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Development of a Decision Support System for the Diagnosis of Neuromuscular Disorder using Neural Network

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Abstract: Since past few years, researchers have been concentrating on the classification of Electromyography Signal. This method is very beneficial in detecting the neuro-muscular disorders, which consists of wide spread diseases affecting peripheral nervous system. Progressive muscle weakness is the major form of these disorders. Out of various proposed methods, scholars are commonly focusing on Neural Network for its accuracy. And the basic variant feature, Motor Unit Action Potential is selected for classification. Out of various available tools, this research uses Discrete Wavelet Transform as a tool for classification and for the training of N-Network, a multilayer feed forward neural network with back propagation algorithm is used.

Keywords: Artificial neural network (ANN); Discrete wavelet transform (DWT); feed forward neural network (fNN); Motor unit Action Potential (MUAP); Amyotrophic Lateral Sclerosis (ALS); k-Nearest Neighbors (kNN); Electromyography (EMG)

I. INTRODUCTION

Nervous system works as a network, which passes electric signals to and fro between brain and body organs. These signals generate a potential, which is a function of time. A process called Electromyography evaluates and records electrical variations of skeletal muscles with time.

Our interest is to make a tool for diagnosing neuromuscular disorders. The neurons that connect muscles and brain surface i.e. grey matter generates electrical signals to and fro ash shown in figure 1.

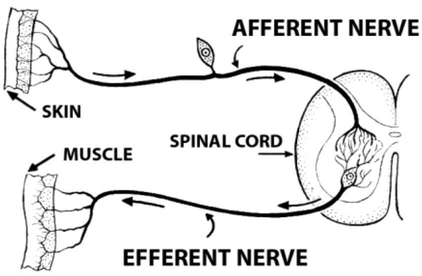

Figure 1. Nerve fiber taking the signal from skin or muscles to brain

These neuron fibers actually take the signal from brain to muscle or skin and from muscle to brain, thereby control the muscle movements. Multiple types of electrodes are available for recording of EMG signal.

Needle Electrode is used to read muscle EMG signal and Surface Electrode is used to read skin EMG signal. For this research, a 25 mm Needle Type Electrode is suitable under hygienic clinical environment to read potential of motor nerve. This is called as Motor Unit Action Potential or MUAP. These signals are generated by muscles and goes to Central Nervous System CNS through motor nerve. This is shown in figure 2.

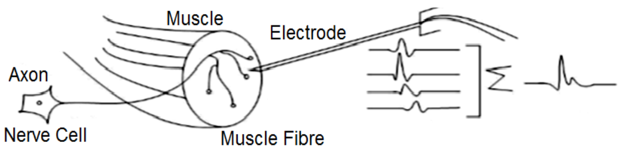

Figure 2. Anatomical Model for recording of EMG Signal.

The Neurophysiologist usually decode the MUAPs information from graphical patterns using oscilloscope [1]. As a single needle electrode makes the contact with multiple nerves, therefore receives a composite signal of different shapes and sizes on graphical screen. To classify muscular disorders visually from the received composite signal is very difficult, thus various algorithms have been developed.
In this work, to classify between myopathy, ALS and healthy patient signals we have used wavelet based classification scheme. This has been accomplished through Feed Forward Neural Network using Back Propagation Neural Network.

Here, features are extracted using DWT (discrete wavelet transform). As we know that in practical case, EMG signal is a continuous composite signal varying with time, thus, decomposing it using wavelet transform is quite efficient. For decomposing a software known as EMG-LODEC is specially developed for recording multichannel long-term signals. The wavelet based algorithm distinguishes single MUAP by superposing the input signal [3].

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II. METHODOLOGY

Classification of EMG signal needs following steps, which include (1) Reading EMG signal in wave format, (2) Feature extraction by wavelet, (3) Classification by NN. The block diagram of proposed work is shown in figure 3.
The EMG signal samples of a myopathy, ALS and a normal person were collected from [4]. Signals from arm biceps of different persons are taken. The recording is done at low level but just above the threshold of constant contraction. The HPF of EMG amplifier is set at 2 Hz while LPF is set at 10 kHz [5].

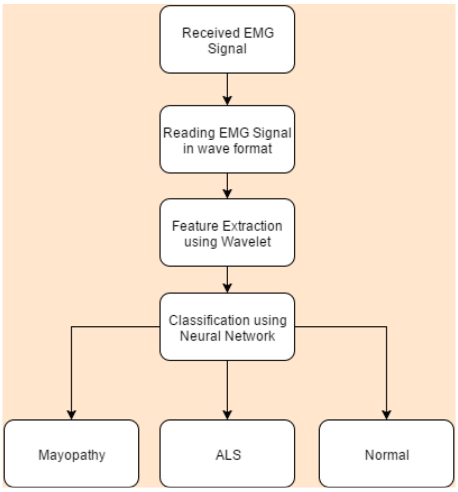

Figure 3. Block Diagram for Classification of EMG signal.

III. DWT FEATURE EXTRACTION

Any classification method can't be directly to the EMG samples, due to the large amount and the high dimension of the examples are necessary to describe such a big variety of clinical situations. A set of algorithms is usually adopted to perform a numerical description of the signal and a parameter extraction from the signal conditioning to the calculation of average wave amplitudes, its durations, and its areas, [6].
Discrete wavelet transform (DWT) in comparison with discrete Fourier transform (DFT) is an efficient time-frequency approach which has been used for processing multiple biomedical engineering signals, viz. EMG. Thus, for EMG, DWT provides the time and frequency information simultaneously [7]. Equation (1) shows wavelet function.

$$X(a,b) = \frac{1}{\sqrt{b}} \int_{-\infty}^{\infty} x(t) \Psi\left(\frac{t-a}{b}\right) dt$$

Where 'a' and 'b' are the dilation and the translation parameters respectively. In this present work Db4 (Wavelet Daubechies-4) wavelet is used. For best result, the pre-processed EMG signal is decomposed by using the discrete wavelet transform up to the 10th level because only 262134 samples are available with this work. The feature set consists of levels 1 to 10 and coefficients cd1 to cd10 and ca10. The energy peak of the EMG signal falls between a range of frequency from 0.5 Hz to 40 Hz. This energy of the wavelet coefficients is much intense in the lower sub-bands ca10, cd10, and cd9. The levels 1 to 8 and coefficients cd1 to cd8 are ignored as they lack information and intolerable noise is present in the frequency band of these levels. Coefficients cd9 and cd10 shows the highest frequency components and ca10 shows the lowest one. The obtained feature vectors form Db4 and wavelets decomposition is given as an input to the Neural Network classifier.

A. Discrete wavelet algorithm

The EMG Signal information is passed through two convolutions functions (filters), each of which gives an output stream which is half in length to that of original input. One half of the output is produced by the LPF given by equation (2).

$$y_1[k] = \sum_n x(n) h_0[2k-n]$$

While another half of it is produced by the HPF given by equation (3).

$$y_2[k] = \sum_n x(n) h_1[2k-n]$$

Where y1 and y2 are the output of LPF & HPF respectively, which are known as an approximate and detail component. These outputs are down sampled by a factor of 2, which is known as 1-level decomposition. This process is repeated up to 10 levels of decomposition, which results in a reduction of samples from 262134 to 262. This is suitable for training of neural network.

IV. NEURAL NETWORK CLASSIFIER

The neural network is one of the efficient and accurate classifier. It has dense parallel structure & it learns from previous experience. The accuracy of the classification is based on training of the neural network. In this research, Multilayer Feed Forward NN with Back Propagation Algorithm is used.
The information obtained from experience is stored as connection weights. The weighs updates after training, which runs in multiple iterations to get the desired level of training. Since this algorithm is a supervised training algorithm, three issues need to be solved in designing an ANN for a specific application. In this work, total 14 hidden neurons are used, simplified network is shown in figure 4.

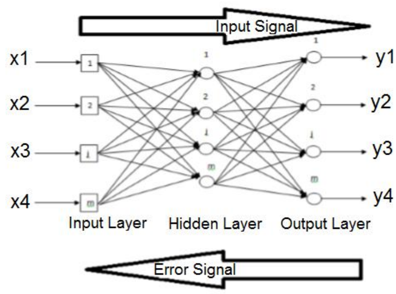

Figure 4. Back Propagation neural network.

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V. K-NEAREST NEIGHBOR TECHNIQUE

The k-Nearest Neighbor is denoted by k-NN. If the cost of error is same for each class, the estimated class of an unknown sample is chosen to be the class, which is normally represented in the collection of its K nearest neighbors. This technique does not consider a priori assumptions about the distributions wherefrom the training samples are taken. For classification of a new sample, the distance to the nearest training case is calculated then the sign (plus or minus) of this point classifies the sample. The k-NN classifier picks the k nearest points and allot the sign of the majority. Large value of k reduces the effects of noisy points within the training data set, and cross-validation is used to choose the value of k. This way, its Euclidean distance d is calculated. Equation (4) with all the training samples classifies to the class of the minimal distance.

$$q(x, y) = \sqrt{\sum_{j=1}^{n} (x_j - y_j)^2}$$

Each training example along with a class label becomes a vector in the multidimensional feature space. The algorithm's training phase includes only storing of the feature vectors and class labels of the training samples. The algorithm's classification phase has 'k' as a user-defined constant, and the unlabeled vector is classified by assigning the label. Even if the Euclidean distance is only applicable to continuous variables, it is used as the distance metric.

VI. RESULT AND DISCUSSION

In this method, features are extracted using wavelet for neural network. Decomposition up to 10 levels for the samples from ALS, Myopathy and Healthy person is shown in figure 5. Decomposition to higher levels depends on the number of samples present in a given signal. To get clear information for a very large number of samples, it can be decomposed to a level higher than tenth level. After tenth level of db4, the Histograms of samples shown in figure (6) distinguish the three classes, which are to be given to neural network.

kNN and fNN classifier produces different results. Confusion matrix for kNN is shown in table I and II simultaneously, where a set of 100 signals are used for training and 50 samples are given for testing. Where a randomized data sets are used having different classes in differently. Since this data sets are randomized before input to kNN classifier each group have different samples. Whereas in fNN the data sets are randomized and it is classified MATLAB environment. In this confusion matrix out of 150 samples the neural network took 60% of sample for training 20% for validation and 20% for testing.

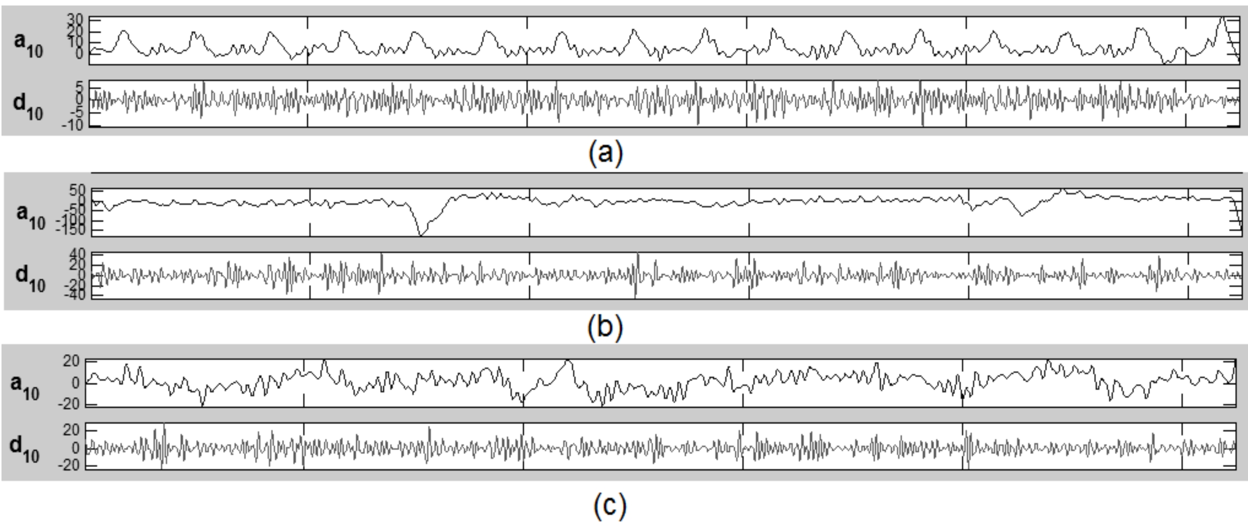

Figure 5. Time varying signal of (a) Healthy (b) ALS (c) Myopathy

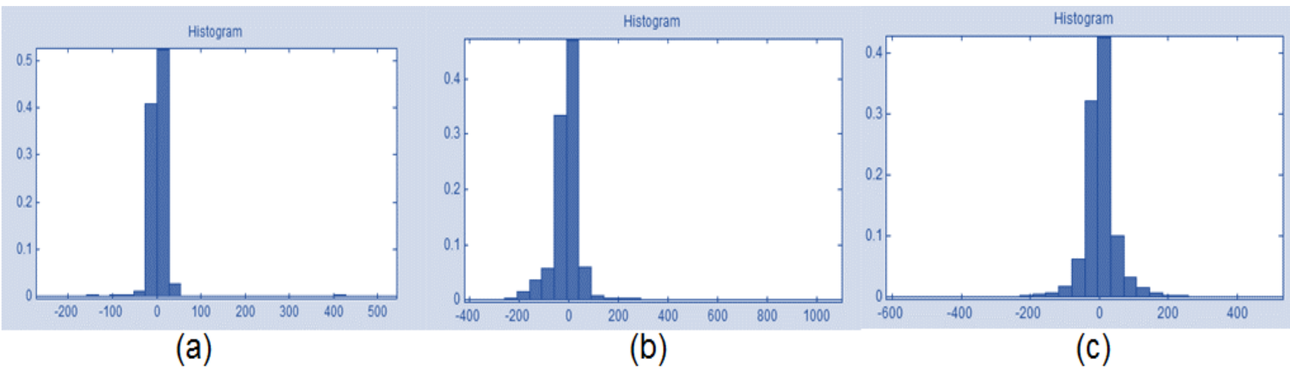

Figure 6. Histogram of (a) Healthy (b) ALS (c) Myopathy

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CONCLUSION

This paper focuses on evaluating two classification strategies to classify the MUAPs into the following classes, normal, myopathic and neuropathic. The proposed classification strategies consist of several base classifiers which take different MUAPs features such as time domain features, time frequency features (wavelet coefficients), These classification strategies can be employed in other pattern recognition applications because they segment a big decision into several detailed decisions where the input of each decision node can be separately optimized. Multi-classifier overcomes limitation of single stage classifier but with a cost of complexity and processing time. Although the result of time-frequency features is superior to the time domain ones, selecting both types of feature result in promising results (97%) for the three classes. These classification strategies can be employed in other pattern recognition applications. Through our experiments, the proposed method always outperforms the DWKNN classifiers among a large range of k and its effectiveness was demonstrated with good performance. For extending this research is to investigate influence of the recording conditions on the classification accuracy.

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