HYBRID APPROACH FOR MULTI-FINGER MOVEMENT CLASSIFICATION

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HYBRID APPROACH FOR MYOELECTRIC CONTROL OF MULTI-FINGER MOVEMENT CLASSIFICATION

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ABSTRACT

Identification of correct multi-finger movement class remains a difficulty in a myoelectric prosthetic hand. This is because only a small amplitude of electromyography (EMG) signal was produced by this multi-finger movement. Hence, powerful classification is needed to solve this problem. Support Vector Machine (SVM) is a classification method that has been widely used in classifying multi-finger movement. However, SVM only able to generate solution of multi-finger classification based on non-optimal default parameter. Hence, the objective of this research is to propose hybridization of Grey Wolf optimizer (GWO) with SVM namely hybrid GWO-SVM approach to enhance multi-finger movement classification. The multifinger movement dataset used in this study was from Khusaba et al. (2012) downloaded from free public database in raw forms. The data were generated from two surface EMG channels patched on the remaining limb using Delsys DE 2.x series EMG sensors. The generated EMG signal was then amplified using Delsys Bagnoli8amplifier and sampling using A 12-bit analogue-to-digital converter (National Instruments, BNC- 2090) at 4000Hz. Both amplified and sampling processes were completed using Delsys EMGWorks Acquisition software. Next, pre-processing and feature extraction are important for the achievement in EMG analysis and control and by utilizing the feature extraction process, we can reduce the computational cost of a multifunction myoelectric control system. Furthermore, Hudgins feature set and Root mean square (RMS) feature extraction method were also employed to produce optimal features. The results showed that the proposed hybrid GWO-SVM approach has improved the classification accuracy, sensitivity, and specificity by 1.52 %, 14.22 % and 18.77 % respectively. Hence, the proposed hybrid approach can help in improving the performance of prosthesis hand for prosthetics people

ABSTRAK

Pengenalpastian kelas pergerakan pelbagai jenis jari yang betul masih menjadi kesukaran dalam penghasilan tangan palsu myoelektrik. Ini kerana hanya isyarat elektromiografi amplitud kecil (EMG) yang dihasilkan oleh pergerakan pelbagai jari ini. Oleh itu, teknik pengkelasan yang jitu diperlukan untuk mengatasi masalah ini. Support Vector Machine (SVM) adalah kaedah klasifikasi yang telah digunakan secara meluas dalam pengkelasan pelbagai pergerakan jari. Walau bagaimanapun, SVM hanya dapat menghasilkan penyelesaian klasifikasi berbilang jari berdasarkan nilai parameter tetap bukan nilai optimum. Oleh itu, objektif kajian ini adalah untuk mencadangkan hibridisasi Grey Wolf Optimization (GWO) dengan SVM iaitu pendekatan GWO-SVM kacukan untuk meningkatkan klasifikasi pergerakan pelbagai jari. Set data pelbagai pergerakan jari yang digunakan dalam kajian ini adalah dari Khusaba et al. (2012) yang dimuat turun dari pangkalan data awam dalam bentuk belum diproses. Data dihasilkan dari dua saluran EMG permukaan yang ditambal pada anggota badan yang tersisa menggunakan sensor EMG siri Delsys DE 2.x. Isyarat EMG yang dihasilkan kemudian diperkuat menggunakan Delsys Bagnoli-8amplifier dan mengambil sampel menggunakan penukar analog-kedigital A 12-bit (National Instruments, BNC- 2090) pada 4000 Hz. Seterusnya, prapemprosesan dan pengekstrakan ciri penting untuk pencapaian dalam analisis dan kawalan EMG dengan menggunakan proses pengekstrakan fitur, dapat mengurangkan kos pengiraan sistem kawalan myoelektrik pelbagai fungsi. Selain itu, kaedah pengekstrakan ciri Hudgins dan kaedah pengekstrakan ciri segi empat (RMS) juga digunakan untuk menghasilkan ciri-ciri yang optimum. Hasil kajian menunjukkan bahawa pendekatan GWO-SVM hibrid yang dicadangkan telah meningkatkan ketepatan klasifikasi, sensitiviti dan spesifikasi masing-masing sebanyak 1.52%, 14.22% dan 18.77%. Oleh itu, pendekatan hibrid yang dicadangkan dapat membantu dalam meningkatkan keberkesanan sistem pengecaman pelbagai pergerakan jari dalam tangan palsu.

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LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
EMG	-	Electromyography
FN	-	False Negative
FP	-	False Positive
GA	-	Genetic Algorithm
GWO	-	Grey Wolf Optimizer
GWO-SVM	-	Hybrid Grey wolf optimizer with Support Vector Machine
HC	-	Hand Close
I	-	Index
L	-	Little
LDA	-	Linear Discrimination Analysis
M	-	Middle
MCS	-	Myoelectric control system
PSO	-	Particle Swarm Optimization
R	-	Ring
RBF	-	Radial Basic Function
RMS	-	Root Mean Square
SVM	-	Support Vector Machine
T	-	Thumb
T-I	-	Thumb-Index
T-L	-	Thumb-Little
T-M	-	Thumb-Middle
TN	-	True Negative
TP	-	True Positive
T-R	-	Thumb-Ring

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CHAPTER 1

INTRODUCTION

This chapter discusses the introduction of this research. The contents include information about problem background, research questions, research objectives and significance of the research.

1.1 Problem Background

The prosthetic hand is a device that assists amputated person for living independently in daily life (Chadwell et al. 2016). Even there are different types of prosthetic hand, myoelectric prosthetic hand devices are the most similar to original function of human hand. However, this myoelectric prosthetic hand still not achieves fully satisfaction especially in identification of multi-finger movement because of their low accuracy and slow in processing (Christian et al. 2007; Biddiss and Cau, 2007; Peerdeman et al. 2011; Head, 2014; Engdahl et al. 2015). One of the reasons that caused this result is their inefficiency of myoelectric control system (MCS) itself.

Myoelectric control refers to as the process of controlling an external device (prosthetic hand) by utilizing electromyography (EMG) signals from the human muscles. In general, MCS consists of several main processes which are pre-processing, feature extraction and classification. If any of this process is not perform well, the performance of MCS will degrade. Hence, researchers have proposed many methods to ensure this system is functioning well. As for pre-processing, there are many works had been done to ensure the data is noise-free and segmented in suitable frame size. Englehart and Hudgins (2003) and Oskoei and Hu (2008) proposed 256 milliseconds (ms) and 200ms segment frame size for disjoint segmentation. There are also several researchers (Tang et al. 2014; Guo et al. 2015; chan et al. 2007) that employ the overlapping segmentation with different window size and window increment.

However, there is still no proper benchmark for this process. Hence, to identify the optimal segment frame, it needs in comparison to this segmentation methods.

As for feature extraction methods, over the years, many features were suggested for classification of hand movement in terms of a single feature of time-domain (TD), frequency domain, time-frequency domain, autoregressive or any combination of the listed types. Zardoshti et al. (1995) have evaluated eight EMG feature for the control of myoelectric upper arm prostheses. Du et al. (2004) proposed feature extraction technique for both temporal and spectral approaches. Munteanu et al. (2011) also had analyzed the time and frequency domain of EMG followed by Phinyomark (2011) and Phinyomark (2014) that used the scatter plot to evaluate time domain and frequency domain. In 2016, Negi and fellow researcher also had evaluated fourteen-time domain features and extracted the best possible feature and their combination to get high classification accuracy. However, these features are too many, applied all this will cause increasing the computational cost. Then, only the simplest and proven performance are compared and employ in this study to ensure the accuracy and processing time.

For classification, many classification algorithms have been developed. Among them, a classical algorithm such as SVM, LDA and ANN and new algorithm such as fuzzy logic have employed and reported to perform robustly in many studies (Kim et al., 2011; Ahsan et al. 2009; Lorrain et al., 2011; Oskoei and Hu, 2008). However, among this, SVM shows an outstanding and consistent performance in terms of accuracy (Oskoei and Hu, 2008; Chen and Wang, 2013). However, one of the limitations is the optimal parameter value of SVM need to be identified before employ them because the performance of SVM depends on their parameter value. Different case study required different optimal parameter value depends on kernel applied. Thus, the optimization methods are compulsory in order to optimize the performance of SVM classification. For optimizing the parameter, various optimization techniques have been proposed hybridized with SVM such as GA, PSO, DE, GSA. However, these methods usually unstable in their local and global search, a long period of time needs to process and still cannot guarantee the good result for all SVM kernels. GWO one of the recent swarm-based intelligent techniques is seen potentially to be hybridized with SVM due to the ability of GWO in balance in exploration and exploitation, high convergence rate and produce high accuracy. Thus, this research proposed hybridization of SVM with GWO to enhance the performance of finger movement identification for myoelectric control systems.

1.2 Problem Statement

The success of controlling single and multi-finger prostheses depends on the proper feature extraction and classification technique applied based on accuracy and computing time. To establish the simple with an outstanding performance of myoelectric control system that obtains competitive performance result in four main aspects of recognition system which is accuracy, sensitivity, specificity and processing times. The main problem in this area is obtaining the high performance of a system that has high accuracy and low processing time as summarized in the here research questions below.

1.3 Research Question

To answer the problem statement, this study comes out with three research question as stated below:

1. What is the best combination of overlapping segmentation (segment length and segment increment) value based on processing time?
2. Which feature extraction methods performs better based on their performance on classification accuracy
3. How does hybrid GWO-SVM can potentially improve the performance of classification result in terms of accuracy, sensitivity and specificity?

1.4 Aim

To establish the simple with an outstanding performance of myoelectric control system that obtains competitive performance result in four main aspects of a recognition system which is accuracy, sensitivity, specificity and processing times.

1.5 Objectives

The objectives of the research are:

(a) To identify the best data segmentation (window length and window increment) based on processing time.

(b) To implement and compare three feature extraction methods and compare the performance using classification accuracy.

(c) To develop a new hybrid GWO-SVM classification and evaluate the result in terms of accuracy, sensitivity and specificity.

1.6 Scope of Research

The scopes of the study are as follows:

a) Time Domain feature extraction methods. Using Hudgins and RMS feature extraction methods. (**Refer to page 25)**

b) Overlapping segmentation . randomly pick three combination of segment length and segment increments that follows the guidelines.

c) The study focusses on SVM classification technique in myoelectric control system. (**Refer to page 41)**

d) Focus on Khusaba et al. (2012) dataset. Limit to only identified ten types of single and combined finger movement which are single consist of Thumb (T), Index (I), Middle (M), Ring (R), Little (L), and the combined Thumb-Index(T-I), Thumb-Middle (T-M), Thumb-Little (T-L), Thumb-Ring (T-R), and Hand Close (HC). (**Refer to page 57)**

e) Grey Wolf Optimizer (GWO) is used as a parameter setting for SVM classification for this ten-finger movement classified. (**Refer to page 32-33)**

f) Percentage difference of accuracy, sensitivity and specificity between standard SVM and GWO-SVM is used to evaluate the performance of classification technique. (**Refer to page 47)**

1.7 Significant of Research

This study introduce the hybrid GWO and SVM in myoelectric control system classification problem. The proposed classification method increase the effectiveness of the myoelectric control system in overall.

1.8 Thesis Organization

Chapter 1 discusses the problem background, problem statement, research objectives, and research scope of the study. The research significant and contribution are also highlighted in this chapter.

Chapter 2 reviews the details of the prosthetic hand myoelectric system. The review will focus on all stages of the myoelectric control system. The review will also include electromyography dataset followed by pre-processing phase, feature extraction and classification. The review will also discuss the grey wolf optimizer technique for optimization of prosthetic hand myoelectric system.

Chapter 3 describes the research methodology. This research methodology consists of five main phases, they are problem and data definition, experimental setup, development of standard SVM classification, development of proposed GWO-SVM classification and result validation. The dataset of the case study is also discussed. The requirements for hardware and software to conduct the research are explained as well.

Chapter 4 discusses the result and validation of the research. The results are compared between the types of feature extraction and between conventional SVM and proposed hybrid GWO with SVM.

Chapter 5 summarizes and concludes the study. The findings that reflect research questions and objectives are discussed. The future works are also discussed to guide next potential project related to the myoelectric control system.

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1. Esa, N. M., Zain, A. M., & Bahari, M. (2018). Electromyography (EMG) based Classification of Finger Movements using SVM. *International Journal of Innovative Computing*, *8*(3).

2. Esa, N. M., Zain, A. M., Bahari, M., & Yusuf, S. M. (2018, June). Comparative Study of Segmentation and Feature Extraction Method on Finger Movement. In *International Conference of Reliable Information and Communication Technology* (pp. 117-127). Springer, Cham.

3. Esa, N. M., Zain, A. M., Bahari, Kamin, Y & Zakaria, M.A.Z.M (May, 2019). A Grey Wolf Optimizer based Support Vector Machine for Classification of Finger Movement. *Indonesian Journal of Electrical Engineering and Computer Science*. **Accepted to be Published**