Bispectral Analysis of Needle EMG Signals to Detect Differential Patterns of Muscle Activity in Radiculopathy Patients

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***Abstract*—Radiculopathy refers to a set of conditions, in which one or more nerves is affected and does not work properly. The emphasis is, however, on the nerve roots. In addition, L5 radiculopathy is the most common radiculopathy encountered in electrodiagnostic laboratories. Needle electrode examination is known to be the most effective diagnostic tool for this disorder. The objective of the present study was to quantify muscular changes in radiculopathy patients, using needle EMG signals recorded from tibialis anterior muscle of a healthy man without a history of neuromuscular disease and a man with neuropathy due to L5 radiculopathy. Moreover, this paper investigated the utility of HOS analysis by examining bispectral patterns and extracting features based on amplitude and phase of the bispectrum for identifying the differences. The results showed that the mean value of amplitude based features were higher in patient compared with those of healthy control. However, phase entropy indicated a reduction in radiculopathy patient. In addition, bispectral magnitude contour plots enabled us to visually differentiate muscle activities.**

Keywords-bispectrum; entropy; higher order spectra (HOS); needle EMG; radiculopathy

I. INTRODUCTION

Radiculopathy is the consequence of nerve root damage, in which one or more nerves is affected and does not work properly (a neuropathy). Compression of nerve roots or the meninges covering the spinal cord usually presents with back or neck pain [1,2]. Moreover, L5 radiculopathy is the most common single-level radiculopathy encountered in electrodiagnostic laboratories. Muscles affected, include the tibialis anterior, peroneus longus, tibialis posterior, tensor fascia lata, and extensor digitorum brevis. Less often, the semitendinosus, semimembranosus, and gluteus medius show abnormalities [1].

Needle electrode examination (NEE) is the single most useful diagnostic tool in radiculopathy. The NEE definition of chronic radiculopathy is largely dependent on the identification of neurogenic recruitment and motor unit action potential (MUAP) configuration changes in involved muscles with or without fibrillation potentials. These neurogenic abnormalities include MUAPs with increased duration and phases that represent reinnervation resulting from collateral sprouting. In early stages of reinnervation, these MUAPs show a moment-to-moment variation in configuration as immature motor unit junctions are established; with time, this instability is replaced with broad, large, and polyphasic MUAPs. These chronic neurogenic changes usually persist indefinitely after radiculopathy, and it is common to find such abnormalities on NEE, years after patients had their initial symptoms [1].

In this study, needle electromyographic signals (EMG), were used to investigate muscle dysfunction in patients with radiculopathy. EMG signals detected directly from the muscle or from the skin surface by using indwelling or surface electrodes, respectively, indicate a train of MUAPs and noise [3,4]. These signals are a common clinical test to investigate the properties of the neuromuscular system [5]. EMG studies have introduced novel diagnostic and therapeutic findings to manage different types of disorders such as muscular dystrophies and neuropathies. Frequency domain techniques are amongst the most fundamental and useful tools in the area of signal processing [3]. Conventional techniques usually used, are based on first and second order moments and cumulants and their spectral representations such as power spectrum [3,6]. These techniques, however, provide all the information available for Gaussian signals. It is well-accepted today that biomedical signals show significant nonlinear and non-Gaussian characteristics such as the presence of nonlinear effects of phase coupling among the signal frequency components [7,8]. For such a signal, more information can be obtained from higher order moments and cumulants and their spectral representation [9]. In particular, bispectral estimation has been shown to be an effective tool to deal with these processes.

In this work, the focus is on examining bispectral patterns for healthy and neuropathy EMG signals to highlight the differences in patterns in bifrequency domain. In addition, three features were extracted from bispectrum plots to quantify the differential patterns.

II. MATERIALS AND METHODS

A. Data Acquisition

The EMG data for the present study were obtained from [10]. The needle EMG signals were recorded from tibialis anterior muscle of a 44 year old man without history of neuromuscular disease and a 62 year old man with chronic low back pain and neuropathy due to a right L5 radiculopathy.

Data were collected with a Medelec Synergy N2 EMG Monitoring System [1] and a 25mm concentric needle electrode, during dorsiflexion of feet against the resistance. The sampling frequency was chosen at 50 KHz, however, it was 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.

B. Bispectrum Analysis and Estimation

Higher order spectra (HOS) or polyspectra are spectral representations of higher order moments or cumulants of a stochastic process [6,11,12,13]. The bispectrum is a particular form of HOS. Since, it has the least computational complexity among other HOS forms, it is the most accessible and is employed in this study [4,14]. The bispectrum, $B(\omega_1, \omega_2)$, is defined as the two dimensional discrete Fourier transform of the third order cumulant and is given by [6,11]:

$$B(\omega_1,\omega_2) = E\{X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)\} \qquad (1)$$

Where X(.) is the Fourier transform of the signal x(nT), n is an integer index, T is the sampling interval, ω_1, ω_2 are discrete frequency components, E{.} stands for the expectation operation and * denotes the complex conjugate. "Equation (1)" illustrates that the bispectrum measures the correlation among three frequencies, ω_1, ω_2, $\omega_1+\omega_2$ and estimates the phase coupling [13]. The frequency f ($\omega/2\pi$) may be normalized by sampling frequency to be between 0 and 1. Due to symmetry properties, knowledge of bispectrum in the triangular region $\omega_2 \geq 0$, $\omega_2 \geq \omega_1$, $\omega_1+\omega_2 \leq \pi$ is sufficient to describe the rest. This region is shaded in "Fig. 1" and labelled by 1 and ensures that there is no bispectral aliasing [9,13]. In contrast to power spectrum, which is real valued, non-negative and a function of one frequency variable, the bispectrum is a function of two frequencies and complex valued, as a result, retains both magnitude and phase information [15].

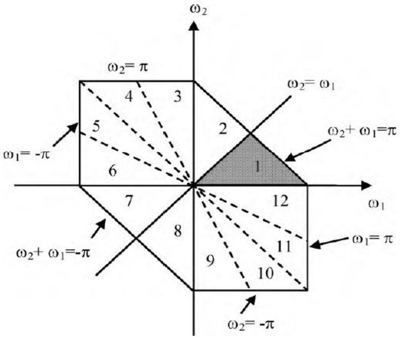

Figure 1. Symmetry regions of the bispectrum and non-redundant region, which is shaded and labeled by 1.

In practice, only an estimate of the bispectrum is available from a finite number of realizations, thus the estimation has a finite bias and variance [7,12]. Conventional approaches for the estimation may be either direct or indirect [12,16]. As defined in "(1)", the direct method is employed in this study. Assuming that x(n) is a finite- length signal divided into K segments, the direct estimation is as follows:

$$BS(\omega_1,\omega_2) = \tfrac{1}{K}\sum_{k=1}^{K} BS_k(\omega_1,\omega_2) \qquad (2)$$

Where $BS_k(\omega_1,\omega_2)$ is the bispectral estimatin in the k^{th} segment, which is calculated as:

$$BS_k(\omega_1,\omega_2) = \tfrac{1}{L^2} X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2) \qquad (3)$$

Where L is the number of samples in the k^{th} segment [13].

It is generally accepted that EMG signals recorded during rest or contraction, can be considered stationary during a period of less than two seconds. Thus, two second periods of data were chosen to estimate the bispectrum. These epochs were then subdivided into 64ms segments corresponding to 256 samples, with 50% overlap. In this way, we could produce roughly 30 realizations to perform averaging and to satisfy the required smoothness and frequency resolution. Moreover, Hamming window was used as the analysis window.

C. Bispectrum Features

In order to quantify the differential patterns of needle EMG signals, a set of features including normalized bispectral entropy, mean magnitude and the phase entropy were extracted. These features were calculated within the region defined in "Fig. 1".

- Normalized Bispectral Entropy (NBE)

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[1] Oxford Instruments Medical, Old Woking, United Kingdom

This entropy based feature was used to characterize the regularity and irregularity of EMG signals from bispectrum plots. “Equation 4”, shows formulae for this feature:

$$NBE = -\sum_{i} p_i \log p_i \tag{4}$$

Where

$$p_i = \frac{|B(\omega_1,\omega_2)|}{\sum_{\Omega} B(\omega_1,\omega_2)} \tag{5}$$

Where Ω is equivalent to the shaded region in “Fig. 1”. The normalization ensures that the entropy is calculated for a parameter, that lies between 0 and 1 (as required for probability). As a result, NBE is also in the same range [7,9,13,15,17].

- Mean Magnitude (mMag)

Mean magnitude is defined as:

$$mMag = \tfrac{1}{L}\sum_{\Omega} |B(\omega_1,\omega_2)| \tag{6}$$

L is the number of points within the region 1 in “Fig. 1” [7,9].

- Phase Entropy (PE)

Phase entropy is derived from the phase of the bispectrum and calculated as “(7)”:

$$PE = \sum_{n} p(\psi_n)\log(\psi_n) \tag{7}$$

$$p(\psi_n) = \tfrac{1}{L}\sum_{\Omega} l(\varphi(B(f_1, f_2)) \in \psi_n) \tag{8}$$

$$\psi_n = \left\{\varphi \middle| -\pi + \tfrac{2\pi n}{N} \le \varphi \prec -\pi + \tfrac{2\pi(n+1)}{N}\right\}, \quad n = 0,1,\ldots,N-1 \tag{9}$$

Where L is the number of points within the region 1 in “Fig. 1”, φ is the phase angle of bispectrum, Ω refers to the shaded space in “Fig. 1” and l(.) is an indicator function which gives 1, when φ is within the range of bin ψ_n in “(9)” [7,9,15].

The probability density function of the phase is estimated by computing the histogram of φ, while each bin is set as 5-degree (i.e. N=36). The entropy used in this study is the Shannon entropy. The PE would be zero if the process were harmonic and periodic and predictable. As the process becomes more random, the entropy increases [7,15].

III. RESULTS

A. *Bispectrum Contour Plots*

In order to perform the analyses, the raw EMG signals were made zero mean. In addition, to provide uniformity, the signals were normalized with respect to the absolute value of their maximum. *“Fig. 2(a),(b)”* represent the resulting bispectrum plots of healthy and radiculopathy subjects, respectively. These figures are useful to visually discriminate two classes. Moreover, they cover the entire two-dimensional bifrequency plane, hence exhibit six- fold symmetry. In addition, the frequencies are normalized by the sampling frequency (4KHz) in these plots.

For normal participant, the bispectrum magnitude diagram illustrated peaks at lower frequencies (*“Fig. 2(a)”*). However, *“Fig. 2(b)”* indicated multiple set of peaks in bispectrum magnitude plot of a radiculopathy patient, which may represent quadratic phase coupling.

Since bispectrum is a square nfft×nfft matrix, where nfft denotes the Fourier transform length used for the estimation of bispectrum (in this study nfft was chosen to be 256), it is not practical to use the whole matrix due to the high dimensionality [18]. Thus, in this study a one dimensional diagonal slice of bispectrum was obtained by fixing (n-2) of the (n-1) indices. The dominant peak was at (0.01,0.01) Hz, for healthy subject, indicating the possibility of the presence of self coupling. However, the dominant peak occurred at (0.03,0.1) Hz for radiculopathy subject, which may indicate the quadratic frequency coupling. Since frequencies were normalized, they should be multiplied by sampling frequency, i.e. 4KHz, to find the correct frequencies.

B. *Bispectrum Features*

To calculate the bispectrum features, five second periods of data were chosen. Then, each epoch was segmented into five frames of one second duration. For each EMG frame, NBE, mMag and PE were estimated, which are depicted in “Fig. 3”. Because of the high mean values of mMag compared with those of NBE and PE, log values were used for this feature. In addition, the mean and standard deviation of these parameters are represented in TABLE I. Results indicated that the amplitude based features, i.e. NBE and mMag, were higher in healthy subject compared with radiculopathy one. However, PE mean value was 2.81 for the patient, while it was 3.22 for healthy volunteer, which demonstrated a decrease in mean value.

TABLE I. MEAN AND STANDARD DEVIATION OF HOS BASED PARAMETERS FOR HEALTHY AND RADICULOPATHY VOLUNTEERS.

Feature / **Class**	**NBE**	**mMag**	**PE**
Healthy	0.74 (0.08)	-0.36 (0.52)	3.22 (0.08)
Radiculopathy	0.91 (0.006)	1.54 (0.02)	2.81 (0.09)

Values are mean (standard deviation).
NBE, Normalized Bispectral Entropy; mMag, Mean Magnitude; PE, Phase Entropy.
Log values are used for mMag.

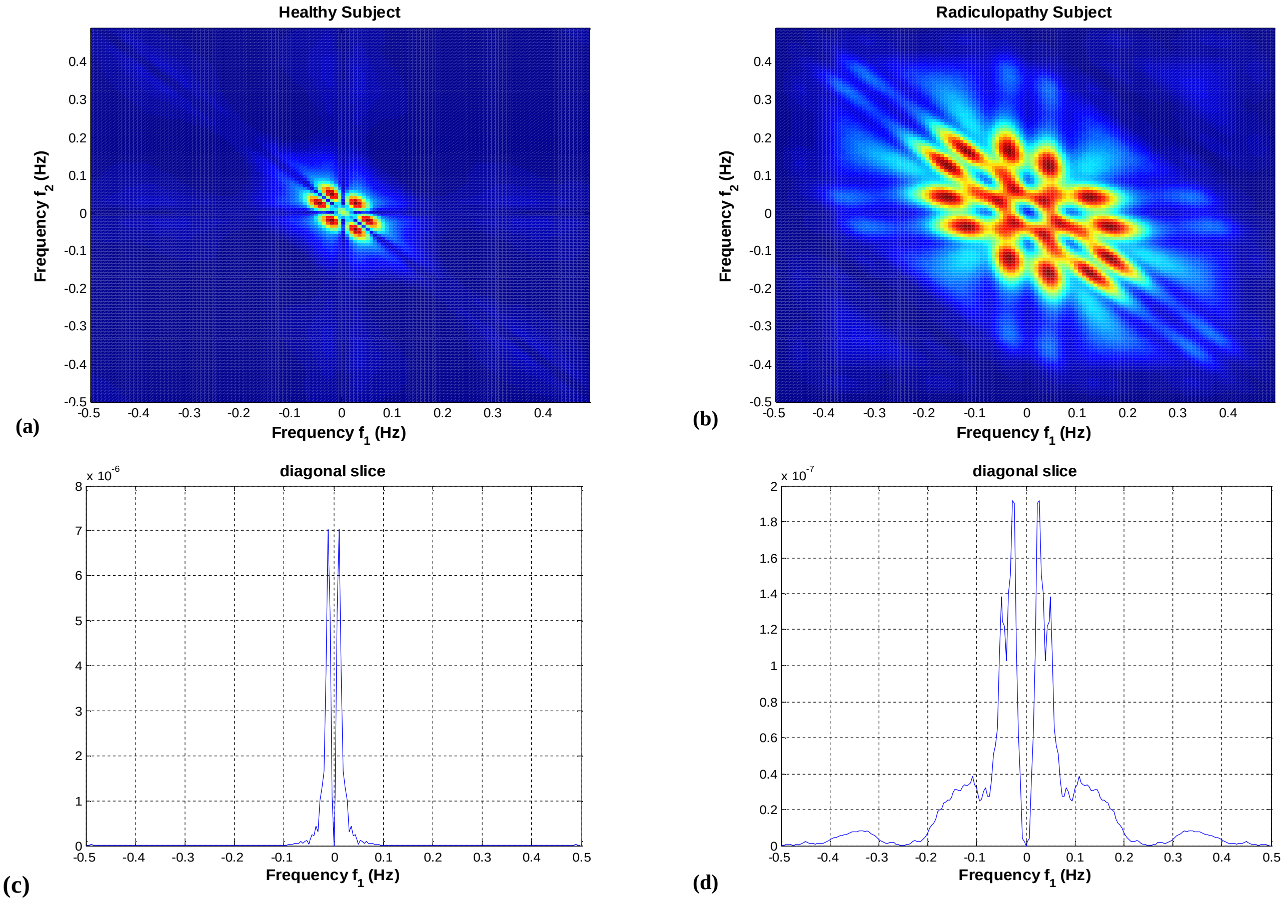

Figure 2. Contour plot of bispectrum magtinude (a,b) and the corresponding diagonal slice (c,d) for a healthy (left) and a radiculopathy (right) subject .

IV. DISCUSSION

Physiological signals are non-stationary, nonlinear and chaotic in nature. Thus, linear and power spectral frequency methods are not very effective in the diagnosis of biosignals [12]. These techniques provide all the information available for Gaussian processes [3]. On the other hand, higher order spectra have the ability to detect nonlinearity, deviation from Gaussianity and phase relations between harmonic components [3,6]. In addition, HOS have zero expected value for Gaussian noise. Therefore, the obtained features have high immunity to additive Gaussian noise [6,8,11]. Furthermore, HOS are translation invariant. Functions can be defined from HOS, satisfying desirable properties such as scaling and amplification invariance. These functions can be utilized as invariant features in pattern recognition [13].

In this work, we presented bispectrum magnitude and its diagonal slice plots for two different classes of signals to highlight the differences in patterns in bifrequency space. Our previous study on chronic tension- type headache patients also showed the efficacy of these diagrams as potential visual aids for the diagnosis [15]. In addition, Chua et al. have successfully employed the bispectrum and bicoherence plots of heart rate variability (HRV) signal to visually distinguish normal heart beats and seven classes of arrhythmia [12]. A recent study on epileptic electroencephalogram (EEG) signals also showed the utility of bicoherence plots in differentiating normal, pre-ictal and ictal EEG signals [7].

Although, the bispectrum magnitude diagrams enabled us to visually differentiate the pathological state, it is not practical to use these plots for automated pattern recognition by computers. Thus, in this study three features were extracted from bispectrum, named NBE, mMag and PE. The entropy, quantifies the regulatory and complexity of time series [12]. The entropy would be zero if the process were harmonic and perfectly periodic and predictable. As the process becomes more random, the entropy increases [7,15]. It is expected that normal subjects indicate higher entropy values, while abnormal ones show the lower values due to smaller variability or inherent periodicity in their biosignals [12]. However, the entropy results in this study showed that amplitude based entropy, i.e. NBE was higher in patient. In contrast, the phase entropy was lower in this class compared with healthy subject. This may indicate the important role of phase in the investigation of muscle function. Chua et al. have reported that bispectral amplitude entropies are lower in

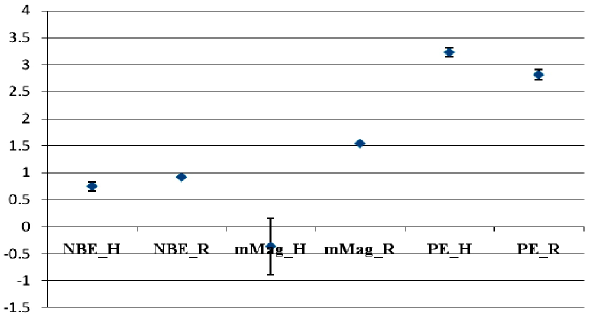

Figure 3. Mean and standard deviation of bispectral features for healthy (H) and radiculopathy (R) subjects.

normal subjects and higher for the highly varying cardiac diseases such as preventricular contraction, atrial fibrillation and sick sinus syndrome [12]. The mean magnitude value was higher in radiculopathy subject. This feature can be useful in discriminating processes with similar power spectra but different third order statistics [12].

This study was a preliminary research, which tried to explore the possibility of differentiation between healthy and radiculopathy subjects using HOS analysis. However, further studies with larger study population are needed to validate these findings.

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