Nonlinear Analysis of Surface EMG Signal to Assess Muscle Fatigue during Isometric Contraction

Fariba Biyouki*, Saeed Rahati**, Katri Laimi***, Ali Shoeibi****, Reza Boostani*****
*Dept. of Biomedical Engineering, Mashhad Branch, Islamic Azad University, Iran,
FaribaBiyouki@mshdiau.ac.ir
**Dept. of Electrical Engineering, Mashhad Branch, Islamic Azad University, Iran, Rahati@mshdiau.ac.ir
***Dept. of Physical Medicine and Rehabilitation, Turku University Hospital, Turku, Finland,
Katri.Laimi@tyks.fi
****Assistant Professor of Neurology, Mashhad University of Medical Sciences, Iran, ShoeibiA@mums.ac.ir
*****Assistant Professor of Neurology, Mashhad University of Medical Sciences, Iran,
BoostaniR@mums.ac.ir

Abstract: *The objective of the present study was to investigate the possible relationship between nonlinear parameters extracted from surface EMG (sEMG) signals and muscle force and fatigue. Our hypothesis was that changes in motor unit recruitment during muscle contraction and fatigue, affect sEMG distribution and the intractions in muscle. Thus, five features based on geometric aspects of time series trajectory and higher order statistics were extracted from sEMG signal, recorded from biceps brachii muscle of a healthy female volunteer during rest, sustained (fatiguing) 50% MVC, 100% MVC and recovery. Results obtained from correlation dimension (CD) and linearity test (sl) analyses showed that the values of these parameters are higher during rest and recovery states, indicating higher chaotic behaviour, while they decreased during MVCs. However, when fatigue occurred, these parameters increased slightly, again. On the other hand, test of non-Gaussianity based on negentropy showed the reverse pattern of CD and sl. Skweness and kurtosis values, which are the quantitative descriptors of probability densities, were positive and negative, respectively during rest and recovery, while this pattern reversed for MVCs.*

Keywords: Biceps brachii muscle, correlation dimension, higher order statistics, surface electromyographic signal, muscle fatigue.

1. Introduction

Biomedical signals carry information about the physiological activities of human or animal organisms and their processing aims at extracting significant information to facilitate understanding different pathologies [1]. Surface electromyographic (sEMG) signals, which represent a train of motor unit action potentials (MUAPs) plus noise, can provide useful information about muscular function and underlying mechanisms of sustained fatiguing contractions [2,3,4]. The MAUPs vary in amplitude, duration and frequency of occurance, which are related to the amount of force the muscle may produce and thus the level of contraction [2,3]. However, extracting information about motor unit (MU) recruitment strategies during muscle contraction from the analysis of sEMG data is a challenging task [5]. Different parameters in time, frequency and higher order statistics domains were extracted from sEMG signals to examine the influence of the increase in voluntary contraction [3]. The most frequently used parameters were the mean frequency (MNF), the median frequency (MDF), the number of zero crossings per second (zc/s), the power spectrum and bispectrum shape and the Gaussianity and linearity test of the normalized bispectrum, which led to many discrepancies between findings. These contradictory results may originate from the fact that different researchers have recruited limited and different number of participants. In addition, various recording protocols and recording durations have chosen that may affect the results, for example, fatigue may occur in large recording times [3]. Kaplanis te al. [3], reported that the time domain parameters (zc/s) and turns per second, increased significantly with force level, while the power spectrum MDF parameter, decreased dramatically in isometric voluntary contraction. Although, test of Gaussianity and linearity using bicoherence analysis did not show significant changes, the sEMG signals revealed a more Gaussian distribution with increase in force level up to 70% of maximum voluntary contraction (MVC). In contrast, the results of [4,6] showed that signals became less Gaussian and more linear with increasing in walking speed/force. However, the study group of Nazarpour [7], measured the non-Gaussianity of sEMG signals using negentropy feature during elbow flexion at four different levels of contraction. Their results demonstrated that the distribution of sEMG signals was non-Gaussian during light contractions (below 30% of MVC) and it tended toward a Gaussian process at higher force levels due to central limit theorem. Kaplanis et al. in [8] achieved even more conflicting results. They reported that the EMG

signal was highly non-Gaussian at low and high levels of force which tended to Gaussian distribution at the mid level of MVC (i.e. 50%).

In this study, we revisit this problem using nonlinear analysis methods, applied to sEMG signals at various muscle contraction/force stages (100% of MVC, rest, fatiguing 50% of MVC, recovery) for right biceps brachii muscle. These nonlinear features, which are either based on phase space geometry, namely correlation dimension, or higher order statistics in time and bifrequency domains such as skewness, kurtosis, negentropy and test for linearity, exploited to enhance the diagnostic character of sEMG signals and to quantify the degree of non-Gaussianity and nonlinearity of signals at each stage.

2. Materials and Methods

2.1 Subjects

One healthy female volunteer (age 20 years, mass 61 Kg, Body Mass Index 23.82 Kg/m^2) with right hand dominant, participated in this study. The subject had not specifically trained her hand and shoulder muscles. The measurments were carried out in the Physiology Laboratory, Department of Biomedical Engineering, Islamic Azad University, Mashhad, Iran.

2.2 Recording Setup

Surface EMG activity was measured from right biceps brachii muscle using PowerLab/ML865[1] system. In addition, recording was done bipolarly using Ag/AgCl circular self-adhesive disposable pre-gelled surface electrodes[2] of 15mm diameter. According to Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM) [9], the electrodes were placed on the line between the medial acromion and the fossa cubit at 1/3 from the fossa cubit, with 20mm spacing. Moreover, the reference electrode was placed on the left wrist (Fig. 1). To keep the interelectrode resistance low, the electrode sites were cleaned with 70% isopropyl alcohol. The leads were fixed by medical tape to reduce motion artifacts.

For sEMG recording, the subject was asked to seat quietly on a comfortable armchair, while instructed to assume a standardized position with her hip and back against the back of the chair, her feet flat on the floor, her right arm fixed on the chair and the left one on her lap. After the adaptation period of one minute, she was asked to perform maximum voluntary contraction (MVC) for three times, using a hand dynamometer/MLT003/D[3] connected to the PowerLab system with two minutes rest intervals between trials. In order to perform 50% of MVC, firstly, the maximum recorded MVC was chosen, then 50% of MVC was calculated using LabChart 7.3 software, which was installed on the computer, lastly, this value fed back to the subject visually on a monitor positioned in front of her. Visual feedback enabled the subject to maintain the requested percentage of MVC as constant as possible till exhaustion. However, after exhaustion, recording was continued for another one minute period to assess the recovery process. The surface EMG signals were recorded online. A computer was connected to the recording system via USB cable for the storage and display of signal. The raw signals were filtered through hardware lowpass and highpass filters with cut-off frequencies at 500Hz and 10Hz, respectively. A notch filter with center frequency at 50Hz was also used to reduce power line noise. The signals were made discrete using 16-bit analogue-to-digital (A/D) converter. Moreover, according to the mentioned frequency band, the sampling frequency was chosen at 2KHz. Furthermore, the sampling frequency and the recording process (start/stop and duration of adaptation and recovery stages and the percentage of MVC) were controlled through LabChart 7.3 software[4].

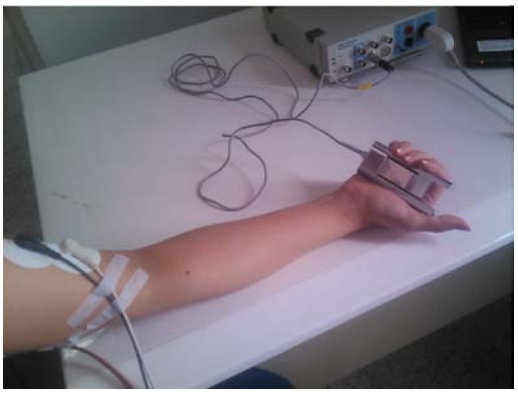

Fig. 1: Bipolar surface electromyographic electrode placement over the biceps brachii muscle.

2.3 Correlation Dimension

Correlation dimension (CD) is a method aimed at quantifying chaotic behaviour. This quantifier emphasizes the geometric aspects of the trajectories in state space, i.e. focuses on how a series of points is distributed in state space [10]. In addition, it has some computational advantages compared to box-counting procedure, since it uses the trajectory points directly and does not require a separate partitioning of the state space [10]. The widely used algorithm for the calculation of CD is the Grassberger-Procaccia. This algorithm, first, constructs a function, named C(R), which reveals the probability that two arbitrary points on the orbit are closer together than R. The correlation sum is calculated as follows:

$$C(R) = \frac{1}{N^2} \sum_{x=1}^{N} \sum_{y=1, x \neq y}^{N} \Theta(R - \left| X_x - X_y \right|) \qquad (1)$$

[1] ADInstruments Pty Ltd. Australia.

[2] Ag/AgCl, F55, Skintact, Leonhard Lang GmbH, Austria.

[3] ADInstruments Pty Ltd. Australia.

[4] ADInstruments Pty Ltd. Australia.

Where X_x and X_y are points of the trajectories in the phase space, N is the number of data points in the phase space, R is the radial distance around each reference point and Θ is the Heaviside function. Finally, the CD can be calculated using "Equation (2)":

$$CD = \lim_{R\to 0} \frac{\log C(R)}{\log(R)} \quad (2)$$

The CD value will be larger for high or chaotic signal variations, while it will be small for low or rhythmic signal variations [11].

2.4 Higher Order Statistical Analysis

Physiological signals are nonlinear and chaotic in nature and uncertainty and imprecision are the inherent characteristics of them. Higher order statistical based nonlinear dynamical techniques, which are also based on the chaos theory, have the ability to detect nonlinearity, deviations from Gaussianity and the phase relationships between harmonic components [12].

For a stationary, discrete, zero mean random process x(n), the higher order spectra (HOS) or polyspectra are defined based on moments or cumulants of order greater than two. The bispectrum is a particular form of HOS, which is defined as the two-dimensional Fourier transform of the third order cumulant [13,14]:

$$B(\omega_1,\omega_2) = \sum_{\tau_1=-\infty}^{+\infty}\sum_{\tau_2=-\infty}^{+\infty} c_3^x(\tau_1,\tau_2) e^{-j(\omega_1\tau_1+\omega_2\tau_2)} \quad (3)$$

The $c^x{}_3(\tau_1,\tau_2)$ variable reveals the third order cumulant, which is defined as "Equation (4)":

$$c_3^x(\tau_1,\tau_2) = E\{x(n)x(n+\tau_1)x(n+\tau_2)\} \quad (4)$$

Where E[.] denotes the expectation operation. By setting $n+\tau_1=m$, $n+\tau_2=k$ and substituting "Equation (4)" in "Equation (3)" and splitting the exponent, it can be shown that [12]:

$$B(\omega_1,\omega_2) = E\{X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)\} \quad (5)$$

As is evident, we can obviously state that the bispectrum measures the correlation among three frequencies, ω_1, ω_2, $(\omega_1+\omega_2)$ and estimates the phase coupling [15]. The frequency $f\ (\omega/2\pi)$ may be normalized by sampling frequency to be between 0 and 1. In contrast with the 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, it has both magnitude and phase.

2.4.1 Time Domain Features

a. Skewness and Kurtosis

A non-parametric density estimation method, named kernel density estimation (KDE) was used to approximate the distribution of surface EMG signals. In the method proposed by Parzen [16], the estimation of the unknown density is calculated as follows:

$$p_{KDE}(x) = \frac{1}{Nh^D}\sum_{n=1}^{N} K\left(\frac{x-x^{(n}}{h}\right) \quad (6)$$

Where K(.) is the kernel function, N is the total number of examples, $\{x^{(1}, \ldots, x^{(n}\}$ are the samples drawn from sEMG distribution, h is the smoothing parameter or bandwidth and D is the number of dimensions. Choosing appropriate kernel function is crucial in density estimation. Usually, a smooth kernel function which is radially symmetric and unimodal such as Gaussian kernel with fixed width σ_0 is used:

$$K(x) = \frac{1}{2\pi\sigma_0} e^{-\left|x-x^{(n}\right|^2 / 2\sigma_0^2} \quad (7)$$

This kernel function satisfies the (asymptotic) unbiasedness and consistency of the estimator [7,16].

Skewness and kurtosis, which are the third and forth order cumulants at zero lag, respectively, are the well known parameters to describe the probability density functions (PDFs) of a random variable such as sEMG signal, quantitatively [12]. This study exploits these parameters to evaluate the shape variations of sEMG amplitude distribution for different contraction levels and during muscle fatigue.

The asymmetry of the distribution can be described by using the skewness statistic, which is defined as "Equation 8":

$$\gamma_1 = \frac{E\left[(x-\mu)^3\right]}{\sigma^3} \quad (8)$$

Where E[.] denotes the expectation operation, x is a random variable (EMG signal), μ is the mean value of the signal and σ is its standard deviation. A positive skewness represents right tail, while the negative one shows the left tail in the distribution. Moreover, a normal distribution has a zero skewness due to its symmetry [5].

On the other hand, the kurtosis of the distribution is defined as follows:

$$\gamma_2 = \frac{E\left[(x-\mu)^4\right]}{\sigma^4} - 3 \quad (9)$$

Kurtosis statistic corresponds to the degree of peakedness of a PDF. Positive kurtosis indicates a peaked distribution, while a negative one shows the flattened distribution. Like skewness, a normal distribution has a zero kurtosis [5].

b. Negentropy

Negentropy, J, is based on the information- theoric quantity of differential entropy. Negentropy is zero for a Gaussian process, while it is always non-negative for other distributions. So, it can be used to measure non-Gaussianity of signals. The classical and simple method for approximating negentropy is based on higher order moments. For a zero mean and unit variance random variable x, J is defined as follows:

$$J(x) \approx \frac{1}{12}\gamma_1^2 + \frac{1}{48}\gamma_2^2 \quad (10)$$

2.4.2 Frequency Domain Features

a. Linearity Test (sl)

To quantify the non-Gaussianity and nonlinearity of a process, the normalized bispectrum or bicoherence is estimated as "Equation 11":

$$B_n = \frac{B(\omega_1,\omega_2)}{\sqrt{P(\omega_1)P(\omega_2)P(\omega_1+\omega_2)}} \quad (11)$$

Where P(.) is the power spectrum. The linearity test, involves deciding whether or not the estimated bicoherence is constant in the bifrequency domain, employing a measure of the absolute difference (dR) between a theoretical inter-quartile range, R', which corresponds to a chi-squared distributed random variable with two degrees of freedom and a non-centrality parameter, λ, and the estimated inter-quartile range, R, derived from the estimated squared bicoherence. In this study, the nonlinearity hypothesis was adopted when dR/ R'>2 [3].

3. Results

In order to perform analyses, the raw EMG signals were made zero mean. In addition, to provide uniformity, the signals were normalized with respect to their standard deviation. Moreover, the blocks of five seconds duration of data were chosen for each trial (rest, 50 MVC, 100% MVC, recovery) and five features were extracted from them to evaluate muscle contraction at various stages, which are also valuable to determine muscle fatigue. TABLE I, summarises the values of the parameters calculated at each stage.

TABLE I: The Values of the Parameters Analyzed During 4 Trials.

Trial \ Features		CD	sl	J	Skewness	Kurtosis
Rest		1.61	0.81	0.004	0.11	-0.32
50% MVC	Start	1.49	0.36	0.027	-0.16	0.90
	Mid	1.46	0.30	0.026	-0.03	0.84
	End	1.50	1.38	0.019	-0.18	0.73
100% MVC		1.48	0.35	0.016	-0.19	0.62
Recovery		1.52	0.87	0.003	0.05	-0.11

3.1 Phase Plane and Correlation Dimension

Fig. 2 (a-f) demonstrates the phase plane diagrams of sEMG signals, which corresponds to 4 trials. As can be clearly seen, the trajectory points of sEMG signal are more distributed in the phase plane during rest, indicating the higher chaotic behaviour. On the other hand, they concentrate along the dashed line $x_n=x_{n+1}$ at MVCs, which represents the more deterministic behaviour. In addition, the diagrams show that the increase of force level from 50% to 100% of MVC, does not cause a significant change in trajectories. However, the trajectory points become more distributed in recovery state.

Fig. 3 shows the CD values versus different trials. As can be clearly seen, CD has its maximum values for the

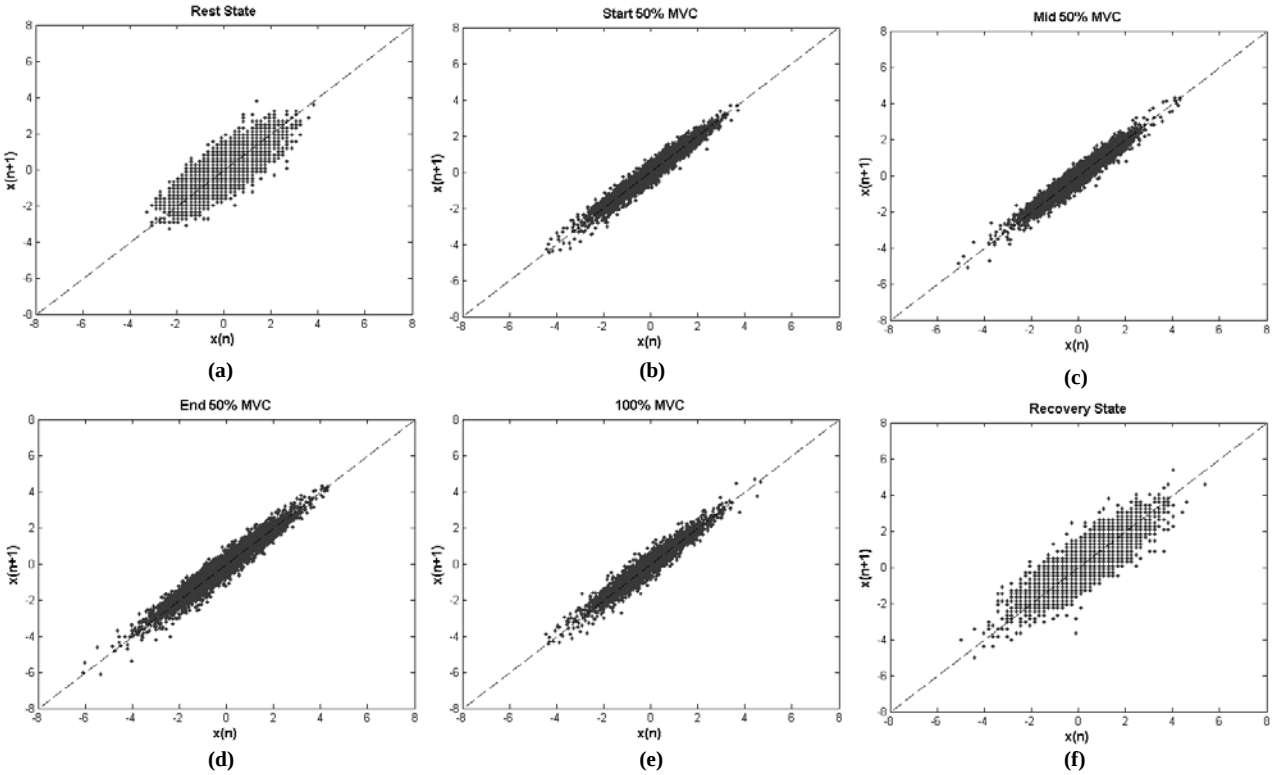

Fig. 2: Phase plane diagrams of sEMG signals recorded during rest (a), start point of 50% MVC (b), mid point of 50% MVC (c), end point of 50% MVC (d), 100% of MVC (e) and recovery (f).

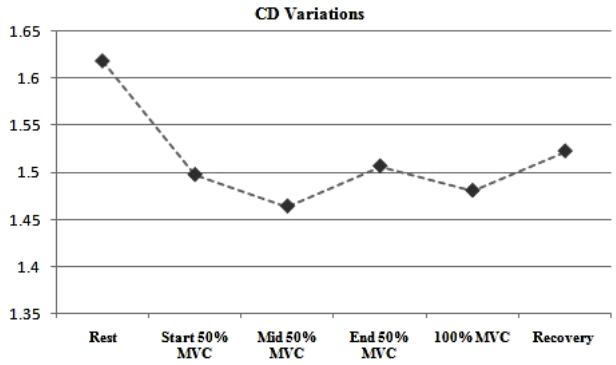

Fig. 3: Variations of CD during rest, fatiguing 50% MVC, 100% MVC and recovery periods.

rest and recovery trails, which indicates the higher chaotic behavior of them. In contrast, the chaotic characteristics decrease with voluntary contraction. Furthermore, the results of CD analysis show that at the beginning of the 50% of MVC, CD is 1.49, which decreases to 1.46 at middle of the trial. While, during exhaustion, i.e. end of 50% MVC, it increases again to 1.5. These results are consistent with the phase plane plots, which are demonstrated in Fig. 2.

3.2 Higher Order Statistical Analysis

Fig. 4 illustrates the estimated densities of sEMG signals recorded at each trial (rest, start point of 50% MVC, mid point of 50% MVC, end point of 50% MVC, recovery). Moreover, a Gaussian probability density is also depicted to facilitate the comparisons. As can be clearly noticed, sEMG signal distribution is closer to Gaussian one at rest and during recovery, while deviates from Gaussianity during 50% and 100% MVC. However, the distribution tends to Gaussian during fatigue, i.e. end of 50% MVC.

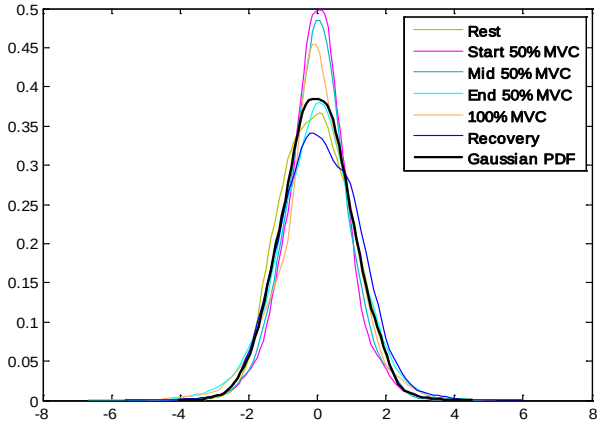

Fig. 4: Coloured lines indicate the PDFs of sEMG signals during rest, fatiguing 50% MVC, 100% MVC and recovery periods, while the black one shows the Gaussian density.

TABLE I, represents the values of the quantitative descriptors of PDFs, named skewness and kurtosis for each experiment. Examining the data, we can obviously state that the distribution has a positive skewness and negative kurtosis during rest and recovery trials, indicating an important right tail and a more flattened distribution, respectively. Conversely, the signals show negative skewness and positive kurtosis during MVCs, representing more peaked densities. Furthermore, the values of the kurtosis have a decreasing trend during fatiguing 50% MVC, which shows that the density tends to more flattened one, during muscle fatigue.

Fig. 5 represents the results of negentropy, which is a classical method of measuring non-Gaussianity. As is evident, the negentropy has its minimum value during rest and recovery periods, meaning that the signal is more Gaussian. However, it increases dramatically during two MVC trials (50% and 100%). Considering the results reported in TABLE I, we can state that the Gaussianity increases with force level, maybe due to the recruitment of extra motor units. This means that the sEMG is highly non-Gaussian during the start point of 50% MVC. Moreover, the increase (decrease) of Gaussianity (negentropy) during this trial determines that there is a decrease in muscle contraction, indicating muscle fatigue. In another words, when fatigue occurs, the negentropy falls.

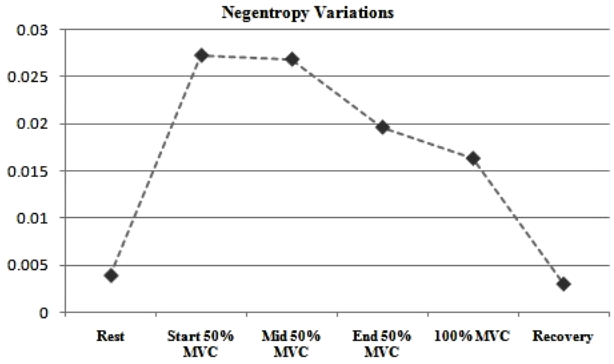

Fig. 5: Variations of negentropy during rest, fatiguing 50% MVC, 100% MVC and recovery periods.

In order to perform linearity test, the bicoherence was estimated using Higher Order Spectral Analysis (HOSA) toolbox [17]. For the estimation, the blocks of 256 samples corresponding to 128ms data with respect to the mentioned sampling frequency with 25% overlap were used. Hamming window was exploited as the analysis window. The linearity test, involves deciding whether or not the estimated bicoherence is constant in the bifrequency domain. Fig. 6 illustrates the linearity test results for the experiments. As is evident, sl, follows the reverse pattern of the Gaussianity test using negentropy, where the signal becomes more linear at MVCs and less linear during rest and recovery states (TABLE I). Furthermore, it can be noticed that the nonlinearity increases during fatigue (end of 50% MVC), which is consistent with the results of CD analysis.

4. Discussion

The present study investigated nonlinear analysis

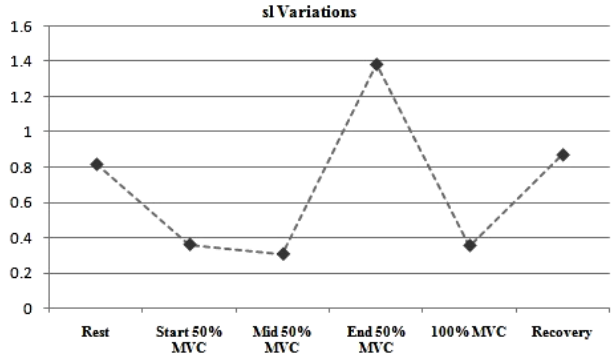

Fig. 6: Variations of sl during rest, fatiguing 50% MVC, 100% MVC and recovery periods.

methods to evaluate muscle force and fatigue. The use of nonlinear dynamical techniques was motivated by the reason that the physiological signals are nonlinear and chaotic in nature. Neglecting these properties and using inappropriate methods for analyzing such as linear and power spectral methods, may lead to false or misleading results. Thus, higher order statistical methods in time and frequency domains were used to investigate possible relations between variations of sEMG probability density and isometric contraction levels and muscle fatigue.

The results achieved using Gaussianity test based on negentropy, showed that Gaussianity decreased during voluntary contractions (50% and 100% of MVC) compared to rest and recovery trials. However, it increased during fatigue, indicating the decrease in muscle contraction and change in motor unit recruitment. Our results were in agreement with Hussain et al. [6] achievements, whose study was on sEMG signals recorded from right rectus femoris muscle during 8-trial walk. The measure of the linearity showed an exact reverse pattern with that of Gaussianity, which supported the outcome of [4], [6] and [8]. In contrast, Nazarpour study group [7] reported that sEMG signal indicated non-Gaussian PDF during light contractions (below 30% of MVC) and it tended to a Gaussian process at higher force levels due to central limit theorem. This contradiction may be due to the positioning of the electrodes, which was investigated by Kaplanis et al. [8]. They found that higher order statistical based analysis methods are position dependant, or may be due to clinical variations (anatomical, instrumentation), which is studied by [5]. In addition, the variations in the experimental conditions and recording time, specially fatigue phenomenon can have decisive role [3].

Moreover, like [7] we also used negentropy concept to measure the non-Gaussianity of sEMG signals. Because the Gaussianity test based on bicoherence index can only be used to reject the Gaussianity null hypothesis. It means that if the bispectrum index is zero, the full Gaussianity of the process may not be inferred, since fourth or even higher order cumulants and polyspectra would not be necessarily zero.

Besides higher order statistical analysis, correlation dimension was also examined as a quantifier of chaotic behaviour. The results of this feature were consistent with linearity test outcomes. This again, verifies the suitability of HOS based techniques to analyze biosignals.

Acknowledgements

The authors would like to express their sincere thanks to Islamic Azad University, Mashhad Branch which provides equipments needed for research and data acquisition and also to Ms. Davarinia for her valuable comments and also a special thanks to the participant who helped us in completing the study.

References

[1] G. Filligoi, "CHAOS THEORY and sEMG," *Journal of Selected Areas in Bioengineering (JSAB)*, pp. 9-16, 2011.

[2] S. Shahid, J. Walker, G. M. Lyons, C. A. Byrne, and A. V. Nene, "Application of Higher Order Statistics Techniques to EMG Signals to Characterize the Motor Unit Action Potential " *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, vol. 52, pp. 1195-1209, 2005.

[3] P. A. Kaplanis, C. S. Pattichis, L. J. Hadjileontiadis, and V. C. Roberts, "Surface EMG analysis on normal subjects based on isometric voluntary contraction," *Journal of Electromyography and Kinesiology*, vol. 19, pp. 157-171, 2009.

[4] M. S. HUSSAIN, M. B. I. REAZ, and M. I. IBRAHIMY, "SEMG Signal Processing and Analysis Using Wavelet Transform and Higher Order Statistics to Characterize Muscle Force," in *12th WSEAS International Conference on SYSTEMS*, Heraklion, Greece, 2008, pp. 366-371.

[5] F. Ayachi, S. Boudaoud, J. F. Grosset, and C.Marque, "Study of the Muscular Force/HOS Parameters Relationship from the Surface Electromyogram," in *15th NBC on Biomedical Engineering & Medical Physics*, 2011, pp. 187-190.

[6] M. S. Hussain and M. Mamun, "Effectiveness of the Wavelet Transform on the Surface EMG to Understand the Muscle Fatigue During Walk," *MEASUREMENT SCIENCE REVIEW*, vol. 12, pp. 28-33, 2012.

[7] Nazarpour, K., Sharafat, A., Firoozabadi, S.: Negentropy analysis of surface electromyogram signal. In: Proc IEEE SSP, Bordeaux, France, pp. 974–977, 2005.

[8] P. A. Kaplanis, C. S. pattichis, L. J. Hadjileontiadis, and S. M. Panas, "BISPECTRAL ANALYSIS OF SURFACE EMG," in *10* Mediterranean Electrotechnical Conference*. vol. 2, 2000, pp. 770-773.

[9] Surface Electromyography for the Non-Invasive Assessment of Muscles. [Online]. Available: http://www.seniam.org/

[10] R. Hilborn, "Measures of Chaos," in *Chaos and Nonlinear Dynamics*, Second ed. Oxford University Press.

[11] U. R. Acharya, G. S. E. Y. K. Ng2, and Y. S. L. Michelle, "Classification of Normal, Neuropathic, and Myopathic Electromyograph Signals Using Nonlinear Dynamics Method," *Journal of Medical Imaging and Health Informatics*, vol. 1, pp. 375-380, 2011.

[12] K. C. Chua, V. Chandran, U. R. Acharya, and C. M. Lim, "Application of higher order statistics/spectra in biomedical signals—A review," *Medical Engineering & Physics*, vol. 32, pp. 679-689, 2010.

[13] G. J. M. MENDEL, "Tutorial on Higher-Order Statistics (Spectra) in Signal Processing and System Theory: Theoretical Results and Some Applications," in *PROCEEDINGS OF THE IEEE*, 1991, pp. 278-305.

[14] C. L. Nikias and J. M. Mendel, "Signal Processing with Higher-Order Spectra," *IEEE SIGNAL PROCESSING MAGAZINE*, pp. 10-37, 1993.

[15] A. Lanatá, G. Valenza, C. Mancuso, and E. P. Scilingo, "Robust multiple cardiac arrhythmia detection through bispectrum analysis," *Expert Systems with Applications*, vol. 38, pp. 6798-6804, 2011.

[16] R.O. Duda, P.E. Hart, and D. G.Stork, “Pattern classification,” 2nd ed., John Wiley and Sons, 2001.

[17] Swami A, Mendel C.M. and Nikias C.L,, Higher-Order Spectral Analysis (HOSA) Toolbox, version 2.0.3, 2000.