UNIVERSITI PUTRA MALAYSIA

CORE LIFTING TASK ASSESSMENT USING TIME-FREQUENCY DISTRIBUTION OF SURFACE ELECTROMYOGRAM SIGNAL

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By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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April 2019

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Manual material handling (MMH) is commonly practised in the majority of industrial working environments. However, prolonged and incorrect MMH can cause fatigue, resulting in musculoskeletal disorders (MSDs). Workers who have suffered and fully recovered from MSDs following treatment and rehabilitation, are constantly evaluated to determine their residual functional abilities. However, the functional capacity evaluation (FCE) presently in use to measure a person's physical ability to perform specific work activities depends on the visual observations of a therapist. A crucial constraint inherent in the FCE test is the likelihood that information other than visual observations could influence the therapist's decision. Recent studies indicate that strong characteristics of surface electromyography (SEMG) on muscle performance exist. Therefore, this study has aimed to extend these findings by improving the reliability and validity of the FCE by considering SEMG signals to automatically determine the work level categories of individuals. Eleven healthy control subjects without a previous history of MSD and eleven validation subjects with a previous history of MSD participated in an experiment in performing the FCE's core-lifting task. Surface EMG signals were collected from four muscles; right and left biceps brachii (BB), and the right and left erector spinae (ES).

Although given the SEMG signal is a highly complex and non-stationary signal, the time-frequency distribution (TFD) technique was used to automatically segment and process the signal. A new auto-segmentation through a spectrogram was utilised to reduce the computation complexity of processing the long EMG signal recording demonstrating excellent performance regarding accuracy, compared to conventional segmentation techniques. For the processing stage, three TFDs; spectrogram, Gabor transform, and

Stockwell transform were tested to determine the best TFD for the pattern recognition system. While Stockwell transform has higher computation complexity, this technique was the best in terms of accuracy.

Three parameters were extracted from the surface EMG signals and three new features (muscle strength, muscle power, and muscle endurance) were estimated from the average RMS voltage ($V_{rms(avg)}$) which became input to the classifier. A hybrid combination of Linear Discriminant Analysis and Support Vector Machine demonstrated a 96% accuracy of, 100% sensitivity, 92% specificity, 100% precision and 0.0035 cross-validation error. In conclusion, this study demonstrated that the new EMG-based FCE was able to analyse the subject's performance, work level categories and automatically classifying these, thereby, lessening the possibility of error caused by the therapist.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsasah

PENILAIAN TUGAS ANGKATAN TERAS MENGGUNAKAN TABURAN FREKUENSI-MASA ISYARAT ELEKTROMIOGRAM PERMUKAAN

Oleh

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Pengendalian bahan secara manual lazimnya dipraktiskan dalam persekitaran kerja. Walau bagaimanapun, pengendalian bahan secara manual yang berterusan dan tidak betul boleh menyebabkan keletihan, dan gangguan otot skeletal (MSD). Pekerja yang telah pulih dari MSD selepas menjalani terapi perlu dipantau secara konsisten untuk menentukan kapasiti fungsinya. Pada masa ini, penilaian kapasiti fungsi (FCE) yang digunakan untuk mengukur keupayaan fizikal seseorang bagi menjalankan tugas kerja tertentu hanya bergantung kepada pemerhatian visual ahli terapi. Satu kekangan penting yang wujud dalam ujian FCE ini adalah kemungkinan keputusan ahli terapi itu boleh dipengaruhi oleh maklumat selain daripada pemerhatian visual. Penemuan baru-baru ini menunjukkan terdapat ciri-ciri kuat isyarat elektromiografi (EMG) pada prestasi otot. Kajian ini bertujuan untuk meningkatkan kebolehpercayaan dan kesahihan FCE dengan mempertimbangkan isyarat EMG sebagai penentu kategori tahap beban kerja setiap pekerja. Kajian telah dijalankan pada sebelas subjek kawalan sihat yang tiada sejarah MSD, dan sebelas subjek yang disahkan mempunyai sejarah MSD, semasa melaksanakan tugas mengangkat teras. Isyarat EMG permukaan dikumpulkan dari empat otot; kanan dan kiri *biceps brachii* (BB), kanan dan kiri *erector spinae* (ES).

Oleh kerana isyarat EMG adalah isyarat yang sangat kompleks dan tidak pegun, teknik taburan frekuensi-masa (TFD) digunakan untuk segmentasi dan memproses isyarat secara automatik. Teknik baru auto-segmentasi melalui spektrogram digunakan untuk mengurangkan kerumitan pemprosen isyarat EMG yang panjang menunjukkan prestasi cemerlang dari segi ketepatan, berbanding teknik sengmentasi konvensional. Untuk peringkat pemprosesan, tiga TFD; spektrogram, transformasi Gabor, dan transformasi Stockwell telah diuji untuk menentukan TFD terbaik bagi sistem pengecaman corak.

Walaupun transformasi Stockwell mempunyai kerumintan pemprosesan yang lebih tinggi, namun teknik ini didapati paling baik dari segi ketepatan.

Tiga parameter disari daripada isyarat EMG dan tiga ciri baru (kekuatan otot, kuasa otot, dan ketahanan otot) kemudian dianggarkan dari purata voltan RMS ($V_{rms(avg)}$) dan menjadi masukan kepada pengelas. Gabungan hibrid Analisis Diskriminasi Linear dan Mesin Vektor Sokongan menunjukkan 96% ketepatan, 100% kepekaan, 92% kekhususan, 100% kepersisan, dan 0.0035 kesilapan rintangan. Kajian ini berjaya menunjukkan bahawa FCE berasaskan EMG yang dapat menganalisis prestasi subjek individu dan kategori tahap kerja boleh dikelaskan secara automatik, dengan itu, mengurangkan kecenderungan kesilapan yang disebabkan oleh ahli terapi.

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This thesis was submitted to the senate of the Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

Ag/AgCl	Silver – Silver Chloride
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
BD	Back Disorder
BW	Bandwidth
CV	Cross-Validation
CVErr	Cross-Validation Error
CWD	Choi-William Distribution
CWT	Continuous Wavelet Transform
DT	Decision Tree
DWT	Discrete Wavelet Transform
ECG	Electrocardiography
EMG	Electromyography
fApEn	Fuzzy Approximate Entropy
FCE	Functional Capacity Evaluation
FD	Frequency Distribution
FL	Fuzzy Logic
F_N	False Negative
F_P	False Positive
FT	Fourier Transform
HW	Heavy Work
ICA	Independent Component Analysis
imEMG	Intramuscular Electromyography
ISEK	International Society of Electrophysiology and Kinesiology
JEK	Journal of Electromyography and Kinesiology
kNN	k-Nearest Neighbour
KURT	Kurtosis
LDA	Linear Discriminant Analysis
LLD	Lower Limb Disorder
MAPE	Mean Absolute Percentage Error
MAV	Mean Absolute Value
MAX	Maximum Amplitude
MAX	Maximum Amplitude
MDCS	Modified Dynamic Cumulative Sum
MDF	Median Frequency
MLP	Multilayer Perceptron
MMDF	Modified Median Frequency
MMH	Manual Material Handling
MMNF	Modified Mean Frequency
MNF	Mean Frequency
MNP	Median Power Frequency
MPF	Median Power Frequency
MSD	Musculoskeletal Disorder
MUAP	Motor Unit Action Potential

MVC	Maximum Voluntary Contraction
MW	Medium Work
N-F	Neuro-Fuzzy
NSM	Normalised Spectrum Moments
PCA	Principle Component Analysis
PSD	Power Spectrum Density
PSO	Particle Swarm Optimization
RF	Random Forests
RMS	Root Mean Square
RTW	Return-to-Work
SD	Standard Deviation
SEMG	Surface Electromyography
SENIAM	Surface EMG for the Non-Invasive Assessment of Muscles
SOCSO	Social Security Organisation
SSC	Slope Sign Changes
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
TD	Time Distribution
TFD	Time-Frequency Distribution
TFR	Time-Frequency Representation
T_N	True Negative
T_P	True Positive
TVAR	Time-Varying Autoregressive
TVARMA	Time-Varying Autoregressive Moving Average
ULD	Upper Limb Disorder
VAR	Variance
WL	Waveform Length
WMSD	Work-related Musculoskeletal Disorder
WT	Wavelet Transform
WVD	Wigner-Ville Distribution
ZC	Zero Crossings

LIST OF SYMBOLS

N	Number of Samples
μ	Population Mean
σ^2	Population Variance
E	Energy
M	Thresholded Energy
E_{thres}	Energy Threshold Value
x_s	Segmented EMG Signal
x	Filtered EMG Signal
w	Observation Window
F_r	Frequency Resolution
T_r	Time Resolution
N_w	Window Length
F_s	Sampling Frequency
f_{min}	Minimum Frequency
t	Time
x_a	Actual Value
x_m	Measured Value
n	Data Point
N_s	Sample Shift
f	Frequency
f_{max}	Maximum Frequency
V_{rms}	RMS Voltage
T	Signal Period
W	Projection Vector
T_P	True Positive
T_N	True Negative
F_P	False Positive
F_N	False Negative
K	K-Fold Value

CHAPTER 1

INTRODUCTION

1.1 Research Background

Manual material handling (MMH) can be described as any moving or supporting of a load by at least one worker and incorporates the holding, lifting, putting down, pushing, pulling, moving or carrying a load (Rajesh, 2016). MMH occurs in every workplace from manufacturing and production lines to distribution centres, building sites, hospitals, farms, offices, etc. According to the 4th European Working Conditions Survey in 2005, 35% of all workers are exposed to the danger of moving or carrying heavy loads for no less than a fourth of their working time (Parent-Thirion, Macias, Hurley, & Vermeylen, 2007). Young workers supposedly are the most exposed of all age groups according to the survey. A sectoral breakdown of the rates of exposure to MMH demonstrates that workers in agriculture (68%), construction (64%), inns and eateries (48%) are well on the way to being exposed to heavy loads, followed by workers in the mining, manufacturing, wholesale and retail trade (42%), communications and transport (35%) sectors.

MMH can cause fatigue, and immediate injuries to the arms, back, shoulders, neck or other body parts. Two groups of injuries may result from MMH; (1) fractures, bruises and cuts because of sudden, unforeseen events, and (2) damage to the musculoskeletal arrangement of the body (muscles, ligaments, tendons, joints, bones, nerves and veins) as a result of progressive and cumulative wear and tear through repetitive MMH. The latter group, called musculoskeletal disorders (MSDs), can be divided into three categories; upper limb disorders (ULDs), lower limb disorders (LLDs), and back disorders (BDs). Work-related MSDs (WMSDs) are a noteworthy and increasing problem in modern societies globally (Yasobant & Rajkumar, 2014). For instance, in 2008, there were 40 cases reported in Malaysia, increasing rapidly to 153 cases in 2014 (Zainal Muktar, Shamsudin, Lukman, & Jeffree, 2017). The Social Security Organisation (SOCSO) of Malaysia revealed that in 2013, the manufacturing industries recorded the most astounding number of WMSD cases with low back disorders (LBDs) and ULDs as the most elevated cases accounted for (SOCSO, 2013). WMSDs due to MMH may have serious effects on workers and may limit their capacity to embrace an extensive variety of work and leisure activities for the remainder of their lives. Therefore, prevention is vital.

The fact that there is a risk of long-haul disability in these MSDs, the majority of injured workers return to work within one to three months after undergoing treatment and rehabilitation. In Malaysia, the total cost of worker's compensation reported in 2009 was

RM 1.04 million, which quickly rose to RM 1.94 million in 2014 (Zainal Muktar et al., 2017). WMSDs are known as the singularly most expensive category of work-related health problems and remain a major issue for individuals, companies and societies (Wahab, Jamal, & Mohd Shah, 2016). After workers with injury have recouped or achieved therapeutic stability, they are regularly assessed to decide their residual functional capacity. Functional capacity evaluation (FCE) is a test used to quantify a person's physical ability to perform particular work activities and to decide on his or her physical preparation in order to return-to-work (RTW) (Trippolini et al., 2014). The motivation behind the FCE is to test the patient's physical capacities to the maximum and to deliver precise documentation concerning work capacity (Oesch, Meyer, Jansen, & Kool, 2015). The obtained data guides RTW decisions and is helpful not only to the medical team and the employer but also to the workers themselves.

Over the past few decades, numerous researchers have attempted to develop FCE instruments. In 1984, Matheson gave a recent example which was followed in 1988 by Isernhagen suggesting that a multidisciplinary group should help with deciding a person's functional capacity. While, in 1994, Hart in collaboration with a physician and physical therapist assessed a patient's impairment. To date, there are more than ten different types of commonly utilised FCEs which include the Joule Valpar FCE, Isernhagen Work System, Ergos Work Simulator and Ergo-Kit variety, Physical Work Performance Evaluation (ErgoScience), Hanoun Medical, Blankenship, WEST-EPIC, etc. (Chen, 2007). An outstanding and economically accessible FCE is the Joule Valpar FCE which is used at the SOCSO Tun Abdul Razak Rehabilitation Centre, Malaysia comprising of 27 function-based test protocols; one of which is the core-lifting task (Cancio, Oliver, & Yancosek, 2017). All of the Joule Valpar FCE tests are based on the work factors of the Dictionary of Occupational Titles (DOT), which depict the work factors that an occupation requires to be undertaken efficiently (Opsteegh, Soer, Reinders-Messelink, Reneman, & van der Sluis, 2010). To test a person's practical limit, he or she needs to perform to a maximal limit, and only visual observations are utilised to decide whether maximum capacity has been reached.

In addition, it is also believed that the improvement of the FCE's validity and reliability can be achieved by taking the electromyography (EMG) signal into account. EMG is a test that is utilised to record the electrical activity of skeletal muscles (Karthick, Makaram, & Ramakrishnan, 2014). There are two categories of EMG: surface EMG (SEMG) and intramuscular EMG (Kamavuako, Scheme, & Englehart, 2013). SEMG assesses muscle function by recording muscle activity from the skin surface above the muscle. Whereas, intramuscular EMG, uses a needle electrode inserted into a muscle. From these two categories, SEMG is the most generally accepted and utilised form in various fields including biomechanics, muscle fatigue monitoring, motor control, functional electrical stimulation and numerous different applications since it involves a non-invasive procedure, is financially savvy and convenient to use (Merlo & Campanini, 2010).

Various signal processing techniques have been utilised to analyse EMG signals, contingent upon which application is used. For the most part, the techniques can be partitioned into three categories: time distribution (TD), frequency distribution (FD) and time-frequency distribution (TFD). For TD, EMG features are assessed based on the signal amplitude which varies with time. The amplitude of the signal relies upon muscle conditions amid the observation process. To keep computational complexity low, most past investigations have concentrated on TD (Boashash, Barki, & Ouelha, 2017). Likewise, this technique does not require extra signal transformation. Though dissimilar to TD, FD contains the power spectrum density of the signals and is computed by a periodogram. Notably, mixed information of time and frequency is characterised as TFD. TFD can portray varying frequency information at various time locations and provides abundant non-stationary information of the analysed signal (Abed & Belouchrani, 2018). Hence, this thesis focuses on developing a new EMG pattern recognition algorithm based on TFD in monitoring muscle performance of the biceps brachii (upper limb) and erector spinae (low back) muscles as an improvement of the conventional FCE's core-lifting task.

1.2 Motivation and Problem Statement

MSDs of the upper limb and low back extremities are an essential and expensive national medical issue. In 2009, SOCSO spent nearly USD$219 million to treat and provide disablement benefits including pensions for this group of injured workers (Murad, Farnworth, O'Brien, & Wen, 2012). Since Malaysia is a developing nation and is concentrating on developing all industry sectors, there is an expanding pattern of patients treated at the SOCSO Tun Abdul Razak Rehabilitation Centre due to this problem. Even though there is the FCE involving core lifting performed in the rehabilitation centre, the results do not accurately reflect the patient's muscle condition (Sinden, McGillivary, Chapman, & Fischer, 2017). The validity of these tests depends critically on the patient's effort during the evaluation. The assurance of whether a person has given maximal effort amid the testing procedure also appears to be troublesome. The reliability of the effort levels in deciding and the decision-making process as to whether the patients are sufficiently fit to return to the industry where they work have been questioned, as the decision is made solely based upon the instructor's observation (Becker, Ogle, Chadbourne, & Andrews, 1993). A major limitation inherent to this design is the likelihood that the instructor's decision could be impacted by information other than visual perceptions (i.e. verbal and non-verbal correspondences with the patient). This issue has been studied by Sinden et al., (2017) where they conclude that a trained instructor is essential to recognise maximal efforts and remains an important factor in validating the core lifting FCE test. Therefore, to address the above issue, a method to extract information from the patient's muscles is highly needed to increase the evaluation efficiency.

EMG signals from human muscles are clinically the best and most common signal to represent the muscle condition either in the field of medicine or engineering (Xi, Tang, & Luo, 2018). Even though the majority of research involving human muscles use the

EMG signal, due to the non-stationary characteristics of the EMG signals itself, a good processing technique is important in order to extract the important features to achieve better performance of the classification for pattern recognition. A standout amongst the most widely utilised tools in signal processing is Fourier analysis. Although, a significant drawback of this tool is that it does not represent temporal information and is not suitable for non-stationary signals such as EMG (Thirumala, Shantanu, Jain, & Umarikar, 2017). To overcome this, Dennis Gabor adjusted the Fourier analysis to small segments of signals and divided the time analysis into small intervals (Smale, Shourijeh, & Benoit, 2016). This strategy is known as short-time Fourier transform (STFT) which is a type of linear TFD. In this case, the interval should be sufficiently small enough to be viewed as stationary and taking the Fourier transform (FT) of each interval. The main disadvantage of this technique is that there is a trade-off between time and frequency resolution (Yu et al., 2016). The more prominent the temporal resolution required, the more terrible the frequency resolution will be and vice versa. Wavelet transform (WT) is another linear TFD that has been explored extensively in various researches as an alternative to STFT. The WT offers a high-time resolution for high-frequency components and high-frequency resolution for low-frequency components (Lv et al., 2017). However, this technique gives poor frequency resolution for high-frequency components and poor time resolution for low-frequency components. In this way, the technique is appropriate for detecting the span of high-frequency signals yet if there should be an occurrence of low-frequency signals, it cannot produce reliable outcomes. Furthermore, the WT likewise displays a few hindrances, for example, its computation burden, sensitivity to noise, and the reliance of its accuracy on the chosen basis wavelet (Liang, Iwnicki, Ball, & Young, 2015; Yi, Wang, & Sun, 2018). In this case, an alternative method that can result in high time-frequency resolution and less sensitive to noise is practical in order to realise the full potential of EMG processing with high accuracy, low computation complexity, and low memory size.

Consequently, the information extracted from the EMG signals is represented as a feature vector and will accordingly be fed into the classifier to map the different patterns and matching them appropriately. Numerous researchers have highlighted the artificial neural network (ANN) classifier in EMG pattern recognition. However, Kaytez et al., (2015) asserted that the training time of ANN is very long and the training data needs to be chosen over an entire range, in which the variables are relied upon to change. Also, it is difficult to decide the correct size and structure of an ANN to address this issue. Another strategy that is superior to the ANN is fuzzy logic (FL) as it is simple and insensitive to over-training. Despite the way in which it is proven, good classification accuracy can be achieved for certain applications via this technique. Moreover, while the right set of fuzzy rules and membership functions are difficult to decide upon in order to depict system behaviour in FL algorithms, likewise, an insufficient number of patterns can interfere with the current EMG, which repeatedly deepens by the inaccuracy of the instrumentation (Paul, Shill, Rabin, & Murase, 2017). Since this research involves a limited data size, it is necessary to implement a machine learning technique that can provide good generalisation performance with a small data size in order to achieve better accuracy, but still having good computational efficiency.

1.3 Aims and Objectives

This thesis aims to develop a new electromyography pattern recognition algorithm in monitoring muscle performance while performing the FCE core-lifting task. The developed system will help to improve the evaluation process of return-to-work patients in the rehabilitation centre and provide guidelines in determining the work level categories, capable of preventing and sustaining future injury.

The specific objectives of the study are as follow:

i. To analyse and compare the linear TFDs' performance on SEMG signal for the FCE's core-lifting task application.
ii. To assess new SEMG signal features' characteristics derived from the time-frequency representation (TFR) of the best linear TFD.
iii. To classify work level categories based on single and multiple features set by using a hybrid combination of linear discriminant analysis (LDA) and support vector machine (SVM).
iv. To validate the system performance based on the RTW patients at the SOCSO Tun Abdul Razak Rehabilitation Centre, Melaka.

1.4 Scope of Work

A total of 11 randomly selected healthy control subjects with no history of MSDs and 11 RTW patients recruited from the SOCSO Tun Abdul Razak Rehabilitation Centre were observed while performing the Joule Valpar FCE core-lifting task. It took about one hour to complete the lifting activities per subject that included the anthropometric measurement, SEMG recording, questionnaires and interview session. The whole experiment was conducted at the SOCSO Tun Abdul Razak Rehabilitation Centre, Melaka, following all the protocols set by the rehabilitation centre. The study was conducted in accordance with the ethical standards of the Declaration of Helsinki and was approved by the Ethics Committee for Research Involving Human Subjects of Universiti Putra Malaysia (Project reference no.: FK(EXP16)P050).

The SEMG recording and analysis were only carried out to the right and left biceps brachii, and right and left erector spinae muscles. A comparison study using three different linear TFDs; spectrogram, Gabor transform, and Stockwell transform in order to find the best technique regarding accuracy, computation complexity, and memory size was used to classify the work level categories. From the TFR, the parameters estimated included the instantaneous energy used for the auto-segmentation, instantaneous root mean square (RMS) voltage used for the window selection and average RMS voltage used for the work level classifications. Three new EMG features; muscle strength, muscle power and muscle endurance were derived from the average RMS voltage and were used as input to the classifier.

The work level categories were classified in accordance with the Dictionary of Occupational Titles, a publication of the United States Department of Labour using SVM. However, only medium work (MW) and heavy work (HW) level categories for frequent lifting were taken into consideration since all subjects recruited fell within these categories. The performance of the classification was assessed given its accuracy, sensitivity, specificity, precision and cross-validation error (CVErr).

1.5 Research Contributions

The general contributions of this study reside in the capacity to distinguish the work level categories of the RTW patients given the EMG signal analysis. Also, the study demonstrates that there are other non-invasive tools, which are simple to use and provide better accuracy in diagnosing muscle performance. Besides that, the study contributes to the general public, as it can be used as an on-site monitoring tool to improve the current FCE's core-lifting task available in rehabilitation centres. Notwithstanding, it can also help to decide the requirements for intervention, to plan and design treatment, to document results, the accomplishment of objectives, and adequacy of the program. Other than serving the purpose towards rehabilitation medicine, the research is also important in occupational medicine to decide upon a person's capacity to perform the demands required in connection with the work setting. In the assessments where RTW is an issue, job analysis should be performed to decide upon the tasks required for the job. The outcomes from the improved FCE would then be able to be coordinated in conjunction with the demands of the job based on the person's muscle strength, muscle power, and muscle endurance. Other than that, the study also serves a purpose in the area of insurance medicine in order to decide the level of disability of the person. Additionally, an FCE might be utilised for the settlement of a worker's compensation claim.

The specific contributions of this study based on the work and findings include:

i. The development of a new EMG auto-segmentation algorithm that can automatically detect and segment each muscle contraction that existed in the EMG signal to reduce the computational complexity.
   In this study, this algorithm utilised the instantaneous energy of the signal and thresholding technique to differentiate between the muscle contractions and the baseline. It was found that the mean absolute percentage error (MAPE) of the auto-segmentation process was 1.32%, therefore, exhibiting excellent performance based on the standard MAPE performance measures. This finding helps in reducing the computational burden in the analysis of time-frequency distribution for a long duration of EMG signal recordings.

ii. Introduce detailed guidelines for linear TFDs' best window length determination and evaluate the performance of the three different TFDs.
The best window lengths for spectrogram and Gabor transform were 512 and 450, respectively. The time resolution, frequency resolution and MAPE for the spectrogram were 0.3413 ms, 2.93 Hz and 0.257 ms, while for Gabor transform it was 0.3003 ms, 3.33 Hz and 0.233 ms. The results indicated that both techniques offered good performance in the time and frequency domain, but Gabor transform had a slightly better performance regarding MAPE as compared to the spectrogram. As for Stockwell transform, the window automatically varied depending on the frequency. Thus, window size determination was not needed. The performances of all three techniques were compared based on accuracy, computation complexity and memory size. The results proved that Stockwell transform was better than spectrogram and Gabor transform.

iii. Derivation of three new EMG signal features from the average RMS voltage.
These features included muscle strength, muscle power and muscle endurance. For the purpose of benchmarking, the conventional average RMS voltage was considered in this study. The experimental results indicated that the new features estimated from the average RMS voltage provided a better representation of muscle performance compared to the conventional average RMS voltage. The three proposed features were then used for classification of the work level categories.

iv. Development of a pattern recognition system to classify the work level categories of the FCE's core-lifting task.
The proposed features from all four muscles obtained from the best TFD were used as inputs to the classifier. Linear discriminant analysis (LDA) and SVM were used as the dimension reduction and classifier, respectively. The system was validated by testing it with the EMG signal of the RTW patients at the SOCSO Tun Abdul Razak Rehabilitation Centre. The results indicated that the developed system could accurately and efficiently classify the work level categories with 96% accuracy, 100% sensitivity, 92% specificity, 100% precision and 0.0035 CVErr for the control subjects and validation subjects separately.

1.6 Thesis Structure

The structure of this thesis is organised into five chapters that address the development of the TFD of the pattern recognition system for the core lifting task.

Chapter 1 which is presented in this present chapter, provides a general introduction, motivation and problem statement of the research, and clarifies the objectives, research scope, contributions and overview of each chapter in the thesis.

Chapter 2 reviews the related research works that have been published so far. The chapter further elaborates the side effects of manual lifting in daily life and the existing FCEs currently available. In addition, this chapter reviews the ability of SEMG signal in work level categories identification. The review includes the SEMG signal's characteristics, acquisition, and analysis.

Chapter 3 details the step-by-step approach employed in this study, starting with the recruitment of subjects, and the data collection procedure followed by proposing a new auto-segmentation technique to segment muscle contraction, to reduce overall computational complexity. Three linear TFDs are described which are used to process the EMG signal based on the TFR to determine the best distributions regarding accuracy, memory size, and computation complexity. New EMG signal features in this chapter are also obtained from the associated EMG signal parameter of the best TFD to become the input to the designed classifier.

Chapter 4 discusses the main findings of the overall research. In this chapter, the performance of auto-segmentation is first presented, followed by the results of the TFDs and classification. The findings are then presented in the form of graphical plots for the extracted EMG signal parameter and EMG signal features. At the end of the chapter, the overall pattern recognition system evaluation metrics for determining the work level categories are discussed regarding accuracy, sensitivity, specificity, precision and CVErr.

Finally, in Chapter 5, the conclusions and suggestions for future research are presented.

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BIODATA OF STUDENT

A student, lecturer and researcher, Ezreen Farina Shair was born in Klang, Selangor on 31st December 1987. She grew up in Shah Alam, Selangor and currently living in Melaka.

After completing secondary school in MARA Junior Science College Beseri, she furthered her study at the Universiti Teknologi Malaysia under the Express MARA-UTM program. She then studied engineering at the same university and received her Bachelor of Engineering (Electrical – Control and Instrumentation) (2009) and Master of Engineering (Electrical – Mechatronics and Automatic Control) (2011).

Upon finishing her Master's degree at the age of 23, she began her career as a lecturer at Universiti Teknikal Malaysia Melaka in March 2011. She teaches various engineering subjects including Measurement, Instrumentation & Measurement, Electronic Devices and Communication System. During her career at the university, she actively involves in the Rehabilitation and Assistive Technology research group under the Center of Robotics and Industrial Automation. She received several awards due to her participation in various research competitions, actively published indexed journals, attending international conferences and also managed to get research grants amounted more than 100,000 MYR.

Her research interest includes bio-signal processing, digital signal processing and control system. Due to her passion in these areas, she continues her PhD in September 2015, which focuses on bio-signal processing.

LIST OF PUBLICATIONS

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N.F. Jamaluddin, S.A. Ahmad, **E.F. Shair**, "Performance of Different Threshold Estimation Method on SEMG Wavelet De-noising in Prolonged Fatigue Identification", *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES 2018),* pp. 293-296, 2018.

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E.F. Shair, S.A. Ahmad, A.R. Abdullah, M.H. Marhaban, S.B. Mohd Tamrin, "Performance of Gabor Transform on SEMG Signal in FCE's Work Levels Categories Identification", **Presented** in *6th Symposium on Applied Engineering and Sciences (SAES 2018).*

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