Nagineni *et al. Health Inf Sci Syst (2018) 6:13*
https://doi.org/10.1007/s13755-018-0050-4

Health Information Science and Systems

RESEARCH

Features based on variational mode decomposition for identification of neuromuscular disorder using EMG signals

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Abstract

Neuromuscular disorder is a muscular and nervous disorder resulting in muscular weakness and progressively damages nervous control, such as amyotrophic lateral sclerosis (ALS) and myopathy (MYO). Its diagnosis can be possible by classification of ALS, MYO, and normal electromyogram (EMG) signals. In this paper, an effective method based on variational mode decomposition (VMD) is proposed for identification of neuromuscular disorder of EMG signals. VMD is an adaptive signal decomposition which decomposes EMG signals nonrecursively into band-limited functions or modes. These modes are used for extraction of spectral features, particularly spectral flatness, spectral spread, spectral decrease and statistical features like kurtosis, mean absolute deviation, and interquartile range. The extracted features are fed to the extreme learning machine classifier in order to classify neuromuscular disorder of EMG signals. The performance of obtained results shows that the method used provides a better classification for neuromuscular disorder of EMG signals as compared to existing methods.

Keywords: Electromyogram, Neuromuscular disorder, Variational mode decomposition, Extreme learning machine

Introduction

Electromyography is a technique for evaluating and assessing of electrical signals generated from a muscular movement. This accumulated electrical signal is known as an electromyogram (EMG) [1]. EMG is a useful tool for clinicians and researchers for the faithful diagnosis of neuromuscular disorders. These disorders are related to impacts on muscle, motor neurons, nerves and muscle tissues. EMG signals are important in enormous fields, like medical science, rehabilitation, ergonomics, and sports science. The vast usage of EMG is in medical research for identification and analysis of neuromuscular disorders, motor neurons by using an electrical activity of a signal [2, 3]. Electrical impulses produced by brain controls the function of muscles. The generated electrical impulses are carried to every fiber of muscles by motor neurons, familiar as a nerve cell. All disorders, which affects the working function of motor neurons creates various diseases [4]. The EMG signal is a valuable source for functioning and to show status of a muscle diagnosis of amyotrophic lateral sclerosis (ALS) and myopathy (MYO).

Motor neuron disorder creates a lot of diseases, mainly the ALS. ALS greatly impacts neuron groups which results in inability to control the voluntary movement of muscles in the body and also makes muscles more weaker and much smaller. ALS progressively damages nervous control because of which weakness, paralysis, respiratory failure and harm to cells in spinal cord and brain occur [5]. Myopathy is a non-progressive type neuromuscular disorder affecting people mostly between the age group of 20–50 years. Myopathy is a muscle disease, affecting mainly skeletal fiber muscles and is caused by inflammatory, metabolic and endocrine disorders. Myopathy effects bones of quadriceps and biceps muscles that results in muscles cramp, spasm, stiffness, and dysfunction. It stops proper working of muscles which means, it does not cause muscles to die and it makes weaker, but it affects mostly at the center part of a muscle. These diseases mimic with other diseases, so that early stage

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detection reduce pain in patient and medical expenses [4, 6]. The visual inspection of neuromuscular disorders by using EMG is a laborious task due to nonstationary nature of a signal. For that reason, the diagnosis of neuromuscular disorder of EMG signals requires an accurate and automatic methodology.

Extracted parameter from EMG signals is useful for analysis of diagnostics. The parameters extraction mainly depends on time, frequency, and time-frequency domain. The time-frequency based short time fourier transform (STFT), frequency based mean frequency, and time based ZCR, ACR features are used with KNN in order to classify the myopathy and normal EMG signals [6]. The time based features are autocorrelation (ACR), zero crossing rate (ZCR), and spectral features are mean frequency, spectral peak which classify myopathy and normal EMG signals [7]. Features extracted from analytic IMF are area computation, mean of first derivative instantaneous frequency are used for discrimination of myopathy and normal EMG signals by using kruskal-wallis test [8]. The frequency cepstrum based mel-frequency cepstral coefficient (MFCC) features input to K-nearest neighborhood (KNN) classifier for classification of ALS and normal EMG signals [9]. Extracted analytical features are area computation, normalized instantaneous frequency (IF_n), a spectral moment of PSD (SM_{PSD}), and the first derivative of instantaneous frequency (MFD_{IF}) features with LS-SVM classifier are used to classify ALS and normal EMG signals [5]. The image extracted features that are time-frequency based spectrogram, Wigner–Ville distribution, STFT, and continuous wavelet transform (CWT), are employed to give a conventional neural network for classification of ALS and normal EMG signals [10, 11]. An improved EMD (IEMD) algorithm and Hilbert transform are extracted and its bandwidth features B_{AM}, B_{FM}, SM_{PSD}, and MFD_{IF} are used to discriminate between the ALS and the normal EMG signals [12]. Extraction of MUAP features with higher energy DCT coefficients are used as features with KNN classifier to classify the ALS and normal EMG signals [13].

From EMG signals to extract time based MUAPs features and entropy-based features like spectral, sample, approximate, fuzzy entropy from TQWT sub-bands. These features will be used for the classification of MYONOR EMG signal and ALS-NOR EMG signal by using random forest classifier [14]. The ELM classifier classifies EMG signals based on extracted bispectrum based features, fractal dimension features [15]. The extracted temporal feature, DWT based spectral feature, and direct extraction of spectral features are peak frequency, mean frequency, total power, and median frequency are given to KNN classifier for classification of ALS, myopathic, and normal EMG signal [16]. Multi scale principal component analysis (MSPCA) denoising method presented to decomposition method of multiple single classification (MUSIC) for extraction of features. The KNN, ANN, and SVM are used for classifying ALS, myopathy, and normal EMG signals [17]. The MUAP selection by windowing of EMG signal is based on the highest energy of a divided signal. The statistical DWT features extracted from MUAP are maximum energy of a wavelet. These classify neuromuscular diseases using KNN and LSSVM classifiers [18]. Feature extraction of DWT based decomposition method with MSPCA denoising approach classifies ALS, myopathy, and normal EMG signals by using decision tree algorithms [19].

In this paper, adaptive signal decomposition method VMD is used for decomposition of EMG signal into modes. spectral and statistical features namely spectral flatness (SF), spectral spread (SS), spectral decrease (SDec), kurtosis, MAD, and IQR are used for classification of the neuromuscular disorders. The remaining paper has been depicted as follows: the EMG dataset, the variational mode decomposition method is presented in "Methodology". The extracted features from modes and ELM classifier are present in the upcoming "Feature extraction". The results and discussions from simulations are used for classification of ALS, myopathy, and normal EMG signal as explained in "Results and discussions".

Methodology

The block diagram of proposed method is shown in Fig. 1.

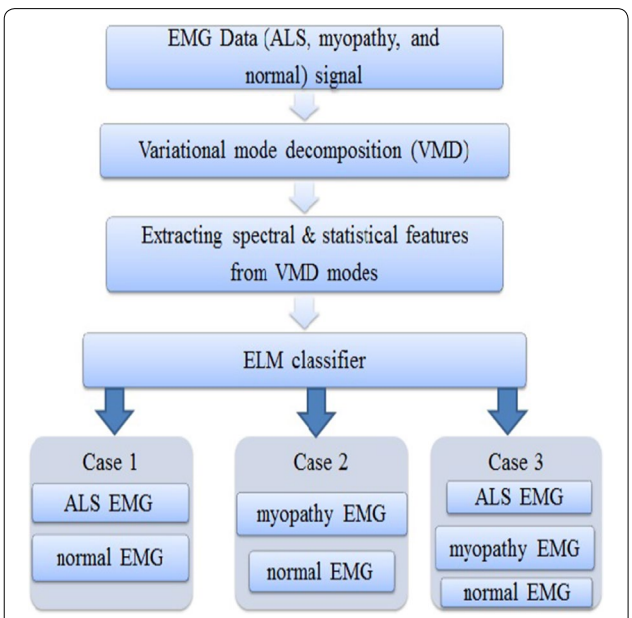

Fig. 1 Overview diagram of EMG signals classification using VMD method

Dataset

The online link http://www.emglab.net [20] gives us the dataset of the recorded EMG signals. Dataset has three main groups such as ALS, myopathy, and normal. ALS group consists of eight subjects: 4 male and 4 female age group of 35–67 years. Five subjects from ALS group died within few years after the occurrence of disease. Myopathy group consists of seven subjects: 2 male and 5 female age group of 19–63 years. In normal group, ten subjects as 6 males and 4 females of age 21–37 years are present. No one from the normal group has any signs or history of neuromuscular disorders. Brachial biceps muscles are used for investigating these three groups. Signal acquisition is achieved using a standard needle electrode having area of 0.07 mm^2. Tuning sampling rate was 24 KHz and digitized by A/D converter contained the resolution of 16 bits. Recorded signal was filtered by a high and low pass filters set to 2 Hz and 10 KHz respectively, (i) The signal quality is monitored by using visual and audio feedback, (ii) EMG amplifier uses the set of 2 Hz and 10 KHz low and high pass filters, (iii) Signal collection is through three level insertion from five various places, (iv) Recording was made at above threshold and constant level of contraction. In this 89 ALS, 107 myopathy, and 133 normal EMG signals [20] are being used with following considerations.

Case 1 One abnormal class forms the ALS class and subset of healthy class forms the normal (NOR) class.
Case 2 One abnormal class forms the myopathy (MYO) class and subset of healthy class forms the normal (NOR) class.
Case 3 Subset of ALS, MYO forms the abnormal class and subset of healthy class forms the NOR class.

Variational mode decomposition

Variational mode decomposition (VMD) decomposes a real-valued signal into a band-limited variational mode function or modes (u_k). These modes occur concurrently and exhibit specific sparsity property to reproduce an input signal [21]. So, VMD nonrecursively decomposes signal into k modes (u_k), each compact around its own center pulsation ω. Before formulation of the constrained optimization problem, we compute the analytic signal to get a unilateral frequency spectrum using Hilbert transform. The frequency shifting property is applied on each mode tuned to the corresponding center frequency. Its bandwidth is predicted by applying H1 Gaussian smoothness to the demodulated signal. The constrained variational problem is expressed as [21]

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad \text{subject to} \quad \sum_k u_k(t) = x(t) \tag{1}$$

The Lagrangian multiplier (λ) and a quadratic penalty factor (α) converts (1) into unconstrained optimization problem as addressed below (2)

$$\begin{aligned} l(u_k, \omega_k, \lambda) := \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \\ + \left\| x(t) - \sum_k u_k(t) \right\|_2^2 \\ + \left\langle \lambda(t), x(t) - \sum_k u_k(t) \right\rangle \end{aligned} \tag{2}$$

Above augmented lagrangian function (ℓ) is used to solve (2) by using the alternate direction method of a multiplier (ADMM). ADMM is an optimization technique to estimate center frequencies and modes centered around their frequencies in the spectral domain. The embedded wiener filter in VMD updates optimally each mode $u_k(\omega)$ and center frequency in the fourier domain. The VMD algorithm for decomposition of EMG signal shown below.

Algorithm 1 VMD algorithm to decompose the EMG signal

1: Define the number of modes K.
2: Initialization: $\hat{u}_k^1$, $\hat{\omega}_k^1$, $\hat{\lambda}^1$, and $n = 0$;
3: Assign $n = n + 1$ and repeat loop completely
4: As long as $k = 1 : K$ for $\omega \geq 0$; update $u_k(t)$ according to [21] in the spectral domain.

$$\hat{u}_k^{n+1}(\omega) \leftarrow \frac{\hat{x}(\omega) - \sum_{i<k} \hat{u}_k^{n+1}(\omega) - \sum_{i>k} \hat{u}_k^n(\omega) + \frac{\hat{\lambda}^n(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2} \tag{3}$$

$$\hat{u}_k^{n+1}(t) = R\{ifft(\hat{u}_k^{n+1}(\omega))\} \tag{4}$$

Update ω_k with

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega|\hat{u}_k^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_k^{n+1}(\omega)|^2 d\omega} \tag{5}$$

5: Assign $k = k + 1$; repeat the above step until k equals K and complete n iteration of the loop.
6: update Lagrange multiplier λ, depends on dual-ascent for all $\omega \geq 0$.

$$\hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau(\hat{x}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega)) \tag{6}$$

7: Repeat steps (2)-(5) until the below convergence condition is satisfied to obtain modes.

$$\sum_{k=1}^{K} \frac{\|\hat{u}_k^{n+1} - \hat{u}_k^n\|_2^2}{\|\hat{u}_k^n\|_2^2} < \epsilon \tag{7}$$

where $\hat{}$, τ, ϵ represent the Fourier transform, time steps of dual ascent, and tolerance of convergence respectively. $R(.)$ and $ifft(.)$ represent the real part of analytic signal and the inverse fast fourier transform of a signal.

The decomposed modes of ALS, myopathy and normal EMG signals are shown in Fig. 2a, b, and c, respectively, which signifies that the higher modes shoes higher frequency oscillations.

Feature extraction

Spectral features

If $x(n)$ is an N sample EMG signal and $X(m)$ gives the magnitude spectrum of $x(n)$.

1. *Spectral flatness* (*SF*) Noisiness of the magnitude spectrum gives the SF. The signal spectrums geometric mean to arithmetic mean ratio determines SF. It can be denoted [22, 23] as:

$$SF = \frac{\prod_{m=0}^{N-1} |X(m)|^{\frac{1}{N}}}{\frac{1}{N}\sum_{m=0}^{N-1} |X(m)|} \tag{8}$$

2. *Spectral spread* (*SS*) Sometimes known as instantaneous bandwidth, given by magnitude spectrum concentration around spectral centroid. Standard deviation of magnitude spectrum around spectral centroid can also be assumed as SS. Mathematically, SS can be described [22, 23] as:

$$SS = \frac{\sum_{m=0}^{N-1} (m - SC)^2 |X(m)|}{\sum_{m=0}^{N-1} |X(m)|} \tag{9}$$

Frequency weighted sum of magnitude spectrum of signal normalized by its unweighted sum is SC i.e. center point of spectrum can be given as

$$SC = \frac{\sum_{m=0}^{N-1} m|X(m)|}{\sum_{m=0}^{N-1} |X(m)|} \tag{10}$$

3. *Spectral decrease* The slope at which the spectral envelope decreases with respect to frequency gives the spectral decrease (SDec) [22]. SDec is denoted [23] as

$$SDec = \frac{\sum_{m=1}^{N-1} \frac{1}{N}(|X(m)| - |X(0)|)}{\sum_{m=1}^{N-1} |X(m)|} \tag{11}$$

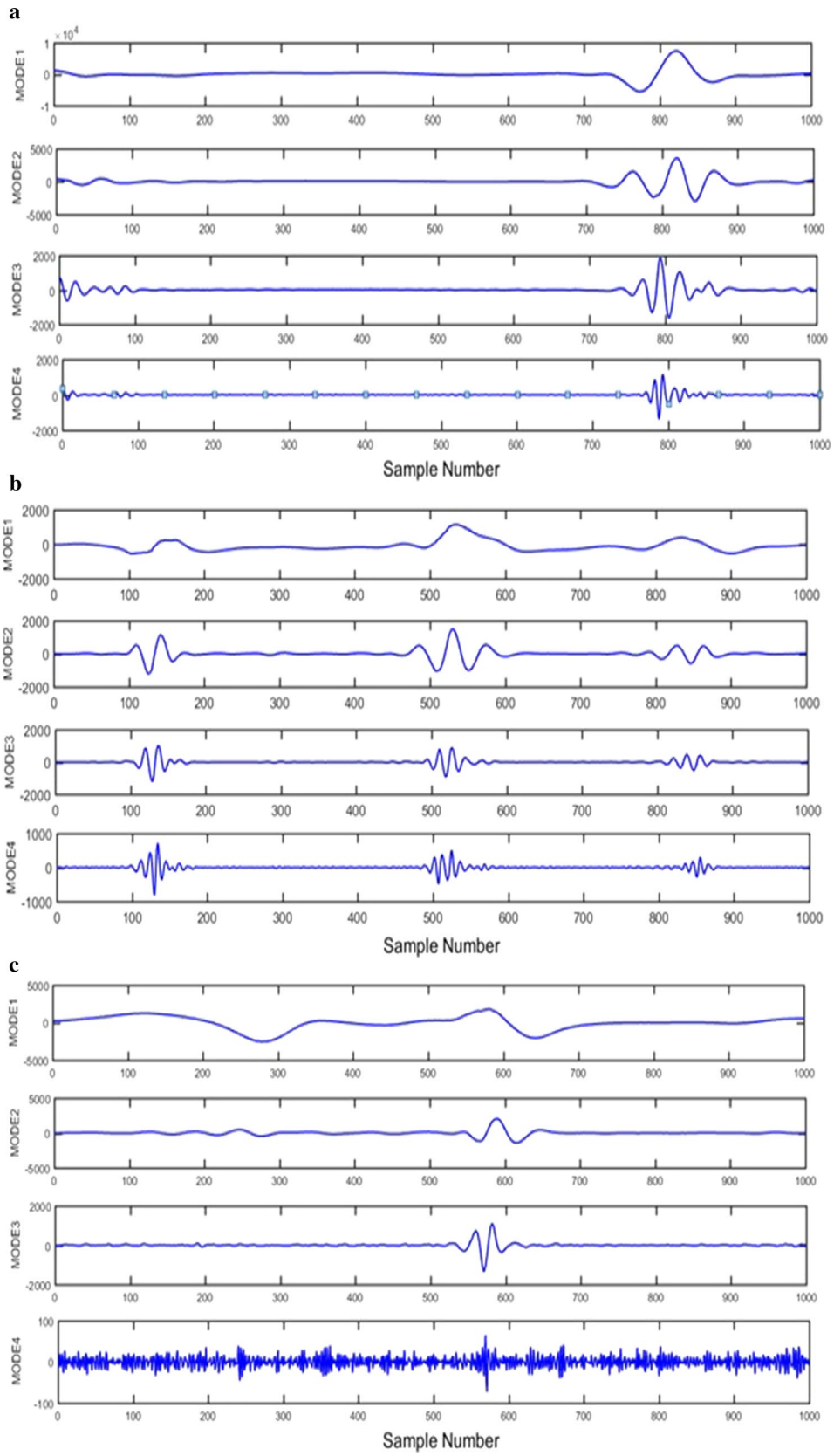

Fig. 2 Example four modes of VMD **a** ALS signal, **b** myopathy signal, **c** normal EMG signal

Statistical features

1. *Kurtosis* In this work, we used statistical moments such as kurtosis which shows the peaked nature of time series [24]. Mathematically it can be expressed as

$$k = \frac{1}{N}\sum_{m=1}^{N}\left(\frac{x_m - \mu}{\sigma}\right)^4 \tag{7}$$

2. *Mean absolute deviation* It is difference between actual value and their mean value of variational modes [25]. It is formulated as

$$MAD = \frac{1}{N}\sum_{m=1}^{N}|x_m - \mu| \tag{8}$$

3. *Inter quartile range* It gives a variability of measuring data set. It is defined by difference of 75th and 25th percentiles samples of modes [24] as given by

$$IQR = Q_3 - Q_1 \tag{9}$$

Here, Q_1 and Q_3 are first and third quartile respectively.

Total six-features are extracted for each class EMG signals. The dimensions of feature vectors for ALS, myopathy, and normal classes are 89×6, 107×6, and 133×6, respectively. Feature normalization is needed when there is a large variation in different classes or size of the feature is large. At that time, it shows biased classifier nature towards a particular set of attributes. The unit length feature normalization method is applied on extracted features [26].

Extreme learning machine (ELM)

A feed forward neural network with single hidden neuron is termed as ELM in which first weighted matrix is selected arbitrarily. It enables the fast estimation of output matrix using the least square method [27]. ELM due to its simple structure and high training speed is advantageous for multi-class classification of N number of arbitrary samples (x_r, t_r). Here $x_r = [x_{r1}, x_{r2}, \ldots, x_{rn}]^T$ and $t_r = [t_{r1}, t_{r2}, \ldots, t_{rn}]^T$. The simplified architecture of ELM classifiers is shown in Fig. 3.

A single hidden layer feed forward neural network having the activation function $g(x)$ and a number of hidden layers can be given by:

$$\sum_{r=1}^{N}\beta_r g_r(x_r) = \sum_{r=1}^{N}\beta_r g(a_r.x_i + b_r) = t_i \tag{10}$$

By using the weight vector of $a_r = [a_{r1}, a_{r2}, \ldots, a_{rn}]^T$ for connected to rth hidden input node and output node

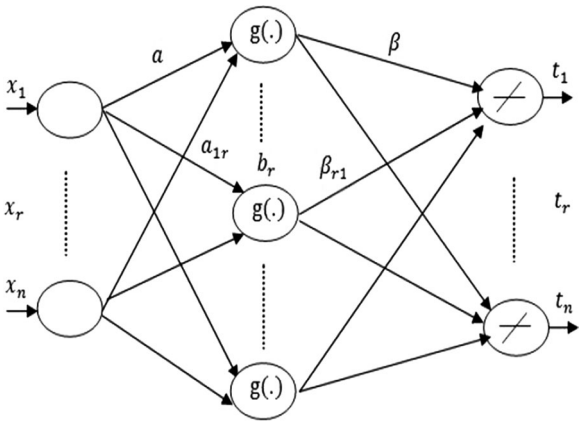

Fig. 3 The structure of the ELM classifier with input training samples

is connected to rth hidden node by the weight vector $\beta_r = [\beta_{r1}, \beta_{r2}, \ldots, \beta_{rn}]^T$. where b_r is the threshold of rth hidden node, above objective function and inner product as shown in [28].

Results and discussions

VMD method is used to decompose EMG signals into various modes from which spectral and statistical analysis features namely SF, SS, SDec, Kurtosis, MAD, and IQR are extracted and have been used for the classification of neuromuscular disorder of EMG signals. Tables 1 and 2 show clearly the spectral and statistical features range of mean and standard deviation of ALS, myopathy, and normal EMG signals. In Table 1, SS and SDec features show a higher value for myopathy signals compared to other EMG signals for all modes except the first mode. Myopathy signals have higher SS because of the change in spreadness of spectrum and higher spectral decrease. In myopathy signal, the higher SDec is because of the variation in spectral envelope of the signal. In Table 1, spectral flatness shows a higher value for normal EMG compared to other EMG signals for all modes except the second mode. Higher SF in normal EMG signal is due to the presence of lower noisiness in the signal. In Table 2, IQR is higher in ALS signals compared to other signals except for the third and fourth mode. The higher value signifies the variability of the signal. In Table 2, kurtosis exhibits a higher value for myopathy signals compared to other EMG signals, because of its high peaked nature. In Table 2, MAD feature of ALS signals is higher for all modes due to their higher amplitude variation compared to other EMG signals.

The modes of ALS signal, myopathy signal, and normal EMG signal obtained using the VMD method represent band-limited frequency components. The ELM is a popular classifier and is used in various biomedical

Table 1 Range (mean ± SD) values of the SF, SS, SDec features for the MODES

Mode no.	Signal type	SF (Mean ± SD)	SSx 10^{+04} (Mean ± SD)	SDec (Mean ± SD)
Mode 1	ALS	0.1817 ± 0.1287	20.7 ± 34.1	− 0.8910 ± 1.1400
	Myopathy	0.1733 ± 0.1112	21.3 ± 17.2	− 0.7245 ± 0.8385
	Normal	0.1848 ± 0.1240	21.5 ± 17.4	− 0.5268 ± 0.7243
Mode 2	ALS	0.1868 ± 0.1450	19.3 ± 4.04	0.0087 ± 0.0240
	Myopathy	0.1686 ± 0.1274	19.9 ± 2.41	0.0102 ± 0.0107
	Normal	0.1790 ± 0.1336	19.8 ± 2.75	0.0087 ± 0.0130
Mode 3	ALS	0.2501 ± 0.1419	13.4 ± 59.3	0.0044 ± 0.0061
	Myopathy	0.2256 ± 0.1200	14.5 ± 43.6	0.0049 ± 0.0051
	Normal	0.2501 ± 0.1292	13.9 ± 49.3	0.0046 ± 0.0037
Mode 4	ALS	0.2904 ± 0.1281	52.8 ± 53.5	0.0025 ± 0.0016
	Myopathy	0.3103 ± 0.1030	56.1 ± 48.1	0.0026 ± 0.0013
	Normal	0.3109 ± 0.1120	48.9 ± 45.3	0.0024 ± 0.0036

Table 2 Range (mean ± SD) values of the Kurtosis, MAD, and IQR features for the MODES

Mode no.	Signal type	Kurtosis (mean ± SD)	MAD (mean ± SD)	IQR (mean ± SD)
Mode1	ALS	5.6997 ± 3.6335	379.0688 ± 377.74	482.068 ± 663.175
	Myopathy	5.7829 ± 3.7625	145.133 ± 9.747	188.34 ± 127.59
	Normal	5.7379 ± 4.0974	267.5919 ± 174.7	355.274 ± 253.852
Mode2	ALS	11.830 ± 9.7675	115.349 ± 112.325	70.2151 ± 87.8979
	Myopathy	17.6392 ± 14.3120	62.6392 ± 43.772	44.4956 ± 41.8095
	Normal	15.1808 ± 12.8608	84.7781 ± 70.2146	62.5675 ± 59.5657
Mode3	ALS	18.8185 ± 19.7368	31.3720 ± 35.208	18.6233 ± 13.2062
	Myopathy	28.2276 ± 24.0196	24.8728 ± 20.043	17.5099 ± 11.6085
	Normal	22.1241 ± 22.0079	27.3465 ± 25.463	21.4836 ± 9.8366
Mode4	ALS	14.4458 ± 24.2355	13.903 ± 18.033	14.6786 ± 4.6094
	Myopathy	17.9045 ± 27.8752	13.6581 ± 25.372	15.0258 ± 10.3923
	Normal	14.8647 ± 27.2291	13.4135 ± 12.237	17.0077 ± 5.9226

signal classifications. In m-fold cross-validation, the data is broken into m parts. Each $m-1$ subsets at a time are used for training the classifier, and the remaining each one subset is used to test the classification model. ELM classifier provides satisfactory classification performance of signal with 10-fold cross-validation procedure. Simple structure and multiclass classification without any change in classifier parameters is provided by ELM classifier. It is extremely useful for the multi class EMG signals classification. Classification performance of ELM classifier is in terms of sensitivity (SEN), specificity (SPE), and accuracy (ACC) [29]. These can be expressed as:

$$SEN = \frac{TP}{TP + FN} \tag{11}$$

$$SPE = \frac{TN}{TN + FP} \tag{12}$$

$$ACC = \frac{TN + TP}{TN + TP + FN + FP} \tag{13}$$

TP and FP signify true positive and false positive rate of normal class EMG signals. TN and FN signify true negative and false negative rate of abnormal class EMG

Table 3 SEN, SPE, and ACC of modes with ELM classifier for classification between ALS and normal EMG signals

Modes	SEN (%)	SPE (%)	ACC (%)
Mode 1	97.86	99.17	98.52
Mode 2	98.48	98.50	98.47
Mode 3	96.74	98.65	98.83
Mode 4	95.84	98.72	97.57

Table 4 SEN, SPE, and ACC of modes with ELM classifier for classification between MYO and normal EMG signals

Modes	SEN (%)	SPE (%)	ACC (%)
Mode 1	99.44	99.55	99.50
Mode 2	87.20	98.20	93.29
Mode 3	83.36	84.81	84.17
Mode 4	97.57	98.05	97.83

Table 5 SEN, SPE, and ACC Modes with ELM classifier for classification between ALS, MYO, and normal EMG signals

Modes	SEN (%)	SPE (%)	ACC (%)
Mode 1	97.75	98.97	97.75
Mode 2	93.00	96.35	93.04
Mode 3	84.71	91.77	84.08
Mode 4	94.35	97.41	94.83

Table 6 Confusion matrix of ALS and normal EMG signals for Mode 1 by ELM classifier

Signal	ALS (%)	NOR (%)
ALS	97.86	2.14
NOR	0.83	99.17

Table 7 Confusion matrix of myopathy and normal EMG signals of Mode 1 by ELM classifier

Signal	MYO (%)	NOR (%)
MYO	99.44	0.56
NOR	0.45	99.55

signals. In Tables 3, 4 and 5, mode wise classification performance of the ELM classifier is in terms of SEN, SPE, and ACC of ALS-NOR, MYO-NOR, and ALS-MYO-NOR EMG signals. The overall classification performance of Cases 1–3 EMG signals based on accuracy is 98.52%, 99.50%, and 97.75% and are highest for the first mode among all modes.

The confusion matrix of the respective EMG signals of the first modes is shown in Tables 6, 7 and 8. The

Table 8 Confusion matrix of ALS, MYO, and normal EMG signals for Mode 1 by ELM classifier

Signal	ALS (%)	MYO (%)	NOR (%)
ALS	95.74	2.69	1.57
MYO	0.93	98.79	0.28
NOR	0.67	0.60	98.73

detection rate of normal EMG is higher compared to ALS signals as shown in Table 6. It gives better classification rate for ALS-NOR signals with an accuracy of 98.52% for the first mode. Table 7 shows less misclassified myopathy and normal EMG signals. The detection rate of MYO-NOR gives an accuracy of 99.50% by ELM for the first mode. Table 8 shows a detection rate of myopathy and normal EMG signals compared to ALS signals is higher, but overall classification accuracy of ALS-MYO-NOR are 97.75% for the first mode by ELM classifier.

In Tables 9, 10 and 11 present a comparison with the proposed method and other existing methods in the literature for ALS-NOR, MYO-NOR, and ALS-MYO-NOR detection which has been studied on the same EMG dataset. It is clear from the Tables 9, 10 and 11 that the proposed method has provided better classification performance as compared to existing methods. It has been observed VMD decomposes signals into variational modes having the robustness to noise and sampling. The extracted spectral and statistical features given a good response to classification of EMG signals. These results show that proposed methodology provides better performance for automatic identification of neuromuscular disorder.

Conclusion

In this paper, the identification of neuromuscular disorder of ALS, myopathy is carried out using VMD-based features. VMD concurrently decomposes EMG signals into modes, which are used in extraction of features like SF, SS, SDec, kurtosis, MAD, and IQR. The extracted features are normalized using unit length normalization method and fed as inputs for the ELM classifier in order to classify neuromuscular disorders. A classification accuracy of 98.52%, 99.50%, and 97.75% corresponds to ALS-NOR, MYO-NOR, and ALS-MYO-NOR classes is achieved for the features extracted with the ELM classifier for the first mode. SEN, SPE, and ACC parameters

Table 9 Comparison of classification between ALS and normal EMG signal performance with same dataset

Authors	Methods and classifier	SEN (%)	SPE (%)	ACC (%)
Joshi et al. [14]	Time based MUAPs and entropy features, RF	–	95.65	89.16
Fattah et al. [9]	MFCC features, KNN	76	98	92.5
Misra et al. [5]	Area, IF_n, MFD_{IF}, and SM_{PSD} features, LS-SVM	93	92.5	95
Doulah et al. [13]	MUAP based DCT coefficients features, KNN	86	98	95.0
Mishra et al. [12]	B_{AM},B_{FM}, SM_{PSD}, and MFD_{IF} features, LS-SVM	–	–	96.33
Krishna et al. [16]	DWT spectral features, KNN	88	99.33	96.5
Sengur et al. [10]	Time-frequency based STFT features, CNN	94.24	97.59	96.69
Sengur et al. [11]	CWT, spectrogram, and WVD features, CNN	94.8	98.8	96.8
Proposed method	SF, SS, SDec, kurtosis, MAD, and IQR features based ELM	97.86	99.17	98.52

RF Random forest, *CNN* convolutional neural network, *WVD* Wigner–Ville distribution

Table 10 Comparison of classification between and myopathy signal and normal EMG signal performance with same dataset

Authors	Methods and classifier	SEN (%)	SPE (%)	ACC (%)
Joshi et al. [14]	Time based MUAPs and entropy features, RF	–	81.77	81.14
Krishna et al. [16]	DWT spectral features, KNN	66	89.33	83.5
Fattah et al. [6]	Autocorrelation features, KNN	88.9	83.3	86.1
Doulah et al. [7]	STFT based features, KNN	–	–	91.67
Proposed method	Spectral and statistical based features, ELM	99.44	99.55	99.50

Table 11 Comparison of classification between ALS-MYO-NOR EMG signals performance with same dataset

Authors	Methods and classifier	ACC (%)
Krishna et al. [16]	DWT spectral features, KNN	84
Mishra et al. [15]	Bispectrum, fractal dimensional based features, ELM	88
Defino et al. [18]	Statistical DWT extracted MUAP features, SVM	88.6
Gokgoz et al. [17]	MSPCA denoising with MUSIC feature extraction, SVM	92.5
Gokgoz et al. [19]	DWT based features with MSPCA denoising, random forest classifier	96.67
Proposed method	Spectral based SF, SS, SDec, and statistical features, ELM	97.75

are showing good results. The classification results of proposed method shows a better performance in comparison to other existing methods. The suggested method can be beneficial for the diagnosis of neuromuscular disease in clinical application.

Received: 15 May 2018 Accepted: 20 August 2018
Published online: 20 September 2018

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