Detection of EMG Myopathy Signal Using Wavelet Transform and Neural Network Techniques

G. Kanimozhi

Abstract--- *This paper recognizes signals from two sources, where one is a normal person and the other is a myopathy patient. The signals under experimentation were acquired from the branchial biceps (BB) muscles using a needle electrode. This paper focuses on the technique of Wavelet Transformation (WT) to extract the features from an EMG (Electromyogram) signal. It includes decomposing the EMG signal into different levels to generate the coefficients. Self-Organising feature map (SOFM) and Linear Vector Quantisation (LVQ) neural networks were constructed from the extracted coefficients and both of these were trained with supervision. These two networks proved to be a powerful tool for diagnostic purposes, clearly separating normal EMG from a myopathic one.*

Keywords--- *Electromyogram, Myopathy, Wavelet Transformation, Self-Organising Feature Map, Learning Vector Quantisation*

I. INTRODUCTION

MYOPATHY is also known as the dysfunction of muscles. Though this paper uses a particular muscle set – biceps brachii (BB), but myopathy is not localised only to this area. This paper concentrates only on this muscle set. BB, or simply biceps, falls under the category of skeletal muscles. These are connected to the bones located in the upper forearm of the body. This muscle set is responsible for the two actions, namely – elbow flexion and forearm supination. For EMG recordings, both these actions were performed by the subjects.

Myopathy causes weakening of muscles it affects. Cramping, stiffness, fatigue, pain, spasms, atrophy etc., as shown in Fig. 1, are some general symptoms of this disease. BB along with other central muscles, like that of thighs and shoulders are often affected by this disease.

Diagnosis of this disease is necessary so as to avoid permanent disability or paralysis in some cases. Myopathy can be detected by physicians using several techniques, of which one includes reading the aforementioned general symptoms. Other techniques include blood testing, neurological testing, biopsy, studying family disease history, EMG recording etc.

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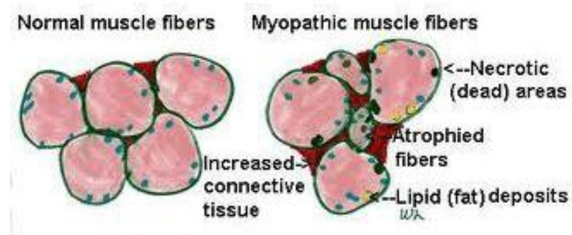

Fig. 1 Structure of Muscle fibres (Normal versus Myopathic)

Electromyograph records muscular activity of a patient. And the recording is known as EMG. Surface and needle electrodes are the two ways of recording an EMG. This paper focuses on needle electrodes for its proven advantages over surface electrodes. Example has been shown in Fig. 2. Needle electrodes are inserted into the muscle tissue. The rest and the contraction state of the muscles are recorded by the instrument. The recorded pattern is an indication of the state of the muscles. Normally, there are not much specific differences between a normal EMG and a myopathic EMG. However, myopathic EMG signal may have decreased amplitude or decrease in area of action potential. The differences may vary from patient to patient. The signals were collected from multiple subjects, which included 6 myopathy patients and 10 normal subjects. The aim was to generalize the networks so that their applicability can be extended to the medical field.

Since it has been observed that the signal differences may vary from patient to patient, therefore, the key to distinguish these signals lies in proper extraction of the features which serve as the input to the neural networks.

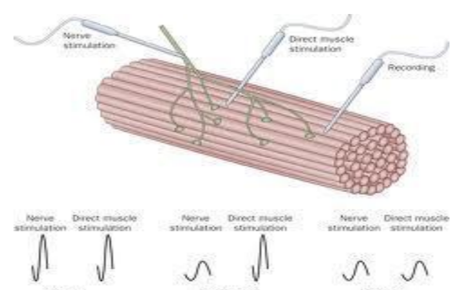

Fig. 2 EMG Signal Acquisition

The advantage with the WT lies in the selection of coefficients based on the reconstructed signal so that the appropriate signal range can be included. That is to say, the signal can be analysed both in time and frequency after it has been transformed. Here 'sym8'wavelet decomposition technique has been used.'Sym8'is a type of WT which falls under 'Symlet' family of discrete wavelet transforms, known for its orthogonal properties. The pulses of the mother wavelet are almost symmetric. The preference for this family of transformation was formed on tested results.

II. METHODOLOGY

2.1 Self-Organising Feature Map

These come under unsupervised category of neural networks. They are trained with algorithms that do not need specified output targets. However, it is possible to use supervised algorithms so that the results produced are better. The making of this network in MATLAB starts with specifying the learning rate, initial neighbourhood and epochs. The algorithm for this network is competitive type. That means the weight of only the winner neuron and its neighbouring neurons is updated. Here the winner neuron is decided by the distance. The neuron whose weight is close to a particular input vector is a winner. This allows winner neuron to further get close to the input vector it depicts, while all the other neurons are left unchanged. The weight equation of a winner neuron and all the neurons in its neighbourhood N (d), after 1 iteration, is given as follows:

$$w(n) = w(n-1) + [\, I(n) - w(n-1)] \qquad (1)$$

where w(n) is the updated weight, is the learning rate, I(n) is the input vector, w(n-1) =randomised weight at the starting or weight at previous step

EMG signal was exported into the MATLAB, one patient at a time. Using the commands like *wavedec*, *appcoef*, *detcoef*, the signal was decomposed into 6 levels [1]. Now each level was reconstructed and appropriately the maximum values [1] of the last 3 levels of detailed coefficients d4, d5, d6 along with approximate coefficient at level 6 (a6) were chosen to be the input to the neural network. Same procedure was adopted for all the signals. After arranging the signals column wise, the coefficients were normalised.

For training purpose, target vectors were specified. Each target vector was a column matrix with all its elements as zeroes except for one row which depicted the class it belonged to. The number of rows was dependent on the number of classes being worked upon. Here, the no. of rows is 2 since two types of EMG were to be classified.

SOFM using the command *newsom* was created with all the default parameters. Since there were two classes to differentiate, the focus was on one dimensional map having just two output nodes. The training function used was *trainr*. This function randomises all the weight parameters and according to the algorithmic function as discussed above, the weights are updated. At no point did the network goal performance reach zero level, even with the variation of the learning function. The test signals were arranged in the similar manner as the input. Using the command *sim*, the network was tested against the arranged test set. The answer was converted to indices for better result interpretation. Considerable accuracy was achieved at α=0.1.

2.2 Learning Vector Quantisation

This type of network also comes under the category of competitive learning. The difference lies in this being a supervised one, and it has a two layer network. The first layer classifies the inputs and the second layer assigns the classes to the inputs as specified by the programmer. The equation for weight update is will be discussed as follows:

Suppose several inputs x1(t), x2(t), x3(t). Let the corresponding outputs classes be i, j, k where $i \neq j \neq k$

$$wi1(t) = wi1\,(t-1) + \alpha\, [\, x1(t) - wi1(t-1)] \qquad (2)$$

where α is the learning rate, wi1(t) present value of weight between output i and input x1(t), wi1 (t-1) previous value of weight between output i and input x1(t),

This equation is valid as x1(t) belongs to class i or output i. But in case of x2(t) here the equation will become as:

$$wi2(t) = wi2(t-1) - [\, x2(t) - wi2(t-1)] \qquad (3)$$

I.e. the correctly classified inputs will move closer to the output and the others will move further apart.

The reason for its selection lies in the fact that this network took less iteration for learning. Moreover, the results were better [6], as will be discussed later.

The data preparation was done in the same manner as discussed for the SOFM network. LVQ was created using the command „lvqnet". The number of hidden neurons was taken to be 20, with 10 neurons classifying each class. The learning function was chosen to be „learnlv1" which follows the same weight update procedure as discussed in this section above. The learning rate of 0.07 was able to train the network within a matter of few seconds. The created network was tested for the same test set as the SOFM.

III. RESULTS

Signals were obtained from 6 myopathic patients and 10 normal subjects. Moreover, each patient contributed for multiple signal sets. Ten sets of signals from each myopathic patient, and 10 sets from normal ones, were taken. Out of the 60 myopathic signals and 100 normal ones, only 20 myopathic and 40 normal signals were used for training purposes. Rest were used for testing of the networks. For testing, the mean values of multiple test vectors were fed. LVQ fared better between the two with lowest accuracy of 83.33% whereas SOFM had accuracy as low as 40.00%. Table 1 shows some of the results observed for 5 samples- 4 myopathic(M), 1 normal(N) signal.

For better interaction with the evaluation procedure, a MATLAB Graphic User Interface (GUI) for a few test signals was made as shown in Fig. 3. Along with the ease of access to the whole procedure, it proved to be less cumbersome and more presentable as shown in Fig. 4.

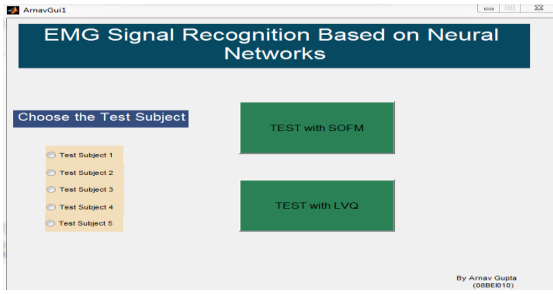

Fig. 3 GUI Main Screen

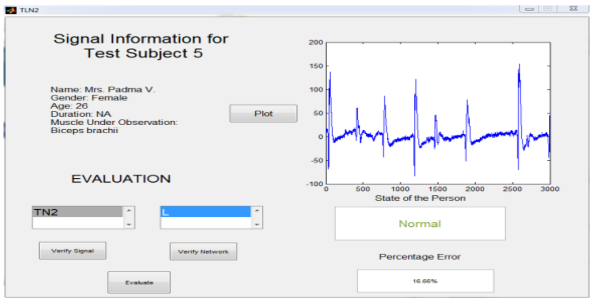

Fig. 4 Signal Evaluation

IV. DISCUSSION

This paper described the technique of combining the use of WT along with either the SOFM or LVQ to detect the presence of Myopathy disease. Here, wavelet transformation served the purpose of feature extraction. The features extracted or the coefficients generated by „sym8" were used as input to the neural networks in vector form. The two methods mentioned above have a fairly large accuracy percentage for them to be used as a diagnostic tool in medical field. The technique mentioned in this paper is a mathematical tool for the detection of myopathy as compared to the conventional instrumental ones. Hence, it is faster, efficient and robust as it is resistant to environmental hazards.

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