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EMG Signal Based Finger Movement Recognition for Prosthetic Hand Control

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Abstract— **Electromyography (EMG) signal can be defined as a measure of electrical activity produced by skeletal muscles. It can be used in handling electronic devices or prosthesis. If we are able recognize the hand gesture captured using EMG signal with greater reliability and classification rate, it could serve a good purpose for handling the prosthesis and to provide the good quality of life to amputees and disabled people. In this paper, we have worked on recognizing the 9 classes of individual and combined finger movement captured using 2 channel EMG sensor. We have used two different classification techniques such as Artificial Neural Network (ANN), and k- nearest neighbors (KNN), to classify the test samples. Seven time domain features a) Mean absolute value, b) root mean square, c) variance, d) waveform length, e) number of zero crossing, f) complexity, g) mobility have been used to uniquely represent the EMG channel data. Tuning parameters like number of hidden layers, learning constant and number of neighbors have been determined from the experimental results to achieve the better classification results. Classification accuracy has been selected as a metric to evaluate the performance of each classifier.**

Keywords—EMG signal; Artificial Neural Network; K-NN, ANN, prosthesis, Time Domain Features

I. Introduction

Surface Electromyography (EMG) Signal is the recording of skeletal muscle activity with surface electrodes. Electromyography is widely studied and extensively applied in the field of engineering. It finds its application in the field of rehabilitation robotics. It can be used to control prosthetic devices as well as other electronic devices [1, 2] and as means of hand gesture recognition system [3]. There also have been many attempts to fuse the EMG data with accelerometer [4, 5] however, if proper feature and classification techniques are used EMG signal alone can provide good results. As we know Human forearm amputation severely limits the capability of a human. But it can be restored by designing a myoelectric prosthesis with the Electromyogram signal which can be used to control the forearm prosthesis. We recognize the EMG signal generated by forearm into some previously known class with the help of some pattern recognition system [6]. However, recognizing the generated gesture or movement using EMG data is not a trivial task because the surface EMG signal generally suffers from information deficiency and noise. Many authors used many different classification techniques and feature set i.e. time domain features and frequency domain features to recognize the movement generated by human hand or fingers. The artificial neural network is very popular in literature to classify the EMG signal as it has the good learning capability. However, another classification technique such as k nearest neighbor and SVM are also popular for EMG signal recognition as they too provide good results [7, 8]. Some of the researchers also utilized the combination of different neural and fuzzy classification techniques for classification [9, 10, 11, 12] like a combination of wavelet neural network and fuzzy classifier. Fuzzy based classifiers also have been used by many researchers [13, 14]. Subasi, M. Yilmaz, and H.R. Ozcalik [15] Used wavelet neural network and feed-forward backpropagation neural network to classify the EMG signal obtained from healthy subjects and patients of myopathy and neurogenic disease. They reported to have an accuracy of 90.7% and 88%, respectively. Rami N. Khushaba, Sarath Kodagoda, Maen Takruri and Gamini Dissanayake [16] applied SVM and KNN for classification technique along with Bayesian post-processing technique and achieved an accuracy of around 90%. He used features like waveform length, Auto-regressive parameter, slope sign change, Hjorth parameter [17, 18] etc. for the classification. Tenore *et al.* [19] Proposed a framework for the classification of 12 hand and finger generated movement using neural networks with an accuracy of more than 98% with 32 channel surface EMG signal and 15 channels [20]. Tenore *et al.* [21] also decoded the 10 individual finger flexion and extension with an accuracy of more than 90% using 32 channel surface EMG signal for Trans radial amputee. Cipriani *et al.* [22] designed a recognition system to recognize the EMG signal data obtained from five amputee and five able bodied subjects with 8 pair of

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electrode and reported to achieve an accuracy of 79% and 89% for able bodied and amputees respectively. There have been many attempts towards recognizing the individual finger movements, but there is a very less focus towards individual and combined finger movement using only few channel EMG signal. Research on the individual and combined finger movement recognition with only two channel EMG signal will open the doors for low cost, affordable and more practical prosthesis. In our paper, we proposed a system to recognize the 9 classes of individualized and combined finger movement using only two channel surface EMG signal with K-NN and ANN and compared the accuracy of both the classification techniques. Fig. 1 shows the block diagram of our proposed finger movement recognition system.

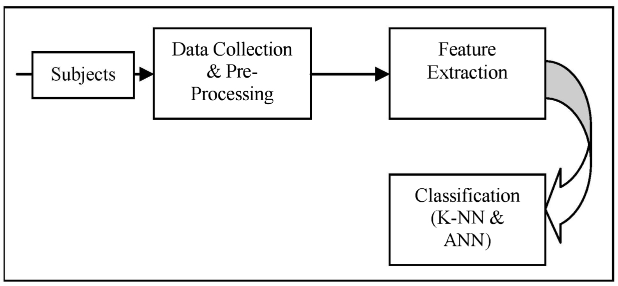

Fig. 1. Block Diagram of our Finger Movement Recognition System

II. Data Collection and Pre-Processing of Data

A. Data Acquisition

We have captured EMG data for four normal subjects for nine finger movement. Out of nine movements of fingers, five movements are flexion of each individual finger and four movements are combined flexion of the thumb and each of four fingers. Data is captured using two channel EMG kit which has three electrodes, two electrodes are for signal recording and one electrode works as a reference electrode. Signal electrodes were placed on brachioradialis and flexor Cuprum ulnaris muscles respectively, while reference electrode has been placed on the wrist because this position of electrodes is found to be optimal. Fig. 2 shows the placement of electrodes. Here each gesture is taken for 5 seconds and is repeated six times of which four 4 trials were included in the training set and 2 trials were included in the testing set. The sampling rate of data is 1000 samples/ second.

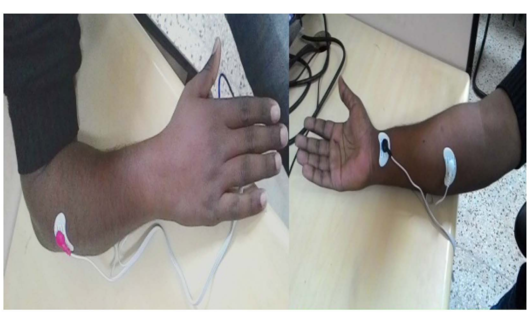

Fig. 2. Placement of EMG Device Electrodes on Forearm

B. Pre-processing of Data

Raw EMG data always suffers from less information content. It always has lots of noises that have to be removed for acceptable classification rate. The noises which EMG signal generally suffer from are like line noise, motion artifacts, inherent equipment noise and random noise and electromagnetic interference in the environment. Power line noise, electrode noise and motion artifacts can be removed by using proper filtering and precautions. Filtering scheme like band-pass, band-stop and notch filter are popular. We have used third order butter filter in the frequency range of 10-500 Hz to remove the noise. Re-sampling may also be done to reduce the no. of samples recorded per second. Fig. 3a & 3b shows the raw data and band-pass filtered data respectively.

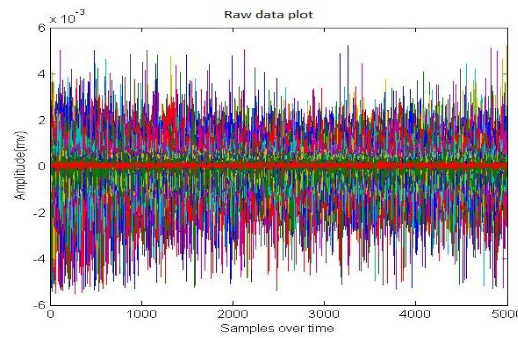

Fig. 3. Raw EMG Signal Data

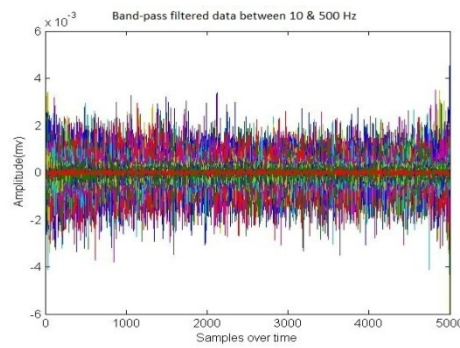

Fig. 3b. Band-pass filtered EMG Signal Data

III. Feature Extraction

Proper selection of features in EMG signal is very much crucial step as classification accuracy largely and mainly depends upon selection of features, both time domain and frequency domain features are popular in the literature, but time domain features are more popular than frequency domain features because they have good discrimination power and are less computationally intensive than frequency domain features. We have used time domain features like root mean square (RMS), number of zero cross (NZC), sample skewness (SS), waveform length (WL), variance (VAR), complexity(CY) and mobility(MY).

A. Mean Absolute Value (MAV)

MAV is the average of the absolute value of all the sample of data of which MAV is to be calculated. Mathematical formula to calculate the MAV is given by (1).

$$MAV = \frac{1}{N}\sum_{k=1}^{N}|C_k| \tag{1}$$

Where N is no. of data points in *Ck* and *Ck* is a row or column of data for our case it may be referred to as single EMG channel data. MAV feature can work as discriminating feature between the classes but only to a limited extent as the two different data sets may have same mean value. So it is used with some other features.

B. Variance

It is a measure of spread in data. It tells us how much spread is present in data, mathematically it is the average of squared distance from data point to its mean of the channel and is calculated as given in (2).

$$Variance = \frac{1}{N}\sum_{k=1}^{N}\left(Ck - \overline{C}\right)^2 \tag{2}$$

Where $\overline{C}$ is mean of C_k.

C. Mobility

It is square rooted ratio of variance of signal derivative and that of the variance of the signal itself and calculated as given in (3).

$$Mobility = \sqrt{\frac{Variance(C'_k)}{Variance(C_k)}} \tag{3}$$

Where C'_k is derivative or difference of C_k.

D. Complexity

It is the ratio of mobility of the derivative of the signal to that of a mobility of the signal itself and is a measure of signals closeness to pure sine wave and tends to 1 as signals' shape becomes more and more similar to pure sine wave, mathematical formula to calculate complexity is given by (4).

$$Complexity = \sqrt{\frac{Mobility(C'_k)}{Mobility(C_k)}} \tag{4}$$

E. Number of Zero Cross (NZC)

It tells us how many times our signal has crossed the zero line, i.e. how many times it has traversed from negative to positive or vice versa. The threshold is added to reduce the effect of noise. Equation (5) is used to calculate the number of zero cross and is written below.

$$NZC = \begin{pmatrix} Signum\left(-C_k \times C_{k+1}\right) \text{ is positive and} \\ \left(C_k - C_{k+1}\right) > 0 \end{pmatrix} \tag{5}$$

F. Waveform Length (Wl)

It is the mean of change in successive samples over the time period. It is like stretching the spring and measuring its length. It is a good measure of duration of EMG signal along with amplitude and frequency information of signal. Formula to calculate the waveform length is given by (6).

$$Wl = \frac{1}{N}\sum_{k=1}^{N-1}\left(C_{k+1} - C_k\right) \tag{6}$$

G. Sample Skewness (SK)

It is a measure of asymmetry in the probability distribution of random variable about its mean. Skewness of data may come out to be positive, negative or even undefined in some cases. Equation (7) gives the formula for sample skewness for univariate data

$$SK = \frac{\sqrt{N(N-1)}}{N-1}\,\frac{\sum_{k=1}^{N}\left(Ck - \overline{Ck}\right)^3 / N}{S^2} \tag{7}$$

IV. Classifiers

The final step of recognition system is a classification. To construct a good recognition system a suitable classifier must be used so that we can achieve a good classification rate. We have used k-NN and ANN for classifying the finger movements. Results are mentioned in the result section.

A. Classification Using K- Nearest neighbors (K- NN)

KNN is lazy learning algorithm and it is the simplest learning algorithm. It is called lazy because in this an object is classified according to majority rule and readily, the distance between objects and other data point is calculated and object is classified to class of nearest neighbors .If neighbors are more than one in numbers the class is assigned according to majority rule. Generally an odd value of K is fed to the algorithm to not let the algorithm involve in the tie. Although K-NN is memory intensive as classification of an object involves computing the distance to all data points, but it can give good classification result if the dataset is not large. The value of K (numbers of nearest neighbors to be considered) affects the classification rate, hence a proper value of k must be chosen. We have used the following distance in our k-NN classification.

1) Euclidean Distance (Ed)

Equation (8) is used to calculate the Euclidean Distance.

$$Ed = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left(C_k - C_j\right)^2} \tag{8}$$

Where C_k & C_j column of data or channel of EMG signal data.

2) Cosine Distance (Cd)

Equation (9) is used to calculate the Euclidead Distance.

$$Cd = 1 - \frac{\left(C_k - \overline{C_k}\right)\left(C_j - \overline{C_j}\right)}{\sqrt{\left(C_k - \overline{C_k}\right)\left(C_k - C_k\right)'\left(C_j - \overline{C_j}\right)\left(C_j - C_j\right)'}} \tag{9}$$

Where denotes the transpose of matrix or column.

3) Correlation Distance (Cod)

Equation (11) is used to calculate the Euclidead Distance.

$$Cod = 1 - \frac{C_k C'_j}{\sqrt{\left(C_k C'_j\right)\left(C_j C'_j\right)}} \tag{10}$$

4) City Block Distance (Cbd)

Formula to calculate city block distance is given in (11).

$$Cbd = \sum_{k=1}^{N}\left|C_k - C_j\right| \tag{11}$$

B. Classification using ANN

We used error back propagation feed-forward neural network for classification purpose. It has three layers, namely input layer which simply accepts external input, the second layer is hidden layer, the tan sigmoid unction is utilized as activation function in this layer and the third layer is the linear output layer. In our neural network input layer has 7 neurons, the output layer has 9 neurons and 20 neurons in the hidden layer has been used. Levenberg-Marquardt and scaled conjugate gradient algorithms have been used for back-propagation training, results have been mentioned in result section. Levenberg-Marquardt gave better results in our case. Fig. 4 shows the architecture of the neural network utilized in our methodology.

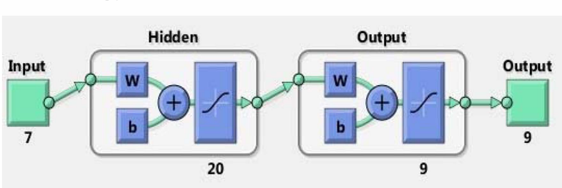

Fig. 4. The Architecture of ANN Utilized in our Recognition System

V. Results

C. Result for K-NN Classifications

As the type of distance used and the value of the k parameter in K-NN affects the accuracy of classification, we have varied both the parameters and analyzed the performance. Table I shows the effect of different distance used in K-NN classifiers like Euclidean, Cosine, Correlation and City-block distance on the accuracy. It is noted that the Euclidean distance gave the best result among all the distances. Out of 6 trials for each finger movement, 2 trials were taken for testing the accuracy of the classifier. Fig. 5 shows the confusion matrix of our k-NN classifier in the form of bar graph. An accuracy of ≈86% has been achieved using K-NN for k=6.

TABLE 1. Accuracy of Recognition System Versus type of Distance and k Value

Type of Distance Used	Accuracy for the value of k						
	k=1	k=2	k=3	k=4	k=5	k=6	k=7
Euclidean	82.50	82.50	80	80	82.5	86.11	77.50
Cosine	80	80	77.5	80	72.5	80	75
Correlation	77.5	77.5	77.5	82.5	72.5	80	72.5
City-block	82.5	82.5	75	80	70	80	70

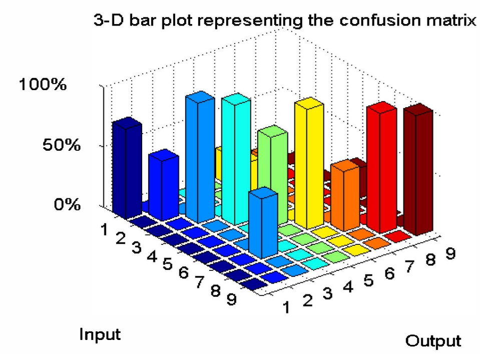

Fig. 5. Confusion Matrix of k-NN Classifier

D. Result for ANN Classification

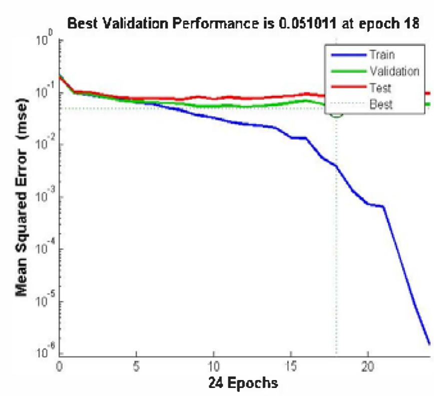

Fig. 6: Error Performance of ANN Used for Classification

Next we have classified the same data using error back-propagation neural. ANN was fed with features from 216 sets of data, out of these sets of data, we have taken 70% data for training, 15% data is taken for validation and 15% for testing. It is noted that Levenberg-Marquardt algorithm provided the best result for 20 hidden neurons. We achieved a maximum test accuracy of ≈93% with Levenberg-Marquardt algorithm with 20 hidden neurons. Fig. 6 shows the error performance of our network. Best validation performance has been achieved at 18 epochs while maximum epochs are 24 epochs. Table II shows the confusion matrix for ANN classifier with Levenberg-Marquardt algorithm.

TABLE 2: CONFUSION MATRIX FOR ANN CLASIIFIER USED FOR CLASSIFICATION

Class	1	2	3	4	5	6	7	8	9
1	100%	0	0	0	0	0	0	0	0
2	0	75%	0	0	0	0	0	25%	0
3	0	0	100%	0	0	0	0	0	0
4	0	0	0	50%	50%	0	0	0	0
5	0	0	0	0	100%	0	0	0	0
6	0	0	0	0	0	100%	0	0	0
7	0	0	0	0	0	0	100%	0	0
8	0	0	0	0	0	0	0	100%	0
9	0	0	0	0	0	0	0	0	100%

VI. CONCLUSION

Recognition of single and combined finger movement using EMG signal has been successfully carried out. This recognition system can be used for a prosthetic hand. KNN and ANN have been used for classification. Classification accuracy of ≈86% & ≈93 has been achieved for KNN and ANN respectively. The Accuracy of all the four classifier has been analyzed and it has been observed with experiments that ANN with Levenberg-Marquardt outperformed the KNN, LVQ and Adaboost classifiers in our recognition system. Accuracy can still be improved if classification system is supplied with better quality of the EMG signal. Future work includes further improvement of accuracy and expansion of dataset, i.e. inclusion of more subject for data collection.

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