

# Upper Limb Movements Identification through EMG Signal using Artificial Neural Network

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**Abstract:** Nowadays, analysis of electromyography (EMG) signal is one of the powerful areas of interest in medical, rehabilitation, robotic and industrial fields. The measurement refers to the recording of electric signals that appear during muscle contraction. As these signals are related to human process of action, because of uncertainty of EMG signals proper prediction of a specific motion is difficult. An Identification of a specific wrist motion by means of the EMG signal pattern will help in controlling prosthetic hand. A movement recognition technique is required to segregate different wrist movements for instance extension, flexion, pronation, supination. In this direction the EMG signal pattern recognition includes feature extraction and classification of proper EMG signals obtained from human forearm muscles using Artificial Neural Network to establish control over the prosthetic hand. Training of ANN was performed using four input neurons, four output layers, and with 10 hidden layers achieved 90% overall accuracy.

**Index Terms:** Electromyography signal, EMG, Feature Extraction, Artificial Neural Network.

## I. INTRODUCTION

The chance of a person losing wrist is quite high in the present days where accidents, military action on natural calamities like earthquakes occur so often. Myoelectric arm can help such person to do necessary action by sEMG signal recording from the residual forearm muscles of upper limb. Such techniques of non invasive nature have been proposed for controlling myoelectric prosthetic devices to ensure that amputated people to have fundamental movements. Other rehabilitation robots are also available [1-4]. Signals of sEMG are time series variety emanating from neuromuscular system as recorded from skin surface having nonlinear dynamical characteristics. These are sensitive to the nature of muscular dynamics. Analysis of sEMG has focussed on time and frequency domains so far [5]. Time-domain features are

extracted from the detected signals of EMG and are used for identifying limb movements [6]. These features can be fed to ANN for classifying of action potentials of set of muscles [7]. A simple ANN is used in this research work, and it can be trained with extracted optimum features from single channel EMG signal. Huge computational work and complexity can be avoided by using ANN [8]. Scaled conjugate gradient (traincsg) algorithm [9] is used for classification. Four statistical features: Mean, Root Mean Square, Variance, and Mean Absolute Value [10-12] are used as the inputs of ANN as shown in fig.1.



Fig.1 Block Diagram of Method of approach

For robust and efficient classification is important to preserve important discriminatory information resulting in improved accuracy for classification. Different types of ANN models consist of various interconnected network elements to develop internal classification strategies based on training data. ANN models can work in parallelism and providing higher performance where as traditional classifiers function sequentially.

## II. METHOD OF APPROACH

### A. Data Collection

The experiment was conducted on 5 healthy male subjects without loss of hand (aged 21 years). Surface electrodes are placed at specified forearm muscle activity with a distance of 2cm which are made up of Ag-AgCl. After placing the electrodes, subject was instructed to perform wrist actions twice such as Extension, Flexion, Pronation, Supination and then muscle signal is detected and acquired using EMG detecting circuit and Digital CRO setup. Finally we receive 40 (5x4x2) samples in this experiment.

### B. Feature Extraction

Time domain features have been extensively used in both medical and engineering researches and practices. The one set of extracted features from one subject forearm muscle signals are shown in table.1

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Activity	M	RMS	MAV	VAR
Extension	0.008	0.485	0.393	0.236
Flexion	0.002	0.099	0.072	0.009
Pronation	0.028	0.298	0.230	0.088
Supination	0.007	0.134	0.104	0.018

Table.1 Different features of muscle signals

1). **Mean (M):** It is as the average value of signal amplitudes of EMG and it is defined as:

$$M = \frac{1}{N} \sum_{n=1}^N x_n$$

2). **Root mean square (RMS):** Square root of the mean of the squares of a set of randomly varying quantities of electromyography signal at regular intervals during a cycle and is defined as:

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

3). **Mean Absolute Value (MAV):** It is a middling of absolute value of electromyography signal amplitudes and is defined as:

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

4). **Variance (VAR):** It is a calculated as the middling of square value of deviation of variable and is defined as:

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

### C. ANN Classification

The extracted features are fed to neural network classifier using NN tool in MATLAB tool box. In which neural network pattern recognition tool with Scaled conjugate gradient (trainscg) algorithm is used for classifying the movements. The network architecture is based on Multi-layered pattern of ANN whose inputs we extracted features with output in class 1 to 4. Number of input neurons is 4 and output neurons are also 4 as shown in fig.2 and basic architecture with approximate universal ten hidden layer chosen for classifying the extracted features of various movements.

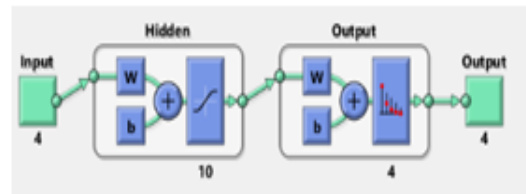


Fig.2 Artificial Neural network classifier

### III. Results and Discussions

After feature extraction ANN with supervised learning technique with 10 number of hidden layer has given maximum accuracy as shown confusion matrix fig.3. Input and target are fed to ANN. Size of matrix is of order 4x40. Four rows are related to feature set. 40 columns are related to 4 movements of 5 subjects with 2 sets of each. The target of signal movement is 1 while the rest is 0.

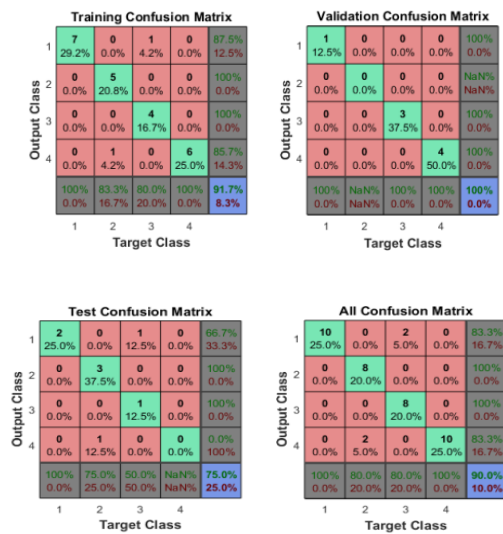
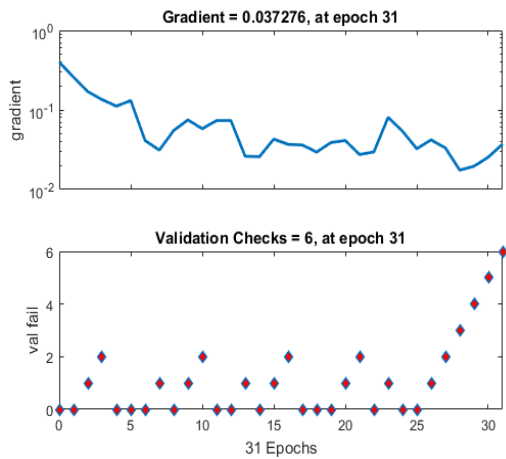


Fig.3 ANN Classifier based Training, Validation, Test and All confusion matrixes

The data is divided for, training 60% of samples, validation 20% of samples, and testing 20% of samples are used and continued the process such as error is minimised on validation. Ends when increase in error. The process of training is stopped if any of the following condition fulfilled: The number of epochs reached highest or the performance measure became less than the least gradient or validation performance exceeds more than the most fail times after the final validation shown in fig.4. From confusion matrix 2 samples are misclassified as extension instead of pronation, 2 samples are misclassified as supination instead of flexion. The overall accuracy 90% is achieved in this proposed work.



**Fig.4 Training State.**

#### IV. CONCLUSION

The proposed work with 90% accuracy of and commonly used time-domain features were reported for predicting the various movements by identifying different patterns of forearm muscle signals. The result has shown best promising for movement classification for the purpose of designing and in the case of developing the prosthesis hand to support the disable persons. The accuracy further can be improved by selecting optimum features for identifying the exact movements.

#### REFERENCES

1. Hargrove LJ , Li G , Englehart KB , Hudgins BS . Principal components analysis preprocessing for improved classification accuracies in pattern-recognition-based myoelectric control. *IEEE Trans Biomed Eng* 2009;56(5):1407-14 .
2. Li X , Samuel OW , Zhang X , Wang H , Fang P , Li G . A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees. *J NeuroEng Rehab* 2017;14(2):1-13 .
3. Bouteraa Y , Abdallah IB , Ghommam J . Task-space region-reaching control for medical robot manipulator. *Comput Elect Eng* 2017;0:1-17
4. Koochaki F , Sharifi I , Talebi HA . A novel architecture for cooperative remote rehabilitation system. *Comput Elect Eng* 2016;56:715-31 .
5. G. M. Hagg, Interpretation of EMG spectral alterations and alteration indexes at sustained contraction, *Journal of Applied Physiology* 73 (1992) 1211-1217.
6. Li G , Schultz AE , Kuiken TA . Quantifying pattern recognition-based myoelectric control of multifunctional transradial prostheses. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* , Volume: 18 , Issue: 2,Page s: 185 - 192 2010.
7. C. N. Schizas, C. S. Pattichis, I. Schofield, P. Fawcett, L. Middleton, Artificial neural nets in computer-aided macro motor unit potential classification, *IEEE Eng. Med.Biol. Mag.* 9 (1990) 31-38.
8. Rose M.: Expert systems, available at:<http://searchhealthit.techtarget.com/definition/expert-system>, accessed June 8, 2017.
9. Abraham, A. (2005). Artificial neural networks. handbook of measuring system design.
10. A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for {EMG} signal classification," *Expert Systems with Applications*, vol. 39, no. 8, pp. 7420 - 7431, 2012.
11. Mahyar Zardoshti-Kermani, Bruce C. Wheeler," EMG Feature Evaluation for Movement Control of Upper Extremity Prostheses" *IEEE Transactions on rehabilitation engineering*, VOL. 3, pp.324-333,1995.
12. Angkoon Phinyomark, Chusak Limsakul, and Pornchai Phukpattaranont," A Novel Feature Extraction for Robust EMG Pattern Recognition," *Journal of Computing*, vol.1,