DCT domain feature extraction scheme based on motor unit action potential of EMG signal for neuromuscular disease classification

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A feature extraction scheme based on discrete cosine transform (DCT) of electromyography (EMG) signals is proposed for the classification of normal event and a neuromuscular disease, namely the amyotrophic lateral sclerosis. Instead of employing DCT directly on EMG data, it is employed on the motor unit action potentials (MUAPs) extracted from the EMG signal via a template matching-based decomposition technique. Unlike conventional MUAP-based methods, only one MUAP with maximum dynamic range is selected for DCT-based feature extraction. Magnitude and frequency values of a few high-energy DCT coefficients 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 neighbourhood 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.

1. Introduction: Electromyography (EMG) signal analysis plays a major role in the diagnosis of neuromuscular diseases, for example, the most common, 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 paralysed. 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 fibres it activates. The EMG signal serves as a reliable source of information about different features of muscle function [1]. As the nervous system controls the muscle activity, the EMG signals can be viewed and examined to detect the vital features of the ALS disease in individuals. Neurophysiologists assess MUAPs from their shape by watching the oscilloscope and hearing their audio characteristics [2]. However, a robust feature extraction scheme based on a MUAP signal is still demanding for the assistance of neurophysiologists with clinical decision. 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, whereas 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, 3]. Also, some frequency-domain features are available in the literature, such as spectral analysis and median frequency [4–7]. The wavelet transform, a multi-resolution time–frequency analysis, is widely employed for EMG analysis [8, 9]. The robustness of the wavelet domain method, proposed in [9], depends on the feature dimension. Recently in [10], by using AR modelling 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 utilise only local information. Preliminary results on a small dataset that was obtained by using global statistics extracted from few consecutive frame information are reported in [11] where some time, frequency and DWT features are investigated.

In MUAP-based methods for disease classification, the MUAPs are either collected by inserting needle electrode precisely in single fibre [12] or extracted by using EMG decomposition algorithms [13]. Generally, different morphological features of MUAPs or corresponding statistical behaviour are used along with different classifiers. For example, methods proposed in [14] utilise a set of morphological features (duration, spike duration, amplitude, area, spike area, number of phases and number of turns) and artificial neural network classifier. Along with morphological features in [14], an EMG decomposition scheme is introduced and it provides comparatively superior classification performance. 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 utilises only selected MUAPs and considers frequency-domain analysis need to be investigated.

The objective of this Letter is to develop a robust scheme based on frequency-domain characteristics of MUAP signal for the classification of normal and ALS subjects. In this regard, we propose to utilise the discrete cosine transform (DCT) which, unlike the discrete Fourier transform (DFT), generates a real spectrum of real signals and thereby avoids the computation of redundant data. Moreover, it offers an ease of implementation in practical applications. The MUAPs are extracted from the EMG data by using a template matching-based decomposition technique and only one MUAP with maximum dynamic range is selected. A few high-energy DCT coefficients along with corresponding frequencies are extracted from the selected MUAP. In the proposed method, *K*-nearest neighbourhood (KNN) classifier is employed. Finally, experimental results with comparative analysis are presented.

2. Background of DCT-based EMG signal analysis: EMG signals are generally recorded by inserting needle electrodes deep ($\sim 0.25 - 0.5$ cm) inside the muscle (needle EMG) or by placing electrodes on the skin surface. Needle EMG offers better selectivity and is considered in this Letter. Typical EMG data patterns of a normal person and a patient with ALS disease are shown in Fig. 1. It is to be mentioned that the ALS is the most common variant of motor neuron diseases. A lower motor neuron lesion is characterised by muscle atrophy and weakness, while the

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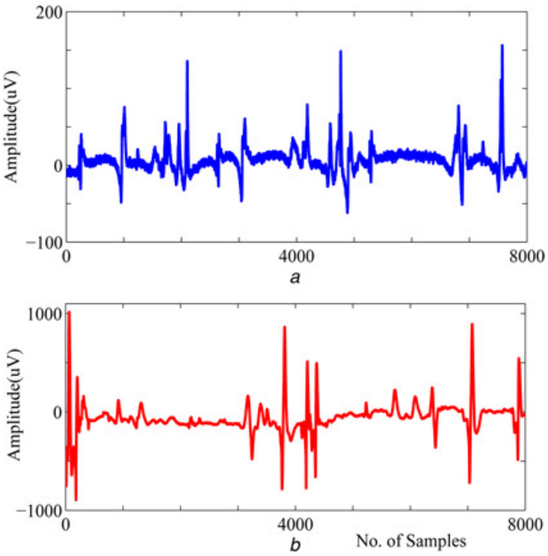

Figure 1 *EMG data pattern*
a Normal
b ALS

upper one can manifest as stiffness and weakness. It is difficult to diagnose the ALS in the early stages because its symptoms may mimic other disorders. Over time, it destroys motor neurons that are vital in the functioning of the nervous system. Life expectancy of newly diagnosed people is roughly 3–5 years.

Feature extraction is a crucial step for EMG-based neuromuscular disease classification. Owing to significant physiological change in muscle activity of ALS subjects, during the classification of normal and ALS subject from EMG data, it is expected that distinguishable features can be extracted from frequency-domain analysis. In the proposed classification scheme, for frequency-domain feature extraction DCT is used. The DCT of a signal $x(n)$ is computed as

$$y(k) = w(k)\sum_{n=1}^{N} x(n)\cos\frac{\pi(2n-1)(k-1)}{2N}, k = 1, \ldots, N \quad (1)$$

where

$$w(k) = \begin{cases} \frac{1}{\sqrt{N}}, & k=1 \\ \sqrt{\frac{2}{N}}, & 2 \le k \le N \end{cases}$$

One of the main reasons behind choosing the DCT is that it is superior to DFT for the transformation of real signals. For a real signal, the DFT gives a complex spectrum and leaves nearly half of the data unused but the DCT generates a real spectrum and avoids the computation of redundant data. The energy compaction property of DCT allows representation in lower dimensions. This facilitates reducing the number of coefficients to be employed as feature in an intended classification task. Owing to strong energy compaction property, most of the important information tends to be concentrated in a few low-frequency DCT coefficients and thus better noise immunity is expected. Moreover, it offers an ease of implementation in practical applications.

One common approach of analysing EMG data is to extract spectro-temporal features directly from the 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 that case, selecting consistently behaving frame zones of a given EMG recording is a difficult task. One may select these frames of the EMG data depending on the RMS energy of frames [11]. In Fig. 2, the RMS values obtained from frames of the EMG data considering 150 normal persons and 50 ALS patients are shown. In this Figure, RMS values obtained from successive non-overlapping four frames are averaged and then plotted. It can easily be observed that the RMS values corresponding to the ALS patients fluctuate abruptly in the initial and final frames. However, the RMS values corresponding to a normal person exhibits a relatively steady range all over the recording. To overcome the above problems of working directly on EMG recordings, an alternative approach is to decompose the whole EMG data into few MUAPs and extract features from the MUAPs. In what follows, we propose to utilise MUAP-based feature extraction for EMG signal classification.

3. Proposed MUAP-based classification scheme using DCT: The MUAP is a compound signal reflecting the summation and cancellation of phases of the action potentials from individual muscle fibres in the motor unit. Here, motor unit refers to a single alpha motor neuron and the muscle fibres it activates. Neuromuscular disorders, especially ALS, can change the morphology and physiology of motor units causing changes in MUAP shapes and thus the EMG signals that they produce. For example, generally the shapes of MUAPs affected by the ALS are larger compared with 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 [15]. Quantifying the changes in firing rate and variability from the firing patterns can reveal changes in the central nervous system and can help in differentiating neuromuscular disorders compared to normal condition. However, one prior condition here is to find the exact firing pattern, which can only be obtained by full EMG decomposition. In the proposed method, the tool EMGLAB, proposed in [15], is used for EMG decomposition because of its ability to resolve superimpositions and subtract 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 classifies the remaining spikes by using template matching.

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 characterise the class they

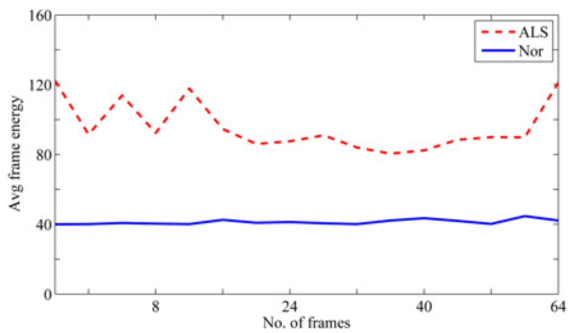

Figure 2 *Variation of average frame energy for normal and ALS EMG data*

belong to. Possible reasons behind such discrimination could be the variation in firing characteristics, cross-talk (interference from neighbouring muscle fibres) and acquisition process. 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. One may recall the deep booming sound of a neurogenic MUAP that sometimes rattles the EMG machine, which reveals the concept of amplitude of a MUAP. It is evident that the amplitude of an individual MUAP will be different in different groups (i.e. normal and ALS). For example, in case of ALS, MUAPs exhibit higher amplitude and longer duration than normal cases. The magnitudes of maximum peaks located both in the positive and negative sides of the MUAP with respect to *Y*-axis can provide significant information about the EMG signal and an idea about pathology. Hence, we propose to use only a single MUAP that has the maximum dynamic range (summation of maximum absolute amplitudes in positive and negative sides of *Y*-axis). The selection criteria for the maximum dynamic range of MUAP is proposed to be the sum of its maximum absolute amplitudes located in the positive and negative sides of *Y*-axis. It is to be mentioned that the dynamic range of MUAP is generally higher for the ALS group compared with that of the normal group. Among the extracted MUAPs from a particular EMG recording, the MUAP with the highest dynamic range is selected for further feature extraction. It is to be mentioned that MUAP extraction via EMG decomposition involves some additional computational time. Hence, use of only the highest amplitude MUAP, instead of all MUAPs during training and testing phases, will help in mitigating that time requirement and will provide better consistency in feature quality.

Temporal patterns of all six acquired MUAPs extracted via the decomposition of an EMG recording of normal subject are shown in Fig. 3*a* (i) – (vi) in 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. 3*b* (i) – (v) in descending order of the dynamic range. Note that, as expected, the amplitude of the ALS group is higher than the normal group and here also the first MUAP can be easily selected based on the proposed MUAP selection criterion. Once the MUAPs of maximum dynamic range for different datasets are obtained, these are then used for the feature extraction. It is to be mentioned that the firing rate of the MUAP (the number of occurrence of a particular MUAP in an EMG recording) is also inquired for selection of the MUAP. However, selection of the MUAP considering the highest firing rate may not be very suitable because of its complete dependence on the decomposition.

In the proposed method, the DCT-based feature extraction is carried out on the selected MUAP of an EMG recording. To present the typical DCT pattern of the MUAP signals, in Fig. 4*a* and *b*, selected MUAPs of EMG recordings of a normal and an ALS subject are shown, respectively, and in Fig. 4*c* and *d*, corresponding smoothed absolute DCT coefficients are shown. In the DCT representation, for a better visual understanding, frequency axis is shown up to 500 Hz. One common phenomenon in these two cases is that the high-energy coefficients are mainly present in the low-frequency region. However, the differences in DCT pattern between the normal and ALS cases can be clearly observed, such as the magnitude levels are significantly higher in ALS and

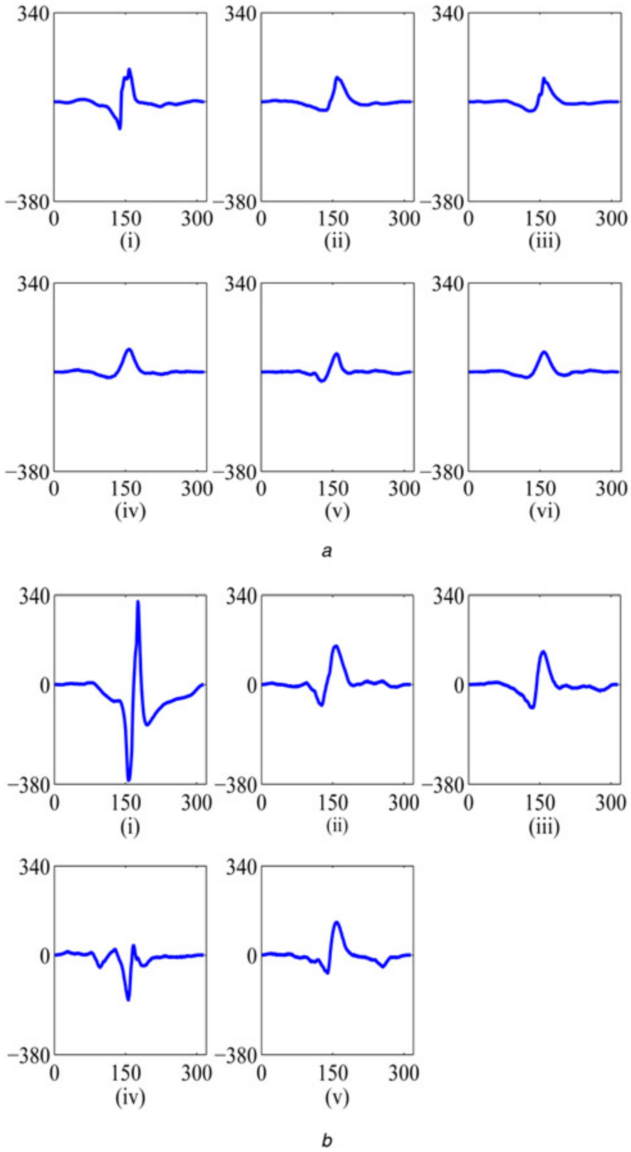

Figure 3 *MUAP waveforms extracted via EMG decomposition*
a Normal
b ALS

also the frequency locations corresponding to high-energy DCT coefficients are quite different. Since most of the energy is concentrated in the low-frequency zone of DCT representation of MUAP signals and DCT exhibits strong energy compaction property, it is expected that high-energy coefficients will carry significant information that can sufficiently be utilised to distinguish normal groups from the diseased group. Hence, we propose to utilise the magnitudes and frequency values corresponding to high-energy DCT coefficients as the features. Arranging the high-energy DCT coefficients in a descending order, first M coefficients are considered as the proposed feature for neuromuscular disease classification.

The 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 neighbouring EMG patterns from both the normal and diseased group 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 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 performance. In the proposed method, the

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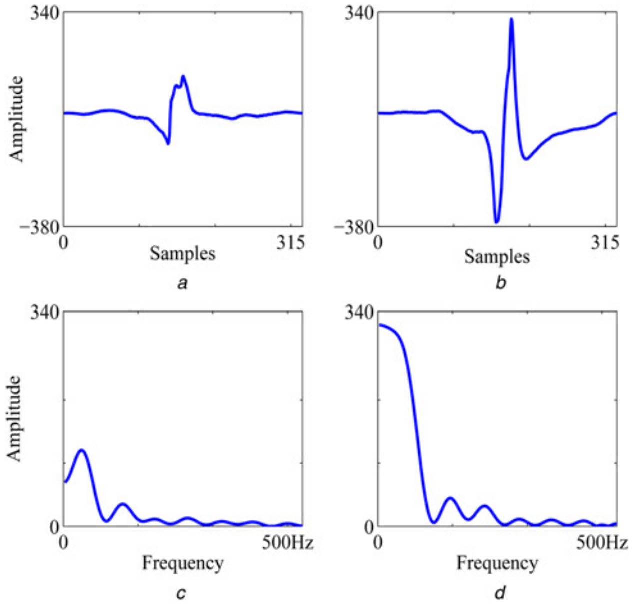

Figure 4 *MUAP waveshapes*
a Normal and
b ALS and corresponding DCT representation
c Normal and
d ALS

value of K is varied within a large range and it is found that because of the better feature quality, consistent performance is achieved, which is demonstrated in the next Section.

4. Results and analysis: The proposed methods are 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 ten normal (six males, four females) aged 21–37 years and eight ALS (four males, four females) aged 35–67 years. Recording conditions are: (i) low voluntary and constant level of contraction, (ii) visual and audio feedback, (iii) concentric needle electrode, (iv) five places in the muscle at three levels of insertion (deep, medium and low) and (v) high-pass and low-pass filters of the EMG amplifier were set at 2 Hz and 10 kHz [16]. To show the effect of variation of size of the database on classification accuracy, two sizes are used: (i) small dataset: 30 recordings (15 normal, 15 ALS) from 5 normal and 5 ALS subjects and (ii) large dataset: 200 recordings (150 normal, 50 ALS) from 10 normal and 8 ALS subjects. Each set of EMG recording has a total of 262 134 samples corresponding to 11.184 s at 23 438 samples/s sampling rate. For the performance evaluation, the following parameters are used:

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

Sensitivity (SeA): Ratio of the number of correctly classified subjects suffering from an ALS disease to the number of total subjects suffering from that ALS disease.

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

In the proposed MUAP-based method, the raw EMG signal is first decomposed into its constituent MUAPs using the template matching algorithm [15]. To decompose the signal, the autodecomposition feature is utilised on the 11.2 s given dataset in three 5 s overlapping portion of the signal. The MUAP width is set to 25 ms, as used in conventional methods. A median-based averaging is performed over all MUAPs 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, the DCT operation is carried out on each selected MUAP. The absolute DCT coefficients are then arranged in descending order and M number of high-energy coefficients along with the corresponding frequency values are taken as proposed features. To demonstrate the quality of the proposed selected MUAP-based DCT features obtained from the EMG recordings of large dataset, in Fig. 5, only the maximum energy DCT coefficients are plotted. For the purpose of comparison, the average of maximum energy DCT coefficients obtained from frame-by-frame EMG analysis on the large dataset are depicted in Fig. 6. In case of frame-by-frame analysis, as a feature value the average over all the frames is considered. For a better visualisation, 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 features extracted by using the proposed MUAP-based method are satisfactorily distinguishable for the two classes in comparison with those obtained from frame-by-frame analysis. It is observed that the level of proposed DCT features corresponding to the ALS patients is considerably higher than the level of the normal persons. Although it is observed here that the first element of the proposed feature vector offers high between-class separation, further analysis on statistical distributional characteristics of extracted features are presented using the box

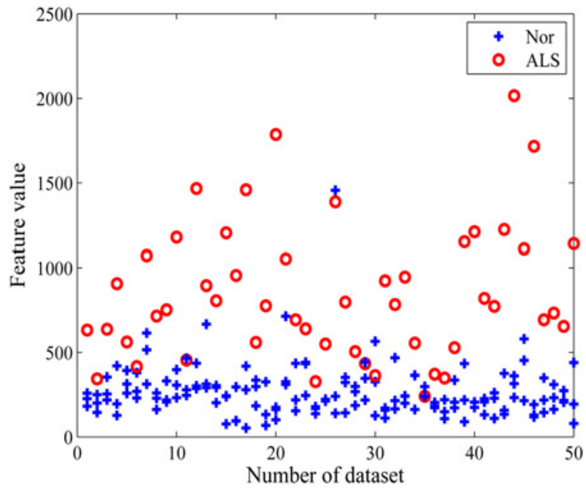

Figure 5 *Proposed DCT-based feature considering only the maximum energy coefficient*

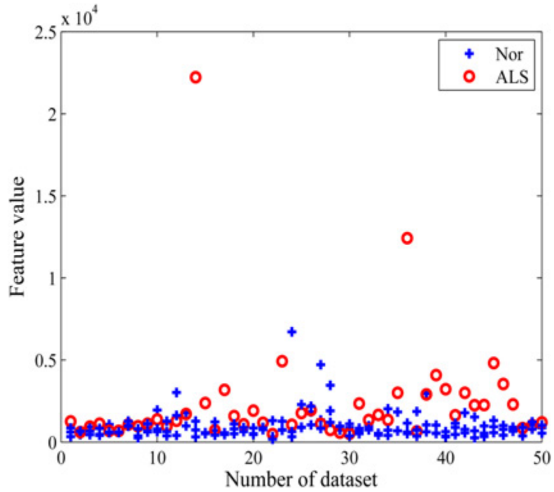

Figure 6 *Maximum energy DCT coefficient obtained from frame-by-frame EMG analysis*

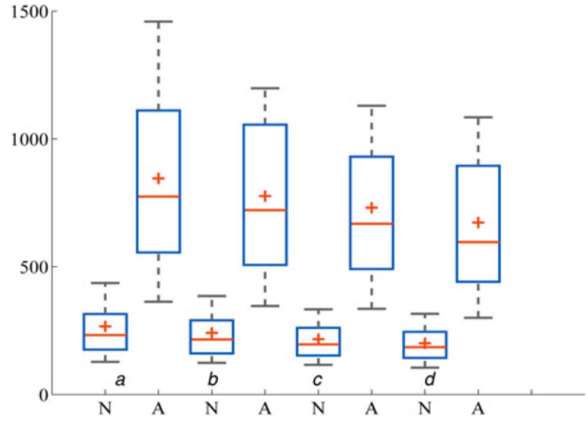

Figure 7 *Box plot of the distribution of proposed DCT features*
a First max
b Second max
c Third max and
d Fourth max

plots, which provides information in terms of median and quartiles. Fig. 7 depicts the box plot of the distribution of four higher energy absolute DCT coefficients of the proposed feature obtained for the large dataset. On the box plot, a plus sign is used to indicate the mean value of the feature. It is clearly observed that there exists a high between-class separation but the within-class compactness is comparatively better for normal subject for all four plots. It is found that the combination of both ten higher coefficients and the corresponding frequency values offer a very high quality of features. Next, the classification performance of the proposed methods in terms of Sp, SeA and TAcc obtained by using the two datasets are presented in Tables 1 and 2. For the purpose of comparison, some other feature-based classification methods are considered. However, for fair comparison, in all methods, similar to the proposed methods, KNN classifier is used. In the table, the results are reported for the value of *K* which provides the best total accuracy. In the proposed method, 10 higher energy DCT coefficients are considered, which results in a feature dimension of 20. The direct EMG-based method proposed in [10] utilises 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. Another direct EMG-based method reported in [11] utilises ten maximum-valued DWT coefficients. In this case, an averaging of the DWT values over the frames is performed to extract the features. A total of five morphological features (amplitude, duration, rise time, area and the number of phases) are extracted from selected MUAPs as proposed feature in [14]. It is observed that for the small dataset, the classification performance is comparable with the method proposed in [11]. However, for the large dataset, the proposed method offers better performance in comparison with all other methods. It is observed that the SeA of the proposed method is not very satisfactory in comparison with its Sp. Such a performance pattern is expected and also observed for other methods because of the inherent nature of ALS data pattern.

One important aspect of the proposed scheme is to select the number of higher energy DCT coefficients. The classification performance of the proposed method is extensively investigated over a wide range of values of chosen number of coefficients. In Fig. 8, the classification performance of the proposed method in terms of Sp, SeA and total accuracy is shown against the variation of chosen number of coefficients. It is evident that the overall performance of the proposed method is consistently satisfactory and it does not vary significantly with the variation of number of chosen coefficients. In this regard, the effect of reduction in the number of DCT coefficients by using the principal component analysis (PCA) is also investigated and the results are shown in Fig. 9. It is vividly shown that the feature reduction using PCA cannot provide better classification performance. For the purpose of classification, the KNN classifier is employed in supervised classification. In the KNN classifier, it is required to find the optimal *K* value for achieving the best classification performance. Since it is validated that the very high-quality feature can provide satisfactory performance with KNN classifier hence, for the purpose of comparison with other methods, KNN classifier is employed. The variable *K* in the KNN classifier is also varied in a wide range and the corresponding change in the classification performance is investigated. In Fig. 10,

Table 1 Performance comparison on small dataset

Methods	Sp	SeA	TAcc, %
proposed	100.00	100.00	100.00
method in [11]	100.00	100.00	100.00
method in [10]	82.67	80.00	81.33
method in [14]	100.00	53.33	76.67

Table 2 Performance comparison on large dataset

Methods	Sp	SeA	TAcc, %
proposed	98.00	86.00	95.00
[11]	97.33	74.00	91.50
[10]	77.07	77.93	77.50
[14]	94.00	44.00	81.50

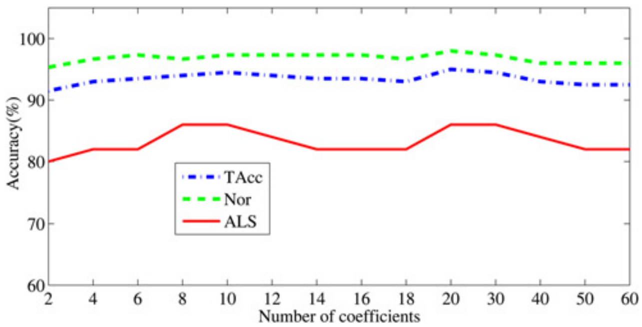

Figure 8 *Effect of variation of number of chosen high-energy DCT coefficients on accuracy obtained by proposed method*

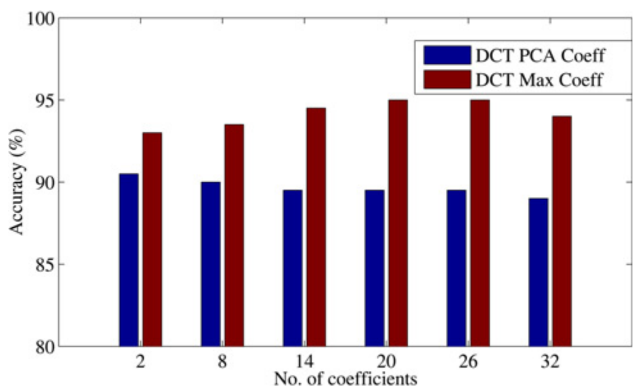

Figure 9 *Effect of feature dimension in classification accuracy*

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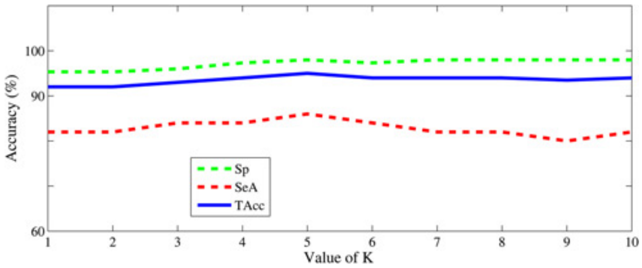

Figure 10 *Performance of KNN classifier with the variation of K*

Table 3 Performance comparisons for different classifiers

Classifier	Sp	SeA	TAcc, %
LDA	98.00	72.00	91.50
SVM	96.67	72.00	90.50
Naïve	96.67	86.00	94.00
KNN	98.00	86.00	95.00

the effect of the variation of K value on the classification performance in terms of overall accuracy is reported for a wide range of values of K. It is evident that the variation in K results in consistently satisfactory performance. To demonstrate the quality of the proposed features, different other classification algorithms have been tested. In Table 3, the classification performance of the proposed method obtained by using the KNN (with $K = 5$), support vector machine (SVM), linear discriminate analysis (LDA) and Naïve Bayes classifiers are presented. It is observed that in all cases very high accuracy is obtained. However, the Naïve Bayes classifier provides almost similar level of accuracy in comparison with the KNN classifier.

It is to be observed that the feature dimension is kept low in comparison with the case of taking all the DCT coefficients in the proposed method. Moreover, in the proposed method, only one selected MUAP is used. As a result, the computational complexity is expected to be within the acceptable limit. The proposed selected MUAP-based method requires 0.92 s excluding the MUAP extraction time. An average of 15 s is required for MUAP extraction. For the purpose of comparison, the computational time for the method proposed in [11] is evaluated and found to be 22.62 s. Thus, the proposed method not only offers better classification performance, it also offers less execution time. Since the MUAP decomposition tool serves a number of MUAPs, there might be some other potential MUAP present apart from the selected MUAP. It is to be noted that the MUAPs whose represent amplitude is very close to that of the selected MUAP have also been tested individually for proposed feature extraction. However, it is found that the selected MUAP with maximum dynamic range performs consistently better.

5. Conclusion: For the classification of normal and ALS subjects from given EMG data, MUAP-based DCT feature extraction scheme is proposed. One major aspect here is the introduction of DCT in EMG signal classification, which is more advantageous than the DFT for frequency-domain analysis. The novelty of the proposed scheme lies in the use of only one selected MUAP for DCT feature extraction, which offers several advantages in comparison with direct use of EMG data. For example, in direct EMG analysis, a large number of frames need to be investigated resulting in huge computational burden. In contrast, in the proposed method, since only one selected MUAP is used, significant computational savings is achieved. From the DCT of MUAP signal, magnitude and frequency values of few high-energy DCT coefficients are considered as the proposed features, which exhibit high within-class compactness and between-class separation. Effect of variation of the number of chosen DCT coefficients on the classification accuracy is investigated and found that the accuracies consistently lie within the acceptable range. It is observed that the KNN classifier used in the proposed method offers consistent performance with the variation of K values. Classification performance is tested using leave-one-out cross-validation technique for both small and large datasets. The proposed MUAP-based DCT features provide significantly better classification accuracy in comparison with that obtained by some existing methods.

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