TEMPORAL SPECTRAL APPROACH TO SURFACE ELECTROMYOGRAPHY BASED FATIGUE CLASSIFICATION OF BICEPS BRACHII DURING DYNAMIC CONTRACTION

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ABSTRACT

Muscle fatigue is defined as a reduction in muscle's ability to contract and produce force due to prolonged submaximal exercise. Since fatigue is not a physical variable, fatigue indices are commonly used to detect and monitor muscle fatigue development. One suggested approach to quantitative measurement of muscle fatigue is based on surface electromyography (sEMG) signal. Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) are commonly used techniques to obtain time-frequency representation of sEMG signals. However, S Transform (ST) technique has not been applied much to physiological signals. No found literature has used ST technique to extract muscle fatigue indices. Thus, this study intends to determine the feasibility of using ST technique to extract muscle fatigue indices from sEMG signal. Thirty college students with no illness history were randomly selected to perform bicep curl activities for 130 seconds while holding a 2 kg dumbbell. Using the three time-frequency techniques (STFT, CWT, and ST), four commonly extracted muscle fatigue indices (Instantaneous Energy Distribution (IED), Instantaneous Mean Frequency (IMNF), Instantaneous Frequency Variance (IFV) and Instantaneous Normalize Spectral Moment (INSM)) were extracted from the acquired biceps sEMG signals. Indices from fatigue signals were found to be significantly different (p-value < 0.05) from the non-fatigue signals. Based on the Normalization of Root Mean Square Error (NRMSE) and Relative Error, ST technique was found to produce less error than STFT and CWT techniques in extracting muscle fatigue indices. Through the use of 3-fold cross validation procedure and with the help of Support Vector Machine (SVM) classifier, IMNF-IED-IFV was selected as the best feature combination for classifying the two phases of muscle fatigue with consistent classification performance (accuracy, sensitivity and specificity) of 80%. Therefore, this study concludes that ST processing technique is feasible to be applied to sEMG signals for extracting screening or monitoring measures of muscle fatigue with a good degree of certainty.

ABSTRAK

Keletihan otot ditakrifkan sebagai pengurangan keupayaan otot untuk mengecut dan menghasilkan daya disebabkan oleh senaman submaksimum yang berpanjangan. Oleh kerana keletihan bukan satu pemboleh ubah fizikal, indeks keletihan sering digunakan untuk mengesan dan memantau pengorakan keletihan otot. Salah satu pendekatan yang dicadangkan untuk pengukuran kuantitatif keletihan otot adalah berdasarkan kepada isyarat permukaan Elektromiografi (sEMG). Jelmaan Fourier Masa Pendek (STFT) dan Jelmaan Wavelet Berterusan (CWT) adalah teknik yang biasa digunakan untuk mendapatkan perwakilan masa-frekuensi bagi isyarat sEMG. Walau bagaimanapun, teknik Transformasi S (ST) tidak banyak digunakan pada isyarat-isyarat fisiologi. Tiada penulisan dijumpai yang menggunakan teknik ST untuk mengekstrak indeks keletihan otot. Oleh itu, kajian ini bertujuan menentukan kemungkinan penggunaan kaedah ST dalam mengekstrak indeks keletihan otot daripada isyarat sEMG. Tiga puluh pelajar kolej yang tiada sejarah penyakit telah dipilih secara rawak untuk melaksanakan aktiviti ikal bisep selama 130 saat sambil memegang dumbel 2 kg. Dengan menggunakan tiga teknik masa-frekuensi (STFT, CWT, dan ST), empat indeks keletihan otot yang sering diekstrak (Taburan Tenaga Ketika (IED), Frekuensi Min Ketika (IMNF), Frekuensi Varians Ketika (IFV) dan Spektrum Momen Ternormalisasi Ketika (INSM)) telah diekstrak daripada isyarat sEMG bisep. Indeks daripada isyarat keletihan didapati berbeza dengan signifikan (nilai-p < 0.05) daripada isyarat tak-keletihan. Berdasarkan kepada Normalisasi Ralat Punca-Min-Kuasa Dua (NRSME) dan Ralat Relatif, teknik ST didapati menghasilkan kurang ralat daripada teknik STFT dan teknik CWT dalam mengekstrak indeks keletihan otot. Melalui penggunaan tatacara 3-lipat pengesahan silang dan dengan bantuan pengelas Mesin Vektor Sokongan (SVM), IMNF-IED-IFV telah dipilih sebagai kombinasi sifat terbaik untuk mengklasifikasikan kedua-dua fasa keletihan otot dengan prestasi klasifikasi yang konsisten (ketepatan, kepekaan dan kekhususan) iaitu 80%. Maka, kajian ini menyimpulkan bahawa teknik pemprosesan ST boleh dilaksanakan pada isyarat sEMG untuk mengekstrak pengukur penyaringan atau pengukur pemantauan keletihan otot dengan kepastian yang boleh diterima.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACC	-	Accuracy
AR	-	Auto Regression
BMI	-	Body Mass Index
BPNN	-	Back Propagation Neural Network
CC	-	Cepstrum Coefficients
cm	-	centimeter
CNS	-	Central Nervous System
CWD	-	Choi William Distribution
CWT	-	Continuous Wavelet Transform
Db	-	Daubechies
ECG	-	Electrocardiography
EEG	-	Electroencephalography
EMG	-	Electromyography
F	-	Fatigue
FT	-	Fourier Transform
FMD	-	Frequency Median
FMN	-	Frequency Mean
FN	-	False Negative
FP	-	False Positive
FNR	-	False Negative Rate
FPR	-	False Positive Rate
FS	-	Frequency Spectrum
Hz	-	Hertz
IED	-	Instantaneous Energy Distribution
IEMG	-	Integrated Electromyography
IFV	-	Instantaneous Frequency Variance
IMNF	-	Instantaneous Mean Frequency

INSM	-	Instantaneous Normalization Spectral Moment
kg	-	kilogram
kHz	-	kiloHertz
kNN	-	k-Nearest Neighbour
LDA	-	Linear Discriminant Analysis
MAR	-	Mean Absolute Ratio
MAV	-	Mean Absolute Value
MDF	-	Median Frequency
MF	-	Mean Frequency
MLPNN	-	Multilayer Perceptron Neural Network
MMG	-	Mechanomyography
mm	-	milimeter
MP	-	Mean Power
ms	-	milisecond
MUAP	-	Motor Unit Action Potential
NF	-	Nonfatigue
NIRS	-	Near Infrared Spectroscopy
NRMSE	-	Normalization of Root Mean Square Error
PSD	-	Power Spectral Density
PSOSVM	-	Particle Swarm Optimization Support Vector Machine
RBF	-	Radial Basis Function
RBFN	-	Radial Basis Function Networks
RMS	-	Root Mean square
s	-	seconds
SD	-	Standard Deviation
SMG	-	Sonomyography
SSC	-	Slope Sign Changes
ST	-	S Transform
STFT	-	Short Time Fourier Transform
SVM	-	Support Vector Machine
TN	-	True Negative
TNR	-	True Negative Rate or Specificity
TP	-	True Positive
TPR	-	True positive Rate or Sensitivity

uV	-	microVolt
VAR	-	Variance
WAMP	-	William Amplitude
WL	-	Wavelength
WT	-	Wavelet Transform
WVD	-	Wigner Ville Distribution
ZC	-	Zero Crossing

LIST OF SYMBOLS

a	-	Translation of Wavelet Transform
b	-	Scale of Wavelet Transform
C	-	User Adjustable Parameter of SVM Classifier
e	-	Natural Exponential
f	-	Frequency
$F1 \ldots F4$	-	Features or Indicators
min	-	Minimal Value of the Features
max	-	Maximal Value of the Features
n	-	Number of Inputs
ND	-	Number of Data Samples
PSD	-	Power Spectral Density
p-value	-	Probability of Same Mean Between Two Population
t	-	Time
$w(t)$	-	Window Function
x	-	Input Signal
τ	-	Time Shift
Ψ	-	Mother Wavelet of Wavelet Transform
σ *or* SD	-	Standard Deviation
ξ	-	Slack Variable
γ, r, d	-	Kernel Parameters of SVM
μ	-	Mean or Average of Population
∞	-	Infinity
y'	-	Model of Predictors
$\sum$	-	Summation
%	-	Percentage

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Muscle fatigue index is a concept used in the study of fatigue development which is defined as the rate of decline of the muscle's ability to contract and produce force. Since fatigue index is very important in detecting or predicting fatigue development, there is a need to find a reliable and sensitive muscle fatigue index. Quantitative measurement of fatigue is normally conducted through the analysis of electro-myographic signal in time, frequency, and time-frequency domains.

Time domain analysis has been widely used by previous researchers because of its low computational difficulty and low noise environments (Tkach *et al.*, 2010). However, there are situations where some of the information cannot be analysed in time domain. This requires the signal information to be studied in frequency domain. However, frequency domain only describes the frequencies in a waveform, but not the timing. In addition, frequency representation is only suitable for stationary signal since the frequency of the stationary signal does not change with time. Yet, real life signals almost always exhibit some degree of non-stationarity (frequency of the signal changes constantly). For these signals, it is not enough to know the global frequency content. It is also important to know the timing in which these changes in frequency occur, in order to follow the dynamics of the signal. Time and frequency information can be obtained from the time-frequency representation.

1.2 Background of Study

Movement of the human body through muscles is controlled by the brain. The brain sends excitation signals through Central Nervous System (CNS) whenever the muscles of the body are to be used for certain activities; messages from the nerve cells in the brain (upper motor neurons) are transmitted to the nerve cells within the brain stem and spinal cord (lower motor neurons) which are then transmitted to particular muscles (Vincent and Wray, 1990). In general, movements in the arms, legs, chest, face, throat, and tongue are produced by the lower motor neurons which were directed by the upper motor neurons.

A motor unit is the junction point where the muscle fibres and the motor neuron meet. An illustration of the Motor Unit is shown in Figure 1.1. A group of motor units often work together to coordinate the contractions of a single muscle.

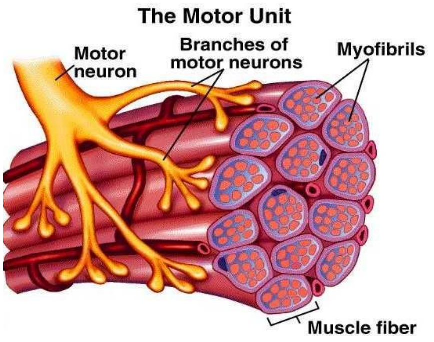

Figure 1.1 Motor Unit (Jamal, 2012)

Dynamic contraction is the most common type of muscle contraction within the body. Dynamic contractions typically involve the rhythmic and repetitive motion of large muscle groups. This is the type of muscular exertion that is often used during strength training and cardiovascular exercise, resulting in net gains in muscular size, strength, and endurance.

Electromyography (EMG) is a measurement of the electrical activity in muscles as a by-product of contraction (Konrad, 2006). A small electrical current during muscle activation, known as the myoelectric signal, is generated when a motor neuron action potential from the spinal cord arrives at a motor end plate. All muscle fibres contract when a motor unit is activated. The summation of action potentials from the muscle fibres is called 'Motor Unit Action Potential' (MUAP). The MUAP size, shape, and firing rate provide important information for diagnosing muscle disorders such as neuromuscular disease (Subasi, 2013; Wu *et al*., 2013), low back pain (Larivière *et al*., 2003), and motor control disorder (Oliveira *et al*., 2010).

Recent developments in the analysis and evaluation of EMG signal have spurred researches in muscle fatigue assessment (Shaw and Huang, 2010; Al-Mulla *et al*., 2011b; Rogers and MacIsaac, 2013), muscle endurance (Lee *et al*., 2011), and muscle geometry (Phinyomark *et al*., 2012b). A muscle may experience fatigue when excessive force (above the level of muscle's strength) is applied to the muscle. Generally, muscle fatigue is a body's way of saying take a break when one is doing too much work with one's muscle. The symptoms of muscle fatigue such as soreness, cramping, pain, tenderness and weakness may last for a few days as people recover. It is important to monitor muscle fatigue as its effect varies from temporary disability to death. Treatment is usually unnecessary if muscle fatigue is induced by exercise or overload weight. However, the treatment and rehabilitation differ if the cause was not exercise-induced. As a rule of thumb, medical attention should be sought if the fatigue persists and affects the mechanics and performance of daily activities.

1.3 Problem Statement

Fatigue is not a physical variable. Its assessment requires the definition of indices based on physical variables that can be measured. One possible approach to quantitative measurement of muscle fatigue is based on the analysis of the surface electromyography (sEMG) signal. According to Al-Mulla *et al*. (2012), the most suitable clinical research tool for muscle fatigue assessment is electromyography (EMG). Studies on muscle fatigue using EMG signal have been widely discussed (see Farina *et al*., 2004; Reaz *et al*., 2006; Chowdhury *et al*., 2013). The changes in EMG signals due to fatigue can best be monitored in time-frequency domain

(Bartuzi and Roman-Liu, 2014). This representation which is suitable for a time-varying (non-stationary) signal is used to obtain the information on the time localisation of the spectral components.

Short-Time Fourier Transform (STFT), S Transform (ST), Wavelet Transform (WT), Wigner-Ville Distribution (WVD), and Cohen Class Transformation (CCT) are examples of time-frequency method. STFT extends the applicability of Fourier transform method (for frequency representation) by dividing the input signal into segments. STFT is the most often used by researcher since it has less computational burden. However, the resolution of STFT method is poor. Therefore, WT was proposed to overcome the limitations of the STFT. The advantages and the better performance of the WT over STFT, WVD and CCT have been reported in the literatures (Karlsson *et al*., 2000; Bonato *et al*., 2001; Camata *et al*., 2010; Subasi and Kiymik, 2010). One advantage of CWT is good in extracting information from both time and frequency domains. It extracts the time and frequency components within its entire spectrum by using small scales for decomposing high frequency parts and large scales for low frequency component analysis. Although WT is better than other methods, it produces time-scale plot that are unsuitable for intuitive visual analysis (Sahu *et al*., 2009). It also suffers from computational burden and its accuracy depends on the chosen mother wavelet.

ST was introduced by Stockwell *et al*. (1996) to provide the supplementary information about spectra which is not available from WT. Furthermore, ST combines the advantages and strength of both STFT and WT to provide multi resolution analysis. For example, if the window of ST is wider in time-domain, it can provide better frequency resolution for lower frequency component and if the window is narrower, it can provide better time resolution for higher frequency component. Due to its ability to track changes in amplitude and frequency simultaneously, ST method is widely used in engineering field. However, the application of ST to electro-physiological signal is very few. Only two found published articles had applied ST method; Rakovic *et al*. (2006) considered ST in heart sound analysis and Assous and Boashash (2012) applied ST to electroencephalography (EEG) signal to estimate the robustness of the method to noise. So far, no research has used ST in muscle fatigue assessment and compared the performance of ST with other time-frequency analyses in tracking and monitoring muscle fatigue. Thus, this study was conducted to investigate the good-of-fit of ST method in extracting muscle fatigue indices. For that reason, three signal processing methods in time-frequency domain (STFT, WT, and ST) were compared for their good-of-fit in extracting muscle fatigue indices.

Muscle fatigue indices (indicators) are not only important in muscle fatigue detection and classification but also for prediction. The detection and classification of muscle fatigue provides important information for sport performance prediction as well as rehabilitation program. Thus, the classification and prediction of muscle fatigue using predictive model need to be investigated and enhanced in order to improve athletes' performance and prevent injury. Even though Artificial Neural Network (ANN) (Al-Mulla *et al*., 2009), Support Vector Machine (SVM) (Oskoei and Hu, 2008; Ahmad Sharawardi *et al*., 2014), Fuzzy Classifier (Shalu George *et al*., 2012), Linear Discriminant Analysis (Al-Mulla *et al*., 2011b), and K-nearest neighbour (K-NN) (Ahmad Sharawardi *et al*., 2014) are among the promising techniques in predicting muscle fatigue, SVM has been shown to outperform the other techniques (Subasi, 2013). Thus, with the assistance of SVM classifier, it is also the intention of this study to classify muscle signals (fatigue or non-fatigue) based on the extracted fatigue indicators.

1.4 Research Objectives

This research aims to classify fatigue phases based on time-frequency analysis of sEMG signal via the following objectives:

i. To extract significant fatigue indicators from biceps brachii sEMG signal (during dynamic contractions) using three time-frequency methods: Short Time Fourier Transform (STFT), S Transform (ST) and Continuous Wavelet Transform (CWT).

ii. To compare the good-of-fit of the three time-frequency methods in extracting fatigue indicators based on Normalization of Root Mean Square (NRMSE) and Relative Error.

iii. To classify the fatigue and non-fatigue phases of EMG signal using SVM classifier based on the significant fatigue indicators which were extracted using the best good-of-fit among the three time-frequency methods.

1.5 Research Scope

The scopes of this research are:

i. The participants that took part in this research were healthy college students with no historical muscle disorder.

ii. The NEUROPRAX full band DC-EEG system was used for dynamic EMG data collection.

iii. The muscle signals were acquired by using surface Electromyography (sEMG).

iv. The electrodes of sEMG were applied to the biceps brachii of right upper arm.

v. The fatigue indicators were extracted from three time-frequency methods: STFT, CWT, and ST.

vi. The data or signal processing was performed using MATLAB software.

vii. SVM classifier was used as the predictive model.

1.6 Research Contributions

The contributions of this research are:

i. The application of ST method to the sEMG signal. The findings show that the ST method produces lower error than STFT and WT methods when assessing muscle fatigue during dynamic contractions.

ii. The reliable muscle fatigue indicators which were extracted in time-frequency domain. The selected fatigue indicators (instantaneous mean frequency (IMNF), instantaneous frequency variance (IFV), instantaneous energy distribution (IED), and instantaneous normalized spectral moment (INSM)) characterize muscle fatigue and serve as significant indices in muscle fatigue assessment.

iii. The good performance of a simple yet effective predictive model (Support Vector Machine, SVM) in detecting or predicting muscle fatigue during dynamic contraction. The findings show that the signals with and without fatigue are effectively classified and the combination of fatigue indicators increase the accuracy of the classification.

iv. This study produces two articles which are attached in Appendix A.

1.7 Thesis Organization

This thesis is structured into five chapters. Chapter 1 introduces the background of the research as well as highlighting the problem statement, objectives, and scopes of this research. The research contributions are also highlighted in this chapter.

Chapter 2 covers the literature review and theoretical background of the research. The review focuses on the background of muscle fatigue, surface Electromyography, time-frequency analysis, and predictive modelling method (which includes model design and model validation). Knowledge gap are highlighted along the reviews.

Chapter 3 describes the methodology that was used to experimentally acquire the data, analyse the acquired data, and validate the performance of the SVM predictive model. All research activities in analysing muscle fatigue signal are described in details.

Chapter 4 presents the analyses of the result along with discussion. The significance of the extracted fatigue indicators and the good-of-fit of the three time-frequency methods are reported in this chapter. The performances of SVM classifier in classifying fatigue phases are discussed comprehensively. Statistical analysis of the outcome measures and the classification performance are presented as well.

Chapter 5 concludes the findings of the research. In order to improve the performance of the proposed method and the development of muscle fatigue research, this chapter provides some suggestions and recommendations for potential future study.

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