Multi-Class Support Vector Machine Classifier in EMG Diagnosis

GURMANIK KAUR[1], AJAT SHATRU ARORA[2] AND V.K. JAIN[3]
EIE Department,
SLIET (Deemed University),
Longowal, Sangrur (Punjab),
INDIA.
Email: GURMANIK KAUR- mannsliet@gmail.com
AJAT SHATRU ARORA- ajatsliet@yahoo.com
V. K. JAIN- vkjain27@yahoo.com

Abstract: - The shapes of motor unit action potentials (MUAPs) in an electromyographic (EMG) signal provide an important source of information for the diagnosis of neuromuscular disorders. In order to extract this information from the EMG signals recorded at low to moderate force levels, it is required to: i) identify the MUAPs composed by the EMG signal, ii) cluster the MUAPs with similar shapes, iii) extract the features of the MUAP clusters and iv) classify the MUAPs according to pathology. In this work, three techniques for segmentation of EMG signal are presented: i) segmentation by identifying the peaks of the MUAPs, ii) by finding the beginning extraction point (BEP) and ending extraction point (EEP) of MUAPs and iii) by using discrete wavelet transform (DWT). For the clustering of MUAPs, statistical pattern recognition technique based on euclidian distance is used. The autoregressive (AR) features of the clusters are computed and are given to a multi-class support vector machine (SVM) classifier for their classification. A total of 12 EMG signals obtained from 3 normal (NOR), 5 myopathic (MYO) and 4 motor neuron diseased (MND) subjects were analyzed. The success rate for the segmentation technique used peaks to extract MUAPs was highest (95.90%) and for the statistical pattern recognition technique was 93.13%. The classification accuracy of multi-class SVM with AR features was 100%.

Key-Words: - Electromyography, motor unit action potentials, segmentation, pattern recognition, classification, multi-class support vector machine.

1 Introduction

Electrical potentials measured from a skeletal muscle result from the summed resting membrane potentials and the action potentials which occur when its muscle fibers are stimulated. Skeletal muscle fiber action potentials are generated by the integrated neural motor output of the central nervous system. Each single motor nerve fiber stimulates several muscle fibers to produce muscle action potentials. The spatial and temporal summation of the potentials arising from the activity of a single motor nerve is referred to as a single motor unit action potential (MUAP). The superposition of all MUAPs within the vicinity of the electrode constitutes the electromyogram (EMG) signal.

Observation of the EMG signal of a patient is a key initial step taken by a physician for the assessment of neuromuscular disorders. The shapes of MUAPs composing the EMG signal provide useful information in this context. The changes brought about by a particular neuromuscular disorder alter the properties of the muscle and nerve cells, causing characteristic changes in the MUAPs. Distinct MUAPs can be seen only during weak contractions when few motor units are active. When a patient maintains low level of muscle contraction, individual MUAPs can be easily recognized. As contraction intensity increases, more motor units are recruited. Different MUAPs will overlap, causing an interference pattern in which the neurophysiologist cannot detect individual MUAP shapes reliably. Traditionally, in clinical electromyography, neurophysiologists assess MUAPs from their shape using an oscilloscope and listening to their audio characteristics. On this way, an experienced neurophysiologist can detect abnormalities with reasonable accuracy. Subjective MUAP assessment, although satisfactory for the detection of unequivocal abnormalities, may not be sufficient to delineate less obvious deviations or mixed patterns of abnormalities [1]. These ambiguous cases call for quantitative MUAP analysis.

With the aid of computer technology, today it is possible to analyze EMG signal quantitatively that helps in saving time, standardizes the measurements and enables the extraction of additional features which cannot be easily calculated manually. Several methods have been implemented in the past for MUAP recognition and pattern recognition. Richard Gut et al used a sliding time window for extraction of MUAPs. If the mean slope within this window exceeds a certain threshold, the beginning of an active segment is postulated. The end of a segment is reached when the total variation of the EMG within the window falls below another threshold [2]. E Chauvet et al used an amplitude detection scheme where the threshold value is set at each iteration. For a given iteration, the threshold is determined by lowering its precedent value. This principle allows the detection of a reduced number of MUAPs, thus facilitating the identification of a MUAPT [3]. Later on, E Chauvet et al detected MUAP spikes when their amplitudes were higher than a detection threshold value. At the first iteration, the detection threshold was initialized at the maximum amplitude of the signal segment under study. After thresholding, the number of detected spikes was counted, if this number did not reach at least 5 spikes per second, the threshold level was lowered to 90% of its previous value [4]. C.D. Katsis et al used a threshold T to identify peaks in the EMG signal and a window with a constant length[5], [6], [7]. Constantinos S Pattichis et al identified the BEP and EEP of the of the MUAPs by sliding a window of length 3 ms and width ±40 μV throughout the EMG signal [8]. Jianjun Fang et al set a horizontal cursor at a level to distinguish spike potentials from background noise. Upon detection of a spike, a segment of spike waveform with its peak aligned at the center is collected [9]. Guglielminotti and Merletti theorized that if the wavelet analysis is chosen so as to match the shape of the MUAP, the resulting WT yields the best possible energy localization in the time-scale plane [10]. Laterza and Olmo found out that WT is an alternative to other time frequency representations with the advantage of being linear, yielding a multiresolution representation and not being affected by crossterms; this is particularly relevant when dealing with multicomponent signals. Under certain conditions, the EMG signal can be considered as the sum of scaled delayed versions of a single prototype. Based on Guglielminotti's theory, Laterza and Olmo have used wavelet analysis to match the shape of the MUAP [11]. For a unipolar recorded signal and under certain hypotheses presented by Gabor [12], the typical MUAP shape can be approximated as the second-order derivative of a Gaussian distribution. The result suggested using the well-known Mexican hat wavelet, which is indeed the second-order derivative of a Gaussian distribution. Based on the research, Laterza and Olmo concluded that the WT is particularly useful for MUAP detection in the presence of additive white noise. In this situation, the noise contributions are spread over the entire time scale plane, independently of the wavelet used The disadvantage of this proposal was that the Mexican hat wavelet is not perfectly matched to the MUAP shape [11]. Therefore, the obtained results are likely to be subject to further improvement if a perfect matching is performed. Ismail and Asfour came with a theory saying that, the most common method used to determine the frequency spectrum of EMG are the fast and short term Fourier transforms. But they also concluded that the major drawback of these transformation methods is that they assume that the signal is stationary [13]. However, EMG signals are nonstationary. Pattichis and Pattichis discovered that the wavelet transform can also be used to analyze signals at different resolution levels. The wavelet transform algorithm consists of the decomposition phase and reconstruction phases. They briefly outlines how coefficients from each stage of the WT can be used to construct functional approximation to the original signal [14]. To further the development of quantitative EMG techniques, the need has emerged for adding automated decision making support to these techniques so that all data is processed in an integrated environment. Towards this goal, Towards this goal, Blinowska [15] proposed the use of discriminant analysis for the evaluation of MUAP findings, Coatrieux and associates [16]-[18] applied cluster analysis techniques for the automatic diagnosis of pathology based on MUAP records. Andreassen and co-workers [19]-[21] developed the MUNIN(Muscle and Nerve Inference Network) which employs a causal probabilistic network for the interpretation of EMG findings, Fuglsang-Frederiksen and his group [22], [23] developed a rule-based EMG expert system named KANDID, and Jamieson [24], [25] developed an EMG processing system based on augmented transition networks. In most of these systems, the generation of the input pattern assumes a probabilistic model, with the matching score representing the likelihood that the input pattern was generated from the underlying class [26]. In addition, assumptions are typically made concerning the probability density function of the input data. Pattichis et al gave a series research yield of classifying MUAPs for differentiation of motor neuron diseases and myopathies from normal [27]. The classifier they used were mainly neural networks, e.g. back propagation, the radial basis function and the self organizing feature map network. However, the aforementioned techniques used to train the neural network classifiers are based on the idea of minimizing the train error, which is named empirical risk. As a result, limited amounts of training data and over high training accuracy often lead to over training instead of good classification performance. Support vector machines (SVMs) introduced by Vapnik [28] is founded in the framework of the statistical learning theory, which is appropriate for approaching classification and regression problems. SVMs represent a new approach to pattern classification that has attracted a great deal of interest in the machine learning community. They operate on the induction principle of structural risk minimization, which minimizes an upper bound on the generalization error. SVMs have shown to be successful in solving many pattern recognition problems and perform much better than non-linear classifiers such as artificial networks in many situations [29].

To contribute to the quantification of the routine needle EMG examination, we have evaluated three segmentation techniques for detection of MUAPs. In the first technique, the EMG signal is segmented using an algorithm that detects areas of low activity and candidate MUAPs. Second technique, identified the BEPs and EEPs of the possible MUAPs by sliding a window throughout the signal. And in the third technique, EMG signal is decomposed with the help of daubechies4 (db4) wavelet to detect MUAPs.

2 Material and Methodology

2.1 Data acquisition and pre - processing

Our data contain real time EMG signal obtained from the Department of Computer Science, University of Cyprus, Cyprus. All the EMG signals were acquired from the biceps brochii muscle at upto 30% of the maximum voluntary contraction (MVC) level under isometric conditions. The signals were acquired for 5 seconds, using the standard concentric needle electrode, from NOR, MYO and MND subjects. The typical EMG recordings are given in Fig.1, Fig.2 and Fig.3. The EMG signals were analogue band pass filtered at 3-10 KHz, sampled at 20 KHz with 12-bit resolution and then low pass filtered at 8 KHz.

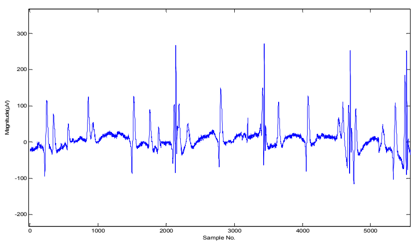

Fig.1 Raw EMG signal of a NOR subject.

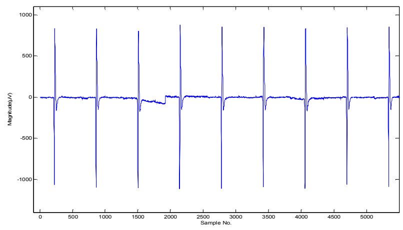

Fig.2 Raw EMG signal of a MYO subject.

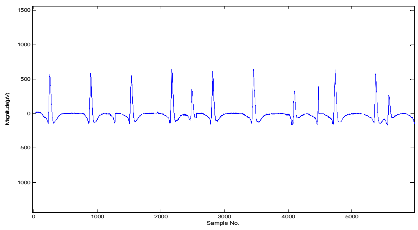

Fig.3 Raw EMG signal of a MND subject.

2.2 Segmentation

EMG signal is the superposition of the electrical activities of the several motor units. The segmentation of EMG signal is necessary to understand the mechanisms related to muscle and nerve control. Three techniques are discussed with regards to segmentation of EMG signal.

2.2.1 Segmentation by identifying the peaks of the MUAPs

This segmentation algorithm calculates a threshold depending on the maximum value $\max_i\{x_i\}$ and the mean absolute value $(1/L)\sum_{i=1}^{L}|x_i|$ of the whole EMG signal, where x_i are the discrete input values and L is the number of samples in the EMG signal. The threshold (T) is calculated as follows:

$$\text{If } \max_i\{x_i\} > \frac{30}{L}\sum_{i=1}^{L}|x_i|, \text{ then } T = \frac{5}{L}\sum_{i=1}^{L}|x_i|$$

$$\text{else } T = \max_i\{x_i\}/5$$

Peaks over the calculated threshold are considered as candidate MUAP's. Then a window of 120 sampling points (i.e., 6 ms at 20 kHz) is centered at the identified peak. If a greater peak is found in the window, the window is centered at the greater peak; otherwise the 120 points are saved as MUAP waveform. This algorithm is described in detail in [30]. The segmented EMG signals of normal, myopathic and motor neuron diseased subjects in segments of 6ms and centered at the maximum peak, are shown in Fig.4, Fig.5 and Fig.6 respectively.

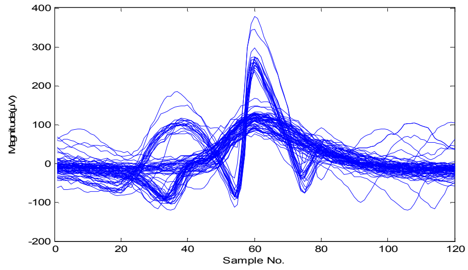

Fig.4 Segmented EMG signal of a NOR subject in segments of 6ms and centered at the maximum peak.

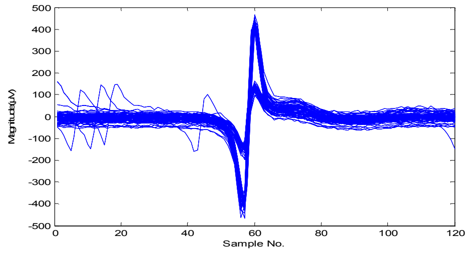

Fig.5 Segmented EMG signal of MYO subject in segments of 6ms and centered at the maximum peak.

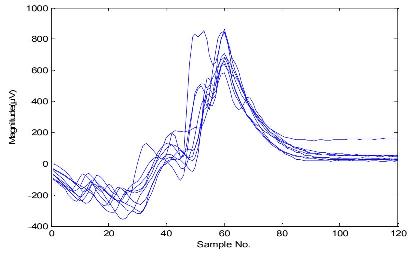

Fig.6 Segmented EMG signal of a MND subject in segments of 6ms and centered at the maximum peak.

2.2.2 Segmentation by identifying the BEPs and EEPs of the MUAPs

The EMG signal is high-pass filtered at 250 Hz and the BEPs and EEPs are identified by sliding an extraction window of length 3 ms and width ±40 µV. BEP is the first point that satisfies the criterion searching to the left of the EMG waveform, the signal to the left of BEP remains within ± 40 µV for 3ms. EEP is the point to the right of which signal remains within the range of ±40 µV for 3ms. These extraction points are then mapped to the original signal [8].

Fig.7, Fig.8 and Fig.9 shows a portion of the extracted MUAPs. In these figures triangular marks indicate the peaks and circle marks indicate the BEPs and EEPs.

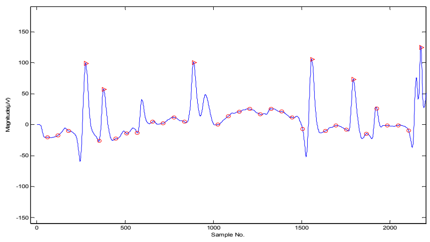

Fig.7 A portion of the extracted MUAPs by finding BEPs and EEPs of the MUAPs in case of a NOR subject.

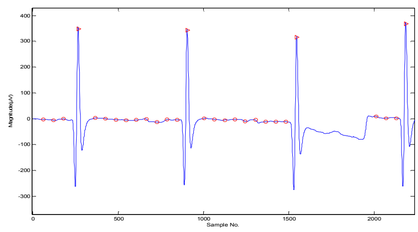

Fig.8 A portion of the extracted MUAPs by finding BEPs and EEPs of the MUAPs in case of a MYO subject.

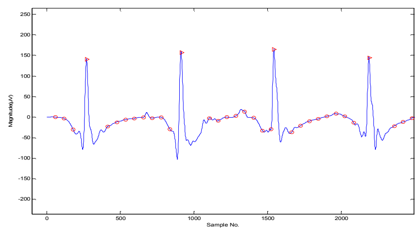

Fig.9 A portion of the extracted MUAPs by finding BEPs and EEPs of the MUAPs in case of a MND subject.

2.2.3 Segmentation by using DWT

DWT is a transformation of the original temporal signal into a wavelet basis space. The time-frequency wavelet representation is performed by repeatedly filtering the EMG signal with a pair of filters that cut the frequency domain in the middle. Specifically, the DWT decomposes a signal into an approximation signal and a detail signal. The approximation signal is subsequently divided into new approximation and detail signals. This process is carried out iteratively producing a set of approximation signals at different detail levels (scales) and a final gross approximation of the signal [14]. In our work, we used db4 discrete wavelet to find the location of MUAP peaks on the time axis. We decomposed the signal up to 4th level and used a threshold of 50 μV to find the peaks of the MUAPs and then scaled the index of MUAP peaks to the original signal. A portion of the extracted MUAPs by using db4 wavelet in case of NOR, MYO and MND subjects, is shown in Fig.10, Fig.11 and Fig.12 respectively. In these figures circle marks indicate the peaks of the identified MUAPs and star marks indicate 40 points around each peak.

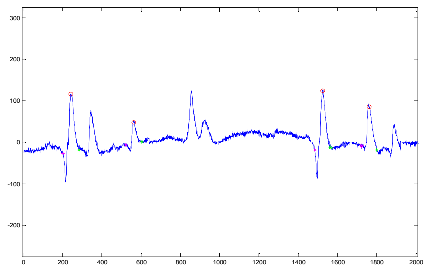

Fig.10 A portion of the extracted MUAPs by using db4 wavelet in case of a NOR subject.

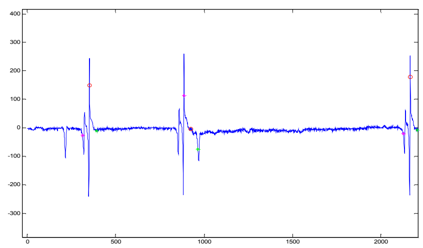

Fig.11 A portion of the extracted MUAPs by using db4 wavelet in case of a MYO subject.

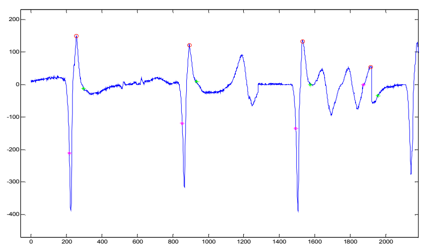

Fig.12 A portion of the extracted MUAPs by using db4 wavelet in case of MND subject.

2.3 MUAP clustering

In this step, the MUAP clusters are automatically detected and for each cluster the average or template shape is determined. We have used statistical pattern recognition technique for clustering of similar MUAPs. In this technique the euclidian distance is used to identify and group similar MUAP waveforms. The group average is continuously calculated and is used for the classification of MUAPs using a constant threshold [31]. The implementation steps are:

Step 1: Start with the first waveform x as input (the first member of the class).

Step 2: Calculate the vector length of x and the distance between it and the other segmented waveforms y as:

$$l_x = \sum_{i=1}^{N} x_i^2 \text{ where } N = 120$$

and

$$d_{xy} = \sum_{i=1}^{N} (x_i - y_i)^2$$

Step 3: Find the waveform y with the minimum distance $d_{\min}$. The waveform y having minimum distance with the x has the greatest similarity with x and remove it from the input data.

Step 4: *if* $d_{\min} / l_x < 0.3$ then group, calculate group average and go to step 1 with group average as input.

else if number of group members > 2, then form a new class.

else waveform is superimposed, go to step 1 with y as input.

If the minimum distance divided by the vector length of x is less than the threshold, set to 0.3, then the two waveforms form a class, the class average is calculated and the procedure is repeated (go to Step 2 with the class average as input). Now compare the class average with all the rest waveforms in order to find the next waveform with the minimum distance. If the above condition is satisfied, then a new waveform is added to the class and a new class average is calculated, and so on. If not, the process stops; if the class members are more than or equal to three, then a MUAP class is formed and its averaged waveform is saved. If they are less than three, they are considered as superimposed waveforms. This process continues where it stopped comparing the last encountered waveform with all the remaining until all waveforms are processed. The threshold values were chosen heuristically after extensive testing. It is noted that again there are no widely applicable threshold criteria for assigning a MUAP to a class. The threshold used in this work is critical because a smaller value may split a MUAP class with high waveform variability in two or more subclasses, whereas a greater threshold value may merge resembling MUAP classes. The averaged class waveforms are again the unique MUAP waveforms composing the EMG signal. Fig.13, Fig.14 and Fig.15 illustrates the clustered EMG signals of NOR, MYO and MND subjects respectively.

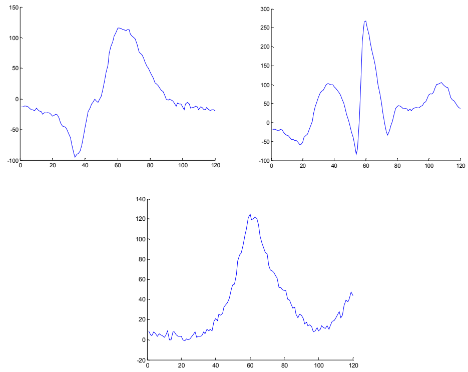

Fig.13 Clustered EMG signal of a NOR subject.

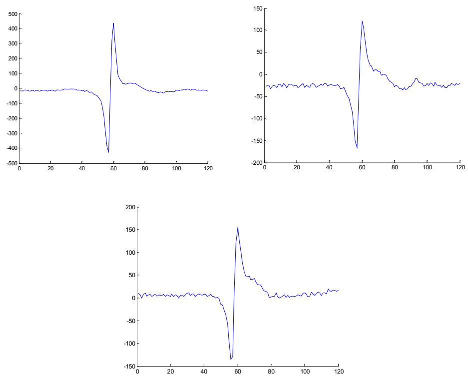

Fig.14 Clustered EMG signal of a MYO subject.

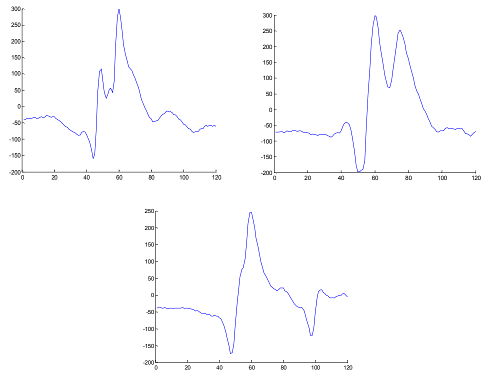

Fig.15 Clustered EMG signal of a MND subject.

2.4 Feature extraction

The next step is to decide for the correct features to be extracted from the EMG signal. A number of experiments have shown that AR features contain enough information and are simple enough for fast training and running of the classifier [32]. In this work, we have extracted the AR features of the MUAP clusters. In AR model the current signal x(n) is described as linear combination of previous samples x(n-k) weighted by a coefficients [33]. The coefficients of AR model of order 3 were computed by the Burg's algorithm. It provides an iterative and fast method to figure out the parameters of AR model adaptively. These coefficients are the features for multi-class SVM classifier.

2.5 MUAP classification

In order to classify the clustered MUAPs into NOR, MYO and MND classes, a SVM classifier is employed [34], [35]. A classification task based on SVM usually involves training and testing data, which consist of a number of data instances. Each instance in the training set contains one ''target value'' (class labels) and several ''attributes''. Although initially developed for binary classification problems, SVMs can be adapted to deal with multi-class problems. There are two schemes for this purpose: i) the one-against-all strategy to classify between each class and the remaining; ii) the one-against-one strategy to classify between each pair. In this work, we have used one-against-all strategy. It constructs k SVM models where k is the number of classes. The i^{th} SVM is trained with all of the examples in the i^{th} class with positive labels and all other examples with negative labels. Thus given l training data (x_1, y_1),..., (x_l, y_l), where $x_i \ \varepsilon \ R^n$, $i = 1,\ldots,l$ and $y_i \ \varepsilon \ \{1,....,k\}$ is the class of x_i, the i^{th} SVM solves the following problem:

$$\min_{w^i, b^i, \varepsilon^i} \quad \frac{1}{2}\left(w^i\right)^T w^i + C\sum_{j=1}^{l} \xi_j^i \left(w^i\right)^T$$

$$\left(w^i\right)^T \phi\left(x_j\right) + b^i \geq 1 - \xi_j^i, \text{ if } y_j = i$$

$$\left(w^i\right)^T \phi\left(x_j\right) + b^i \leq -1 + \xi_j^i, \text{ if } y_j \neq i$$

$$\xi_j^i \geq 0, \quad j = 1,....,l \qquad (1)$$

where the training data x_i are mapped to a higher dimensional space by function ϕ and C is the penalty parameter.

Minimizing $(1/2)\ \left(w^i\right)^T w^i$ means that we would like to maximize $2/\left\|w^i\right\|$, the margin between two groups of data. When data are not linear separable, there is a penalty term $C\sum_{j=1}^{l} \xi_j^i$ which can reduce the number of training errors. The basic concept behind SVM is to search for a balance between the regularization term $(1/2)\ \left(w^i\right)^T w^i$ and the training errors.

After solving (1), there are k decision functions:

$$\left(w^1\right)^T \phi(x) + b^1$$

$$\vdots$$

$$\left(w^k\right)^T \phi(x) + b^k$$

We say x is in the class which has the largest value of the decision function:

$$\text{class of } x \equiv \arg \max_{i=1,\ldots k} \left(\left(w^i\right)^T \phi(x) + b^i\right) \quad (2)$$

Practically, we solve the dual problem of (1) whose number of variables is the same as the number of data in (1). Hence k, l-variable quadratic programming problems are solved [36].

3 Results

EMG data collected from 12 subjects were analyzed using the methodology described in Section 2. Data were recorded from 3 NOR, 5 MYO and 4 MND subjects. Only subjects with no history or signs of neuromuscular disorders were considered as normal. MATLAB was used for implementing the algorithms.

Following the pre-processing, EMG signals are segmented by using three segmentation techniques. Table1 tabulates the comparison of the results of three segmentation techniques. The technique used for the extraction of MUAPs by identifying their peaks, yielded best results when compared with the manually observed true MUAPs, so we have taken the MUAPs identified by using this technique for further analysis. Moreover, the segmented MUAPs are of same length and hence can be classified easily. Table2 tabulates the success rates of three segmentation techniques. The success rate is the percentage ratio of the correctly identified MUAPs by the segmentation algorithm and the number of true MUAPs identified by manual observation. The success rate for the technique using peaks to extract MUAPs is 95.90%, for the technique using BEPS and EEPs, is 75.39% and for the technique using DWT, is 66.64%. Examining the success rate for each class, the highest success rate (96.07%) was obtained for the NOR group. The success rate for other classes is attributed to the more complex and variable waveform shapes.

Table 1- Comparison of the Results of Segmentation Techniques.

Subjects	Total No. of MUAPs identified			
	By identifying the peaks of MUAPs	By identifying the BEPs and EEPs of the MUAPs	By using DWT	By manual observation
NOR (3)	196	196	107	204
MYO(5)	278	124	243	290
MND(4)	182	166	121	190
Total(12)	656	486	471	684

Table 2- Success Rate of the Segmentation techniques.

Segmentation Technique	Success Rate (%)			Total Success Rate (%)
	NOR	MYO	MND	
By identifying the peaks of MUAPs	96.07	95.86	95.78	95.90
By identifying the BEPs and EEPs of the MUAPs	96.07	42.75	87.36	75.39
By using DWT	52.45	83.79	63.68	66.64

The similar MUAPs are clustered by using statistical pattern recognition technique. Sometimes due to waveform variability, MUAP classes coming from the same motor unit, although they looked simiIar, were not grouped together. Merging of these classes can be achieved with a greater constant threshold and the averaged class waveforms as input. This is the major advantage of statistical pattern recognition technique. The total success rate obtained by using this technique is 93.13%. Table 3 presents the results of clustering for each of the three MUAP classes.

Table 3- MUAP Clustering Success Rate.

MUAP classes	Success rate (%)
NOR	93.13 (192/204)
MYO	93.10 (270/290)
MND	92.10 (175/190)
Total	93.13 (637/684)

After clustering of MUAPs, AR features of the template MUAPs are extracted. It is observed, that the standard deviation (SD) of all the AR parameters of a signal will be zero, if the total numbers of classes are less than two. The two important advantages of extracting AR features over time domain features are: 1) variations in the positioning of the electrodes on the surface of the muscle do not severely affect the AR coefficients. 2) the amount of information to be presented to the classifier is greatly reduced. Therefore, the total processing time is also reduced.

Finally the extracted AR features are given to a multi-class, one-against-all, SVM classifier for classification of MUAPs. The classification accuracy of SVM was 100%.

4 Conclusion

In conclusion, the methodology described in this work make possible the development of a fully automatic EMG signal analysis system which is accurate, simple, fast and reliable enough to be used in routine clinical environment. This work can provide a good understanding of EMG analysis procedures to the researchers to identify neuromuscular diseases. Future work will evaluate the algorithms developed in this study on EMG data recorded from more muscles and more subjects. In addition, this system may be integrated into a diagnostic system for neuromuscular diseases based on neural network where EMG, muscle biopsy, biochemical and molecular genetic findings and clinical data may be combined to provide a diagnosis.

References:

[1] Richfield EK, Cohen BA, Albers JW, Review of quantitative and automated needle electromyographic analyses, *IEEE Transactions on Biomed Eng*, 1981, pp. 506-514,

[2] Richard Gut and George S. Moschytz, High Precision EMG Signal Decomposition Using Communication Techniques, *IEEE Tranactions on Signal Processing,* Vol. 48, No.9, 2000, pp. 2487-2494.

[3] E. Chauvet, O. Fokapu, J. Y. Hogrel, D. Gamet and J. Duchene, Automatic identification of motor unit action potential trains from electromyographic signals using fuzzy techniques, *Medical and Biology Engineering and Computing* Vol. 41, No.6, 2003, pp. 646-653.

[4] E. Chauvet, Fokapu O, Hongrej J Y, Garnet D, Duchene J, A method of EMG decomposition based on fuzzy logic, *Proceedings of the 23rd Annual EMBS International Conference*, Vol. 2, 2001, pp. 1948-1950.

[5] C.D. Katsis, D.I. Fotiadis, A. Likas and I. Sarmas, Automatic discovery of the number of MUAP clusters and superimposed MUAP decomposition in electromyograms, *Proceedings of the 4th Annual IEEE Conf. on Information Technology Applications in Biomedicine*,2003, pp. 177-180.

[6] C.D. Katsis, Y. Goletsis, A. Likas, D.I. Fotiadis, I. Sarmas, A novel method for automated EMG decomposition and MUAP classification, *Artificial Intelligence in Medicine,* Vol. 37, No.1, 2006, pp. 55-64.

[7] C. D. Katsis, T. P. Exarchos, Costas Popaloukas, Yorgos Goletsis, Dimitrios I. Fotiadis, Loannis Sarmas, A two stage method for MUAP classification based on EMG decomposition, *Computers in Biology and Medicine,* Vol. 37, No. 9, 2007, pp. 1232-1240.

[8] Constantinos S. Pattichis, Christos N. Schizas and Lefkos *T.* Middleton, Neural Network Models in EMG Diagnosis, *IEEE Transactions on Biomedical Engg,* Vol. 42, No. 5, 1995, pp. 486-496.

[9] Jianjun Fang, Gyan C. Agarwal, B. T. Shahani, Decomposition of EMG signal by wavelet spectrum matching, *Proceedings of the 19th International Conference - IEEE/EMBS*, Vol. 3, 1997, pp. 1253-1256.

[10] Guglielminotti P, Merletti R, Effect of electrode location on surface myoelectric signal variables: a simulation study.*9th Int. Congress of* ISEK ,1992.

[11] Laterza F, Olmo G, Analysis of EMG signals by means of the matched wavelet transform. *Electronics Letters,* Vol.33, No.5, 1997, pp. 357-359.

[12] Gabor D, Theory of communication. *J Inst Elect Eng*, 1946, Vol. 93, pp. 429-457.

[13] Ismail AR, Asfour SS, Continuous wavelet transform application to EMG signals during human gait, *32nd Asilomar Conference on Signals, Systems & Computers*, 1998, Vol. 1, pp. 325-329.

[14] Pattichis CS, Pattichis MS, Time-scale analysis of motor unit action potentials. *IEEE Transactions on Biomedical Engg,* Vol. 46, No. 11, 1999, pp. 1320-1329.

[15] K. J. Blinowska, I. Hausmanowa-Petrusewicz, A. Miller-Larsson and J. Zachara, The analysis of single EMG potentials by means of multivariate methods, *Electromyogr. Clin. Neurophysiol,* Vol. 20, 1980, pp. 105-123.

[16] J. L. Coatrieux, P. Toulouse, B. Rouvrais, and R. Le Bars, Automatic classification of electromyographic

signals, *EEG Clin. Neurophysiol.,* Vol. 55*,* 1983, pp. 333-341.

[17] B. Rouvrais, P. Toulouse, J. L. Coatrieux. and R. Le Bars, A possible method of automatic electromyographic analysis and diagnosis on line, *Electmmyogr. Clin. Neurophysiol.*. Vol. 23, 1983, pp. 457-470.

[18] P. Toulouse, J. L. Coatrieux. and B. Le Marec, An attempt to differentiate female relatives of Duchenne type dystrophy from healthy subjects using an automatic EMG analysis, *J. Neurolog. Sci.,* Vol. 67, 1985, pp. 45-55.

[19] S. K. Andersen, S. Andreassen, and M. Woldbye, Knowledge representation for diagnosis and test planning in the domain of EMG. *In Proc. 7th Eur. Conf. Artijcicial 1ntell.,* Brighton, U.K., 1986, pp. 357-368.

[20] S. Andreassen, S. K. Andersen, F. V. Jensen, M. Woldbye, A. Rosen- falck, B. Falck, U. Kjaerluff, and A. R. Sorensen, MUNIN- An expert system for EMG, *Electroenceph,ph. Clin. Neurophvsiol.,* Vol. 66, 1987.

[21] S. Andreassen, F. Jensen. S. K. Andersen, B. Falck, U. Kjaerulff, M. Woldbye, A. R. Sorensen, A. Rosenfalck, and J. Frank, MUNIN-An expert EMG assistant, *In Computer Aided Electromygraphy and* E*xpert Systems,* J. E. Desmedt, Ed. New York : Elsevier Science Publisher B.V., 1989, pp. 255-277.

[22] A. FugIsang-Frederiksen and S. M. Jeppesen, A rule-based EMG expert system for diagnosing neuromuscular disorders, *In Computer Aided Electromyography and Expert* Systems, J. E. Desmedt, Ed. New York: Elsevier Science Publishers B.V., 1989, pp. 289-296.

[23] A. Fuglsang-Frederiksen, J. Ronager, and S, Vingtoft, A plan-test-diagnose expert system for EMG: KANDID, *J. Neurolog. Sci*., Vol.98 (suppl.), 1990 pp. 150.

[24] P. W. Jamieson, Computerized interpretation of electromyographic data, *Electroencephalogr. Clin. Neurophysiol.,* Vol. 75, 1990, pp. 392.

[25] P. W. Jamieson, A model for diagnosing and explaining multiple disorders, *Comput. Biomed. Res.,* Vol. 24, 1991, pp. 307-320.

[26] R. P. Lippmann, An introduction to computing with neural nets, *IEEE ASSP Mag.,* 1987, Apr. 4-22.

[27] Contantinos S Pattichis, Andread C Elia, Autoregressive and ceptral analyses of motor unit action potentials. *Med. Engg. Physic.,* Vol. 21, 1999, pp. 405-419.

[28] V.P. Vapnik, *The nature of statistical learning theory*, New York: Springer-Verlag, 1995.

[29] Yu-Dong Cai, Xiao-Jun Liu, Xue-Biao Xu, et al, Prediction of protein structural classes by support vector machines, *Comput. Chemi,* Vol. 26, 2002, pp. 293-296.

[30] Christodoulos I. Christodoulou and Constantinos S. Pattichis, Unsupervised Pattern Recognition for the Classification of EMG Signals. *IEEE Transactions on Biomedical Engg.* Vol. 46, No. 2, 1999, pp. 169-178.

[31] C. I. Christodoulou and C. S. Pattichis, A new technique for the classification and decomposition of EMG signals," *In Proc. IEEE Int. Conf. on Neural Networks*, Perth, Western Australia, Vol. 5, 1995, pp. 2303–2308.

[32] A. O. Andrade, Methodology for classifying EMG signals for artificial limb control, *M.Sc. Thesis*, Federal University of Uberlandia, Faculty of Electrical Engineering, 2000.

[33] Marple S. L. Jr., *Digital Spectral analysis with applications,* Prentice-Hall, USA, 1987.

[34] Boser B, Guyon I, Vapnik V, A training algorithm for optimal margin classifiers. *Proceedings of the 5th Annual Workshop on Computational Learning Theory*. ACM Press, 1992.

[35] Cortes C, Vapnik V. Support-vector network. *Machine Learn,* Vol. 32, 1995, pp. 273-97.

[36] Chih-Wei Hsu and Chih-Jen Lin, A Comparison of Methods for Multiclass Support Vector Machines. *IEEE Transactions on Neural*

Networks, Vol. 13, No. 2, 2002, pp. 415-425.