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Performance evaluation of pattern recognition networks using electromyography signal and time-domain features for the classification of hand gestures

S Mary Vasanthi[1] and T Jayasree[2]

Abstract

The problem of classifying individual finger movements of one hand is focused in this article. The input electromyography signal is processed and eight time-domain features are extracted for classifying hand gestures. The classified finger movements are thumb, middle, index, little, ring, hand close, thumb index, thumb ring, thumb little and thumb middle and the hand grasps are palmar class, spherical class, hook class, cylindrical class, tip class and lateral class. Four state-of-the-art classifiers namely feed forward artificial neural network, cascaded feed forward artificial neural network, deep learning neural network and support vector machine are selected for this work to classify the finger movements and hand grasps using the extracted time-domain features. The experimental results show that the artificial neural network classifier is stabilized at 6 epochs for finger movement dataset and at 4 epochs for hand grasps dataset with low mean square error. However, the support vector machine classifier attains the maximum accuracy of 97.3077% for finger movement dataset and 98.875% for hand grasp dataset which is significantly greater than feed forward artificial neural network, cascaded feed forward artificial neural network and deep learning neural network classifiers.

Keywords

Finger movements, time-domain features, discrete wavelet transform, pattern recognition, artificial neural network

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Introduction

A hand amputee person can perform basic hand movements with the help of a prosthetic hand (PH). Designing PH to perform accurate hand movement is very difficult.[1] PH can be controlled using electroencephalogram (EEG) signals or electromyogram (EMG) signals. Retrieval of EEG signals is complex as it requires proper positioning of electrodes on the scalp.[2] The accurate classification of EMG signals is necessary for designing an effective controller for PH.[3] In real-time applications, various noises like muscle artefacts, baseline wander noise and powerline interference contaminate the EMG signal during its acquisition. These noises should be eliminated for the proper retrieval of features from the signal.[4] The applications of pattern recognition using EMG signal include human–machine interfaces, functional electrical stimulation (FES) devices, rehabilitation and limb prosthetics.[5]

EMG signals are easily retrieved using surface electrodes and they differ with different muscle movement. These variations are high when they are recorded from forearm.[6] EMG signals provide information about the electrical activity of muscles, when the muscles undergo contraction.[7,8] Hence, these signals are used in the prediction and generation of movements in exoskeletons and in active prosthetics.[9,10]

Research on EMG-based recognition of finger movements has been more concentrated on the classification of complicated operations.[11] This classification process is mainly used for pattern recognition and real-time recognition system with high accuracy.[12] Many

[1]Department of Electronics and Communication Engineering, St. Xavier's Catholic College of Engineering, Nagercoil, India
[2]Department of Electronics and Communication Engineering, Government College of Engineering, Tirunelveli, Tirunelveli, India

Corresponding author:
S Mary Vasanthi, Department of Electronics and Communication Engineering, St. Xavier's Catholic College of Engineering, Nagercoil 629003, Tamilnadu, India.
Email: vasanthi@sxcce.edu.in

methods are proposed for finger movement and hand grasp classification using EMG signals. In literature, different studies are presented for classifying various finger movements using EMG signals.[13] The development of myoelectric prosthesis control system relies on classification of EMG signals. The classification of EMG signals is very tough since there are a lot of fluctuations and interferences in the EMG signal.[14] Hence, it is very difficult to have an exact mathematical model for EMG signals that relates the retrieved signals with the motion commands.[15]

The accurate classification of EMG signals is necessary for designing an effective controller for PH. This is carried out using advanced biosignal processing and pattern recognition techniques.[16] Artificial neural networks (ANNs) are mainly used for processing biosignals and for complex hand gesture recognition and classification tasks.[17,18] The ability to learn and the ability to replicate random non-linear functions of input and extremely regularize the structure of ANNs make them suitable for pattern recognition tasks.[19–21]

With the intention of classifying the finger movements effectively, the remaining part of this article is organized as follows: section 'Related works' outlines some of the very recent literature works related to finger movement classification. Section 'Time-domain features–based classification' briefs the process of the proposed work followed by the simulation results and performance analysis in section 'Simulation results'. Finally, the proposed work is concluded in section 'Conclusion'.

Related works

When the EMG signal is acquired from the subject, it is interfered by the presence of different noises like power line interference, channel noise, baseline wander, electrode contact noise and motion artefacts that may lead to wrong interpretation in diagnosis.[22] In medical signals, noise removal requires specific care, since denoising involves smoothing of the noisy signal which may cause the loss of fine details. Different types of filters are used for denoising.

The traditional way of eliminating the noise from the signal is to use a low-pass or band-pass filter with certain cut-off frequencies. However, the traditional filtering techniques are able to remove only a relevant portion of the noise and are not effective if the noise is in the band of the signal to be analysed.[23] The simplest way of removing narrow bandwidth interference from the retrieved surface electromyography (sEMG) signal is to use a linear, recursive digital notch filter. But the disadvantage of the notch filter is that it distorts the signal. Hence, many denoising techniques are proposed to overcome these problems. As a multiresolution signal analysis technique, the wavelet transform offers the possibility of selective noise filtering and reliable parameter estimation. For this reason, wavelets have been extensively used in biomedical signal processing, mainly due to the versatility of the wavelet transform tools.[24]

The myoelectric pattern recognition predominantly lies on features extracted and classifier employed.[25] The parameters considered in the time domain could be very pertinent. A variety of time-domain features have been proposed and applied to different pattern recognition methods. Riillo et al.[26] used seven different time-domain features for recognizing five different hand gestures. In fact, the time-domain features in EMG analysis have to be carefully evaluated in order to reduce the time delay and generate good controllability in practical applications.

Panwar et al.[27] presented a two-layer convolution neural network (CNN), a type of deep learning neural network (DLNN) for classifying the upper limb movements of the human arm. The limb movements taken into consideration were flexion, extension and rotation of the forearm. The proposed framework was validated on EMG data collected from the forearm.

Sezgin[28] investigated that extreme learning machine (ELM) was suitable for classifying sEMG signals. Bicoherence analysis of the sEMG signal was used as features for classifying hand finger movements. This classification was based on phase matches in the EMG signal.

Lei[29] used a back propagation neural network for creating the discrete motion control and continuous motion control models of exoskeleton robotic arms. Recognizing the intention of patients' movement using EMG signals was the key to control the exoskeleton to assist their movement. Features were attained by weighted summation. Drawback of this work was the angles estimated by the continuous movement control model had smaller errors.

Cote-Allard et al.[30] proposed a hand gesture classification technique using a DLNN. Transfer learning algorithm was applied on EMG signals retrieved from multiple users. The classifier was tested on raw EMG, spectrograms and continuous wavelet transform (CWT) of input EMG signal. The proposed work effectively enhanced the classification accuracy.

Malesevic et al.[31] presented a novel algorithm for classifying individual finger movements in order to control activated fingers in the PH. Following the extraction of time-domain features, vector autoregressive modelling was performed. Hidden semi-Markov models were used to obtain variations between piecewise segments of movements and between different movements. Bayesian classifier was used for pattern recognition.[32]

This article presents a novel methodology to classify 10 basic hand movements and 6 basic hand grasps to enable automated hand gesture recognition system. The classification is done using EMG signals, each obtained from two electrodes only. Hence, the proposed method can be used for designing cost-effective

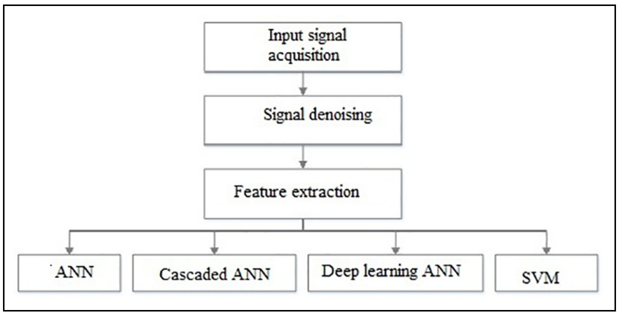

Figure 1. Process flow of the proposed work.

Figure 2. Experimental setup for signal acquisition.

PH. In this article, the effectiveness of discrete wavelet transform (DWT) is considered together for developing an efficient EMG denoising technique.

Various features such as variance (VAR), root mean square (RMS), integrated EMG (IEMG), mean absolute value (MAV), simple square integral (SSI), mobility (M), skewness (SK), and kurtosis (K) are computed from the denoised EMG signals. These features are fed as input to the classifiers for the classification of hand gestures. Different types of classifiers are used for the recognition of hand gestures. Support vector machine (SVM) and neural networks such as feed forward artificial neural networks (FANN), cascaded FANN (CFNN) and deep learning FANN (DLNN) are widely used classifiers providing good classification accuracy for the last few decades.

Time-domain features–based classification

To classify the finger movements and hand grasps from EMG signals, we propose four stages in this work. The four stages and the process flow of the proposed work are shown in Figure 1.

Input signal acquisition

The input signals used in this work are obtained by placing the electrodes on the muscle groups of multiple individuals and each individual is asked to produce n and m number of continuous movements to create two different datasets D_1 and D_2, respectively. The experimental setup for signal acquisition is shown in Figure 2.[32] A 12-channel USB-DAQ, TMI system is used to retrieve EMG signal from the subjects. A group of 27 volunteers including 12 males and 15 females, aged 19–22, free of any muscular or neurological disorders participated in the experiment. Subjects were seated on an armchair, with their arms fixed at one end so that they could perform finger and hand movements without any constraints. The skin is wiped with 70% alcohol and sensors are adhered using medical grade adhesive tapes. Each electrode is separated from the other by 2 cm interval. A conductive adhesive reference electrode (dermatrode reference electrode) was placed on the wrist of each subject.

The subjects were inquired to carry out a certain posture of finger movements and hand grasps. EMG signals evoked through the 16 tasks were recorded. Each participant was asked to hold a gesture for 5 s. Ten trials were recorded for each task. Subjects were given an interval of 5 min between each trial and data were collected in two sessions. Each session lasted five trials per each task. From each subject 160 datasets were acquired and a total of 20,000 data samples were obtained from each data set. The signals were sampled at 2 kHz. The collected data were divided into training data and testing data.

The n number of finger movements recorded in the dataset D_1 including index (I), middle (M), ring (R), little (L), thumb index (TI), thumb middle (TM), thumb ring (TR), thumb little (TL), hand close (HC) and thumb (T) are shown in Figure 3.

The m number of hand grasp movements recorded in the dataset D_2 including palmar class (PC), spherical class (SC), hook class (HC), cylindrical class (CC), tip class (TC) and lateral class (LC) are shown in Figure 4.

Let the 10 finger movements in D_1 be represented as $\{X_1, X_2, \ldots, X_n\}$ and the 6 hand grasp data in D_2 be represented as $\{Y_1, Y_2, \ldots, Y_m\}$. Now the input datasets D_1 and D_2 can be mathematically represented as

$$D_1 = \sum_{i=1}^{n} X_i \quad \text{where } n = 1, 2, \ldots, 10 \tag{1}$$

$$D_2 = \sum_{j=1}^{m} Y_j, \quad \text{where } m = 1, 2, \ldots, 6 \tag{2}$$

The quality of these input datasets D_1 and D_2 may be degraded by the motion of the individual, background and environmental conditions. This brings the essentiality to process or denoise the input datasets as a primary step in this work.

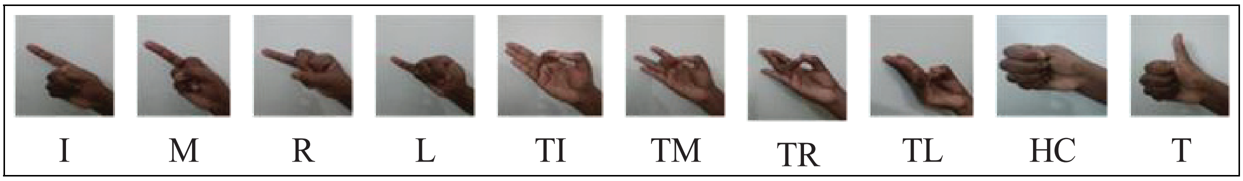

Figure 3. Ten finger movements.

Figure 4. Six hand gestures.

Signal denoising

Denoising is the technique of removing unwanted noise from the signal and improving the quality of the signal. DWT is one of the recent wavelet transforms which is used to denoise the input signal in this work. We apply DWT to both the datasets D_1 and D_2 which can be mathematically written as

$$Denoised(D_1) = DWT\{D_1\} \tag{3}$$

$$Denoised(D_2) = DWT\{D_2\} \tag{4}$$

DWT requires decomposition of noised input images to get the wavelet coefficients of the image. The algorithmic steps used in DWT are presented below.

Begin
Perform N level decomposition of each signal which results in 3N + 1 sub-band.

The decomposed sub-bands are LL, LH, HL and HH.

Apply wavelets to the sub-bands of low frequency and then threshold the sub-bands of high frequency.

Perform inverse transform to get the denoised signal.

End

Feature extraction

Extracting possible or available information from the input signal is necessary to classify the signal. In this work, we intend to extract the time-domain features of each signal in both datasets D_1 and D_2. The extracted time-domain features are VAR, RMS, IEMG, MAV, SSI, M, SK and K. If I is the input signal from any dataset, then the time-domain features are extracted as

$$VAR = \begin{cases} \frac{1}{n-1}\sum_{i=1}^{n} I_i^2, & \text{if } I \text{ is taken from } D_1 \\ \frac{1}{m-1}\sum_{j=1}^{m} I_j^2, & \text{if } I \text{ is taken from } D_2 \end{cases} \tag{5}$$

$$MAV = \begin{cases} \frac{1}{n}\sum_{i=1}^{n} I_i, & \text{if } I \text{ is taken from } D_1 \\ \frac{1}{m}\sum_{j=1}^{m} I_j, & \text{if } I \text{ is taken from } D_2 \end{cases} \tag{6}$$

$$IEMG = \begin{cases} \sum_{i=1}^{n} I_i, & \text{if } I \text{ is taken from } D_1 \\ \sum_{j=1}^{m} I_j, & \text{if } I \text{ is taken from } D_2 \end{cases} \tag{7}$$

$$SSI = \begin{cases} \sum_{i=1}^{n} I_i^2, & \text{if } I \text{ is taken from } D_1 \\ \sum_{j=1}^{m} I_j^2, & \text{if } I \text{ is taken from } D_2 \end{cases} \tag{8}$$

$$RMS = \begin{cases} \sqrt{\frac{1}{n}\sum_{i=1}^{n} I_i^2,} & \text{if } I \text{ is taken from } D_1 \\ \sqrt{\frac{1}{m}\sum_{j=1}^{m} I_j^2,} & \text{if } I \text{ is taken from } D_2 \end{cases} \tag{9}$$

$$M = \sqrt{\frac{VAR - DIFF}{VAR}}, \quad \text{if } I \text{ is taken from } D_1 \text{ or } D_2 \tag{10}$$

$$SK = \begin{cases} \sqrt{\frac{\sum_{i=1}^{n}(I-I_i)^3}{(n-1)VAR^3},} & \text{if } I \text{ is taken from } D_1 \\ \sqrt{\frac{\sum_{j=1}^{m}(I-I_j)^3}{(m-1)VAR^3},} & \text{if } I \text{ is taken from } D_2 \end{cases} \tag{11}$$

$$K = \begin{cases} \sqrt{\dfrac{\sum_{i=1}^{n}(I-I_i)^4}{(n-1)VAR^4}}, & \text{if } I \text{ is taken from } D_1 \\ \sqrt{\dfrac{\sum_{j=1}^{m}(I-I_j)^4}{(m-1)VAR^4}}, & \text{if } I \text{ is taken from } D_2 \end{cases} \tag{12}$$

The time-domain features extracted from each signal in the dataset using equations (5)–(12) creates a feature vector for each signal. The feature vectors created for any signal can be represented as

$$F=\{VAR, \rightleftarrows MAV, SSI, IEMG, RMS, M, SK, K\} \tag{13}$$

In this way, the dataset D_1 creates n set of feature vectors and the dataset D_2 creates m set of feature vectors which are given as input to the classifiers for further processing.

Classification

The created feature vectors offer enough information about the input signal to the classifiers, so that the input finger movements and hand grasps can be classified effectively. In this work, four state-of-the-art classifiers are selected for the classification process.

FANN classifier. A feed forward network having three layers with a sigmoid transfer function $t(s)$ in hidden layer and a softmax transfer function $h_\theta(k)$ in the output layer is used in this work. The sigmoid and softmax transfer functions are given by

$$t(s) = \frac{1}{1 + e^{-s}} \tag{14}$$

$$h_\theta(k) = \frac{1}{1 + \exp(-\theta^T k)} \tag{15}$$

The network has n neurons in the hidden layer for dataset D_1 and m neurons in the hidden layer for dataset D_2. The network is trained using scaled-conjugate gradient back-propagation. The structure of FANN is shown in Figure 5.

The first output neuron in the hidden layer is given by

$$g^1 = t^1(IW_P + b^1) \tag{16}$$

where g^1 is the output vector from the input layer, IW is the weight matrix of input, t^1 is the transfer function of hidden layer and b^1 is the bias function of hidden layer. Similarly, the first output neuron of the output layer is given by

$$g^2 = t^2(LW(t^1(IW_P + b^1)) + b^2 \tag{17}$$

where g^2 is the output vector of output layer, LW is the weight matrix of output, t^2 is the transfer function of the output layer and b^2 is the bias function of the output layer.

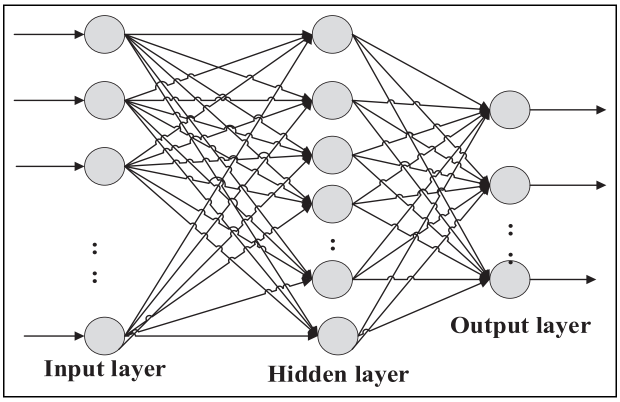

Figure 5. Structure of FANN.

CFNN classifier. The structure of CFNN is same as that of a simple FANN structure with no hidden neurons. The structure of CFNN is shown in Figure 6.

In CFNN, a weight connection is included from the input to every other layer and from every layer to the following layers. In this structure, each layer of neurons is related to all the previous layers of neurons. This network can learn any input–output relationship, given adequate hidden neurons.

DLNN classifier. Feed forward neural network (FFNN) and CFNN need long training time and they are inefficient since there is redundancy when the number of total parameters is high. Another disadvantage is that they disregard spatial information. These drawbacks are overcome by DLNN. In DLNN, the nodes of each layer are trained by a distinct set of features based on the output of previous layer. DLNN learn to correlate relations between certain relevant features and optimal results. The output layer is a classifier that assigns likelihood to a particular outcome or label.

DLNN is a modified form of FANN which consists of a number of hidden layers. They work on three simple ideas, including local receptive field, shared weights and pooling. Deep learning algorithms have become increasingly more prominent for their unparalleled ability to automatically learn discriminant features from large amount of data. With the use of deep architecture, the learned features are considered as the higher-level abstract representation of low-level raw time series signals. By considering the labelled information via supervised learning, the learned features are distinct with more discriminative power. The main steps of the learning DLNN algorithm are described below:

Step 1. Randomly initialize the weights of the network.
Step 2. Apply gradient descent using back propagation network.

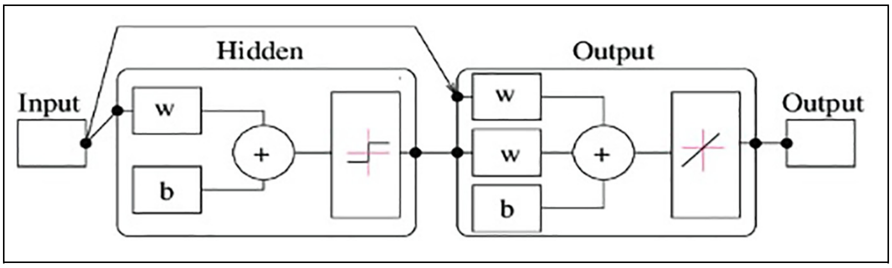

Figure 6. Structure of CFNN.

Step 3. Sample the labelled data called batch.
Step 4. Samples are forwarded through the network to get predictions.
Step 5. An error signal is generated which is the difference between predictions and target values.
Step 6. These errors are back propagated to update the weights and to get more accurate predictions.
Step 7. Subtract a fraction of the gradient to get the local minimum of the cost function.

SVM classifier. SVM is a binary classifier which uses supervised learning technique for classification. SVM is used to solve non-linear problems by mapping the input data into a feature space. The mapping data is linearly separable in feature space. SVM requires a function data $\varphi(x_i)$ to map the training feature vector into a high-dimensional space, requires belonging to a dot product space termed as kernel

$$K(x_i, y_i) = \varphi(x_i)^T \varphi(x_j) \tag{18}$$

The group of data that is mapped in high-dimensional linear space is divided into two labelled classes by a hyperplane. So that the final decision function can be written as

$$f(x) = \mathrm{sgn}\left\{ \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b \right. \tag{19}$$

where α_i is the Lagrangian multiplier.

Simulation results

In this section, we have presented the simulation results of the proposed work. In addition, the performance of the four selected classifiers is evaluated in terms of accuracy, sensitivity and specificity for comparison.

Simulation setup

The proposed work is implemented and validated using MATLAB software with the following configurations:

- Windows: XP;
- Processor: i3 Intel;
- RAM: 8 GB.

Performance analysis and comparison

The simulation and performance results obtained for the two datasets are presented in this section. The best validation performance of ANN classifier obtained for both finger movement and hand grasp datasets is shown in Figure 7.

Figure 7(a) shows the best validation performance of finger movement dataset, and Figure 7(b) shows the best validation performance for hand grasp dataset. It was observed that the ANN classifier showed the best performance of 3.333 at epoch 1 for finger movement dataset and 2.315 at epoch 0 for hand grasp dataset.

Figure 8(a) and (b) shows the gradient values obtained during the training state of ANN classifier for finger movement and hand grasp dataset, respectively.

From Figure 8, it is observed that, for finger movement dataset, the training data will be validated in 6 epochs with gradient $3.74\mathrm{e}^{-14}$. Similarly, for hand grasp dataset, the training data will be validated in 4 epochs with gradient $2.601\mathrm{e}^{-08}$.

Figure 9(a) and (b) shows the error histogram of ANN and Figure 10(a) and (b) shows the regression plot of ANN classifier for finger movement and hand grasp dataset, respectively.

Figures 9 and 10 give the performance analysis of the ANN classifier for both datasets. The error histograms in Figure 9 display the difference between the expected targets and the estimated output. Figure 9 displays the output values during training and testing phases with dynamic regression values. From Figures 7 to 10, we come to know that ANN classifier is stabilized with minimum mean square error (MSE) during its training, testing and validating stage at 6 epochs for finger movement dataset and at 4 epochs for hand grasp movement dataset.

The performance of each classifier is evaluated in terms of accuracy, sensitivity and specificity as follows

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{20}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{21}$$

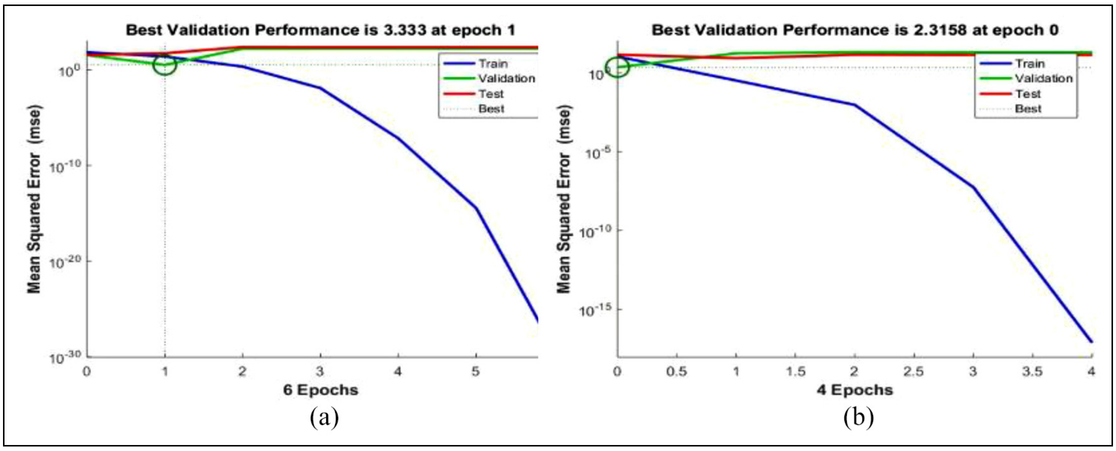

Figure 7. Best validation performance of ANN classifier for (a) finger movement and (b) hand grasp dataset.

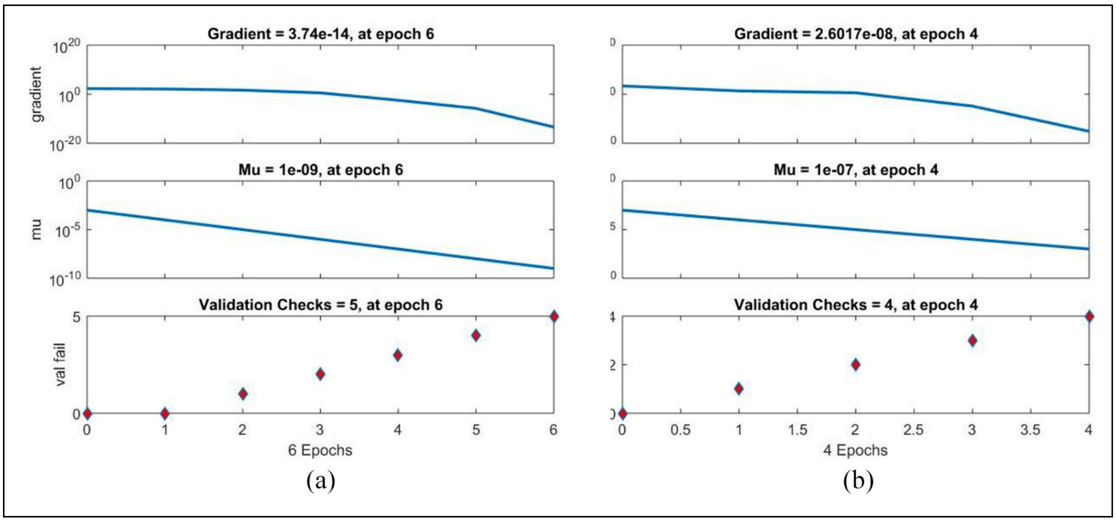

Figure 8. Training state of ANN for (a) finger movement and (b) hand grasp dataset.

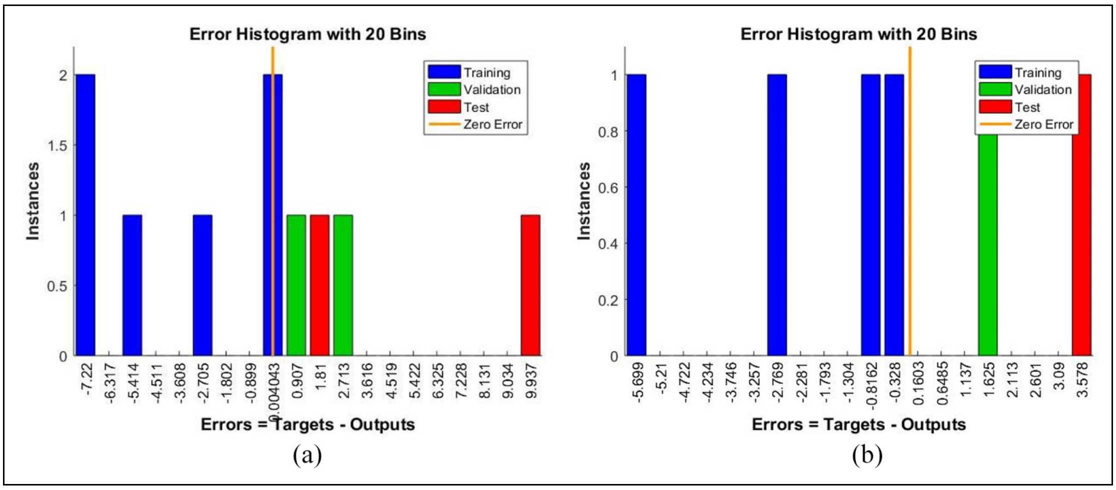

Figure 9. Error histogram of ANN for (a) finger movement and (b) hand grasp dataset.

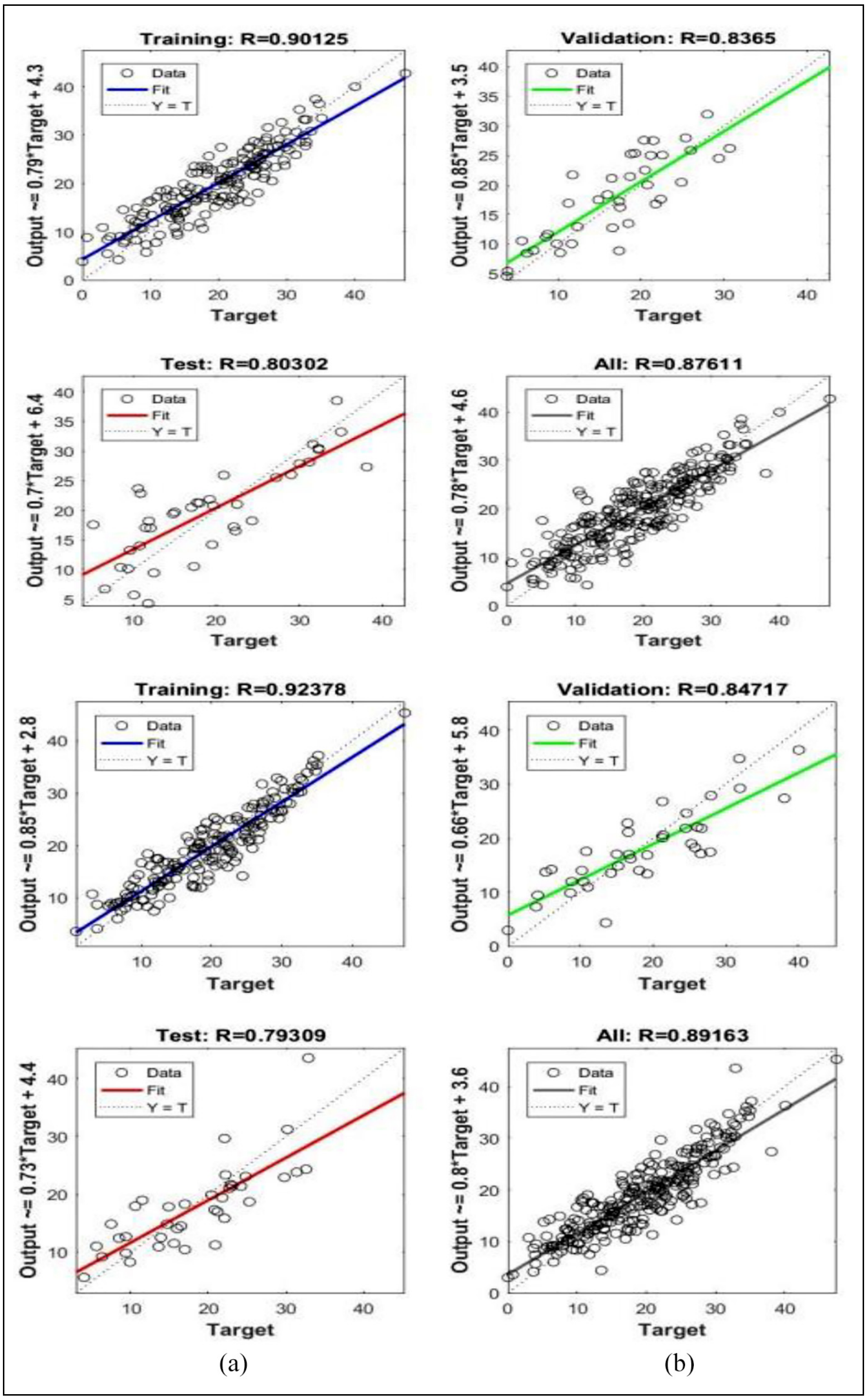

Figure 10. Regression of ANN for (a) finger movement and (b) hand grasp dataset.

$$Specificity = \frac{TN}{TN + FP} \tag{22}$$

where TP is the true positive (correctly identified), TN is the true negative (correctly rejected), FP is the false positive (incorrectly identified) and FN is false negative (incorrectly rejected). The performance of the four selected classifiers for both finger movement and hand grasp dataset are presented in Table 1.

From Table 1, it is visible that SVM attains the maximum accuracy of 97.3077% for finger movement dataset and 98.875% for hand grasp dataset. Similarly, SVM shows the best results in terms of sensitivity and specificity. This shows that SVM classifier is superior to the other selected classifiers (FANN, CFNN and DLNN). SVMs have better generalization capacity and less variability when classification trials are repeated using different training sets. The ANN classifiers

Table 1. Performance of the classifiers.

Dataset used	Classifiers used			
	FANN	CFNN	DLNN	SVM
Finger movement dataset				
Accuracy (%)	85.5769	82.6923	88.4615	**97.3077**
Sensitivity (%)	11.1100	22.2200	50.0000	66.6667
Specificity (%)	88.4211	89.4737	89.2157	95.6522
Hand grasp dataset				
Accuracy (%)	81.2500	92.1875	87.5000	**98.8750**
Sensitivity (%)	25.0000	71.4286	50.0000	87.5000
Specificity (%)	89.2857	94.7368	88.7097	98.2143

FANN: feed forward artificial neural network; CFNN: cascaded feed forward artificial neural network; DLNN: deep learning neural network; SVM: support vector machine. Bold values represent maximum accuracy.

Table 2. Performance in terms of PSNR and MSE.

Dataset used	Performance measures	
	PSNR	MSE
Finger movement		
Little	41.72	1.9865
Thumb	32.44	1.2704
Middle	37.97	2.9021
Index	33.65	3.1255
Ring	43.89	1.2788
Thumb little	40.22	4.1466
Thumb index	34.90	2.1197
Thumb ring	37.12	4.0981
Thumb middle	38.32	3.0021
Hand close	33.56	2.7611
Hand grasp		
Lateral	30.94	1.8964
Spherical	31.67	1.5462
Palm	35.92	1.4927
Tip	29.05	0.9823
Hook	28.34	0.7351
Cylinder	30.76	1.0239

PSNR: peak signal-to-noise ratio; MSE: mean square error.

perform better on very large datasets while SVMs will probably perform better on small size training samples.

SVMs are mainly used for classification problems. They depend on support vectors, which are the training samples that lay exactly on the hyperplanes, which are used to define the margin. In case of not linearly separable data, SVMs use kernel, which allows in mapping the data to a very high-dimensional space.

In addition to the classifier performance, the peak signal-to-noise ratio (PSNR) and MSE are measured and the results are presented in Table 2.

For effective classification, the input dataset must produce high PSNR value and low MSE value. On considering this, Table 2 shows that the ring data from finger movement dataset (D1) and palm data from hand grasp dataset (D2) are effectively classified with high PSNR and low MSE.

Conclusion

This research work has been carried out for the classification of various hand gestures using two datasets (finger movements and hand grasps) based on EMG signals using four different classifiers such as FANN, CFNN, DLNN and SVM.

- The experimental results show that the SVM classifier recognizes the desired motions efficiently than the other classifiers.
- It has been found that the SVM has successfully classified the finger movement dataset with an average success rate of 97.3077% and the hand grasp dataset with an average success rate of 98.875%.
- It can be concluded that the classification efficiency may increase with changes in feature sets.
- The classified EMG signal can be effectively used to develop a human computer interface to help the people with disabilities who wish to interact with computer devices.

Declaration of conflicting interests

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ORCID iD

S Mary Vasanthi https://orcid.org/0000-0002-9745-6922

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