# Diagnosis of Neuromuscular Disorders Using Softcomputing Techniques

**Akhila Devi B V,S.Suja Priyadharsini**

***Abstract***— ***Biomedical signals are collection of electrical signals which generated from any organ that signal represents a physical variable of interest. Electromyography (EMG) is a technique for evaluating and recording of electrical activities produced from skeletal muscles. There are so many applications of EMG signals. Major interests lies in the field of clinical as well as biomedical engineering.EMG is used as a diagnostic tool for identifying neuromuscular disorders .Motor unit action potentials (MUPS) provides information about neuromuscular disorders. Traditionally neurophysiologist can access MUPs information from their shapes and patterns using an oscilloscope. But MUPs from different motor neurons will overlap leads to the formation of interference pattern and it is difficult to detect individual shapes accurately. For this reason a number of computer based quantitative EMG analysis algorithm have been developed. In this work, different types of learning methods were used to classify EMG signals. The model automatically classifies EMG signals into normal, myopathy and neuropathy. In order to extract useful information from the EMG signals different feature extraction methods such as discrete wavelet transform(DWT) and auto regressive modeling(AR)are implemented. Adaptive neuro-fuzzy inference system (ANFIS) with hybrid learning algorithm, support vector machine (SVM) and fuzzy support vector machine (FSVM) were compared in relation to their accuracy in the classification of EMG signals. Based on the impacts of features on the EMG signal classification, different results were obtained through analysis of the soft computing techniques.***

***Index Terms***— ***Adaptive neuro-fuzzy inference system (ANFIS), Discrete Wavelet Transform (DWT), Electromyography (EMG) Fuzzy SVM (FSVM), Support vector machine (SVM)***

## I. INTRODUCTION

Electromyography (EMG) is a data collection technique in which electrical activities are generated from a contracting muscle using a needle electrode is used to diagnose neuromuscular disorders in clinical neurology. There are more than 100 neuromuscular disorders that affect the brain, spinal cord, nerves and muscles. Early detection and diagnosis of these diseases by clinical examination and laboratory tests is essential for their management as well as their prevention through diagnosis and counseling. Other major applications of EMG signals are used in many types of research laboratories including biomechanics, motor control, neuromuscular physiology, movement disorders, postural control and physical treatment.EMG is used as a main tool for checking brain death and various injury cases.

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As well as EMG signals are used as control signals for prosthetic arms, lower limbs. The frequency range of EMG signals are from 0 to 500 *Hz* and potential range between less than 50 $\mu v$ and up to 30*mv*.

EMG consists of discrete waveforms called motor unit action potentials (MUPs), which result from the recurring discharges of groups of muscle fibers called motor units (MUs)[2].MUAPs from different MUs tend to have distinct shapes, which remain almost the same for each discharge. These MUAPs can be identified and tracked using different pattern recognition techniques. The resulting information can be used to determine the neuromuscular diseases [5].Neuromuscular disorders are related to pathological changes in the structure of motor units and can be divided into muscular (myopathy) and neuronal disorders (neuropathy). Myopathy is neuromuscular disorders in which the primary symptom is muscle weakness due to dysfunction of muscle fibers[12]. Neuropathy describes damage to the peripheral nervous system which transmits information from the brain and spinal cord to every other part of the body [12]. A particular neuromuscular disease alters the properties of the muscle and nerve cells, causing characteristic changes in the MUAPs.When a patient maintains low level of muscle contraction, the individual MUAPs can be easily recognized.When the force of contraction increased, additional motor units start to fire and the EMG signal becomes more and more complex, and as a result, individual MUPs cannot be identified easily. This signal is recognized as the interference pattern (IP) [1]. Conventionally in clinical electromyography, neurophysiologists assess MUAPs from their shapes using an oscilloscope and analyzing with their audio characteristics. However, subjective MUAP assessment is satisfactory for the detection of abnormalities, may not be sufficient to detect less obvious deviations or mixed patterns of abnormalities.

## II. LITERATURE SURVEY

With the aid of computer technology, today it is possible to analyze EMG signals quantitatively that helps in saving time, standardizes the measurements and enables the counting of additional features which cannot be easily calculated manually.A number of computer based quantitative EMG analysis algorithms have been developed in the past. Pattichis et. al,[4] proposed neural network models in EMG diagnosis which presents the parametric pattern recognition (PPR) algorithm that facilitates automatic MUAP feature extraction and Artificial Neural Network (ANN) models are combined for providing an integrated system for the diagnosis of neuromuscular disorders. Katsis et.al,[4]



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proposed a novel method for automated EMG decomposition and MUAP classification' which presents a method such as support vector machine(SVM) automatically detects the number of template MUAP clusters and classifies them into normal, neuropathic or myopathic. Subasi et. al,[3] proposed classification of EMG signals using wavelet neural network in which feed forward error back propagation artificial neural networks (FEBANN) and wavelet neural networks (WNN) based classifiers were developed and compared in relation to their accuracy in classification of EMG signals. Pino et. al,[11] proposed motor unit potential characterization using pattern discovery in which Naive Bayesian (NB),decision tree(DT), and pattern discovery (PD) classifiers for MUAP classification and discriminant analysis method which is used to select or extract good features were used.

The objective of this work is to detect neuro- muscular disorders from the classification of EMG signals using neuro-fuzzy technique such as ANFIS and machine learning techniques such as SVM and FSVM. Also examine the performance of classifier by calculating classification accuracy. In the existing work ANFIS classifier combined with statistical features extracted from DWT and AR modeling methods were used to classify EMG signals. Proposed system introduce SVM and FSVM techniques for classification with DWT alone. A methodology has been developed for EMG signal classification which consists of two steps. In the first step, the EMG signals are decomposed into different frequency bands using discrete wavelet transform (DWT) and auto regressive modeling(AR). In the second step, an unknown EMG signal is classified as normal (NOR), myopathic (MYO) or neurogenic (NEU) using soft computing techniques

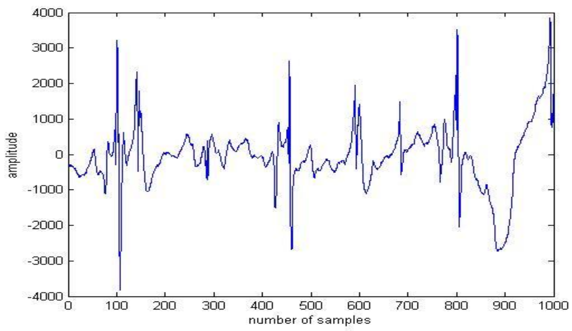


**Fig.1 Raw EMG Signal**

## III. MATERIALS AND METHODOLOGY

### *A. Subject and data acquisition*

All the EMG signals were acquired from the tibialis anterior muscle at up to 30% of the maximum voluntary contraction (MVC) level under isometric conditions. The EMG signals were acquired for 5 seconds, using the standard 25mm concentric needle electrode, from NOR, MYO and NEU subjects. In this study, EMG data collected from 15 subjects were analyzed.

### *B. Feature extraction method*

Any classification method is normally impossible to apply directly to the EMG samples, because of the large amount and the high dimension of the examples signals necessary to describe a variety of clinical situations arise. So feature extraction is a significant method to extract the useful and information which is hidden in EMG signal and to remove the unwanted part and interferences [1]. For the success of EMG signals classification it is desired to select suitable feature vectors to be considered carefully.

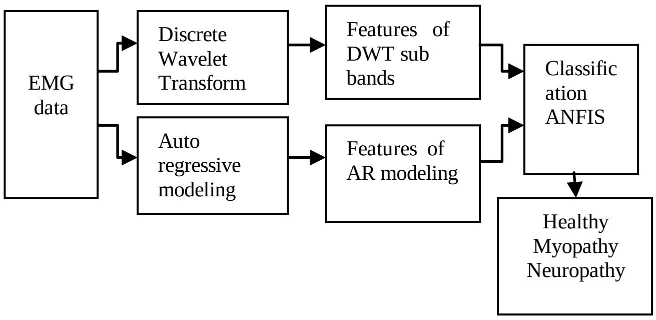


**Fig 2. Block diagram of existing sytem**

### *C. Autoregressive Modeling ( AR modeling)*

The autoregressive (AR) time series model has been used to study EMG signal. AR modeling is one of the parametric method make use of a linear process which can be used to estimate power spectrum of input signals. The given signal is treated as the output of a linear time-invariant system driven by a white Gaussian noise. The AR model can also be treated as an attempt to predict the current signal sample based on *p* past values of the signal weighted by constant coefficients. It estimated the best model by trying to minimize the mean squared error between the signal sample predicted by the model and the actual measured signal sample[7]. The equation of a classical AR complex process, in a non-stationary context, is given by:

$$x(n) = -\sum_{i=1}^{p} a_p(i)x(n-i) + u(n) \qquad (1)$$

Where '$x(n)$' is the model output, '$a_p(i)$' are AR complex parameters, '$p$' is the AR model order, '$u(n)$' is the input or noise function and '$n$' is the sample time.

One of the most popular methods for estimating the AR parameters of a sequence of N data points is using Burg's algorithm. The AR Burg algorithm was applied to a specific EMG signal epochs (1024 samples). One of the most important aspects of the model-based methods is the selection of the model order. Akaike information criterion (AIC) model order estimation works well in combination with the Burg's method.In this work, model order of the AR method was taken as 15 by using AIC and window size is taken as 256. The AR PSDs, which are extracted from normal, myopathic and neurogenic EMG signals respectively, is used as an input to classifiers.

### *D. Feature Extraction using Discrete wavelet transform*

Wavelet transform (WT) is a powerful time-frequency approach which has been applied to multiple domains of bio signal processing, such as EMG. But discrete fourier transform (DFT) which is less useful in non stationary signals , localized only in frequency domain and having issues with time frequency resolution. At the same time WT is able to provide the time and frequency information at the same time, thus giving a time–frequency representation of the signal. The WT allows the discrimination of non-stationary signals with different frequency features. The wavelet transform decomposes a signal into a set of basic functions called wavelets.

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{b}\right) \quad (2)$$

Where $a = 2^m$ is scaling parameter, $b = n2^m$ is translation parameter.

On the other hand, the discrete wavelet transform (DWT) presents adequate information both for the analysis and synthesis of the original signal, with a significant reduction in the computation time. DWT is used to decompose a signal by using filters to extract interesting frequency resolution components within the signal. DWT analyzes the signal by decomposing the signal into approximation and detail coefficients.DWT employs two sets of functions called scaling functions and wavelet functions, which are related to low-pass and high-pass filters, respectively. Each stage of this scheme consists of two digital filters and two down-samplers by 2. x[n] is the original signal to be decomposed, and h[n] and g[n] are low pass and high-pass filters, respectively[13].

$$y_{high}[k]=\sum_n x[n].g[2k-n]$$

$$y_{low}[k]=\sum_n x[n].h[2k-n] \quad (3)$$

Where $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the high-pass and low pass filters, respectively, after sub-sampling by 2. The approximation and detail records are reconstructed from the Daubechies 4 (DB4) wavelet filter and feature set is composed of level 1,2,3, 4, and 5 coefficients cd1,cd2 cd3,cd3,cd4,cd5 and ca5. Most of the energy of the EMG signal lies between 0.5 Hz and 40 Hz. This energy of the wavelet coefficients is concentrated in the lower sub-bands ca5, cd5 and cd4. The level 1, 2 coefficients cd1 and cd2 are the most detail information of the signal and they are discarded. Since the frequency band covered by these levels contains much noise.The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EMG signal in time and frequency. In order to decrease the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients were used [9].

(1) Mean of the of the coefficients in each sub-band.
(2) Variance of the coefficients in each sub-band.
(3) Skewness of the wavelet coefficients in each sub-band.

Features 1 represents the frequency distribution of the signal and the features 2 and 3 the amount of changes in frequency distribution. Total 15 feature are extracted, which are 5 different values for features (1), (2) and (3).These feature vectors, calculated for the frequency bands A5 and D1–D5 and were used as an input to classifiers.

### *E. Neuro- Fuzzy classification techniques*

Due to the nature of the EMG signal, there would be a large variation in the value of particular feature between individuals. Many factors such as changes in electrode position, signal training will produce changes in feature values over time. A suitable recognition method must be able to accommodate the expected individual difference. Fuzzy set theory plays a vital important role in dealing with uncertainty when making decisions in biomedical field of applications. The classifiers proposed for the classification of the EMG signals were implemented by a simple approach based on ANFIS is to classify the EMG signal to one of the categories, NOR, MYO or NEU.

*Adaptive neuro fuzzy inference system(ANFIS)*

The architecture and learning procedure underlying ANFIS is presented which is a fuzzy inference system implemented in the frame work of adaptive networks. By using a hybrid learning procedure the proposed ANFIS can construct a input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs[8]. To present the ANFIS architecture , two fuzzy if-then rules based on a first order Sugeno model are considered:

Rule1:If ( $x$ is $A_1$ ) and ( $y$ is $B_1$ ) then ( $f_1 = p_1x + q_1y + r_1$ )

Rule2: If( $x$ is $A_2$ )and( $y$ is $B_2$ ) then ( $f_2 = p_2x + q_2y + r_2$ )

The ANFIS architecture to implement these two rules is shown in Fig. 3 in which a circle indicates a fixed node, whereas a square indicates an adaptive node. Five layers are used to create this inference system. Each layer involves several nodes described by node function.[6]

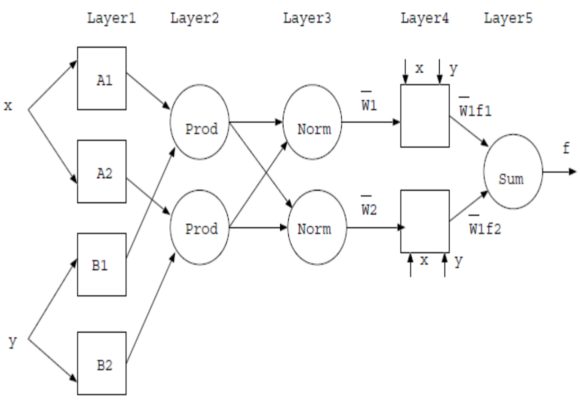


**Fig.3 General Architecture of ANFIS**

**Layer 1**: In this layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O_i^1 = \mu_{A_i}(x) \quad i = 1,2 \quad (4)$$

$$O_i^2 = \mu_{B_{i-2}}(y)$$
$$i = 3,4$$
(5)


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Where $\mu_{A_i}(x)$ , and $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function. For example, if the bell shaped membership function is employed, $\mu_{A_i}(x)$ is given by:

$$\mu_A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \qquad (6)$$

Where $a_i, b_i, c_i$ are premise parameters.

**Layer 2**: Each node in this layer is a fixed node, indicated by circle node, whose output is the product of all incoming signals:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1,2 \qquad (7)$$

The output signal $w_i$ represents the firing strength of a fuzzy rule.

**Layer 3**: In order to find the normalized firing strength, the ratio of the $i_{th}$ rule's firing strength to the sum of all rules' firing strengths can be calculated as:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad (8)$$

**Layer 4**: The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial .Thus the outputs of this layer are given by:

$$O_i^4 = \overline{w}_i f_i = w_i(p_i x + q_i y + r_i) \qquad (9)$$

Where $\overline{w}_i$ is the normalized firing strength from layer 3 and $\{p_{i,} q_i, r_i\}$ is the parameter set in this layer which are referred to as the consequent parameters.

**Layer 5**: Each node in this layer is a fixed node, indicated by circle node, with node function to compute the overall output as the summation of all incoming signals.

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \qquad (10)$$

*Learning Algorithm*

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely {*ai*, *bi*, *ci*} and {*pi*, *qi*, *ri*}, to make the ANFIS output match the training data. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [6].

In this work, a network of 64 nodes, 15 rules, 15 Gaussian membership functions,20 epochs and 16 unknown parameters was used. It must be mentioned that the ANFIS methodology is been used here to obtain a first order Sugeno model. The ANFIS used 12 training data and the step size for parameter adaptation had an initial value of 0.011.After training, 12 testing data were used to validate the accuracy of the ANFIS model for EMG signal classification. The neuro-fuzzy models were designed with different features of EMG signal in the input layer; and the output layer consisted of three nodes representing normal, myopathic or neurogenic disorder. A value of 1was used when the experimental study indicated a normal, 2 for myopathy and 3 for neurogenic.

*Support Vector Machine (SVM)*

SVM is a supervised machine learning method.SVM techniques is an attractive kind of machine learning method introduced by Vapnik and co-workers[13]. Our present analysis is purely based on the multiclass data classification by employing SVM techniques. This method builds a hyper planes for separation of data into two classes in simple binary classification of linear separable training data vector $x_1, x_2, ....x_n$ in n dimensional Space.[14].

hyper-plane can be defined for linearly separable data

$$y(x) = w^T \phi(x) + b \qquad (11)$$

Where $w$ and $b$ are weight vector normal to Hyper-plane and bias value respectively. New test data according to the SVM classifier is assigned to a class according to sign of decision function as:

Testing data belongs to class 1(normal class) if $w^T \phi(x_i) + b \geq 1$. Testing data belongs to class 2(abnormal class) if $w^T \phi(x_i) + b \leq 1$

Support vectors are obtained by maximizing the distance between the closest training point and the corresponding hyper-plane[14]. One of the most efficient method used in SVM is Quadratic Optimization problem. Its solution of the problem involves construction of dual problem with the use of Lagrange multiplier $\alpha_i$ which is given as follows:

$$\sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j x_i x_j \qquad (12)$$

The equation maximized under the conditions.

$\sum \alpha_i y_i = 0 And x_i \geq 0$ for all value of $i = 1,2,...N$

After solving Quadratic optimization problem, the values of weight and bias are obtained as

$$w = \sum \alpha_i y_i x_i \quad \text{and } b = y_i - w^T x_i \qquad (13)$$

Where $x_i$ is support vector for each nonzero value of $\alpha_i$ .

Hence, the classification function for a test data point is inner product of support vector and test data point, which is given as follows

$$y(x) = \sum \alpha_i y_i x_i^T x + b \quad (14)$$

Those data point which are Closest to the Hyper-plane are used to measure the margin and named as support vectors. In dual formulation of quadratic optimization problem instead of using dot product of training data points in high dimensional feature space, kernel trick is used. Kernel function defines the inner product of training data points in high dimensional feature space.

Thus the kernel function is defined as

$$k(x_i, x_j) = \phi^T(x_i)\phi^T(x_j) \quad (15)$$

Gaussian (Radial Basis Function(RBF))kernel is used

$$k(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2} \quad (16)$$

The new classification function using RBF kernel function is defined as follows:

$$y(x) = \sum \alpha_i y_i k(x_i, x_j) + b \quad (17)$$

Because a single SVM classifier is able to distinguish only two classes, then in the case of three classes, it is necessary to use at least two SVM classifiers. The first classifier named *SVMMyo* separated the myogenic cases from other cases i.e., neurogenic and healthy, while the second one named *SVMNeuro* separated the neurogenic cases from other cases (i.e., myogenic and healthy). The third healthy case was to be distinguished based on negative outputs of the two classifiers. An ambiguous situation might occur in which the outputs of both SVM classifiers attain positive values, and it would be a very rare condition when the investigated case belongs to both myogenic and neurogenic classes at once.Further, the testing data signals are classified with these trained binary class model and final decision about class of data point is taken on the basis of majority voting of class. The performance of classifier is measured by classification rate and accuracy.

*Fuzzy support vector machine*

Even though binary SVM for classification problem which converts an n-class problem into n two-class problems there may be some unclassifiable regions. However, in real-time applications, each sample is required to belong to certain class and some samples may be more significant than other ones. Therefore, the significant samples are required to be correctly classified while other samples like interferences should not take part in classification. Here combine SVM with fuzzy membership for the purpose of classification through calculating fuzzy membership of each sample in each class leads to the construction of FSVM model. One of the most important and carefully considering thing to FSVM is choosing appropriate fuzzy memberships for a given classification problem. So here propose a new fuzzy membership function for the nonlinear SVM. First to calculate fuzzy membership in the input feature space and represent it with kernels functions. It will show that this method has good performance on reducing the effects of outliers and significantly improves the classification accuracy and generalization.

The training set will be $x_1, x_2, \ldots. x_N$ for each $X_i \in R^N$ and class labels $y_i = \{-1,1\}$ and a fuzzy membership function $\sigma \prec s_i \leq 1$ for sufficiently small $\sigma \succ 0$.

For FSVM the training set would be changed to such that

$$S_i = \{(X_i, y_i, s_i) i = 1,2, \ldots. N\} \quad (18)$$

In FSVM, each sample is given a fuzzy membership which denotes the attitude of the corresponding point toward one class. The membership represents how important is the sample to the decision surface. The bigger the fuzzy membership, the corresponding point is treated more important; thus, different input points can make different contributions to the learning of decision surface[17] .The fuzzy membership function for reducing the effect of outliers is a function of the distance between each data point and its corresponding class center, and the function is represented with parameters of the input space [ 17].
For the given training set (18), the fuzzy membership function is

$$s_i = \begin{Bmatrix} 1 - \|X_+ - X_i\| / (r_+) if X_i \in C^+ \\ 1 - \|X_- - X_i\| / (r_-) if X_i \in C^- \end{Bmatrix} \quad (19)$$

Denote a set as $Q = \{X_i \mid (X_i, y_i, s_i) \in s$ clearly, it contains two classes. One class contains such sample point $X_i$ with $y_i = 1$, denoting this class by C+, $C^+ = \{X_i \mid X_i \in sandy_i = 1$
The other class contains such sample point $X_i$ with

$y_i = -1$ denoting this class by $C^- = \{X_i \mid X_i \in s$ and $y_i = -1$ Where $X^+ andX^-$ denotes the mean of class $C^+ andC^-$ .
The radius of class C+ is

$$r_+ = \max(X_+ - X_i) \quad \text{Where } X_i = C_+ \quad (20)$$

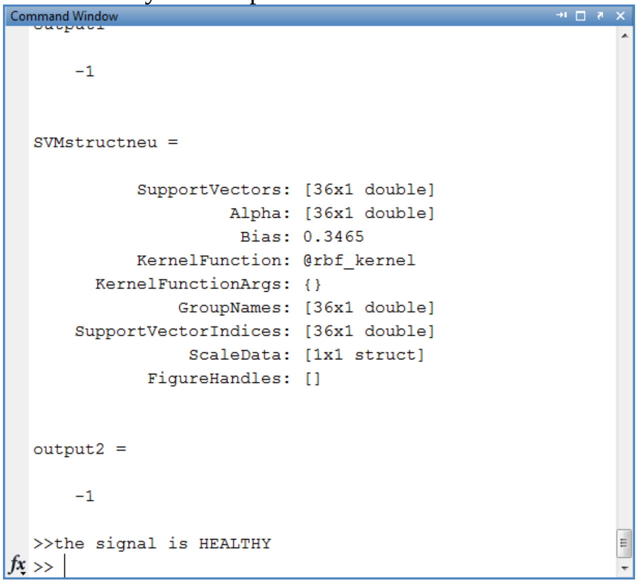
And the radius of class C- is

$$r_- = \max\|X_- - X_i\| where X_i \in C_- \quad (21)$$

The FSVM with the above membership function can achieve good performance since it is an average algorithm. A particular sample in the training set only contributes little to the final result and the effect of outliers can be eliminated by taking average on the samples .

## IV. RESULTS AND DISCUSSIONS

In this study, soft computing techniques were used to classify EMG signals when different feature extraction methods such as AR and DWT were used as to extract feature vectors. EMG data collected from 20 subjects were analyzed using the methodology described in section 2 .In the present study, for DWT the number of decomposition levels was chosen to be 5.Thus the EMG signals were decomposed into the details *D*1–*D*5 and one final approximation, *A*5 shown. The wavelet coefficients were computed using the MATLAB software package.AR modeling was used for power spectral densities of each signals. model order of the AR method was taken as 15 by using AIC and window size is taken as 256. The AR PSDs, which are for normal, myopathic and neurogenic EMG signals respectively, is used as an input to classifiers. In order to calculate the performance of our approach, the whole EMG data is divided into training and test sets, and acceptance rate validation is used subsequently. The training set is used to build a classification model and the test set is used to verify it. The test performance of the neuro-fuzzy models was determined by the computation of classification rate.



```
Command Window

    -1


SVMstructneu =

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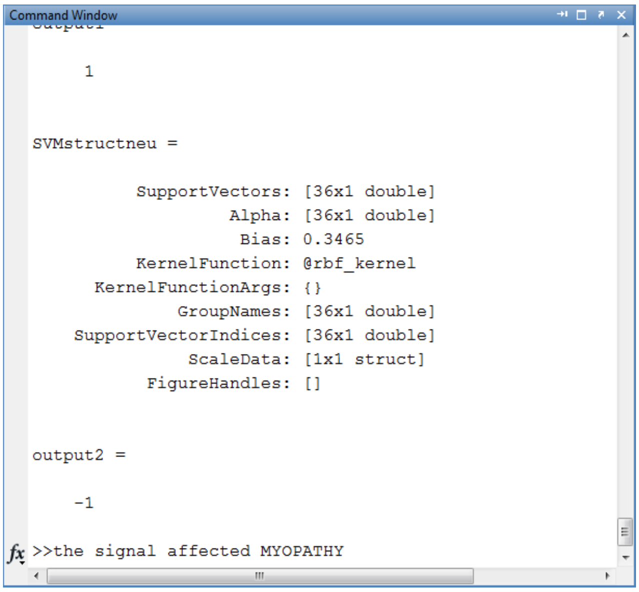
                  Alpha: [36x1 double]
                   Bias: 0.3465
         KernelFunction: @rbf_kernel
     KernelFunctionArgs: {}
             GroupNames: [36x1 double]
   SupportVectorIndices: [36x1 double]
              ScaleData: [1x1 struct]
          FigureHandles: []


output2 =

    -1

>>the signal is HEALTHY
>>
```

**Fig 4 detection of healthy signal**



```
Command Window

     1


SVMstructneu =

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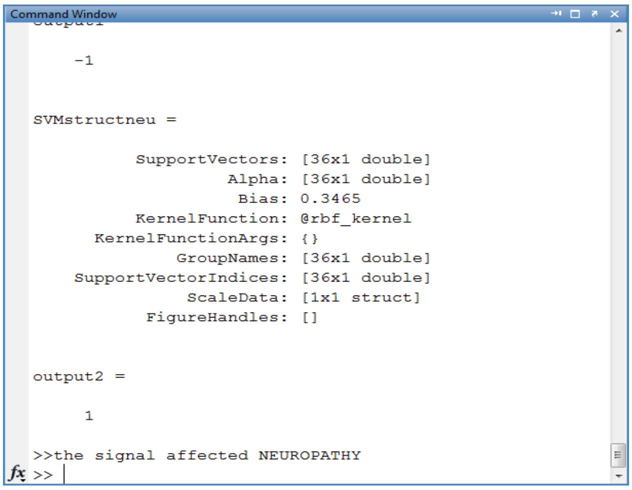
                  Alpha: [36x1 double]
                   Bias: 0.3465
         KernelFunction: @rbf_kernel
     KernelFunctionArgs: {}
             GroupNames: [36x1 double]
   SupportVectorIndices: [36x1 double]
              ScaleData: [1x1 struct]
          FigureHandles: []


output2 =

    -1

>>the signal affected MYOPATHY
```

**Fig 5 detection of myopathy signal**



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Command Window

    -1


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     KernelFunctionArgs: {}
             GroupNames: [36x1 double]
   SupportVectorIndices: [36x1 double]
              ScaleData: [1x1 struct]
          FigureHandles: []


output2 =

     1

>>the signal affected NEUROPATHY
>>
```

**Fig 6 detection of neuropathy signal**

Based on the results of present work we would like to emphasize the following:

1. The conclusion drawn in the applications demonstrated that the DWT coefficients are the features, which well represent the EMG signals, and by the usage of these features a good distinction between classes can be obtained.
2. SVM, ANFIS based classifiers are appropriate for use in diagnosis of neuromuscular disorders; but, FSVM has an advantage over other classification methods based on its higher classification accuracy.
3. The developed ANFIS model classifies EMG signals using different features as the input with an accuracy of greater than 80%.One disadvantage to the use of the ANFIS alone is that there is no memory in this classification scheme, and as a result no way to keep track of previous classification result to decide if the new output value is in agreement with the progression of different events.
4. FSVM had a significant advantage in its ability to maximize the classification accuracy. The classification results and the values of statistical parameters indicated that the FSVM had considerable success in the EMG signals classification by comparing with other classification methods.
5. The FSVM classifier is robust to dynamic noise by setting lower fuzzy membership for the data points with the noises or outliers, whereas the SVM classifier is sensitive to the noise. Some data points with outliers and noises could be support vectors in the SVM classifier.

**Table 1**
**Comparison of classification rates of ANFIS,SVM & FSVM**

| Classifiers | Statistical parameters | |
|---|---|---|
| | True acceptance rate(TAR) | False acceptance rate(FAR) |
| ANFIS | 80% | 20% |

| | | |
|---|---|---|
| SVM | 75% | 35% |
| FSVM | 95% | 5% |

## V. CONCLUSION

The ANFIS ,SVM and FSVM classifiers were used to classify three classes of EMG signals when the combined features of wavelet coefficients of the EMG signals and AR modeling were used as inputs. The FSVM techniques are capable of classifying the EMG signals with a high degree of accuracy and repeatability. The total classification accuracy is also obtained with 95%. This demonstrates that the Fuzzy SVM classifier can be valuable for the capture and expression of knowledge useful to a clinician. These results provide encouragement to develop and evaluate a Fuzzy SVM method for quantifying the level of contribution of a neuro-muscular disorder.

## REFERENCES

[1] Angkoonphinyomark, Pornchai phukpattaranont, Chusak Limsakul, "Feature reduction and selection for EMG signal classification", Expert Systems with Applications,vol. 39 pp(7420–7431),2012

[2] A.Subasi,Classification of EMG signals using combined features and soft computing techniques, Application software computing vol.12,2012,pp 2188-2198

[3] A. Subasi, M. Yilmaz, H.R. Ozcalik, "Classification of EMG signals using wavelet neural network", Journal of Neuroscience Methods ,156 ,pp( 360–367),2006

[4] Constantinos s. Pattichis,, Christos N. Schizas,and Lefkos T. Middleton, "Neural Network Models in EMG Diagnosis" IEEE Transaction on biomedical engineering. Vol. 42(5), 1995

[5] DeLuca CJ, Towards understanding the EMG signal, 4th ed., Baltimore: Williams & Wilkinson, 1978.

[6] Inan Guler , Elif Derya Ubeyli , "Adaptive neuro-fuzzy inference system for classification of signals using wavelet coefficients," Journal of Neuroscience Methods, 49 ,pp(640–650),2005.

[7] Jit Muthuswamy,' Biomedical signal analysis', Standard Handbook Of Biomedical Engineering And Design vol.14,pp(18.1-18.27),2004

[8] J.S.R. Jang, "ANFIS: adaptive network based fuzzy inference system", IEEE Transactions on Systems, Man and Cybernetics, vol .3 ,pp(665–683),1993.

[9] Kandaswamy, C.S. Kumar, R.P. Ramanathan, S. Jayaraman, N. Malmurugan, Neural classification of lung sounds using wavelet coefficients, Computers in Biology and Medicine 34 (6) (2004) 523–537.

[10] Krarup C, Pitfalls in electrodiagnosis, J Neurophysiol, vol. 81, 1999, pp. 1115-1126.

[11] L.J. Pino, D.W. Stashuk, S.G. Boe, T.J. Doherty, Motor unit potential characterization using pattern discovery, Med. Eng. Phys. Vol.30 pp( 563–573),2008.

[12] N. Anand and D. Chad, "The clinical Neurophysiology primer",Humana Press, 2007.

[13] R.Polikar The wavelet tutorial http://users.rowan.edu/polikar/WAVELETS/ WT tutorial.html (accessed at 28.08.11).

[14] Rajesh Ku.Tripathy, Ashutosh Acharya, Sumit Kumar Choudhary,"Gender Classification Fro ECG Signal Analysis Using Least Square Support Vector Machine"American Journal of Signal Processing,2(5),pp(145-149),2012

[15] Sivarit Sultornsaneea, Ibrahim Zeida, Sagar Kamarthia, " Classification of Electromyogram Using Recurrence Quantification Analysis", Proceediang of Computer Science,Elsiever, vol.6 ,pp( 375–380),2011.

[16] V.Vapnik,StatisticalLearningTheory,Wiley,NewYork, 1998.

[17] Xiufeng Jiang ,Zhang Yi ,Jian Cheng Lv, "Fuzzy SVM with a new fuzzy membership function" Neural Comput & Applic ,Vol 15:pp( 268–276),2006

[18] Examples of elecromyograms(emgdb) http://www.physionet.org

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