International Journal of Electrical and Computer Engineering (IJECE)
Vol. 10, No. 6, December 2020, pp. 5694∼5702
ISSN: 2088-8708, DOI: 10.11591/ijece.v10i6.pp5694-5702

Recognition of new gestures using myo armband for myoelectric prosthetic applications

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Article Info

Article history:

Received Feb 18, 2020
Revised May 5, 2020
Accepted May 19, 2020

Keywords:

Electromyography
Gestures
MLPNN
Multilayer perceptron neural network
Myo armband
Myoelectric
Prosthetic
Recognition

ABSTRACT

Myoelectric prostheses are a viable solution for people with amputations. The challenge in implementing a usable myoelectric prosthesis lies in accurately recognizing different hand gestures. The current myoelectric devices usually implement very few hand gestures. In order to approximate a real hand functionality, a myoelectric prosthesis should implement a large number of hand and finger gestures. However, increasing number of gestures can lead to a decrease in recognition accuracy. In this work a Myo armband device is used to recognize fourteen gestures (five build in gestures of Myo armband in addition to nine new gestures). The data in this research is collected from three body-able subjects for a period of 7 seconds per gesture. The proposed method uses a pattern recognition technique based on Multi-Layer Perceptron Neural Network (MLPNN). The results show an average accuracy of 90.5% in recognizing the proposed fourteen gestures.

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1. INTRODUCTION

Upper-limb myoelectric prostheses are the next generation devices aimed at helping the amputees who suffer from the loss of hand. Unlike the traditional hand prostheses which offer cosmetic or body powered limited functionality to the amputee, the myoelectric prostheses use electromyography (EMG) sensors attached to the body muscles to control the prosthesis through a controller and motors that move the synthetic hand. The mechanical aspect of the prosthetics has developed vastly in recent years and many prosthetic hands with multiple movements and Degree of Freedom (DoF) are made available commercially. Examples of these prosthetic hands are Bebionic hand [1], iLimb hand [2], Vanderbilt hand [3], the UNB hand [4], the Yale hand [5], SmartHand [6], the DLR/HIT hand [7], and the Keio hand [8].

Most of the currently developed myoelectric prostheses suffer from two problems. They either offer a limited number of hand gestures or poor recognition rate for a larger number of gestures. Since the role of a prostheses is to approximate the functionality of a real hand, there is a need for a larger number of gestures to be recognized in a myoelectric prosthesis with high recognition rate. The current paper tries to address the above problem.

Developing a controller for multiple hand movements that achieves acceptable recognition accuracy is a challenge. The recognition rate and accuracy of EMG systems has been researched widely in the past [9]. According to [10], the recognition accuracy of such a system will depend mainly on a number of parameters: EMG electrode location, the signal processing methods, feature extraction techniques, and the classification algorithms.

According to [11], in surface EMG, the electrode position is vital for the detection of the signal and can affect the quality of the signal. EMG data can be different when are obtained from different nearby locations of the muscle. The use of multi-channel techniques can improve the quality of the signal with respect to the position of the electrodes. Recently, in some myoelectric prostheses, the Myo armband device has been used to collect EMG data. The Myo armband consists of eight electrodes which can mitigate the position issue. Examining the previous work shows that most of the research in the past used between two to eight EMG sensors in the forearm [12].

In regard to other parameters affecting the recognition accuracy, various feature extraction and classification algorithms were researched in the previous literature, as summarized in [13]. Recognizing multiple gestures is a challenge as the recognition accuracy decreases with the increase in the number of gestures. Table 1 summarizes examples of previous literature attempting to recognize several gestures [10, 14-25].

The proposed method in this work is to use multi-layer perceptron neural network (MLPNN) combined with pre-processing techniques and feature extraction algorithms. In this research, an eight-channel Myo armband EMG device is used to recognize fourteen hand gestures. These are nine gestures more than the five built-in gestures the device can recognize. The novelty in this work lies in the recognition of fourteen gestures with an advanced neural network with high recognition accuracy and improving upon the results reported in the literature shown in Table 1. To the author's knowledge, no myoelectric prosthesis is commercially available today that provides multiple gesture recognition capability. This is due to various factors such as: significant processing time of pattern recognition systems, the lack of reliability of these systems (due to electrode positioning and fatigue), and the lack of intuitive controls [26-28].

Table 1. Recognition accuracy of previous literature with multiple gestures

Reference	Features	No. of EMG Channels	Classifier	No. of Subjects	Time Length (seconds)	No. of Gestures	Recognition Accuracy (%)
10	I-EMG, MAV, MSR, VAR, WL, SSI, SSC, ZC, and WA	6	PCA algorithm and SVM classifier	5	5	6	99.6
						11	95.6
						17	95.1
14	PSD	6	ANN	12	5	9	72.9
						17	63.8
15	IRMS	4	ICA,IRAM,ANN	4	10	4	90.33
16	TD, ACCC, and SPM	4	KNN, LDA, SVM	6	0.064	9	91
17	PSD-Av	5	PNM 4	1	10	80	
18	HD-sEMG	8	MK-MMD	23	3-10	22	84.6
19	Third-order AR model Coefficients, MAV and MAVR	2	Linear Bayesian Classifier	4	1	5	90-93.5
						11	83.1-95.4
						16	78.8-90.3
20	CCA	4	KNN,LDA, and LIBSNM	8	5-10	8	82
21	MAV	64	HD	5	2	9	78.21
22	MAV,ZC, SSC, and WL	2	KNN	30	5	4	94
23	MV, WL	4	MLE	8	1-2	8	85.7
24	MAV, AR, and MNF	4	SVM,LDA, and HMM	18	1	8	89.3
25	MAV,ARSSC ZC,WL, and RMS	6	SVM	5	4	5	96
13	RMS, STD, MAX, and MIN	8	MLPNN	3	5	5	99
This work	RMS	8	MLPNN	3	7	14	91-94

The advance of pattern recognition techniques can potentially help recognizing multiple DoF and mapping them to myoelectric prostheses. However, recognizing gestures which include individual finger movements using the EMG can be a challenging task. The reason is that the EMG signal amplitude variances are small for finger movements compared to arm and wrist movements [14]. In addition, the muscles responsible for controlling the movement of fingers are located in intermediate and deep layers of forearm [27]. In order to recognize various finger movements, multiple EMG sensors are required to provide adequate data.

This paper is organized as follows. Section 2 presents the structure of the Myo armband device, and the Multi-Layer Perceptron Neural Network (MLPNN). Section 3 presents data collection and the training of the MLPNN. Results are discussed in Section 4. Finally the conclusion is presented.

2. THEORY

2.1. Myo armband device

Myo armband is a wearable device that uses eight electrode sensors to measure the EMG signals of forearm muscles. The device sends these data via Bluetooth to a computer. A special driver program is used to analyze the signals and recognize hand gestures of the user. The recognized gestures can subsequently be used by various applications. The Myo armband is also equipped with several other sensors, such as accelerometer, gyroscope, and magnetometer which collect spatial data about the gesture and can facilitate gesture recognition (these additional sensors were not utilized in this work). The device should be in direct contact with the user skin, in order to operate and can work with several operating systems such as Windows, Mac, iOS, and Android. It is powered by an ARM Cortex M4 processor and uses a rechargeable battery to operate [29-30].

2.2. Multi-layer perceptron neural network

Multi-layer perceptron neural network (MLPNN) is a feed-forward network which contains one or more invisible layers called hidden layers. The learning process is performed using a supervised method where the desired output must be known in advance to update the weights of the internal connections between the layers. This update algorithm is called the backpropagation. In this algorithm the error between the desired output and the actual output is calculated every time the input/output training data is presented. Connection weights are continuously adjusted according to the calculated error until the error gradient reaches an appropriate small value, which indicates that the actual output is close to the target [31-34].

3. WORK

3.1. Data collection

In this work, data sets of fourteen gestures were collected from three body-able subjects using Myo armband device, as shown in Figure 1. The first five gestures (1 to 5) were selected based on the standard Myo Armband gestures. The additional nine gestures were selected based on the natural movement of the hand and fingers and some local cultural gestures. Each of the fourteen gestures were repeated twice, and the EMG signal was recorded for a period of seven seconds per gesture with a frequency of 200Hz. Table 2 represents the hand gesture categories and their description.

Table 2. Hand gestures categories and the description

Modes	Gestures	Description
Relax	Rest	The relax state
Wrist Movements	Wave right	Wave hand to the right
	Wave Left	Wave hand to the left
Individual Finger Movements	One Finger	Raise the index finger up
	Thumb	Raise the thumb up
Multi-Fingers Movement	Spread Fingers	Spread all fingers
	Fist	Fist state
	Two Fingers	Raise the index and middle fingers up
	Three Fingers	Raise the index, middle and ring fingers up
	Four Fingers	Raise all fingers except the thumb up
	Grab	Grab gesture (a glass or bottle)
	Pinch	Pinch the fingers
	Shake no Thumb	Shake state while holding thumb inside
	Shake Hand	Shake state with thumb up

Each gesture's data was stored as a sequence with a length varying between 1398 to 1408 EMG values (elements). A remove-silence process was applied to the data followed by removing the extra elements to create equal data sets. Furthermore, the elements in the data sets were overlapped to maximize number of samples. This yielded a data set with a dimension of 50x117 per gesture per EMG channel.

Four features, namely Root Mean Square (RMS), Standard Deviation (STD), minimum (Min) and maximum (Max) values, were extracted from each gesture sequence. This process has obtained a (4x117) matrix of features per each EMG channel. For 8 channels, the result was a (32x117) features' matrix per gesture. 80% of the obtained data were used for training (input vector), 10% were used for validation and the remaining 10% were used for testing the neural network.

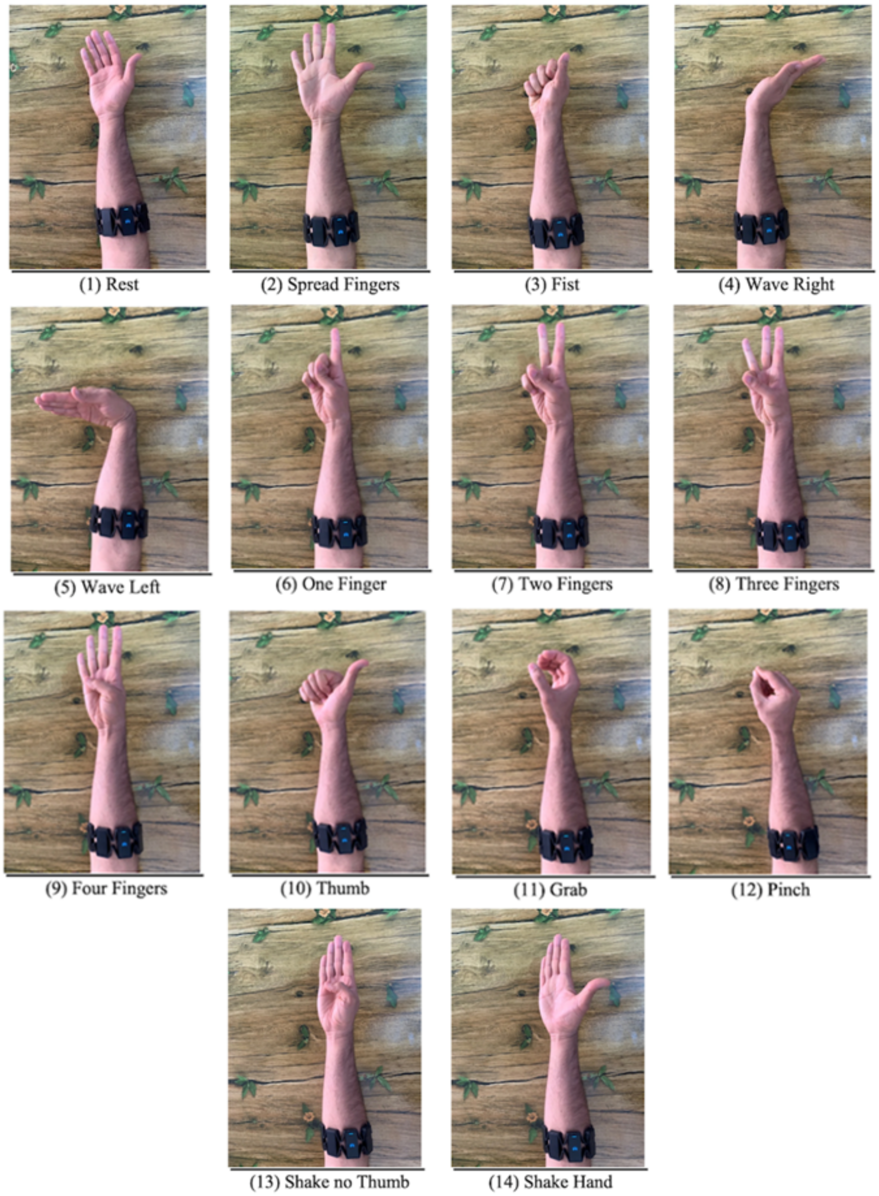

Figure 1. Representation of the fourteen gestures used in the work

3.2. Training of MLPNN

For the pattern recognition, a classifier was designed using the MLPNN and based on time domain features of RMS, STD, Min and Max. The structure of the MLPNN was configured with one hidden layer to reduce processing time in the training process. The number of hidden neurons was selected based on trial and error and from experience to achieve the lowest RMS error possible. In addition, the aim was to minimize the number of training epochs in the network.

Figure 2 shows the neural structure that was used for training. The classifier consisted of 32 neurons in the input layer, 30 hidden processors with tangent function, and 14 output neurons with sigmoidal function to classify 14 determined gestures. Gradient descent back-propagation was used as a training algorithm with an adaptive learning rate to minimize the risks of local minima errors.

The training must be terminated if any of the stopping criteria is obtained to prevent the over fitting problem. These criteria were set to 1000 training iterations and an RMS error of 0.001. Figure 3 shows the algorithms used for training and testing of the MLPNN classifier.

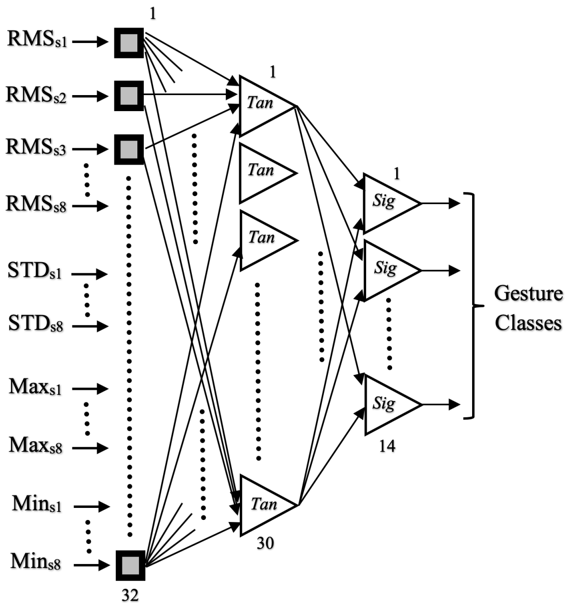

Figure 2. Structure of neural classifier

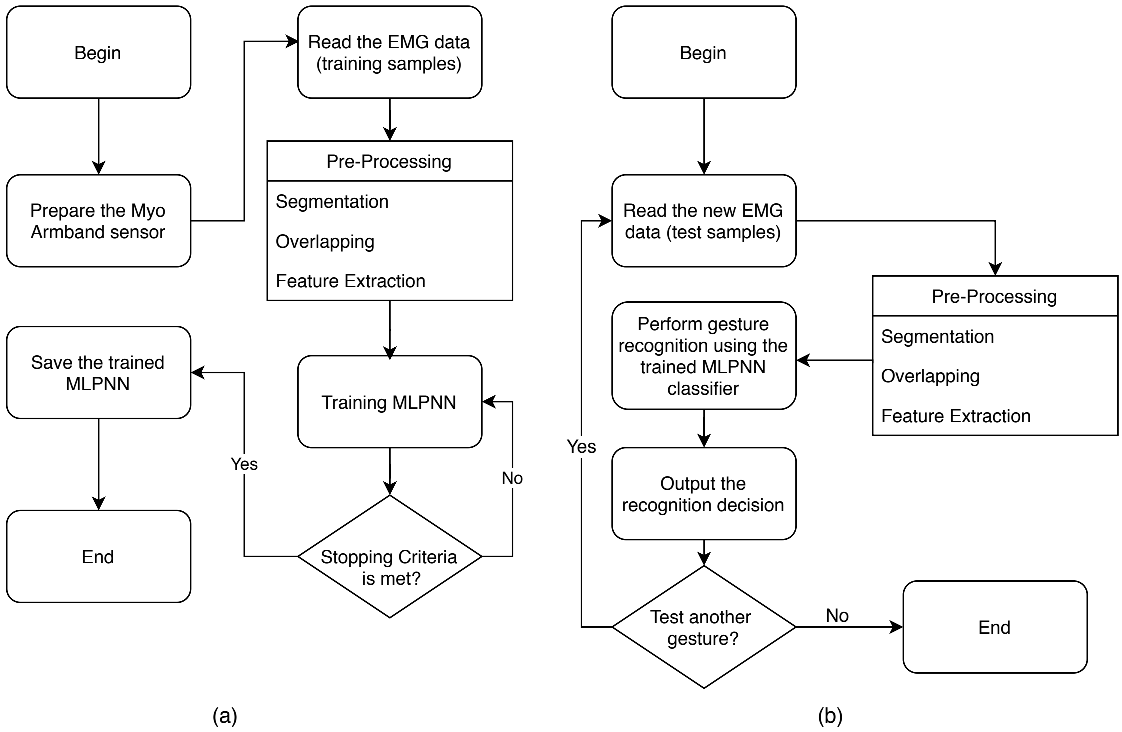

Figure 3. Algorithms used for (a) the training, and (b) the testing of MLPNN classifier

4. RESULTS

Figure 4 shows the performance of the network at training, validation, and test processes. It can be observed that the network was successfully trained with a validation performance of 0.001541. Figure 5 shows the error gradient for all training epochs with the RMS value of 0.00035374 at epoch 101. Number of validation checks was set to six. This validation check was achieved at epoch 101 as shown in the figure.

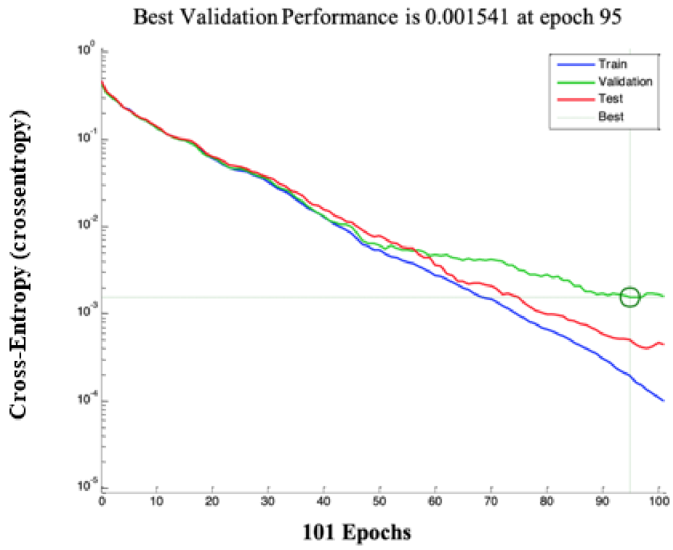

Figure 4. Performance of the neural network at training, validation, and test processes

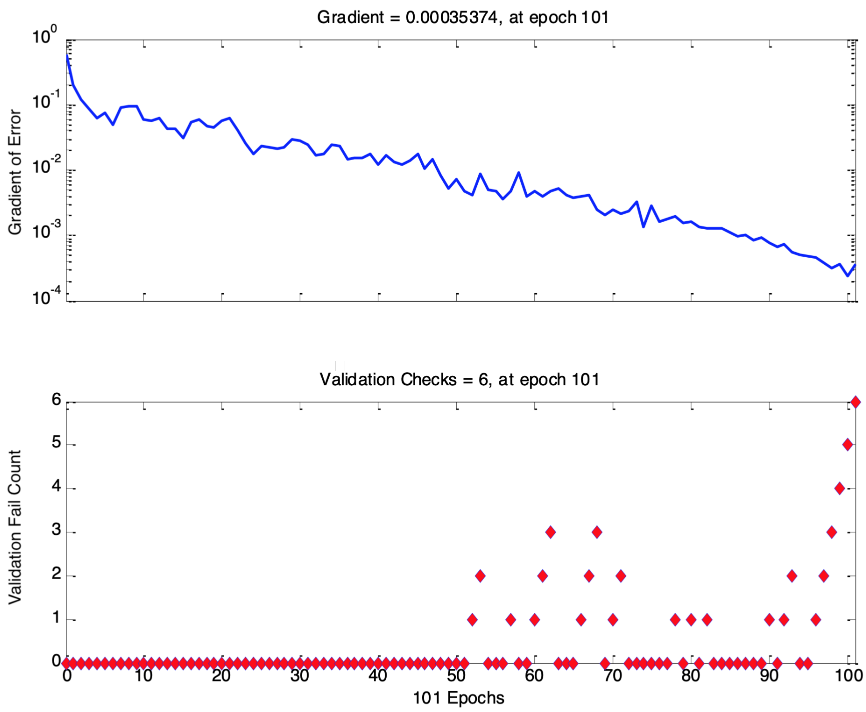

Figure 5. Results of training MLPNN: the x-axis shows the number of epochs, the y-axis is the gradient of error at the top and the validation check value at bottom subfigure

Figure 6 shows the real performance of the MLPNN at the end of the training and testing processes. The gesture number and the class number are represented at X-axis and Y-axis respectively. The training results provide a perfect classification with high accuracy for all of the gestures. The class number of the gesture at any testing process is defined by the largest value from all neurons at the output layer of MLPNN. For binary patterns, the output of the categorized gesture must have a value of one, and the output of the other gestures must have a value of zero. Table 3 shows the numerical representation of gesture classes.

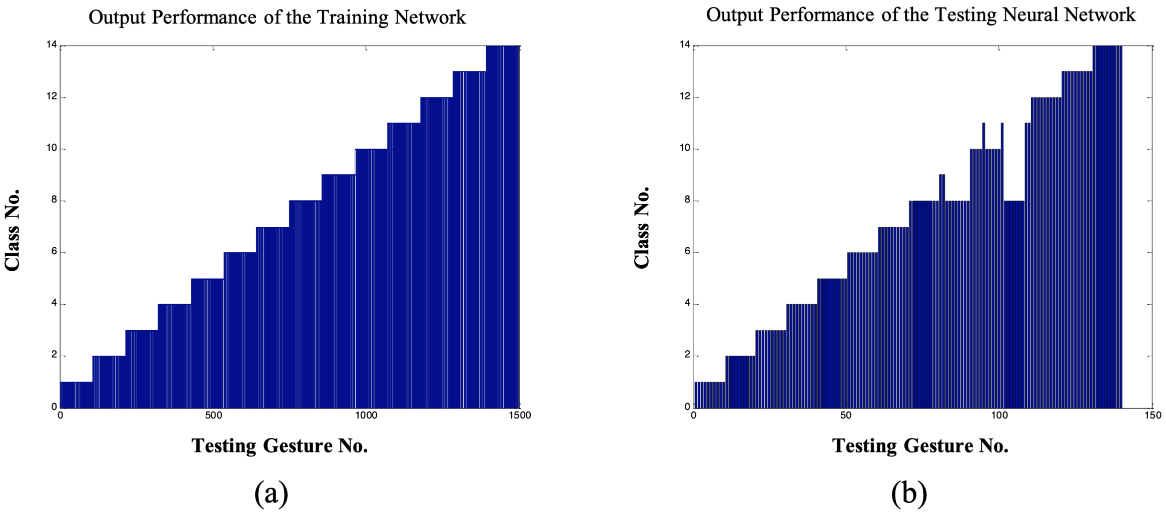

Figure 6. Real performance of MLPNN at (a) training process, (b) testing process

The segmentation and overlapping methods that were used in this work as part of the data pre-processing improved upon the training efficiency by increasing the number of training samples. The accuracy of the trained MLPNN is evaluated by calculating the number of correctly recognized classes in the test process. Thus the recognition rate is calculated by:

$$RecognitionRate = (CorrectlyClassifiedSamples/AllTestSamples) * 100 \tag{1}$$

Table 4 shows the recognition rates results for the three body able subjects. The recognition accuracy was up to 94%. Comparing these results to the previous EMG based recognition systems utilizing neural networks shows that a better recognition accuracy was achieved in this work with respect to number of gestures that can be recognized as shown in Table 5. To the authors knowledge, there were no work available using the Myo armband for recognition of multiple gestures for comparison purposes.

The previous work of the same authors reported 99% of accuracy using similar neural network and 5 gestures. Hence adding 9 new gestures decreased the accuracy of the system to 90.5%. The decreased accuracy can be attributed to an increase in the number of gestures that are differentiated based on finger movements. The EMG signal amplitude variances are small for finger movements compared to arm and wrist movements which results in similar extracted features and less accurate recognition.

Table 3. Assigned class numbers to the gestures

Gestures	Rest	Spread fingers	Fist	Wave Right	Wave Left	One Finger	Two Finger	Three Finger	Four Finger	Thumb	Grab	Pinch	Shake no Thumb	Shake Hand
Real O/P	1	2	3	4	5	6	7	8	9	10	11	12	13	14

Table 4. Recognition rates of the three subjects

Subject No.	1st Set Recognition Rate %	2nd Set Recognition Rate %	Recognition Average %
1	89	89	89
2	89	91	90
3	91	94	92.5

Table 5. Comparison of results with other ANN classifiers in the literature

Reference	No. of EMG Channels	No. of Subjects	Time Length (seconds)	No. of Gestures	Recognition Accuracy (%)
14	6	12	5	9	72.9
				17	63.8
15	I4	4	10	4	90.33
13	8	3	5	5	99
This work	8	3	7	14	90.5

5. CONCLUSION

This research proposed using an MLPNN to classify and recognize additional gestures from the Myo armband device. The proposed system works by measuring the raw EMG signals from the forearm and estimating the muscles activity by extracting the effective time domain features such as RMS, STD, Min and Max. Then the system trains the MLPNN to classify different finger and wrist gestures. The main contribution of this work is the accurate recognition of fourteen gestures using the Myo armband device which can only recognize five gestures. The proposed pre-processing technique based on time domain feature extraction improved the training process and was effective for the recognition of gestures.

The results showed an average recognition accuracy of 90.5% for all the test data. Based on these results, the proposed method can be used as a reliable classifier for different hand gestures in applications where recognizing as many gestures as possible is important such as multi-gesture prosthetic hands. The implemented system can also contribute to the advancing of the intelligent interaction between the human and instruments such as myoelectric prosthetic hands, machine control and Human Computer Interface (HCI).

Future work can design and implement a manageable system for recognition of hand gestures using hardware implementation techniques such as Field Programmable Gate Array (FPGA). The error in recognition could be due to convergent gestures. The trained MLPNN may mis-classify these gestures as a result of similar features calculated from comparable raw EMG signals due to the contiguity of their associative muscles. The mis-recognized gestures vary depending on the subject under test, since each subject could perform the same gesture slightly different each time. An extension to this work can research methods to deal with these incorrect recognitions in order to improve the accuracy of the system. Finally, An MPLNN based recognition algorithm trained by back-propagation could suffer from local minima or high computational cost. Future work needs to examine other intelligent algorithms such as Adaptive Neuro Fuzzy Inference System (ANFIS) for gesture recognition.

ACKNOWLEDGEMENT

This work is carried out by Intelligent Prosthetics Research Group (IPRG) at College of Engineering, University of Kerbala in 2019.

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