

**ACTIVE COMPLIANCE CONTROL OF A HIP
EXOSKELETON ROBOT FOR STOOP LIFTING WITH
MUSCLE FATIGUE EFFECT COMPENSATION**

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Master of Philosophy

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DECLARATION

I declare that this is my own work and this thesis/dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The above candidate has carried out research for the MPhil thesis under my supervision. I confirm that the declaration made above by the student is true and correct.

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DEDICATION

This thesis is dedicated to my beloved parents, whose unwavering support, sacrifices, and encouragement have shaped the person I am today. Their love and guidance have been my greatest source of strength throughout this journey.

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ABSTRACT

Compliance control has emerged as a control feature for robotic devices to ensure safe human-robot interaction and more versatile dynamic adaptation for changing environments. User intention estimation is essential when it comes to compliance control of exoskeleton robots. One prominent method of user intention estimation for exoskeleton robot is Electromyography (EMG). However, due to the non-stationarity of EMG signals, the user intention estimation is not accurate during dynamic musculoskeletal movements. Hence, compliance control will not work as intended. As a solution to this problem, a novel muscle fatigue effect compensation scheme is proposed and integrated with the compliance control algorithm. First, a human muscle fatigue index based on spatial, spectral and temporal features of EMG signals was developed. Dynamic cyclic flexion-extension experiments on four human subjects showed accuracy in estimating the fatigue level with an average coefficient of determination greater than 0.65. Furthermore, an EMG-based trunk muscle torque estimation method was developed using an Artificial Neural Network (ANN). Upon testing on four different human subjects, the trunk muscle torque estimator showed average coefficient of determination of 0.76 against measured muscle torque. Then Model Reference Adaptive Control (MRAC) system was developed for compliance control. The novel fatigue index and muscle torque estimator was incorporated with the controller to compensate for the effect of muscle fatigue. The MRAC was designed to refer to a low impedance reference model of an exoskeleton and human combined plant, thus ensuring the assistance needed for human trunk flexion-extension. System identification schemes for the actuators and, exoskeleton and human combined system were performed separately. The proposed controller was deployed on an existing hip exoskeleton robot and was tested on a single subject. A comparison of the system with and without fatigue compensation showed an improvement in human fatigue level and assistance given by the exoskeleton.

Keywords: Exoskeleton Robot, Compliance Control, Fatigue Estimation, MRAC, Multi-channel EMG

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LIST OF ABBREVIATIONS

Abbreviation	Description
EMG	Electromyography
sEMG	Surface Electromyography
MRAC	Model Reference Adaptive Control
ERFI	Eigen Ratio-based Fatigue Index
ANN	Artificial Neural Network
RMS	Root Mean Square
PSD	Power Spectral Density
JASA	Joint Analysis of Spectrum and Amplitude
FInsm5	Dimitrov's spectral fatigue index
MAV	Mean Absolute Value
Fmed	Median Frequency
INMF	Instantaneous Mean Frequency
CWT	Continuous Wavelet Transform
WD	Wigner Distribution
TVAR	Time-varying autoregressive approach
ICA	Independent Component Analysis
SPWVD	Smoothed-Pseudo Wigner–Ville Distribution
STFT	Short Time Fourier Transform
MLP	Multiple Layer Perceptron
MUAP	Motor Unit Action Potential
NMJ	Neuro-Muscular Junctions
SNR	Signal to Noise Ratio
CNS	Central Nervous System
NMF	Non-negative Matrix Factorization
SVD	Singular Value Decomposition
HD-EMG	High Density Electromyography
ML	Machine Learning
BCI	Brain-Computer Interface
EEG	Electroencephalography
CNN	Convolutional Neural Network
RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory
GRU	Gate Recurrent Units
IMU	Inertial Measurement Unit
SVM	Support Vector Machines
LR	Logistic Regression
k-NN	k-nearest Neighbour
GMM	Gaussian Mixture Models
RF	Random Forest
HMM	Hidden Markov Model
ANOVA	Analysis of Variation
MVC	Maximum Voluntary Contraction
MF	Mean Frequency
MDF	Median Frequency

WIRM1551	Wavelet-based Spectral Index
ROM	Range of Motion
RF	Rectus Femoris
DoB	Disturbance Observer
EMF	Electromotive Force
BEMF	Back Electromotive Force