

Analysis of EMG Signals using Feed forward Neural Network

Belliraj¹, Anci Manon Mary A²

¹Asst Prof, Dept of ECE, Karpagam Academy of Higher Education, India

²Asst Professor, Dept of EEE, Karpagam College of Engineering, India.
belliraj.ts@kahedu.edu.in

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Abstract: Electromyography (EMG) is one of the wide areas in the medical field, to analyze the biological signals for detecting the movements of muscles. The major studies based on recorded electrical signal which helps to diagnose the conditions of muscle disorders. Further, EMG is used for prosthesis control, rehabilitation for clinical diagnosis and the electrical signals are generated to control and activate the myoelectric artificial prosthetic arm. However, this paper provides a comprehensive review on EMG signals with different datasets and experimental results are extracted from Feed forward Neural Network (FNN) for future approaches.

Keywords: Electromyography, Feed forward Neural Network

I. INTRODUCTION

Electromyography (EMG) is a device which is widely used to measure and record the electrical activity of muscles. This recorded electrical signal is called as an electromyogram which helps to diagnose the conditions of muscle disorders. The time duration testing of EMG testing is approximately 30 to 90 minutes that depends on the study of muscles. This leads to analyze the abnormalities of neuromuscular disease. However, EMG is used for prosthesis control, rehabilitation and also for clinical diagnosis [1]. The electrical signals are generated in EMG which helps to control and activate the myoelectric artificial prosthetic arm, and then the electrodes are placed in the arm muscles through the surface of the skin. The types of electrodes are surface electrode, needle electrode and fine wire electrode. The electrical activity of the muscle should concern the clinical examination in EMG and the clinical

abnormalities of chronic denervation of a normal muscle are detected as shown in fig. 1[2]. However, the main issues are concluded during the measurement of EMG signals:

- The intensity and timing of muscle contraction, which is to determine any segments of the muscles in the area of electrode is active.
- The placement of electrode from the measure muscles area and the electrode must be placed in the belly regions of muscles
- The designed properties of muscle and electrodes are combined with two types of electrodes which can be further divided into two categories they are invasive and non invasive electrodes [1].

Besides, this paper represents the review of EMG signals which is based on different datasets then

the overall components and methods are discussed for future approaches.

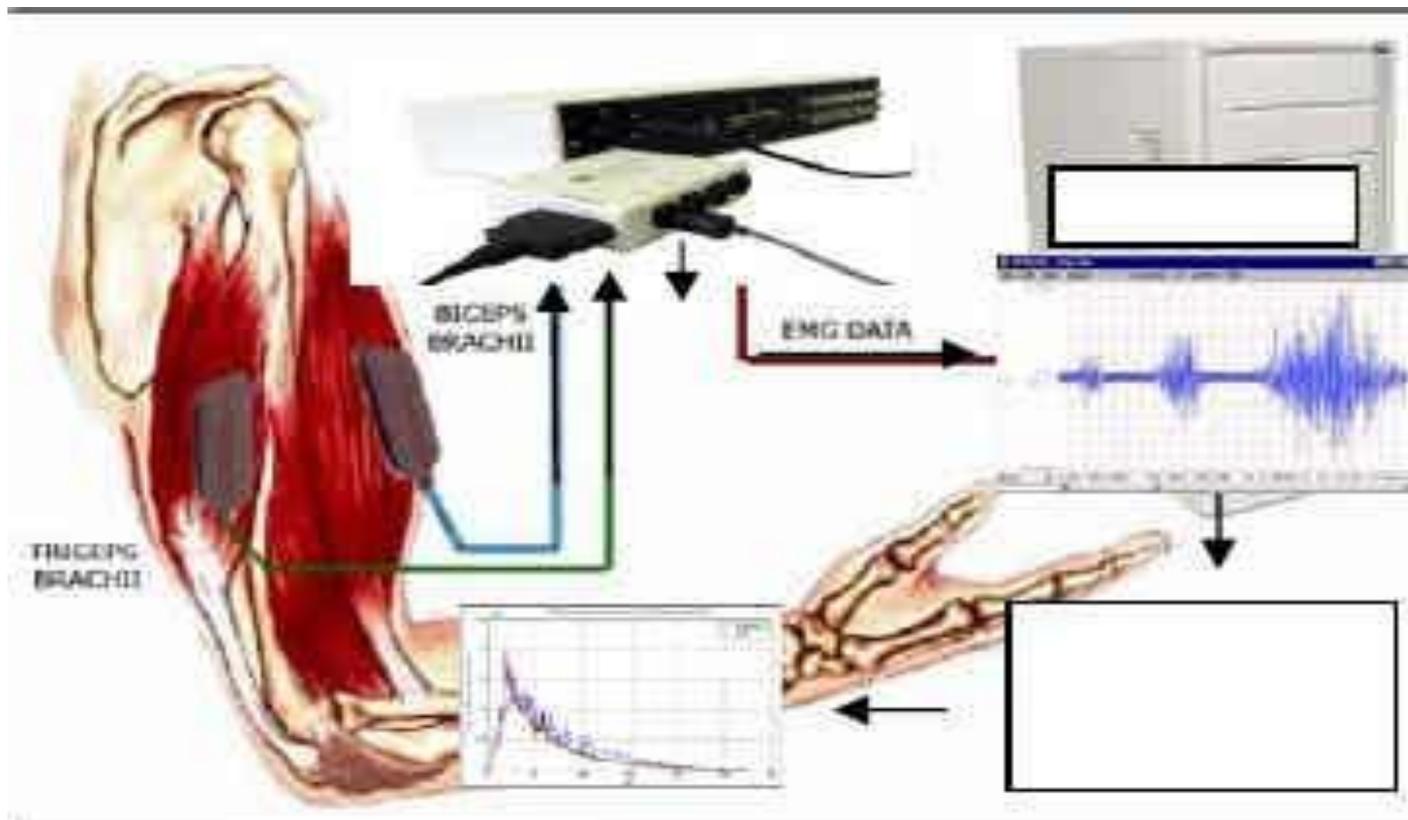


Fig.1 Block diagram of EMG Signal

II. REVIEW ON ELECTROMYOGRAM (EMG)

Joan Lobo-peter, peter N kooren et.al, suggests the EMG signal or force signals which are used as inputs for admittance based controller by using the samples of adult DMD patients (male). This design is used to analyze the interface, which is more suitable for control the wearable devices for activate the arm support [1]. Joan Lobo-prat, mariskajanssen, et.al, proposes the movements with force based control for three male adults with DMD in the age of (21-22 years). This study presents feasibility and performance evaluation of EMG signals [2]. For muscle detection, the ultrasound image acquisition was proposed to predetermine the force. Then, the features of input

images are sieving through edge detection parameters over a training dataset and the system performance are extended by muscle groups [3]. Yinxue Wang, Luca Bello, YueWang, et.al, suggests the machine learning approaches to predict age at LoA based on clinical measures of muscular strength and motor function using CINRG dataset. It is a multivariate model to predict the age at LoA for DMD patients based on clinical outcomes [4]. Further, the inconspicuous and simple planar active arm used to support the adults with DMD which can be controlled within the force or EMG based interfaces [5]

Sathyavikasini K, Vijaya et.al, proposes mutated gene sequences of fifty five genes for disease identification, positional cloning, disease gene

datasets, feature extraction and training dataset [6]. UvaisQidwai, AejazZahidet.al, suggests the detecting muscular movements from facial muscles especially eyebrow movement muscles using children with SMA datasets. This system is to enable the children to use computer system and other control systems [7].

Anne J. Pigula, Jim S. Wu et.al, contributes the ultrasound videos of muscle compression under known pressures in the biceps and quadriceps of 23 boys with DMD within 20 age-matched healthy controls, clinical data and demographics. It can be performed in a few minutes, and requires minimal action from the patient. Kostas Nizamis, Joan Lobo-Pratet.al, conducted the device in a 2-D horizontal tracing using EMG-based control interface to detect the user's movements [9]. Further, Global cardiac function and presence of fibrosis, but changes in these measures are late manifestations using the datasets of boys with DMD and associated with cardiomyopathies. It involves cardiac movement in DMD for improving patient care and aiding the evaluation of emerging therapies [10].

Lev R, Seliktar D, proposes the Cell delivery systems in muscle injuries and ailments, including their mild processing conditions. It uses the patients datasets includes muscular dystrophies and muscle injuries. The muscular dystrophies is the therapeutic repair of muscle injuries and muscle wasting diseases [11]. However the Software designed for use with the device computed several variables to qualify and quantify muscular activity in the non-ambulant subjects [12].

Further, the analyses are taken from different patients with genetic diseases. This problem is handled for non-synonymous single nucleotide variants (SNVs) that capture only missense and nonsense mutations. Then the outcome of trained model reports that the prediction accuracy of 86% in multi-class SVM with the RBF kernel [15]. David Sala, Thomas J. Cunningham et.al, proposes boosting muscle stem cells to treat muscular dystrophy and aging muscles for patients with muscular dystrophy [16]. The Predicting muscular dystrophy with sequence based features for point mutation for patients affected with genetic diseases caused by the deformity in the inherited genes. The resultant shows the prediction accuracy of 100% by estimating using 10-fold cross validation [17].

III. CLASSIFICATION

Feed forward Neural Network (FNN)

In multilayer neural networks, the information processing takes place only in the feed forward path, i.e. through the input layer, the output layer and the hidden layer. A MFNN is said to be static neural network model because it is characterized by non-linear equations that are memory less. In general, a single neuron computes the weighted input values and obtains output values through a non-linear activation function with a threshold. The Feed-forward neural networks (FNN) are widely used for pattern classification, due to probability distribution (or) classify the distant regions. It is mainly used for accurate classification of input data into various classes where these are obtained by pretrained model. Generally, the FNN architecture consists of multilayer neural network for specific application as shown in the fig. 1.

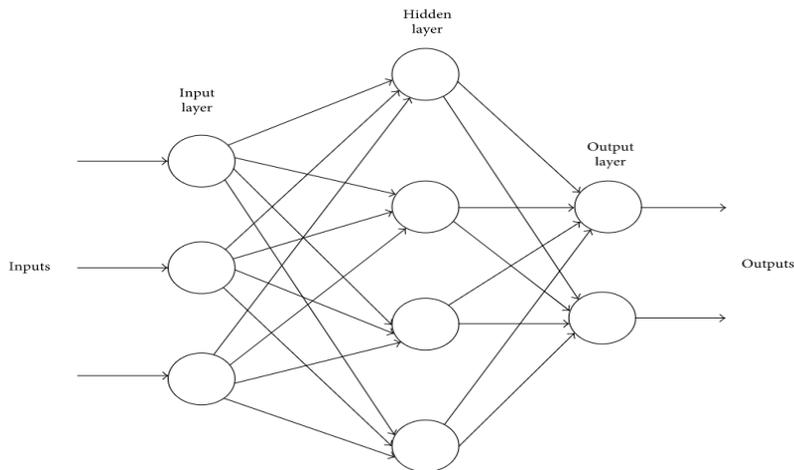


Fig. 2 Diagram of Feed forward Neural Network (FNN) [30]

Table.1 Classification results of Feed forward neural network

Parametric Feature	Accuracy (%)	Sensitivity (%)	Specificity (%)	F measure (%)
AR Pole Tracking with 10 th order	87	89	88	85
AR Pole Tracking with 15 th order	96	95	93	91
AR Pole Tracking with 20 th order	95	93	94	93.5

The major property of FNN are assigned in three ways i) Network topology, ii) the training and iii) activation function of neuron. The network might have more layers of neurons and its architecture supported for a feed-forward network. Similarly, linear neurons are selected for the output layer. Finally, the configuration represents the input neurons, hidden layer, and it indicates the brain under AD.

IV. RESULT AND DISCUSSION

In order to develop a generalized neural network model, the training samples are randomly selected from the total samples and a neural network is trained. 60% of dataset has been used for training

the neural network and the remaining 40% of dataset has been used to test the performances of the neural network.

From the Table 1, it can be observed that AR pole tracking with 15th order using MFNN reported the highest classification of MFNN has obtained specificity 96%, sensitivity 93% and F measure 90% when compared to 10th pole tracking.

V. CONCLUSION

Electromyography (EMG) is a device which is widely used to measure and record the electrical activity of muscles. This article represents the comprehensive review on EMG signals. It is based

on different algorithms using real time datasets interms of bandwidth, efficiency and system performance. Finally, the results are taken from FFNN algorithm and various methods are discussed for future approaches.

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