2019 4th International Electrical Engineering Conference (IEEC 2019)
Jan, 2019 at IEP Centre, Karachi, Pakistan

Hand Motion Recognition from EMG using Artificial Neural Network

Habiba Aziz*, Mohsin Khan, Sajid Hussain, Farah Haroon

Institute of Industrial Electronics Engineering, PCSIR
(habibaaziz.26@iiee.edu.pk, mohsinkhan.26@iiee.edu.pk, sajidhussain@iiee.edu.pk , farah@iiee.edu.pk)

Abstract: **Hand motion recognition has become an active research due to its numerous applications such as its use in human-computer interface. The motivation for this work is to help the disabled people by improving their quality of life. This paper aims to recognize and replicate four hand gestures fist, spread, wave in, and wave out on 3D printed prosthetic hand. Electromyography (EMG) signals are recorded for these gestures using Myo armband consisting of eight electrodes from which five statistical parameters of EMG signals are extracted and employed for classification. These parameters for each electrode accumulate to form feature vector inserted to Artificial Neural Network (ANN) which classifies it into its target classes (gestures). The performance of ANN classifier is assessed over Scaled Conjugate Gradient (SCG) in comparison of different algorithms. Our simulation results are also supported with experimental results run over 3D printed prosthetic hand.**

Keywords: Artificial Neural Network, Electromyography, Hand Motion Recognition, Myo Armband, 3D printed prosthetic hand

I. INTRODUCTION

People who have lost their upper extremity due to some tragedy are unable to do their daily life activities such as holding an object, moving them, even unable to eat by their own. The remaining part of the muscle is active and can be utilized for capturing those useful Electromyography (EMG) signals. This is why EMG signals are being widely used in prosthesis or rehabilitation devices and Human Computer Interface (HCI).

The EMG signal is an electrical activity of the muscle during contraction and relaxation [1]. The two types of EMG are surface EMG (sEMG) recorded by non-invasive electrodes and intramuscular EMG which are recorded by invasive electrodes [2]. A wearable gesture control armband gives simple approach to obtain EMG signal. The EMG data for four gestures Fist, Spread, Wave In and Wave Out are acquired.

The raw data cannot be used directly to classify the gestures therefore features extraction is performed. EMG features exist in time, frequency and even in time-frequency domains. Time domain features are extracted from raw data due to their simplicity whereas time-frequency and frequency domain features are avoided because of high dimensionality and high-resolution [2].

In order to help the amputee to recover the dependency, two types of prosthesis can be approached; body powered or electric powered. The body-powered devices grab the strength from muscles to drive the cable through a link. The electric powered prosthesis is operated with battery and is widely used due to its cosmetic appearance. These externally powered devices might be controlled from pressure or Myoelectric Signals (MES) [3]

There are various myoelectric control schemes but based on the application, Pattern Recognition is used to control the prosthesis. This technique involves machine learning categorized in: Supervised and Unsupervised learning [4].

In order to classify data into already defined classes, supervised learning is employed in which Artificial Neural Network (ANN) is exercised as a pattern recognition classifier. ANN is a computing system consisting of a number of simple, highly interconnected processing nodes. It encompasses different layers: input layer, hidden layer and output layer. It is a classifier having EMG features as input matrix and the four classes as target matrix.

EMG data recording, feature extracting, classifying and using it to control a prosthetic hand is popular research these days.

sEMG data is recorded from two bipolar electrodes for offline classifier training in [5]. Segmentation techniques are applied to separate muscle contraction and rest periods of sEMG time-series data. They used time-frequency algorithm to extract sEMG-based features from the segmented data. The classification algorithm used is Support Vector Machines (SVM) while we used Neural Networks.

Single channel sEMG is used to classify and analyze gestures in [6]. The National Instruments Educational Laboratory Virtual Instrumentation Suite (NI ELVIS) with QNET module is used to acquire single channel EMG data. They extracted time-frequency domain features through Wavelet Transformation. Artificial Neural Network is used for classification of three hand motions.

M. G. B. Fonseca et al [7] used Myo Armband to acquire EMG signal, they extracted seven time-domain features from the data set. They trained a small dataset of 120 samples using Artificial Neural Network to classify four hand gestures using only 30 samples for each gesture. Their research includes only simulation results; they did not implement their work on prosthetic hand.

The contribution of this study is to implement the most efficient classifier on a real prosthetic hand which can be used by lower limb amputee person. EMG data is acquired through Myo Armband and five time-domain features are extracted. EMG signals are random in nature therefore we have used a larger data set to classify the gestures in comparison to [7]. Artificial Neural Network is used to train the model which classifies four gestures into its target classes. The output achieved is then applied through Arduino UNO to drive servo motor employed to the 3D printed prosthetic hand which replicates the gesture performed by human.

This paper is organized as follows: Section II describes the methodology of the work. It explains the functionality of the system in detail. Section III discusses the results obtained from the classifier and implementation of the output on prosthetic hand. Finally, section IV concludes our work and provides future research directions.

II. METHODOLOGY

EMG signals are recorded using Myo Armband. Myo sensors transmit the data to laptop using a Bluetooth adapter. These raw EMG signals are pre-processed. The features are extracted and normalized and then combined to form a feature vector which is the input for ANN model which classifies the hand gestures in accordance with a target matrix. On the basis of classifier's output a control command is generated to control the prosthetic hand. The functionality for this system is shown in Fig. 1 and the detail of each block is described below.

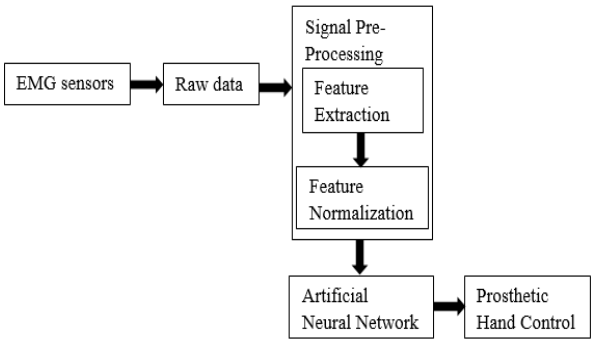

Fig. 1 Hand Motion Recognition

A. EMG data acquisition

Myo Armband sensor consisting of eight EMG sensors is used for EMG signal recording at a rate of 200Hz. It is placed on lower arm muscles to perceive the hand movements and process the signal. Furthermore, it has an accelerometer, gyroscope and magnetometer each having three axes.

The data for four gestures is recorded. 180 readings are taken for each hand gesture. In every data acquisition session, the Myo Armband is placed in a healthy arm. For each reading, the data is stored as a comma separated value (.csv) file.

B. Signal pre-processing

Probabilistic methods are used to extract valuable information from raw data in terms of statistical parameters. The most common time-domain features which are more separable and give energy and complexity information are incorporated from [8]. These are Integral Absolute Value (IAV), Mean Absolute Value (MAV), Variance (σ^2), Root Mean Square (RMS), Waveform Length (WL) given by Eqs. (1) ~ (5).

Integral Absolute Value (IAV):

$$\text{IAV} = \sum_{n=1}^{N} |x_n| \tag{1}$$

where x_n is the *nth* data sample of EMG signal having *N* data samples.

Mean Absolute Value (MAV):

$$\text{MAV} = \frac{1}{N}\sum_{n=1}^{N} |x_n| \tag{2}$$

Variance (σ^2):

$$\sigma^2 = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2 \tag{3}$$

Root Mean Square (RMS):

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{4}$$

Waveform Length (WL):

$$\text{WL} = \sum_{n=1}^{N} |x_n - x_{n-1}| \tag{5}$$

Feature normalization is a method used to standardize the range of features of data. Since the range of values of data varies widely, feature normalization is performed after extraction of features. Moreover, it improves the convergence speed of algorithm and is given by Eq. (6).

$$\text{X\_norm} = \frac{x-\mu}{\sigma} \tag{6}$$

Where x is original feature vector, μ is mean of that feature vector, and σ is standard deviation.

C. Artificial Neural Network

In Artificial Neural Network, inputs and weights (w) are combined to produce a state of activation of the neuron through the Activation Function which is sigmoid function as shown in Fig. 2.

Once the threshold of this function is gained, the output of the neuron is produced, which is treated as input to the next layer. The weights represent the degree of importance that certain input has considering that neuron. Their value is changed corresponding to the intensity of the input signal. Bias (b) is an additional node in the hidden and output layers and is attached to the weights of the successive layer; the activation function of it is permanently set value 1.

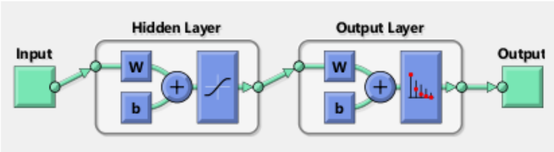

Fig. 2 Architecture of Artificial Neural Network

A Feedforward Neural Network (FF) is formed by interconnected nodes and has the ability to store content and make it accessible. The backpropagation algorithm is widely used for training neural networks. The output generated is compared to the desirable one and an error value is calculated. With this calculated error value, the backpropagation process begins, where this error is propagated back to the network and used to adjust the weights, aiming to reduce the error at each attempt [6].

III. RESULTS AND DISCUSSION

A. Simulation Results

The tests are performed with four participants, one female and three males. Forty recordings of two males and fifty recordings of other two are integrated resulting in 180 executions for each class. Total 760 recordings are gathered from which five features are extracted to form feature vector of dimensions 40x760. The target matrix is an array of ones and zeros having dimensions 40x4. There are four class gestures; Fist, Spread, Wave In and Wave Out represented by 1, 2, 3 and 4 respectively.

For training of ANN Feedforward architecture with Scaled Conjugated Gradient (SCG) backpropagation algorithm is used with single hidden layer comprising of 10 neurons. Both input and target matrices are inserted into ANN for offline training of the model. The accuracy obtained can be evaluated from confusion matrix in Fig 3.

The rows illustrate the predicted class (Output Class) and the columns illustrate the true class (Target Class). The diagonal cells display the observations that are correctly classified (light grey). 178 samples from 180 are correctly classified as Fist, Spread and Wave In. From 180 samples of Wave Out, 179 samples are correctly classified. The off-diagonal cells correspond to incorrectly classified observations (grey). Both the number of observations and the percentage of the total number of observations are shown in each cell.

The column on the far right of the plot shows the percentages of all the samples predicted to belong to each class that are correctly and incorrectly classified. These metrics are called the positive predictive value and false discovery rate, respectively. The last row of the plot demonstrates the percentages of all the samples belonging to each class that are correctly and incorrectly classified. These metrics are called the true positive rate and false negative rate, respectively. Fist, Spread and Wave In holds 98.9% accuracy while Wave Out holds 99.4% accuracy. The cell in the bottom right of the plot indicates the overall accuracy which is 99%.

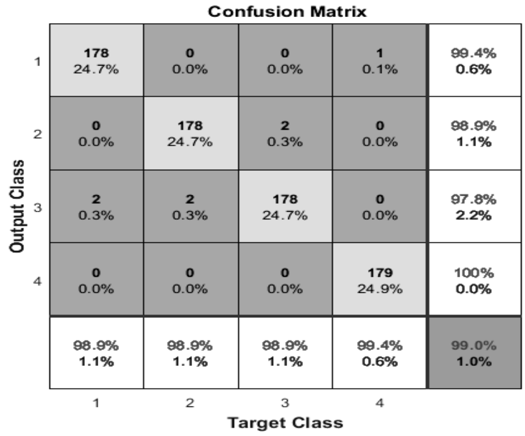

Fig. 3 Confusion matrix for SCG

The same input matrix is then trained using different algorithms. The class accuracy for each class is compared with other training algorithms Bayesian Regularization (BR), Levenberg Marquardt (LM) and Scaled Conjugate Gradient (SCG) shown in Table 1.

Table 1 Comparison of Different Algorithms

Classes	SCG	LM	BR
Fist	98.90%	98.89%	100%
Spread	98.90%	97.22%	99.44%
Wave In	98.90%	98.89%	99.44%
Wave Out	99.40%	99.44%	100%

It is seen that Bayesian Regularization algorithm gives best class accuracy, but it was time taking and could not be implemented practically.

B. Experimental Results

A non-invasive control system is developed and implemented to control a 3D printed prosthetic hand shown in Fig. 4.

Fig. 4 3D-printed Prosthetic Hand

The four gestures which were previously trained in simulation are then tested on a real prosthetic hand. A 3D printed hand replicates the gesture obtained at real-time testing of the network. The 3D printed hand is controlled through servo motors driven by Arduino UNO. Each gesture was performed 50 times and the following accuracy is obtained shown in Fig. 5.

Fig. 5 Experimental Results for each gesture

C. Comparison of simulation and experimental result

We also compared experimental result and simulation result and observed the output. We tested our ANN on 760 readings. Then we checked this network in real time on 50 readings per gesture in which we observed accuracy difference between simulation result and experimental result. This comparison of results is shown in Table 2.

Table 2 Comparison of Simulated and Experimental Results

Classes	Simulated Results	Experimental Results
Fist	98.9%	98.5%
Spread	98.9%	97.5%
Wave In	98.9%	95.4%
Wave Out	99.4%	98.0%

These results show that Artificial Neural Network is viable to classify gestures of a large data set and Scaled Conjugate Gradient algorithm is the best choice in terms of time to implement a pattern recognition classifier on a real prosthetic hand.

IV. CONCLUSION

Signal processing and feature extracting techniques are implemented to extract valuable information from stochastic EMG signals. Myo armband could be a good replacement of conventional Myo-electrodes to acquire EMG signals because it provides a more user-friendly interface, no wiring complexities and easy to setup.

Artificial Neural Network is a good selection as a pattern recognition classifier. The classifier is trained and tested using the recorded data. The Scaled Conjugate Gradient gives better accuracy in comparison with Levenberg Marquardt and is faster in comparison with Bayesian Regularization. The application of machine learning for EMG signal classification to control prosthetic hands has advantages over traditional control systems. The results demonstrate the viability of EMG based pattern recognition system for 3D printed prosthetic hand control.

This work serves as the entrance to deeper and more natural prosthetic hand interactions in future. By focusing on the design of hand a fully functional prosthetic hand with sensory feedback could be manufactured to improve life of amputees in the society. Robotic manipulators in industry with greater number of degrees of freedom could be controlled using hand gestures. Training and testing of advanced gestures could be done and implemented on an amputee person.

REFERENCES

[1] S.Sudarsan *et al*, "Design and Development of EMG Controlled Prosthetics Limb," *Proceedings of the International Conference on Modelling Optimization and Computing*, vol. 38, pp. 3547-3551, 2012.

[2] R. H. Chowdhury *et al*, "Surface Electromyography Signal Processing and Classification Techniques," *Sensors*, vol. 13, no. 9, pp. 12431-12466, 2013.

[3] P. Geethanjali, "Myoelectric control of prosthetic hands: state-of-the-art review," *Med Devices (Auckl)*, vol. 9, pp. 247-255, 27, Jul 2016.

[4] S. Haykin, *Neural Networks and Learning Machines*, Published by Pearson, Canada, 2009.

[5] Gabriel D. Eisenberg et al, "Real-Time Segmentation and Feature Extraction of Electromyography: Towards Control of a Prosthetic Hand," *IFAC (International Federation of Automatic Control) PapersOnLine*, vol. 50, no. 2, pp. 151–156, 2017.

[6] S.M. Mane *et al*, "Hand Motion Recognition from Single Channel Surface EMG Using Wavelet & Artificial Neural Network," *Proceedings of the 4th International Conference on Advances in Computing, Communication and control, ICAC3'15*, pp.58 – 65, 2015.

[7] M. G. B. Fonseca et al, "Artificial Neural Networks Applied to the Classification of Hand gestures using Eletromyographic signals," *Proceedings of 2017 Latin American Robotics Symposium (LARS) and 2017 Brazilian Symposium on Robotics (SBR)*, Curitiba, Brazil, 8-11 Nov. 2017.

[8] M.Hakonen et al, "Current State of Digital Signal Processing in Myoelectric Interfaces and Related Applications" *Biomedical Signal Processing and Control*, vol. 18, pp. 334–359, 2015.