DEVELOPMENT OF A REAL-TIME GRASPING PATTERN CLASSIFICATION SYSTEM BY FUSING EMG-VISION FOR HAND PROSTHESES

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Degree of Master of Science

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Thesis submitted in partial fulfillment of the requirements for the degree Master of Science in Mechanical Engineering

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DECLARATION

I declare that this is my own work and this thesis does not incorporate without acknowledgment 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 acknowledgment is made in the text.

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The above candidate has carried out research for the Masters thesis under our supervision.

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Abstract

The Electromyography (EMG) based trans-radial prostheses have revolutionized the prosthetic industry due to their ability to control the robotic hand using human intention. Although recently developed EMG-based prosthetic hands can classify a significant number of wrist motions, classifying grasping patterns in real-time is challenging. However, the wrist motions alone cannot facilitate a prosthetic hand to grasp objects properly without performing appropriate grasping pattern. The collaboration of EMG and vision has addressed this problem to a certain extent. However they have not been able to achieve significant performance in real-time.

This study proposed a vision-EMG fusion method that can improve the real-time prediction accuracy of the EMG classification system by merging a probability matrix that represents the usage of the six grasping patterns for the targeted object. The You Only Look Once (YOLO) object detection algorithm was utilized to retrieve the probability matrix of the identified object, and it was used to correct the classification error in the EMG classification system by applying Bayesian fusion. Experiments were carried out to collect EMG data from six muscles of 15 subjects during the grasping action for classifier development. In addition, an online survey was conducted to collect data to calculate the respective conditional probability matrix for selected objects. Finally, the five optimized supervised learning EMG classifiers; Artificial Neural Network (ANN), K-nearest neighbor (KNN), Linear Discriminant Analysis (LDA), Naive Bayes (NB), and Decision Tree (DT) were compared to select the best classifier for fusion.

The real-time experiment results revealed that the ANN outperformed other selected classifiers by achieving the highest mean True Positive Rate (mTPR) of $M = 72.86\%$ ($SD = 17.89\%$) for all six grasping patterns. Furthermore, the feature set identified at the experiment (Age, Gender, and Handedness of the user) proved that their influence increases the mTPR of ANN by $M = 16.05\%$ ($SD = 2.70\%$). The proposed system takes $M = 393.89\ ms$ ($SD = 178.23\ ms$) to produce a prediction. Therefore, the user did not feel a delay between intention and execution. Furthermore, proposed system facilitated the user to use suitable multiple grasping patterns for a single object as in real life. In future research works, the functionalities of the system should be expanded to include wrist motions and evaluate the system on amputees.

Keywords **-Surface Electromyography, Real-time Classification, vision feedback, Grasping Pattern, Sensor Fusion**

DEDICATION

In memory of late Dr. Kanishka Madusanka

and

to my loving family who keeps lifting me and inspiring me

in every second of my life.

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ABBREVIATIONS

AC	Alternative Current
ADL	Activities of Daily Living
ANN	Artificial Neural Network
AR	Autoregressive Coefficient
BDE	Binary Differential Evolution
BF	Bayesian Fusion
BPSO	Binary Particle Swarm Optimization
CART	Classification and Regression Trees
CNN	Convolutional Neural Network
COG	Center Of Gravity
CVS	Cognitive Vision System
DNN	Deep Neural Network
DSOD	Deeply Supervised Object Detectors
DSSD	Deconvolutional Single Shot Detector
DT	Decision Tree
DV	Dependent Variables
ECG	Electroencephalography
EEG	Electroencephalography
EMG	Electromyography
FCNN	Fuzzy Clustering Neural Network
FD	Frequency Domain
F-RCNN	Faster Region-based Convolutional Neural Networks
GLM	General Linear Model
HD-EMG	High Density Electromyography
HL	Hidden Layer

HMM	Hidden Markov Model
HSV	Hue Saturation Value
iEMG	intramuscular Electromyography
IV	Independent Variables
IMU	Inertia Measurement Unit
KNN	K-Nearest Neighbor
LDA	Linear Discriminant Analysis
LR	Learning Rate
mAP	mean Average Precision
MAV	Mean Absolute Value
MBTGA	Modified Binary Tree Growth Algorithm
MC	Metacarpals
MC	Momentum Constant
MLP	Multi-layer Perceptron
MMG	Mechanomyography
mTPR	mean True Positive Rate
MV	Majority Vote
NB	Naive Bayes
NCS	Nerve Conduction Study
NOD	Normalized Onset Distance
non-PR	non-Pattern Recognition
PBPSO	Personal Best Guide Binary Particle Swarm Optimization
PCA	Principle Component Analysis
PR	Pattern Recognition
PSO	Particle Swarm Optimization
RGB	Red Green Blue
RMS	Root Mean Square
ROI	Region Of Interest
RTG	Reach-To-Grasp
SD	Standard Deviation
SFS	Sequential Forward Selection
SOM	Self-Organizing Map

SSC	Sign Slope Change
SVM	Support Vector Machine
TD	Time Domain
TDAR	Time Domain Autoregressive Coefficients
TD-AR	Time Domain-Autoregression
TFD	Time-Frequency Domain
WAMP	Willison Amplitude
WL	Waveform length
YOLO	You Only Look Once
ZC	Zero Crossing