



Bio-driven control system for the rehabilitation hand device: a new approach

By
Khairul Anam

*Submitted in fulfilment of the requirement for the
degree of Doctor of Philosophy*

Supervisor: Assoc. Prof. Adel Al-Jumaily

School of Electrical, Mechanical and Mechatronic Systems
Faculty of Engineering and Information Technology
University of Technology, Sydney (UTS)

January 2016

Certificate of Original Authorship

I, Khairul Anam, certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged.

In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of Student:



Date: 8 January 2016

This page is intentionally left blank

Acknowledgment

First and foremost, my sincere thanks to God, Allah Al-Mighty, who endowed me to complete my PhD study.

I would like to express my deep gratitude to my principal supervisor, **Associate Professor Dr. Adel Al-Jumaily** for all his support, help, guidance, understanding, discussions, ideas, patience, and chances given to me to work with him during my PhD study.

I would also like to thank **Dr. Rami Khushaba** and **Dr. Ali H Al-Timemy** who generously supported me with the EMG datasets and valuable discussions.

I would like to extend further my genuine appreciations to **Dr. Ananda Modan Sanagavarapu** and **Dr. Steve Ling** for giving me the chance of working as a casual academic at UTS.

I wish to acknowledge the PhD scholarship provided by the Directorate General of Higher Education (DGHE), the Republic of Indonesia that has supported my study for four years.

I am sincerely grateful to the Vice Chancellor's Postgraduate Research Student Conference Funding and the Faculty of Engineering and Information Technology (FEIT) travel funding committees for their generous financial support for my conference trips.

I would also like to express my deep thanks to the Centre for Islamic Dakwah and Education (CIDE) committee who invited me to be an imam of Al-Hijrah Mosque during my stay in Sydney and gave me a wonderful trip to the Holy cities, Mecca and Medina, to perform the Islamic pilgrimage/Hajj.

I am very keen to express my appreciation to Tanvir Anwar, Dr. Yashar Maali, Dr. Muhammad Khalid, Dr. Yee Mon Aung, Sahar, Gadeh, Marwah, Dr. Van Linh Nguyen, Dr. Delwar, Dr. Nuryani, Sonki Prasetya, Dessi Wanda, Muhammad Anshar, Dwi Linna Suswardany, and all the people that I could not mention, for help, support and kindly relationship during my PhD life.

Last but not least, I would like to express my special gratitude to my parents and parents-in-law for their continuous support and prayers so that I could complete my PhD. A very special thanks goes to my beloved wife, Aniek Rachmawati, for her endless support, love, encouragement, motivation, and patience. In particular, my heartfelt thanks to my daughters, Maryam and Khodijah, and my sons, Hanif and Taqin, for being patient living without their dad for four years.

Table of Contents

Certificate of Original Authorship.....	i
Acknowledgment.....	iii
Table of Contents	v
List of Figures	ix
List of Tables	xv
List of Abbreviations	xix
Abstract	xxi
Chapter 1	1
Introduction.....	1
1.1 Background.....	1
1.2 Problem statement	6
1.3 Objectives	7
1.4 Contribution of the doctoral thesis	8
1.5 Organization of the thesis	11
1.6 Publication outcomes of the doctoral research	12
Chapter 2	15
Literature review	15
2.1 Introduction	15
2.2 The hand anatomy and bio-signal.....	15
2.2.1 The hand anatomy	15
2.2.2 Electromyography as a bio-signal	19
2.3 Myoelectric control system.....	22
2.3.1 Myoelectric pattern recognition (M-PR).....	23
2.3.2 Myoelectric non-pattern recognition (M-non- PR) system.....	37
2.4 EMG signal for hand rehabilitation devices	39
2.4.1 EMG-based prosthetic hand.....	40
2.4.2 EMG-based exoskeleton hand.....	46
2.5 Summary.....	53
Chapter 3	55

Extreme Learning Machine-Based Classification of Finger Movements Using Surface Electromyography	55
3.1 Introduction	55
3.2 Evaluation of ELM-based myoelectric finger recognition for amputees and non-amputees.....	56
3.2.1 Data acquisition and processing.....	56
3.2.2 Feature Extraction	59
3.2.3 Dimensionality Reduction	60
3.2.4 Classification using Extreme Learning Machine (ELM)	60
3.2.5 Post-processing	61
3.2.6 Simulation Environment.....	62
3.3 Experiments and Results	62
3.3.1 The Number of channels	62
3.3.2 Window Length.....	63
3.3.3 Feature Extraction	65
3.3.4 Feature Reduction.....	66
3.3.5 Majority Vote.....	67
3.3.6 Classification.....	68
3.4 Discussion.....	78
3.5 Summary.....	81
Chapter 4	83
Novel ELM-Based Classifications for myoelectric finger recognition using two EMG channels	83
4.1 Introduction	83
4.2 Performance evaluation of adaptive wavelet extreme learning machine (AW-ELM)	84
4.2.1 Background.....	85
4.2.2 Wavelet extreme learning machine (W-ELM).....	86
4.2.3 Adaptive wavelet extreme learning machine (AW-ELM).....	87
4.2.4 Experimental setup	91
4.2.5 Experiments and Results	93
4.2.6 Conclusion	102
4.3 Performance evaluation of spectral regression extreme learning machine (SR-ELM)	103

4.3.1	Background	103
4.3.2	Extreme learning machine	105
4.3.3	Spectral regression extreme learning machine (SR-ELM)	106
4.3.4	Experiments and results	107
4.3.5	Conclusion	120
4.4	Evaluation of swarm based extreme learning machine (S-ELM) for myoelectric finger recognition.....	121
4.4.1	Background	121
4.4.2	Kernel-based extreme learning machine	122
4.4.3	Particle swarm optimization (PSO)	123
4.4.4	Optimization of the parameters of the kernel based ELM using PSO	124
4.4.5	Experimental setup	125
4.4.6	Experiments and Results	126
4.4.7	Conclusion	128
4.5	Evaluation of swarm-wavelet extreme learning machine (SW-ELM) for myoelectric finger recognition.....	129
4.5.1	PSO with wavelet mutation	129
4.5.2	The experimental setup	131
4.5.3	Experiments and Results	132
4.5.4	Experiment on the amputee database	138
4.5.5	Conclusion	141
4.6	Summary.....	141
	Chapter 5	143
	Toward robust myoelectric pattern recognition for real-time finger movement classification.	143
5.1	Introduction	143
5.2	Evaluation of real-time myoelectric finger motion recognition using two EMG channels	143
5.2.1	Background	144
5.2.2	Methodology	145
5.2.3	Experiment 1: offline classification	149
5.2.4	Experiment 2: online classification.....	152
5.2.5	Conclusion	156

5.3	Evaluation of myoelectric finger motion recognition with motion rejection for an exoskeleton hand.....	157
5.3.1	Background.....	158
5.3.2	Methodology.....	158
5.3.3	Experiments and results.....	161
5.3.4	Conclusion.....	169
5.4	Evaluation of online sequential extreme learning (OS-ELM-R) for robust myoelectric finger recognition.....	169
5.4.1	Introduction.....	169
5.4.2	Methodology.....	171
5.4.3	Experiments and results.....	174
5.4.4	Conclusion.....	182
5.5	Summary.....	182
	Chapter 6.....	185
	Summary, conclusion and future research.....	185
6.1	Thesis summary.....	185
6.2	Recommendation for future research.....	190
6.3	Conclusion.....	191
	APPENDIX A: ETHICAL APPROVAL.....	193
	Bibliography.....	197

List of Figures

Figure 2.1 Right hand, proximal view (Doyle & Botte, 2002)	16
Figure 2.2 Flexion of three joint of the fingers. A. Flexion of the MCP joint. B. Flexion of the PIP joint. C. Flexion of DIP joint (Nordin & Frankel, 2012)	17
Figure 2.3 Flexor Muscles (Marieb, 2009)	18
Figure 2.4 Extensor muscles (Marieb, 2009)	19
Figure 2.5 The basic motor control mechanism (Moritani <i>et al.</i> , 2005)	20
Figure 2.6 The example of the EMG signal (top) and its energy (bottom) (C. J. De Luca, 2002)	21
Figure 2.7 EMG signal generation and collection (Farina <i>et al.</i> , 2014).....	21
Figure 2.8 Data instrumentation of the EMG signal (Criswell, 2010).....	22
Figure 2.9 The myoelectric pattern recognition system.....	23
Figure 2.10 The EMG-based non-pattern recognition	23
Figure 2.11 The data segmentation: disjoint windowing (a) and overlapped windowing (b) (Kevin Englehart & Hudgins, 2003)	24
Figure 2.12 The time-frequency tilling of three different TFD features: a. SFFT b. WT and c. WPT (Kevin Englehart <i>et al.</i> , 2001)	28
Figure 2.13 Single feed-forward networks for extreme learning machine	33
Figure 2.14 The proportional myoelectric control of Neuroexos exoskeleton (Lenzi <i>et al.</i> , 2012).....	38
Figure 2.15 Regression based myoelectric control (Farina <i>et al.</i> , 2014)	39
Figure 2.16 The high-cost prosthetic hands : i-limb ultra (a) and bebionic (b) and the low-cost prosthetic hands: openbionic’s hand (c) and openhandproject’s hand (d).....	40
Figure 2.17 The hand of hope: a commercial exoskeleton hand.....	40
Figure 2.18 The Russian EMG controlled hand (Popov, 1965).....	41
Figure 2.19 Myoelectric pattern recognition for a prosthetic hand using FFT and Artificial neural network (Uchida <i>et al.</i> , 1992)	42
Figure 2.20 The experimental procedure (left) and the electrode positions (right) (Tenore <i>et al.</i> , 2009).....	43
Figure 2.21 The EMG pattern recognition of Cipriani (Cipriani <i>et al.</i> , 2011).....	44

Figure 2.22 Ten finger movement involved in the experiment.....	44
Figure 2.23 The stages of the EMG pattern recognition.....	45
Figure 2.24 Various schemes of the myoelectric pattern recognition investigated	46
Figure 2.25 The Mulas's exoskeleton hand	47
Figure 2.26 The placement of the electrodes	47
Figure 2.27 The wege's exoskeleton hand.....	48
Figure 2.28 Control diagram of the Wege's exoskeleton	49
Figure 2.29 The electrode placement for the wege's exoskeleton hand	49
Figure 2.30 Mechanical design of Tong's exoskeleton hand.....	50
Figure 2.31 The Tong's exoskeleton hand.....	50
Figure 2.32 The electrode placement for the Tong's exoskeleton hand	51
Figure 2.33 Finger exoskeleton.....	52
Figure 3.1 The proposed pattern recognition for classifying finger movements	56
Figure 3.2 Electrode's position of an intact-limbed subject and an amputee subject.....	57
Figure 3.3 Accuracy of the number of channel experiments across nine able-bodied subjects and five amputees using four-fold cross validation.....	63
Figure 3.4 Average classification accuracy across 10 different window lengths	64
Figure 3.5 Averaged processing time of the finger recognition	64
Figure 3.6 Average classification accuracy of different feature extraction on nine able-limbed subjects (a) and five amputee subjects (b) using 4-fold cross validation	65
Figure 3.7 Averaged classification accuracy of different reduction dimensionality methods across nine and five non-amputee and amputee subjects, respectively ..	67
Figure 3.8 Averaged reduction time of different reduction dimensionality methods across nine and five non-amputee and amputee subjects respectively	67
Figure 3.9 The results of the majority vote experiment using RBF-ELM classifier validated by four-fold cross validation.....	68
Figure 3.10 Average accuracy of various ELMs across five amputees and nine able- bodied subjects using four-fold cross validation	70
Figure 3.11 Average classification accuracy of RBF-ELM on five-amputee subjects using four-cross validation	72
Figure 3.12 Average classification accuracy of RBF-ELM on 12 finger movement classes over five amputee subjects.	72

Figure 3.13 Average confusion matrix plot of six-channel RBF-ELM on five amputee subjects.....	73
Figure 3.14 Average classification accuracy of RBF-ELM on nine able-bodied subjects	73
Figure 3.15 Average classification accuracy of RBF-ELM on 15 finger motion over nine non-amputee subjects.....	74
Figure 3.16 Average confusion matrix plot of six-channel RBF-ELM on nine non-amputee subjects.....	74
Figure 3.17 Average accuracy comparison between RBF-ELM and other famous classifiers	75
Figure 4.1 The proposed adaptive wavelet extreme learning machine.....	88
Figure 4.2 The mother wavelet of the Mexican hat	88
Figure 4.3 A nonlinear function to produce b_j	89
Figure 4.4 Myoelectric finger classification using AW-ELM and other classifiers	91
Figure 4.5 The placement of the electrodes	92
Figure 4.6 Ten different finger movements	92
Figure 4.7 The classification accuracy of three node base ELM across eight subjects using 4-fold cross validation.....	94
Figure 4.8 The training time (LEFT) and testing time (RIGHT) of the node-based ELMs	95
Figure 4.9 The performance of AW-ELM and well-known classifiers in recognizing 10 finger motions on eight different subjects using 3-fold cross validation	97
Figure 4.10 The performance of AW-ELM and other classifiers in classifying ten finger movements across eight subjects using 3-fold cross validation.....	98
Figure 4.11 The myoelectric finger motion recognition for testing SR-ELM.....	108
Figure 4.12 The experiment result for searching the optimal number of nodes	109
Figure 4.13 The relation of the number of nodes and alpha (α) using classifier AW-ELM (LEFT) and RBF-ELM (RIGHT).....	110
Figure 4.14 The performance of SR-ELM and others across eight subjects without using a majority vote	111
Figure 4.15 The performance of SR-ELM and others across eight subjects with a majority vote.....	111
Figure 4.16 Processing time consumed by some dimensionality reduction methods...	112

Figure 4.17 SR-ELM performance on different classifiers without majority vote across eight subjects	113
Figure 4.18 SR-ELM performance on different classifiers plus majority vote across eight subjects	113
Figure 4.19 Anova test of SR-ELM and other methods across eight subjects using 10 classes with majority vote.....	114
Figure 4.20 Scatter plot of the original features before projected	114
Figure 4.21 Scatter plot of the projected features using ULDA (LEFT) and OFNDA (RIGHT)	115
Figure 4.22 Scatter plot of the projected features using SRDA (LEFT) and SR-ELM (RIGHT)	115
Figure 4.23 The pseudo code of PSO for the optimization of the kernel-based ELM parameters.....	124
Figure 4.24 The myoelectric pattern recognition using integration PSO and the kernelized ELM	125
Figure 4.25 The average fitness function for different kernels across eight subjects using 3-fold cross validation.....	126
Figure 4.26 The classification accuracy of the optimized ELM averaged from eight subjects	127
Figure 4.27 The classification accuracy of the optimized ELM for different finger movements.....	128
Figure 4.28 The pseudo code for PSO with wavelet mutation for optimizing the parameters of ELM.....	130
Figure 4.29 The experimental setup of the PSO-wavelet mutation for ELM parameters optimization	131
Figure 4.30 The fitness values for variable p_m when $\xi=0.2$ and $g=10000$ over eight subjects	132
Figure 4.31 The fitness values for variable ξ when $p_m = 0.5$ and $g = 10000$	134
Figure 4.32 The fitness values for variation of the parameter g when $p_m=0.5$ and $\xi=0.2$	135
Figure 4.33 The accuracy of RBF-ELM with mutation and without mutation using 3-fold cross validation	136

Figure 4.34 The accuracy of the finger movement classification across eight subjects using 3-fold cross validation.....	137
Figure 4.35 The confusion matrix plot of the classification result of SW-RBF-ELM .	138
Figure 4.36 Average classification accuracy of three different ELM methods	139
Figure 4.37 The fitness value of PSO and wavelet-PSO across five amputees	139
Figure 4.38 The accuracy of different finger motions across five amputees	140
Figure 5.1 Stages of online myoelectric pattern recognition system	146
Figure 5.2 The electrodes placement	146
Figure 5.3 Procedure for the online classification	148
Figure 5.4 The Interface for EMG signal acquisition	149
Figure 5.5 The offline classification menu done after data collection.....	150
Figure 5.6 The accuracy of the system using two and three channels	150
Figure 5.7 The accuracy of the myoelectric pattern recognition in the offline classification	151
Figure 5.8 The experimental environment for the online myoelectric pattern recognition	152
Figure 5.9 The average accuracy of the online experiment from four trials.....	153
Figure 5.10 The accuracy of the online MPR in various finger movements across eight subjects	153
Figure 5.11 The performance comparison between offline and online classification across eight subjects	154
Figure 5.12 The performance of the online classification across time on subject S6...	155
Figure 5.13 Myoelectric control system developed to control the exoskeleton hand...	159
Figure 5.14 Myoelectric finger movement recognition using RBF-ELM with rejection mechanism	160
Figure 5.15 Proportional controller for the exoskeleton hand	161
Figure 5.16 The exoskeleton hand used in the experiment.....	161
Figure 5.17 The variation of rejection threshold on the system performance without majority vote.....	162
Figure 5.18 The accuracy achieved by RBF-ELM and RBF-ELM-R (threshold = 1.0) across 8 subjects suing 3-fold cross validation using majority vote	164
Figure 5.19 An example of online experiment on the implementation of myoelectric pattern recognition with motion rejection on the exoskeleton hand.....	165

Figure 5.20 An example of real-time experiment over time using threshold 0.7 on 10-classes experiment.....	166
Figure 5.21 The real-time experiment results over time using threshold 0.3 using 5 trained classes and 5 untrained classes.	168
Figure 5.22 Online myoelectric pattern recognition for finger motion recognition using OSELM-R.....	174
Figure 5.23 Average errors on the node experiments across eight subjects using 3-fold validation.....	175
Figure 5.24 Average errors on the class number experiments across eight subjects using 3-fold validation.....	175
Figure 5.25 The overall performance of the OS-ELM compared with other classifiers across eight subjects using 3-fold cross validation.....	176
Figure 5.26 The performance of the M-PR with rejection using 3-fold cross validation without a majority vote: the accuracy (TOP) and the rejection rate (BOTTOM).....	177
Figure 5.27 The classification results of M-PR using OS-ELM and RBF-ELM.....	178
Figure 5.28 Online classification of OS-ELM and OS-ELM-R for recognition of 10 finger motions on one subject on one trial	179
Figure 5.29 Daily classification performance of OS-ELM and RBF-ELM.....	180
Figure 5.30 An example of online classification result of OS-ELM and OS-ELM-R in reconizing 10 finger motions for the second day	181
Figure 5.31 An example of online classification result of OS-ELM and OS-ELM-R in reconizing 10 finger motions for the third day.....	181

List of Tables

Table 2.1 Extrinsic muscles for digit movements (Muscolino, 2014).....	19
Table 3.1. Demographics of the amputees involved in the experiment.....	57
Table 3.2 Averaged classification accuracy of the system using different features across all subjects using four-cross validation	66
Table 3.3 The optimum parameters of the classifiers used in the experiment.....	69
Table 3.4 <i>p</i> -values from a pair-wise comparison of various ELM classifiers on Five Amputee Subjects.....	70
Table 3.5 <i>p</i> -values from a pair-wise comparison of various ELM classifiers on Nine Able-bodied Subjects.....	71
Table 3.6 <i>p</i> -values from a pair-wise comparison of different classifiers on five amputee subjects.....	76
Table 3.7 <i>p</i> -values from a pair-wise comparison of different classifiers on nine non- amputee subjects.....	76
Table 3.8 Training time of amputee subjects	76
Table 3.9 Training time of non-amputee subjects.....	77
Table 3.10 Testing Time of amputee subjects	77
Table 3.11 Testing Time of non-amputee subjects	78
Table 3.12 Comparison of Various Research on Finger Movement Recognition	81
Table 4.1 The average classification accuracy of AW-ELM across eight subjects using four-fold cross validation compared with W-ELM and Sig-ELM.....	94
Table 4.2 Processing time of different ELM classifiers.....	95
Table 4.3 The p-value of anova test on the classification accuracy between AW- ELM and other tested classifiers.....	96
Table 4.4 The parameters of classifier involved in the experiment	96
Table 4.5 The average accuracy of different classifiers for myoelectric finger motion classification using 3-fold cross validation.....	97
Table 4.6 <i>p</i> -value of AW-ELM and other famous classifiers	97

Table 4.7 The confusion matrix of accuracy of AW-ELM in classifying ten finger movements across eight subjects using 3-fold cross validation	98
Table 4.8 Data specification for benchmarking	99
Table 4.9 The optimal parameters used by each classifier in the UCI dataset experiments.....	100
Table 4.10 The accuracy of seven classifiers on various data using 5-fold cross validation for small and medium size data and 3-fold cross validation for large size data	100
Table 4.11 One way ANOVA test results on the comparison of AW-ELM and other classifiers (the black box shows $p < 0.05$).....	100
Table 4.12 The training time of seven classifiers on various data using 5-fold cross validation for small and medium size data and 3-fold cross validation for large size data	101
Table 4.13 The testing time of seven classifiers on various data using 5-fold cross validation for small and medium size data and 3-fold cross validation for large size data	101
Table 4.14 The parameters of classifier involved in the experiment	109
Table 4.15 Various classes involved in the experiment.....	110
Table 4.16 Various features used in the experiment.....	115
Table 4.17 The accuracy achieved employing AWELM on the feature test using 3-fold cross validation.....	116
Table 4.18 The accuracy achieved employing LDA on the feature test using 3-fold cross validation.....	117
Table 4.19 The accuracy achieved employing RBF-ELM on the feature test using 3-fold cross validation.....	117
Table 4.20 The accuracy achieved employing SVM on the feature test using 3-fold cross validation.....	117
Table 4.21 Various datasets used in the experiments from UCI Library.....	118
Table 4.22 The accuracy attained using AW-ELM	119
Table 4.23 The accuracy attained using RBF-ELM using 3-fold and 5-fold cross validation for satimage and other than satimage, respectively	119
Table 4.24 The accuracy attained using LIBSVM using 3-fold and 5-fold cross validation for satimage and other than satimage, respectively	119

Table 4.25 The accuracy attained using LDA using 3-fold and 5-fold cross validation for satimage and other than satimage, respectively	120
Table 4.26 The accuracy attained using kNN using 3-fold and 5-fold cross validation for satimage and other than satimage, respectively	120
Table 4.27 The optimal parameter optimized by a swarm technique	126
Table 4.28 The average classification accuracy across eight subjects	127
Table 4.29 p -values resulting from a pair wise comparison of classification accuracy	128
Table 4.30 The accuracy of SW-RBF-ELM when $\xi=0.2$ and $g=10000$	133
Table 4.31 The accuracy of SW-RBF-ELM when $p_m=0.5$ and $g=10000$	134
Table 4.32 The accuracy of SW-RBF-ELM when $p_m=0.5$ and $\zeta = 0.2$	135
Table 4.33 The confusion matrix of the classification result of SW-RBF-ELM	138
Table 4.34 The confusion matrix of the classification results of swarm-wavelet elm averaged for five amputees (Units : %)	140
Table 5.1 The hardware and software needed for real-time application	145
Table 5.2 One-way ANOVA test between two-channel and three-channel experiment	151
Table 5.3 Confusion matrix of the online classification	154
Table 5.4 The controller delay of the online experiment	156
Table 5.5 The accuracy achieved by varying the threshold of the rejection mechanism across eight subjects using 3-fold cross validation without using the majority vote	163
Table 5.6 The accuracy achieved by varying the threshold of the rejection mechanism across eight subjects using 3-fold cross validation using the majority vote	163
Table 5.7 The rejection rate of threshold experiments on eight subjects using 3-fold cross validation	163
Table 5.8 The accuracy of the real-time experiment using 10 trained classes	166
Table 5.9 The accuracy of the real-time experiment using five trained classes and five untrained classes	168
Table 5.10 The comparison of OS-ELM with and without rejection rate using 3-fold cross validation across eight subjects	178
Table 6.1 The summary of the M-PR developed in this thesis	189

This page is intentionally left blank

List of Abbreviations

AR	: Autoregressive
AW-ELM	: Adaptive wavelet extreme learning machine
ELM	: Extreme learning machine
EMG	: Electromyography
FFNN	: Feed forward neural network
FFT	: Fast Fourier transform
kNN	: k nearest neighbourhood
LDA	: Linear discriminant analysis
Lin-ELM	: Linear extreme Learning Machine
MES	: Myoelectric signal
ML	: Multilayer perceptron
M-PR	: Myoelectric pattern recognition
OFNDA	: Orthogonal fuzzy neighbourhood discriminant analysis
OS-ELM	: Online sequential extreme learning machine
OS-ELM-R	: Online sequential extreme learning machine with rejection
PCA	: Principal component analysis
Poly-ELM	: Polynomial extreme learning machine
RBF-ELM	: Radial basis function extreme learning machine
RBF-ELM-R	: Radial basis function extreme learning machine with rejection
SLin-ELM	: Swarm linear extreme learning machine
SPoly-ELM	: Swarm polynomial extreme learning machine
SRBF-ELM	: Swarm radial basis function extreme learning machine
SRDA	: Spectral regression discriminant analysis
SR-ELM	: Spectral regression extreme learning machine
SVM	: Support vector machine
SW-RBF-ELM	: Swarm wavelet radial basis function extreme learning machine
TD	: Time domain
W-ELM	: Wavelet extreme learning machine
LIBSVM	: Library support vector machine

MAV	:	Mean absolute value
MAVS	:	Mean absolute value slope
ZC	:	Zero crossing
SSC	:	Slope sign changes
WL	:	Waveform length
RMS	:	Root mean square
MNF	:	Mean frequency features
MDF	:	Median frequency

Abstract

The myoelectric pattern recognition (M-PR) for hand rehabilitation devices has shown its efficacy in the laboratory environment. However, the performance of the M-PR in the clinical application is very poor. There is a big gap between the success of the laboratory experiment and the clinical application. The researchers found that the major cause of the gap was the robustness of the M-PR. Many aspects influence the robustness of the M-PR including the limb position, skin humidity, muscle fatigue, improvement in the muscle function, electrode shifts, and other clinical reasons. The aim of this thesis is to introduce novel M-PRs dealing with the robustness issues in real-time implementation. The goal was accomplished through the following actions.

1. Developing a new M-PR that can work well on the amputees and non-amputees. The proposed M-PR consists of time-domain and autoregressive features (TD-AR), spectral regression discriminant analysis (SRDA) as a feature reducer, and radial basis function extreme learning (RBF-ELM) as a classifier. The experimental results showed that the proposed system was able to detect the user's intention with accuracy of roughly 99% on the able-bodied subjects and around 98% on the trans-radial amputees using six EMG channels.
2. Introducing new classifiers. The first classifier is adaptive wavelet extreme machine learning (AW-ELM). AW-ELM is the node-based ELM that can adapt to the changes that occur in the input. In general, AW-ELM could classify ten finger movements from two EMG channels with a good accuracy of 94.84 %. The second classifier is swarm radial basis extreme learning machine (SRBF-ELM). SRBF-ELM is a hybridization of particle swarm optimization (PSO) and the kernel-based ELM. The role of PSO is to optimize the kernel parameters. The last classifier is swarm wavelet extreme learning machine (SW-RBF-ELM). The role of the wavelet is to avoid PSO being trapped in local optima. The experiments have been done on the healthy subjects and amputees for both, SRBF-ELM and SW-RBF-ELM. On the healthy subjects, the accuracy of SW-RBF-ELM is 95.62 % while SRBF-ELM is 95.53 %. On the amputees, the SW-RBF-ELM achieved the average accuracy of 94.27 %, while SRBF-ELM produced the average accuracy of 92.55 %.

3. Developing a new feature projection and feature reduction called spectral regression extreme learning (SR-ELM). SR-ELM can enhance the class separability of the features to improve the classification performance. The experimental results showed that SR-ELM can work well on different classifiers and various numbers of classes with an average accuracy ranging from 95.67 % to 86.73 %
4. Developing a robust M-PR by involving the transient state of EMG signal along with the steady state of it in the real-time experiment. The classification accuracy is 90.46 % and 89.19 % on the offline and online classification, respectively.
5. Introducing a new myoelectric controller for the exoskeleton hand. The myoelectric controller consists of two main parts: the myoelectric pattern recognition (M-PR) and myoelectric non-pattern recognition (M-non-PR). In the system, RBF-ELM-R (radial basis extreme learning machine with a rejection mechanism) represents the M-PR, and the proportional controller represents the M-non-PR. The power actuated to the linear motors is proportional to the amplitude of the EMG signals. The experimental results showed that, in the offline experiment of 10 classes, the accuracy is around 90 % and 92 % for RBF-ELM and RBF-ELM-R, respectively. In the online experiment, the accuracy is about 89.22 % and 89.73 % for RBF-ELM and RBF-ELM-R, respectively.
6. Introducing an adaptive mechanism to the M-PR to adapt to changes in the characteristic of the electromyography (EMG) signal. The thesis proposes a new M-PR with online sequential extreme learning machine (OS-ELM) and OS-ELM with rejection (OS-ELM-R). The experimental results showed that the accuracy is around 89 % and 91 % for OS-ELM and OS-ELM-R on the first-day experiment.