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Design and Performance Analysis of Artificial Neural Network for Hand Motion Detection from EMG Signals

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Abstract: Besides prosthetic device control and neuromuscular disease identification, electromyography (EMG) signals can also be applied in the field of human computer interaction (HCI) system. This article represents the classification of Electromygraphy (EMG) signal for the detection of different predefined hand motions (left, right, up and down) using artificial neural network (ANN). The neural network is of backpropagation type, trained by Levenberg-Marquardt training algorithm. Before the classification process, the EMG signals have been pre-processed for extracting some features from them. The conventional and most effective time and time-frequency based features are extracted and normalized. The neural network has been trained with the normalized feature set with supervised learning method. The obtained results show that the designed network can successfully classify the hand motions from the EMG signals with the success rate of 88.4%. The performance of the designed network has also been compared to similar research work, whereby it certainly shows the outperformance.

Key words: Electromyography · Wavelet Transform · Artificial Neural Network · Backpropagation · Classification · Human Computer Interaction

INTRODUCTION

With the rapid development of information technology, the quantity of information sharing by human is increasing accordingly. Since early eighty, numbers of researchers are engaged to develop alternative interfaces for elderly and disabled people. More recently, the technological advancements have been attracting the researchers' attention with respect to extracting user's intention data from neural signals. These types of signals can provide information related to body or limb motion faster than other means [1]. The EMG signals is a type of neural signal which find its application in various area: diagnoses of neuromuscular diseases, rehabilitation through controlling assistive devices like prosthetic/ orthotic devices and human computer interfacing. The idea behind EMG signal controlled human computer interface development is to efficiently convert the user's intention (in the form of EMG signals) into corresponding computer commands. The heart of this conversion process is the signal classifier, which is the most difficult part for developing electromyographic control based interfaces. Upon the contraction of muscle, properly positioned surface electrodes on muscle site detect the signal and then feed it to the classifier unit. The efficiently designed classifier unit then analyzes the incoming signal and generates appropriate classified command for human computer interface. However, there are a numbers of physiological processes which may complicate the interpretation of the recorded EMG signal. A large variation in EMG signals can be observed, having different signatures depending on age, muscles activity, motor unit paths, skin-fat layer and gesture style. Compared to other biosignals, EMG signal contains complicated types of noise that are caused by inherent equipment and environment noise, electromagnetic radiations, motion artifacts and the interaction of different tissues. Sometimes it is difficult to extract useful features from the residual muscles of an amputee or disabled. This difficulty becomes more critical when it is resolving multiclass classification problems [2]. The dynamic activities related to muscle often confuses the processing

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unit, resulting in erroneous classification. To maximize the classification accuracy, many researchers have studied various types of different statistical and learning algorithm-based classifiers. Beside this, number of researchers have attempted to extract more information from the EMG signals to help the classifiers for better classification of user's intended motion. A variety of signal features representing both amplitude and spectral property have been used to supplement the information given to the classifier and have been shown to increase classification accuracies [1], [3], [4], [5].

The signal classification is achieved by first extracting the EMG pattern signatures from each type of movements and then applying proper discrimination technique. However, there is difficulty in developing a precise structural or mathematical model for EMG signal patters that can relate the recorded signals to corresponding motion command. Many researchers have attempted various types of pattern recognition/ classification techniques to discriminate the functionality in extracted features. Upon extensive review, it has been found that most of researchers used Artificial Neural Network (ANN) for the processing and classification of biosignals [1]. In early 90's, the pattern recognition approach in different research area have been developed with the help of applying ANN classifiers. The capability of learning from examples, the ability to reproduce arbitrary non-linear functions of input and the highly parallel and regular structure of ANNs make them especially suitable for pattern classi?cation tasks [2]. Moreover, efficiently designed ANN can also be employed in different area for resolving varieties of issues. These may include prediction/forecasting, signal/image denoising, data processing, function/data approximation etc. [6], [7], [8], [9], [10].

Autoregressive (AR) parameter based neural network has been designed by Putnam *et al*. for the classification of EMG signals [11]. The claimed efficiency was 95% for classifying only two types of motions which is impractical. Some other researchers have employed ANN for the classification of EMG signals. Most relevant research works have been mentioned here with the features they tried. Hiraiwa *et al.* [12] have attempted with integral absolute value (IAV) feature for feed-forward ANN, Naik *et al*. [13] have successfully applied independent component analysis (ICA) based ANN, Englehart *et al*. [14] and Kelly *et al*. [15] have approached with different types of multi-layer perceptron (MLP) based ANN, Hudgins *et al*. [16] have used Hopfield and ART based neural network and later finite impulse response neural network (FIRNN). The findings of the review also outlines that most of the ANN inspired research works have been carried out with MLP containing at least one hidden layer and trained with backpropagation learning algorithm. Varying accuracy which is observed in above mentioned neural network based classification techniques may be due to quality of collected signal, signal conditioning and different physiological characteristics of the subjects. The focus of this article is to demonstrate the designing process of ANN for the classification of EMG signals and compare the performance with some of the relevant research. Levenberge-Marquardt algorithm based backpropagation learning is employed for the training of ANN. Some of the effective features have been calculated for EMG signals and used as input for the neural network to recognize different hand motions. Acceptable success rate of classification has been achieved and reported in result and discussion section. Finally, the classification performance of the designed neural network has been verified by comparing with other researchers' findings.

MATERIALS AND METHODS

Acquisition of EMG Signal: For the research work, the EMG signals have been recorded with the help of BIOPAC-MP100 data acquisition system. The data acquisition system comprises with data acquisition unit MP100A-CE, universal interface module UIM100C, electromyogram amplifier module EMG100C and acquisition software AcqKnowledge v3.1.9. Three able-bodied person of age between 27-32 have voluntarily engaged as test subject for the EMG signal acquisition processes. The default standard values have been chosen for sampling (1000 Hz) and amplification (gain 1000). By performing some acquisition experiments, the best site for the electrodes placement have been determined. The single channel differential electrodes are placed on brachioradialis and flexor carpum ulnaris muscle and the reference electrode is placed on the wrist. The EMG signals have been collected for the subjects' hand movements. For this purpose, the subject is requested to do some predefined volunteer movements of hand in different direction (Left, Right, Up, Down). During the signal acquisition trials, it has been found that on average around 500 miliseconds is required by a subject to perform each type of movements. For this research, the collected signal data set is duration of 70 seconds EMG signals including 5 seconds rest in start and stop of the signal acquisition. The acquisition system converts the incoming signals to digital signals which are stored in a Windows XP based personal computer for post analysis and processing.

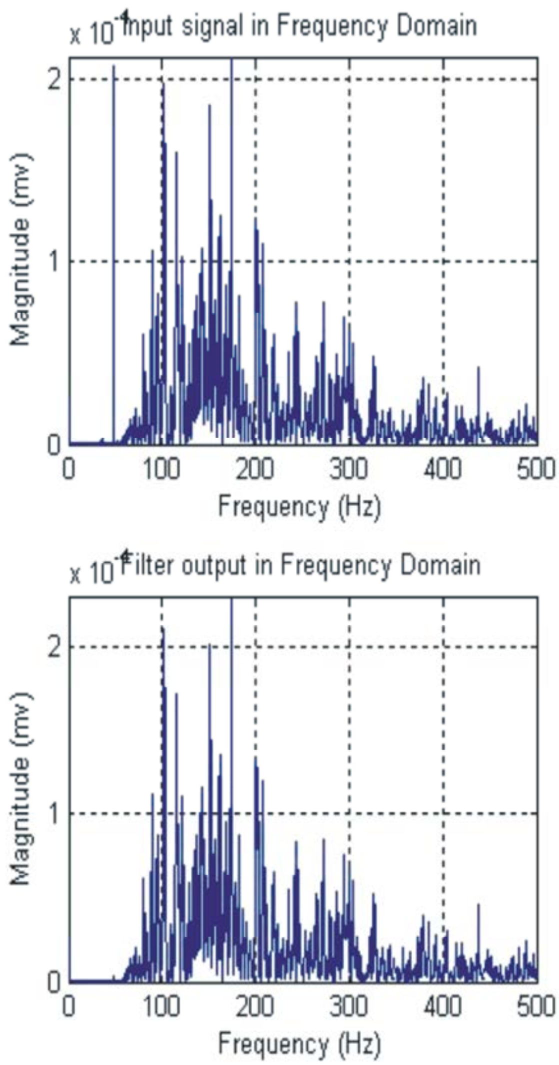

Fig. 1: Removing of 50 Hz electrical noise

Preprocessing of EMG Signal: Generally, the acquired EMG signal has the amplitude range up to 10mV peak to peak (±5mV) before amplification process [5]. Before reaching to electrode terminals, the electrochemical process propagates through nerve fibers. Hence, the EMG signals can be easily contaminated by various noises while passing through different fibers. Further amplification of this low amplitude signals may lead to participation of noise and artifacts to the electronic circuitry of the instrument. Some of the source of noise/artifacts can be managed by proper detection methods, whereas the current technology cannot easily regulate other sources. If noisy EMG signal is used for classification process, it will yield certainly produce poor classification result which is unexpectble. There are some types of noise that can be reduced by using the conventional signal conditioning method such as bandpass filter, bandstop filter and by using good quality of equipment with a proper electrodes placement. However, yet it is difficult to remove the effect of other noises/artifacts and interferences of random noises whose frequencies are in the range of dominant frequency of EMG signals [5]. The preprocessing of EMG signals has been started with a typical band pass filter (Butterworth, order-6 and cut-off 20-500 Hz) to reduce noises from electrodes, motion artifacts and electric power line. A notch filter of 3dB gain and 49-51 Hz has been used to remove the 50 Hz power line noise since this frequency is not within the dominant frequency (70-300 Hz) range of recorded EMG signals. The frequency domain presentation of filter input and output is presented in Fig. 1. Further EMG signal processing has been done with wavelet transform method for the purpose of denoising. The wavelet transform techniques are advantageous than any other method since it can successfully localize both time and frequency components; the signals can be processed in different scales/resolutions; and it can provide good frequency resolution at high frequencies. These properties of wavelet thus help to identify and isolate the noise components in the signal by preserving important high-frequency transients [17]. For denoising the EMG signals, a discrete wavelet transform (DWT) of four level decompositions has been applied. Daubechies (db2) mother wavelet function has been selected and applied on detail wavelet coefficients for noise reduction. Later on, the denoised EMG signals from the output of wavelet transform have been used to extract the features for each type of predefined hand movement.

Feature Extraction: Selection of proper and most effective feature set is the key for efficient EMG signal classification [16]. In most of the cases it is advantageous to utilize multiple feature parameters for the classification of EMG signals. This is because of the difficulties in extracting a single feature which can exactly reflect the EMG signals pattern to a motion command. The reason why most of the researchers have selected time domain, frequency domain, time-frequency domain and time-scale domain feature set for the classification of EMG signals. Various type of features extracted by different researchers such as mean absolute value (MAV), root mean square (RMS), auto-regression (AR) coefficients, variance (VAR), standard deviation (SD), zero crossing (ZC), waveform length (WL), Willson amplitude (WA), mean absolute value slope (MAVS), mean frequency (MNF), median frequency (MDF)slope sign change (SSC), cepstrum coefficients (CC), fast Fourier transform (FFT) coefficients, short time Fourier transform (STFT) coefficients, integrated EMG (IEMG), wavelet transform (WT) coefficients and wavelet packet transform (WPT) coefficients [16], [18], [19]. This research work has been carried out with seven statistical features namely MAV, RMS, VAR, SD, ZC, SSC and WL. These features have been extracted from the EMG signal which is acquired for different hand movements and short description of the feature calculation is given below.

Mean Absolute Value (MAV): it is the average rectified value (ARV) and can be calculated using the moving average of full-wave rectified EMG. More specifically, it is calculated by taking the average of the absolute value of EMG signal. Since it represents the simple way to detect muscle contraction levels, it becomes a popular feature for myoelectric controlled applications. It is defined as

$$MAV = \frac{1}{N}\sum_{n=1}^{N} | x_{n^2} |:$$

where N denotes the length of the signal and x_n represents the EMG signal in a segment.

Root Mean Square (RMS): it is represented as amplitude modulated Gaussian random process whose RMS is related to the constant force and non-fatiguing contraction. It can be expressed as

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_{n^2}}$$

Variance of EMG (VAR): it uses the power of the EMG signal as a feature. Generally, the variance is the mean value of the square of the deviation of that variable. However, mean of EMG signal is close to zero. Variance of EMG can be calculated by

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_{n^2}$$

Standard Deviation (SD): it can be used to find the threshold level of muscle contraction activity. The general equation used to find SD by

$$SD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\left(x_n - \bar{x}\right)^2}:$$

where $\bar{x}$ is the mean value of the EMG signal.

Waveform Length (WL): it is the cumulative length of the waveform over the time segment. WL is related to the waveform amplitude, frequency and time. It is given by

$$WL = \sum_{n=1}^{N-1} | x_{n+1} - x_n |$$

Zero Crossing (ZC): it is the number of times that the amplitude value of EMG signal crosses the zero y-axis. This feature provides an approximate estimation of frequency domain properties. It can be formulated as

$$ZC = \sum_{n=1}^{N-1}\left[\operatorname{sgn}\left(x_n \times x_{n+1}\right) \cap | x_n - x_{n+1} | \geq threshold\right]:$$

$$\operatorname{sgn}(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases}$$

Slope Sign Change (SSC): it is similar to ZC and another method to represent the frequency information of EMG signal. The number of changes between positive and negative slope among three consecutive segments are performed with the threshold function for avoiding the interference in EMG signal. The calculation is defined as

$$SSC = \sum_{n=1}^{N-1}\left[f[\left(x_n \times x_{n+1}\right) \times (x_n - x_{n+1})]\right]:$$

$$f(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases}$$

EMG Signal Classification with Neural Network: Backpropagation learning algorithm is based on the generalized form of Widrow-Hoff learning rule to multiple-layer network and nonlinear differentiable transfer function. Backpropagation learning algorithm is applied to a neural network for supervised training so that it can minimize the differences between the simulated and target output(s). The training of the neural network will continue until it can approximate a function, or associate input vectors with specific output vectors, or classify input vectors in an appropriate way based on certain criteria. An ANN has been designed for the classification of EMG signals which consists of three layers: input layer, tan-sigmoid hidden layer and linear output layer. Each of the hidden layer and output layer has a weight matrix W, a bias vector b and an output vector a. The weight matrices connected to input vectors called input weights (IW) and weight matrices coming from hidden layer outputs called

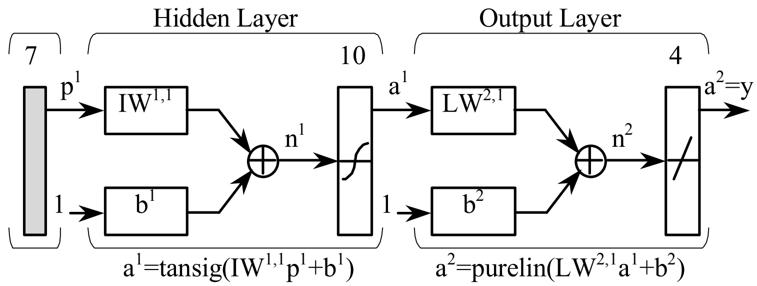

Fig. 2: Architecture of Artificial Neural Network

Table 1: Sample feature sets for different movement with target vectors of corresponding movement

		Movement type			
Extracted from EMG signal	Feature	Left	Right	Up	Down
	MAV	0.11862	0.10395	0.10554	0.07303
	RMS	0.16918	0.14866	0.14803	0.09834
	VAR	0.02862	0.02210	0.02191	0.00967
	SD	0.16910	0.14861	0.14811	0.09841
	WL	72.66327	65.94147	62.51984	45.28778
	SSC	234	214	220	230
	ZC	207	204	191	219
Input Vectors	After normalization in the range [-1 1]				
	MAV	0.62547	0.36995	0.39767	-0.16858
	RMS	0.57261	0.33743	0.33016	-0.23938
	VAR	0.32669	0.01320	0.00415	-0.58431
	SD	0.57222	0.33665	0.33096	-0.24050
	WL	0.55323	0.37111	0.27841	-0.18846
	SSC	0.10811	-0.43243	-0.27027	0.00000
	ZC	-0.03226	-0.12903	-0.54839	0.35484
Target Vectors	Target Vector				
	1	0	0	0	
	0	1	0	0	
	0	0	1	0	
	0	0	0	1	

layer weights (*LW*). The superscripts are used to denote the source (second index) and the destination (first index) for the various weights and other associated elements of the network.

A typical architecture design of backpropagation neural network has been shown in Fig. 2 with 7 neurons in input layer, 10 tan-sigmoid neurons in hidden layer and 4 linear neurons in output layer. The tuning of the network can be done by changing the number of neurons in hidden layer. However, there is no definite rule or way to find out the number of hidden neurons for efficient signal classification. Hence, it has been determined from best classification result by selecting different numbers of hidden neurons for the network. The predefined features were extracted for four types of hand movements from five different EMG signals. For the training of the network, 204 sets of input feature vectors from four EMG signals and their corresponding target vectors have been fed to the network. The feature vectors from remaining EMG signal have been used for testing the network performances. For efficient training of the network, feature vectors were normalized before feeding them to the network. The sample input vectors and corresponding target vectors for four movements are shown in Table 1.

The key function of the training algorithm has already been defined in previous paragraph. More specifically, the training algorithm calculates the adjustment values for the weights in order to minimize error by utilizing the gradient of the performance function. Levenberg-Marquardt (trainlm) algorithm has been employed for backpropagation training. It is considered as the fastest algorithm to train a moderate-sized feedforward neural network and it is based on numerical optimization techniques. The training of the neural network has also been made generalized to avoid overfitting. This has been done by splitting the input data for training: 70% for training, 15% for validation and 15% for testing. Furthermore, it has been ensured that the numbers of data points in training set are more than sufficient to estimate the total number of network parameters associated for different layers. To improve the generalization of the network, 2 early stopping criteria have been provided. The training of the network will stop if the total mean squared error (MSE) is less than or equal to 0.001, or when it reaches to 1000 epochs. For each iteration and session, the weight and bias values associated with different layers are saved automatically. If the simulation results from ANN are not satisfactory, the network has been tuned and trained again with the last saved weight and bias values. This has been done to improve the network performance and to reduce time consumption for training. The designed network has also been tested by applying another type of backpropagation learning algorithm named scaled conjugate gradient (trainscg) and its performance is reported in result section.

RESULTS AND DISCUSSION

The summery of the classification performance using back-propagation neural network is presented in Table 2. It has been mentioned before that 204 set of training data for different movements has been used for the training of the network. Each of the training data set consists of input feature vector which is extracted from EMG signal for specific type of hand movement and corresponding output vector. For the purpose of finding optimum number of hidden neuron for best classification performance, different numbers of hidden neurons have been chosen for both type of training algorithm and their classification efficiency are also reported accordingly. It has been found that Levenberg-Marquardt algorithm based neural network with 10 neurons in its hidden layer achieves the best classification rate and required processing time is less. Considering the iteration numbers, elapsed time and classification rate, this network structure outperforms the others. The average of best overall classification rate during training is found 88.4%.

Table 2: Experimental result and performance comparison for algorithm

				Classification Rate				
Training Function	Stop Epochs	Regression	Time Elapsed (s)	Training	Validation	Test	Overall	Hidden Neurons
trainlm	15	0.8597	1.047	88.6	83.3	90	88	10
	18	0.87251	0.921	94.3	86.7	80	88	
	16	0.87401	0.8721	88.7	90.3	90.3	89.2	
	Avg.	0.86874	0.9467	90.533	86.767	86.767	88.4	
	33	0.85706	2.797	91.4	70	83.3	87	20
	14	0.85508	1.218	90	80	86.7	88	
	12	0.84772	1.094	92.9	76.7	83.3	89	
	Avg.	0.85329	1.703	91.433	75.567	84.433	88	
	16	0.86112	2.36	92.1	80	76.7	88	30
	11	0.85018	1.703	91.4	90	73.3	88.5	
	14	0.85102	2.125	89.3	76.7	83.3	86.5	
	Avg.	0.8541067	2.06267	90.933	82.233	77.767	87.667	
trainscg	37	0.7839	0.703	80.7	83.3	83.3	81.5	10
	24	0.79567	0.657	81.4	79.7	81.9	80.2	
	30	0.81724	0.682	82.5	77.2	83.3	81	
	Avg.	0.7989367	0.68067	81.533	80.067	82.833	80.9	
	31	0.85202	0.797	78.7	90	86.7	81.5	20
	33	0.81245	0.813	85.2	78.8	81	82.1	
	39	0.80523	0.847	81.3	75.3	78.5	79.5	
	Avg.	0.823233	0.819	81.733	81.367	82.067	81.033	
	34	0.80767	0.859	83.6	83.3	86.7	84	30
	29	0.83842	0.8432	86	87.4	75.9	83	
	37	0.82035	0.8675	84.3	82.2	77	81	
	Avg.	0.822147	0.85657	84.6333	84.3	79.867	82.67	

Table 3: Comparison with related research work

Researcher	Method	Number of Classes	Number of Channels	Classification Rate
Putnam *et al*. (1993)	ANN with AR parameters	2	2	95%
Itou *et al*. (2001)	Neural Network	7	2	70%
Tsenov *et al*. (2006)	RBF and LVQ type Neural Network	4	2	93%
Jung *et al*. (2007)	LVQ type Neural Network	7	4	78%
This research	ANN with *trainlm* algorithm	4	single	88.4%

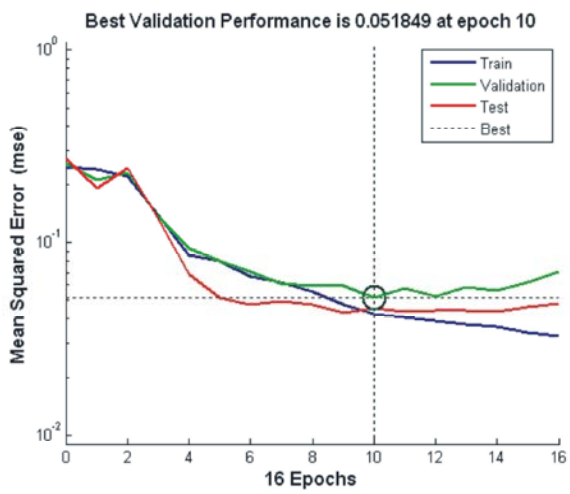

Fig. 3: Validation performance of the designed ANN with the early stopping criteria

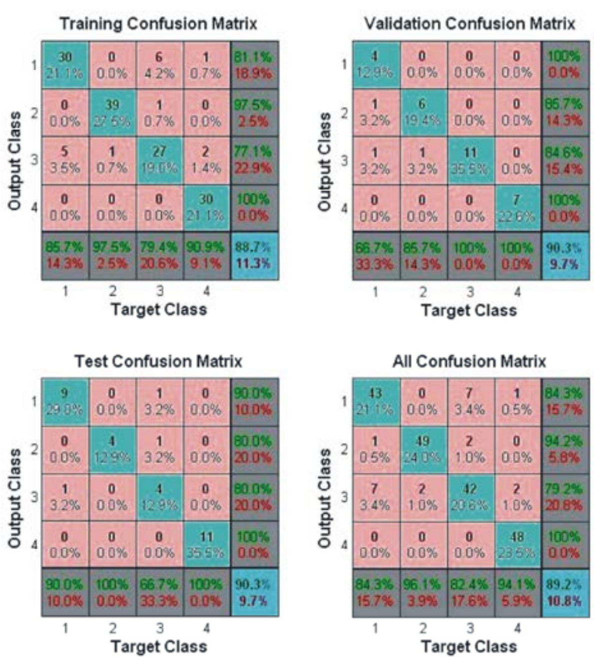

Fig. 4: Classification efficiency of the network

The best validation performance achieved at 10 epochs and the training stopped at 16 epochs as shown in Fig. 3. The detailed performances of network during training, validation, testing and overall during a single trial are shown by confusion matrix for different class in Fig. 4. The number presentations of the classes are: 1 for left, 2 for right, 3 for up and 4 for down. A comparison table has also been presented with related research work in Table. 3. The classification rate of the neural network trained with Levenberg-Marquardt algorithm for single channel EMG signals classification has been improved compared to previous research works where multiple channels were utilized (Table 3). It clearly pointed out that that a better classification performance can be achieved without any prior training to the subject. The result significantly demonstrates the suitability of proposed design of neural network with Levenberg-Marquardt algorithm for the classification of single channel EMG signal.

CONCLUSION

In this paper the EMG signal classification for different hand movements has been discussed in details which include signal acquisition, preprocessing, classification and comparison with most relevant research work. The presented classification result clearly indicates that the ANN with Levenberg-Marquardt training algorithm recognizes the hand motions efficiently and time consumption is minimum. It has been found that the designed ANN has successfully classified the EMG signals from hand movements and the average success rate is 88.4%. Moreover, it shows that among the backpropagation learning algorithms, the Levenberg-Marquardt algorithm outperforms Scaled Conjugate Gradient algorithm. The classification performance has been obtained without any prior training to the subject’s hand movements. It can be concluded that the classification efficiency will increase if the network is provided with enriched EMG signals. This can be done either by short training of the subject which can reproduce repeatable signals or by allowing the network to adapt with changes of feature value. The same thing can happen also with amputees or disabled person (unable to walk) if the muscles of the lower arm are maintained properly. In that situation, a good classification can be obtained and which will lead to the development of suitable human-computer-interaction system. In future study it has been planned to improve the classification performance by giving proper training to the subject for specific intended hand motion and, by modifying the ANN structure and algorithm to adapt with change of feature/user.

REFERENCES

1. Ahsan, M.R., M.I. Ibrahimy and O.O. Khalifa, 2009. EMG Signal Classification for Human Computer Interaction: A Review. European Journal of Scientific Research, 33(3): 480-501.
2. Ahsan, M.R., M.I. Ibrahimy and O.O. Khalifa, 2011. Neural Network Classifier for Hand Motion Detection from EMG Signal. In the 2011 IFMBE Proceedings, 35: 536-541.
3. Merletti, R., M. Aventaggiato, A. Botter, A. Holobar, H. Marateb and T. M. Vieira, 2010. Advances in Surface EMG: Recent Progress in Detection and Processing Techniques. Critical Reviews in Biomedical Engineering, 38(4): 305.
4. Ahsan, M.R., M.I. Ibrahimy and O.O. Khalifa, 2010. Advances in electromyogram signal classification to improve the quality of life for the disabled and aged people. Journal of Computer Sciences, 6(7): 706-715.
5. Reaz, M.B.I., M.S. Hussain and F. Mohd-Yasin, 2006. Techniques of EMG signal analysis: detection, processing, classification and applications. Biological procedures online, 8(1): 11-35.
6. Taghizadeh, H. and M.S.Z. Kermani, 2011. Application of Artificial Neural Networks to Recognize the Relationship between Corporate Social Responsibility and Financial Performance. World Applied Sciences Journal, 12(10): 1910-1919.
7. Kanani, S., G. Asadollahfardi and A. Ghanbari, 2008. Application of Artificial Neural Network to Predict Total Dissolved Solid in Achechay River Basin. World Applied Sciences Journal, 4(5): 646-654.
8. Al-Sbou, Y., 2012. Artificial Neural Networks Evaluation as an Image Denoising Tool. World Applied Sciences Journal, 17(2): 218-227.
9. Nikoo, M., P. Zarfam and M. Nikoo, 2012. Determining Displacement in Concrete Reinforcement Building with using Evolutionary Artificial Neural Networks. World Applied Sciences Journal, 16(12): 1699-1708.
10. Hayati, M. and Z. Mohebi, 2007. Temperature Forecasting Based on Neural Network Approach. World Applied Sciences Journal, 2(6): 613-620.
11. Putnam, W. and R.B. Knapp, 1993. Real-time computer control using pattern recognition of the electromyogram. In the Proceedings of the 15th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp: 1236-1237.
12. Hiraiwa, A., N. Uchida and K. Shimohara, 1992. EMG pattern recognition by neural networks for prosthetic fingers control. Annual Review in Automatic Programming, 17: 73-79.
13. Naik, G.R., D.K. Kumar, V.P. Singh and M. Palaniswami, 2006. Hand gestures for HCI using ICA of EMG. In the Proceedings of the 2006 HCSNet workshop on Use of vision in human-computer interaction, 56: 67-72.
14. Englehart, K., B. Hudgins, M. Stevenson and P.A. Parker, 1995. A dynamic feedforward neural network for subset classification of myoelectric signal patterns. In the Proceedings of the 17th IEEE Annual Conference of Engineering in Medicine and Biology Society, 1: 819-820.
15. Kelly, M.F., P.A. Parker and R.N. Scott, 2002. The application of neural networks to myoelectric signal analysis: a preliminary study. IEEE Transactions on Biomedical Engineering, 37(3): 221-230.
16. Hudgins, B., P. Parker and R.N. Scott, 1993. A new strategy for multifunction myoelectric control. IEEE Transactions on Biomedical Engineering, 40(1): 82-94.
17. Hussain, M.S., M.B.I. Reaz and M.I. Ibrahimy, 2008. SEMG signal processing and analysis using wavelet transform and higher order statistics to characterize muscle force. In the Proceedings of the 12th WSEAS international conference on Systems, pp: 366-371.
18. Phinyomark, A., C. Limsakul and P. Phukpattaranont, 2009. A novel feature extraction for robust EMG pattern recognition. Journal of Computing, 1(1): 71-80.
19. Tsenov, G., A.H. Zeghbib, F. Palis, N. Shoylev and V. Mladenov, 2007. Neural networks for online classification of hand and finger movements using surface EMG signals. In the proceedings of the 8th Seminar on Neural Network Applications in Electrical Engineering, pp: 167-171.