## Faculty of Electrical Engineering

# SPECTRAL ESTIMATION AND SUPERVISED CLASSIFICATION TECHNIQUE FOR REAL TIME ELECTROMYOGRAPHY PATTERN RECOGNITION

**Nuradebah binti Burhan**

**Master of Science in Electrical Engineering**

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# SPECTRAL ESTIMATION AND SUPERVISED CLASSIFICATION TECHNIQUE FOR REAL TIME ELECTROMYOGRAPHY PATTERN RECOGNITION

**NURADEBAH BINTI BURHAN**

**A thesis submitted**
**in fulfillment of the requirements for the award of the degree of Master of Science**
**in Electrical Engineering**

**Faculty of Electrical Engineering**

**UNIVERSITI TEKNIKAL MALAYSIA MELAKA**

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## DECLARATION

I declare that this thesis entitled "Spectral Estimation and Supervised Classification Technique for Real Time Electromyography Pattern Recognition" 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.

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Name : ……..

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**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 Master of Science in Electrical Engineering.

Signature : ……..

Supervisor Name : ……..

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**DEDICATION**

To my beloved mother and father

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## ABSTRACT

Electromyography (EMG) signal is a biomedical signal which measures physical activity of human muscle. It has been acknowledged to be widely used in rehabilitation or recovery application system assisting physiotherapist to monitor a patient's physical strength, function, motion and overall well-being by addressing the underlying physical issues. In application system associated with rehabilitation, a signal processing and classification techniques are implemented to classify EMG signal obtained. For real time application in the rehabilitation, the classification is crucial issue. The success of the signal classification depends on the selection of the features that represent a raw EMG signal in the signal processing. Therefore, a robust and resilient denoising method and spectral estimation technique have been acknowledged as necessary to distinguish and detect the EMG pattern. The present study was undertaken to determine the characteristic of EMG features using denoising method and spectral estimation technique for assessing the EMG pattern based on a supervised classification algorithm. In the study, the combination of time-frequency domain (TFD) and time domain (TD) were identified as the preferred denoising method and spectral estimation techniques. In the first part of study, the recorded EMG signal filtered the contaminated noise by using wavelet transform (WT) approach which implemented discrete wavelet transform (DWT) method of the wavelet-denoising signal. Subsequently, the filtered signal containing useful information was extracted by three methods – root mean square (RMS), mean absolute value (MAV), and autoregressive (AR) covariance, all of which are commonly used in TD. A comparative analysis of the three different techniques was performed based on the accuracy performance of the EMG pattern classification using linear vector quantization (LVQ) neural network. In the experimental work undertaken, six healthy subjects comprised of males and females were selected. Three sets of resistance band loads, namely 5 kg, 9 kg, and 16 kg, were used as a force during the biceps brachii muscle contraction in the rehabilitation exercise. Each of the subject was required to perform three levels of the arm angle positions (30˚, 90˚, and 150˚) for each set of resistance band load. The results of the experiment showed that Daubechies6 (db6) was the most appropriate DWT method including a 6-level decomposition, upholding soft rigrsure and heursure threshold rules, and a single-level threshold rescaling for the wavelet denoising signal analysis. From the three different techniques in extract feature vector as an input for LVQ classifier, the study concluded that the best system performance was the AR covariance method, where it obtained the average percentage of 95.56% for all classes in the EMG pattern recognition.




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## *ABSTRAK*

*Isyarat elektromiografi (EMG) adalah satu isyarat biomedikal yang mengukur aktiviti fisikal otot manusia. Ia telah diterima umum sebagai satu aplikasi yang digunakan secara meluas dalam sistem rehabilitasi atau pemulihan bagi membantu ahli fisioterapi memantau kekuatan fisikal, fungsi, pergerakan dan kesejahteraan umum dengan menangani isu semasa fizikal pesakit berkenaan. Dalam sistem aplikasi berkaitan dengan pemulihan, teknik pemprosesan isyarat dan pengkelasan dilaksanakan untuk mengkategorikan isyarat EMG yang diperolehi. Untuk aplikasi masa nyata dalam pemulihan, klafikasi adalah isu penting. Kejayaan pengiktirafan isyarat bergantung pada pemilihan ciri-ciri yang mewakili isyarat EMG asli dalam pemprosesan isyarat. Oleh itu, satu kaedah pengkhususan yang teguh dan bingkas adalah dianggap perlu untuk meminimumkan bunyi. Kajian ini dijalankan untuk mengenal pasti ciri-ciri EMG dengan menggunakan kaedah pembuangan gangguan bunyi dan teknik anggaran spektrum untuk menilai corak EMG berdasarkan algoritma klasifikasi yang dipantau. Teknik optimum yang diperolehi telah dilaksanakan dalam sistem pemulihan masa yang nyata. Dalam kajian ini, gabungan domain masa-frekuensi (TFD) dan domain masa (TD) adalah kaedah pilihan untuk pembuangan gangguan bunyi dan teknik anggaran spektrum. Di bahagian pertama kajian, isyarat EMG yang dirakam telah ditapis daripada bunyi yang tercemar dengan menggunakan pendekatan transformasi gelombang kecil (WT) yang melaksanakan kaedah transformasi gelombang kecil diskret (DWT) dalam isyarat pembuangan gangguan bunyi-wavelet. Selepas daripada itu, isyarat yang ditapis yang mengandungi maklumat yang berguna telah diekstrak dengan menggunakan tiga kaedah yang biasa digunakan dalam TD iaitu punca min kuasa dua (RMS), nilai mutlak min (MAV), dan kovarians autoregresif (AR). Analisis perbandingan keatas tiga teknik berbeza telah dilakukan berdasarkan prestasi ketepatan klasifikasi pola EMG dengan menggunakan rangkaian neutral linear vector quantization (LVQ). Dalam melaksanakan kajian ini, enam subjek yang sihat terdiri daripada lelaki dan perempuan telah dipilih. Tiga set beban band rintangan, iaitu 5 kg, 9 kg, dan 16 kg, yang digunakan sebagai daya semasa pengecutan otot biseps brakii dalam latihan pemulihan berkenaan. Setiap subjek diperlukan untuk melaksanakan tiga peringkat posisi sudut lengan (30˚, 90˚, dan 150˚) bagi setiap set beban band rintangan. Keputusan eksperimen menunjukkan bahawa Daubechies6 (db6) adalah kaedah DWT yang paling sesuai bersama dengan tahap penguraian 6 dengan pengekalan tahap rigrsure lembut dan peraturan ambang batas, dan tahap tunggal ambang untuk analisis pembuangan gangguan bunyi isyarat gelombang kecil. Daripada tiga teknik yang berbeza dalam vektor ciri ekstrak sebagai input untuk pengkelasan LVQ, kajian mendapati hasil sistem yang terbaik adalah kaedah kovarians AR, di mana ia memperolehi peratusan purata 95.56% untuk semua kelas dalam pengenalpastian pola EMG.*



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## LIST OF ABBREVIATIONS

| | | |
|---|---|---|
| EEG | - | Electroencephalography |
| ECG | - | Electrocardiography |
| ENG | - | Electronystagmography |
| EMG | - | Electromyography |
| CNS | - | Central Nervous System |
| MUAP | - | Motor Unit Action Potential |
| MUAPTs | - | Motor Unit Action Potential Trains |
| kNN | - | k-Nearest Neighbors |
| HMM | - | Hidden Markov Model |
| ANN | - | Artificial Neural Network |
| LVQ | - | Linear Vector Quantization |
| CNN | - | Convolutional Neural Network |
| SVM | - | Support Vector Machine |
| LDA | - | Linear Discriminant Analysis |
| SENIAM | - | Surface Electromyography for non-invasive Assessment of Muscles |
| Ag-AgCI | - | silver-silver chloride |
| TD | - | Time Domain |
| FD | - | Frequency Domain |
| TFD | - | Time-Frequency Domain |
| MAV | - | Mean Absolute Value |
| MAVS | - | Mean Absolute Value Slope |
| ZC | - | Zero Crossings |



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| | | |
|---|---|---|
| SSC | - | Slope Sign Changes |
| SSI | - | Simple Square Integral |
| VAR | - | Variance of EMG |
| RMS | - | Root Mean Square |
| WAMP | - | William Amplitude |
| IAV | - | Integrated Absolute Value |
| MYOP | - | Myopulse percentage rate |
| AR | - | Autoregressive |
| TM | - | Temporal Moment |
| WL | - | Waveform Length |
| PSD | - | Power Spectral Density |
| MNF | - | Mean Frequency |
| MDF | - | Median Frequency |
| PKF | - | Peak Frequency |
| MNP | - | Mean Power |
| TTP | - | Total Power |
| SM | - | Spectral Moment |
| FR | - | Frequency Ratio |
| PSR | - | Power Spectrum Ratio |
| VCF | - | Variance of Central Frequency |
| STFT | - | short-time Fourier Transform |
| WT | - | Wavelet Transform |
| WPT | - | Wavelet Packet Transform |
| CWT | - | Continuous Wavelet Transform |
| DWT | - | Discrete Wavelet Transform |



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SE - Standard Error



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## LIST OF SYMBOLS

| | | |
|---|---|---|
| $W_n$ | - | Window function |
| $S_n$ | - | Time-shift |
| $\tau$ | - | Modulation |
| $t$ | - | Translation parameters |
| $\psi(t)$ | - | Mother wavelet function |
| $\phi(t)$ | - | Scaling function |
| $h(n)$ | - | Low-pass filter |
| $g(n)$ | - | High-pass filter |
| $x(n)$ | - | Noise EMG signal |
| $cA_n$ | - | Approximation coefficient |
| $cD_n$ | - | Detail Coefficient |
| $\sigma^2$ | - | Variance |



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## LIST OF PUBLICATIONS

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2. **Burhan, N.,** Kasno, M.A., Ghazali, R., Jali, M.H., Said, M.R., 2017. Electromyography Signal Analysis using Wavelet Transform Approach for Resistance Band Rehabilitation. *Proceeding Mechanical Engineering Research Day 2017*, pp. 99-100.



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# CHAPTER 1

# INTRODUCTION

The present chapter discusses the concept of biomedical signals, with emphasis on electromyography as a diagnosis process of the human muscle health and the problems occurred during electromyography signal processing and its rehabilitation applications. The chapter also covers the objectives of the study, its scopes and contribution of the research on spectral estimation and supervised classification technique for real time surface electromyography pattern recognition.

## 1.1 Project Background

With the advance of science and technology, there has been a quantum leap in the development of automated and semi-automated systems supporting physiotherapy and rehabilitation. The purpose of these system development is to assist patients' recovery from health issues and to return to their previous state of health. Rehabilitation treatments are usually used by patients after a major operation, chronic pain, stroke, or severe accident that caused injury to any body part. The human body consists of many component systems involving biomedical signals such as the nervous system, cardiovascular system, and musculoskeletal system.

The rehabilitation system for biomedical signal-based device generally contains a biomedical signal sensor to detect the different types of biomedical signals. Biomedical signal is an observation of physiological activities and is crucial as a collective electrical



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signal of the human organ part. Basically, the biomedical signals can be classified into four types: electroencephalography (EEG), electrocardiography (ECG), electronystagmography (ENG), and electromyography (EMG). Each of these biomedical signals has their own specifications that are used to measure the electrical signals for different types of organ parts.

The oldest technique in biomedical signal that had been practiced in clinical situation is the EEG as shown in Figure 1.1. This is a method for recording the electrical activity of brain either in healthy or diseased conditions using small, flat metal discs or electrodes attached to the scalp (Millett et al., 2015). This method represents the graphics of the electrical potential generated by the cerebrum. Essentially, the brain is the major part which controls and coordinates the entire parts of the human body such as muscles and nerves. It is necessary to identify the function and cognitive behavior of the human brain in order to find out the good solution related to brain issues.

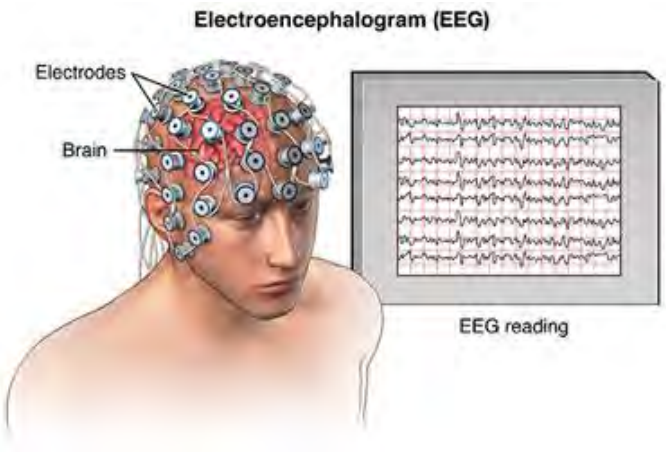


Figure 1.1 Electroencephalography signal recording (Millett et al., 2015)

Basically, the brain is divided into two parts which are right part and left the part. The two parts mutually control each other, where the left part of the brain is liable for



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