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Automatic amyotrophic lateral sclerosis detection using tunable Q-factor wavelet transform

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ABSTRACT

Early diagnosis of amyotrophic lateral sclerosis (ALS) based on electromyography (EMG) is crucial. The processing of a non-stationary EMG signal requires powerful multi-resolution methods. Our study analyzes and classifies the EMG signals. In the present work, we introduce a novel flexible method for classification of EMG signals using tunable Q-factor wavelet transform (TQWT). Different sub-bands generated by the TQWT technique were served to extract useful information related to energy and then the calculated features were selected using a filter selection (FS) method. The effectiveness of the feature selection step resulted not only in the improvement of classification performance but also in reducing the computation time of the classification algorithm. The selected feature subsets were used as inputs to multiple classifier algorithms, namely, k-nearest neighbor (k-NN), least squares support vector machine (LS-SVM) and random forest (RF) for automated diagnosis. The experimental results show better classification measures with k-NN classifier compared with LS-SVM and RF. The robustness of the classification task was tested using a ten-fold cross-validation method. The outcomes of our proposed approach can be exploited to aid clinicians in neuromuscular disorders detection.

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1. INTRODUCTION

Amyotrophic lateral sclerosis (ALS) is a neuromuscular disease mainly characterized by the gradual degeneration of the lower and upper motor neurons situated in the spinal cord and brain, respectively [1-3]. ALS is a rapidly progressive disease which mostly occurs in people aged between 40 and 65 years [1, 4-5]. The majority of patients suffering from motor neuron diseases have muscle weakness, muscle atrophy and respiratory failure which often leads to death after 3 to 5 years of the onset of symptoms [3, 5]. Hence, early diagnosis is desired. Electromyography (EMG) depicts the state of the muscle and can be used for the detection and prevention of ALS based on analysis of motor unit action potential (MUAP) [3-4].

In fact, EMG is a test that measures the electrical activity of the muscle and nerves in the body, and it can tell us how well the information is transferred from the brain down to the nerves in the skeletal muscle or from the nerves back up to the brain [6-8]. It can help to identify different types of disease such as ALS and myopathy or injury to the nerves. It can also be helpful for expert doctors and neurologists to determine what further treatment would be needed in the event of disease. Moreover, EMG is used in many fields and applications such as medicine prosthesis control, rehabilitation, and clinical diagnosis [9-10]. Generally, the use of an invasive electrode is preferable in investigating neuromuscular disorders. Understanding the behavior and characteristics of an EMG signal, which is generated either from the muscle during its contraction or by stimulation, requires knowledge of different signal processing tools [6].

Over the past decade, many studies have significantly contributed to the aim of distinguishing between ALS patients and healthy subjects. The features extracted from an EMG signal can be useful in the diagnosis of neuromuscular diseases. The works presented in [11-13] exported time domain features like root mean square, autocorrelation and zero crossing rate for EMG classification, while in [13] frequency domain features such as mean frequency and spectral peak were used for normal and ALS classification. However, due to the non-stationary nature of an EMG signal, time-frequency/scale parameters were adopted in many works [6, 14]. Hence, wavelet transform based techniques, short time fourier transform (STFT), and distribution transform (DT) provide more accurate signal information. Discrete wavelet transform (DWT) has been successfully used for the analysis of EMG signals. This approach decomposes the EMG signal directly through the use of a filter bank and down-sampling into detail coefficients and approximation coefficients. In [15], after having applied DWT, the noise reduction was made based on multiscale principal component analysis (MSPCA) in order to improve the performance of EMG classification. Therefore, six coefficient-related features including mean value, average power, standard deviation and the ratio of the mean value of neighbors sub-bands were given as inputs to decision tree algorithms, including classification and regression trees CART, 4.5 algorithm and random forest classifier. In [16] tunable Q-factor wavelet transform (TQWT) based features were tested on least squares support machines and k-nearest neighbor classifiers. The conventional MUAP based method consists of breaking an EMG signal into segments known as MUAPs. This indirect approach has attracted enormous attention in recent years. For example, in [17] wavelet coefficients in each sub-band were extracted from the dominant MUAPs of an EMG signal, and then statistical features were extracted for further classification and performance evaluation. Moreover, the TQWT method and entropy parameters have been used for the classification of MUAPs with random forest classifier [18]. Meanwhile, STFT, continuous wavelet transform (CWT) and smoothed pseudo-wigner-ville-distribution (SPWVD) have been introduced into the identification of neuromuscular disorders [19].

Another nonlinear signal processing method was proposed in [20-21]. The authors investigated the neuromuscular disorder algorithms by using empirical mode decomposition (EMD). It was found that nonlinear features are more suitable for evaluating the dynamic behavior of neuromuscular disorders. Essentially, the EMD method involves narrowband intrinsic mode functions (IMFs). EMG classification was performed using least squares support machine (LS-SVM) and EMD related features in [21]. Higher classification accuracy was achieved by using improved mode decomposition (IEMD). The main idea of this method is to decompose the EMG signal into IMFs, followed by the median filter to remove impulse noise from IMFs. The reconstitution of the filtered IMFs was carried out, and then new IMFs were generated by the EMD. Furthermore, four parameters were extracted to feed the support vector machine (SVM) classifier, and the obtained result was compared with other methods such as EMD and adaptively fast ensemble empirical mode decomposition (AFEEMD) [20].

In this study, we propose an approach to diagnose ALS. The proposed method uses tunable Q-factor wavelet analysis to extract energy-related features and multiple classifiers for performance evaluation. Hence, in the tunable Q-factor wavelet transform, generation of sub-bands is required. We first applied the TQWT to the EMG signals, and then three parameters based on energy, namely the relative tunable Q-factor wavelet transform energy, ratio, and difference of energy values of neighbor TQWT sub-bands were extracted. Considering the irrelevant and redundant information of the extracted dataset, the effective features were selected by the filter feature selection method. The selected features were considered as input data for k-NN, LSSVM, and RF classifiers, which have been previously successfully employed for neuromuscular disorders detection [15-16, 18]. The flowchart in Figure 1 depicts the steps followed in classifying EMG signals.

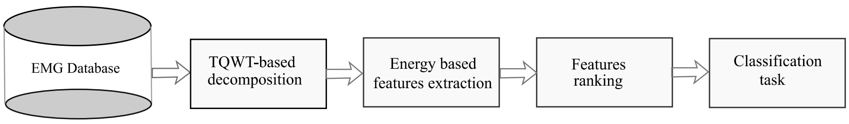

Figure 1. Flowchart of the proposed scheme for neuromuscular disorder detection

The remainder of this paper is structured as follows. Section 2 describes the experimental background of EMG data and the basic theory behind the suggested method. We present the classification task in section 3. In section 4, we give the experimental results and discuss our work. Finally, conclusions are drawn in section 5.

2. MATERIALS AND METHODS
2.1. Data collection
EMG recordings were collected at the Clinical Neurophysiology department, Rigs hospital, the University of Copenhagen in 2001. The EMG datasets for both the ALS and the healthy control group are publicly available on the website emglab.net, which is widely exploited by researchers [13, 15-16, 18, 20-21]. The healthy control group contains ten normal subjects with an average age between 21-37 years (four females and six males). Six of the ten are in perfect shape and the rest, except one, are generally in good shape. The ALS group comprises eight patients; four males and four females and their ages are between 19 and 63. The EMG signals were acquired from the brachial biceps and medial vastus muscles using concentric needle electrodes. The sampling rate of each EMG signal recorder was $Fs = 23437.5Hz$ and digitalized by an A/D converter of 16 bits resolution. The EMG signals were filtered at 2Hz and 10kHz by high and low pass filters, respectively. More detailed information on the EMG data can be obtained from the online EMGLAB collection [22]. In this study, 200 healthy and 200 ALS EMG signals were investigated for neuromuscular disorder detection. For data increasing, we divided each EMG record into six segments with 35,000 samples, leading to 1,200 records for each class. Typical examples of an EMG signal for healthy and ALS classes are depicted in Figure 2.

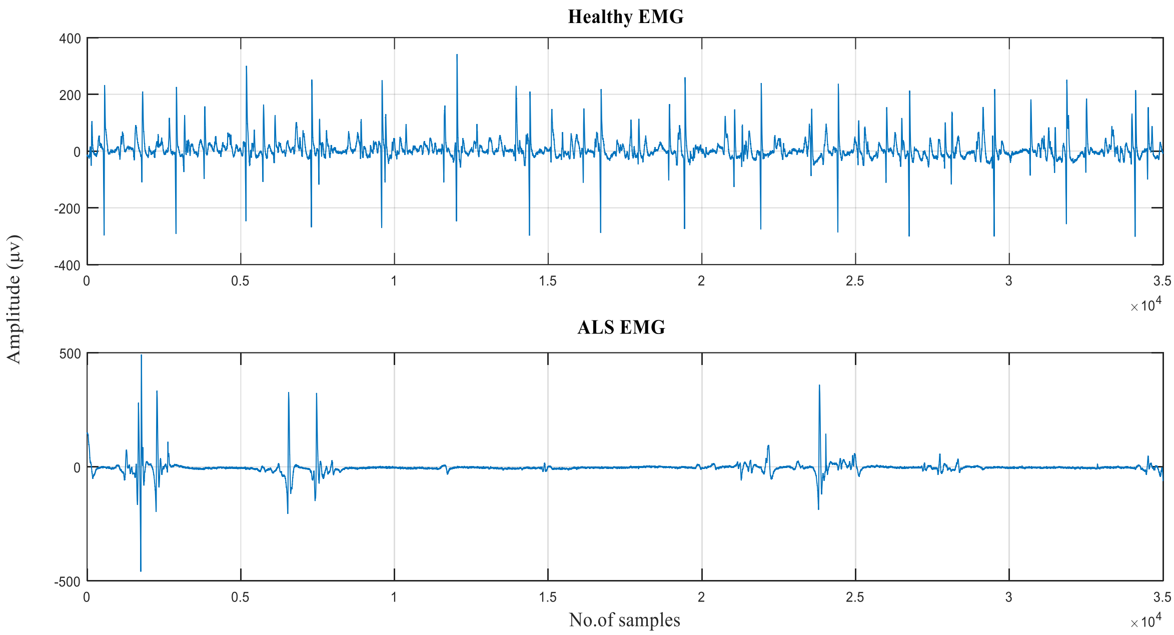

Figure 2. Example plot of ALS and healthy EMG signals for 35,000 samples

2.2. EMG signal decomposition based on tunable Q-factor wavelet transform
Ivan Selesnick in 2006 introduced a new wavelet transform known as tunable Q-factor wavelet transform (TQWT). This method is a flexible discrete wavelet transform which is used for analyzing the oscillatory behavior of signals. The Q-factor should, on the one hand, be higher to evaluate oscillatory signals like an electroencephalogram (EEG), electro cardiac (ECG), electromyography (EMG), speech and so on; otherwise, the wavelet transform should have a low Q factor. The TQWT was developed to easily adjust the Q-factor of the wavelet [23]. The TQWT method is parameterized with the help of three adjustable parameters, namely Q-factor, redundancy denoted as (r), and the number of the level of decomposition (j). Furthermore, as can be seen in Figure 3, TQWT repeatedly uses the concept of a two-channel filter bank for the process and synthesis of the signal. The filter bank includes a mother wavelet and scaling filters to extract the frequency content of the signal. Basically, at each level of TQWT decomposition, the input of the analyzed signal with sampling rate Fs can be decomposed into sub-bands; the first sub-band signal, known as

a low pass (LPS), and the second sub-band, known as a high pass (HPS), have sampling rate $\alpha.Fs$ and $\beta.Fs$, respectively, where α and β are scaling parameters and should be chosen in the range of $0\ to\ 1$ to satisfy the condition $\alpha + \beta > 1$. This process is iteratively realized to create a set of high-frequency component vectors $w_1, w_2, w_3, w_4, \dots\dots, w_j$ and a low-frequency component w_{j+1}. The low and high pass filters' frequency responses obtained from j-stages (levels) are mathematically expressed by $F_0(\omega)$ and $F_1(\omega)$, respectively as follows:

$$F_0(\omega) = \begin{cases} 1\,, & |\omega| < (1-\beta)\pi \\ \theta(\frac{\omega+(\beta-1)\pi}{\alpha+\beta-1}), & (1-\beta) \le |\omega| < \alpha\pi \\ 1, & \alpha\pi \le |\omega| < \pi \end{cases} \tag{1}$$

$$F_1(\omega) \quad = \begin{cases} 0, & |\omega| < (1-\beta)\pi \\ \theta\left(\frac{\omega-\alpha\pi}{\alpha+\beta-1}\right), & (1-\beta) \le |\omega| < \alpha\pi \\ 1, & \alpha\pi \le |\omega| < \pi \end{cases} \tag{2}$$

$\theta(\omega)$ is considered as the frequency response of Daubechies filter with two vanishing moments and can be given as follows:

$$\theta(\omega) = 0.5(1+\cos\omega)\sqrt{2-\cos\omega},\ |\omega| \le \pi \tag{3}$$

The adjustable parameters, Quality-Factor (Q), redundancy (r) and maximum number of decomposition level (j_{max}) can be written in terms of α and β as follows:

$$Q = \frac{2-\beta}{\beta}\ , r = \frac{\beta}{1-\alpha}, j_{max} = \frac{\log(\frac{\beta N}{8})}{\log(\frac{1}{\alpha})} \tag{4}$$

Where N refers to the total number of data samples,

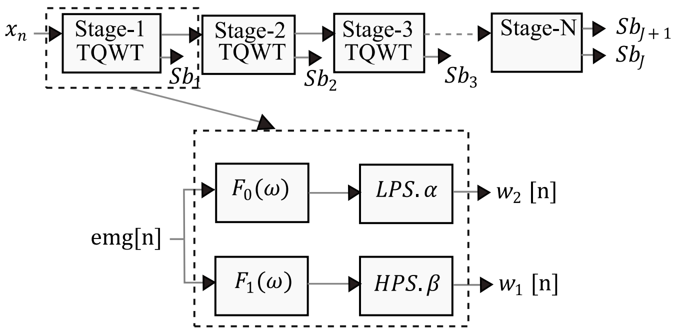

Figure 3. Example of TQWT decomposition at the first stage

Recently, the TQWT method has been widely employed to assess the different biological signals, especially EMG signals. The decomposed ALS and healthy EMG signals are illustrated in Figure 4, using TQWT parameter values $Q = 1, j = 10$, and $r = 3$. Generally, it is strongly recommended to choose $r > 3$ [23]. From Figure 4 the difference between healthy and ALS EMG data appear in the last six sub-bands. Figure 4 (a-b) clearly show that the first four sub-bands contain no information, and the useful EMG signal information is concentrated in the remaining sub-bands.

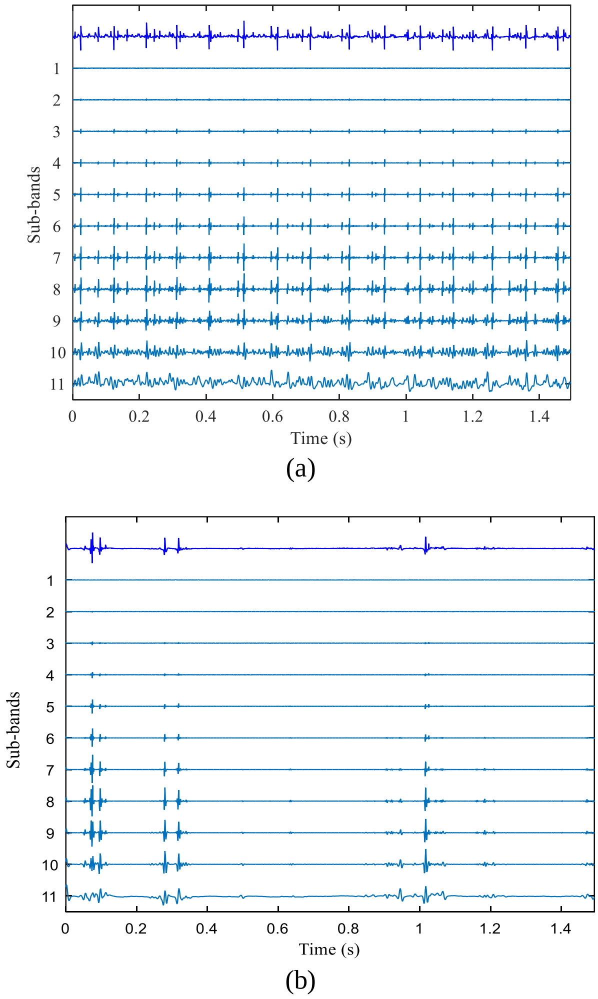

Figure 4. Plot sub-bands based on TQWT: (a) healthy and (b) ALS EMG signals

2.3. Feature extraction

The second step of our automated system is feature extraction, which is a very important step in the neuromuscular classification process. Based on TQWT sub-bands, three energy-related features are extracted. Those features reduce the dimensionality of sub-band signals. It is to be mentioned that according to j-level TQWT-based decomposition, j +1 sub-bands are obtained and they can be represented by a cell array:

$$C_{array} = \{w_1, w_2, w_3, w_4, \dots \dots, w_j, w_{j+1}\} \tag{5}$$

The energy associated with tunable Q-factor wavelet transform for every sub-band is defined by:

$$Energy_j = \sum_{i=1}^{n} \left| w_{ji} \right|^2 \tag{6}$$

The total signal energy can be written as follows:

$$E_{tot} = \sum_{j=1}^{j_{max}} Energy_j \tag{7}$$

In consequence, the relative energy value, which corresponds to the energy of each TQWT sub-band is given by:

$$\rho_j = \frac{Energy_j}{E_{tot}} \tag{8}$$

Clearly, $\sum_j \rho_j = 1$ and evaluate the probability distribution of each sub-band.

The following mathematical expression expresses the ratio and difference of energy values of neighbor TQWT sub-bands:

$$Ratio = \frac{\sum_{i=1}^{n} |w_{ji}|^2}{\sum_{i=1}^{n} |w_{ki}|^2} \tag{9}$$

$$\text{Diff} = \sum_{i=1}^{n} |w_{ji}|^2 - \sum_{i=1}^{n} |w_{ki}|^2 \tag{10}$$

The two features, (9) and (10), measure the changes in the frequency distribution.

From the features expression, $i \in \{1,2,3,4,5 \ldots n\}$ the length of each sub-band and $j,k \in \{1,2,3,4,5 \ldots j_{max}\}$ are the TQWT decomposition levels. Considering an example j_{max}=10, these features are calculated from w_1 to w_{10} and w_{11} which correspond to high- and low-frequency signal sub-bands, respectively. Eleven different features are computed from (8) and twenty different features are obtained from both (9) and (10). Hence, thirty-one features are extracted and then the filter method is used for feature selection.

2.4. Filter method based on feature selection

After the desirable features have been extracted, the next task is to select the relevant features and rank them in order of importance. Generally, a neuromuscular disorder classification process involves a lot of features, and most of them contain little or no information. The relevant features are necessary for improving classification performance and reducing computational time of the classification system. In the literature, there are various methods for feature selection (FS): wrapper, filter, embedded, or hybrid methods [24-25].

The filter method is deemed to be suitable for FS and is faster than the wrapper method. In our study, we focus on the filter method, which consists of using statistical measurements as evaluation criteria to investigate the importance of extraction features without any loss of useful information [25]. The relief feature selection algorithm is one of the currently existing algorithms based on the filter method, and was proposed by [26]. The relief algorithm determines feature weights for each extracted feature, which can be applied to rank and selects the most optimal scoring features [27]. As already mentioned, the total number of features is thirty-one, which are extracted from three different energy-related features. So, the mean and standard deviation values of the first ten ranked features as shown in Table 1. We also calculated the probability values using the ANOVA test. In recent years, many researchers have used this test to check the discriminate ability of the parameters for assessing EMG signals.

Since the ANOVA test is a statistical analysis, it can clearly demonstrate the significance of the selected feature. We can see in Table 1 that p-values are significantly lower than 0.05 for the first ten ranked features. Therfore, it can be observed from the Table 1 that the ratio of energy values of neighbor TQWT sub-band feature show much better signifigance than other two features. Figure 5 is a boxplot of the first selected features. It represents the dispersion of numerical EMG data in which both ends of the boxplot are interquartile distances, its central value is the median, and the plus sign indicates the outliers' values. As can be seen, the first selected features are clearly distinguishable.

Table 1. Mean, standard deviation and probability values of the top ten ranked features for ALS- Healthy classes using TQWT parameters Q-Factor=1, j=10, and r=3

Ranked Corresponding features feature	ALS EMG signals($\mu \pm std$)	Healthy EMG signals($\mu \pm std$)	p-value
1st feature Ratio(Sb_1, Sb_2)	0.8553 ± 0.6308	1.1718 ± 0.8006	$2.2433.10^{-26}$
2nd feature Ratio(Sb_2, Sb_3)	0.4398 ± 0.1582	0.5048 ± 0.1579	$1.9100.10^{23}$
3rd feature Ratio(Sb_3, Sb_4)	0.4440 ± 0.1626	0.5177 ± 0.1635	$7.9297.10^{-28}$
4th feature Ratio(Sb_4, Sb_5)	0.4595 ± 0.1735	0.5654 ± 0.2153	$8.9087.10^{-39}$
5th feature Ratio(Sb_9, Sb_{10})	1.1429 ± 0.3185	1.1759 ± 0.2683	0.0061
6th feature Ratio(Sb_7, Sb_8)	0.6599 ± 0.1764	0.7297 ± 0.1668	$6.1611.10^{-23}$
7th feature Ratio(Sb_5, Sb_6)	0.5531 ± 0.1921	0.6286 ± 0.2078	$4.8752.10^{-20}$
8th feature Diff(Sb_5, Sb_6)	$1.1907.10^7 \pm 2.2226.10^7$	$1.9308.10^6 \pm 2.646410^6$	$2.4288.10^{-51}$
9th feature Ratio(Sb_8, Sb_9)	0.8482 ± 0.2195	0.9227 ± 0.2096	$3.1518.10^{-17}$
10thfeature Diff(Sb_6, Sb_7)	$1.8789.10^7 \pm 3.4715.10^7$	$3.0757.10^6 \pm 4.1204.10^6$	$3.7686.10^{-52}$

Where Sb: sub-band, μ : mean value, std: standard diviation value, and p-value: probability value.

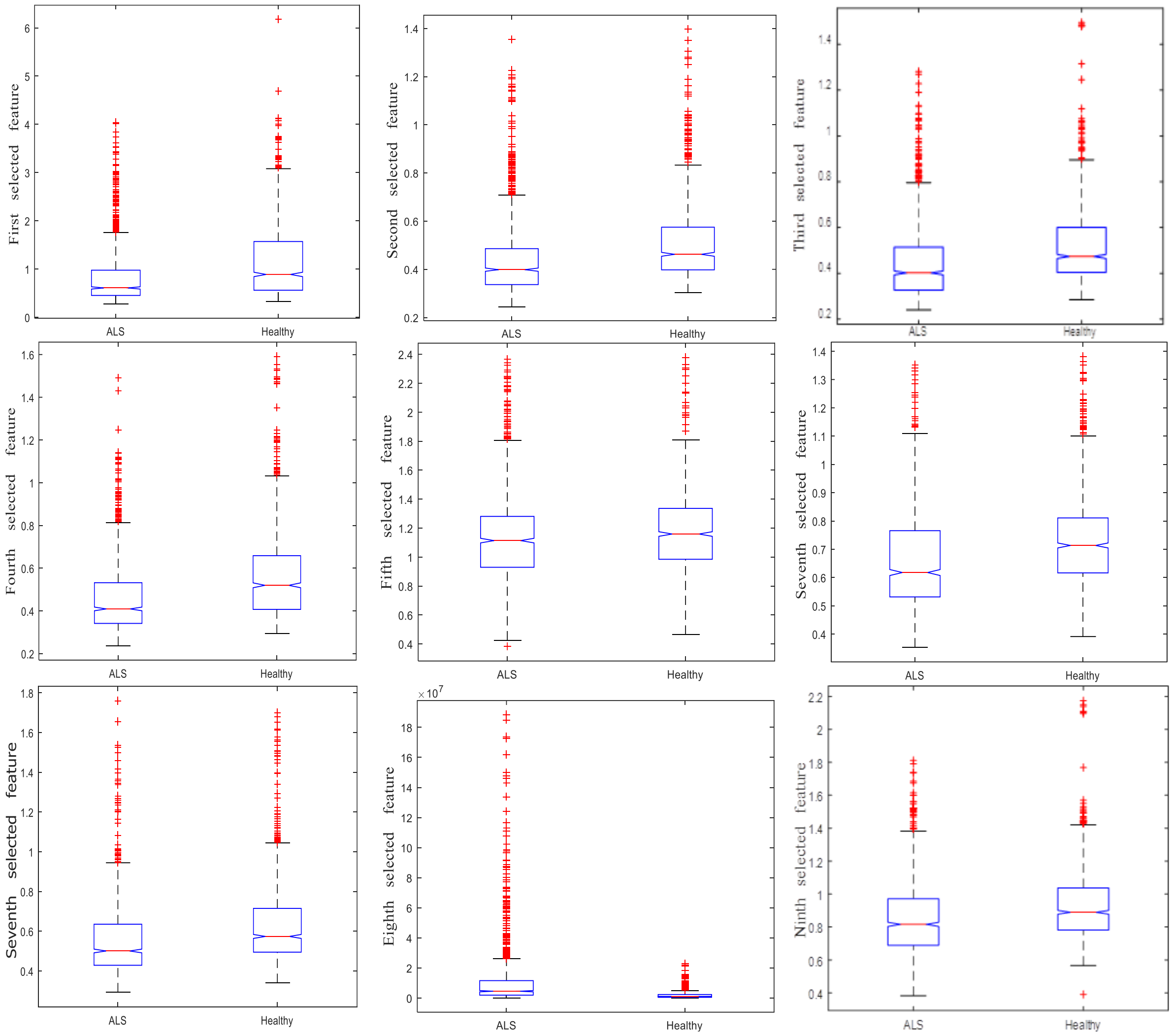

Figure 5. Boxplot of the first selected feature for the ALS and healthy EMG signals

3. CLASSIFICATION

The proposed relief algorithm selects the most optimal features matrix from the extraction feature phase for the kNN, LS-SVM, and RF classifiers to perform the neuromuscular disorder classification task. In the present section, we give more detailed information about each classifier.

3.1. k-Nearest neighbor classifier (k-NN)

kNN is efficiently used as a supervised machine learning algorithm for classification problems due to its flexibility and architectural simplicity [16]. The principle idea of the k-NN algorithm consists of classifying the unknown label by calculating the distance between the test sample and each training sample and then selecting the k closest samples. Finding exact k-nearest neighbors is the first challenge, followed by measuring the distance parameter. Generally, the distance can be calculated by Manhattan, Euclidean distance, and so on. Given a training set of instances label pairs$\{ (x_i, y_i)\}$ where the $x_i \in \mathbb{R}^d$, the d is dimensional instances in the input space, and the associated $y_i \in \{+1, -1\}$ represents a class label. The Euclidean distance is commonly used and can be expressed as follows:

$$d(x_i, x_j) = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{ik} - x_{jk})^2} \tag{11}$$

Where $x_i = (x_{i1}, x_{i2}, x_{i3}, \dots \dots, x_{id})$

3.2. Least squares support vector machine classifier (LS-SVM)

LS-SVM was developed by Vandewalle and Suykens as a modified algorithm of support vector machine (SVM) [28]. The higher computational demand and complexity of the optimization process are two major drawbacks of SVM. LS-SVM overcomes the SVM problems by using a set linear equation instead of a quadratic programming problem [16]. Considering the given training samples: $\{(x_i, y_i)\}_{i=1}^{N}$, N is the number of data points, the dataset $x_i \in \mathbb{R}^d$ indicates the input feature vector of d dimension and $y_i \in \{+1, -1\}$ represents the class label of x_i. The LS-SVM-based automated decision function of signal x can be given as follows:

$$y(x) = sgn[\sum_{i=1}^{N} \alpha_i y_i K(x, x_i + b)] \quad (12)$$

Where α_i is the Lagrange multiplier and $K(,)$ is the kernel function. In this work, we adopted an empirical radial basis function (RBF) as the kernel function since it has excellent classification performance:

$$K(x, x_i) = \varphi(x)^T \varphi(x_i) = e^{-\frac{\|x+x_i\|^2}{2\sigma^2}}, \sigma \neq 0 \quad (13)$$

Where σ denotes the width parameter of the RBF kernel.

3.3. Random forest classifier (RF)

Random forest (RF) is one of the most popular and most powerful supervised machine learning algorithm developed by breiman and can be employed for regression and classification [29]. RF, so-called random decision forest, is a technique that operates by building multiple decision trees during training. The decision of the majority of the tree is selected by the random forest as the final decision. The decision tree is a tree-shaped diagram used to determine a course of action. Each branch of the tree represents a possible decision, occurrence, or reaction [15]. The pseudo algorithm processs of RF using Matlab-programming software is [30, 31]:

Pseudo algorithm: Random forest

```
N=Number of nodes
M=Number of features
D=Number of trees
For i=1 to D
 1st step:
 Randomly draw a bootstrap sample ℤ* of size N from the training data
2nd step:
 Construct a random forest tree Tᵢ to bootsrapped data
 I - Select m variable at random M where m<M
 II- Pick the best variable/ split point among the m feature for node d
 II- split the node into two daughter nodes
 End
3rd step:
 Output the ensemble of the trees {{Tᵢ}}₁ᴰ
4th step:
 To make aprediction at a new point x
 Let Ĉᵢ(x) be the class prediction of the ith random forest tree. Then Let Ĉᵢᴰ(x)= majority vote{ Ĉᵢ(x)}₁ᴰ
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4. EXPERIMENTAL RESULTS AND DISCUSSION

In this study, TQWT feature extraction and multiple classifiers were applied for neuromuscular disorder detection. The relief feature selection algorithm was applied after the TQWT feature extraction method to observe the effect of the relevant features with different Q-Factor and decomposition level settings on classification performances. The classifiers were used to build a model via a training dataset. The obtained model can predict the label of data testing. The performances of the classifiers were assessed by running k-fold cross-validation (CV), which is very reliable. Traditionally, the k-fold cross-validation technique randomly splits the dataset into k-fold equal sizes to further train on $k - 1$ folds and evaluates on one fold. In this way, we repeat this k times for each fold. In this study, k=10 was selected and the average accuracy for all validation is expressed by [15]:

$$CV_i = \frac{1}{10} \sum_{i=1}^{10} A_i \quad (14)$$

Statistical key metrics can evaluate the classification performances of the neuromuscular disorder detection system. The sensitivity is defined as the percentage of the patients with ALS, whereas the specificity is the percentage of the patients without the disease. The accuracy classification is the proportion of the correct classifications from the overall number of cases. These key metrics are respectively defined as follows:

$$\text{Sensitivitiy} = \frac{\text{TP}}{\text{TP+FN}} \times 100\% \tag{15}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \times 100\% \tag{16}$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FN+FP}} \times 100\% \tag{17}$$

- TP: true positives (is the number of normal EMG signals identified as normal EMG signals).
- TN: true negatives (is the number of ALS EMG signals classified as ALS EMG signals).
- FP: false positives (is the number of ALS EMG signals recognized as normal EMG signals).
- FN: false negatives (is the number of normal EMG signals distinguished as ALS signals).

The main objective of this work is to analyse EMG signals by applying tunable Q-factor transform in order to extract the highly distinguishable features, to improve classification performance. In the TQWT technique, the parameters such as quality factor and redundancy can easily be adjusted. Additionally, TQWT offers the possibility to improve the frequency resolution in the wavelet due to its flexibility. Initially, the EMG signal was decomposed into several sub-bands using MATLAB TQWT toolbox. These sub-bands provide detailed information regarding the high- and low-frequency component of the EMG signal, but some of them can generate noise and redundant information. Once the EMG signal was decomposed into sub-bands, three parameters related to energy were measured from each sub-band of the EMG signal and arranged depending on their importance. Finally, the ranked parameters were forwarded to three different classifiers: k-NN, LS-SVM, and RF.

To study the effect of the level of decomposition, we carried out three simulation tests. In the first test, the value of decomposition level j was kept at three. Then in the next test, we considered the decomposition level j at six. In the last test, we maintained j at ten. Therefore, in each test, we kept the fixed the value of redundancy at three. The mean $\pm$ standard deviations of the performance evaluation measures obtained during ten cross-validation procedures using multiple classifiers and three different setting values of the quality factor based on TQWT are shown in Tables 2-4. As mentioned in section 3, the variation of the quality factor enabled the evaluation of the oscillatory behavior of the analyzed signal. The suitable parameters of the used classifiers were picked based on numerous trial and error experiments. After the testing period, the best values of the parameters of k-NN, LS-SVM, and RF, which contribute to achieving maximum classification performance, are listed in Tables 2-4.

Table 2. Classification results obtained with j=3 for different Quality-factor values

j=3 r=3, Max No. of features=10			Performance measure ($mean \pm std\%$)			
Class	Parameters	Quality-factor	Accuracy	Sensitivity	Specificity	Best No. of features
k-NN	k=3	Q=1	$88.37 \pm 2.51\%$	$86 \pm 2.68\%$	$90.75 \pm 3.32\%$	1-7
LS-SVM	$rbf(\sigma = 0.1)$		$78.95 \pm 2.91\%$	$76.33 \pm 2.48\%$	$81.58 \pm 3.54\%$	1-6
RF	NTrees=30		$89.33 \pm 1.83\%$	$88.33 \pm 3.01\%$	$90.31 \pm 2.62\%$	1-5
k-NN	k=3	Q=5	$83.79 \pm 2.07\%$	$84.6 \pm 3.31\%$	$82.91 \pm 4.30\%$	1-7
LS-SVM	$rbf(\sigma = 0.1)$		$77.25 \pm 2.88\%$	$82.66 \pm 2.88\%$	$71.83 \pm 3.76\%$	1-6
RF	nTrees=30		$84.75 \pm 2.61\%$	$84.50 \pm 3.81\%$	$85.0 \pm 3.74\%$	1-5
k-NN	k=3	Q=10	$79.29 \pm 2.32\%$	$79.25 \pm 3.47\%$	$79.33 \pm 2.96\%$	1-7
LS-SVM	$rbf(\sigma = 0.1)$		$74.33 \pm 4.54\%$	$64.50 \pm 1.88\%$	$85.25 \pm 5.18\%$	1-6
RF	nTrees=30		$82.7 \pm 2.61\%$	$84.83 \pm 2.83\%$	$80.58 \pm 2.22\%$	1-5

Table 3. Classification results obtained with j=6 for different Quality-factor values

j=6, r=3, Max No. of feature=19			Performance measure ($mean \pm std$%)			
Class	Parameters	Quality-factor	Accuracy	Sensitivity	Specificity	Best No. of features
k-NN	k=3		$93.16 \pm 1.62\%$	$90.41 \pm 2.83\%$	$95.91 \pm 1.26\%$	1-10
LS-SVM	$rbf(\sigma = 0.1)$	Q=1	$83.41 \pm 3.02\%$	$77.83 \pm 4.10\%$	$89 \pm 3.06\%$	1-10
RF	nTrees=30		$92.87 \pm 1.83\%$	$92.08 \pm 3.29\%$	$93.66 \pm 2.78\%$	1-10
k-NN	k=3		$82.16 \pm 2.45\%$	$82.25 \pm 3.26\%$	$82.08 \pm 2.97\%$	1-10
LS-SVM	$rbf(\sigma = 0.1)$	Q=5	$77.54 \pm 2.87\%$	$80.75 \pm 3.56\%$	$74.33 \pm 3.42\%$	1-10
RF	nTrees=30		$81.20 \pm 3.23\%$	$81.75 \pm 2.81\%$	$80.66 \pm 5.04\%$	1-10
k-NN	k=3		$81.50 \pm 1.82\%$	$79.33 \pm 2.57\%$	$78.66 \pm 1.97\%$	1-10
LS-SVM	$rbf(\sigma = 0.1)$	Q=10	$75.16 \pm 2.99\%$	$78.41 \pm 2.4\%$	$73.91 \pm 5.55\%$	1-10
RF	nTrees=30		$80.54 \pm 2.49\%$	$80.33 \pm 4.59\%$	$78.75 \pm 3.36\%$	1-10

Table 4. Classification results obtained with j=10 for different Quality-factor values

j =10, r=3, Max No. of feature=31			Performance measure ($mean \pm std$%)			
Class	Parameters	Quality-factor	Accuracy	Sensitivity	Specificity	Best No. of features
k-NN	k=3		$96.33 \pm 0.83\%$	$95.58 \pm 1.75\%$	$97.08 \pm 0.80\%$	1-10
LS-SVM	$rbf(\sigma = 0.1)$	Q=1	$89.70 \pm 2.20\%$	$85.83 \pm 3.46\%$	$93.58 \pm 2.77\%$	1-10
RF	nTrees=30		$93.58 \pm 2.29\%$	$93.45 \pm 1.64\%$	$94.50 \pm 2.77\%$	1-10
k-NN	k=3	Q=5	$82.66 \pm 2.45\%$	$82.25 \pm 3.26\%$	$82.08 \pm 2.97\%$	1-10
LS-SVM	$rbf(\sigma = 0.1)$		$77.54 \pm 2.87\%$	$80.75 \pm 3.56\%$	$74.33 \pm 3.42\%$	1-10
RF	nTrees=30		$81.20 \pm 3.23\%$	$81.75 \pm 2.81\%$	$80.66 \pm 5.04\%$	1-10
k-NN	k=3	Q=10	$80.62 \pm 1.82\%$	$78.33 \pm 2.57\%$	$77.66 \pm 1.97\%$	1-13
LS-SVM	$rbf(\sigma = 0.1)$		$78.16 \pm 2.99\%$	$79.41 \pm 2.4\%$	$73.91 \pm 5.55\%$	1-13
RF	nTrees=30		$79.54 \pm 2.49\%$	$78.33 \pm 4.59\%$	$70.75 \pm 3.36\%$	1-13

It can be seen from Tables 2-4 that the maximum average accuracy achieved by the k-NN classifier was higher than the other classifiers. The accuracy obtained by the RF classifier was very close to the one reached by the k-NN in the three Q-factor cases, and the performance of the LS-SVM was poor most of the time. Also, it should be noted that increasing the Q-factor value does not increase the classification accuracy obtained from each classifier. It can be concluded from all the tables that a Q-factor equal to one with the k-NN classifier gave the best classification performance in the three simulation tests. Consequently, when the number of decomposition levels becomes enormous, the classification measures significantly increase, and the increasing number of features containing noise and redundant information causes the dimensionality problem. Therefore, we chose the third simulation test and the k-NN classifier in the proposed approach and varied the Q-factor to calculate the features related to energy and to classify the EMG signals. The different Q-factors chosen were 1, 5 and 10.

We can see from Table 4 and Figure 6 that classification accuracy with Q–factor =1 achieved the highest point of 96.33%. From the sensitivity value of 95.58%, it can be noticed that the patients affected by ALS were well detected. In the case of Q-factor=5, the maximum accuracy of classification was 82.66%. However, it can be observed from this table that the classification accuracy reached the lowest point of 80.62% when Q-factor=10. We can see from this table that the performance classification with Q-factor=1 was higher than the others. The highest classification measures using optimal ranked features for Q-Factor=1 and using the k-NN LS-SVM and RF classifiers are presented in Figure 6 (a-c). After many tests, it was found that the first ten selected features were more suitable for getting the best classification result. As can be seen in Table 5, the classification performance deteriorated when other irrelevant features were added. As presented in Figure 6 (a-c), the experimental results show that the classification measures increased with the increasing of the selected features number.

Table 5. Classification result obtained with j=10 for Quality-factor value equal to 1

j =10, r=3			Performance measure ($\boldsymbol{mean} \pm \boldsymbol{std}$%)			
Class	Parameters	Quality-factor	Accuracy	Sensitivity	Specificity	Max No. of features
k-NN	k=3		$94.91 \pm 1.15\%$	$96.08 \pm 1.18\%$	$93.75 \pm 2.01\%$	1-31
LS-SVM	$\sigma = 0.1$	Q=1	$86.33 \pm 1.50\%$	$84.25 \pm 2.73\%$	$88.41 \pm 2.81\%$	1-31
RF	nTrees=30		$93.12 \pm 1.99\%$	$91.58 \pm 2.92\%$	$94.66 \pm 2.64\%$	1-31

To demonstrate the efficiency of our proposed methodology in neuromuscular disorder detection, a comparison between other methods is necessary. Table 6 provides the classification measures from the proposed approach and from other important studies. It should be noted that we have compared our experimental results with those of previous studies which used the same EMG dataset and TQWT method. Our approach yielded higher classification performance compared with the others.

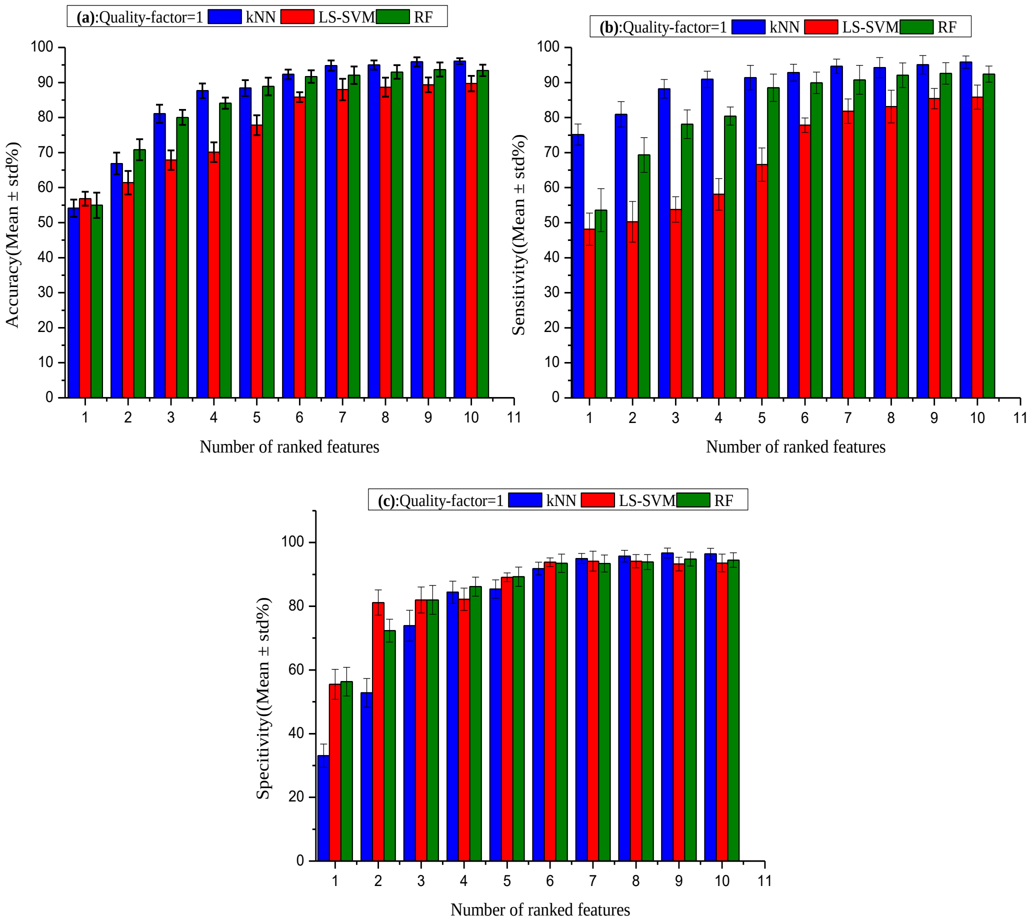

Figure 6. The classification measures of different classifiers versus the number of ranked features

Table 6. Performance comparison of EMG classification methods

Methods	Accuracy	Sensitivity	Specificity
[18]	87.40 %	-	87.40 %
[16]	95%	92.47%	96.85%
Our approach	96.33%	95.58%	97.08%

5. CONCLUSIONS

In this paper, we have improved the results of EMG classification using tunable Q-factor transform. The suggested TQWT method was applied to EMG signals, and different sub-bands were generated. These sub-bands contained rich information regarding high- and low-frequency components, which is valuable for making a distinction between ALS and healthy EMG records. Prior to features selection, the energy-related features were calculated to capture the probability distribution and changes in frequency distribution present in the sub-band signals. After that, k-nearest neighbor, LS-SVM, and RF classifier were used to evaluate the relevance of selected features. The challenge of this work was to determine the appropriate value of TQWT parameters, such as quality factor and level of decomposition, in order to reach the highest classification performance. It was found that TQWT parameters have a significant effect on classification performance. Classification measures of different classifiers vary significantly with the varying of decomposition level, and the suitable value was found to be j=10. We also observed a significant fluctuation in classification efficiency when the Q-factor was parametrized to high values. The k-NN classifier results were better than the other classifiers' results in all simulation tests, and the maximum classification accuracy was 96.33% and was obtained using k=3.

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