Zhu, "A frequency-weighted method combined with Common Spatial Patterns for electroencephalogram classification in brain-computer interface," *Biomedical Signal Processing and Control*, vol. 5, issue 2, pp. 174-180, April 2010.
- [123] R. Tomioka, G. Dornhege, G. Nolte, B. Blankertz, K. Aihara and K.R. Muller, "Spectrally weighted common spatial pattern algorithm for single trial EEG classification," Dept. Math. Engineering, University Tokyo, Japan, Tech. Rep. 40, 2006.
- [124] G. Pfurtscheller and F. H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clinical Neurophysiology*, vol. 110, issue 11, pp. 1842-1857, November 1999.
- [125] B. Blankertz, M. Kawanabe, R. Tomioka, F. U. Hohlefeld, V. Nikulin and K.R. Muller, "Invariant Common Spatial Patterns: Alleviating Nonstationarities in Brain-Computer Interfacing," *Advances in Neural Information Processing Systems*, vol. 20, 2008.
- [126] A. G. Barwinska and J. Zygierecz, "A model of event-related EEG synchronization changes in beta and gamma frequency bands," *Journal of Theoretical Biology*, vol. 238, pp. 901-913, 2006.
- [127] G. Dornhege, B. Blankertz, M. Krauledat, F. Losch, G. Curio and K. R. Muller, "Optimizing spatio-temporal filters for improving Brain-Computer Interfacing," *Advances in Neural Inf. Proc. Systems (NIPS 05)*, vol. 18, pp. 315-322, 2006.
- [128] R. Leeb, F. Lee, C. Keinrath, R. Scherer, H. Bischof and G. Pfurtscheller, "Brain-computer communication: motivation, aim, and impact of exploring a virtual apartment," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 15, pp. 473-482, 2007.
- [129] D. Guido, B. Blankertz, G. Curio and K. R. Muller, "Boosting bit rates in non-invasive EEG single-trial classifications by feature combination and multi-class paradigms," *IEEE Transactions on Biomedical Engineering*, vol. 51, pp. 993-1002, June 2004.

- [130] B. Blankertz, K. R. Muller, D. Krusienski, G. Schalk, J. Wolpaw, A. Schloegl, G. Pfurtscheller, J. del R. Millan, M. Schroeder and N. Birbaumer, "The BCI competitionIII:Validating alternative approaches to actual BCI problems," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, pp. 153-159, 2006.
- [131] R. Mahesh and A. P. Vinod, "Coefficient-Decimation approach for realizing reconfigurable finite impulse response filters," *Proceedings of 2008 IEEE International Symposium on Circuits and Systems*, pp. 81-84, USA, May 2008.
- [132] R. Mahesh and A. P. Vinod, "Low complexity flexible filter banks for uniform and non-uniform channelization in software radios using coefficient decimation," *IET Circuits, Devices and Systems*, Accepted in June 2010.
- [133] S. Lu, C. Guan and H. Zhang, "Unsupervised Brain Computer Interface Based on inter subject Information and Online Adaptation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 17, pp. 135-144, 2009.
- [134] P. Xiaomei and Z. Chongxun, " Classification of left and right hand motor imagery tasks based on EEG frequency component selection," *The secondnd International Conference on Bioinformatics and Biomedical Engineering*, pp. 1888 - 1891, 2008.
- [135] B. D. Ripley, Pattern Recognition and Neural Networks. Cambridge, U.K.: Cambridge Univ. Press, 1996.
- [136] Th. Mulder, J.B.H. Hochstenbach, M.J.G. van Heuvelen and A.R. den Otter, " Motor imagery: The relation between age and imagery capacity," *Human Movement Science*, vol. 26, pp. 203-211, 2007.
- [137] A. Kubler, B. Kotchoubey, K. Kaiser, J. R. Wolpaw and N. Birbaumer, " Brain-computer communication, unlocking the locked in," *Psychological Bulletin*, vol. 127, pp. 358-375, 2001.
- [138] P. Z. Brendan, L. H. Jonathan L Hansen, K. H. Narelle, M. G. Gina, G.M. Nicholas and J. W. Margaret, "Common and specific genetic influences on EEG power bands delta, theta, alpha, and beta," *Biological Psychology*, vol. 75, pp. 154164, 2007.
- [139] C. Guger, H. Ramoser and G. Pfurtscheller, "Real time EEG analysis with subject specific spatial patterns for a Brain-computer interface," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 447-456, December 2000.
- [140] C. Vidaurre, A. Schloogl, R. Cabeza, R. Scherer and G. Pfurtscheller, "A fully on-line adaptive BCI," *IEEE Transactions on Biomedical Engineering*, vol. 53, pp. 1728-1731, June 2006.
- [141] P. Shenoy, M. Krauledat, B. Blankertz, R. P. Rao and K. R. Muller, "Towards adaptive classification for BCI," *Journal of Neural Engineering*, vol. 3, pp. 13-23, March 2006.
- [142] F. Lotte, M. Congedo, A. Lecuyer, F. Lamarche and B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces," *Journal of Neural Engineering*, vol. 4, pp. R1-R13, 2007.

- [143] M. G. Wentrup and K. Gramann, "Adaptive Spatial Filters with predefined Region of Interest for EEG based Brain-Computer-Interfaces," *Advances in Neural Information Processing Systems*, vol. 19, pp. 537-544.
- [144] S. Sun and C. Zhang, "Adaptive feature extraction for EEG signal classification," *Medical and Biological Engineering and Computing*, vol. 44, pp. 931-935, 2006.
- [145] V. Carmen, Claudia Sannelli, K. R. Muller and B. Blankertz, "Machine-Learning Based Co-adaptive Calibration: A Perspective to Fight BCI Illiteracy," *Lecture notes in Computer Science*, vol. 6076, pp. 413-420, 2010.
- [146] H. Flor, N. Birbaumer, LA Roberts, B. Feige, W. Lutzenberger, C. Hermman and B. Kopp, "Slow potentials , gamma-band activity, and motor responses during aversive conditioning in humans" *Experimental Brain Research*, pp. 298-312, 1996.
- [147] S.D. Cranstoun, H. C. Ombao, R.von Sachs, Wensheng Guo and B. Litt, "Time-frequency spectral estimation of multichannel EEG using the Auto-SLEX method" *IEEE transactions on Biomedical Engineering.*, vol. 49, pp. 988 - 996, 2002.
- [148] D. J. McGonigle, A. M. Howseman, B. S. Athwal, K. J. Friston, R. S. J. Frackowiak and A. P. Holmes, "Variability in fMRI: An Examination of Intersession Differences" *NeuroImage*, vol. 11, pp. 708-734, 2000.
- [149] B. Hamadicharef, "AUC Confidence Bounds for Performance Evaluation of Brain-Computer Interface" *2010 Third International Conference on Biomedical Engineering and Informatics (BMEI 2010)*, 2010.

Appendix A

Publication list

Journals

- [1] Kavitha P. Thomas, Cuntai Guan, Lau Chiew Tong, A. P. Vinod and Kai Keng Ang, “Adaptive tracking of discriminative frequency components in EEG for a robust Brain-Computer Interface,” *Journal of Neural Engineering*, vol. 8, 036007, 2011.
- [2] Kavitha P. Thomas, Cuntai Guan, Lau Chiew Tong, A. P. Vinod and Kai Keng Ang, “A New Discriminative Common Spatial Pattern Method for Motor Imagery Brain-Computer Interfaces,” *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 11, pp. 2731-2733, November 2009.

Conferences

- [1] Kavitha P. Thomas, Guan Cuntai, Lau Chiew Tong and A. P. Vinod, “ A study on the impact of spectral variability in brain-computer interface,” *Proceedings of IEEE International Symposium on Circuits and Systems*, Paris, France, May-June 2010.
- [2] Kavitha P. Thomas, Cuntai Guan, Lau Chiew Tong and A. P. Vinod, “ Discriminative filter bank selection and EEG information fusion for brain-computer interface,” *Proceedings of IEEE International Symposium on Circuits and Systems*, Taipei, Taiwan, May 2009.
- [3] Kavitha P Thomas, C. T. Guan, Lau Chiew Tong and A. P. Vinod, “ An Adaptive Filter Bank for Motor Imagery based Brain-Computer Interface,,” *Proceedings of 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Vancouver, Canada, August 2008.