Polish Journal of Medical Physics and Engineering
The Journal of Polish Society of Medical Physics
ISSN 1898-0309, doi: 10.2478/pjmpe-2020-0017

September 2020
Vol 26, Issue 3

Scientific Paper

Application of the continuous wavelet transform for the analysis of pathological severity degree of electromyograms (EMGs) signals

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(received 31 March 2020; accepted 6 June 2020)

Abstract

The aim of this work was twofold: first, to propose signal processing methods for assessing the temporal and spectral changes of parameters (mean absolute value, the energy and standard deviation as temporal parameters, total and mean power as frequency parameters) of the surface myoelectric signal of the various patient groups like normal, myopathic and neuropathic during muscles contraction of biceps. Secondly, to analyze this electrical manifestation of neuromuscular disorders by the implementation of time-frequency analysis using continuous wavelet that allows us to qualify this method to evaluate, appreciate the pathology and determine its degree of severity which was unable by extracting mentioned parameters. Our results showed that this approach presents satisfactory performances especially to follow patients with the least severe pathology.

Key words: EMG; parameters; time-frequency; continuous wavelet; severity.

Introduction

Electromyography (EMG) is the analytical study of electrical activity produced by skeletal muscles that measure the electrical potential between the surface skins to muscle contraction that represent neuromuscular activities which is able to assist in diagnosing Musculoskeletal Disorders (MSDs) problem[1] myopathy and neuropathy are the two types of MSDs.

Myopathy is known as the dysfunction of muscles, while neuropathy refers to a variety of syndromes in which one or more nerves are affected by any or several known or unknown causes. Analyzing the change in the EMG signal parameters of the affected muscles can identify the pathological signs because it tests the electrical activity and function of nerve and muscle.[2] For that reason, many different extracted parameters are used to check and follow the evolution of pathology in biceps muscles. Among them, we find: the temporal parameters as a mean absolute value (MAV), energy (En), standard deviation (Std)[3,4] and frequency parameters as the total power (TTP) and mean power (MNP).[5]

But with the aim of estimating, appreciating and evaluating pathological's severity degree**,** we used an approach based on the continuous wavelet as a method that quantifies temporal changes of the frequency content of non-stationary signals without losing resolution in time or frequency, this is because EMG signal acquires noise while travelling through different tissue in the human body.[6] But, it is different with continuous wavelet transform (CWT) that able to show better performing in extracting indices in time-frequency domain.[7]

In reference 8, mother wavelet Daubechies of order 4 with 6 levels of decomposition (db4) has been chosen to implement the wavelet transform, because of its suitability for detecting signal changes and because of its shape is similar to the shape of motor unit action potentials.[9-11]

To reach our main goal mentioned from the beginning and evaluate the degree of pathological severity, our proposed model is to apply the continuous wavelet to distinguish neuropathy and Myopathy characteristics from EMG signal of the individual.

Materials and Methods

Database

Data has been generated for Normal, Myopathic and Neuropathic subjects using the simulator published as Hamilton-Wright A, Stashuk DW. Physiologically based simulation of clinical EMG signals. IEEE Trans Biomed Eng, 52: 171-183, 2005. Myopathic/Neuropathic data has been simulated for 75% fiber/motor unit involvement. All these data are collected from the surface electrode.

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EMG signal analysis

Signal filtering and thresholding

Removing some unwanted components of features of the signal is an important process, the appropriate filter will significantly improve the visibility of a defect signal and limit the frequency spectrum of a recorded signal which are normally comprised of low-frequency component and remove high pass filter which is described by range of frequency from 0- 500 Hz and amplitude of 0-10 millivolts (peak-to-peak). It is a complicated and non-stationary signal with highly complex time and frequency characteristics.[12] Then, the EMG signal cut into segments of possible MUAP waveforms to eliminate areas of low activity.[13] The segmentation algorithm basically calculates a threshold depending on the maximum value and the mean absolute value of the whole EMG signal,[4]

If maxi {xi}> (30÷*L*) $\left|\text{xi}\right|_{li=1}$ then (5÷*L*) $\left|\text{xi}\right|_{li=1}$

Else maxi {xi}/5,

Normal and pathological EMG signals analysis

Features extraction

Digital signal processing is concerning the extraction of features and information from measured raw signals, the time and frequency domain parameters are computed using to evaluate the severity of pathology this method assumes the data in stationary signal[12] such as:

Mean Absolute Value (MAV)

which provide the energy information and calculated by the following formula[3]:

$$MAV = \frac{1}{N}\sum_{n=1}^{N} |S(n)| \quad \text{Eq. 1}$$

where S(t) is the EMG signal.

Energy (E_n)

The aim set through this parameter is defining the amount of information carried by the signal. It's given by the following formula:

$$En[S] = \int |S(t)|^2 dt \quad \text{Eq. 2}$$

Standard deviation (Std)

The standard deviation of EMG signal is calculated by the sample of signal shown by equation:[4]

$$Std = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(S_n - \overline{S})} \quad \text{Eq. 3}$$

Where $\overline{S}$ is the mean value of EMG signal S(t).

Mean (MNP) and total power (TTP).

TTP is an aggregate of EMG power spectrum. its equation can be expressed as:

$$TTP = \sum_{j=1}^{M} P_j \quad \text{Eq. 4}$$

MNP is an average power of EMG power spectrum. It can be defined as:

$$MNP = \frac{\sum_{j=1}^{M} P_j}{M} \quad \text{Eq. 5}$$

where P_j and M are the EMG power spectrum at the frequency bin j and the length of frequency respectively.[5]

Time-frequency analysis (CWT)

In this study, starting from pre-processed EMG signals s(t), we evaluated the Continues Wavelet Transform (CWT) defined as:

$$CWT(a,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} s(t)\, W^*\left(\frac{t-\tau}{a}\right), a \neq 0 \quad \text{Eq. 7}$$

Where w(t) is a prototype function called mother wavelet, $\boldsymbol{\tau}$ is the translation index, and $\boldsymbol{a}$ is the scale parameter related to the frequency content. Indeed, the CWT may be a useful tool for detecting the presence of muscle activity in EMG signals.

In this work, mother wavelet Daubechies of order 4 with 6 levels of decomposition (db4) has been chosen to implement the wavelet transform, CWT decomposes a signal into several multiresolution components (coefficients) and performs a series of high and low-pass filter operations followed by down-sampling. Thus, the EMG signal was decomposed into its frequency content form and then was reconstructed.[10]

Results and Discussion

The representative EMG signal segments of healthy muscle and pathological conditions as a function of time are shown in **Figure 1a-c** filtered with a bandpass filter of 4th order and Butterworth type, thresholded where the signal amplitude of a neuropathic patient has exceeded 1 mV while it is between 0.5 and 1 mV when the pathology affects only the muscles (myopathy). In healthy patients, it is set to not exceed 0.5 mV.

Further, **Table 1** represents the extracted temporal parameters using the MAV, the energy, and Std, its histograms is shown by **Figure 2**. **Table 2** and **Figure 3** are the frequency features using the TTP and the MNP and its histograms respectively, where notable variations are observed in neuropathic patients compared with myopathic patients, the extracted features are found to have a statistically significant difference in healthy and pathological conditions.

From the histograms, we noted progressive increasing while the pathology affects muscles and nerves; it's the most important where the nerves are achieved that allows considering neuropathy to be the most severe compared to myopathy (less severe) because the extraction of temporal parameters indicated a strong increase of the energy of the neuropathic signal in the time domain and the widening of the frequency vector of the same case by the calculation of the frequency parameters, we conclude that the temporal and the frequency extracted parameters exhibit statistically highly significant difference of most and least severe pathology.

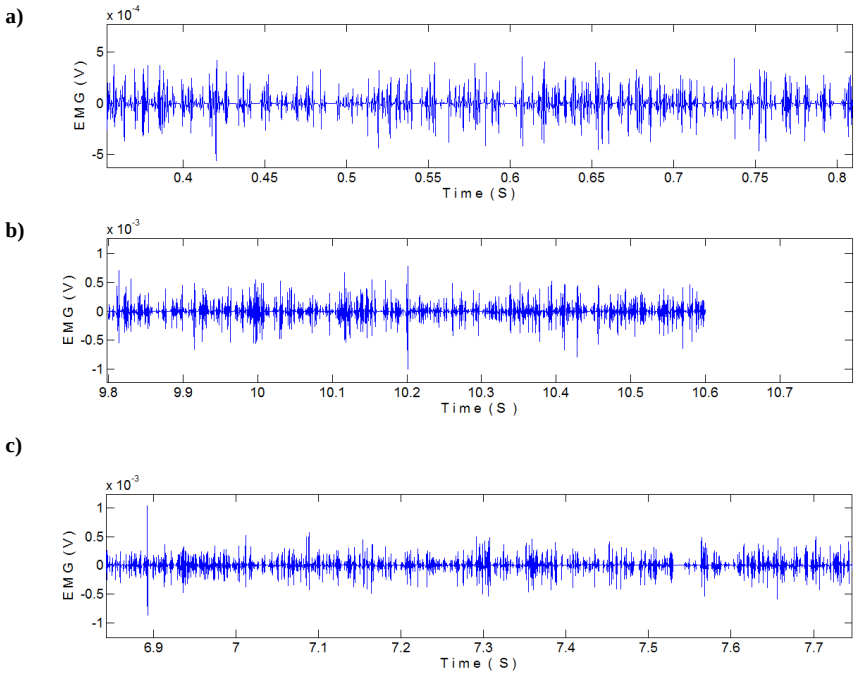


Figure 1. Raw Surface electromyogram (SEMG) signal as a function of time of: (a) Healthy, (b) myopathy, and (c) neuropathy EMG signal of patient 2.

Table 1. Temporal parameters of EMGs signals analysis.

Type of signals		Mean Absolute Value [MAV] (mV)	Energy [En] (Jouls)	Std (mV)
Patient 1	S003C000101	4.42×10^{-4}	7.23×10^{10}	343.53
	S003M750102	4.45×10^{-4}	7.30×10^{10}	345.24
	S003N750101	$4.4517^{*}\times10^{-4}$	7.32×10^{10}	345.68
Patient 2	S003C000205	4.41×10^{-4}	7.19×10^{10}	342.67
	S003M750201	4.437×10^{-4}	7.27×10^{10}	344.38
	S003N750201	4.46×10^{-4}	7.35×10^{10}	346.33
Patient 3	S003C000301	4.43×10^{-4}	7.26×10^{10}	344.37
	S003M750303	4.43×10^{-4}	7.31×10^{10}	345.44
	S003N750302	4.4605×10^{-4}	7.34×10^{10}	346.12

Table 2. Frequency parameters of EMGs signals analysis.

Type of signals		Total Power [TTP] (mV^2/Hz)	Mean Power [MNP] (mV^2/Hz)
Patient 1	S003C000101	2.77×10^{9}	4.5217×10^{3}
	S003M750102	2.79×10^{9}	4.5667×10^{3}
	S003N750101	2.80×10^{9}	4.5784×10^{3}
Patient 2	S003C000205	2.75×10^{9}	4.4990×10^{3}
	S003M750201	2.78×10^{9}	4.5439×10^{3}
	S003N750201	2.81×10^{9}	4.5956×10^{3}
Patient 3	S003C000301	2.78×10^{9}	4.5437×10^{3}
	S003M750303	2.80×10^{9}	4.5719×10^{3}
	S003N750302	2.81×10^{9}	4.5899×10^{3}

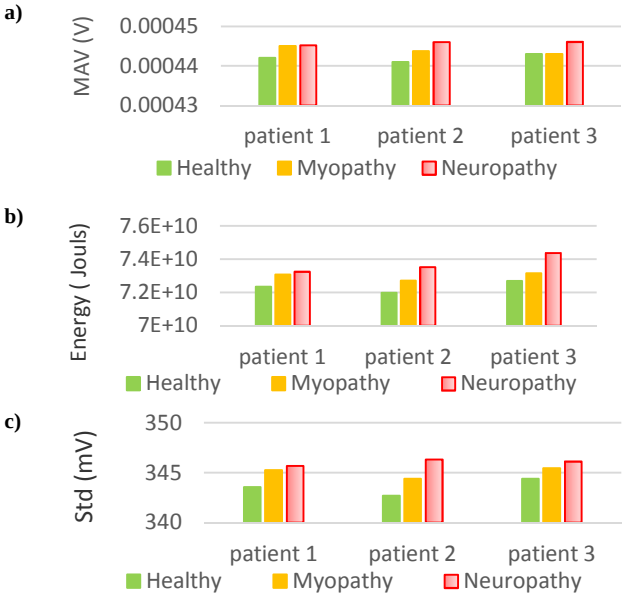


Figure 2. Histograms of the time analysis of the EMG signals: (a): Mean absolute value of the signal, (b): Energy of the signal (En), (c): the variation of the Standard deviation (Std)

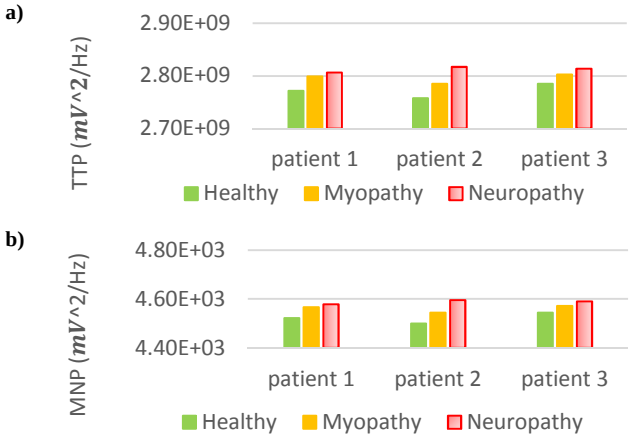


Figure 3. Histograms of frequency analysis of EMG signals: (a): Total power, (b): Mean power.

Figure 4 shows the time-frequency analysis of the representative sEMG signals obtained from the time-frequency methods, namely, CWT using to address the goal of determining variations in biceps muscle of patients which are dependent on recruitment of motor units, the time-frequency energy percentage distribution corresponding to healthy patients of muscle contraction shown in **Figure 4a-c** are less energy in comparison with a pathological condition (**Figure 4d-i**).

In this study, the analysis is made by extracting the contour the most energetic of these figures allowed us to fish for information. **Figure 4** represents the parameters that serve to differentiate these 9 cases, it is the percentage of the energy of the muscular activity of the most energetic contours that evolves progressively from the healthy patient towards the other which has a myopathy up to the patient with neuropathy that confirm the interest of this parameter in the normal cases analysis and even pathological cases because of the existence of a correlation between degree and the severity of the pathology.

The study of the maximum energy percentage of these contours in all the cases confirmed that the neuropathy with the highest percentage of energy that evolves from 10% to 85% and consider the neuropathy the most severe pathology with the average percentage of 47.5%. Then the myopathy has counted a percentage of energy from 5% to 40%, the myopathy appeared at the percentage of 20% and started spread with their symptoms which allow us considering them as the least severe with an average percentage of 22.5% of the neuropathic case, the reference case reached till 10% starting with 1%.

The percentage of energy goes up to 80% for the 2nd neuropathic patient and therefore to declare the latter to be the most accentuated severity, also to announce the 1st neuropathic patient to be the least accentuated severity because it has a percentage 55%, it allows considering it to be the first stage of neuropathy.

An energetic study of myopathic patients allowed us to state that the 3rd patient is the most advanced stage (40%) and this requires a precautionary treatment to solve this problem.

The analysis of the EMG signal's contours using the Daubechies continuous wavelet of order 4 has been used extensively to evaluate the degree of pathological severity by calculating the energy percentage signal's contours and qualified this analysis to be the most effective not only for the analysis of normal cases and even pathological cases because it serves to offer the level of evolution of the pathology.

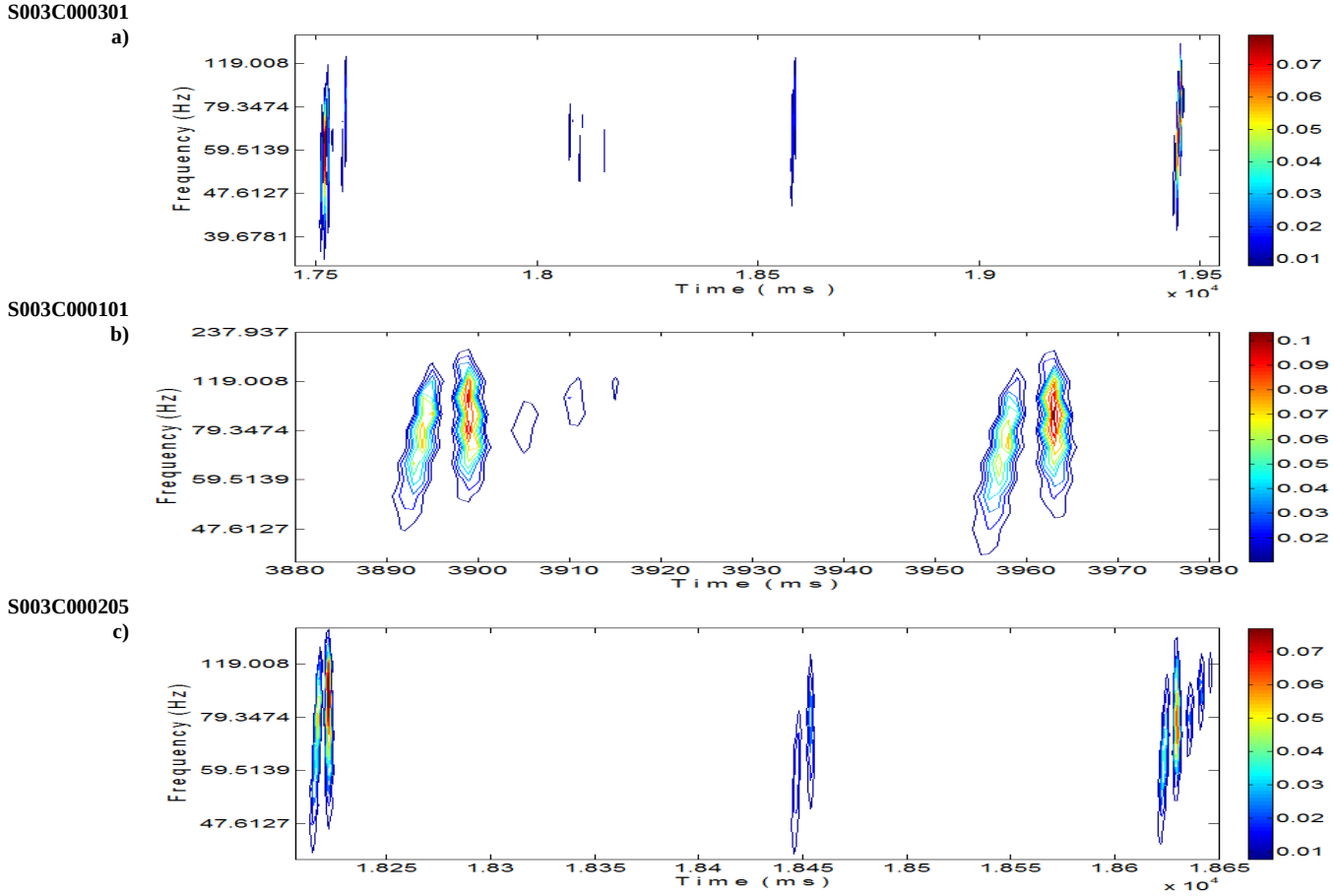
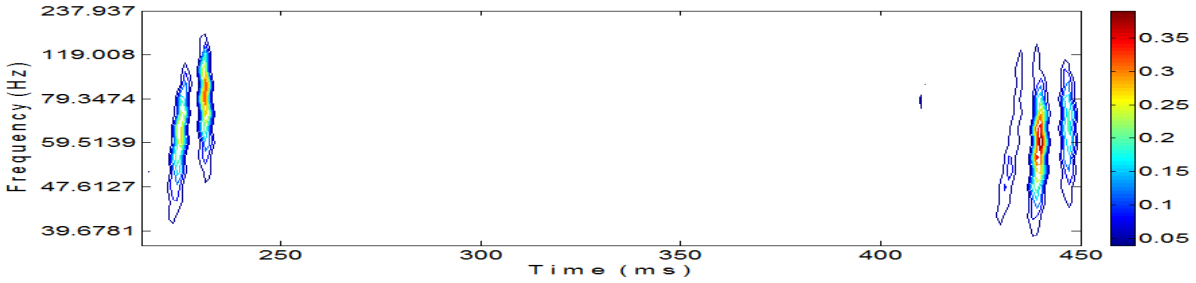
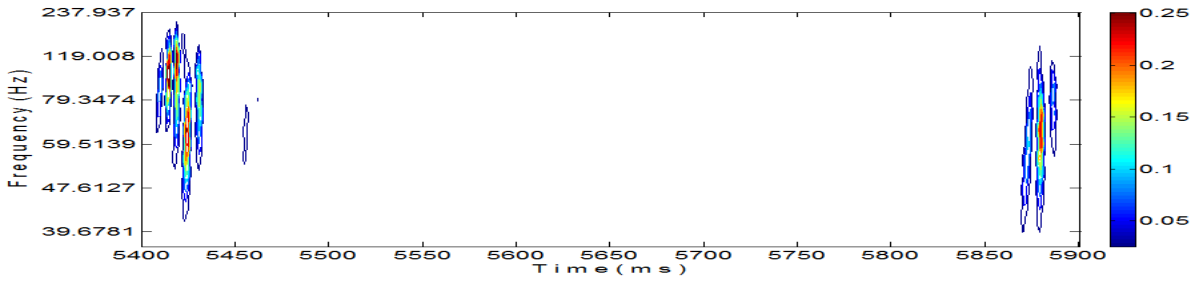


Figure 4. Scalogram percentage of energy for each wavelet coefficient of: (a), (b), (c) healthy, (d), (e) (f) myopathy and (g), (h), (i) neuropathy EMG signal (continued on the next page).

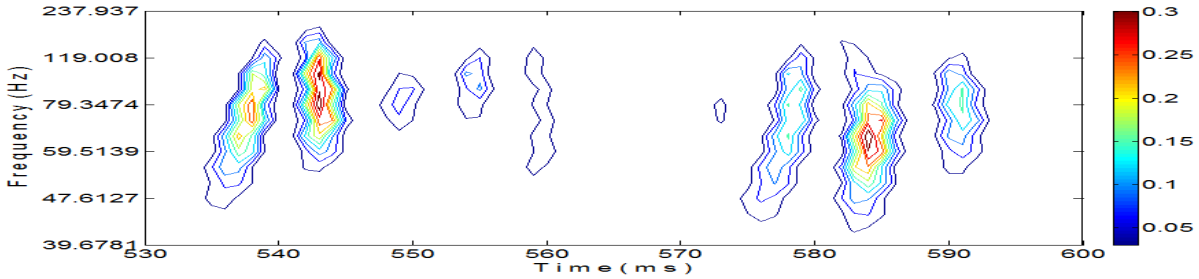
S003M750303
d)



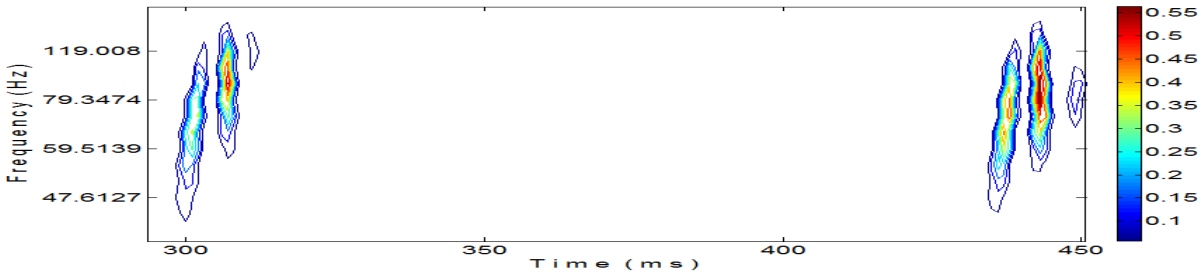
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e)



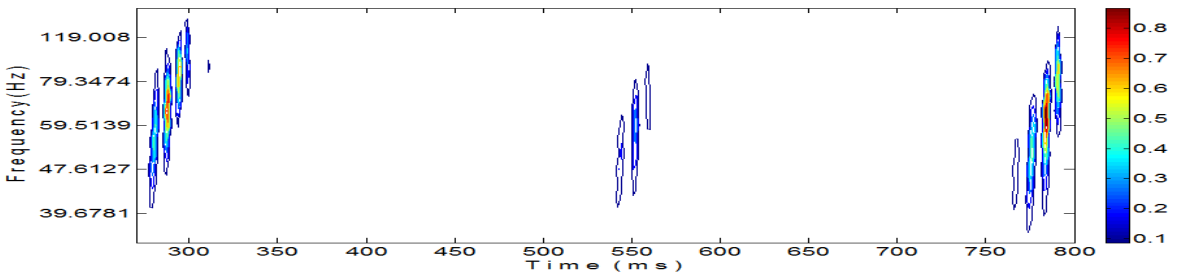
S003M750102
f)



S003N750101
g)



S003N750201
h)



S003N750302
i)

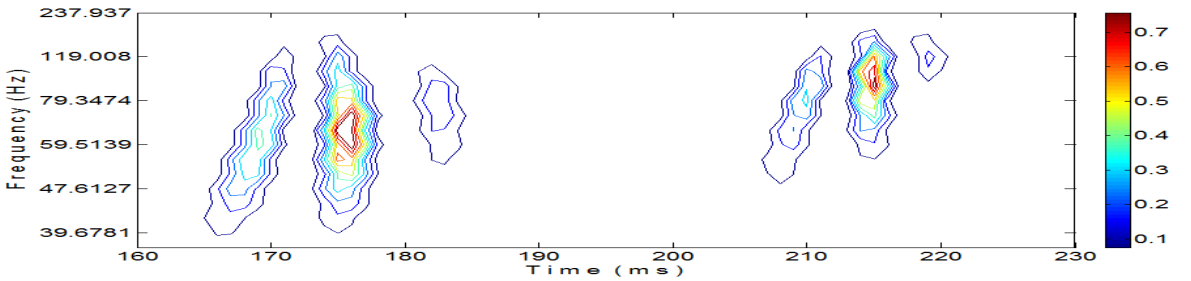


Figure 4. Scalogram percentage of energy for each wavelet coefficient of: (a), (b), (c) healthy, (d), (e) (f) myopathy and (g), (h), (i) neuropathy EMG signal (continued from the previous page).

Conclusion

In order to separate MUAPs into neuropathy, myopathy and healthy, time and frequency methods were applied to select the stage of pathological severity, so several parameters were extracted, they present an important issue that muscle which is affected by the disease (myopathy) is less severe because only some of the motor units can be affected and that neuropathic disorders are more severe than myopathy disorders due to neural carrier dysfunction. then, a powerful tool for analyzing the multicomponent and nonstationary variations of EMG signals is to introduce the CWT and the analysis of its features, their results demonstrate that the proposed time-frequency techniques are able to represent the severity degree of different cases of EMG signal because it does not just give differentiation between healthy and pathological cases but also its evolution's degree These results qualified the CWT method for quantifying the level of involvement of a neuromuscular disorder.

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