

Signal Processing for a Brain Computer Interface

By
Ruiting Yang

Thesis submitted for the degree of
Master of Engineering Science



School of Electrical & Electronic Engineering
Faculty of Engineering, Computer & Mathematical Sciences

The University of Adelaide
Adelaide, South Australia

2009

Contents

Statement of Originality	iii
Acknowledgements	v
Abstract	vii
Abbreviations	ix
List of Figures	xi
List of Tables	xiii
Publication	xiii
Chapter 1 Introduction and Literature Review	1
1.1 Concept of Brain Computer Interface	1
1.2 Physiology background	3
1.2.1 The human brain.....	3
1.2.2 Electroencephalography (EEG)	3
1.3 Key components of a Brain Computer Interface system.....	6
1.3.1 Signal acquisition and pre-processing	6
1.3.2 Signal Processing	7
1.3.3 Application	7
1.3.4 Feedback.....	8
1.4 Literature review.....	9
1.4.1 BCI experiments	9
1.4.2 Feature selection	10
1.4.3 Classification.....	11
1.4.3.1. Nearest neighbour classifiers	12
1.4.3.2. Neural network	12
1.4.3.3. Linear classifiers.....	13
1.4.3.4. Bayesian statistical classifiers	13
1.4.4. Adaptive classification.....	14
1.5 Major aims of this thesis.....	14
Chapter 2 Feature Extraction	15
2.1 What is feature and feature extraction?.....	15
2.2 Time series waveform template.....	16
2.3 Autoregressive components	17
2.3.1 AR coefficients	18
2.3.2 AR poles	18
2.3.3 Optimal AR order	20
2.4 Spectral components.....	21
2.4.1 Alpha and Beta band power.....	21
2.4.2 Spectrum density peak	23
2.4.3 Asymmetry ratio	23
2.5 Eigenvector elements analysis	24
2.5.1 Introduction	24
2.5.2 Principal Eigenvector	25
2.5.3 Common spatial pattern.....	26
Chapter 3 Classification	29
3.1 Template matching	29
3.1.1 Build the template for each class	30
3.1.2 Using cross correlation sequence to improve classification	33
3.2 Nearest neighbour classifier	33

3.2.1 The nearest neighbour.....	34
3.2.2 K-nearest neighbour	35
3.2.3 Fast nearest neighbour	35
3.3 Linear discriminant analysis classifier.....	36
3.3.1 LDA classifier in BCI	36
3.3.2 Improved LDA.....	37
3.4 Bayesian statistical classifier	38
3.4.1 Gaussian models from evenly divided feature space.....	40
3.4.2 Gaussian models from EM algorithm.....	40
3.5 Fuzzy Logic classifier	43
3.5.1 Foundations of Fuzzy Logic.....	44
3.5.2 Training and building membership functions.....	44
3.5.3 If-then rules.....	45
3.5.4 Define output membership functions.....	46
3.5.5 Fuzzy logic classification process	46
3.5.6 An example of the fuzzy logic classification process.....	48
Chapter 4 Application to Graz data	51
4.1 Data description	51
4.2 Evaluation criteria of BCI performance	52
4.2.1 Classification accuracy	52
4.2.2 Other criteria	53
4.3 Cross validation.....	55
4.4 Performance of feature and classifier pairs	55
4.4.1 Classification results using time series	56
4.4.2 Classification results using AR components	58
4.4.3 Classification results using spectral components.....	59
4.4.4 Classification results using eigenvector components.....	61
4.5 Analysis of data length of feature extraction, optimal training time and computation time	63
4.6 Comparisons and discussion.....	65
Chapter 5 Application to Adelaide data	68
5.1 Experiment and Data Acquisition	68
5.1.1 Experiment procedure.....	68
5.1.2 Recording methodology	69
5.2. Classification and performance	70
5.2.1 Classification results using time series waveform.....	71
5.2.2 Classification results using AR coefficients.....	72
5.2.3 Classification results using band powers	72
5.2.4 Classification results using common spatial pattern.....	73
5.3 Comparisons and analysis	75
Chapter 6 Conclusion.....	77
Bibliography	79

Declaration

NAME: Ruiting Yang PROGRAM:

This work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

I give consent to this copy of my thesis, when deposited in the University Library, being made available for loan and photocopying, subject to the provisions of the Copyright Act 1968.

I also give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library catalogue, the Australasian Digital Theses Program (ADTP) and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

SIGNATURE:

DATE:

Acknowledgements

I would like to express my gratitude to those people who have given me support and assistance throughout my time as a master student.

First of all, I would like to thank my principal supervisor, Professor Doug Gray. It would have been impossible to finish this thesis without his constant guidance, encouragement, support and understanding.

Many thanks also go to my co-supervisor, Dr. Brian Ng who contributed more than I would have expected from a usual co-supervisor. It has been so important to get his academic advice and particular understanding in our regular meetings. His communication with the School of Molecular & Biomedical Science was crucial for the experiments in this thesis, and I will always appreciate his contributions.

Thanks to Dr. Michael Ridding from the School of Molecular & Biomedical Science, for sharing his experimental equipment and organizing the experiments. Similarly, thanks must go to the organizer of the BCI competition II for sharing their dataset, on which we relied for much of our research.

Thanks to my Chinese supervisor, Professor Mingyi He for his constant encouragement and kind help during these years. He was one of founders of the agreement of exchanging students between the University of Adelaide and Northwestern Polytechnical University, which brought me to Australia.

Thanks to Associate Professor Cheng Chew Lim, another founder of this program. I can clearly remember the interview in China, which actually has changed my life already. Thanks also to Associate Professor Michael Liebelt and the school committee, who decided to grant me a fee remission scholarship to study here.

Thanks to Mr. Matthew Trinkle, whose enthusiasm and patience has been an inspiration for me. His help and kindness made it much easier for me to fit into this unfamiliar country.

Thanks to other colleagues in Sensor Signal Processing Group, their kind help, suggestions and news shared during coffee break and Friday drinks

were always pleasant, and gave me a chance to know Australian culture better. Thanks also to other friends in Australia, who provided valuable support and companionship in my time here and without whom I would be much lonelier in Australia.

Finally, thanks must go to my parents and other family members, their consistent financial support and encouragement is the basis of my overseas study. Their love is always the force driving me forward.

Abstract

Brain computer interface (BCI) systems measure brain signal and translate it into control commands in an attempt to mimic specific human thinking activities. In recent years, many researchers have shown their interests in BCI systems, which has resulted in many experiments and applications. However, most methods are just based on a specific selected dataset or a typical feature. As a result, there are questions about whether some methods generalise well on other datasets. Therefore, the major motivation of this thesis is to compare various features and classifiers described in the literature.

Pattern recognition is considered as the core part of a BCI system in our research. In this thesis, a number of different features and classifiers are compared in terms of classification accuracy and computation time. The studied features are: time series waveform, autoregressive (AR) components, spectral components; these are used with different classifiers: such as template matching, nearest neighbour, linear discriminant analysis (LDA), Bayesian statistical and fuzzy logic decision classifiers.

In order to assess and compare these different features and classifiers, an extensive investigation was carried out on a public dataset (imagined left or right hand movement) from an international BCI competition and the results are reported in this thesis. The classification was done in a continuous fashion, to match a real time application. In this process, the average and best accuracy, as well as the computation time, were analysed and compared. The results showed that most classifiers achieved very high accuracies and short computation times for most features.

A BCI experiment based on imagined left or right hand movement was carried out at the University of Adelaide and some investigations on the data from this experiment are discussed. The result shows that the selected classifiers can work well with this new dataset without much additional preprocessing or modifications.

Finally, this thesis culminates with some conclusions based on our research, and discusses some further potential work.

Abbreviations

ALS:	Amyotrophic Lateral Sclerosis
ANN:	Artificial Neural Network
AR:	Autoregressive
BCI:	Brain Computer Interface
CSP:	Common Spatial Pattern
CSSD:	Common Subspace Decomposition
DFT:	Discrete Fourier Transform
ECoG:	Electrocorticography
EEG:	Electroencephalography
EM:	Expectation Maximization
EMG:	Electromyography
EOG:	Electrooculography
ERD:	Event Related Desynchronization
ERS:	Event Related Synchronization
FFT:	Fast Fourier Transformation
fMRI:	Functional Magnetic Resonance Imaging
GMM:	Gaussian Mixture Models
LDA:	Linear Discriminant Analysis
LMS:	Least Mean Square
LOO:	Leave One Out
MLP:	Multi-Layer Perceptron
PDF:	Probability Density Function

List of Figures

Figure 1.1 A typical Brain Computer Interface system	2
Figure 1.2 Main parts and functional areas of the brain	3
Figure 1.3 Geometric mapping between body parts and motor cortex.....	5
Figure 1.4 International 10-20 System of Electrode Placement	5
Figure 1.5 Feedbacks in a closed loop BCI system	8
Figure 2.1 The process of pattern recognition.....	16
Figure 2.2 Averaged time series waveforms of two thinking activates	17
Figure 2.3 Extracting AR coefficients feature	18
Figure 2.4 Spectral peaks and AR poles.....	19
Figure 2.5 Different R values with different AR order in channel C3 or C4 and class of imaginary left or right hand movement	20
Figure 2.6 Distribution of alpha band powers in channels C3 and C4.	22
Figure 2.7 Averaged asymmetry ratios over time in different classes.....	24
Figure 2.8 Distribution of CSP features.....	28
Figure 3.1 Averaged time courses (imaginary left hand movement) of the absolute amplitudes	32
Figure 3.2 Averaged time courses (imaginary right hand movement) of the absolute amplitudes	32
Figure 3.3 Using LDA for the alpha band power in channels C3 and C4	37
Figure 3.4 The same number of Gaussian prototypes for different classes ...	38
Figure 3.5 Evenly divided alpha band power feature space.....	40
Figure 3.6 Feature space is divided by k -means algorithm.....	41
Figure 3.7 Estimated clusters of the alpha band power feature using the EM algorithm	43
Figure 3.8 A Fuzzy logic classification system.	44
Figure 3.9 Membership functions for two inputs of the fuzzy logic classification system.....	45
Figure 3.10 Different if-then rules are combined to make a final decision.....	46
Figure 3.11 The alpha band power feature space is divided by an output surface.	48
Figure 3.12 Output Membership functions of the fuzzy logic classification system.....	49
Figure 4.1 Relationships of the Kappa and ITR with accuracy for the 2-class problem.....	54
Figure 4.2 Classification accuracy versus time for the band power feature and the LDA classifier.....	56
Figure 4.3 Classification accuracies versus time for 3 template building methods.	56
Figure 4.4 Classification accuracy versus time for the correlation sequence method	57
Figure 4.5 Classification accuracies versus time for the AR coefficients feature with 3 classifiers.....	58
Figure 4.6 Classification accuracies versus time for the band power feature with 3 classifiers.....	59
Figure 4.7 Classification accuracies versus time for the principal eigenvector feature with 3 classifiers.....	62

Figure 4.8 Classification accuracies versus time for the common spatial pattern feature with 3 classifiers.....	62
Figure 4.9 Classification accuracies of all possible combinations of training and testing periods runs.....	64
Figure 4.10 The best classification accuracies for different features and classifiers	66
Figure 4.11 Computation times for different features and classifiers.	67
Figure 5.1 The equipment and indicator used in the experiment.....	69
Figure 5.2 Sequence of experimental events.....	69
Figure 5.3 Classification accuracies versus time for time series waveform template(s) for the reference recording dataset	71
Figure 5.4 Classification accuracies versus time for the AR coefficients feature with the LDA and Bayesian statistical classifiers for the reference recording dataset.....	72
Figure 5.5 Classification accuracies versus time for the band power feature with the LDA and Bayesian statistical classifiers for the reference recording dataset.....	73
Figure 5.6 Classification accuracies versus time for the common spatial pattern feature with the LDA and Bayesian statistical classifiers for the reference recording dataset.....	74

List of Tables

Table 1.1 Common EEG waves and their frequency range	3
Table 4.1 An example of confusion matrix	53
Table 4.2 Classification results using template matching.....	58
Table 4.3 Classification results using AR components	59
Table 4.4 Classification results using spectral components	60
Table 4.5 Classification results using eigenvector components	62
Table 4.6 Classification results using features extracted in two different ways	64
Table 5.1 Classification results for the reference recording dataset.....	74
Table 5.2 Classification results for the bipolar recording dataset.....	74

Publication

Ruiting YANG, Douglas A. GRAY, Brian W. NG, Mingyi HE, Comparative Analysis of Signal Processing in Brain Computer Interface, accepted by the 4th IEEE Conference on Industrial Electronics and Applications, Xi'an China 25-27, May, 2009

