

# Pathological Electromyogram (EMG) Signal Analysis Parameters

F. Meziani, S. Rerbal and S. M. Debbal\*

Consultant Intervention Cardiologist Nepal Mediciti Hospital Lalitpur, Nepal

\*Corresponding Author: M. Debbal, Genie Biomedical Laboratory (GBM) Faculty of Technology University A.B.Belkaid-Tlemcen BP 119 Tlemcen; Algeria

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## ABSTRACT

Clinical analysis of the electromyogram is a powerful tool for diagnosis of neuromuscular diseases. There fore, the detection and the analysis of electromyogram signals has he attracted much attention over the years. Several methods based on modern signal Processing techniques such as temporal analysis, spectro-temporel analysis ..., have been investigated for electromyogram signal treatment. However, many of these analysis methods are not highly successful due to their complexity and non-stationarity. The aim of this study is to analyse the EMGs signals using nonlinear analysis. This analysis can provide a wide range of information's related to the type of signal (normal and pathological

**Key words:** electromyogram; EMG; signal; nonlinear analysis; parameters; pathology

## I. Introduction:

The EMG signal is a biomedical signal that measures electrical currents generated in muscles during its contraction representing neuromuscular activities. The nervous system always controls the muscle activity (contraction/relaxation). Hence, the EMG signal is a complicated signal, which is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles.

Detection and analysis of EMGs signals with powerful and advance methodologies is becoming a very important requirement in biomedical engineering. More recently, nonlinear tools have been introduced to analyze the EMGs signals; among them, the recurrence quantification analysis (RQA) and the bispectral analysis.

The recurrence quantification analysis (RQA) was shown to be particularly promising for the detection of muscle status changes [1]. The recurrence plots have been widely explored scientific fields for understanding the dynamics of system. Recurrence quantification analysis (RQA) methods for biological signals such as electroencephalogram [2] and EMG [3], are useful since it does not require large data and does not depend on statistical nature of signal [4].

In addition, many signals have nonlinearity and non-Gaussian behavior, and such signals cannot be examined properly by 2nd-order statistical methods. Thus, higher-order statistical methods have been proved. The HOS was first applied to real signal processing problems in the 1970s and since then it has continued to be applied in many different areas, such as economics, speech signal processing, noisy and artifact removal, biomedical signal processing, and optics. Since EMG signals are nonstationary and non-Gaussian signals, they should be examined by HOS methods. Bispectrum, which is the Fourier transform of the 3rd-order cumulant, can be applied to nonlinear and non-Gaussian signals to extract nonlinear information. [5]

The electromyographic (EMG) signals are extensively used on feature extraction methods for movement classification purposes. High-order statistics (HOS) is being employed increasingly in myoelectric research. HOS techniques could be represented in the frequency domain (high-order spectra, e.g., bispectrum, trispectrum) or in the time domain (higher-order cumulants).

The objective of this article is to applied the non-linear analyze of the EMGs signals (normal, myopathy and neuropathy)

## I. Study of energy

In the literature various approaches can be found to extract the EMG envelopogram which will be useful in diagnosing various pathological cases. There are several methods to extract the envelope such as the calculation of the square of the signal or absolute value (equations (1–2)). The square of the samples of a given signal (equation (1)) makes it possible to evaluate its energy in the temporal field. However, and as illustrated in **Figure.1**, samples of high amplitude are very heavily favoured over those of low amplitude. The amplitude of the energy calculated by the absolute value [equation (2)] of the samples of the signal also disadvantages samples of low amplitude.

Two other approaches that can be used are Shannon entropy and Shannon energy; see equations (3) and (4). These approaches give greater weight to the average intensities of the signal; therefore, the noise of low intensity and high intensity of disturbance will be mitigated. Similarly, the Shannon entropy [equation (3)] does not yield the true proportions of the signal, attenuating more samples of very low amplitude for the benefit of large-amplitude oscillations. The Shannon energy [equation (4)] proves the median approach, making it possible to generate a representation that takes account of the physiological attenuation of sounds as well as artefacts of large amplitude while recording the EMG signal. The EMG

signal energy representations [Figure.2] highlight the interest of the Shannon energy. According to these figures, we can see that only the Shannon entropy and the Shannon energy can absorb the magnitude of oscillations of high intensity as well as those in low amplitudes. So, they are the most suitable for the treatment of EMG signal.

- Square of the energy:  $E_n = S(t)^2$  (1)

- Absolute value of the energy :  $V = |S(t)|$  (2)

- Shannon entropy :  $E_p = -|S(t)| * \log|S(t)|$  (3)

- Shannon energy:  $E_s = -S(t)^2 * \log S(t)^2$  (4)

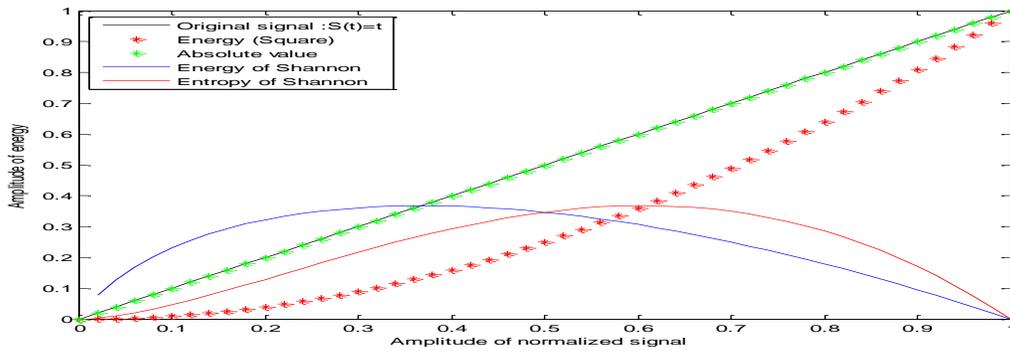
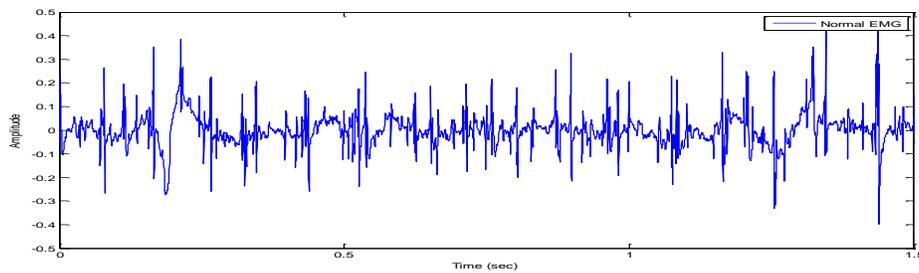
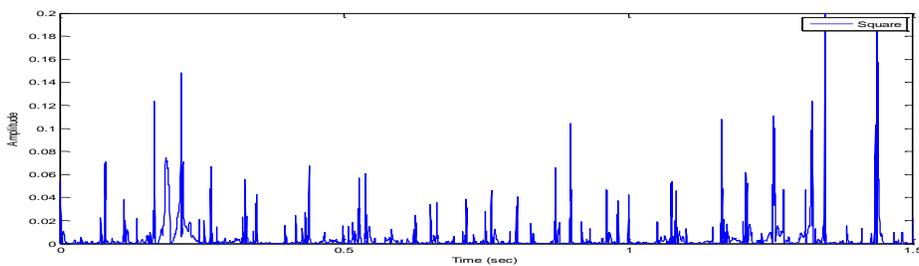


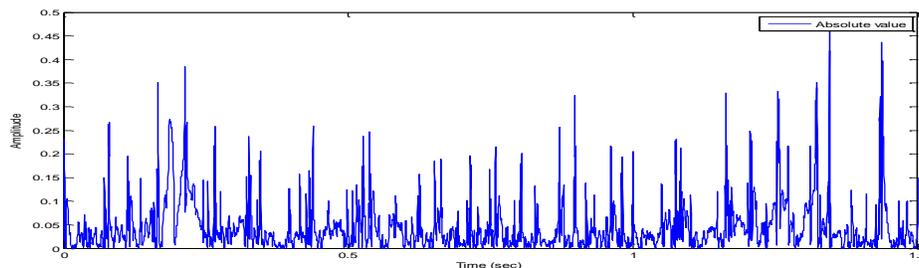
Figure 1: Temporal energy representation of the signal s (t).



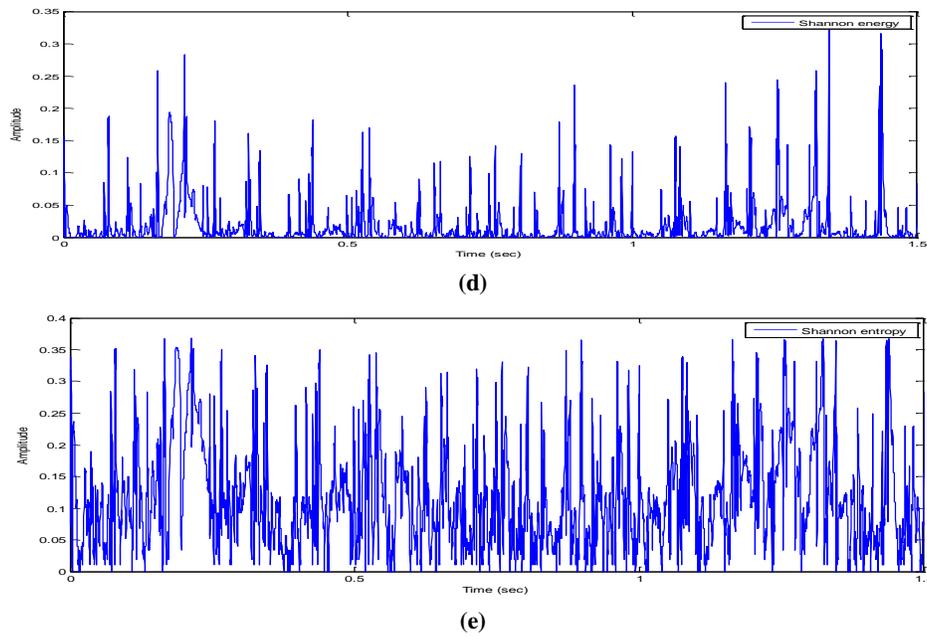
(a)



(b)



(c)



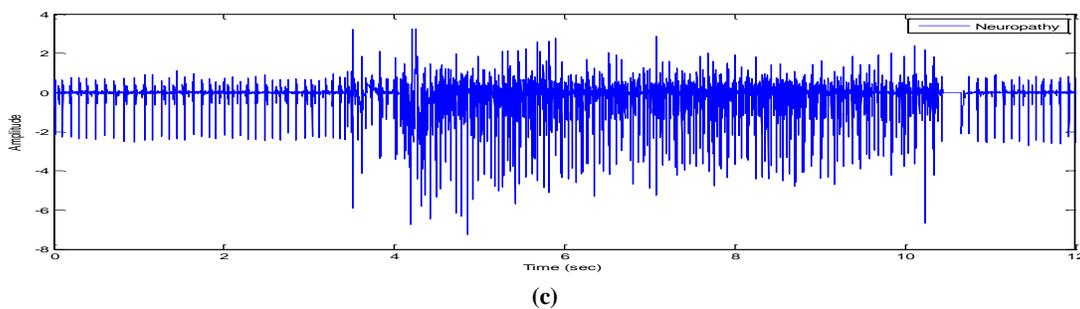
**Figure 2:** Energy representations of Normal EMG signal. (a) EMG signal. (b) Squared EMG signal. (c) Absolute value of the EMG signal. (d) Shannon energy of the EMG signal. (e) Shannon entropy of the EMG signal.

## II. Material and Methods

### 1. Database

In this study, the database of EMG signal, includes three cases of EMGs signals (Normal, myopathy and Neuropathy), set from Medelec Synergy N2 EMG Monitoring System (Oxford Instruments Medical, Old Woking, United Kingdom).[6] A 25mm concentric needle electrode was placed into the tibialis anterior muscle (TA) of each subject. The patient was then asked to dorsiflex the foot gently against resistance. The needle electrode was repositioned until motor unit potentials with a rapid rise

time were identified. Data were then collected for several seconds, at which point the patient was asked to relax and the needle removed. The following figure [Figure.3] and Table.I, shows three examples of EMG data from: a 44 year old man without history of neuromuscular disease; a 62 year old man with chronic low back pain and neuropathy due to a right L5 radiculopathy; and a 57 year old man with myopathy due to longstanding history of polymyositis, treated effectively with steroids and low-dose methotrexate. The data were recorded at 50 KHz and then downsampled to 4 KHz. During the recording process two analog filters were used: a 20 Hz high-pass filter and a 5K Hz low-pass filter. [Figure.3]



**Figure 3:** Temporal representation of Electromyography signals: (a) a normal case (b) a myopathy case (c) a neuropathy case.

Signal	Age	Sex	Pathology	Muscle	Electrode
EMG1	44	Man	Any	tibialis anterior	A 25mm concentric needle electrode
EMG2	57	Man	Myopathy	tibialis anterior	A 25mm concentric needle electrode
EMG3	62	Man	Neuropathy	tibialis anterior	A 25mm concentric needle electrode

**Table I:** Database of EMGs signals.

## 2. Higher Order Statistics (HOS) theory for EMG signal analysis

Frequency domain techniques are amongst the most fundamental and useful tools in the area of signal processing. Conventional techniques are generally based on the analysis of the first and second order moments and cumulants and their spectral representation. These techniques provide all the information available from the signal only if the underlying process is Gaussian and is operated on by a linear system.

For non-Gaussian processes and nonlinear systems, more information can be obtained from the higher order moments and cumulants (3rd order to Nth order) and their spectral representation (higher order spectra). The second order spectrum suppresses phase relationships, whereas information about the phase of the underlying system is available from higher order spectra [7].

Higher order statistics are useful in blind deconvolution and system recovery. As they do not suppress phase information, they may be applied to non-minimum phase and nonlinear systems. As they are able to recover information about non-Gaussian signals, they are useful in systems involving non-Gaussian input signals.

In this paper we will use, the Bispectrum, to estimate the system information. The bispectrum is the most accessible of the higher order spectra as it is the simplest to compute and its properties have been well explored [7] - [13].

## 3. Non-linear parameters Analysis of normal and pathological EMGs signals:

### a. Recurrence quantification analysis :

Recurrence quantification analysis (RQA) is a nonlinear method that discovers recurring patterns, commonly referred to as hidden rhythms. This nonlinear method can be used to analyze physiological signals. To be specific, recurrence plots are used to investigate the nonlinear prediction of timeseries generated by dynamical systems driven by slowly varying external forces. Recurrence plots are established based on time series data. The first step is to form a vector:

$$X_n = [x(n)x(n + L), \dots, x(n + (m - 1)L)] \quad (5)$$

Where  $m$  is the embedding dimension and  $L$  is the lag.  $X_n$  represents a multi-dimensional process as a trajectory in  $m$ -dimensional space. We can define two different points on that trajectory, say  $X_i$  and  $X_j$ . The index pair  $(i,j)$  is used to specify an element for a binary  $N \times N$  matrix. The entry is defined as

$$a_{i,j} = \begin{cases} 1 & \text{if } \|X_i - X_j\| \leq r \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

Where  $\| \dots \|$  indicates the Euclidean distance and  $r$  is a fixed radius. The binary matrix  $A$  can be represented as a  $N \times N$  image by putting a white pixel whenever  $a_{i,j} = 1$  and a blue pixel otherwise.

The recurrence statistics, which is called recurrence quantification analysis (RQA), has been introduced for measuring quantitative information within recurrence plots [14]; subsequently it was extended with new measure of complexity by Marwan [15] [16]. It is a method of nonlinear data analysis which quantifies the numbers and duration of recurrence of a dynamical system presented by its state space vector. An EMG recurrence plot, which includes the recurrence statistics, is a representation of the nonlinear EMG signal that provides rich information

about EMG patterns. We focus on the following three features of the recurrence plot as they best describe the behaviour of the underlying EMG signals:

- a. **Recurrence rate (RR)** is the density of recurrence points in a recurrence plot, which is defined as:

$$RR = \frac{1}{N^2} \sum_{i,j}^N R_{i,j} \quad (7)$$

Where  $N$  is number of points on the phase space trajectory

- b. The next measure is the percentage of recurrence (determinism: DET) points that form diagonal structures to all recurrence points in the recurrence plot ( $R$ ) reflecting **deterministic** or **predictable** characteristics in dynamical systems [17] The line segments are parallel to the main diagonal. Higher value of DET means higher periodicity. The vector point  $(i$  and  $j)$  in the recurrence plot is considered as recurrent if the distance between the vectors  $y_i$  and  $y_j$  is less than the threshold. The value of DET is given as below. The DET is usually expressed as a percentage. In this analysis, the DET value is taken between 0 and 1 for representation.

$$DET = \frac{\sum_{l=l_{min}}^N lP(l)}{\sum_{l=1}^N lP(l)} \quad (8)$$

Where  $P(l)$  is the [frequency distribution](#) of the lengths  $l$  of the diagonal lines.

- c. Complexity feature (CPX) is derived from the RQA measure determinism. This feature is previously reported for analyzing physiological signals (EEG) and found to be useful [18] Higher value of CPX indicates origin of signal from highly irregular or chaotic system. This may be due to presence of random series and may be due to higher nonlinearity. Its represented as :

$$CPX = -20 \log_{10} DET \quad (9)$$

### b. Bispectral Analysis

Bispectrum analysis reveals the phase relation between components of a signal [8][19]. Unlike the power spectrum, the bispectrum is capable of extracting extra information from biological signals such as an EMG signal, which is non-Gaussian and nonlinear. The bispectrum is defined as the Fourier transform of the 3rd-order cumulant.

The 3rd-order cumulant of a discrete signal  $x(k)$ , which is stationary and has a 0 mean, is defined as [19]

$$C_{3x}(n_1, n_2) = \text{cum}\{x(k)x(k + n_1)x(k + n_2)\} = \langle x(k)x(k + n_1)x(k + n_2) \rangle - \langle x(k) \rangle \{ \langle x(k)x(k + n_1) \rangle + \langle x(k)x(k + n_2) \rangle + \langle x(k + n_1)x(k + n_2) \rangle \} + 2\langle x(k) \rangle^3 \quad (10)$$

Where  $\langle \cdot \rangle$  denotes the expected process.

The  $r$ th degree moment of  $x(k)$  is defined as

$$m_{rx}(n_1, n_2, \dots, n_{r-1}) = \langle x(k)x(k + n_1) \dots x(k + n_{r-1}) \rangle \quad (11)$$

Thus, (10) can be rewritten as:

$$C_{3x}(n_1, n_2) = m_{3x}(n_1, n_2) - (m_x(m_{2x}(n_1) + m_{2x}(n_2) + m_{2x}(n_2 - n_1)) - 2m_{3x}) \quad (12)$$

Alternatively, the 3rd-order cumulant can be written as

$$C_{3x}(n_1, n_2) = m_{3x}(n_1, n_2) - m_{3x}^G(n_1, n_2) \quad (13)$$

where  $m_{3x}(n_1, n_2)$  is the 3rd-order moment function of  $x(k)$  and  $m_{3x}^G(n_1, n_2)$  is the 3rd-order moment function of a Gaussian random process with the same 1st- and 2nd-order characteristics of  $x(k)$

$$m_{3x}^G(n_1, n_2) = m_x(m_{2x}(n_1) + m_{2x}(n_2) + m_{2x}(n_2 - n_1)) - 2m_{3x} \quad (14)$$

The Fourier transform of the 3rd-order cumulant is bispectrum and defined as

$$B(w_1, w_2) = \sum_{n_1=-\infty}^{+\infty} \sum_{n_2=-\infty}^{+\infty} C_{3x}(n_1, n_2) W e^{-j(w_1 n_1 + w_2 n_2)}, \quad (15)$$

$$|w_1|, |w_2| \leq \pi$$

where  $W(n_1, n_2)$  is the 2-dimensional window function that decreases the variance of the bispectrum. In this study, a Hanning window was used. Equation (15) can also be defined in the Fourier transform of  $x(k)$  as

$$B(w_1, w_2) = \langle X(w_1)X(w_2)X^*(w_1 + w_2) \rangle \quad (16)$$

where \* denotes a complex conjugate.

$B(\omega_1, \omega_2)$  is a symmetric function, such that a triangular region  $0 \leq \omega_2 \leq \omega_1, \omega_1 + \omega_2 \leq \pi$  could completely describe the whole bispectrum. The other regions in the bispectrum are the symmetry of the defined triangular region.

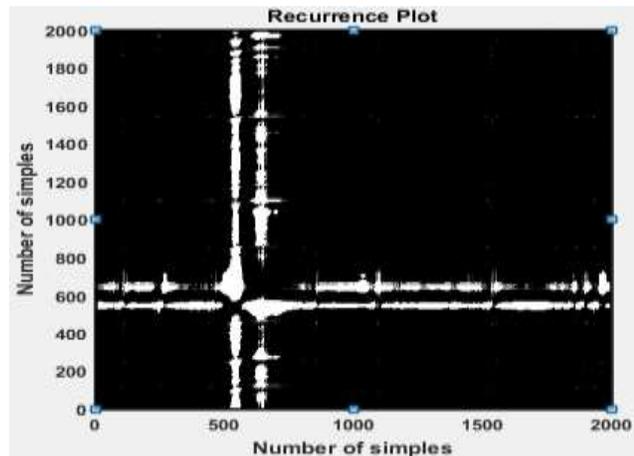
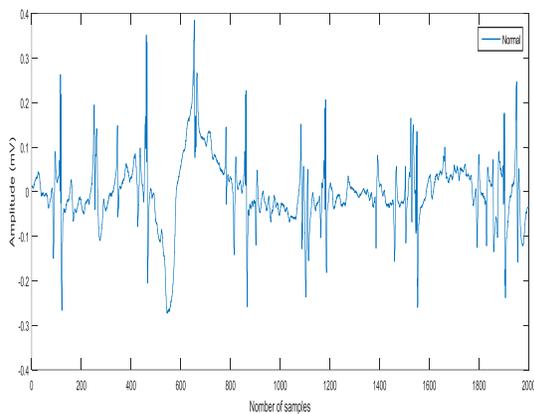
### III. Results and discussion

Analyzing nonlinear time series through recurrence quantification analysis has been investigated for many years [20] [21]. RQA has been proven to be effective in analyzing nonstationary signals. Not unexpectedly, RQA has demonstrated advantages over linear techniques in the analysis of EMG [22]. To test whether electromyogram is a nonlinear signal or just random noise, we analyze EMG signals of neuromuscular diseases using recurrence plot [see Figure. 4].

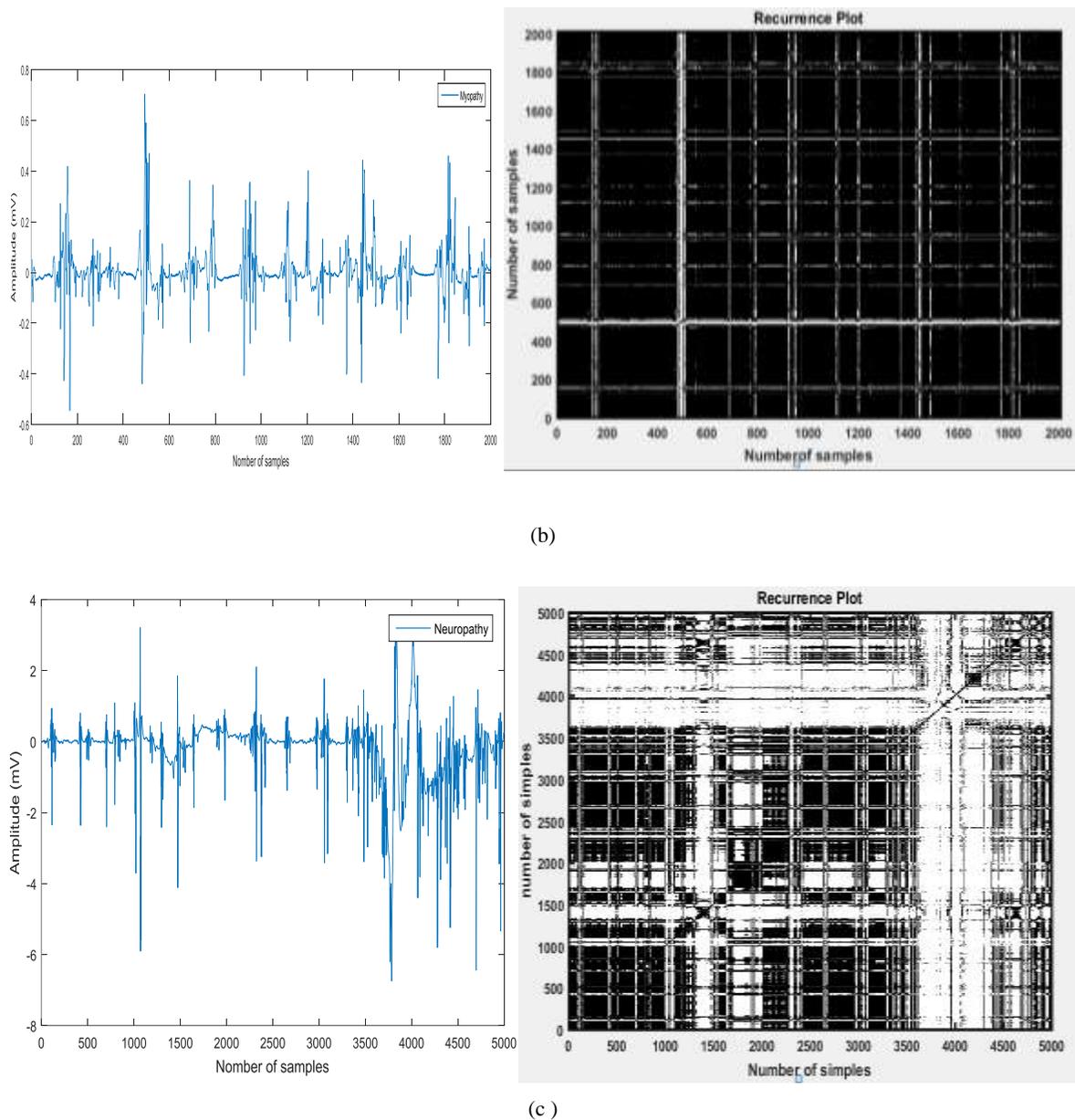
The recurrence plots, shown in Figure.4, describe the natural, but subtle, time correlation within the EMG signals. The recurrence plots are almost symmetric with respect to the diagonal  $i=j$ .

The recurrence plots for normal case and Myopathy case are quite distinct compared to Neuropathy case. This is because a recurrence plot picks up similarities in the EMG signals, therefore, the recurrence plot reflects the degree of similarity present in the EMG signal.

From all the results, we conclude that EMG obeys a certain nonlinear deterministic law and non-stationarity is significant within these signals. It is therefore possible to study and analyze these signals as a non-linear system using recurrence quantification analysis. This result confirms what is found by Sivarit Sultornsanee, Ibrahim Zeid and Sagar Kamarthi [23]



(a)



**Figure 4:** Recurrence plots of Electromyography signals: (a) a normal case (b): a myopathy case (c): a neuropathy case.

To distinguish the difference between the EMGs signals and hence to estimate the evolution of their disease severity, histograms of the variation of the same parameters mentioned previously given in the table below [Table. II] (Recurrence rate (RR), Determinism (DET%) and Complexity feature (CPF)) will be plotted. Thus, a comparison of these cases will be performed. [Figure.5]

The histogram of the Recurrence rate (RR) variation represented by [Figure.5. (a)], shown an inversely relative proportionality between the value of the Recurrence rate (RR) and the type of the signal. The first recording (the normal case) represents a higher value ( $\approx 181$ ), that the other case. The second with a myopathy, also has an important value, closer to the normal case (165.5) and more important than the neuropathy

case ( $\approx 47.7$ ). This variation shows that the myopathy case has properties similar to the normal case that neuropathy case.

The DET feature is the measure of determinism and periodicity in time series. The lower DET is an indication of higher randomness and lower predictability.[24]

For the same cases studied, the result of the variation in DET shown in [Figure.5. (b)], makes clear the differences that may exist between these signals. For the normal case, the EMG signal is highly random and nonstationary in nature. This may be due to higher firing rates of motor units and increased recruitment of motor units for force generation. However, for the pathological cases, the DET value appeared to be increase steadily to higher values.

Here, the DET value of myopathy, are much closer to the normal case as the neuropathy. These results, so well confirm what was found by the recurrence rate (RR) and consequently the myopathy is less severe than the neuropathy. These findings are confirmed by those given in [23].

Complexity feature variations of three different cases studied represented by [Figure.5. (c)], shows that the first recording (the normal case) is the

least case. It represents 16% of the value of myopathy and about 5% of the neuropathy case. Higher complexity means that the signal is random and highly non stationary. Lower values of complexity are an indication of repetitive regular structures and hence considered to be predictable. [24]. In this context the CPX variation, present an important parameter to complete differentiation and classification pathological severity between EMGs signals: Neuropathy is the most severe cases.

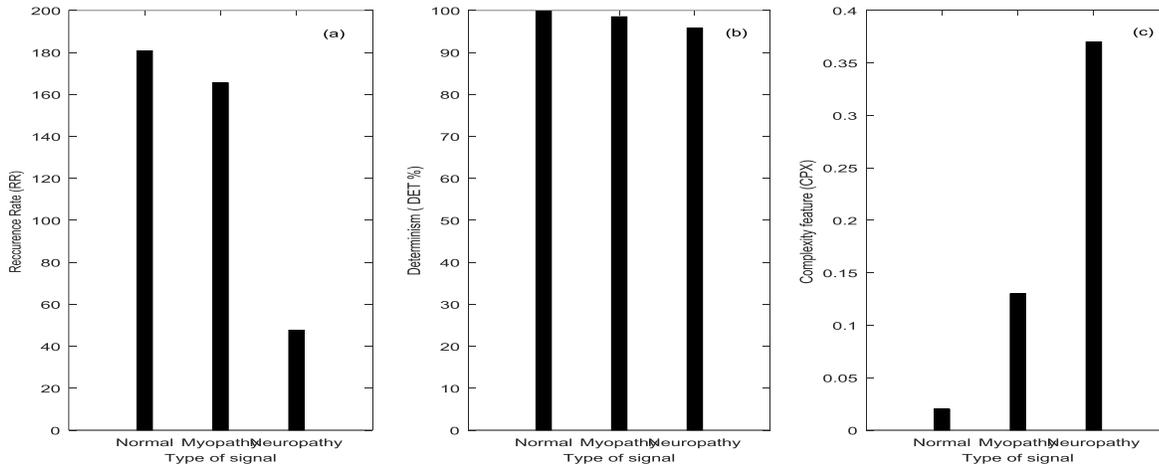


Figure 5: histograms of the variation of the non-linear parameters

Signal	RR	DET (%)	CPX
Normal	166.4477	99.68	0.02
Myopathy	165.5	98.52	0.13
Neuropathy	47.6976	95.8296	0.37

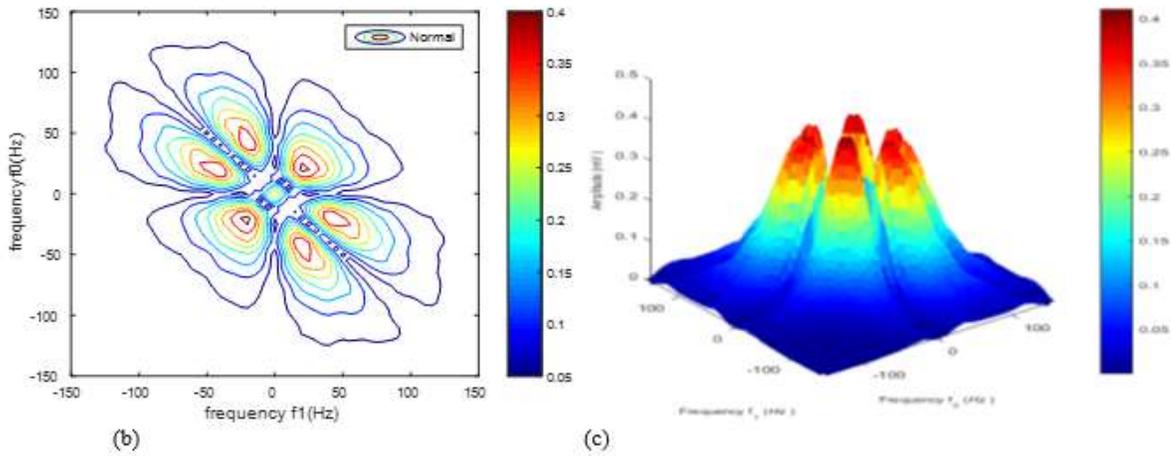
Table II: Nonlinear parameters analysis of the EMGs signal

The frequency representation by applying the bispectrum analysis [Figure.6 , Figure.8 and Figure.10 ]and the estimating study of the frequency and amplitude variation given by the diagonal slice : Amp=f(Freq) of the three cases of EMGs signals [ Figure.7 , Figure.9 and Figure.11]: normal, myopathy and neuropathy, shows that important frequencies to maintain the muscle signal range from 20 to 500 Hz.

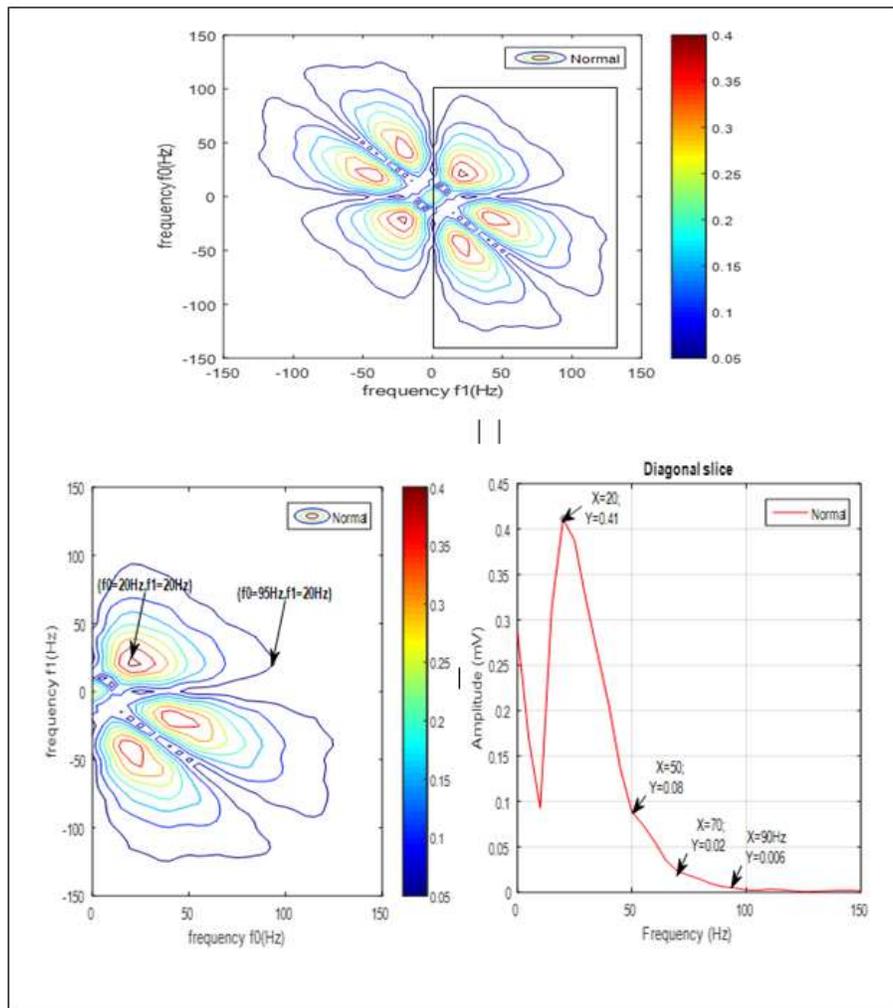
For the first case, the resulting bispectrum [Figure.6. (b)], shows a well contoured representation with maximum amplitude for a frequency of

20Hz. Thus, the most important energy is conserved in the range 20 to 120 Hz. The diagonal slice of a portion of the bispectral representation proves what was represented before and shows that the maximum amplitude is 0.41 mV for a frequency of 20Hz, from amplitude 0.08 mV and frequency 50Hz the information begins to decrease until 95 Hz, beyond that the information begins to disappear. [Figure.7]

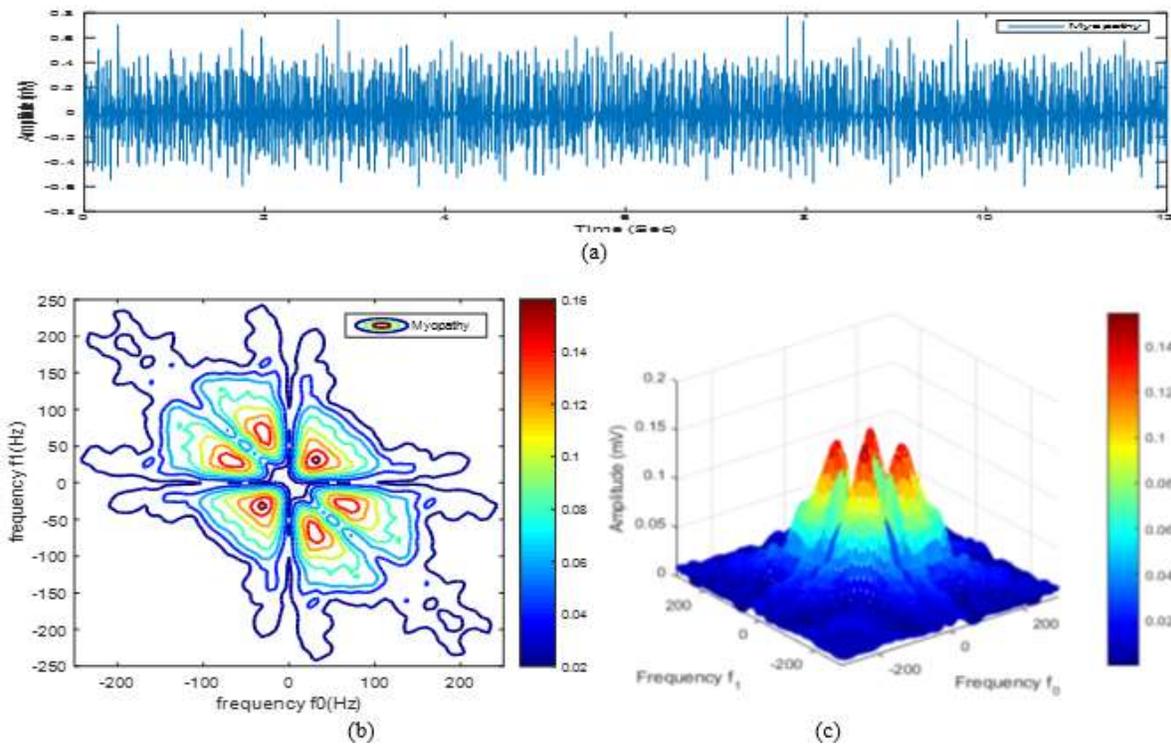
The second case with a electromyopathy signal, the resulting bispectrum analysis shows a primary deformation of the contour, as well as a dilation towards high frequencies with maximum amplitude for a frequency of 32 Hz. Thus, the most important energy is conserved in the range 20 to 200 Hz. [Figure.8. (b)]



**Figure 6:** (a): Temporal representation of a normal case, (b) and (c): bispectral representation (contour in (a), surface in (b))



**Figure 7:** The diagonal slice of a portion of the bispectral representation of a normal case.



**Figure 8:** (a): Temporal representation of a Myopathy case, (b) and (c): bispectral representation (contour in (a) and surface in (b))

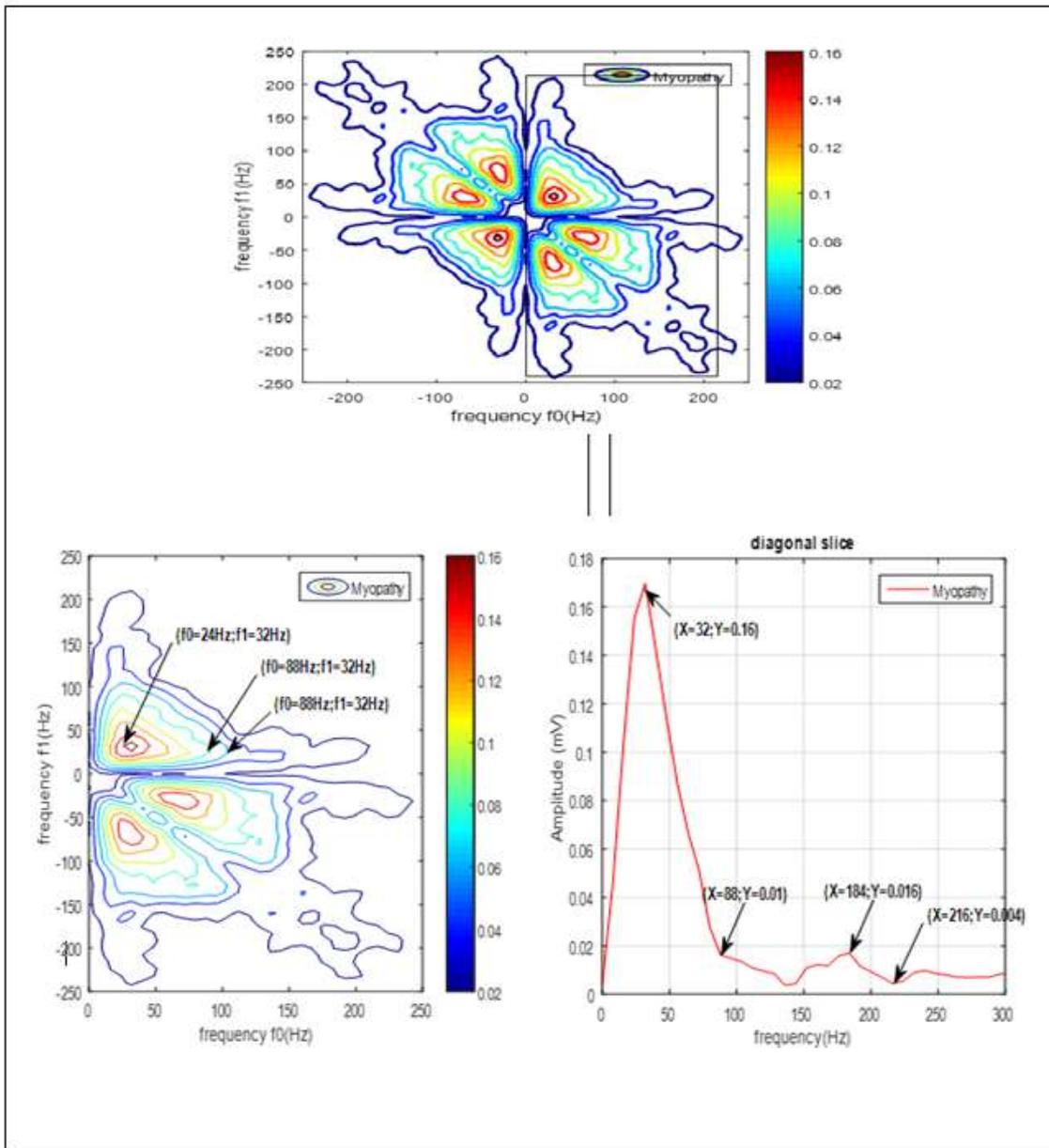
The diagonal slice of a portion of the bispectral representation shows also that the maximum amplitude is 0.16 mV for a frequency of 32Hz, from amplitude 0.01 mV and frequency 88Hz the information begins to decrease to 216 Hz, beyond that the information begins to disappear. **[Figure.9]**

The third case for a neuropathic type, the application of the bispectrum analysis and the diagonal slice of a portion of the bispectral representation, proves again that the most suitable frequency range to analyze EMG signals is 20 to 500 Hz. In this pathological type, the signal bispectrum is a contour very distorted and dilated towards the high frequencies with maximum amplitude for the frequency of 60 Hz. Thus, energy is conserved in the range 20 to 480 Hz. **[Figure.10. (b)]**

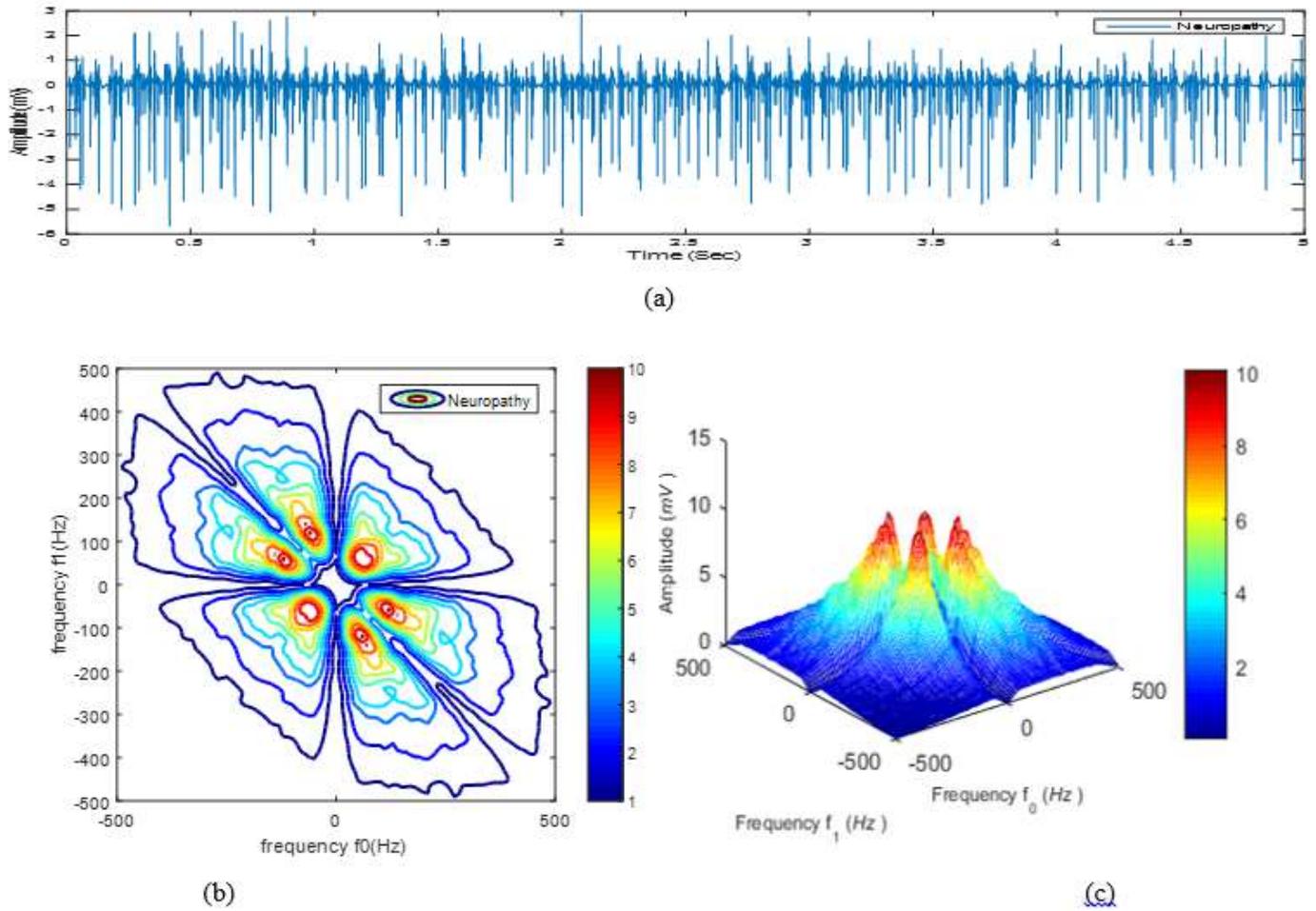
The diagonal slice of a portion of the bispectral representation shows that the maximum amplitude is 9.9 mV for a frequency of 60Hz, from amplitude 0.84 mV and frequency 270Hz the information starts to

decrease until 400 Hz at 500 Hz, beyond the information begins to disappear. **[Figure.11]**

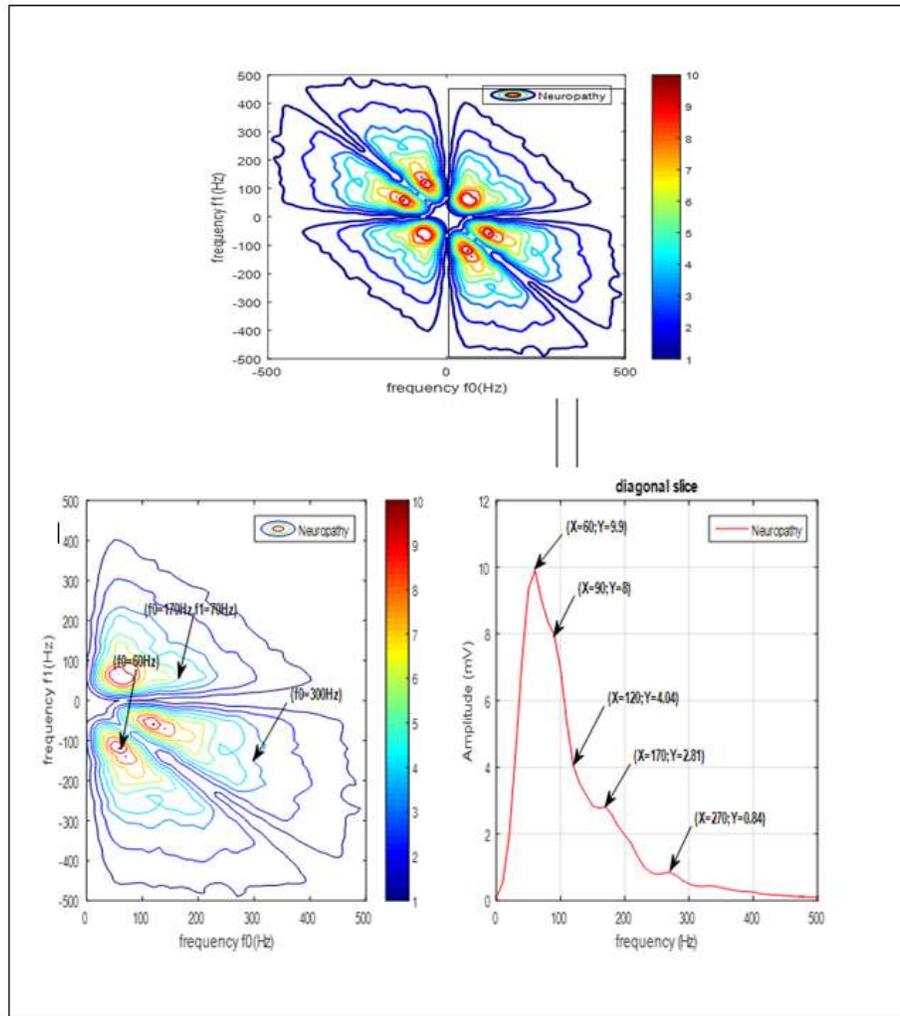
The time domain representation (higher-order cumulants) **[Figure.12]** of the three cases of EMGs signals: normal, myopathy and neuropathy, shows that: for the first case, the resulting cumulant shows a well contoured representation with maximum information is located in the center. Thus, the most important energy is conserved in the very short range (few ms.). **[Figure.12. (a)]**. The second case with a electromyopathy signal, the resulting cumulant representation shows a primary deformation of the contour, with a large dilation, with a maximum amplitude going up to  $5 \cdot 10^{-4}$  mv. Thus, the most important energy is conserved around to  $5 \cdot 10^{-3}$  ms. **[Figure.12. (b)]**. The third case for a neuropathic type, the application of the cumulant analysis show a contour very distorted and dilated towards 0.05 ms. with maximum amplitude 0.1mv. **[Figure.12. (c)]**



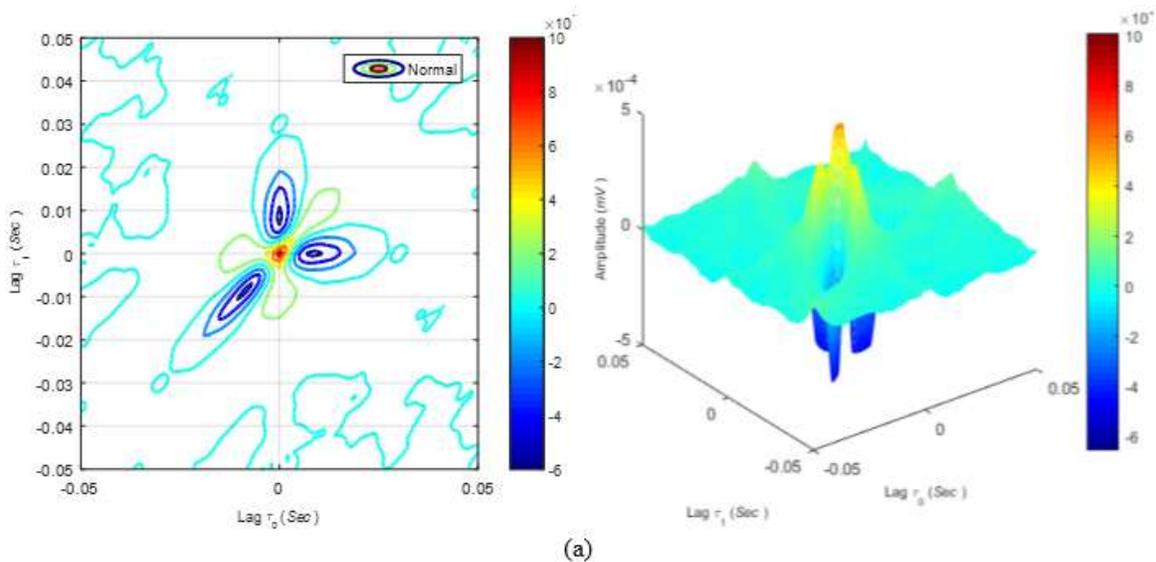
**Figure 9:** The diagonal slice of a portion of the bispectral representation of a Myopathy case.



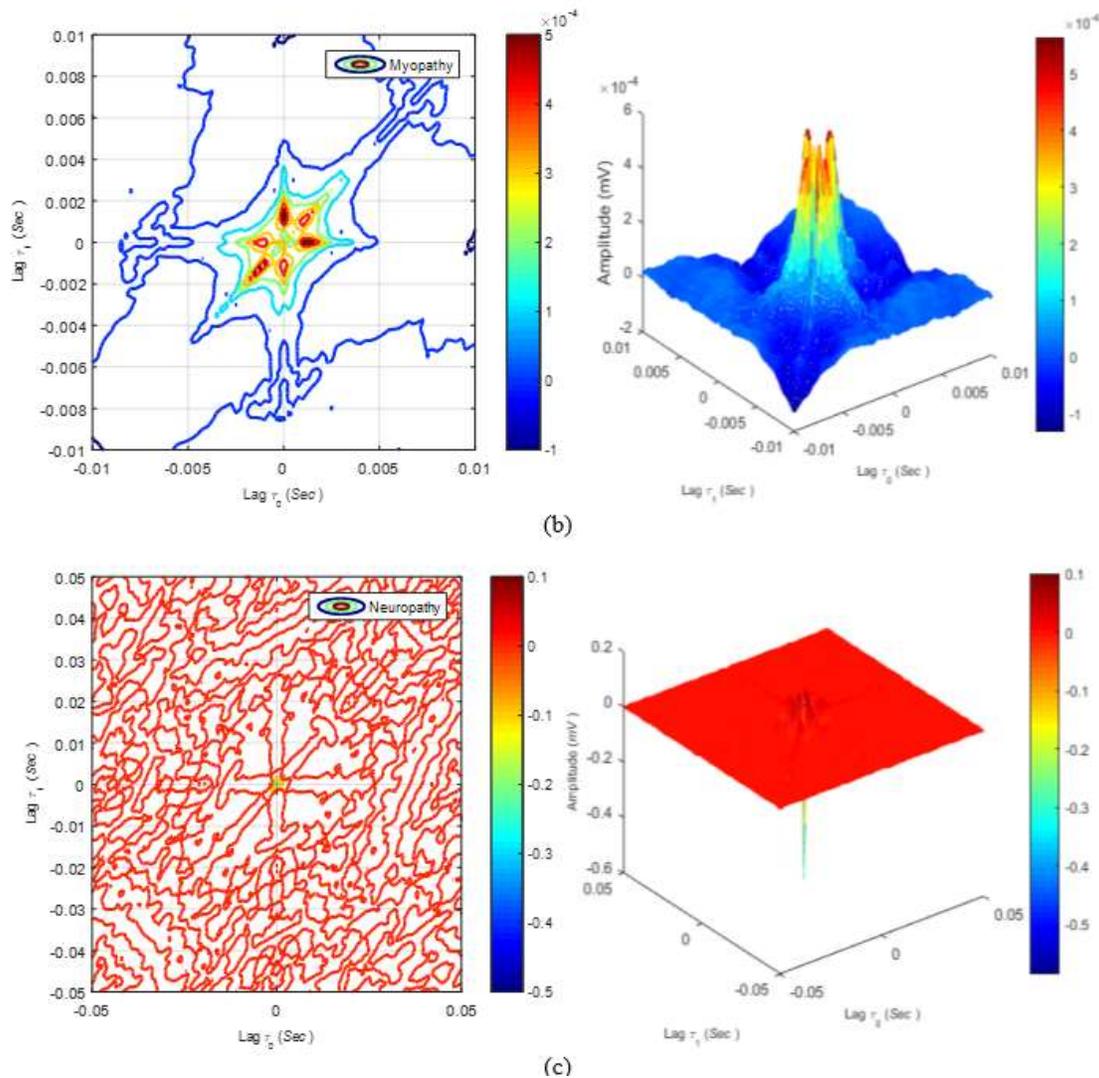
**Figure 10:** (a): Temporal representation of a Neuropathy case, (b) and (c): bispectral representation (contour in (a) and surface in (b))



**Figure 11:** The diagonal slice of a portion of the bisppectral representation of a Neuropathy case.



(a)



**Figure 12:** Cumulant plots (contour and surface) for: (a) Normal case, (b): Myopathy case and Neuropathy case in (c).

**IV. Conclusion:**

Electromyography plays an important role in clinical neurological diagnosis; it can confirm or dismiss clinical diagnoses, indicate the location and type of an abnormality or expose disorders that are clinically uncertain.

Several methods based on modern signal Processing techniques, have been investigated.

The non lineaire analysis of the EMG signal based on the recurrence quantification analysis (RQA) and bispectrum representation, was shown to be particularly promising for the detection of muscle status changes. It appears that RQA and bispectrum methods may be a useful technique in differentiating pathological cases from normal cases. The results obtained from this analysis are acceptably high enough. This simple and effective method may help experts in defining pathological cases and this can give important clues about some abnormalities related to EMG signals.

**Ethical statement**

- No, I have nothing to report
- This study was not funded by any party: it is an academic PhD study

- No conflict of interest
- No animal or other used in this study
- all authors were involved in the work leading up to the manuscript.
- The results are appropriately placed in the context of prior and existing research.
- All sources used are properly disclosed (correct citation).

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