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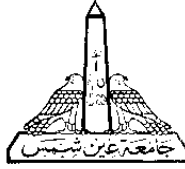
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AIN SHAMS UNIVERSITY

FACULTY OF ENGINEERING

Electronics Engineering and Electrical Communications

EMG Pattern Recognition Based Neural System of Lower Locomotive Modes Used For the Controlling of Lower Limb Prosthesis

A Thesis submitted in partial fulfillment of the requirements of the degree of

Doctor of Philosophy in Electrical Engineering
(Electronics Engineering and Electrical Communications)

Submitted by

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Master of Science in Electrical Engineering
(Electronics Engineering and Electrical Communications)

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The author carried out the work included in this thesis, and no part of
it has been submitted for a degree or a qualification at any other
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Thesis Summary

Surface Electromyography (sEMG) signals have a lot of biomedical applications and modern human-machine interactions. sEMG signals received from muscles that require advanced methods for detection, pre-processing, and classification. Current research technologies are focused, principally on deep neural network architectures that collect spatial data from sEMG signals. Low-cost traditional prosthetic leg, available worldwide, can make walking and stair climbing possible but still difficult. This thesis presents the hardware implementation to the sEMG Powered Prosthesis Actuation (PPA) system using recurrent neural network (RNN) model based on three models long-term short-term memory (LSTM), Convolution Peephole LSTM and gated recurrent unit (GRU), which are used to train sEMG benchmark databases, and find the correlation between the input (sEMG) and outputs (gesture). The following techniques were evaluated by calculating the success of a variety of variables like training time, accuracy loss and hyper-parameters which were applied on eight benchmark datasets, in order to demonstrate the validity of these models, with prediction accuracy at almost 99.6 %. The data were collected from benchmark datasets describing different subjects during performance, and analyzing various gait patterns were used to construct the neural network and to alleviate significant model errors in a real-time setting. Processing circuits, interfacing the output with

the controller board, signal amplification, motor driving circuit and single-board computer programming are included in the implementation.

Keywords — sEMG, Recurrent Neural Network, LTSM, Pattern Recognition, RNN, Long-Short Term Memory, Prosthesis leg.

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List of Abbreviations

ABS	Acrylonitrile Butadiene Styrene
ADAM	Adaptive Moment Estimation
ADALINE	Adaptive Linear Element algorithm
AI	Artificial Intelligence
APs	Action Potentials
ANN	Artificial Neural Network
BPTT	Backpropagation through time
CNN	Convolutional Neural Network
CPU	Central Processing Unit
CSV	Comma-separated values
DL	Deep Learning
DoF	degrees of freedom
DC	Direct Control
EMG	ElectroMyoGraphy
FN	False negatives
FP	False positives
GPIO	General-Purpose Input/Output
GRU	Gated Recurrent Unit
IMU	Inertial measurement units
Kp,Ki,Kd	Proportional, Integral, Derivative gain
K+	Sodium ion
k-NN	k-th Nearest Neighbours