



Faculty of Electrical Technology and Engineering

**EARLY SIGNS OF UNDERBONE MOTORCYCLIST MUSCLE
FATIGUE ANALYSIS USING S-TRANSFORM BASED ON SURFACE
ELECTROMYOGRAPHY SIGNALS**

Tengku Nor Shuhada binti Tengku Zawawi

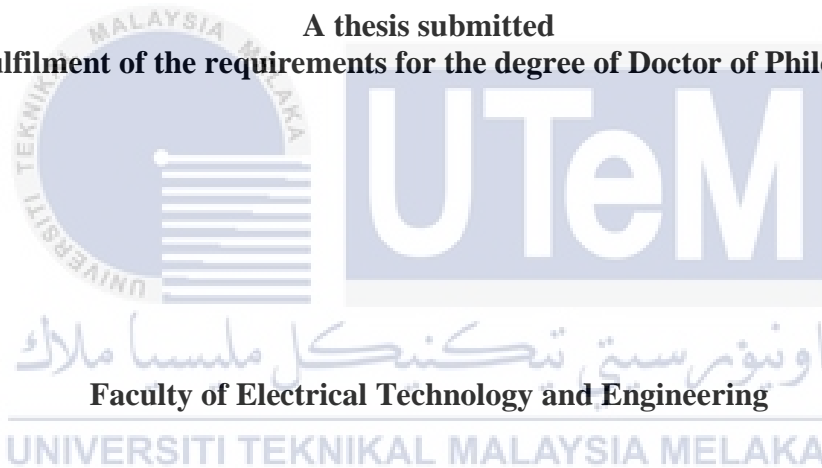
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ANALYSIS USING S-TTRANSFORM BASED ON SURFACE
ELECTROMYOGRAPHY SIGNALS**

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



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DEDICATION

I dedicate my dissertation work towards my beloved mother, Raja Mariam bin Abu Bakar and my late father Tengku Zawawi bin Raja Jaafar, my husband Mohd Soufi bin Anual, my family, supervisor, co-supervisor (internal), co-supervisor (external), examiners, Dr. Rokat, collaboration lecturers and all my friends especially from Advanced Digital Signal Processing Group (ADSP) for their support cooperation in helping me to complete this research and thesis.

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ABSTRACT

Seven out of ten deaths on the road in Malaysia were motorcycle users and there are 48% probability that the accident is connected to fatigue. In muscle fatigue for underbone motorcycles, there are unavailable detection types of muscle fatigue with standard feature indicators. Identifying early signs of muscle fatigue is important to avoid injury and accidents from prolonged motorcycle riding. The current method is to analyse muscle fatigue for motorcycles in terms of ergonomic assessment tools in the time domain and frequency domain limited to the rider's specific condition during prolonged rides and automated classification type of muscle fatigue for motorcycles is still not being explored. However, it is crucial to know to avoid muscle injuries and accidents. Therefore, this research aim is to detect the onset of muscle fatigue using time-frequency distribution in riders on motorcycles with automated classification type of muscle fatigue during prolonged riding motorcycle. For this purpose, 24 secondary data respondents of riding underbone motorcycle for prolonged ride have been used for signal pre-processing, signal processing using time domain, frequency domain, and time-frequency domain analysis and classification type of muscle fatigue. Eight muscles of the upper limb side are selected as the most activated involved in riding motorcycles which are the Left and Right Extensor Carpi Radialis, Left and Right Trapezius, Left and Right Erector Spinae, and Left and Right Latissimus Dorsi. The time domain and frequency domain are utilised for determining muscle activation of high intensity which Extensor Carpi Radialis for both regions with the highest value of 11.208 of standard deviation (STD) which features reflect the changes in muscle activation of movement intensity. The second question of the research to find the best method TFD method for detecting and measuring muscle fatigue using time-frequency distribution (TFD) methods either are Spectrogram or S-transform. Five time-frequency representation (TFR) from TFD method features which are instantaneous RMS voltage ($V_{rms}(t)$), instantaneous mean frequency (IMNF), instantaneous median frequency (IMDF), instantaneous energy distribution (IED) and instantaneous frequency variance (IFV) used as muscle fatigue indicators for finding muscle fatigue onset and types of muscle fatigue. S-Transform is chosen as the best method of TFD analysis with lower relative error, higher accuracy, and lower computational complexity for 20% for better performance. The automation classification process from ML is applied to five types of classifiers: linear discriminant analysis (LDA), support vector machine (SVM), K-Nearest Neighbour (KNN), artificial neural network (ANN), and Naive Bayes (NB). The results show that ANN offers the highest accuracy 98.8% for classification performance evaluation to automate recognising the pattern of types of muscle fatigue. Therefore, this study concludes S-Transform technique with the proposed muscle fatigue indicators feasible to be apply for muscle fatigue detection and to classify the types of fatigue for awareness of rider motorcycle to be alert. Knowing the early signs of muscle fatigue can prevent a serious degree of muscle fatigue that would increase the risk of musculoskeletal disorders injuries accidents not only among rider motorcycle but also driver for other vehicles.

**ANALISIS TANDA AWAL KELEMAHAN OTOT BAGI PENUNGGANG
MOTOSIKAL MENGGUNAKAN KAEDAH JELMAAN - S BERDASARKAN
ISYARAT PERMUKAAN ELEKTROMIOGRAFI**

ABSTRAK

Tujuh daripada sepuluh kematian di jalan raya di Malaysia adalah pengguna motosikal dan terdapat 48% kebarangkalian bahawa kemalangan itu dikaitkan dengan kepenatan pada otot. Dalam keletihan otot untuk motosikal bawah tulang, terdapat jenis pengesanan kelelahan otot yang tidak mempunyai penunjuk ciri yang standard. Mengidentifikasi tanda-tanda awal kelelahan otot adalah penting untuk mengelakkan kecederaan dan kemalangan kepada menunggang motosikal yang melibatkan perjalanan jarak jauh. Kaedah analisis semasa bagi kepenatan otot untuk motosikal adalah melibatkan penilaian terhadap ergonomik dalam domain masa dan frekuensi yang terhad kepada keadaan spesifik pemandu dan jenis pengklasifikasian automatik bagi kepenatan otot yang lebih tepat bagi motor masih perlu dipelajari. Ini adalah penting untuk mengetahui untuk keadaan sebenar otot bagi mengelakkan berlakunya kecederaan otot dan kemalangan. Oleh itu, matlamat penyelidikan ini adalah untuk mengenal pasti permulaan berlakunya keletihan otot dengan menggunakan pengedaran maklumat frekuensi dalam masa semasa penunggang motosikal dengan jenis klasifikasi automatik jenis tahap keletihan otot yang berlaku semasa menunggang motosikal. Untuk tujuan ini, 24 responden data sekunder bagi penunggang motosikal bawah tulang untuk perjalanan jauh telah digunakan untuk pra-pemprosesan isyarat, pemprosesan isyarat dengan menggunakan domain masa, domain frekuensi, dan analisis domain masa-frekuensi serta menklasifikasikan tahan keletihan otot. Lapan otot dipilih sebagai otot yang paling aktif yang terlibat dalam penunggang motosikal iaitu Extensor Carpi Radialis kiri dan kanan, Trapezius kanan dan kiri, Spinae Erector kanan dan kanan dan Latissimus Dorsi kanan dan kiri. Domain masa dan frekuensi digunakan untuk menentukan keaktifan otot yang berintensiti tinggi yang menunjukkan Extensor Carpi Radialis untuk kedua-dua kawasan mencatatkan nilai tertinggi dengan 11.208 dari perbezaan standard (STD) terhadap ciri-ciri perubahan dalam pengaktifan otot daripada intensiti pergerakan. Soalan kedua penyelidikan adalah dengan menggunakan kaedah TFD yang terbaik untuk mengesan dan mengukur keletihan otot dengan menggunakan kaedah pengagihan frekuensi masa (TFD) sama ada adalah Spectrogram atau S-transform yang terbaik. Lima taburan masa-frekuensi (TFR) daripada ciri-ciri kaedah TFD ialah tegangan RMS dalam masa ($V_{rms}(t)$), frekuensi purata dalam masa (IMNF), frekuensi median dalam masa (IMDF), pengedaran tenaga sementara (IED) dan varians frekuensi sementara (IFV) yang digunakan sebagai penentuan S-Transform dipilih sebagai kaedah yang terbaik untuk analisis TFD dengan kesilapan relatif yang lebih rendah, ketepatan yang lebih tinggi, dan kesukaran pengiraan yang rendah sebanyak 20% untuk prestasi yang lebih baik. Proses klasifikasi automatik dari ML telah menggunakan lima jenis klasifikasi iaitu analisis diskriminatif linier (LDA), mesin vektor sokongan (SVM), K-Nearest Neighbour (KNN), rangkaian saraf buatan (ANN), dan Naive Bayes (NB). Hasilnya menunjukkan bahawa ANN memcatatkan ketepatan tertinggi 95.8% untuk penilaian prestasi klasifikasi untuk mengotomatiskan pengenalan ciri bagi setiap tahap keletihan otot. Oleh itu, kajian ini menyimpulkan teknik S-Transform dengan ciri keletihan otot yang disyorkan yang boleh digunakan untuk mengenalpasti masa

berlakunya keletihan otot dan seterusnya mengklasifikasikan tahap kelemahan otot bagi kesedaran penunggang motosikal untuk lebih berhati-hati bila mencapai tahap kepenatan otot mereka. Dengan mengetahui tanda-tanda keletihan otot lebih awal, ia boleh mengelakkan otot terlampau penat yang lebih serius yang akan meningkatkan risiko kecederaan muskuloskeletal bukan sahaja di kalangan pemandu motosikal tetapi juga pemanduan untuk kenderaan lain.



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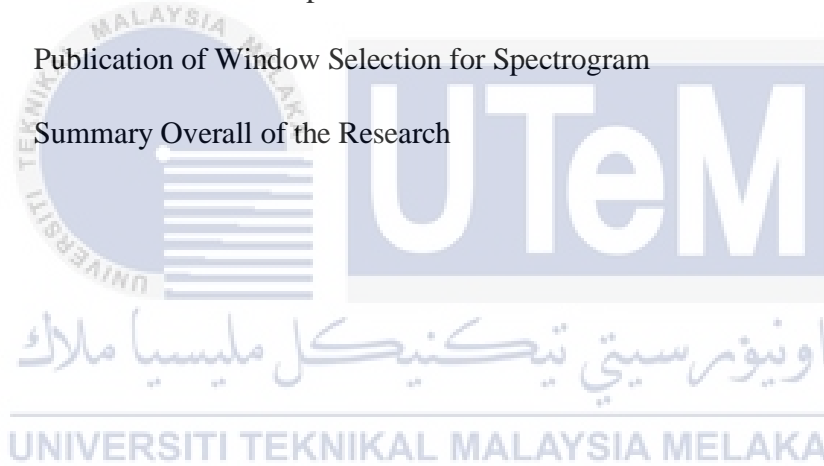
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LIST OF ABBREVIATION

ACC	-	Accuracy
ANN	-	Artificial Neural Network
BMI	-	Body Mass Index
CNN	-	Convolution Neural Network
CV Error	-	Cross Validation Error
CWD	-	Choi-William Distribution
ECG	-	Electrocardiogram
EEG	-	Electroencephalogram
EMG	-	Electromyography
FD	-	Frequency Domain
FFT	-	Fast-Fourier Transform
F_{max}	-	Maximum Isometric Torque
FR	-	Frequency Ratio
HFC	-	High-Frequency Components
HT	-	Holding Time
IARV	-	Instantaneous Average Rectified Value
IED	-	Instantaneous Energy Distribution
IEMG	-	Integrated Electromyography
IFV	-	Instantaneous Frequency Variance
IMDF	-	Instantaneous Median Frequency

IMNF	-	Instantaneous Mean Frequency
JASA	-	Joint Analysis of sEMG Spectrum and Amplitude
INSM	-	Instantaneous Normalized Spectral Moment
KNN	-	K-Nearest Neighbour
LBP	-	Lower Back Pain
LDA	-	Linear Discriminant Analysis
LECR	-	Left Extensor Carpi Radialis
LES	-	Left Erector Spinae
LFC	-	Low-Frequency Components
LLD	-	Local Latissimus Dorsi
LMF	-	Left Muscle Fatigue
LT	-	Left Trapezius
LR	-	Linear Regression
MA	-	Muscle Activity
MAPE	-	Mean Absolute Percentage Error
MAV	-	Mean Absolute Value
MAPE	-	Mean Absolute Percentage Error
MDF	-	Median Frequency
MES	-	Myoelectric signals
METAL	-	Motorcycle Engineering Technology Laboratory
MIROS	-	Malaysian Institute of Road Safety Research
ML	-	Machine Learning
MLPNN	-	Multi-Layer Perceptron Neural Network
MNP	-	Mean Power
MPF	-	Mean Power Frequency

MSD	-	Musculoskeletal Disorders
MTE	-	Mechanical-to-Electrical
MU	-	Motor Unit
MUAP	-	Motor Unit Action Potential Trains
MVC	-	Maximum Voluntary Contraction
NB	-	Naive Bayes
NF	-	Normal Fatigue
PF	-	Prolonged Fatigue
PKF	-	Peak Frequency
PSD	-	Power Spectrum Density
PSR	-	Power Spectrum Ratio
PSSI	-	Prolonged Standing Strained Index
SD	-	Standing Duration
SEN	-	Sensitivity
sEMG	-	Surface Electromyography
SPC	-	Specificity
S-Transform	-	Stockwell Transform
SVM	-	Support Vector Machine
REBA	-	Rapid Entire Body Assessment
RECR	-	Right Extensor Carpi Radialis
RES	-	Right Erector Spinae
RFD	-	Rate of Force Development
RIPOC	-	Riding Posture Classification
RLD	-	Right Latissimus Dorsi
RMI	-	Research Management Institute