

## ACKNOWLEDGEMENTS

Through this page, I offer my salutation to **Mahamana Pt. Madan Mohan Malviya Ji**, the creator of this pious seat of learning.

It is indeed my proud privilege to express my deep sense of gratitude, respect, indebtedness and sincere regards to my Supervisor, **Dr. Shiru Sharma**, for her excellent supervision, skilled and valuable guidance, stimulating discussion, unfailing support, immense help, and constant encouragement over the entire period of my association with her. I am grateful to her for her sincere concern both for academics and personal welfare and parental care throughout the research period that she has extended to me for the successful completion of my research work. I can never forget her affectionate, caring nature and moral support which provides the feeling of being at home always. I have no words in my dictionary to explain about her. I am proud to have a teacher like her who is always motivative and supportive, even in most adverse situations. In fact, she has been a source of inspiration for me to have an optimistic approach in life and do my best.

I wish to express my heartfelt thanks to **Prof. Prasun Kumar Roy**, the Coordinator, of School of Biomedical Engineering, Indian Institute of Technology (Banaras Hindu University), Varanasi, School of Biomedical Engineering, IIT (BHU) for his constant support and blessings.

It is a profound privilege to be a student of School of Biomedical Engineering. I would like to express my thanks to the faculty members of the school to **Prof. Neeraj Sharma, Retired Prof. Ranjana Patnaik, Retired Prof. Nira Misra, Retired Prof. A.K. Ray, Dr. Sanjay Kumar Rai, Dr. Sanjeev Kumar Mahto, Dr. Marshal, Dr. Pradip Paik and Dr. A. R. Jac Fredo** who have helped me a lot in overcoming the bottlenecks I encountered during my studies with their valuable advice.

I am thankful to **Prof. Sanjay Kumar Singh**, my external RPEC member, Department of Computer Science and Engineering, IIT (BHU) for giving me valuable suggestions throughout my research period.

I am highly thankful to my lab mates **Dr. Anuranjeeta, Dr. Hemlata Shakya, Mr. Alok Prakash, Mr. Romel Bhattacharjee, Mr. Alok Tiwari, Mr. Taresh Sarvesh Sharan, Mr. Neeraj Sharma, Mr. Sharique Ahmed, and Mr. Soni Deep**. for their affection and support during whole journey.

I have been highly blessed with a friendly and cheerful group of fellow research scholars. I would like to express my heartfelt gratitude to especially **Mr. Alok Tiwari, Ms. Neelima Varshney, Mr. Rahul Kumar, and all my seniors and juniors** who directly or indirectly supported my research work. Their companionship and lively discussions in and outside the laboratory were great sources of inspiration.

I am also grateful to the non-teaching staff members **Dr. Anuj Srivastava Mr. Avinash Kumar Srivastava, Mr. Divyanshu Singh, Mr. Vipin Kumar Verma, Mr. Ajay Kumar, Mr. Bhuwaneshwari Sharan, Mr. Bharat Kumar Vishwakarma, Mr. Kishori Lal, Mr. Parmatma Nand Singh, Mr. Suresh Kumar, Mr. Sri Prakash Sharma** for their support and cooperation during my research work.

Words plunge insufficient to express my regards and deep emotions to my beloved parents **Mr. Hamvir Singh Malan & Mrs. Rekha Rani Malan** and my sister **Ms. Ruchika Chaudhary** for being the source of unconditional love and inspiration to move on the way to my goal of achieving higher education. Their everlasting encouragement, patience, sacrifice, and blessings have brought me up to this stage. Parents being earthly God deserve much more than what I can express in words. I would like to express my gratitude towards the departments of IIT (BHU), Varanasi for providing me the necessary

facilities for conducting my research work smoothly. School of Biomedical Engineering for providing the lab facilities like Computer, CRO, EEG acquisition Device, GPU, NI ELVIS-II Board, and the softwares like LabView, and MATLAB.

I take this occasion to acknowledge the financial assistance provided by the **Ministry of Human Resource and Development** in the form of Teaching Assistantship.

Again, I wish to express a word of thanks to all those hands that helped me in some way or the other in pursuing my research work and for the completion of the thesis. I apologize unreservedly for any mistakes, omissions or failure to acknowledge fully.

Finally, I bow my head humbly before the almighty **God** without whose consent and blessings, this work would have been impossible.

Date:

Place: IIT (BHU), Varanasi

(Nitesh Singh Malan)

---

## LIST OF ABBREVIATIONS AND SYMBOLS

---

ABC	Artificial Bee Colony
BSC	Bayesian Classifier
BCI	Brain-Computer Interface
CCA	Canonical Correlation Analysis
CCA	Canonical Correlation Analysis
CNS	Central Nervous System
CAR	Common Average Reference
CSSSP	Common Sparse Spectral Spatial Pattern
CSP	Common Spatial Pattern
CSSP	Common Spatio-Spectral Pattern
CFS	Correlation-based Feature Selection
DE	Differential Evolution
DFBCSP	Discriminative Filter Bank Common Spatial Pattern
DTCWT	Dual-Tree Complex Wavelet Transform
ECoG	Electrocorticography
EEG	Electroencephalogram
ERD	Event-Related Desynchronization
ERP	Event-Related Potentials
ERS	Event-Related Synchronization
EB	Eyeblink
FFT	Fast Fourier Transform
FBCSP	Filter Bank Common Spatial Pattern
FIR	Finite Impulse Response

FA	Firefly Algorithm
fNIRS	Functional Near-Infrared Spectroscopy
GA	Genetic Algorithm
HMM	Hidden Markov model
ICA	Independent component Analysis
IT-CCA	Individual Template-based CCA
ITR	Information Transfer Rate
IPD	Instantaneous Phase Difference
KNN	K-nearest neighbours
LLAP	Large Laplacian derivation
LDA	Linear Discriminant Analysis
LR	Logistic Regression
MEG	Magnetoencephalography
MD	Mahalanobis distance
MPD	Mean Phase Difference
MWT	Morlet Wavelet Transform
MI	Motor Imagery
Multi-set CCA	Multi-set CCA
MwayCCA	Multi-way CCA
NN	Neural network
OAs	Ocular Artifacts
PSO	Particle swarm optimization
PCCA	Phase Constrained CCA
PLV	Phase Locking Value
PET	Positron Emission Tomography

PSD	Power spectral density
PSDA	Power Spectrum Density Analysis
PCA	Principal Component Analysis
RNCA	Regularized NCA
SMR	Sensorimotor Rhythms
STFT	Short-Time Fourier Transform
SSA	Singular Spectrum Analysis
SCP	Slow Cortical Potentials
SLAP	Small Laplacian Derivation
SSVEP	Steady-State Visual Evoked Potential
SBCSP	Sub-Band Common Spatial Patterns
SVM	Support Vector Machine
SLD	surface Laplacian derivation
VEP	Visually Evoked Potentials
WPD	Wavelet Packet Decomposition
$\emptyset$	Hilbert Transform
$\omega$	Wavelet Coefficient
$T$	Threshold Value
$\lambda$	RNCA Regularization Parameter
$p_0$	Classification Accuracy
$L$	RNCA Hyperparameter
mV	mili Volts
$\mu$ V	micro Volts

---

**LIST OF FIGURES**

---

<b>Figure No.</b>	<b>Figure description</b>	<b>Page No.</b>
<b>Figure 1.1</b>	International 10-20 system.	2
<b>Figure 1.2</b>	Block diagram representing the components of an MI-based BCI Device.	5
<b>Figure 1.3</b>	Basic building blocks in SSVEP based BCI.	7
<b>Figure 3.1</b>	(a) Analysis Filter bank of DTCWT and (b) Synthesis Filter bank of DTCWT.	32
<b>Figure 3.2</b>	Labview Model for the generation of synthetic clean EEG signal.	37
<b>Figure 3.3</b>	The clean EEG signal (upper graph). EOG signal (middle graph) and Contaminated EEG signal (lower graph).	38
<b>Figure 3.4</b>	Comparison of Clean EEG, Contaminated EEG, and DTCWT-QAT corrected EEG.	38
<b>Figure 3.5</b>	RRMSE curves for corrected EEG signal using (a) DTCWT-QAT (b) DWT-QAT (c) DWT soft threshold, and (d) DWT hard threshold.	39
<b>Figure 3.6</b>	EEG signal from c3 Channel acquired while performing motor imaginary task with two eyeblinks at 0.6 sec and 1.8 sec.	40
<b>Figure 3.7</b>	Comparison of real EEG signal from c3 Channel with eyeblink artifacts and DTCWT-QAT corrected EEG.	41
<b>Figure 4.1</b>	DTCWT (a) Analysis filter bank of DTCWT and (b) synthesis filter bank of DTCWT.	45
<b>Figure 4.2</b>	Workflow elucidates the proposed method used to reduce the high dimensionality of MI Dataset.	53
<b>Figure 4.3</b>	Weights assigned to different features using (a) ReliefF algorithm and (b) Principal Component Analysis (PCA).	54
<b>Figure 4.4</b>	Regularized Neighbourhood component analysis as feature selection (a) Estimation of the regularization parameter $\lambda_{Best}$ at minimum loss value. (b) feature weights calculated using $\lambda_{Best}=0.0077$ .	55
<b>Figure 4.5</b>	Comparison of the average number of features selected between four feature selection algorithms: ReliefF, PCA, GA, and RNCA for 19 different training sessions of 2 motor imagery datasets from BCI competition II (dataset III) and IV (dataset 2b). It also indicates the standard deviation from the mean value.	56
<b>Figure 4.6</b>	The number of times a feature is selected by RNCA for ten subjects. Results indicate that the RNCA feature selection method is capable of selecting optimal features that occur at different frequency bands for different subjects.	62
<b>Figure 4.7</b>	Change in classification Accuracy (CA) with respect to parameter L of RNCA for five subjects BT102, BT301, BT502, BT702, and BT902, respectively.	63
<b>Figure 5.1</b>	Workflow presents the working of the proposed MI spectral-spatial feature optimization algorithm.	73
<b>Figure 5.2</b>	Dispersion of the best two features in 2-D, selected by the FBCSP (MI), DFBCSP (MI), and the proposed DTCWT-CSP (NCA) for (a) subject "B0503T" from BCI Competition IV	84

	(Dataset 2b), (b) subject “k6b” from BCI competition III Dataset IIIa right hand vs. left hand MI, and (c) subject “L1b” from BCI competition III Dataset IIIa for tongue vs. foot MI.	
<b>Figure 5.3</b>	Time-frequency plots and averaged subband power topographic head plots estimated after filtering using (a) DTCWT based filter bank, (b) Butterworth filter, (c) Elliptical Filter, and (d) Chebyshev Type II filter. Filter of frequency band 8-32Hz filtered the EEG for time-frequency analysis. Whereas topographic head plots present averaged band power at 8-16Hz during MI task. Red lines indicate start and end of the cue at $t=3s$ and $t=4s$ , respectively. MI tasks started with the cue at $t=3s$ .	86
<b>Figure 5.4</b>	Spatial filters at feature indices for (a) Subject “K3b” of BCI competition III Dataset IIIa and (b) subjects “B0103T” and “B0603T” of BCI Competition IV (Dataset 2b). Corresponding feature weights estimated by the proposed method are listed in Table IV and V.	89
Figure 5.5	Classification accuracies obtained by each subject from BCI Competition IV (Dataset 2b) for varying number of trials. Note: the trend line shows the linear degradation in the average classification accuracy as the length of the trials decreases.	90
<b>Figure 6.1</b>	Illustration of multi-view feature extraction from MI-related EEG dataset for classification. Naturally, EEG data has three modes: channels, time, and trials. In the first stage, EEG time series of each trial is segmented into K multiple time windows. Next, each time window is filtered at three frequency bands using DTCWT filter bank. Afterward, CSP is executed on filtered EEG to evaluate MI-related features. The final feature space has K matrices. Columns of each such matrix have DTCWT CSP features, and rows represent trials.	99
<b>Figure 6.2</b>	Flow chart presents the approach of tuning the regularization parameter within the NCA framework for optimal feature selection.	103
<b>Figure 6.3</b>	The workflow elucidates the proposed feature selection method to optimize time windows and frequency band CSP features of MI-related EEG. Optimization is performed under a structured-based multi-view learning environment where RNCA is applied on each of the matrices of feature space (extracted in Figure 6.1) for optimal feature selection. Subsequently, all the selected features are combinedly used to train an SVM classifier. During the test phase, similar multi-view features are extracted from the Test data and predict the MI class.	105
<b>Figure 6.4</b>	Performance of the proposed method for time window optimization: a), Pictorial representation of the feature space learned by the proposed method for subject A05T. In each time window, we have three frequency bands, each of which contains 4 CSP features. Blue boxes show the selected features at different time windows and frequency bands. b) Presents the feature weights assigned to all the six time windows at CSP	114

feature index 11 (i.e., features marked by orange outline in 4.a).  
 c) spatial filters all time windows (i.e., features marked by orange outline in 4.a). From spatial filters, it can be observed that the presence of ERD/ERS in sensorimotor cortex is strong at time windows -0.5s to 1.5s, 0.5s to 2.5s, and 2s to 4s, and that's why the proposed algorithm has chosen CSP features of these time windows.

**Figure 6.5** Performance of the proposed method for frequency band optimization: a), Pictorial representation of the feature space learned by the proposed method for subject k6b. In each time window, we have three frequency bands, each of which contains 4 CSP features. Blue boxes show the selected features at different time windows and frequency bands for subject k6b. b) Presents the feature weights assigned to six frequency band csp features at time window 0.5s to 2.5s (i.e. features marked by red outline in 5.a). c) spatial filters of six frequency band csp features at time window 0.5s to 2.5s (i.e. features marked by red outline in 5.a). From spatial filters, it can be observed that the presence of ERD/ERS in sensorimotor cortex is strong for CSP feature index 3,4, and 6 and since the proposed algorithm selected only these features proves its robustness in optimizing frequency bands.

**Figure 6.6** Average number of features selected by the RNCA for three BCI datasets for different motor imagery tasks classification.

**Figure 6.7** Feature optimization at a particular time window for subject k3b from dataset 2 (right vs. left-hand MI task) (a) Estimation of the regularization parameter  $\lambda=\lambda_{best}$  at minimum loss value. (b) Feature weights calculated using  $\lambda_{best}$ . Although these graphs show feature selection in single time window, with similar tuning and weight assigning technique CSP features at different time windows are optimized. 117

**Figure 6.8** Change in classification accuracies according to the varying length of trials. 118

**Figure 6.9** Computational time consumed by CSP, CSP<sub>STW</sub>, FBCSP, FBCSP<sub>STW</sub>, DFBCSP, and DFBCSP<sub>STW</sub>, and the proposed algorithm for best feature space generation. 120

**Figure 7.1** Workflow of the proposed method. 125

**Figure 7.2** Framework of experiment performed. 127

**Figure 7.3** Comparison of SSVEP detection between three methods: CCA with threshold, FFT, and proposed training method for (a) subject 1 (b) subject 2, and (c) Subject 3. Zero detected frequency corresponds to idle-state. 129

**Figure 7.4** Real-time control of a LED panel using the proposed method. 130

---

**LIST OF TABLES**

---

<b>Table No.</b>	<b>Table description</b>	<b>Page No.</b>
<b>Table 2.1</b>	Comparison of Different modalities used for the recording of the Brain activities.	12
<b>Table 2.2</b>	Signal processing algorithms in pre-processing.	17
<b>Table 2.3</b>	Feature extraction methods in MI signal processing.	20
<b>Table 2.4</b>	Classification methods in MI signal processing.	24
<b>Table 2.5</b>	Spatial filtering-based models in MI signal processing.	26
<b>Table 2.6</b>	Advance CCA methods in SSVEP signal processing.	29
<b>Table 4.1</b>	Description of different features extracted using statistical, frequency and phase analysis.	47
<b>Table 4.2</b>	Comparison of classification accuracy (CA), kappa coefficient and the number of features selected (FS) between ReliefF, PCA, GA and RNCA for motor imagery data of 19 different training sessions of 2 different datasets from BCI competition II (dataset III) and IV (dataset 2b). Values in boldness indicate the largest value compared with all others.	58
<b>Table 4.3</b>	Mean rank of feature selection methods for the Friedman test.	60
<b>Table 4.4</b>	Statistical analysis of classification accuracy differences between the compared methods on BCI competition IV Dataset IIb: Results of Wilcoxon signed ranks test as post hoc with alpha=0.05.	60

<b>Table 4.5</b>	Averaged classification performance metrics of SVM classifier on BCI competition IV dataset 2b present a comparison between compared feature selection methods. Values in boldness indicate the largest value compared with all others.	60
<b>Table 4.6</b>	Comparison of the average processing time of four feature selection methods: ReliefF, PCA, GA, and RNCA. SVM. Values in boldness indicate the largest value compared with all others.	64
<b>Table 5.1</b>	Comparison of classification accuracies (CA) (in %) achieved by the CSP (7-30 Hz), CSP (7-13 HZ), FBCSP (MI), DFBCSP (MI) and the proposed DTCWT-CSP (NCA) method respectively. CA is evaluated using an SVM classifier for BCI Competition IV (Dataset 2b). For each subject, Values in boldness indicate the largest value compared with all others. Further, p-values are obtained by the paired t-test between the results of DTCWT-CSP (NCA) and each of the other methods.	81
<b>Table 5.2</b>	Comparison of classification accuracies (%) achieved by the CSP (7-30 Hz), CSP (7-13 HZ), FBCSP (MI), DFBCSP (MI) and the proposed DTCWT-CSP (NCA) method respectively. CA is evaluated using an SVM classifier for BCI competition III Dataset IIIa. For each subject, Values in boldness indicate the largest value compared with all others. Further, p-values are obtained by the paired t-test between the results of DTCWT-CSP (NCA) and each of the other methods.	82

<b>Table 5.3</b>	Lists the classification accuracies (CA) (in %) achieved by feature selection methods: ReliefF, Mutual Information, Genetic Algorithm, and NCA for BCI Competition IV (Dataset 2b). The number of features selected (FS) by the algorithms are written in brackets. The feature extraction method used for all these algorithms is DTCWT-CSP and SVM classifier is trained to evaluate classification accuracies using k-fold cross validation. Values in boldness indicate the largest value compared with all others. Further, p-values are obtained using paired t-test between the results of DTCWT-CSP (NCA) and each of the other methods.	83
<b>Table 5.4</b>	Feature weights estimated by the proposed algorithm for Dataset2. Boldface values indicate selected features. Threshold value for the selection of a feature is 5% of the maximum feature weight in each subject.	87
<b>Table 5.5</b>	Feature weights estimated by the proposed algorithm for Dataset1. Boldface values indicate selected features. Threshold value for the selection of a feature is 5% of the maximum feature weight in each subject.	88
<b>Table 6.1</b>	Classification accuracies (CA) (%) achieved using CSP, CSP <sub>STW</sub> , FBCSP, FBCSP <sub>STW</sub> , DFBCSP, and DFBCSP <sub>STW</sub> , and the proposed algorithm on BCI competition IV dataset 2a (between two classes Left Hand vs. Right Hand, Left Hand Vs. Foot, and Right Hand vs. Foot). SVM classifier is learned and CA is calculated using 10-fold Crossvalidation. The highest CA	110



obtained is marked in boldface for each subject. In addition, p-values are calculated using paired t-test between the proposed method and each of competing methods.

**Table 6.2** Classification accuracies (CA) (%) achieved using CSP, CSP<sub>STW</sub>, FBCSP, FBCSP<sub>STW</sub>, DFBCSP, and DFBCSP<sub>STW</sub>, and the proposed algorithm on BCI competition III dataset IIIa. SVM classifier is learned and CA is calculated using 10-fold Crossvalidation. The highest CA obtained is marked in boldface for each subject. In addition, p-values are calculated using paired t-test between the proposed method and each of competing methods. 111

**Table 6.3** Classification accuracies (CA) (%) achieved using CSP, CSP<sub>STW</sub>, FBCSP, FBCSP<sub>STW</sub>, DFBCSP, and DFBCSP<sub>STW</sub>, and the proposed algorithm on BCI Competition IV dataset 2a. SVM classifier is learned and CA is calculated using 10-fold Crossvalidation. The highest CA obtained is marked in boldface for each subject. In addition, p-values are calculated using paired t-test between the proposed method and each of competing methods. 111

**Table 7.1** Details of the subjects who performed the SSVEP task. 127

**Table 7.2** Comparison of classification accuracy, confusion matrices and ITR between three methods: CCA with threshold, FFT, and proposed CCA+LDA training method. 128

---

## PREFACE

---

The research work presented in this thesis is divided into eight chapters as follows. In chapter 1, motor imagery (MI)- based and steady-state visual evoked potentials (SSVEP)-based brain-computer interfaces (BCIs) are introduced, incorporating the explanation of key components required to design a practical BCI device. The objectives of this thesis are briefly explained. Chapter 2 reviews state-of-the-art signal processing techniques in MI and SSVEP EEG-based BCIs with specific attention on the feature extraction, feature selection, and classification techniques used. The first objective of this thesis is covered in chapter 3. We have proposed the use of dual-tree complex wavelet transform (DTCWT) with quantum-inspired adaptive wavelet threshold algorithm for the elimination of OAs from single-channel EEG signal. Chapter 4 comprises the second objective of this work and proposes a novel method to regularize neighborhood component analysis (NCA) to select the MI data. In chapter 5, we covered the third objective and designed a dual-tree complex wavelet transform-based filter bank to filter the EEG into sub-bands instead of traditional filtering methods, which improved the spatial feature extraction efficiency. Chapter 6 covers the fourth objective and presents a novel multi-view feature selection method based on regularized neighbourhood component analysis to simultaneously optimize time windows and frequency bands. In chapter 7, we have presented the work for the fifth objective; we propose a class labeling method where a classifier is trained against the non-target class. Chapter 8- presents a summary and conclusions of the experimental work and suggests scope for further work.

## TABLE OF CONTENTS

<b>List of Figures</b> .....	<b>xiii</b>
<b>List of Tables</b> .....	<b>xix</b>
<b>List of abbreviations and symbols</b> .....	<b>xxiii</b>
<b>Preface</b> .....	<b>xxvi</b>
<b>Chapter 1</b> .....	<b>1</b>
<b>1 Introduction and Objectives</b> .....	<b>1</b>
<b>1.1 Background</b> .....	<b>1</b>
<b>1.2 Motor Imagery (MI)-based BCI</b> .....	<b>3</b>
<b>1.2.1 Block Diagram of an MI-Based BCI Device</b> .....	<b>4</b>
<b>1.2.2 MI task</b> .....	<b>6</b>
<b>1.3 Steady state visual evoked potentials (SSVEPs)-based BCI</b> .....	<b>6</b>
<b>1.4 Challenges</b> .....	<b>8</b>
<b>1.4.1 Removal of Ocular artifacts from single-channel EEG:</b> .....	<b>8</b>
<b>1.4.2 Feature selection of MI-EEG signals:</b> .....	<b>8</b>
<b>1.4.3 Spectral- Spatial feature optimization of MI-EEG signals:</b> .....	<b>8</b>
<b>1.4.4 Multi-view MI-EEG classification</b> .....	<b>9</b>
<b>1.4.5 Improving recognition rate of SSVEP in real-time</b> .....	<b>9</b>
<b>1.5 Objectives</b> .....	<b>9</b>
<b>Chapter 2</b> .....	<b>11</b>
<b>2 Literature Review</b> .....	<b>11</b>
<b>2.1 Background</b> .....	<b>11</b>
<b>2.2 Brain Signals Recording</b> .....	<b>12</b>
<b>2.3 Signal processing in BCI</b> .....	<b>13</b>
<b>2.3.1 Pre-Processing: Removal of artifacts and noises</b> .....	<b>14</b>
<b>2.4 Signal processing in MI-based BCI</b> .....	<b>16</b>
<b>2.4.1 Feature Extraction in MI-BCI</b> .....	<b>18</b>
<b>2.4.2 Feature Selection</b> .....	<b>19</b>
<b>2.4.3 Classification</b> .....	<b>22</b>
<b>2.4.4 Spatial filtering-based models in MI-BCI:</b> .....	<b>24</b>
<b>2.4.5 Time- window optimization models in MI-BCI:</b> .....	<b>27</b>
<b>2.5 Signal processing in SSVEP-based BCI</b> .....	<b>27</b>
<b>Chapter 3</b> .....	<b>30</b>

<b>3</b>	<b>Removal of Ocular artifacts from Single channel EEG signal using DTCWT with Quantum inspired Adaptive Threshold.....</b>	<b>30</b>
3.1	Introduction .....	30
3.2	Materials and methods.....	31
3.2.1	Dual-Tree Complex Wavelet Transform (DTCWT).....	31
3.2.2	Thresholding.....	32
3.2.3	Quantum inspired adaptive threshold (QAT) .....	34
3.3	Application of DTCWT-QAT for removal of ocular artifacts from EEG	35
3.4	Results and Discussion .....	37
3.4.1	EEG simulation .....	37
3.5	Application to Real EEG data .....	40
3.6	Conclusion .....	41
	Chapter 4.....	42
<b>4</b>	<b>Feature Selection using Regularized Neighbourhood Component Analysis to Enhance the Classification Performance of Motor Imagery Signals. ....</b>	<b>42</b>
4.1	Introduction .....	42
4.2	Methods and Materials .....	43
4.2.1	EEG Dataset and paradigm .....	43
4.2.2	Preprocessing.....	44
4.2.3	Feature Extraction .....	45
4.2.4	Feature Selection .....	47
4.2.5	Neighbourhood component analysis.....	50
4.2.6	Proposed Method: RNCA as Feature Selection .....	51
4.2.7	Classification.....	53
4.3	Results.....	54
4.3.1	Feature selection results: .....	54
4.3.2	Classification Performance: .....	56
4.4	Discussion .....	59
4.4.1	Selection of optimal features by RNCA.....	60
4.4.2	Configurable parameter .....	62
4.4.3	Computational complexity .....	63
4.5	Conclusion .....	65
	Chapter 5.....	66
<b>5</b>	<b>Motor imagery EEG spectral-spatial feature optimization using Dual-Tree Complex Wavelet and Neighbourhood Component Analysis.....</b>	<b>66</b>
5.1	Introduction .....	66
5.2	Methods and Materials .....	68
5.2.1	Notations .....	68
5.2.2	Band Pass Filter design using dual-tree complex wavelet transform	68
5.2.3	Common Spatial Patterns .....	69
5.2.4	Neighbourhood Component Analysis .....	71
5.2.5	Proposed spectral-spatial feature optimization approach .....	72
5.3	Experimental study .....	75
5.3.1	Datasets.....	75
5.3.2	Competing Methods.....	76
5.3.3	Performance measures .....	78
5.4	Results .....	79
5.5	Discussion.....	84
5.5.1	Time- frequency analysis of DTCWT-filtered EEG.....	84
5.5.2	Spectro-spatial feature optimization.....	86
5.5.3	Training with different length of trial data .....	90
5.5.4	Extension.....	91
5.6	Conclusion.....	91
	Chapter 6.....	93
<b>6</b>	<b>Time window and frequency band optimization using regularized neighbourhood component analysis for Multi-View Motor Imagery EEG classification .....</b>	<b>93</b>
6.1	Introduction.....	93
6.2	Methods.....	95
6.2.1	Preprocessing of EEG.....	95
6.2.2	Feature extraction from Multi-view EEG data.....	96
6.2.3	Multi-view Feature selection approach: Regularized Neighbourhood component analysis.....	100
6.2.4	Classification .....	105
6.3	Experimental study .....	106
6.3.1	Dataset description .....	106
6.3.2	Performance evaluation .....	107
6.4	Results .....	108
6.5	Discussion.....	112
6.5.1	Selected spatial patterns at multiple frequency bands and time windows .....	112
6.5.2	Feature dimensionality reduction.....	116

6.5.3	Performance with different trial length .....	118
6.5.4	Limitations and Future scope.....	119
6.6	Conclusion .....	121
Chapter 7.....		123
7	CCA Model with Training Approach to Improve Recognition Rate of SSVEP in Real Time.....	123
7.1	Introduction .....	123
7.2	Methods and Materials .....	124
7.2.1	Canonical Correlation Analysis (CCA).....	124
7.2.2	Linear Discriminant Analysis (LDA) .....	124
7.2.3	Proposed Method.....	125
7.3	Experimental Setup.....	126
7.3.1	Generation of visual stimulus.....	126
7.3.2	Data Acquisition .....	126
7.3.3	Experiment paradigm .....	127
7.4	Result and Discussion.....	128
7.5	Conclusion .....	130
Chapter 8.....		132
8	Conclusion and Summary .....	132
8.1	Scope for Further Work.....	135
References .....		136
List of Publications.....		157