

EMG-based Assessments for Rehabilitation Application

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and

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Certificate of Original Authorship

I, Ghada Muneer Bani Musa, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Computer Science at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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List of Abbreviations

AD	Deltoid Anterior
ANN	Artificial Neural Networks
AP	Action Potential
APR	Automatic Posture Response
BI	Biceps Brachii
Brac	Brachioradialis
C	Consist Parameter
CBGWO	Competitive Binary Grey Wolf Optimizer
CNMF	Concatenated Non-Negative Matrix Factorisation
CNN	Convolutional Neural Network
CNS	Central Nervous System
COP	Centre of Pressure
ELM	Extreme Learning Machine
EMG	Electromyography
ERM	Empirical Risk Minimization
FD	Frequency Domain Features
FIM	Functional Independence Measure
FNN	Feedforward Neural Network
FNNs	Feedforward Neural Networks
FP	Feature Projection
FS	Feature Selection
FSM	Finite State Machines
Gamma (γ)	Kernel Parameter
HCI	Human Computer Interaction

Hjorth	Hjorth Parameters
IDI	Inter Discharge Intervals
IPI	Inter-Pulse Interval
IS	Infraspinatus
kEMG	Kinesiology Electromyography
kNN	k-nearest Neighbour
LD	Latissimus Dorsi
LDA	Linear Discriminant Analysis
LKF	Linear Kernel Function
MAE	Mean Absolute Error
MAV	Mean Absolute Values
MFAP	Muscle Fibre Action Potential
MKF	Multi-Kernel Function
MLP	Multilayer Perceptron
MME	Multilevel Mixed-Effects
MPR	Myoelectric Pattern Recognition
MS	Myoelectric Signal
MSE	Mean Square Error
MU	Motor Unit
MUAP	Motor Unit Action Potential
MUAPT	Motor Unit Action Potential Train
nEMG	Neurological Electromyography
NMF	Non-Negative Matrix Factorisation
PKF	Polynomial Kernel Function
PM	Pectoralis Major
PSD	Power Spectral Density

PSO	Particle Swarm Optimisation
RC	Rotator Cuff
RBF	Radial Basis Function
RMS	Root Mean Square
RMSE	Root Mean Square Error
sEMG	Surface Electromyography
SENIAM	Surface EMG for Non-Invasive Assessment of Muscles
SBS	Sequential Backward Selection
SFN	Single Feedforward Network
SFS	Sequential Forward Selection
SIAS	Stroke Impairment Assessment Set
SKF	Sigmoid Kernel Function
SKW	Sample Skewness
SLFNs	Single Hidden Layer Feedforward Networks
SSC	Slope Sign Change
STFT	Short Term Fourier Transform
SVM	Support Vector Machine
T	Triceps Brachii
T_{Thr}	The Threshold
TD	Time Domain
TFD	Time–Frequency Domain Features
TM	Teres Major
TSD	Time Scale Domain
V_{EMG}	Electromyography Voltage
VAF	Variance Accounted for Threshold
WHO	World Health Organization

WL	Waveform Length
WPT	Wavelet Packet Transform
WT	Wavelet Transform
ZC	Zero Crossings

Abstract

Biomedical signals–based human control systems have been studied in the biomedical field to improve quality of life. The muscle signal—electromyography (EMG)—is one of the main types of biomedical signals. The muscles are controlled by the central nervous system (CNS). The CNS does not directly control the activation of a large number of muscles, but it still shapes voluntary synergy motion. This research investigated and developed pattern-recognition approaches for EMG signals by studying the automatic body response and voluntary actions to support and understand how the CNS shapes voluntary synergy motion. The purpose of this study is extended to investigate the possible recovery improvement of human rehabilitation movement for stroke patients. This thesis answer core questions: How the automatic body response and voluntary movements can help to improve the quality of life for people with disability?, How can we predict rehabilitation for post-stroke patients?, and how to predict the possible recovery performance ahead of three months?.

My doctoral study contributes to knowledge both theoretically and practically. The main research objective was to develop computational intelligence-based EMG for upper limb rehabilitation applications.

After building stable procedures for signal processing, we predicted the functional motor recovery of severe, moderate, and mild post-stroke patients during their rehabilitation programs based on support vector machine regression (SVMR). The EMG signals from the upper limb muscles of the patients during their initial rehabilitation sessions were used to train the model. In this thesis we achieved good results with error < 0.5 .

We developed the non-negative matrix factorisation (NMF) method to extract the synergy EMG to express some features that could support the CNS in shaping the voluntary movement and reducing error. After building our model and extracting the synergy, we calculated the Variance Accounted for Threshold (VAF) to identify the minimum number of synergies that adequately reconstructed the characteristics of the recorded EMGs; our result was $> 95\%$ VAF overall.

We developed the multilevel mixed-effects (MME) model to predict human recovery based on biomarker assessment sets. We also predicted future rehabilitation for post-stroke patients three months ahead using time series prediction based on synergy EMG.

In summary, this pilot study's results promise the ability to predict the future muscle performance of post-stroke patients based on their current motor ability as well as this summary aims to be easiest for the reader to know upfront everything in the coming chapters.