Cost-Effective System for the Classification of Muscular Intent using Surface Electromyography and Artificial Neural Networks

Anmol Khanna
Heriot-Watt University, Dubai Campus
Dubai, United Arab Emirates
E-mail: ak547@hw.ac.uk

Senthil Arumugam Muthukumaraswamy
Department of Electrical and Electronic Engineering
Heriot-Watt University, Dubai Campus
Dubai, United Arab Emirates

***Abstract*—This paper presents the implementation of a cost-effective system to classify muscular intent. A neural network is used for this purpose. After skin preparation, feature extraction, network training and real-time testing, an average overall classification accuracy of 93.3% over three possible gestures was obtained. Ultimately, the results obtained speak to the suitability of an Arduino-based system for the acquisition and decoding of muscular intent. This result is indicative of the potential of the Arduino microcontroller in this application, to provide effective performance at a far lower price-point than its competition.**

Keywords—Electromyography; orthosis; prosthesis; neural network; muscular intent; Arduino; cost-effective

I. INTRODUCTION

Damage or trauma to the human body's neuromuscular system is capable of causing long-standing impairment to the daily functioning of an affected individual. Injuries such as these are widespread enough to warrant the development of technologies to counteract their effects. Strokes, for example, affect nearly 795,000 individuals per year in the US alone [13]. Apart from being sentenced to a vastly impaired quality of life, mundane tasks such as using buttons or zippers become painstakingly difficult. Often, the aftermath of such injuries involves rehabilitative measures, or, failing that, permanent alternatives. Mechanical support structures called orthoses serve to perform this function.

However, the vast majority of modern commercially available orthoses are simply too expensive for most people to afford. The Luke Hand, developed with the backing of DARPA, costs upwards of $100,000 [1]. The Bebionic arm, another cutting-edge prosthetic limb, costs $11,000 [2]-[3]. Thus, the lack of readily available yet economical remedial options presents a serious challenge in the rehabilitation of affected individuals. This paper, therefore, aims to present a more cost-effective approach without sacrificing ease of control.

A means of operating an orthosis based on muscular intent would offer natural and intuitive control that the user would already be accustomed to, such as developed in [6]. As a result, the chances of the wearer actually continuing to use the device would increase, thereby providing faculties that may not have been possible without it. A real-world example of this was implemented by Kiguchi and Hayashi (2012), in the form of a robotic power-assist orthotic, using electromyography as the control signal [10]. It was discovered that myoelectric orthoses and prostheses increase cosmesis and reduce phantom-limb pain in the case of limb loss [12].

A method to classify muscular intent through the use of a neural network is discussed in [15], wherein four channels of electromyography are used to specify the movement of the elbow joint. Dimensionality reduction in the form of extracting the RMS of the signal is carried out. These four extracted RMS values (one per channel) are then used as inputs to the network, the output being an angle measure. The arm was actuated through the use of pneumatic muscles. Potentiometers located at the elbow joint were used to track the physical movement of the prosthesis. The success of this paper proves the effectiveness of the RMS of an EMG signal as an extracted feature, although further differentiation would be possible with the extraction of more features.

A novel method for feature extraction of the electromyogram is discussed in [14], which uses a 16-bit National Instruments NI-DAQ data acquisition card. This paper aims to avoid the use of expensive instruments in the interest of being cost-effective. In addition, the NI-DAQ card is not particularly convenient to source in certain parts of the world. Thus, it was decided to investigate the suitability of an Arduino microcontroller for the purpose of data acquisition. The development of a system based on these principles, primarily intuitive control at a reasonable price point using the Arduino microcontroller, is thus the focus of this paper. This task could be broadly split up into two processes-signal acquisition and signal classification.

A. Signal Acquisition

This paper tackles signal acquisition through the use of an Arduino Mega 2560 microcontroller. The primary reasons for this choice are the ready availability and low cost of the Arduino, which puts it within the reach of the large number of people worldwide that require orthotic devices but cannot currently afford them.

When the brain issues a command to a muscle to contract, it does so by sending a series of electrical impulses through certain neurons called 'motor neurons'. These motor neurons innervate (activate) several motor units each. Each motor unit is in turn made of up several muscle fibers. This is shown in Fig. 1.

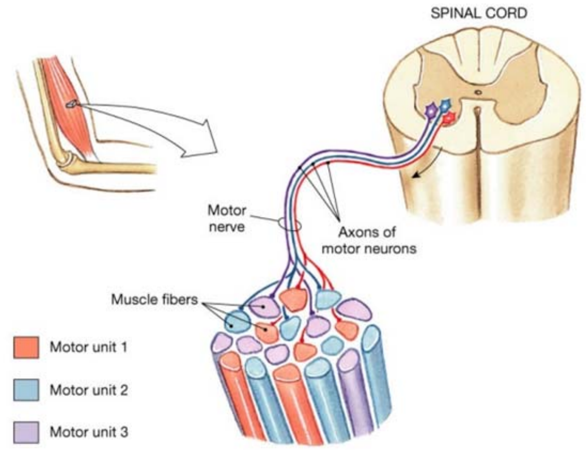

Fig. 1. Diagram of the nuromuscular system.

Due to a mechanism called the sodium-potassium pump, the relative concentrations of sodium and potassium ions causes the inside of each muscle cell to rest at a slightly negative potential. Each time a motor neuron delivers an electrical impulse to the motor unit, the ionic balance of each muscle cell in the motor unit is disturbed. This disturbance temporarily causes a positive potential inside the cell at the instant of muscular recruitment. After a certain period of time, the sodium-potassium pump reactivates, returning the cell to its resting potential. This process is shown in Fig. 2.

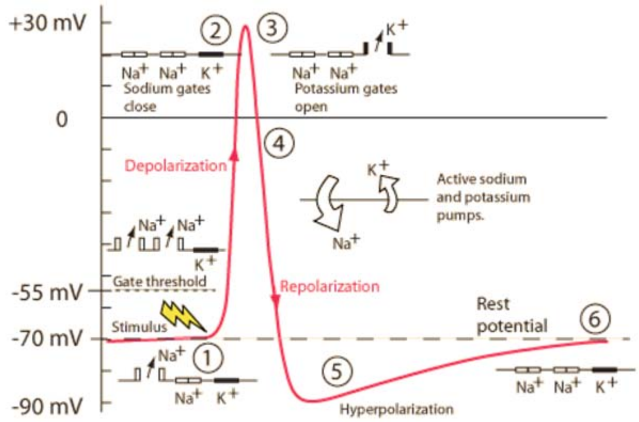

Fig. 2. Action potential graph (Acquired from [4]).

Fig. 2 shows the arrival of the electrical impulse as stimulus, and the resulting spike in muscular potential. This is followed by a return to the resting potential, during which time muscular activation is not possible for that particular cell. This time period during which the cell is unresponsive to recruitment is called the Absolute Refractory Period.

A summation of these individual action potentials over a motor unit yields the Motor Unit Action Potential (MUAP). The summation of several MUAPs over a muscular region yields the electromyogram, shown in Fig. 3.

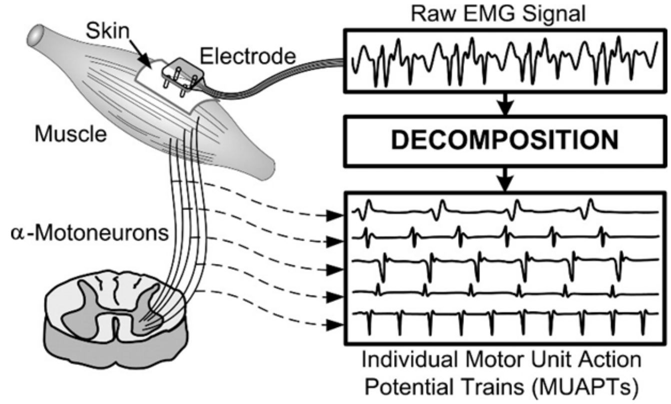

Fig. 3. Decomposition of electromyogram (EMG) into MUAPTs (Acquired from [5]).

The nature of the signal, as shown in Fig. 3, requires it to be processed to a form acceptable by the Arduino microcontroller. The input voltage range for the analog pins of the Arduino microcontroller is 0-5 Volts. Therefore, the raw EMG signal must be amplified, owing to its natural amplitude of a few microvolts to a few millivolts [3], rectified, due to its ability to take both positive and negative values [11], and band-pass filtered, due to unnecessary signal components that obfuscate those of interest, such as ECG artifacts.

The signal is acquired through the use of a third party signal conditioning circuit, the MyoWare Muscle Sensor, used in conjunction with gelled electrodes. These electrodes are reusable and employ a conductive gel to boost signal transfer between the user's skin and the AgCl detection surface on the electrode. Each channel of EMG signal acquired this way required three electrodes- two to pick up the differential EMG signal over the muscle under investigation, and one to offer a ground reference. This ground reference is attached over a part of the arm with little to no musculature beneath it, such as the elbow.

B. Signal Classification

The process of acquiring muscular intent is called 'Electromyography'. The signal obtained through the process of electromyography, called the Electromyogram, is a measure of muscular recruitment. During the initial activation, this electromyogram is roughly equivalent to the muscular force desired by the individual. Therefore, if these electromyogram signals can be detected and the muscular intent deciphered, they can be used to provide intuitive control over an orthotic or prosthetic device.

The task of signal classification is tackled through the use of a neural network. Neural networks are a perfect fit for this decoding of muscular intent due to their ability to approximate unknown functions. Given the random nature of the electromyogram, the necessity of a robust tool of this nature becomes apparent.

The popularity of neural networks rose during the 1950's, and represented a significant step in mankind's development of systems that were able to reason more along the lines of human beings.

There are two primary uses of neural networks, regression and pattern recognition.

a) Regression: The prediction of future data points/ trends based on previous data points.

b) Pattern Recognition/Classification: Training the network correctly classify novel inputs it has not encountered before.

The scope of this project was seen to be a perfect fit for the pattern recognition ability of neural networks. Based on the work done in [7], the results obtained from able-bodied individuals are applicable to those with amputations as well. This conclusion validates the tests performed and results presented within this paper as being relevant despite involving only able-bodied users.

II. Methodology

A. Electrode Placement

Electrodes were placed upon the flexor carpi radialis, shown in Fig. 4, and the flexor digitorum superficialis, shown in Fig. 6.

Fig. 4 shows the location of the flexor carpi radialis (in blue). Electrode placement was therefore as shown in Fig. 5.

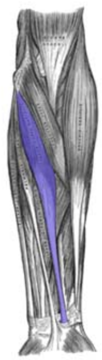

Fig. 4. Location of flexor carpi radialis.

Fig. 5. Electrode placement upon the flexor carpi radialis.

Fig. 6 shows the location of the flexor digitorum superficialis, and its insertions at the central phalanx on each finger. This muscle is responsible for the flexion of the phalanges. Electrodes were placed upon it as shown in Fig. 7.

Fig. 7 shows the placement of three electrodes per channel upon the arm. The MyoWare Muscle Sensors were clipped onto the electrodes and wired up to the Arduino microcontroller through braided cables as shown in Fig. 8.

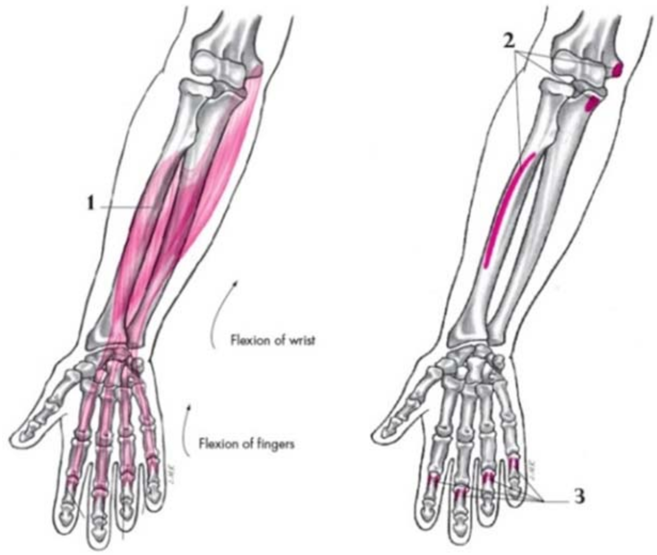

Fig. 6. Flexor digitorum superficialis.

Fig. 7. Placement of electrodes upon the flexor digitorum superficialis.

Fig. 8. Braided cables.

The cables shown in Fig. 8 were braided in order to reduce cable noise.

Three output classes, in this case hand gestures, were selected based on usefulness and ubiquity. These were:

a) Class 1- Hand closed/ grip, shown in Fig. 9.

Fig. 9. Gesture 1- Closed fist.

b) Class 2- Point index finger, shown in Fig. 10.

Fig. 10. Gesture 2- Point index finger.

c) Class 3- Natural resting position, shown in Fig 11.

Fig. 11. Gesture 3- Natural rest position.

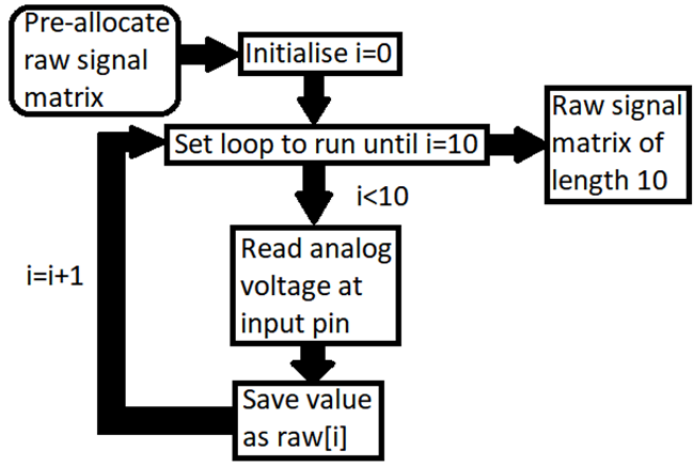

Fig. 12. Signal acquisition process per channel.

These gestures were chosen to be the output classes of the neural network.

The processed EMG signal was sampled by the Arduino microcontroller and thus made available for recording within the MATLAB environment. The neural network was built within the MATLAB r2015a environment.

Code was written to record values at the analog input pins to a one-dimensional vector of length 10 cells. Pauses and messages were provided to the user for the sake of orientation, ensuring only the desired signal was recorded. A block diagram of this process is shown in Fig. 12.

Fig. 12 shows the population of the initial matrix for a single channel through the process of serially reading the analog voltages at the pins of the Arduino. Features were then extracted from the raw signal matrix, in order to reduce the dimensionality of the problem. The need for dimensionality reduction arises from the fact that classification accuracy is sometimes improved in a reduced feature space [8]. The high-dimension nature of the EMG signal qualified the use of dimensionality reduction in this paper.

B. Feature Extraction

Four time-domain features were selected and programmed, namely Mean Absolute Value (MAV), Root Mean Square (RMS), Variance (VAR) and Integrated EMG (iEMG).

Mean Absolute Value is defined as the average of the absolute value of the raw electromyogram signal. MAV is given by (1).

$$MAV = \frac{1}{N}\sum_{n=0}^{N-1} |x_n| \quad (1)$$

Where, N denotes the length of the signal being recorded and x_n is the value of the signal.

Root Mean Square can be expressed as in (2).

$$RMS = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} {x_n}^2} \quad (2)$$

Variance of a variable is defined as the mean value of the squared deviation from the mean. The mean of the electromyogram, however, is very nearly zero, and thus Variance is given by (3).

$$VAR = \frac{1}{N}\sum_{n=0}^{N-1} {x_n}^2 \quad (3)$$

The integrated EMG of a signal is defined as the area under the curve of the absolute value of the electromyogram. This quantity is given by (4).

$$iEMG = \sum_{n=0}^{N-1} |x_n| \quad (4)$$

The functions written to calculate these features accepted the raw signal matrix formed in Fig. 12, and performed calculations upon it in order to each yield an individual feature. The individual features thus calculated were then appended together to form a single feature vector, as shown in Fig. 13.

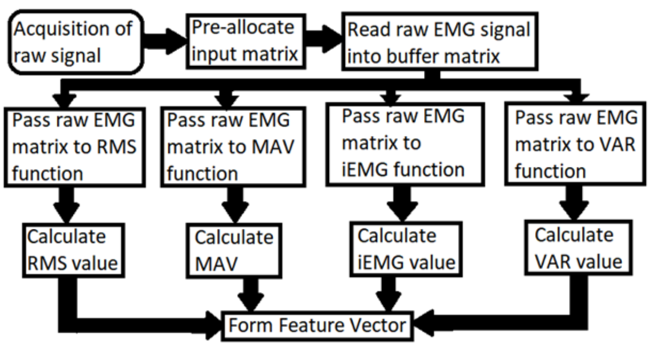

Fig. 13. Formation of feature vector from initial signal matrix.

This Feature Extraction occurred for each repetition per channel, per gesture. Appending the resultant feature vectors together resulted in the formation of the Input Matrix. Thus, the size of the input matrix was set according to (5).

$$size\ of\ input\ matrix = (no.of\ features)\ x(\ no.of\ channels * no.of\ repetitions * no.of\ gestures) \quad (5)$$

Equation 5 therefore gave the size of the input matrix to be equal to 4 features x (2 channels *10 repetitions per channel per gesture* 3 gestures). This implied the size of the input matrix to be equal to 4x60, i.e. the input matrix contained 4 features, one per row, and 60 instances of gestures, one per column.

C. *Type of Neural Network*

The type of neural network employed was a 3-layer feed-forward neural network. This implied the existence of a single hidden layer between an input and output layer. The input layer was required to have four nodes, one for each feature extracted from the EMG signal. The number of hidden layers selected was 10, and the number of output nodes had to correspond with the number of output classes, i.e., 3.

The optimization algorithm used was the Levenberg-Marquardt algorithm. The input matrix was divided into training: cross-validation: testing sets randomly in a 70:15:15 ratio. This division of training data was implemented in order to prevent a phenomenon called 'Over-fitting', wherein the network fails to generalize during real-time operation despite good theoretical performance [9]. This configuration was repeatedly trained until the best possible classification accuracy was obtained.

D. *Real-time Testing Methodology*

During real-time testing, the program constantly recorded input matrices of length 10 values from the Arduino's analog input pins, immediately extracting features and passing these as input to the neural network. The neural network then classified the current input and displayed a picture of the classified gesture for easy viewing. This process was seen to occur once every second, resulting in a reasonable tradeoff between classification accuracy and response time.

Four independent test sessions were held in order to ascertain system effectiveness. Electrode placement was attempted to be recreated faithfully between successive test sessions. Each test session involved several instances of the three target gestures. A success was defined as the accurate classification of the gesture made by the user, and failure was defined as a misclassification by the system. In total, each gesture was tested 60 times, and the results were tallied. Percentages of accurate classifications were calculated and used in order to gauge overall system efficacy.

III. Results

Training of the network yielded results in the form of a confusion matrix as well as a Receiver Operating Characteristic plot.

A. *Network Training Performance*

Network training results are shown in Fig. 14.

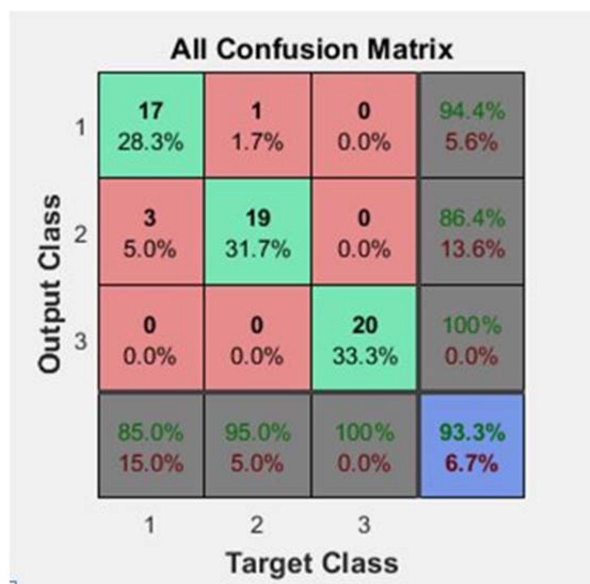

Fig. 14. Confusion matrix.

Fig. 14 shows the confusion matrix for the classification accuracy obtained amongst the various datasets used. It was seen that the overall classification accuracy obtained was **93.3%**. Fig. 15 shows the Receiver Operating Characteristic plot.

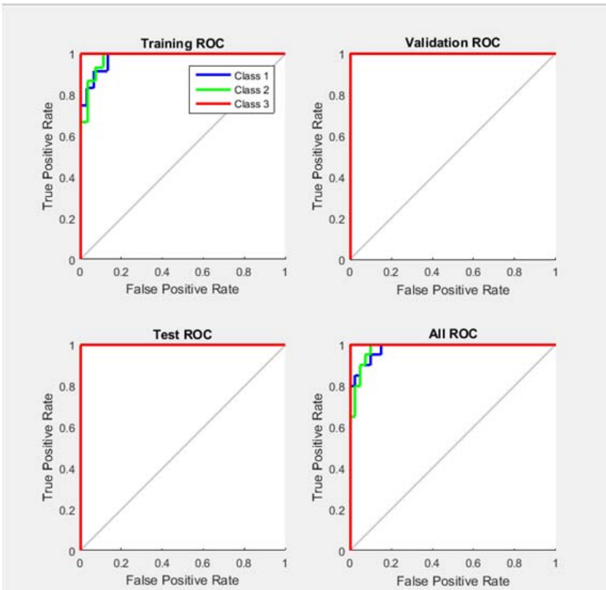

Fig. 15. Receiver operating characteristic plot.

Fig. 15 shows a visual representation of the classification accuracy attained. Based on the areas under the curves of the individual class traces, it was judged that the network correctly classified novel inputs with reasonable accuracy.

B. Real-time Test Results

Real-time classification accuracies were as is shown in Table 1.

TABLE I. CLASSIFICATION ACCURACY PER CLASS

Test Session	Class 1	Class 2	Class 3	Total
1	61.1%	86.66%	80.95%	**76.23%**
2	61.90%	91.30%	100%	**84.4%**
3	73.68%	93.33%	85%	**84%**
4	60%	95.65%	100%	**85.21%**

Table 1 shows the classification accuracies obtained by observing the number of correctly classified gestures divided by the total number of trials for each class over four independent real-time testing sessions. It was observed based on this data that the average classification accuracy during real-time testing was **82.46%.** Class-wise average classification accuracies were calculated and seen to be:

Class 1- **64.17%**
Class 2- **91.72%**
Class 3- **91.48%**

IV. CONCLUSIONS

The neural network obtained a classification accuracy of 93.3%, as shown in Table 1, resulting in a classification accuracy of 82.46% during real-time testing.

This result indicated the potential for a truly economical and robust device using an Arduino microcontroller as a data acquisition module. The inclusion of additional points of EMG signal acquisition and/or a greater number of extracted features would serve to further increase the efficacy of the system, at the tradeoff of increased system cost.

ACKNOWLEDGMENT

I would like to thank my project supervisor, Dr. Senthil, without whose support and faith in me this project could not have been realized in its current form. I would like to thank my parents for their patience and understanding. I would also like to thank my friends and colleagues for their camaraderie, and providing support in the face of seemingly insurmountable problems the way only friends can.

REFERENCES

[1] "DARPA's 'Luke Skywalker' Prosthetic Arm Could Soon Have Sense Of Touch, But It Will Cost $100k", International Business Times, 2017. [Online]. Available: http://www.ibtimes.com/darpas-luke-skywalker-prosthetic-arm-could-soon-have-sense-touch-it-will-cost-100k-2001214. [Accessed: 17- Mar- 2017].

[2] "Life changing myoelectric hand packed with the latest technology - bebionic", Bebionic.com, 2017. [Online]. Available: http://bebionic.com/the_hand. [Accessed: 17- Mar- 2017].

[3] “”How much is the newest advanced artificial hand"", singularityhub.com, 2017. [Online]. Available:https://singularityhub.com/2010/06/30/how-much-is-the-newest-advanced-artificial-hand-11000-usd-video/. [Accessed: 17- Mar- 2017].

[4] "Action Potentials", Hyperphysics.phy-astr.gsu.edu, 2017. [Online]. Available: http://hyperphysics.phy-astr.gsu.edu/hbase/Biology/actpot.html. [Accessed: 18- Mar- 2017].

[5] C. De Luca, "Decomposition of Surface EMG Signals", 2017.

[6] M. Kimura, H. Pham, M. Kawanishi and T. Narikiyo, "EMG-force-sensorless power assist system control based on Multi-Class Support Vector Machine", in 11th IEEE International Conference on Control & Automation (ICCA), 2014.

[7] S. Muceli, Multi-channel surface electromyography for simultaneous and proportional control of prostheses, 1st ed. River Publishers, 2013.

[8] "Dimensionality reduction", En.wikipedia.org, 2017. [Online]. Available: https://en.wikipedia.org/wiki/Dimensionality_reduction. [Accessed: 24- Mar- 2017].

[9] i. whats is the difference between train, "whats is the difference between train, validation and test set, in neural networks?", Stackoverflow.com, 2017. [Online]. Available: http://stackoverflow.com/questions/2976452/whats-is-the-difference-between-train-validation-and-test-set-in-neural-networ. [Accessed: 20- Mar- 2017].

[10] K. Kiguchi and Y. Hayashi, "An EMG-Based Control for an Upper-Limb Power-Assist Exoskeleton Robot", IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 42, no. 4, pp. 1064-1071, 2012.

[11] A. Suberbiola, E. Zulueta, J. Lopez-Guede, I. Etxeberria-Agiriano and B. Van Caesbroeck, "Arm Orthosis/Prosthesis Control Based on Surface EMG Signal Extraction", 2017. .

[12] S. L. Carey PhD., D. J. Lura PhD. and M. J. Highsmith. Differences in myoelectric and body-powered upper-limb prostheses: Systematic literature review. Journal of Rehabilitation Research and Development 52(3), pp. 247-262. 2015. Available: https://search-proquest-com.ezproxy1.hw.ac.uk/docview/1696888717?accountid=16064.

[13] “Rehabilitation Therapy after a Stroke", *Stroke.org*, 2017. [Online]. Available: http://www.stroke.org/we-can-help/stroke-survivors/just-experienced-stroke/rehab. [Accessed: 08- Jul- 2017].

[14] 2017.[Online].Available:https://arxiv.org/ftp/arxiv/papers/0912/0912.3973.pdf.[Accessed:18-Mar-2017].

[15] Z. Tang, K. Zhang, S. Sun, Z. Gao, L. Zhang, and Z. Yang, “An Upper-Limb Power-Assist Exoskeleton Using Proportional Myoelectric Control,” Sensors, vol. 14, no. 4, pp. 6677–6694,Apr.2014.