IDENTIFYING THE MOTOR NEURON DISEASE IN EMG SIGNAL USING TIME AND FREQUENCY DOMAIN FEATURES WITH COMPARISON

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ABSTRACT

Motor neuron diseases are the most common neurological disorders found in the age ranges between 35-70 years, which selectively affect the motor neurons. Amyotrophic lateral sclerosis (ALS) is a fatal motor neuron disease that assails the nerve cells in the brain. This disease progressively degenerates the motor cells in the brain and spinal cord, which are responsible for controlling the muscles that enable human to move around, breathe, speak, and swallow. The electromyography (EMG) signals are the biomedical signals that are used to study the muscle function based on the electrical signal originated from the muscles. As the nervous system controls the muscle activity, the EMG signals can be viewed and analyzed in order to detect the indispensable features of the ALS disease in individuals. In this paper, analyzing the time and frequency domain behaviour of the EMG signals obtained from several normal persons and the ALS patients, some characteristic features, such as autocorrelation, zero crossing rate and Fourier transform are proposed to identify the ALS disease. For the pupose of classification, K-nearest neighbothood classifier is employed in a leave-one out cross validation technique. In order to show the classification performance, an EMG database consisted of 7 normal subjects aged 21-37 years and 6 ALS patients aged 35-67 years is considered and it is found that the proposed method is capable of distinctly separating the ALS patients from the normal persons.

KEYWORDS

Amyotrophic lateral sclerosis (ALS), electromyography (EMG), autocorrelation, zero crossing rate, Fourier transform, KNN classifier.

1. INTRODUCTION

The electromyography (EMG) signal is a biomedical signal that is obtained via electrical response generated in muscles during its contraction representing neuromuscular activities. The muscle activity (contraction/relaxation) is always controlled by the nervous system. The EMG signal exhibits complicated characteristics since it is dependent on the anatomical and physiological properties of muscles and controlled by the nervous system. However, it serves as a reliable source of information about different features of muscle function [1-3]. A good understanding of the EMG signal can lead to successful clinical diagnosis for different biomedical applications. One of the important application areas is the identification of motor disability. The structural unit

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of contraction is the muscle fibre. An EMG signal is the train of motor unit action potential (MUAP). The shapes and firing rates of MUAPs in EMG signals render significant source of information for the diagnosis of neuromuscular disorders.

Surface EMG (sEMG) is a method of recording the information present in the muscle action potentials. This sEMG signal can be measured by employing conductive elements or electrodes on the skin surface. In the process of acquiring sEMG signal from the electrodes mounted directly on the skin, it is found that the signal consists of all the MUAPs occurring in the muscles. As these action potentials occur at random intervals, the generated voltage corresponding to the EMG signal may be either positive or negative. The EMG signal can also be acquired invasively by inserting the wire or needle electrodes directly in the muscle. Combination of the muscle fiber action potentials generated from all the muscle fibers of a single motor unit, namely the MUAP, can be detected by a skin surface electrode (non-invasive) placed near this field, or by a needle electrode (invasive) inserted in the muscle [4]. In view of analyzing the EMG signal, generally it is first picked up from the electrodes, amplified using differential amplifiers and then pre-processed to eliminate low- and high-frequency noises and possible artifacts. Finally, the noise-reduced signal is rectified and averaged in some format to indicate the EMG amplitude. Surface EMG is the more common method of measurement, since it is non-invasive and can be conducted by personnel other than physicians with minimal risk to the subject. Measurement of sEMG is dependent on a number of factors and its amplitude varies from the microvolt to a low millivolt range [1]. The time and frequency domain properties of the sEMG signal depend on different factors, such as the timing and intensity of muscle contraction, the distance of the electrode from the active muscle area, the properties of the overlying tissue (e.g. thickness of overlying skin and adipose tissue), the electrode and amplifier properties and the quality of contact between the electrode and the skin [5-9].

The amytrophic lateral sclerosis (ALS) is the most common variant of motor neuron diseases. It is also known as Lou Gehrig's disease (after Lou Gehrig, a famous baseball player who was diagnosed with ALS in 1939). It is a progressive neurodegenerative disorder that affects both the upper and lower motor neurons. Motor neurons are nerve cells that control muscle movement. Upper motor neurons send messages from the brain to the spinal cord and lower motor neurons send messages from the spinal cord to the muscles. Hence the motor neurons are the most important part of the body's neuromuscular system. The ALS disease damages motor neurons in the brain and spinal cord. It causes these motor neurons to shrink and disappear, so that the muscles no longer receive signals to move. As a result, the muscles become smaller and weaker. Gradually the body becomes paralyzed, which means that the muscles no longer work [10]. The ALS can occur among young individuals, but it most commonly affects people between the ages of 35-70, with a slight male predominance. It is difficult to diagnose in the early stages because its symptoms may mimic other disorders. However, there are some clinical signs which may be treated as indication of damages either in the upper or in the lower motor neurons. A lower motor neuron lesion is characterized by muscle atrophy, weakness, fasciculation and cramps.

One possible way to determine the existence of the ALS is to analyze the EMG signal. In order to observe the effect of ALS on the recorded EMG signal, in most of the cases, changes in values of some selected EMG parameters are monitored and these individual parameters are achieved as a consequence of processing the EMG signal in time and frequency domains [11-15]. The objective of this paper is to develop a method to classify the ALS patients and the normal persons based on distinguishable characteristic features of the EMG signal. In this respect, some time and frequency domain features of the EMG signal are proposed with detailed experimental validation considering some standard EMG databases.

The paper is organized as follows. First, a brief description of the EMG signal and a preliminary idea about the ALS disease are presented. Next, proposed features of the EMG signal and an

analysis of the robustness of those features are shown. Finally, classification between the normal control group and the ALS patients has been carried out using the proposed method.

2. MATERIAL AND METHODS

2.1. Experimental Dataset

The experimental dataset is consisted of a normal control group and a group of patients with the ALS. In the control group, there are 6 normal subjects, 3 females and 3 males, all within the age limit 21-37 years. All of them are in general good physical shape and none had signs or history of neuromuscular disorders. The ALS patient group is consisted of 6 patients, 2 females and 4 males aged 35-67 years. Besides clinical and electrophysiological signs compatible with the ALS, 4 of them died within a few years after onset of the disorder, supporting the diagnosis of the ALS. The brachial biceps muscles were used in this study because they were the most frequently investigated in the two patient groups. During the recording of the EMG signals, following conventional conditions for MUAP analysis were maintained: (1) the recordings were made at low (just above threshold) voluntary and constant level of contraction, (2) visual and audio feedback were used to monitor the signal quality, (3) a standard concentric needle electrode was used, (4) the EMG signals were recorded from five places in the muscle at three levels of insertion (deep, medium, low), and (5) the high and low pass filters of the EMG amplifier were set at 2 Hz and 10 kHz [16].

2.2. Time and Frequency Domain Features of EMG Signals

Because of the complicated nature of the EMG signals, it would not be a convincing approach to classify them directly based on the time variation of the data as observed. The variation in data pattern of the EMG signals obtained from a normal person and an ALS patient is generally not uniquely distinguishable. As a result, further detailed analysis using both temporal and spectral representations would be definitely helpful in EMG data classification. It is well known that different time and frequency domain analyses turn out to be very effective for the analysis of transient signals [17-18]. Considering the computational simplicity and well acceptance in clinical practice, in this paper, fast Fourier transform (FFT) is used to obtain frequency domain features and for time domain characteristics, autocorrelation and zero crossing rates are utilized.

2.2.1 Spectral feature

In order to investigate the spectral characteristics of the EMG signal, in the proposed method, only magnitude spectrum of the EMG signal is taken into consideration. Especial attention has been given on some specific spectral characteristics, such as spectral energy distribution pattern at different frequencies, tendency of concentrating maximum energy at any particular frequency, and average and peak spectral amplitude and frequency. For the purpose of spectral analysis, short time Fourier transform is employed, which is most widely used for the data analysis in areas, such as biomedical signal and image processing [19], [20]. In particular, the fast Fourier transform (FFT) is used for determining the magnitude spectrum of the EMG signal. It is expected that within a short duration of the EMG data, the spectral behaviour remains consistent. Hence from a long duration of the EMG recording, for short time spectral analysis, smaller frames are extracted by using windowing techniques. However, effect of windowing in time domain may generate unwanted ripples in spectral domain.

In Figs. 1 and 2, the FFT magnitude spectra of the frame of EMG data for the first and last three normal persons are shown, respectively. For each person, five different frames are chosen arbitrarily. In a similar fashion, in Figs. 3 and 4, the FFT magnitude spectra of the frame of EMG data for the first and last three ALS patients are shown, respectively.

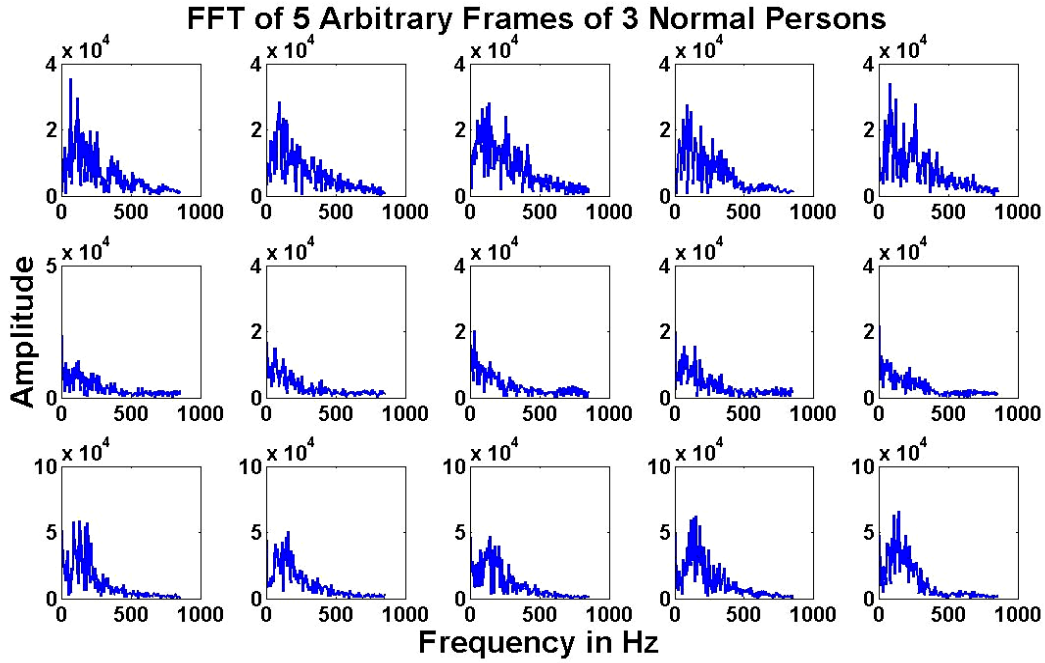

Figure 1. Magnitude spectra of the frame of EMG data for the first three normal persons.

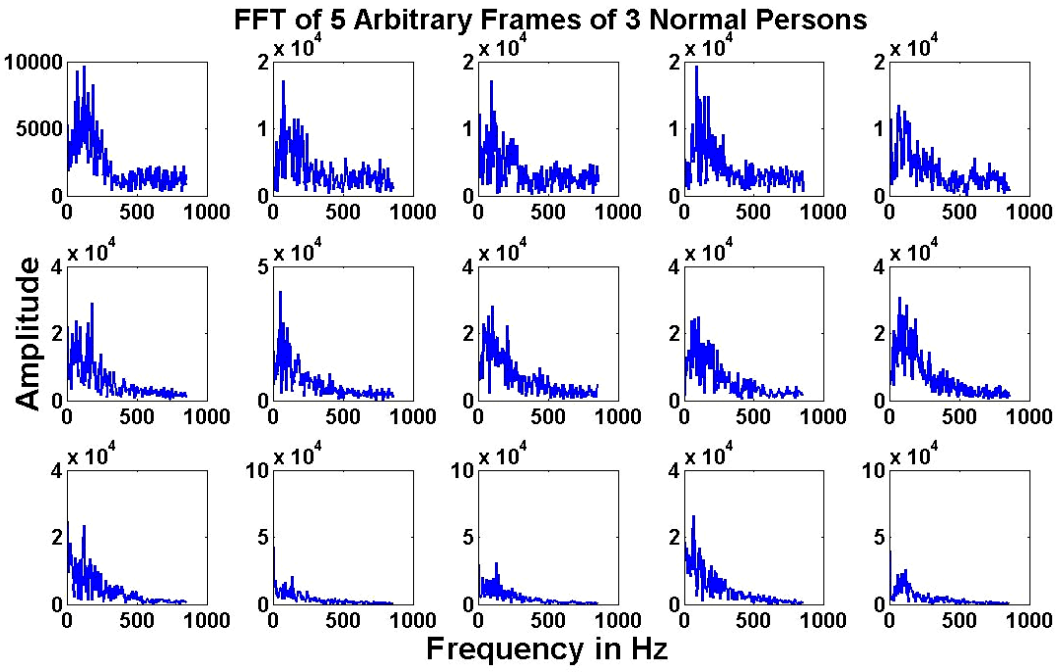

Figure 2. Magnitude spectra of the frame of EMG data for the last three normal persons.

It is observed from the above figures that the height of the magnitude spectra for the case of ALS patients is comparatively higher than that obtained for the normal persons. It is also evident from magnitude spectra that spectral energy is mostly concentrated in the low frequency

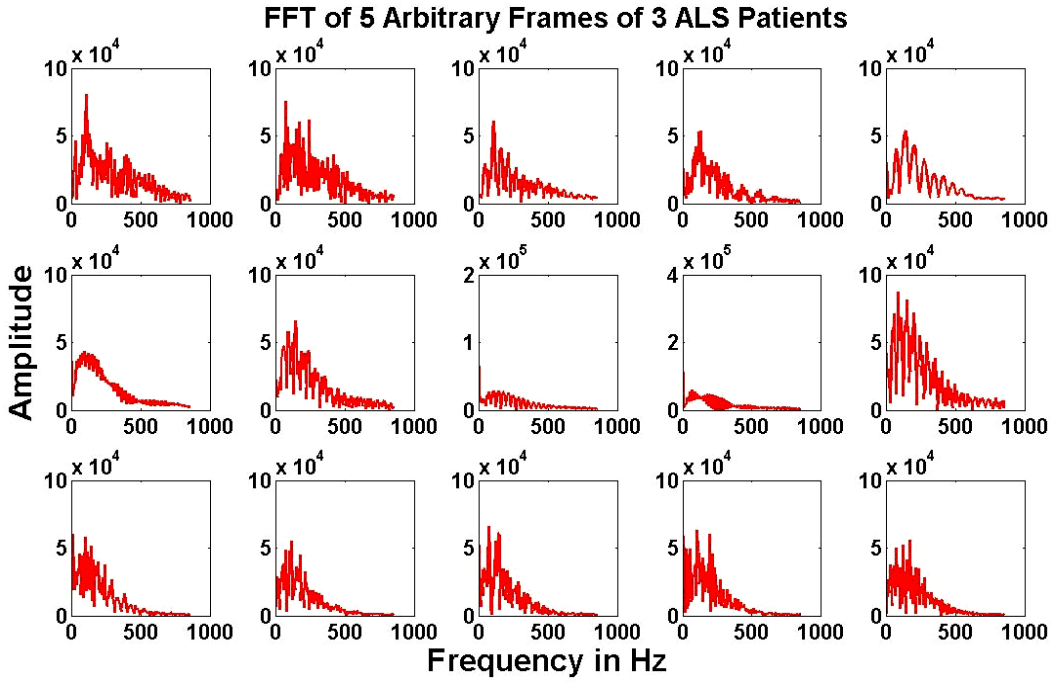

Figure 3. Magnitude spectra of the frame of EMG data for the first three ALS patients.

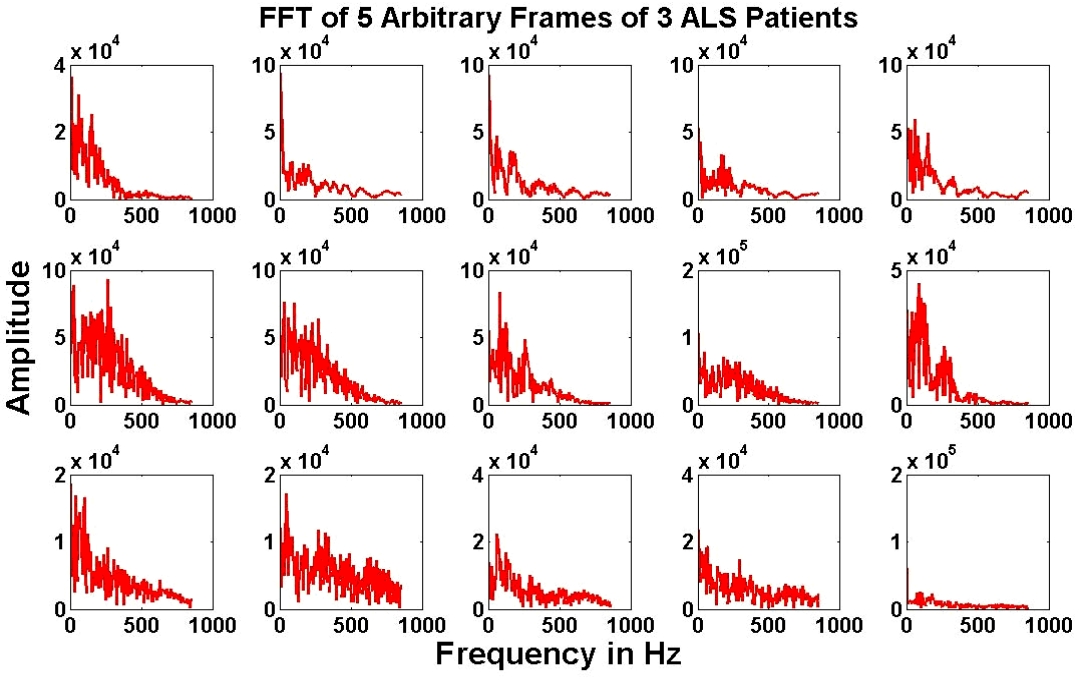

Figure 4. Magnitude spectra of the frame of EMG data for the last three ALS patients.

regions for both normal persons and ALS patients. Maximum peaks of the magnitude spectra for different cases appear at different frequency locations at a random fashion. As a result, instead of considering the frequency values of the maximum spectral peaks, only their amplitude values are taken into consideration as a distinguishing spectral feature.

Table 1. Maximum, minimum and average values of the frequencies and corresponding amplitudes of the spectral peaks for normal persons

Normal persons	Amplitude of spectral peak			Frequency of spectral peak		
	Maximum	Minimum	Average	Maximum	Minimum	Average
1	0.4154×10^5	0.23582×10^5	0.30356×10^5	257.4292	40.0445	107.0906
2	0.5185×10^5	0.18621×10^5	0.37576×10^5	160.1782	0	78.9450
3	0.3613×10^5	0.16801×10^5	0.24577×10^5	97.2510	0	36.1545
4	0.7041×10^5	0.37541×10^5	0.54207×10^5	171.6195	11.4413	91.5304
5	1.4237×10^5	0.19048×10^5	0.56231×10^5	148.7369	0	34.3239
6	0.4283×10^5	0.22630×10^5	0.30195×10^5	245.9879	28.6032	100.2258

Table 2. Maximum, minimum and average values of the frequencies and corresponding amplitudes of the spectral peaks for the ALS patients

ALS patients	Amplitude of spectral peak			Frequency of spectral peak		
	Maximum	Minimum	Average	Maximum	Minimum	Average
1	0.0760×10^6	0.31793×10^5	0.5615×10^5	251.7086	17.1619	172.5348
2	0.2243×10^6	0.50187×10^5	0.7012×10^5	177.3401	0	97.9375
3	0.1530×10^6	0.42769×10^5	0.7263×10^5	200.2227	0	75.0549
4	0.1064×10^6	0.36374×10^5	0.6486×10^5	80.0891	0	10.7548
5	0.8864×10^6	0.29999×10^5	1.7667×10^5	11.4413	0	1.8306
6	0.0848×10^6	0.42084×10^5	0.6111×10^5	234.5466	0	119.6760

2.2.2 Mean Frequency

The frequency locations and amplitude values of the peaks of the magnitude spectra of the EMG signals at different frames have been carefully investigated. It is found that these values exhibit significant variation at different frames of the EMG data both in case of normal persons and ALS patients. In order to visualize the level of variations among different frames of a particular person, in Table 1, maximum, minimum and average values of both the frequency and amplitude of the spectral peaks for different normal persons are shown. In a similar fashion, in Table 2, maximum, minimum and average values of both the frequency and amplitude of the spectral peaks for different ALS patients are shown. It can be observed that none of these parameters are consistently distinguishable. As an alternate, in this paper, we propose to utilize mean and median frequencies as spectral features. Considering the product of the frequency and corresponding amplitude at each frequency points of the magnitude spectrum, the mean frequency is computed by taking the average of all such products throughout the entire spectrum. Since in this case both frequency and amplitude values have been given equal weights and all frequencies in the range are considered, a better feature consistency is thus expected.

2.2.3 Autocorrelation

The cross-correlation between two signals is a measure of dependency of these two signals on each other. Higher the dependency, larger will be the cross-correlation value. When the two signals involved in the cross-correlation operation become exactly same, the operation is then termed as autocorrelation. In fact, an autocorrelation sequence reflects the degree of similarity at different portions of a time series data. Hence it is a well known operation for measuring the

hidden periodicity of a signal [21]. In this paper, the characteristics of the autocorrelation function of different frames of EMG data have been investigated.

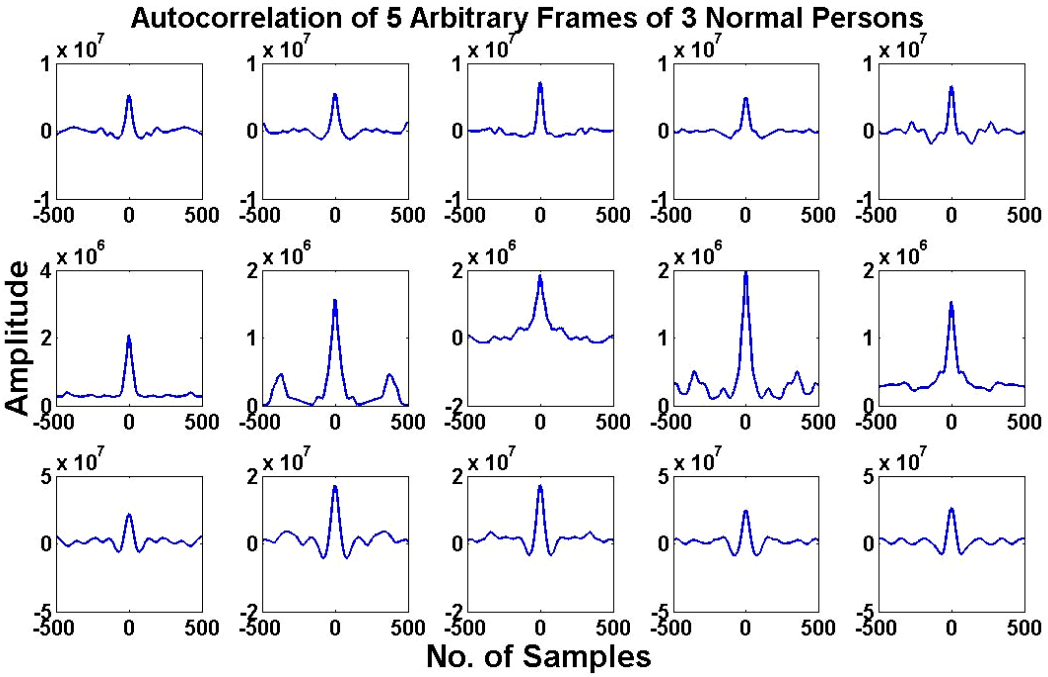

Figure 5. Autocorrelation sequence of the frame of EMG data for the first three normal persons.

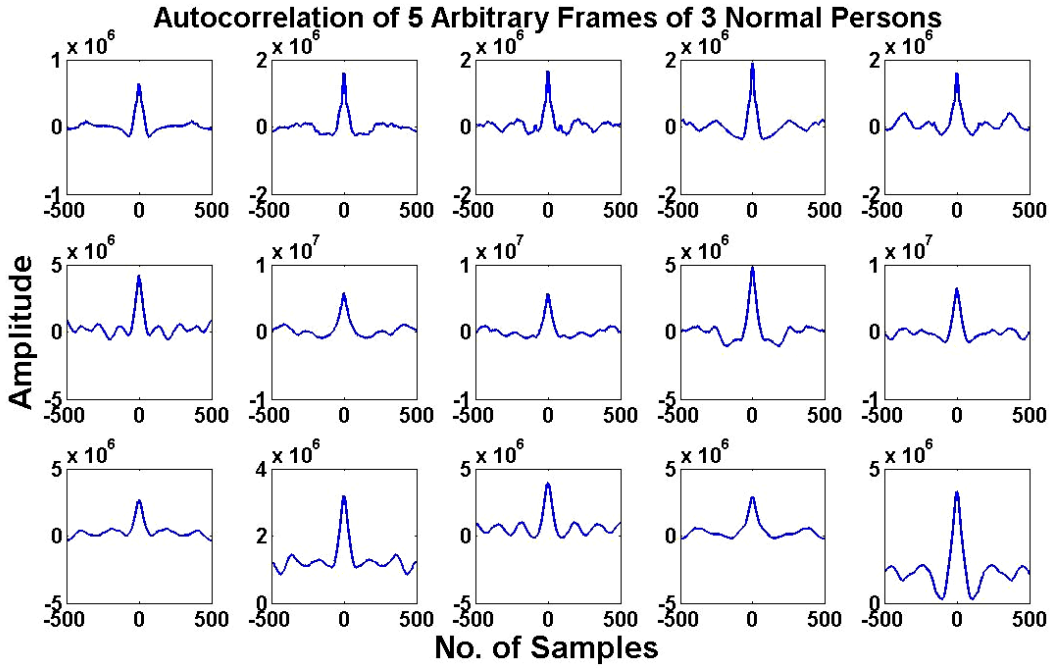

Figure 6. Autocorrelation sequence of the frame of EMG data for the last three normal persons.

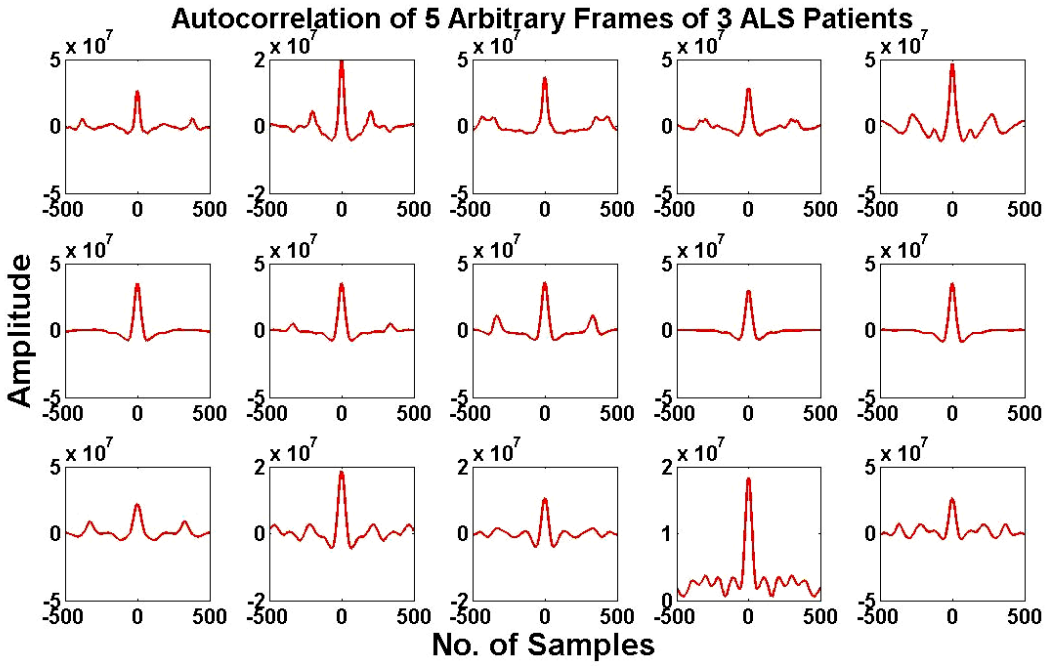

Figure 7. Autocorrelation sequence of the frame of EMG data for the first three ALS patients.

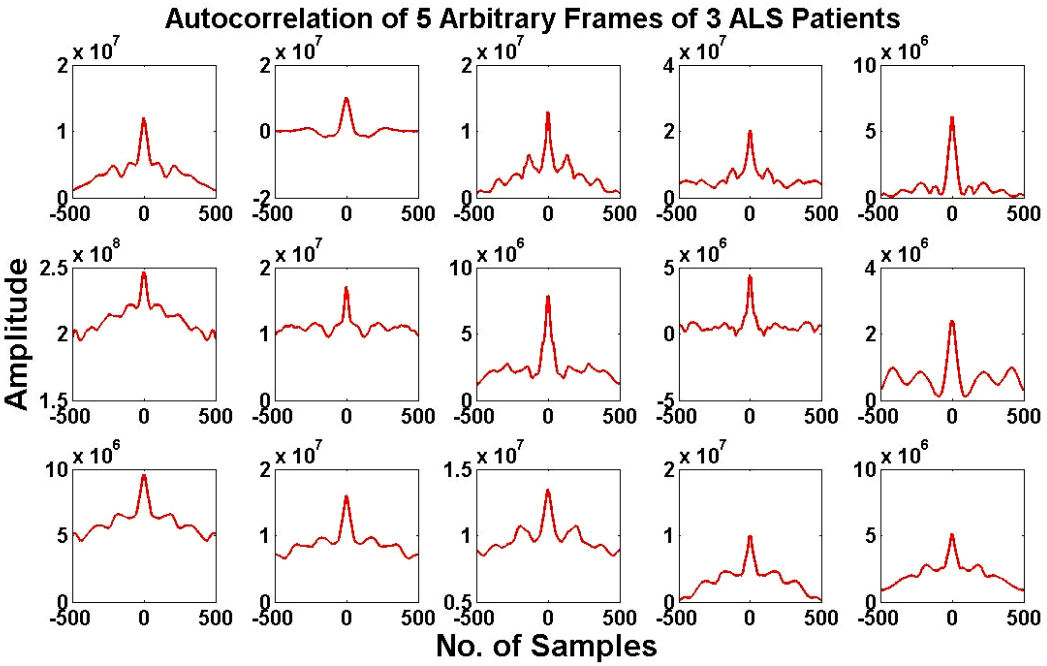

Figure 8. Autocorrelation sequence of the frame of EMG data for the last three ALS patients.

For an N-length sequence of EMG data $f(n)$, its autocorrelation function $r_f(\tau)$ can be computed as

$$r_f(\tau) = \frac{1}{N} \sum_{n=0}^{N-1-|\tau|} f(n) f(n+|\tau|), \qquad (1)$$

where τ denotes the correlation lag. In Figs. 5 and 6, the autocorrelation sequence of the frame of EMG data for the first and last three normal persons are shown, respectively. For each person, five different frames are chosen arbitrarily. In a similar fashion, in Figs. 7 and 8, the autocorrelation sequence of the frame of EMG data for the first and last three ALS patients are shown, respectively.

It can be inferred from these figures that no consistent information regarding the hidden periodicity of the EMG signal is readily observable from the autocorrelation sequence. However, a major distinguishable feature observed in these figures is the overall shape of the correlation functions in case of the normal persons and the ALS patients. In case of the normal persons, the magnitude of the correlation sequence drastically falls right after the zero lag and remains very small at all lags located further from the zero lag. On the contrary, the magnitude of the correlation sequence decreases comparatively at a slower rate and it possesses more strength over the entire lags of the autocorrelation function. Magnitude of the zero lag of the autocorrelation function is taken as a feature in this research.

2.2.4 Zero-crossing rate (ZCR)

The Zero-crossing rate (ZCR) expresses the number of times a signal crosses the axis of abscissas. It can be defined as

$$ZCR = \frac{1}{2N}\left\{\sum_{k=1}^{N-1}\left|\mathrm{sgn}[x(k)] - \mathrm{sgn}[x(k-1)]\right|\right\} \tag{2}$$

where

$$\mathrm{sgn}[x] = \begin{cases} 1, x \geq 0 \\ -1, x \leq 0 \end{cases}$$

The random temporal fluctuations of the EMG signal may serve as distinguishable feature. Hence, the ZCR is also considered as a distinguishable feature to comment on the detection of diseases.

2.2.5 KNN classification

In pattern recognition, the k-nearest neighborhood algorithm (KNN) is one of the most reliable but simple method of classifying objects based on closest training examples in the feature space. KNN is a type of instance-based learning or lazy learning where the function is only approximated locally and all computations are deferred until the classification. In this paper, for the classification of the EMG data into two classes based on the time and frequency domain features, the KNN classifier is employed.

3. EMG SIGNAL ANALYSIS AND FEATURE EXTRACTION

For the purpose of detecting the ALS patients from the given EMG data, 18 datasets of 6 normal persons and 18 datasets of 6 ALS patients are used. Each EMG dataset has a total number of 262,134 samples at a rate of 23,438 samples per second. Thus, each of these single channel datasets has total time duration of 11.184 sec.

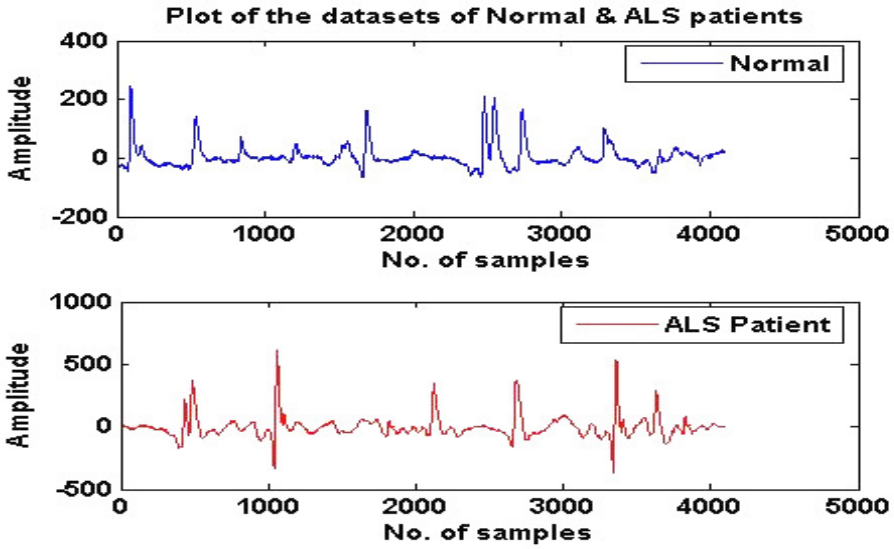

Figure 9. EMG data pattern of a normal person and the ALS patient.

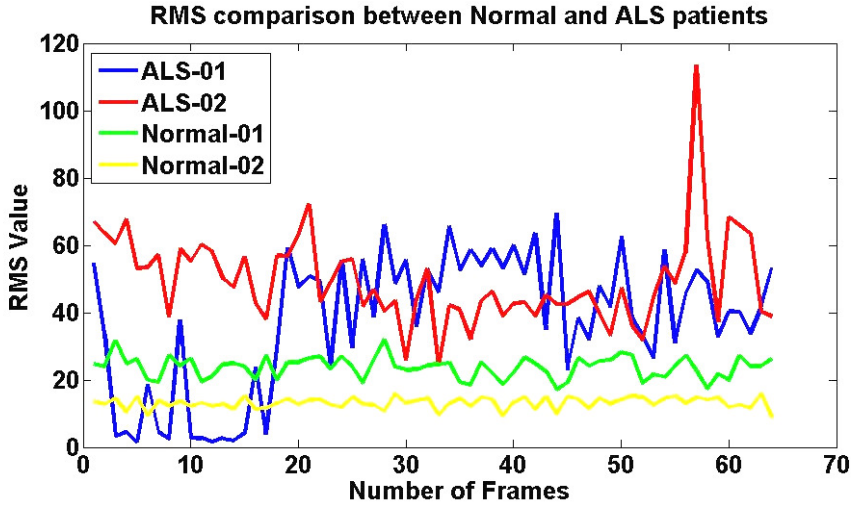

Figure 10. RMS values obtained from each frame of the EMG data considering two normal persons and two ALS patients.

At first, a single dataset is segmented into 64 distinct frames, each consisting of 4096 number of samples. In Fig. 9, the pattern of the EMG data are shown for a normal person and an ALS patient, respectively. Next, the root-mean-square (RMS) value of each frame of data is calculated for both normal and ALS datasets. In Fig. 10, the RMS values obtained from each frame of the EMG data considering two normal persons and two ALS patients are plotted. It is found from the analytical results as well as from Fig. 10 that the RMS values corresponding to the ALS patients fluctuate abruptly in the initial and final frames but exhibit a stable range of values between 30 and 56 in the middle frames of every datasets. On the other hand, RMS values corresponding to a normal person show a steady range of values which does not exceed 28 for all the frames in a dataset. Finally, 25 frames (from 30th frame to 55th frame) are selected out of 64 frames of both the normal persons and ALS patients for further processing to extract different features.

Since the energy of the EMG signal is mostly concentrated in the low frequency regions, a low pass filter is used to reduce the effect of high frequency regions. The low pass filtered EMG signal is then used for feature extraction. Proposed time and frequency domain features, such as

magnitude spectrum, mean frequency, autocorrelation and ZCR are computed on an individual frame basis. For both the cases of normal persons and the ALS patients, average results obtained from 25 frames of every datasets are considered to construct the feature vector. Finally the KNN classifier is employed to detect the ALS affected EMG signals from the normal signals.

4. RESULT AND DISCUSSIONS

In this paper, we propose different time and frequency domain characteristics for the classification of EMG signals to detect the ALS patients and distinguish them from the normal group. It is found that the proposed features, such as the spectral peak level, mean frequency value, zero crossing rate and the value of the zero lag of the autocorrelation function have the capability of distinguishing the EMG data of the ALS patients from that of the normal persons.

In Fig. 11, average amplitude values of spectral peaks of different datasets corresponding to normal persons and the ALS patients are shown. As expected the level of average values of spectral peaks corresponding to the ALS patients is much higher than that of corresponding to normal persons. In Fig. 12, average zero lag values of the autocorrelation function of different datasets corresponding to normal persons and the ALS patients are shown. Here also a similar distinguishable behaviour is observed between the normal persons and the ALS patients. It is clearly observed from Figs. 11 and 12 that the proposed features offer a high degree of separability between the two classes, which ensures a better classification accuracy.

In Fig. 13, the average ZCR values of EMG signals of different datasets corresponding to normal persons and the ALS patients are shown. Unlike the previous two cases, in this case the degree of separability is not much satisfactory. In Fig. 14, the average mean frequency values of the magnitude spectrum of different datasets corresponding to normal persons and the ALS patients. Here also a moderate degree of separability is obtained. Hence, it is expected that in comparison the last two features, namely the ZCR and mean frequency, the first two features based on the spectral peak and autocorrelation function may provide better classification performance.

In order to show the classification performance, each feature has been tested using the KNN classifier. The most widely used leave-one-out cross validation algorithm is utilized for the testing purpose. In this case, among several datasets only one dataset is taken away at a time for the purpose of testing against the remaining all datasets. Excluding the test dataset, remaining datasets are used for the training of the classifier. Depending on the classifier output value as defined in the group parameter of the classifier, the EMG signals are classified as normal or ALS affected EMG signals. Some statistical performance measures, such as specificity, sensitivity and accuracy are computed to investigate the clsssification performance. These statistical performance measures are defined as follows:

Specificity: Number of correctly classified normal subjects/number of total normal subjects.

Sensitivity: Number of correctly classified ALS subjects/number of total ALS subjects.

Classification accuracy: Number of correctly classified subjects/number of total subjects.

Table 3 gives the overall prformance measurement of the clssifier for the 4 features individually. As expected, the highest success rate of 100% is obtained for both the proposed autocorreltion and spectral peak based features. It is observed from the table that the features like ZCR and the mean frequency provide comparatively low classification accuracy.

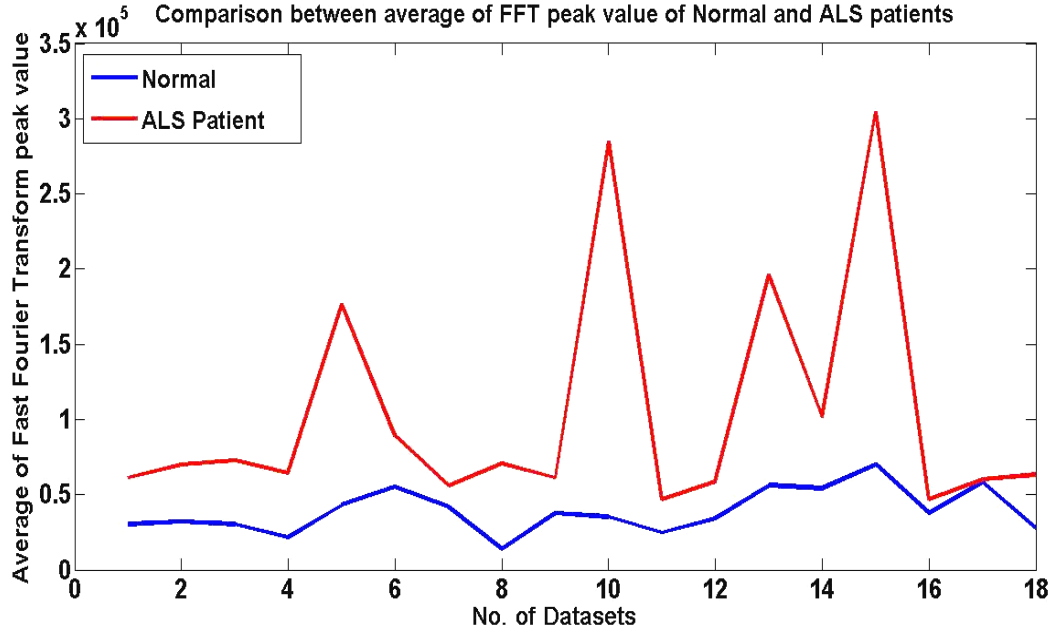

Figure 11. Average amplitude values of spectral peaks of different datasets corresponding to normal persons and the ALS patients.

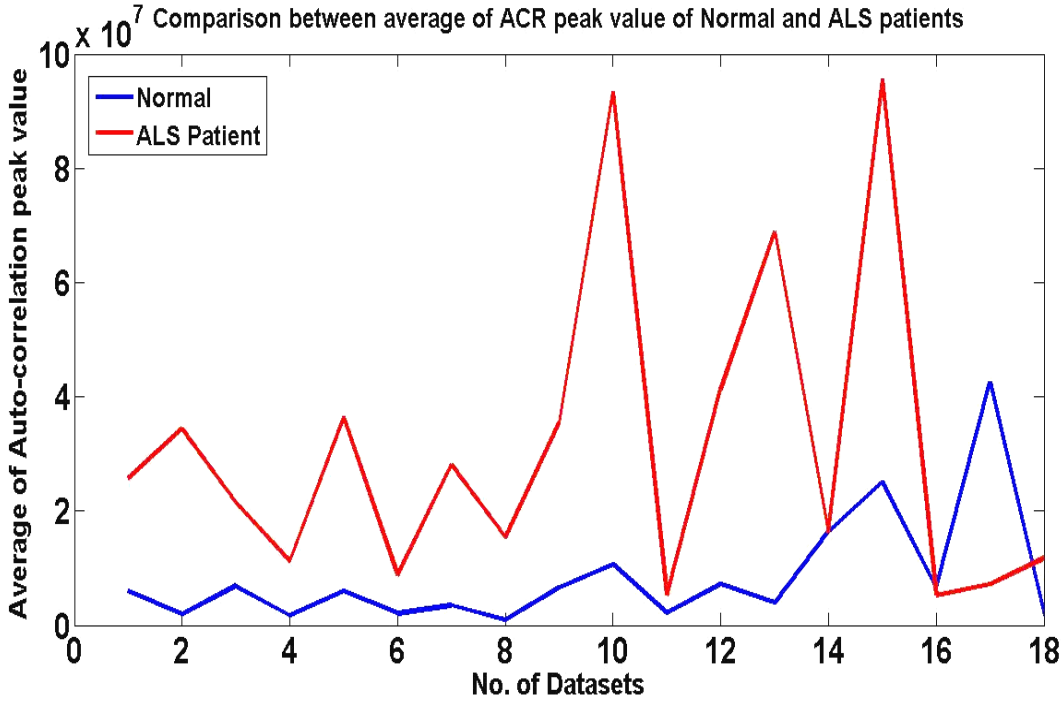

Figure 12. Average zero lag values of the autocorrelation function of different datasets corresponding to normal persons and the ALS patients.

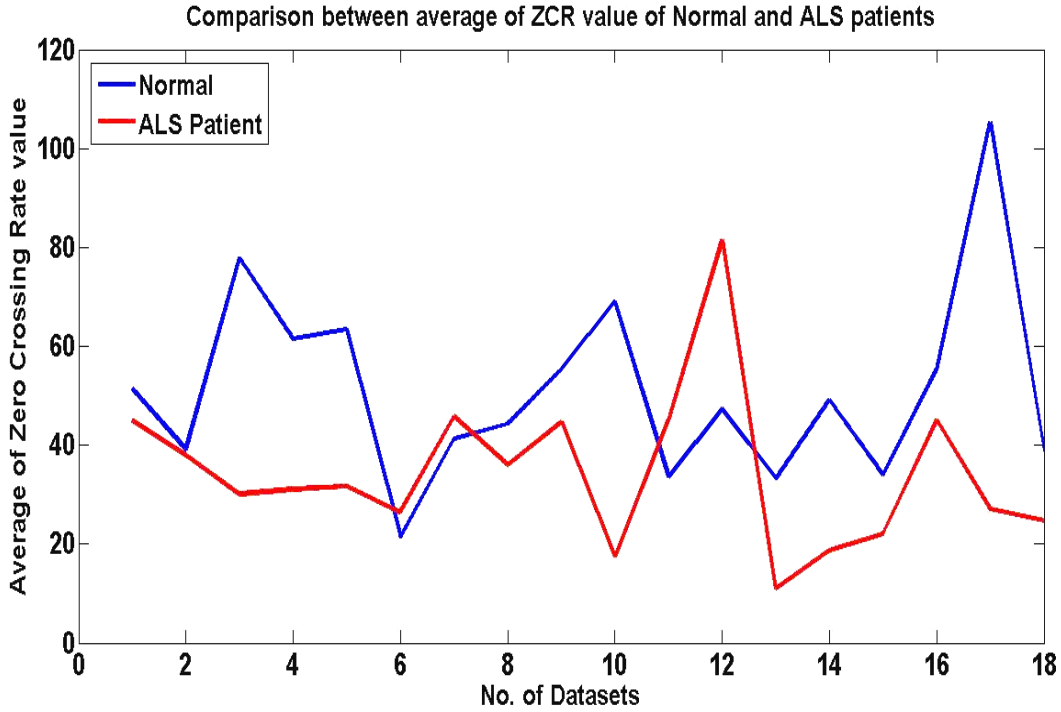

Figure 13. Average ZCR values of EMG signals of different datasets corresponding to normal persons and the ALS patients.

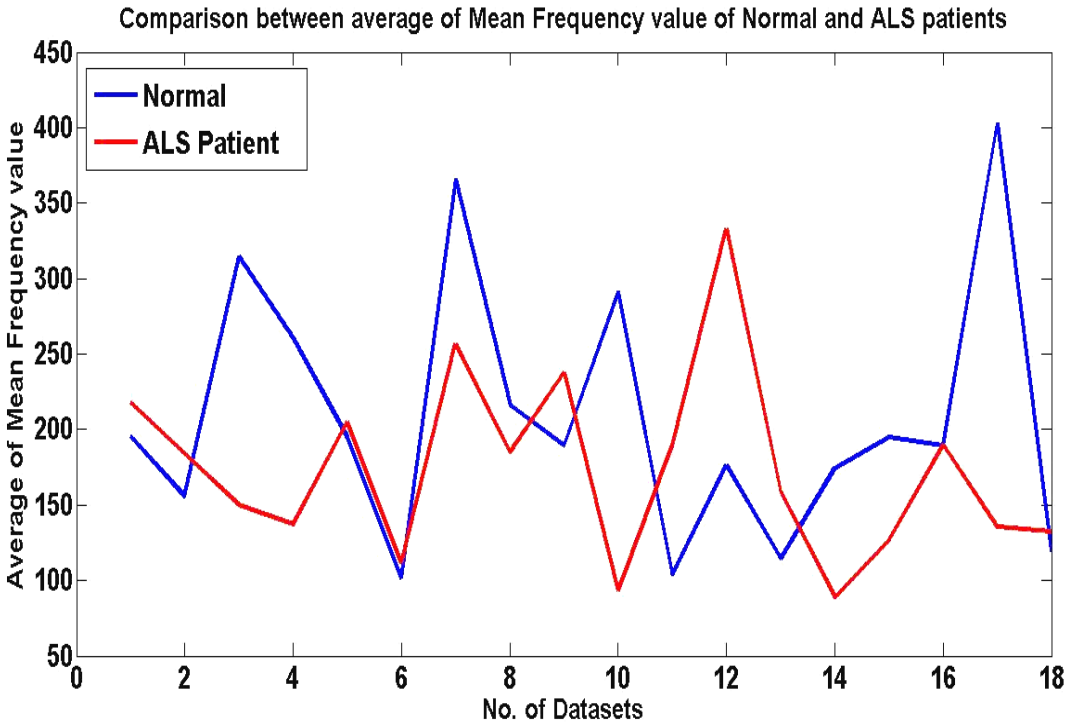

Figure 14. Average mean frequency values of the magnitude spectrum of different datasets corresponding to normal persons and the ALS patients.

Table 3. Classification performance of the proposed features

Feature	Accuracy (%)	Specificity (%)	Sensitivity (%)
Spectral peak	100	100	100
Mean Frequency	69.5	66.7	72.2
Autocorrelation	100	100	100
ZCR	72.2	72.2	72.2

5. CONCLUSION

A comprehensive analysis of time and frequency domain features of EMG signals is presented in this paper with an objective to develop an efficient classification scheme to handle the two class problem of separating the EMG signals of normal control group and the ALS patients. It is shown that proper feature selection can provide an excellent classification performance even for a very complicated biomedical signal like EMG. Among the proposed spectral features, the average values of spectral peak exhibits better performance in comparison to the mean frequency. On the other hand, among the proposed time domain features, average zero lag values of the autocorrelation function offers better classification performance than the most common ZCR feature. The main reason behind the superiority of the classification performance obtained by using the proposed two features is the high degree of inter-class feature separability. Because of the robustness of the proposed features, even use of a simple KNN classifier can result in 100% classification accuracy for the case of spectral peak and autocorrelation based features.

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