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Classification of EMG Signals Using Spectral Features Extracted from Dominant Motor Unit Action Potential

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Abstract*— In this paper, disease classification of electromyogram (EMG signal) based on the spectral features extracted from the dominant motor unit action potential (MUAP) is discussed. This scheme provides an improved accuracy and reduces the computational complexity to a great extend. The MUAPs are extracted from the EMG signal using a matlab program known as EMGLAB and the highest energy MUAP is selected as dominant MUAP. The main goal of this study is to extract the relevant spectral features for the classification so that the redundant features can be eliminated. For spectral feature extraction direct and DWT based methods are used. K-nearest neighborhood (KNN) classifier is used for the classification purpose. The performance is evaluated using three clinical dataset in terms of specificity sensitivity and accuracy. The results show that the classification based on the proposed method gives better accuracy than the existing methods for disease classification.

***Index Terms*— Electromyography (EMG), motor unit action potential(MUAP), EMGLAB, amyotrophic lateral sclerosis(ALS), Myopathy, K-nearest neighborhood (KNN) classifier.**

I. INTRODUCTION

The recording of electrical activity of skeletal muscle during different levels of muscle contraction is known as electromyogram (EMG signal). Muscle fibers are linked with motor neuron and the combined unit is known as motor unit. Electrical potential is generated by motor unit when these units are electrically or neurologically activated. When the motor neuron is fired all the muscle fibers under its control generates a signal referred to as motor unit action potential (MUAP) and the repeated firing of motor unit generates EMG signal which contains MUAP trains. Thus EMG signal is a complicated biomedical signal, which is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. EMG signal recording can be classified into two based on the location of the electrode placement, surface EMG and intramuscular EMG. The non invasive type of recording by the electrode placed on the surface of the muscle over the skin is known as surface EMG and the recorded signal is a composite of all the muscle fiber action potentials occurring in the muscles underlying the skin.

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The intramuscular EMG is an invasive type of recoding from the muscle by inserting needle or wire electrode into the muscle and the individual muscle action potential of single motor unit is recorded. The peak to peak amplitude of EMG signal is 0 to 10 milli volts and frequency of an EMG signal is between 0 to 500Hz.EMG signals can be used to analyze medical abnormalities related to muscles and nervous system and also used to study the activation level and biomechanics of human movement. Amyotrophic lateral sclerosis (ALS) is a specific neurological disorder that causes the abnormal death of motor neurons. Myopathy is a muscular disorder resulting in muscular weakness. The EMG data pattern for three classes (normal, ALS, myopathy) is shown in figure 1. These neuromuscular abnormalities can be identified from the analysis of the recorded EMG signal. EMG signals are non stationary signals and the muscles form the nonlinear medium for such signals. There exist many methods for feature extraction of EMG signal by analyzing it in time domain [2]-[5] or in frequency domain [6]-[8]. Wavelet Transform (WT) has been used as a powerful tool for the non-stationary time series analysis since it provides both time and frequency information of the signal simultaneously. The proper feature extraction scheme is necessary for the better performance of the classification. Neuromuscular disease classification based on the EMG signal characteristic can be either direct [2]–[8] or MUAP based [10]-[12] methods. In direct method the EMG signal is analyzed in a frame by frame manner and classification is done according to the features extracted from each frame. In MUAP based method the analysis is performed on the extracted MUAPs from the EMG signal using decomposition algorithms [10], [11]. The shapes and firing rates of Motor Unit Action Potentials (MUAPs) in EMG signals provide an important source of information for the diagnosis of neuromuscular disorders [1]. In this work, a novel method for disease classification of EMG signals based on spectral features extracted from the dominant MUAP [1] is proposed. The extracted features are classified using KNN classifier. The results show that classification of features using KNN yields better performance. The paper is structured as follows: Section II presents the materials and methods used for the study. Proposed method is explained in section III. Results and discussions are covered in section IV. Paper concludes in section V.

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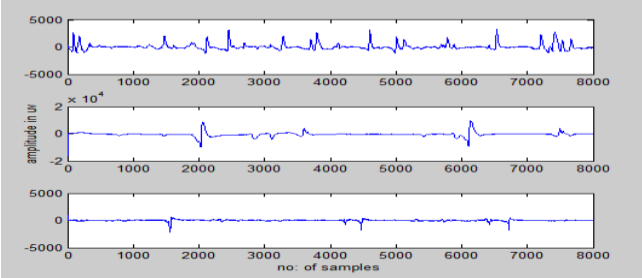

Fig. 1: EMG signal pattern from top to bottom a) normal b) ALS c) myopathy

II. MATERIALS AND METHODS

A. Database description

The publicly available clinical EMG database described by M. Nikolic, (2001) is used in this work. This database available at http://www.emglab.net [13] and data are available as N2001.This database consists of three different classes of data corresponding to normal, ALS and Myopathy subjects. The database contain 10 normal subjects consist of 6 males and 4 females aged between 21 and 37 years,8 ALS subjects consist of 4 males and 4 females aged between 35 and 67 years, and 7 myopathy subjects consists of 5 males, 2 females aged between 19 and 63 years. Each set of EMG recording has total 262144 samples corresponding to 11.184 sec at 23438 samples/sec sampling rate. Recording conditions are: (a) low voluntary and constant level of contraction, (b) visual and audio feedback, (c) concentric needle electrode, (d) five places in the muscle at three levels of insertion (deep, medium, low), and (e)high-pass and low-pass filters of the EMG amplifier were set at 2 Hz and 10 kHz [13]. To show the effect of variation of sensitivity, specificity and accuracy on different classes of data three sets of data are used here. Myo-normal Dataset consist of 50 signals of 7 Myopathy patients and 150 signals of 10 normal subjects. ALS-normal dataset consists of 50 signals of 8 ALS patient and150 signals of 10 normal subjects. 3-class dataset consists of 50 myopathy signal, 50 ALS signal and 150 normal signal.

B. Discrete Wavelet Transform (DWT)

The DWT is a multi-resolution technique that offers localization both in time and frequency [9]. It exhibits good frequency resolution at low frequencies and good time resolution at high frequencies. The DWT of a signal can be obtained as

$$C(a,b)=\sum_{n\in Z} x(n)\psi_{a,b}(n) \tag{1}$$

where a is the dilation or scale and b is the translation. The discrete wavelet is expressed as

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

The DWT decomposes the signal into a coarse approximation and detail information. Moreover, it offers the advantages of low computational cost and ease of implementation. Hence, the DWT is chosen to extract features from the EMG signal. In direct analysis of EMG using DWT gives global features of the EMG signal since it consider each and every frame in the analysis. It is obvious that the features extracted from each frame, only provide the local information of an EMG recording. In the proposed work the spectral features are extracted directly from the dominant MUAP and also from the decomposed dominant MUAP using DWT is used. It offers huge reduction of total computational burden.

C. Spectral features

Frequency or spectral domain features are mostly used to investigate fatigue of the muscle and also used for the motor unit analysis. Power spectral density (PSD) analysis is an important method in frequency domain signal analysis. PSD of the EMG signal is defined as the Furrier transform of the autocorrelation function of the EMG signal. PSD can be estimated using either periodogram or parametric methods. The spectral features used in the proposed work are as follows [14] 1). Total power (TP)

Total power represents the aggregate of the EMG power spectrum.

$$TP=\sum_{i=1}^{n} p_i \tag{3}$$

Where P_i represents the EMG power spectrum at frequency bin i and n is the length of the frequency bin.

2) Peak frequency (PF)

Peak frequency is the frequency at which maximum power occurs.

$$PF=\max(P_i),\ \text{Where i=1….n} \tag{4}$$

3) Median frequency (MF)

Median frequency is the half of total power.

$$MF=\frac{1}{2}\sum_{i=1}^{n} P_i \tag{5}$$

4) Mean power (MP)

Mean power is the average power of the EMG power spectrum.

$$MP=\frac{\sum_{i=1}^{n} P_i}{n} \tag{6}$$

D. KNN classifier

The K-nearest neighborhood (KNN) classifier is one of the simplest but efficient classifiers. It considers a distance function which is computed between the features belonging to the EMG pattern in the test set and neighboring EMG patterns from both normal and diseased group in the training set. The EMG pattern from the test set is classified based on the class labels of closer EMG patterns. In the proposed method, the Euclidean distance is used. In the KNN classifier, it is required to find a suitable value of K for achieving the best classification.

E. Performance parameters

The performance of proposed method is evaluated in terms of statistical parameters such as sensitivity, specificity and accuracy [1].Specificity (SP) represents the ratio of number of correctly classified normal subjects to the total number of normal subjects. Sensitivity of Myopathy (SM) and sensitivity of ALS (SA) together known as sensitivity of classification is defined as the ratio of number of correctly classified subjects suffering from a particular disease (ALS or Myopathy) to number of total subjects suffering from that particular disease (ALS or Myopathy).

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Classification accuracy (CA) is defined as the ratio of number of correctly classified subjects to number of total subjects.

III. Proposed Dominant Muap Based Disease Classification Scheme

A. *MUAP Extraction and Dominant MUAP selection*

An EMG signal is the train of motor unit action potential. The shapes and firing rates of MUAPs in EMG signal contains significant information for the diagnosis of neuromuscular disorders. The first step is to identify and extract MUAPs of an EMG signal by using a decomposition program called EMGLAB. It is written in matlab and is a user friendly graphical user interface which facilitates the exportation of MUAP waveforms for further analysis. Different EMG signal contains different number of MUAPs and energy content of each MUAP will be different in different class of diseases such as ALS and Myopathy. In Myopathy patient, MUAP become low in amplitude and short in duration and in Neuropathy patients MUAP exhibit higher amplitude and longer duration compared to normal person MUAP. Thus the energy content of MUAPs provides significant information about the EMG signal and idea about pathology. In most MUAP based disease classification method all the MUAPs are equally treated. This method encounter some complication such as variation in firing characteristics, cross talk and the number of extracted MUAPs varies significantly for different EMG data. Hence selecting a single MUAP from an EMG signal based on energy content of that particular MUAP is proposed (1). The dominant MUAP from N number of MUAPs is selected based on the temporal energy content of the MUAPs present in an EMG signal.

$$e_f = \sum_{n=0}^{N-1} x(n)^2 \qquad (7)$$

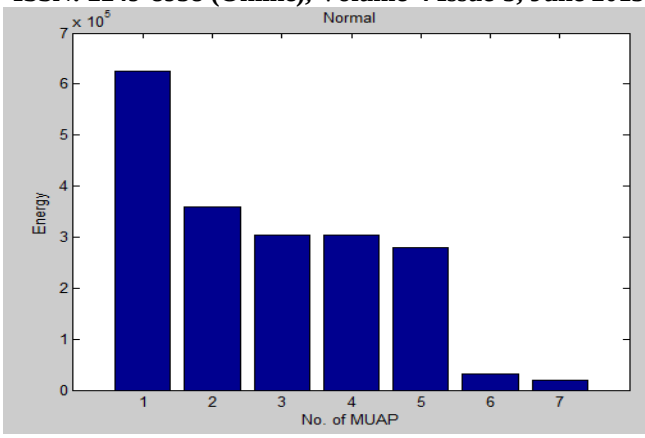
Where x (n) is the nth MUAP of an EMG signal. Hence MUAP with highest energy content is selected as dominant MUAP. The energy pattern of MUAPs present in an EMG signal for different three classes (normal, ALS, myopathy) is shown in figure 2.

B. *Proposed Direct Spectral Feature Extraction*

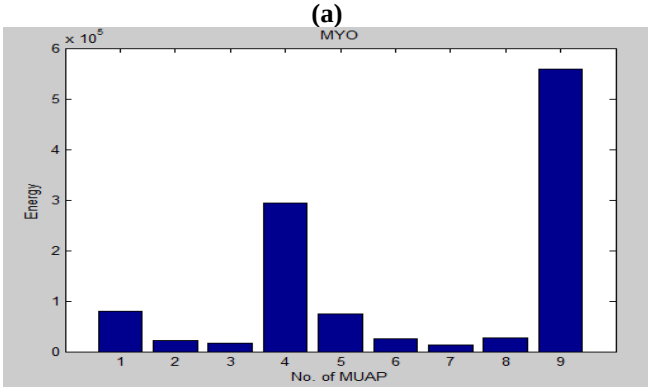
Here the spectral features are extracted directly from the dominant MUAP. The peak frequency, total power, mean power and median frequency are the spectral features considered for the classification of diseases. The other spectrum features such as mean frequency and spectral moment reduces the sensitivity of ALS and sensitivity of Myopathy.

C. *Proposed DWT spectral feature Extraction*

Here DWT is used to decompose the dominant MUAP to approximate coefficient and detail coefficient. Level one decomposition is used since higher level decomposition reduces the size and increases the computational burden. Then the spectral features are extracted from the approximate coefficient. The spectral features from the detail coefficient significantly reduce the accuracy of the classification. Thus the peak frequency, total power, mean power and median frequency are the spectral features used here.



(a)



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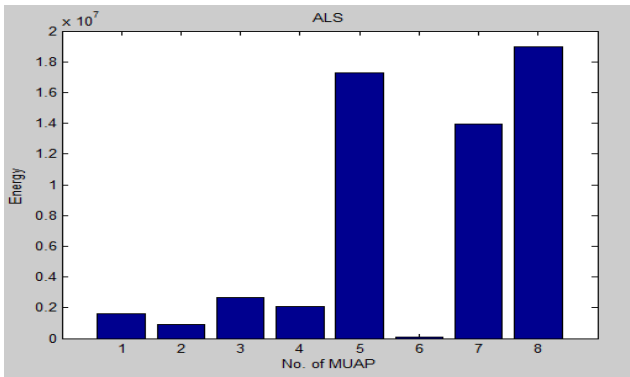

(c)

Fig. 2: Energy pattern of MUAPs of a) normal subject b) myopathy subject c) ALS subject

As KNN is treated as a benchmark classifier, for the purpose of comparison, in all methods, KNN classifier is employed. Block diagram of the proposed method is shown in the figure 3. The performance is evaluated in terms of standard parameters specificity, sensitivity and accuracy [1].

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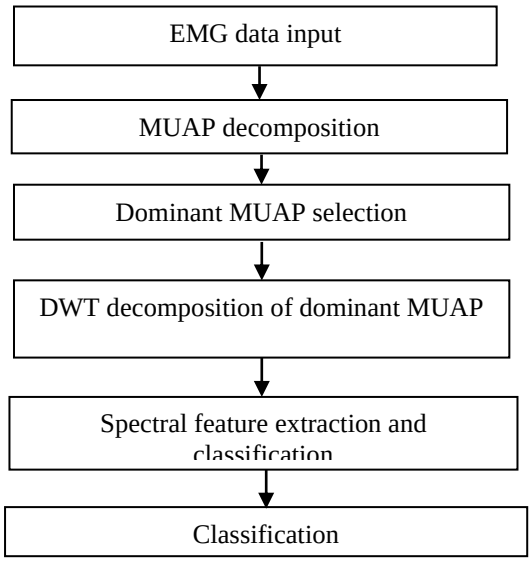

Fig. 3: Block diagram of the proposed method

IV. RESULTS AND DISCUSSION

In the proposed method the first step is the extraction of MUAPs from the EMG signal is involved. This is done by using EMGLAB, an auto decomposition program in which the raw EMG signal is decomposed to its constituent MUAPs using the pattern matching tool [25]. The auto decomposition feature is carried on the 11.2 sec given dataset in three 5 sec overlapping portion of the signal. The MUAP width is set to 25 msec, as used in conventional methods. A median based averaging is performed over all MUAPs in order to reduce the noise caused by interference from other MUAPs. Next, temporal energies of all individual MUAPs are investigated and the dominant MUAP is selected as per the criterion presented in the previous section. Three sets of data used for the proposed work are 2 two class dataset named as myo-normal dataset (consists of 50 myo signals and 150 normal signals) and ALS-normal dataset (consists of 50 ALS signals and 150 normal signals) and 1 three class dataset named as 3-class dataset (50 ALS signals, 50 myo signals and 150 normal signals). The simulation platform is matlab R2013a. The performance is evaluated using performance parameters such as sensitivity (SA, SM), specificity (SP) and accuracy of classification (CA). The results of the proposed methods are compared with the classification based on temporal features extracted from the dominant MUAP (1). The temporal features extracted from the dominant MUAP are maximum of approximate and detail coefficient (A_{max}, D_{max}) and standard deviation of approximate and detail coefficient (A_{std}, D_{std}). The results are shown in table I, table II and table III

TABLE I. PERFORMANCE COMPARISON USING ALS-NORMAL DATASET

METHOD	SPECIFICITY (SP, %)	SENSITIVITY OF ALS (SA, %)	CLASSIFICATION ACCURACY (CA, %)
TEMPORAL FEATURES	100	86	96.5
DIRECT SPECTRAL FEATURES	99.33	88	96.5
DWT SPECTRAL FEATURES	99.33	88	96.5

TABLE II. PERFORMANCE COMPARISON USING MYO-NORMAL DATASET

METHOD	SPECIFICITY (SP, %)	SENSITIVITY OF MYO (SM, %)	CLASSIFICATION ACCURACY (CA, %)
TEMPORAL FEATURES	91.33	60	83.5
DIRECT SPECTRAL FEATURES	86.66	62	80.5
DWT SPECTRAL FEATURES	89.33	66	83.5

TABLE III. PERFORMANCE COMPARISON USING 3-CLASS DATASET

METHOD	SPECIFICITY (SP, %)	SENSITIVITY OF MYO (SM, %)	SENSITIVITY OF ALS (SA, %)	CLASSIFICATION ACCURACY (CA, %)
TEMPORAL FEATURES	83.33	64	86	80
DIRECT SPECTRAL FEATURES	86.66	60	88	81.6
DWT SPECTRAL FEATURES	89.33	64	88	84

The results shows in ALS-normal dataset the sensitivity of ALS increases when spectral features are used for the classification. In myo-normal dataset the sensitivity of myo increases when spectral features are used for the Classification and in 3-class dataset the sensitivity, specificity and accuracy of the proposed methods shows better results than the existing methods.

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V. CONCLUSION

In this paper, two methods namely direct spectral feature extraction and DWT based spectral feature extraction are used to extract features from dominant MUAP are discussed. For the classification of EMG signals KNN classifier is used in the proposed methods. The main advantage of the proposed methods is that the feature dimension is extremely low, which reduces the computational complexity of the classification. The amount of manual effort is more in EMG signal decomposition using EMGLAB. However, the great advantage of using dominant MUAP is that the feature extraction needs to be carried out only on the dominant MUAP. Classification performance is evaluated using 50% of training data in KNN classifier. The results shows spectral features give better classification accuracy for different datasets. Moreover sensitivity of myopathy and ALS are increased when spectral features are used for classification.

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