

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

Gamage Dulanjana Manoj Perera

(198115E)

Degree of Master of Science

Department of Mechanical Engineering

University of Moratuwa

Sri Lanka

August 2021

# Development of a Real-time Grasping Pattern Classification System by Fusing EMG-Vision for Hand Prostheses

Gamage Dulanjana Manoj Perera

(198115E)

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

Department of Mechanical Engineering

University of Moratuwa

Sri Lanka

August 2021

## 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.

Also, I hereby grant to University of Moratuwa the non-exclusive right to reproduce and distribute my thesis, in whole or in part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as articles or books).

Signature:

Date:

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

Dr. H. K. G. Punchihewa  
Head/Senior Lecturer,  
Department of Mechanical Engineering,  
University of Moratuwa, Sri Lanka.

Late, Dr. D. G. K. Madusanka  
Lecturer,  
Department of Mechanical Engineering,  
University of Moratuwa, Sri Lanka.

## 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.*

## ACKNOWLEDGMENTS

---

I received invaluable support and guidance from many people to complete this research work successfully throughout this intense period. I would like to express my sincere gratitude towards all these people who were there for me during my ups and downs.

I am indebted to my thesis supervisor, Late Dr. Kanishka Madusanka, for the encouragement and insightful guidance that he gave me during this intensive period. He was a teacher and a supportive friend who was always there for me when I was down. He allowed this thesis to be my own work, but steered me in the right direction with valuable suggestions. Furthermore, I am incredibly grateful to my co-supervisor, Dr. Himan Punchihewa, for his precious support and suggestions rendered at a crucial stage of the research. I owe my deepest gratitude to him for agreeing to be my supervisor after Dr. Kanishka and spiritually uplifting me to complete the research.

I would like to express my sincere gratitude to Professor Ruwan Gopura for the insightful feedback and endless support he gave me during hard times. Without his administrative support, this thesis would not have been possible. I would also like to extend my gratitude towards Dr. Damith Chathuranga for providing supportive comments and suggestions at the progress reviews. His suggestions have made this thesis more professional and valuable.

I would be amiss if I did not mention Mr. Pubudu Ranaweera and my lab mates, Mr. Achintha Abayasiri, Mr. Sanka Chandrasiri, and Mr. Achintha Iroshan, who were always with me during my ups and downs. I am also thankful

to all my fellow batchmates from the 14<sup>th</sup> batch especially, Mr. Lakshitha De Silva, Mr. Charuka Lihini, and Mr. Rawisha Serasinghe, for their friendly and insightful feedback. A special token of appreciation is also extended towards Miss. Supipi Fernando who was there with me from the beginning and encouraged me to do my best. I greatly appreciate her caring support.

I would also like to thank Dr. Nalaka Samaraweera for the administrative guidance and support he gave me during final stages of the thesis work.

Last but not least, I am very grateful to my parents and my brother Mr. Kanushka Perera for their continuous support and encouragement.

Dulanjana Perera,  
dulanjana.perera@ieee.org

# TABLE OF CONTENTS

---

<b>Declaration</b>	<b>i</b>
<b>Abstract</b>	<b>ii</b>
<b>Dedication</b>	<b>iii</b>
<b>Acknowledgments</b>	<b>iv</b>
<b>Table of Contents</b>	<b>v</b>
<b>List of Figures</b>	<b>xi</b>
<b>List of Tables</b>	<b>xvi</b>
<b>List of Abbreviations</b>	<b>xxi</b>
<b>1 INTRODUCTION</b>	<b>1</b>
1.1 Motivation . . . . .	5
1.2 Aim and objectives of the research . . . . .	6
1.3 Contribution to knowledge . . . . .	6
1.4 Thesis overview . . . . .	7



<b>2</b>	<b>LITERATURE REVIEW</b>	<b>9</b>
2.1	History of the prosthetic devices . . . . .	10
2.1.1	Cosmetic prosthetic devices . . . . .	10
2.1.2	Body-powered prosthetic devices . . . . .	11
2.1.3	Externally-powered prosthetic devices . . . . .	12
2.2	State-of-the-art electric prosthetic control systems . . . . .	15
2.2.1	EMG and vision sensory inputs for prosthetic control . . . . .	16
2.3	EMG-based prosthetic hand control systems . . . . .	17
2.3.1	EMG acquisition . . . . .	17
2.3.2	Pre-processing of EMG signal . . . . .	21
2.3.3	Segmentation of EMG data . . . . .	22
2.3.4	Feature extraction . . . . .	23
2.3.5	Classification methods . . . . .	27
2.3.6	Post-processing for final prediction . . . . .	31
2.4	Vision-based prosthetic hand control systems . . . . .	33
<b>3</b>	<b>PRELIMINARY STUDY ON CLASSIFIER DEVELOPMENT</b>	<b>38</b>
3.1	EMG and onset distance data collection . . . . .	38
3.1.1	Muscle selection . . . . .	40
3.1.2	Sample size selection . . . . .	41

3.1.3	Experimental setup . . . . .	43
3.1.4	Experimental protocol . . . . .	45
3.1.5	EMG and distance data pre-processing . . . . .	47
3.2	Statistical analysis . . . . .	48
3.2.1	RMS study of EMG data . . . . .	49
3.2.2	Normalized onset distance study . . . . .	51
3.3	Summary . . . . .	53
<b>4</b>	<b>DEVELOPMENT OF GRASPING PATTERN CLASSIFICATION SYSTEMS</b>	<b>56</b>
4.1	Development of EMG classification system . . . . .	56
4.1.1	Preprocessing of EMG data . . . . .	57
4.1.2	Feature selection . . . . .	63
4.1.3	Development protocol of classifiers . . . . .	67
4.1.4	Optimization of classifiers . . . . .	73
4.2	Development of vision-based classification system . . . . .	86
4.2.1	Proposed probability matrix . . . . .	87
4.2.2	Vision algorithm . . . . .	89
4.3	Summary . . . . .	91
<b>5</b>	<b>EMG-VISION HYBRID SYSTEM</b>	<b>92</b>

5.1	Data fusion using Bayes theorem . . . . .	93
5.2	Post-processing of fused data using majority vote and Bayesian fusion . . . . .	95
5.3	Algorithm of the proposed hybrid system . . . . .	96
<b>6</b>	<b>REAL-TIME VALIDATION OF HYBRID SYSTEM</b>	<b>98</b>
6.1	Grasping pattern simulation . . . . .	99
6.2	Validation of the EMG system . . . . .	101
6.3	Validation of the vision system . . . . .	104
6.4	Validation of proposed hybrid system . . . . .	105
6.5	Discussion . . . . .	106
<b>7</b>	<b>CONCLUSION AND FUTURE DIRECTION</b>	<b>108</b>
7.1	Conclusion . . . . .	108
7.2	Future direction . . . . .	109
	<b>List of Publications</b>	<b>110</b>
	<b>References</b>	<b>110</b>
	<b>Appendices</b>	<b>130</b>
<b>A</b>	<b>PCA of the Channel selection for RMS study</b>	<b>131</b>
<b>B</b>	<b>Pilot Test Data of the experiment</b>	<b>132</b>

B.1	Distance Data . . . . .	132
B.2	RMS Data . . . . .	133
<b>C</b>	<b>ANOVA GLM results of the RMS study</b>	<b>134</b>
<b>D</b>	<b>ANOVA GLM results of the Onset study</b>	<b>135</b>
<b>E</b>	<b>Filter parameters</b>	<b>136</b>
<b>F</b>	<b>Survey Questionnaire</b>	<b>137</b>
<b>G</b>	<b>Signal Filtering</b>	<b>138</b>
<b>H</b>	<b>Grid search Optimization</b>	<b>139</b>
H.1	Neural network parameters and hyperparameters . . . . .	139
H.2	Trend Analysis of the hidden layers . . . . .	140
<b>I</b>	<b>Bayesian Optimization Results</b>	<b>141</b>
I.1	Optimized results of the conventional classifiers . . . . .	141
<b>J</b>	<b>YOLO Algorithm</b>	<b>142</b>

## LIST OF FIGURES

---

1.1	Basic categorization of hand prostheses . . . . .	2
1.2	(a) Cosmetic leg developed by Ottobock [1]. (b) Body-powered upper limb developed by Ottobock [1]. (c) i-Limb developed by Ossure [2] . . . . .	3
1.3	Adaptation of visuomotor system of a human to the EMG-based prosthetic hand. . . . .	5
2.1	(a) First known prosthetic toe [3]. (b) Roman leg [3]. (c) Artificial iron arm [3]. . . . .	11
2.2	(a) First EMG-controlled hand by Reinhold Reiter [4]. (b) First electric hand [5]. . . . .	14
2.3	Pattern recognition (PR) control scheme for EMG-based prosthetic hand . . . . .	17
2.4	(a) iEMG crosstalk among 6 electrodes. (b) sEMG Crosstalk among 16 electrodes. (c) Classification results of Linear Discriminant Analysis (LDA) and Multilayer perceptron for iEMG (Type 1) and sEMG (Type 2). AR- Autoregressive coefficient; TD- Time Domain features; TDAR- Time Domain Autoregressive coefficients [6] . . . . .	19

2.5	Optimum number of electrodes for symmetrical arrangement and optimum place arrangement [6] . . . . .	20
2.6	Optimum number of electrodes for symmetrical arrangement and optimum place arrangement [6] . . . . .	21
2.7	Classification error of MLP and LDA with respect to different feature set [7]. . . . .	27
2.8	Classification result of different classifiers for AR feature [6] . . . .	29
2.9	Effect of majority vote of classification results [6] . . . . .	31
2.10	Comparison of classification error rates of KNN and SVM when MV and BF are used for post-processing [8] . . . . .	32
2.11	The propose Eye-in-Hand method for vision-based grasping pattern classification system by Joseph <i>et al.</i> [9]. . . . .	35
3.1	Overview of hand onset experiment during the RTG motion. . . .	39
3.2	Anatomy of the selected muscle at forearm. FDS - Flexor Digitorum Superficialis; PL- Palmaris Longus; ECU - Extensor Carpi Ulnaris; EDM - Extensor Digiti minimi; ED - Extensor Digitorum; ECRL - Extensor Carpi Radialis Longus. (image is adapted from BioDigital.com) . . . . .	40
3.3	The flex sensor with glove is marked with green color and the object (cylindrical, lateral power grasp) is marked with blue color for the distance calculation. $d_i$ is the initial distance and $d_2$ is the hand onset distance. . . . .	43
3.4	Schematic diagram of the experiment setup. . . . .	44

3.5	Three flex sensors were connected to the Arduino Uno micro-controller. The green color mark is identified by the distance calculation python program. . . . .	45
3.6	The selected grasping patterns and corresponding object used for the experiment. . . . .	46
3.7	The finger motion variation and the hand distance ( $d_i$ in the Figure 3.3) variation. TC- Top camera and SC- Side camera. (Key Grasp- Participant 9) . . . . .	48
3.8	The interval plot of mean RMS of each grasping pattern. Orange dot indicate the median whereas the blue line indicates the 95% CI.	50
3.9	The summary of the ANOVA GLM of RMS study. The main effects illustrates how different factors affect the RMS of the signal.	51
3.10	Interaction analysis of <i>grasping pattern</i> , <i>gender</i> , <i>age</i> and <i>handedness</i> on RMS of the signal. . . . .	52
3.11	The interval plot of mean/median normalized onset distance of each grasping pattern. Orange dot indicate the median whereas the blue line indicates the 95% CI. . . . .	52
3.12	The summary of the ANOVA GLM of Onset study. The main effects illustrates how different factors affect the normalized onset distance of the signal. . . . .	53
3.13	Interaction analysis of <i>grasping pattern</i> , <i>gender</i> , <i>age</i> and <i>handedness</i> on Normalized onset distance. . . . .	54
4.1	Overview of a classifier. The grasping pattern with highest likelihood (probability) is considered as predicted user intention. . . .	57

4.2	Saturated raw signal of Extensor Digitorum muscle of Subject 2, power grasp - trial 2. Subject is weighted 92Kg. Red ellipses indicate the saturated signal regions (4th and 5th attempts). . . .	58
4.3	Illustration of positive and negative DC offset of the EMG channels.	59
4.4	Illustration of initial stage of spikes detection and DC offset. DC offset is represented by the 0 Hz frequency and it is denoted by black dot on the graph. . . . .	60
4.5	Overview of the algorithm of the filtering system. . . . .	62
4.6	The erratic (surrounding) frequencies. This is due to the fluctuation of utility frequency. . . . .	62
4.7	TD features have strong positive influence to the PC1 which has approximately 30% variation of the signal in all channels. AR features have both positive and negative influence to the PC2. . .	66
4.8	Development procedure of the classification models. . . . .	67
4.9	Variation of model performances (mTRP) when the training process is iterated ten times. . . . .	68
4.10	Illustration of sub-windowing of the main window. . . . .	70
4.11	Illustration of sub-window of 50ms length. . . . .	71
4.12	Training analysis of the sub-windows. mTPR is presented in the y-axis. This figure shows the training accuracy of each model. . .	72
4.13	mTPR comparison of three networks with different learning rates	75
4.14	mTPR comparison of different feature groups (without the demographic features) and different hidden layer neurons . . . . .	76



4.15	mTPR comparison of different feature groups with demographic features and different hidden layer neurons . . . . .	77
4.16	Performance improvement of different feature groups and different neuron configurations. . . . .	77
4.17	The trend analysis of the TD group. The regression equation is noted at the top of the figure. Other necessary statistical information are mentioned within the figure. . . . .	78
4.18	Double HL analysis of TD features. . . . .	79
4.19	The surrogate function of two variables (LR and MC). The algorithm is searching for the minimum point on the surrogate mean surface (red surface). . . . .	82
4.20	Optimized neural network architecture. . . . .	83
4.21	The feature groups performances on the conventional classifiers. The demographic features are not considered. . . . .	84
4.22	The performance of the feature groups with demographic features on the conventional classifiers. . . . .	84
4.23	The mTPR increment due to the demographic features. . . . .	85
4.24	The real-time object detection. The respective confidence score is also presented. . . . .	86
5.1	Hybrid system overview. . . . .	92
6.1	(a) Eye-in-hand camera setup for real-time experiments. (b) Normal or the rest position of the simulated hand. . . . .	99
6.2	Simulated grasping pattern. . . . .	100

6.3	V-rep simulates the lateral grasp. (a)v-rep simulation with the camera feedback (left window). (b) The isometric view of the experiment. (c) Plan view of the experiment. . . . .	101
6.4	Examples of the prediction errors of Lateral grasp when no fusion was utilized. The object used was the cup. . . . .	103
6.5	Model computation time for different hidden layer configurations .	103
6.6	Model computation time for different hidden layer configurations [10]	104
6.7	Examples of the prediction errors of lateral grasp when no fusion was utilized. The object used was the cup. . . . .	106
G.1	(a) Second stage filter. (b) Bandpass filtering. . . . .	138
H.1	Trend analysis of HL-2 neuron configuration. . . . .	140
J.1	(a) The model architecture of YOLO (b) The model architecture of ResNet (featurized image pyramid). (image is adapted from, <i>Lil'Log</i> [11]) . . . . .	143
J.2	The overview of the YOLO algorithm. It divide the image into grids and predict the object presence in each grid simultaneously while detecting the locations [10]. . . . .	144

## LIST OF TABLES

---

2.1	Merits of three major feature domains [12] . . . . .	26
2.2	Summary of offline and real-time grasping pattern classification. Here only mention the highest performed classifiers only. [HG-Hand Gesture; HC-Hand Close; HO-Hand Open; R-rest; IFP-Index Finger Pinch; MFP-Middle Finger Pinch; KG-Key Grip; CG-Chuck Grip; LG-Lateral Grip; PG-Power Grip; PH-Point; PD-Precision Disk; P2F- Prismatic-2 Finger; P4F- Prismatic-4 Finger, UP-ulnar Pinch] [ECOC-Error Correcting Output Codes; NB-Naive Bayes; ESN-Echo state network] . . . . .	30
2.3	summary of Vision-based Prostheses. (OD-Object Detection; GP-Grasp Prediction; TA-Triggering action; FC-Finger Configuration; WC- Wrists Configuration; P-Pinch; PG-Power Grip; TG-Tool Grip; KG-Key Grip; 2JC- 2Jaw chuck; 3JC- 3 Jaw chuck; LG-Lateral Grip; HG-Hook Grip; PT-Point Grip) (DA- Dictionary Approach; ODA- Object Dimension and Area) . . . . .	37
3.1	Selected Muscle for sEMG Extraction . . . . .	41
3.2	Details of the participants. . . . .	42
4.1	Feature groups selected for the investigation. . . . .	63
4.2	Sub-window Analysis . . . . .	71

4.3	Parameter sets of the ANN structure for the Grid search method. HL- Hidden Layer . . . . .	74
4.4	Hyperparameter of the Learning rate for the Grid search method .	74
4.5	Number of Neurons in each hidden layer . . . . .	78
4.6	summary of the trend analysis . . . . .	79
4.7	The parameters of the Bayesian optimizer . . . . .	81
4.8	Optimized hidden layer neuron count. The bold numbers represents the optimized variable . . . . .	81
4.9	Optimized hyperparameters . . . . .	82
4.10	Optimized hyperparameters of the TD feature-models without demographic features. TD-model without demographic features produced the highest mTPR. . . . .	83
4.11	Optimized hyperparameters for the conventional classifiers. . . . .	83
4.12	Optimized hyperparameters of the TD feature-models with demographic features. TD-model with demographic features produced the highest mTPR. . . . .	85
4.13	5-point Likert scale parameters . . . . .	88
4.14	Optimum testing results of ANN, LDA, Knn, NB and DT for each grasping pattern. The best feature group was TD with demographic factors . . . . .	91
6.1	Online performance of EMG classification without the fusion system . The mean of the six trials were tabulated with respective <i>standard deviations</i> . . . . .	102

6.2	Complete fusion system online performances. The mean of the 6 trials were tabulated with respective <i>standard deviations</i> . . . . .	105
A.1	Eigen analysis of the principal components . . . . .	131
A.2	Eigenvector correspond to the each muscle in each principal component . . . . .	131
B.1	Normalized onset distance data of 5-participants (pilot test). . . .	132
B.2	Pooled SD (every grasping pair) of normalized onset distance data of 5-participants (pilot test). . . . .	132
B.3	Absolute difference (every mean grasping pairs) of normalized onset distance data of 5-participants (pilot test). . . . .	132
B.4	RMS data of 5-participants (pilot test). . . . .	133
B.5	Pooled SD (every grasping pair) of RMS data of 5-participants (pilot test). . . . .	133
B.6	Absolute difference (every mean grasping pair) of RMS data of 5-participants (pilot test). . . . .	133
C.1	ANOVA GLM table of the RMS study. The <i>gender</i> effect has no significant relationship with the RMS. Hence the a error was produced at the analysis . . . . .	134
D.1	ANOVA GLM table of the onset study. . . . .	135
E.1	IIR single notch filter parameters . . . . .	136
E.2	IIR Butterworth bandpass filter parameters . . . . .	136

F.1	Pilot test results of 6 participants. Sample size was calculated for given Margin of Error (MOE) and Standard Deviation (StDev) . . .	137
F.2	Derived conditional probability matrix . . . . .	137
H.1	Parameters and the hyperparameters of selected neural networks .	139
I.1	Optimized results of the conventional classifiers. Feature groups with the demographic features. . . . .	141
I.2	Optimized results of the conventional classifiers. Feature groups without demographic features. . . . .	141

## ABBREVIATIONS

---

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

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



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