



**Faculty of Electrical Engineering**

**DESIGN OF FEATURE SELECTION METHODS FOR HAND  
MOVEMENT CLASSIFICATION BASED ON  
ELECTROMYOGRAPHY SIGNALS**

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**Doctor of Philosophy**

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**DESIGN OF FEATURE SELECTION METHODS FOR HAND MOVEMENT  
CLASSIFICATION BASED ON ELECTROMYOGRAPHY SIGNALS**

**TOO JING WEI**

**A thesis submitted  
in fulfilment of the requirements for the degree of Doctor of Philosophy**

**Faculty of Electrical Engineering**

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**2020**

## DECLARATION

I declare that this thesis entitled “Design of Feature Selection Methods for Hand Movement Classification Based on Electromyography Signals” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature : .....

Name : Too Jing Wei

Date : .....

## **APPROVAL**

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Doctor of Philosophy.

Signature : .....

Supervisor Name : Professor Madya Ir. Ts. Dr. Abdul Rahim bin Abdullah

Date : .....

## **DEDICATION**

Specially dedicated to

My beloved mother,

To my family and friends

Thank you for all the encouragement and support

## ABSTRACT

Recently, electromyography (EMG) has received much attention from the researchers in rehabilitation, engineering, and clinical areas. Due to the rapid growth of technology, the multifunctional myoelectric prosthetic has become viable. Nevertheless, an increment in the number of EMG features has led to a high dimensional feature vector, which not only increases the complexity but also degrades the performance of the recognition system. Intuitively, the accuracy of hand movement classification will be reduced, and the control of myoelectric prosthetic will become highly difficult. Therefore, this thesis aims to solve the feature selection problem in EMG signals classification and improve the classification performance of EMG pattern recognition system. For this purpose, the feature selection (FS) method is applied to evaluate the best feature subset from a large available feature set. According to previous works, conventional FS methods not only minimize the number of features but also enhance the classification performance. However, the performances of conventional FS methods such as Binary Particle Swarm Optimization (BPSO) and Binary Grey Wolf Optimization (BGWO) are still far from perfect. Additionally, there are several limitations can be found within the conventional FS methods. In this regard, this thesis proposes five FS methods for efficient EMG signals classification. The first method is the Binary Tree Growth Algorithm (BTGA), which implements a hyperbolic tangent function to convert the Tree Growth Algorithm into the binary version. The second method is called the Modified Binary Tree Growth Algorithm (MBTGA) that applies swap, crossover, and mutation operators. The third method is the hybridization of BPSO and Binary Differential Evolution, namely Binary Particle Swarm Optimization Differential Evolution (BPSODE). The fourth method is Competitive Binary Grey Wolf Optimizer (CBGWO), which is an improved version of BGWO by utilizing the competition and leader enhancement strategies. The final method is called *Pbest*-Guide Binary Particle Swarm Optimization (PBPSO), which is an improved version of BPSO with a powerful personal best (*pbest*) guide strategy. The performances of proposed methods are tested using the EMG data of 10 healthy and 11 amputee subjects acquired from publicly NinaPro database 3 and 4. Initially, Short Time Fourier Transform (STFT) and Discrete Wavelet Transform (DWT) are used for signal processing. Afterward, several time-frequency features are extracted to form the STFT feature set and DWT feature set. Then, the proposed FS methods are employed to select the most informative feature subset. Five state-of-the-art FS methods are used to evaluate the effectiveness of proposed methods in this work. The experimental results show that proposed PBPSO contributed to a high classification accuracy of 99.84% and 84.05% on healthy and amputee datasets, which offered more accurate of hand movement classification and enables an excellent control on myoelectric prosthetic.

# **REKA BENTUK KAEDAH PEMILIHAN CIRI UNTUK KLASIFIKASI PERGERAKAN TANGAN BERDASARKAN ISYARAT ELEKTROMYOGRAFI**

## **ABSTRAK**

Baru-baru ini, *electromyography (EMG)* telah mendapat banyak perhatian daripada penyelidik dalam aplikasi pemulihan, kejuruteraan dan klinikal. Oleh kerana pertumbuhan pesat teknologi, prostetik myoelektrik pelbagai fungsi telah menjadi berdaya maju. Walau bagaimanapun, peningkatan bilangan ciri EMG telah membawa kepada vektor ciri dimensi yang tinggi, ia bukan sahaja meningkatkan kerumitan tetapi juga merendahkan prestasi sistem pengiktirafan. Secara intuitif, ketepatan pengelasan gerakan tangan akan dikurangkan, dan kawalan prostetik myoelektrik akan menjadi sangat sukar. Oleh itu, tesis ini bertujuan untuk menyelesaikan masalah pemilihan ciri dalam klasifikasi isyarat EMG dan meningkatkan prestasi sistem EMG. Untuk tujuan ini, kaedah pemilihan ciri (FS) digunakan untuk menilai subset ciri terbaik. Kerja-kerja sebelumnya menunjukkan kaedah FS konvensional bukan sahaja meminimumkan bilangan ciri, tetapi juga mempertingkatkan prestasi klasifikasi. Walau bagaimanapun, prestasi kaedah FS konvensional seperti Binary Particle Swarm Optimization (BPSO) dan Binary Grey Wolf Optimization (BGWO) masih jauh dari sempurna. Di samping itu, terdapat beberapa batasan yang boleh didapati dalam kaedah FS konvensional. Dalam hal ini, lima kaedah FS telah dicadangkan dalam tesis ini untuk klasifikasi isyarat EMG yang cekap. Kaedah pertama ialah Binary Tree Growth Algorithm (BTGA), yang melaksanakan fungsi tangen hiperbolik untuk menukar Tree Growth Algorithm ke dalam versi binari. Kaedah kedua dinamakan Modified Binary Tree Growth Algorithm (MBTGA) yang memakai swap, crossover dan operator mutasi. Kaedah ketiga ialah hibridisasi BPSO dan Binary Differential Evolution, iaitu Binary Particle Swarm Optimization Differential Evolution (BPSODE). Kaedah keempat dinamakan sebagai Competitive Binary Grey Wolf Optimizer (CBGWO), yang merupakan versi BGWO yang lebih baik dengan menggunakan strategi persaingan dan peningkatan pemimpin. Kaedah terakhir iaitu Pbest-Guide Binary Particle Optimization (PBPSO), yang merupakan versi BPSO yang lebih baik dengan strategi panduan terbaik. Prestasi kaedah FS baru diuji dengan menggunakan EMG data dari 10 orang sihat dan 11 amputee yang diperoleh dari NinaPro database. Pada mulanya, Short Time Fourier Transform (STFT) dan Discrete Wavelet Transform (DWT) digunakan untuk pemprosesan isyarat. Selepas itu, beberapa ciri frekuensi masa diekstrak untuk membentuk set ciri STFT dan set ciri DWT. Kemudian, cadangan kaedah FS digunakan untuk menilai subset ciri yang paling bermaklumat. Untuk menilai keberkesanan kaedah FS yang dicadangkan, lima kaedah FS yang canggih digunakan untuk perbandingan prestasi. Keputusan eksperimen menunjukkan bahawa cadangan PBPSO menyumbang kepada ketepatan klasifikasi tinggi 99.84% dan 84.05% pada dataset yang sihat dan amputee, ia menawarkan klasifikasi pergerakan tangan yang lebih tepat dan membolehkan kawalan yang sangat baik terhadap prostetik myoelektrik.

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## LIST OF ABBREVIATIONS

2D	- Two Dimensional
ACO	- Ant Colony Optimization
ANN	- Artificial Neural Network
BDE	- Binary Differential Evolution
BGWO	- Binary Grey Wolf Optimization
BPSO	- Binary Particle Swarm Optimization
BPSODE	- Binary Particle Swarm Optimization Differential Evolution
BTGA	- Binary Tree Growth Algorithm
CA	- Classification Accuracy
CBGWO	- Competitive Binary Grey Wolf Optimizer
CM	- Concentration Measure
COV	- Coefficient of Variation
CT	- Computation Time
CWT	- Continuous Wavelet Transform
DB3	- NinaPro Database 3
DB4	- NinaPro Database 4
DE	- Differential Evolution
DWT	- Discrete Wavelet Transform
EMD	- Empirical Mode Decomposition

EMG	- Electromyography
EMG-PR	- EMG Pattern Recognition
ER	- Error Rate
FD	- Frequency Domain
FFT	- Fast Fourier Transform
FM	- F-measure
<i>FN</i>	- False Negative
<i>FP</i>	- False Positive
FS	- Feature Selection
FR	- Feature Reduction Rate
GA	- Genetic Algorithm
GM	- Geometric Mean
GSA	- Gravitational Search Algorithm
GWO	- Grey Wolf Optimizer
KNN	- <i>K</i> -Nearest Neighbour
LDA	- Linear Discriminate Analysis
MAV	- Mean Absolute Value
MBTGA	- Modified Binary Tree Growth Algorithm
MCC	- Matthew Correlation Coefficient
MDF	- Median Frequency
MFL	- Maximum Fractal Length
ML	- Machine Learning
MNF	- Mean Frequency
NB	- Naïve Bayes

NF	-	Number of Selected Features
NFL	-	No Free Lunch
P	-	Precision
PCA	-	Principle Component Analysis
PBPSO	-	<i>Pbest</i> -Guide Binary Particle Swarm Optimization
PSO	-	Particle Swarm Optimization
RE	-	Renyi Entropy
RF	-	Random Forest
RMS	-	Root Mean Square
STD	-	Standard Deviation
SE	-	Spectral Entropy
SFS	-	Sequential Forward Selection
ST	-	Stockwell Transform
STFT	-	Short Time Fourier Transform
SVM	-	Support Vector Machine
TD	-	Time Domain
TF	-	Time-Frequency
TFA	-	Time-Frequency Analysis
TFD	-	Time-Frequency Domain
TGA	-	Tree Growth Algorithm
VAR	-	Variance
WL	-	Wavelength
WPT	-	Wavelet Packet Transform
WT	-	Wavelet Transform

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## B. Conference

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