Neuromuscular Disease Classification Based on Mel Frequency Cepstrum of Motor Unit Action Potential

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***Abstract*—In this paper, mel-frequency cepstral coefficient (MFCC) based feature extraction scheme is proposed for the classification of electromyography (EMG) signal into normal and a neuromuscular disease, namely the amyotrophic lateral sclerosis (ALS). Instead of employing the MFCC directly on EMG data, it is employed on the motor unit action potentials (MUAPs) extracted from the EMG signal via template matching based decomposition technique. Unlike conventional MUAP based methods, only one MUAP with maximum dynamic range is selected for MFCC based feature extraction. First few MFCCs corresponding to the selected MUAP are used as the desired feature, which not only reduces computational burden but also offers better feature quality with high within class compactness and between class separation. For the purpose of classification, the K-nearest neighborhood (KNN) classifier is employed. Extensive analysis is performed on clinical EMG database and it is found that the proposed method provides a very satisfactory performance in terms of specificity, sensitivity, and overall classification accuracy.**

***Index Terms*—amyotrophic lateral sclerosis (ALS), mel-frequency cepstral coefficient (MFCC), electromyography (EMG), feature extraction, KNN classifier, motor unit action potentials (MUAP).**

I. Introduction

Electromyography (EMG) signal analysis is one of the significant tools in the diagnosis of neuromuscular disease, for example the most detrimental amyotrophic lateral sclerosis (ALS) disease. The ALS is a progressive neurodegenerative disorder that affects both the upper and lower motor neurons and eventually the muscles become smaller and weaker and the body becomes paralyzed. The EMG signal represents the electrical responses generated in the muscle during its contraction. It is composed of several motor unit action potentials (MUAPs), where a motor unit refers to a single alpha motor neuron and the muscle fibers it activates. The EMG signal serves as a reliable source of information about different features of muscle function [1]. EMG based disease classification methods can be broadly classified into two categories, direct and MUAP based. The first one involves frame by frame EMG data analysis, while the second one works on extracted MUAPs to deal with the two classes in this case, namely normal and ALS. In direct EMG analysis, several time domain features are used, such as zero crossing rate, turns-amplitude ratio, root-mean-square (RMS) value and autoregressive (AR) coefficients [1]- [2]. Also some frequency domain features are available in literature, such as spectral analysis [3]. The wavelet transform, a multi-resolution time-frequency analysis, is widely employed for EMG analysis [4]. Recently in [5], by using AR modeling and wavelet domain features in adaptive neuro-fuzzy based classifier promising performance is achieved. Most of the direct schemes consider a single frame for feature extraction, thereby utilize only local information. Preliminary results on a small dataset that was obtained by using global statistics extracted from a few consecutive frame information are reported in [6], where some time, frequency and DWT features are investigated.

In MUAP based methods different morphological features, such as duration, amplitude, area, number of phases and number of turns are used along with different classifiers [7]- [8]. In [8], considering the audio characteristics of MUAPs, AR and cepstral analyses combined with time domain analysis of MUAPs are introduced. It is to be noted that the MUAP based methods consider all available MUAPs equally, although there is always some non-stationary MUAPs which may provide misleading information. Therefore, a method that utilizes only selected MUAPs needs to be investigated.

The objective of this paper is to develop a robust feature extraction scheme based on MUAP signal for the classification of normal and ALS subjects. Motivated from a clinical approach of hearing the audio characteristics of EMG signal for disease detection, in this paper, the mel-frequency cepstral coefficient (MFCC) of MUAP signal is proposed as potential features. The MUAPs are extracted from the EMG data by using template matching based decomposition technique and only one MUAP with maximum dynamic range is selected. First few MFCCs are extracted from the selected MUAP. For the classification, K-nearest neighborhood (KNN) classifier is employed. Finally experimental results with comparative analysis are presented.

II. Proposed MUAP based classification scheme using MFCC

A. MUAP Based EMG Analysis

EMG signals are generally recorded by inserting needle electrodes deep (approximately $0.25-0.5$cm) inside the muscle (needle EMG) or by placing electrodes on the skin surface. Needle EMG offers better selectivity and it is considered in this paper. Typical EMG data patterns of a normal person and

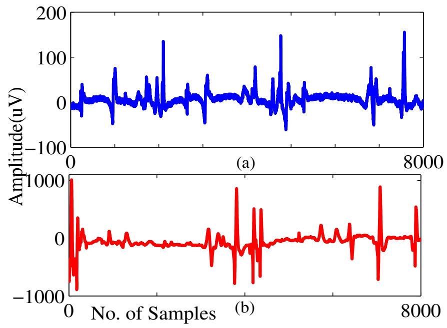

Fig. 1. EMG data pattern: (a) normal and (b) ALS.

a patient with ALS disease are shown in Fig. 1. One common approach of analyzing EMG data is to extract spectro-temporal features directly from frames of EMG recordings. There are some drawbacks of this approach: (i) A large number of frames need to be investigated depending on the frame size and total duration of EMG recording of a subject. (ii) Characteristics to be extracted from a frame depend on the frame size and amount of overlap between successive frames. In case of a very large frame size, information corresponding to a few number of firing instances may be included within a frame or for a very small frame size, there may exist incomplete information corresponding to a single firing. (iii) At the beginning portions of the EMG recordings, especially in case of ALS patients, successive frames may not exhibit consistent characteristics. In order to overcome the above problems of working directly on EMG recording, an alternative approach is to decompose the whole EMG data into few motor unit action potentials (MUAPs) and extract features from the MUAPs. In what follows we propose to utilize MUAP based feature extraction for EMG signal classification.

The MUAP is a compound signal reflecting the summation and cancellation of phases of the action potentials from individual muscle fibers in the motor unit. Neuromuscular disorders, especially in the ALS, the shapes of MUAPs affected by the ALS are larger compared to that of normal muscles. Hence, it is more preferable to investigate MUAPs rather than EMG signal in view of extracting distinguishable characteristics. There are number of techniques available for decomposing the recorded EMG data into its constituent MUAPs [9]- [10]. In the proposed method, a pattern matching based decomposition technique, proposed in [10], is used for extracting MUAPs, which is capable of resolving superimpositions and subtracting out the effect of the interference from the other MUAPs. Moreover, it does not usually miss the MUAPs with considerable amplitude. It generates templates from a portion of EMG considering all the spikes that occur at least three times with a high-degree of similarity and then classify the remaining spikes by using template matching.

B. Proposed Criterion for MUAP Selection

In MUAP based disease classification methods, generally all extracted MUAPs are equally treated, although it is well known that not all of them can uniquely characterize the class they belong to. Moreover, the number of MUAPs to be obtained after decomposition significantly varies for different EMG data and in the worst case it could be one. Hence, to be consistent with EMG data obtained from all subjects, instead of considering all extracted MUAPs of a subject, the idea is to consider only one MUAP for feature extraction. It will also help in drastically reducing the computational complexity. However, the concern now is to propose a logical criterion to select a single MUAP from a set of extracted MUAPs.

There is potentially an attractive link between motor unit size, force-generation and the amplitude of a MUAP. It is evident that in case of ALS, MUAPs exhibit higher amplitude and longer duration than normal cases. Hence, we propose to use only a single MUAP that has the maximum dynamic range. The selection criteria for the maximum dynamic range of MUAP is proposed to be sum of its maximum absolute amplitudes located in positive and negative sides of Y-axis. Among the extracted MUAPs from a particular EMG recording, the MUAP with the highest dynamic range is selected for further feature extraction.

Temporal patterns of all six acquired MUAPs extracted via the decomposition of an EMG recording of normal subject are shown in Fig. $2(a)(i)-(vi)$ in a descending order of the dynamic range. It is observed that the first MUAP contains the maximum dynamic range and hence will be selected for feature extraction for this particular EMG recording. In a similar fashion, five extracted MUAPs for the EMG recording of an ALS subject are shown in Fig. $2(b)(i)-(v)$ in a descending order of the dynamic range. Once the MUAPs of maximum dynamic range for the dataset are obtained, these are then used for the feature extraction.

C. Proposed MFCC Based Feature Extraction

Autoregressive modeling has widely been used for feature extraction from EMG signal either directly from the raw data or from MUAPs [5], [8]. Apart from AR modeling, cepstrum analysis which is very popular in speech signal processing, is also employed for investigating EMG movement patterns and MUAP based disease classification [5], [8]. The motivation behind selecting such a speech analysis tool like cepstrum could be the traditional approach of hearing the audio characteristics of EMG signal through loudspeaker for disease classification. For example, in neurogenic disorders like ALS, the excited motor neurons are reduced in number which generate MUAPs of higher amplitude and longer duration than the normal case resulting in duller sound from the loudspeaker [12]. In this regard, it would be more logical to employ mel-frequency cepstrum analysis instead of conventional cepstrum analysis as it incorporates some aspects of audition. A mel is an unit of measure of perceived pitch of a tone and the mel-frequency cepstrum offers advantage of using a perceptual frequency scale that is designed based on human auditory perception. The frequency f Hz can be converted into mel m by using

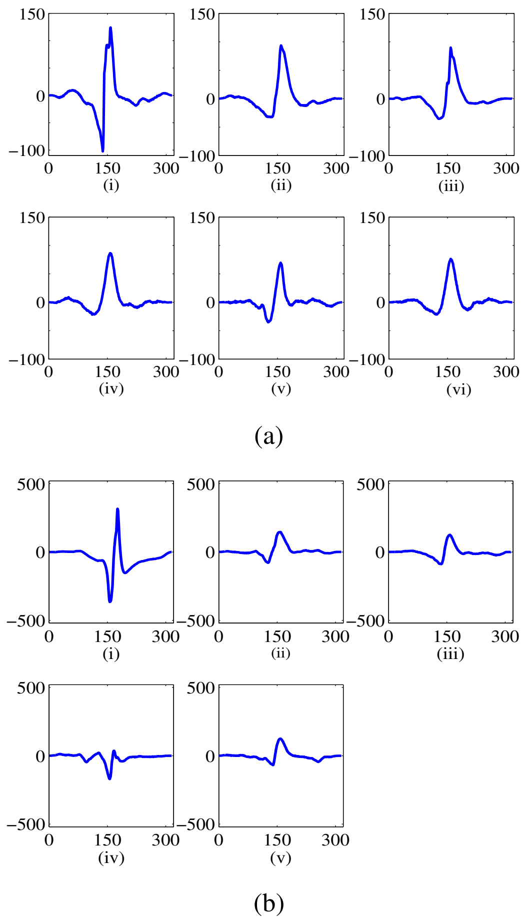

Fig. 2. MUAP waveforms extracted via EMG decomposition: (a) normal and (b) ALS.

the following formula [11]

$$m = 1127.01048 \times log_e(1 + \frac{f}{100}) \quad (1)$$

In order to obtain the mel-frequency cepstral coefficient (MFCC) of MUAP, first the spectrum of MUAP signal is passed through a set of N critical-band filters. Next, using the log energy of resulting filtered outputs, the nth MFCC can be computed as

$$c_n = \sum_{k=1}^{N} X_k cos[n(k - \frac{1}{2})\frac{\pi}{N}], \quad for\ n = 1, 2, ..., M \quad (2)$$

where X_k denotes the log energy output corresponding to the kth critical band and M indicates the number of coefficients to be computed [11]. In general, coefficient c_0 represents the average energy, c_1 reflects the energy balance between low and high frequencies, c_i $(i > 1)$ represents increasingly fine spectral detail. It is to be noted that the frequency range of EMG signal is much smaller than that of speech signal and thus would be sufficient to consider a few MFCCs for EMG analysis.

In the proposed method, the MFCC based feature extraction is carried out on the selected MUAP of an EMG recording. Since the loudspeaker generates different sounds for MUAPs from both groups, it is expected that MFCCs will carry significant information that can sufficiently be used to distinguish normal group from the diseased group. Hence, we propose to utilize first M number coefficients of MFCC as the feature.

D. Disease Classification Using KNN Classifier

The K-nearest neighborhood (KNN) 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 K neighboring EMG patterns in the training set. The EMG pattern from the test set is classified based on the class labels of K closer EMG patterns. In the proposed scheme, the Euclidean distance measure is employed in the KNN classifier. It is to be noted that performance with simple distance based classifier is also observed and found satisfactory.

III. Results and Analysis

The proposed method is tested with a publicly available clinical EMG database consisting of two different classes of data corresponding to normal and ALS subjects. The number of subjects are 10 normal (6 males, 4 females) aged 21-37 years and 8 ALS (4 males, 4 females) aged 35-67 years. Recording conditions are: (1) low voluntary and constant level of contraction, (2) visual and audio feedback, (3) concentric needle electrode, (4) five places in the muscle at three levels of insertion (deep, medium, low) and (5) high-pass and low-pass filters of the EMG amplifier were set at 2 Hz and 10 kHz [13]. For the purpose of validating the proposed method, 200 recordings (150 normal, 50 ALS) from 10 normal and 8 ALS subjects are considered. Each set of EMG recording has total 262,134 samples corresponding to 11.184 sec at 23,438 samples/sec sampling rate. For the performance evaluation, following parameters are used:

Specificity (Sp): Ratio of number of correctly classified normal subjects to number of total normal subjects.

Sensitivity (SeA): Ratio of number of correctly classified ALS patients to number of total ALS patients.

Total classification accuracy (TAcc): Ratio of number of correctly classified subjects to number of total subjects.

In the proposed MUAP based method, given raw EMG signal is first decomposed into its constituent MUAPs using the template matching algorithm [10]. In order to decompose the signal, the auto decomposition feature is utilized 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, the dynamic ranges of all individual MUAPs are computed and the MUAP with the maximum dynamic range is selected as per the criterion presented in the previous section.

Next, first three MFCCs from each selected MUAP are taken as proposed feature. In order to demonstrate the quality of the proposed selected MUAP based MFCC features obtained from

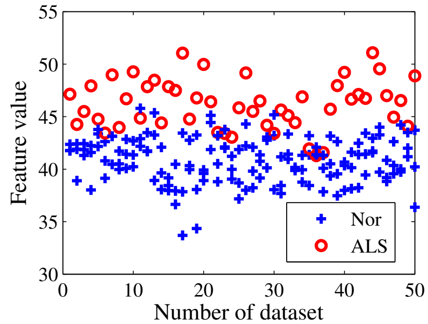

Fig. 3. Proposed MFCC based feature considering only the first coefficient.

TABLE I
PERFORMANCE COMPARISON ON DATASET

Methods	*Sp*	*SeA*	*TAcc* (%)
Proposed	98.00	76.00	92.50
Method in [6]	97.33	74.00	91.50
Method in [5]	77.07	77.93	77.50
Method in [7]	94.00	44.00	81.50

TABLE II
PERFORMANCE COMPARISON ON SMALL DATASET

Methods	*Sp*	*SeA*	*TAcc* (%)
Proposed	100.00	100.00	100.00
Method in [6]	100.00	100.00	100.00
Method in [5]	82.67	80.00	81.33
Method in [7]	100.00	53.33	76.67

the dataset, in Fig. 3, only c_0 values are plotted. For a better visualization, 150 normal subjects are plotted by dividing them into three sets, each containing 50 datasets and then plot them along with ALS dataset. It can undoubtedly be inferred that the feature extracted by using the proposed MUAP based method are satisfactorily distinguishable for the two classes. Next, the classification performance of the proposed method in terms of specificity, sensitivity and total classification accuracy obtained by using the dataset is presented in Table I. For the purpose of comparison, some other feature based classification methods are considered. However, for fair comparison, in all methods, similar to the proposed method, KNN classifier is used. In the table the results are reported for the value of $K = 6$. It is to be noted that a fixed value of K is found to provide satisfactory performance. In the proposed method, three MFCCs are considered which results in a feature dimension of 3. The direct EMG based method proposed in [5] utilizes autoregressive (AR) power spectral density and five level DWT decomposition for feature extraction. Here some statistical measures of the approximate and detail DWT coefficients are considered to form a feature vector of dimension 23. A total of five morphological features are extracted from selected MUAPs as proposed feature in [7]. The proposed scheme is also tested for the small dataset used in [6] and the results are reported in Table II. It is observed that the classification performance is comparable with the method proposed in [6]. It is to be observed that the feature dimension is kept very low in comparison to the other methods and only one selected MUAP is used.

IV. Conclusion

In this paper, a new approach of EMG signal analysis based on MFCC of MUAPs is introduced for the classification of normal and ALS subjects. Unlike conventional MUAP based disease classification schemes, in this paper, from a given EMG signal only a single MUAP is used for MFCC based feature extraction. In comparison to traditional direct EMG analysis schemes or MUAP based methods, the proposed method offers huge computational savings. For the feature extraction, unlike conventional cepstral analysis, mel based cepstrum is employed, where only first three MFCC coefficients are found sufficient to provide high within class compactness and between class separation. It is observed that the use of simple KNN classifier can provide consistent performance. Classification performance is tested using leave one out cross validation technique for the dataset. The proposed MUAP based MFCC features provide significantly better classification accuracy in comparison to that obtained by some existing methods.

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