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

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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.

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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.