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Nonlinear Analysis of Surface Electromyography

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1. Introduction

Electromyography (EMG) detects electrically or neurogically activated muscle cells on the basis of waveform characteristics from a recorded signal. EMG is useful for evaluating and recording movement abnormalities. The EMG signals can also detect neuromuscular activation level and recruitment order in addition to analyze the biomechanics of human or animal movement (De Luca, 1984; Furey, 1963). The EMG signals are generated based on superimposed motor action potentials during active movement. The myoelectric signals are the instantaneous algebraic summation of all electrical discharges produced by a contraction of the muscle fibers. Muscle fatigue is quantified using surface EMG signals based on the power spectrum which is the Fourier transform of EMG time series (Knowlton *et al.*, 1951; Mannion & Dolan, 1994; Mannion *et al.*, 1997c). Normal electrical source is a muscle membrane potential of approximately -90 mV, and measured EMG potentials range between less than 50 μV and up to 20 to 30 mV, depending on the muscle under observation (Herzog *et al.*, 1987; Nigg *et al.*, 1988). Typical repetition rate of muscle motor unit firing is approximately 7–20 Hz, depending on the size of the muscle, previous axonal damage, and other factors (Hoffmann, 1968; Rack & Ross, 1975). Therefore, the EMG range can be utilized in many clinical and biomechanical applications as a diagnostics tool for identifying neuromuscular diseases, assessing low back pain (LBP), kinesiology, and disorders of motor control. EMG signals are also used as a control signal for prosthetic devices such as prosthetic hands, arms, and lower limbs. It is unknown how the median frequency (MF) of an individual depends on posture, extent of physical activity prior to measurements, and other attributing factors. Such factors may influence the shift of the MF in the fatigue measurement, which is not a consistent indicator for injuries to low back muscles. Subjects with LBP have less endurance and thus smaller MF during sustained muscle contractions (Mannion *et al.*, 1997a; Roy *et al.*, 1997). The MF of the EMG signal is used to characterize physiological aspects of skeletal muscles. The signal from surface EMG is the instantaneous algebraic summation of action potentials from muscle fibers, and its power spectrum can be estimated from a fast Fourier transform of the signal.

Fourier transform is a linear analysis of a signal and gives the power spectrum $P(f)$ (Hobbie, 1997). A linear system is described mathematically by equations with oscillatory or exponentially growing solutions. In contrast, EMG time series have an irregular pattern so

that the signal must be interpreted as "noise." The noise is due to the interaction between a particular muscle and all other biomechanical "units" of the body. In many cases, the power spectrum follows an algebraic dependence $P(f) \sim 1/f\alpha$. The case $\alpha=0$ corresponds to "white noise" while $\alpha=2$ characterizes diffusive Brownian motion. Therefore, the MF of the EMG power spectrum is sensitive to physiological manifestations of muscular dysfunction as an alternative assessment tool to identify muscle fatigue (Mannion *et al.*, 1997b; Roy *et al.*, 1997). However, there is a lack of research that compares this tool with other nonlinear measurements based on pain level or dysfunction.

During a fatiguing contraction, a compression of the power spectrum of the EMG signal to lower frequencies is typically observed (Lindstrom *et al.*, 1974). This phenomenon is measured during a contraction as a decrease in the MF of the EMG signal. Individuals with better endurance than others exhibit a less precipitous decay rate of the MF (Mannion *et al.*, 1997b). Thus, it would be necessary to compare the results between Shannon entropy levels of the EMG and MF of the spectral quantities following intervention to enhance outcome measurements.

Other results indicated that subjects with LBP show less fatigue than healthy subjects (Humphrey *et al.*, 2005; Mannion *et al.*, 2001). Thus, despite considerable efforts by many researchers, a link between MF and musculoskeletal pain/dysfunction remains elusive. Moreover, the surface EMG is not a scientifically acceptable tool for the diagnosis of pain/dysfunction, and further studies are recommended to assess the specificity and sensitivity of surface EMG (Pullman *et al.*, 2000). Therefore, a clinical diagnosis and evaluation of LBP is still elusive, and the efficacy of therapeutic intervention and assessment for LBP cannot be tested reliably.

The power spectrum analysis provides an objective and noninvasive assessment of muscle function since EMG changes are associated with fatigue (De Luca, 1984; Mannion *et al.*, 1997a). However, contradictory results have been reported in studies using EMG as an outcome measure. The power spectrum has a limited dynamic range, and the change of the MF does not reflect such long-time correlations. New methods must be designed to capture biologically important characteristics from noisy time series. Researchers using nonlinear time series analysis have developed several mathematical tools to reveal the presence of power-law time correlations.

Investigations of physiologic time series have led to the understanding that some degree of noise is necessary for the proper functioning of biological systems (Belair *et al.*, 1995b; Glass, 2001; Strogatz, 2001). These systems must respond to external stimuli that may vary both in strength and time scale by many orders of magnitude. The "degree of irregularity" of time series can be quantified by computing the (information) entropy of the signal. The time-dependent entropy from the surface EMG signal and the entropy of the signal is lower for subjects with LBP than for healthy subjects. Furthermore, the entropy increases rapidly for short times [$t < 10$ ms], reaches a plateau value for intermediate times [10ms $< t <$ 500 ms], and then increases diffusely for long times [approximately 500 ms] (Belair *et al.*, 1995a). This behavior suggests that the plateau value is relevant for the physiology of skeletal muscles (Chialvo, 2002; Goldberger *et al.*, 2002a). In this chapter, some of these methods to surface EMG time series are discussed, and the potential use of these methods as a diagnostic tool for LBP are explored.

Therefore, the purpose of this chapter is to explore the potential use of nonlinear time series analysis as a tool for the clinical diagnosis of LBP or neuromuscular dysfunction, especially low back muscle fatigue. Of particular interest is a comparison between methods based on

the power spectrum and nonlinear time series analysis of EMG signals. In order to compare quantities derived from the EMG signals, it is important to compare the different types of analyses including nonlinear time series between subjects with and without musculoskeletal dysfunction/pain. Specifically, it is important to record and analyze the EMG signals for a group of subjects with LBP and a control group of healthy subjects using spectral analysis and methods from nonlinear time series analysis. Secondly, the reliability of the results based on power spectrum analysis and nonlinear time series analysis of EMG signals for subjects with and without LBP needs to be investigated. Thirdly, it is necessary to determine the sensitivity of the analyses and the distribution of the values of the entropy for a group of subjects with and without LBP.

2. Clinical assessment of LBP

A clinical assessment of LBP is important as a diagnostic tool since we cannot distinguish subjects with genuine pain from those who fraudulently claim to suffer from pain (Chaffin, 1969). The potential cost to society from malingerers could be quite high. Additionally, the effectiveness of various rehabilitation interventions is difficult to assess without a clinical diagnosis of LBP. The interpretation of surface EMG data is not as reliable as that from needle EMG, for example. A clinical diagnosis based on surface EMG is desirable since it is widely accepted by the general population.

A clinical diagnosis of LBP using EMG should be based on properties of the signal that change drastically in the presence of pain/dysfunction. If this is the case, the observed quantities from subjects with LBP are expected to be different than those from subjects without LBP. Because a shift in the MF of the spectrum is explained by the change in the velocity of the action potential, it reflects a quantitative change of the signal during a fatiguing exercise. On the other hand, a change in the entropy of the signal reflects a qualitative change in the physiologic system.

Subjects with LBP often have reduced muscle strength and endurance, which compromises the functional capacity of the spine and increases the likelihood of re-injury (Cholewicki & VanVliet, 2002; Wilder *et al.*, 1996). In most cases, a compression of the power spectrum of the EMG signal to lower frequencies is observed during a fatiguing contraction. This compression is the result of slower muscle fiber action potential propagation and an alteration in shape due to changes in the excitability of the muscle cell membrane (Lindstrom *et al.*, 1974; Panjabi, 1992). These phenomena are referred to as "myoelectric manifestations of fatigue" and are typically seen during a prolonged muscle contraction. Individuals with better endurance are expected to exhibit a smaller shift of the MF (Mannion *et al.*, 1997b; Mannion *et al.*, 2001). It has been reported that subjects with LBP exhibit a larger shift of the MF than subjects without LBP (Mayer *et al.*, 1989; Roy *et al.*, 1989).

2.1 Noise in biological systems

The characterization of the power spectrum with a single frequency indicates that the time dependence of the signal is approximated by a simple oscillatory behavior. In contrast, the EMG signal looks irregular to the naked eye, and thus cannot be approximated by a periodic behavior. Seemingly irregular time series have been observed in many biological systems such as the electrocardiography signal of the human heartbeat, the electroencephalogram signal in instances of epilepsy and human gait, and others (Costa *et al.*, 2003; Costa, 2002; Goldberger *et al.*, 2002a).

It has recently been suggested that physiological time series contain "hidden information" (Goldberger *et al.*, 2002a). A biomechanical model of the human body emerges in which individual "units" interact in a nonlinear fashion such that feedback loops operate over long temporal and spatial ranges. This self-regulation leads to reduced variability which is important for maintaining physiological control of biological systems. For example, the prediction of homeostasis reveals that the output of a wide variety of systems, such as the normal human heartbeat, fluctuates in a complex manner even under resting conditions.

It is generally believed that the irregularity of the signal allows biological systems to respond to external disturbances that vary over a wide range of time scales. The velocity of the action potential determines the short-time behavior of the surface EMG signal. In contrast, the physiologic origin of its long-time behavior is unknown. It is not even clear whether observed fluctuations ("noise") in the signal are external or are intrinsic to the physiologic system. Intrinsic noise can be explained by the combined action of inhibitory and excitatory "units" or components of the system (Koppell, 2000). The presence of external fluctuations can have important consequences for complex systems. It has been shown, for example, that a system of oscillators can become synchronized, which may then explain the combined action of the entire system (Costa *et al.*, 2003).

It is not known which model of skeletal muscles explains the presence of intrinsic noise in the EMG signal. This is a common situation encountered in many studies of complex systems. Nonlinear time series analysis has developed numerous tools to distinguish nonlinear or chaotic behaviors within the system from external noise. For chaotic systems, the number of dynamic degrees of freedom can be determined from the signal that is (roughly) equal to the number of inhibitory and excitatory units in the system.

In nonlinear time series analysis, the characteristic behavior of a system is extracted from a mathematical analysis of the signal. The behavior of the signal is quantified using concepts and ideas borrowed primarily from statistical physics and signal processing. In particular, the information entropy has been proposed as a measure of the irregularity of the signal (Costa *et al.*, 2003; Costa, 2002; Goldberger *et al.*, 2002b; Pincus, 2001). A periodic signal and a complete irregular signal (or "white noise") have zero entropy. A random (or stochastic) signal with long-time correlations is characterized by a finite entropy, $S>0$. For a large variety of physiologic systems, it has been shown that dysfunction is associated with a decrease in the entropy of the time series. This suggests that physiological dysfunction leads to either complete order or excessive disorder.

2.2 Entropy of electromyography

In a mathematical description, the signal at (discrete) "time" n, x_n, is treated as a random, or stochastic, variable (Kantz, 2003; Sprott, 2003). It is assumed that the signal is "stationary," i.e., the quantity $\Sigma_{i=1}^{t} x_{n-1+i}$ does not depend on the initial time n. The mean-square displacement is then defined by $\Delta(t)=\langle[\Sigma_{i=1}^{t} x_{n-1+i}]^2\rangle$, where the average is taken with respect to the n. If the signal at time n is uncorrelated with the signal at a different time m, $\langle x_n x_m\rangle=0$, the mean-square displacement increases diffusively, $\Delta(t) \sim t$. This case is generally referred to as "white noise." In the presence of long-time correlations, $\langle x_n x_m\rangle \sim 1/|n-m|^{\nu}$ for some exponent $\nu>0$, fractional Brownian walk follows $\Delta(t) \sim t^{2H}$ (Mandelbrot, 1983). Here, the Hurst exponent is $H=2\nu+1$ with $0<H<0.5$ for sub-diffusive and $0.5<H<1$ for super-diffusive "behavior". The presence of long-time correlations implies that the signal has no characteristic time scales and looks the same on all time scales. In a certain mathematical limit, the mean-square displacement and the entropy are related to each other $S \sim \ln \Delta$.

The entropy reflects properties of the signal on many different time scales and, therefore, does not have a simple relationship with the velocity of the action potential. It follows that properties of the surface EMG signal obtained via nonlinear time series analysis are complementary to the analysis of the power spectrum. Entropy has many interdisciplinary applications as in aging psychology or macromolecular engineering (Allen *et al.*, 1998; Allen *et al.*, 2004). Regarding time series applications, biological time series are complex data that need to be distilled to useful information such as assessing an illness. Nonlinear analysis using fractal geometry and random walks theory proved to be useful in the analysis of a variety of time series such as correlations between global temperatures and solar activity (Scafetta & West, 2003), earthquake statistics (Scafetta & West, 2004), human heartbeat (Ivanov *et al.*, 1999), and shapes of red cells under flow stress (Korol & Rasia, 2003). Recently, nonlinear time series generated by the back muscles' electrical activity was investigated between subjects with and without LBP motivated by the need to develop an evaluation tool for LBP (Lee *et al.*, 2010; Sung *et al.*, 2005; Sung *et al.*, 2007a; Sung *et al.*, 2010).

Using random walk concepts, Collins and De Luca have studied the erratic motion of the center of pressure of a standing human body (Collins & De Luca, 1994; Collins & De Luca, 1995). They found a crossover from superdiffusive random walks for short times to subdiffusive random walks for longer times. In our entropic analysis of EMG time series from back muscles, we observed a crossover from subdiffusive, Hurst exponent $H \leq 0.5$, to self-organization, Hurst exponent $H \approx 0$. The Renyi entropy associated with diffusive processes grows linearly with the logarithm of time, and the rate of growth is independent of the Renyi parameter (Kaufman, 1985; Kaufman, 2007). The entropy is the rigorous measure of lack of information. The information, or Shannon, entropy for a particular experimental condition with a set of M possible outcomes is (Gage, 1992; S. Shannon, 1997):

$$S_{\text{inf}ormation} = -\sum_{j=1}^{M} p_j \ln(p_j) \tag{1}$$

where pj is the relative frequency of outcome #j. It is uniquely determined from the Khinchin axioms: (I) it depends on the probabilities p only; (II) the lowest entropy ($S = 0$) corresponds to one of the p's being 1 and the rest being zero (i.e., total information); (III) the largest value for the entropy is lnM and is achieved when all p's are equal to each other (i.e., the absence of any information); and (IV) S is additive over partitions of the outcomes. If the last axiom is relaxed to consider only statistically independent partitions, Renyi found that the information entropy is replaced by a one-variable function (Cybulski *et al.*, 2004):

$$S(\beta) = \frac{1}{1-\beta} \ln\left(\sum_{j=1}^{M} p_j^{\beta}\right). \tag{2}$$

For β = 1, the Renyi entropy equals the Shannon entropy. The Renyi entropy is related to the Tsallis entropy which is central to the current massive research effort in nonextensive statistical mechanics (Vinga & Almeida, 2004).

In the continuum limit: $p_j \approx \rho(x,t)\Delta x$, where x is the random variable, e.g. displacement for random walker, and ρ is the probability distribution function. The actual experiment was conducted for measuring the electrical signal from back muscles (Sung *et al.*, 2005). Consider

a time series x_t. Following Scafetta and Grigolini (Scafetta & Grigolini, 2002), the signal x_n was interpreted as a jump at time n. It was generated at all walks of time length t: $X_{m,t} = \sum_{j=0}^{t-1} x_{j+m}$. For a given time t, the ensemble of all the walks of time length t was considered and distinguished from one another by the initial time m. The range of X was divided in M equal bins, and the probability of finding a walker at that location was estimated by using the fraction of all X that fall in the bin. The results were obtained for M = 500 bins. The entropies were computed using Eqs. (1) and (2). The numerical time series were analyzed searching for a logarithmic dependence of the entropy.

Figure 1 indicates the EMG time series from the right thoracic muscle of the healthy individual and the entropy associated with walks generated from the healthy right thoracic muscle EMG time series as a function of the logarithm of time. At short times, t < 0.01 s, the slope is 0.26, 0.32, 0.34 for the Renyi parameter β = 0, 1, 5 respectively. Since the fit was done on only ten data points, there is a large uncertainty for those values. Similar slope values were extracted from the EMG data from all the muscles (both sides of the thoracic and lumbar erector spinae) for both individuals (HEALTHY and LBP subjects). At longer times, for 0.01 s < t < 1 s, the entropies exhibit a plateau. The plateau occurs at an entropy value well below the maximum possible entropy value lnM. Hence, it is not an artifact of the way we estimate the entropy; but it is an intrinsic property of the time series.

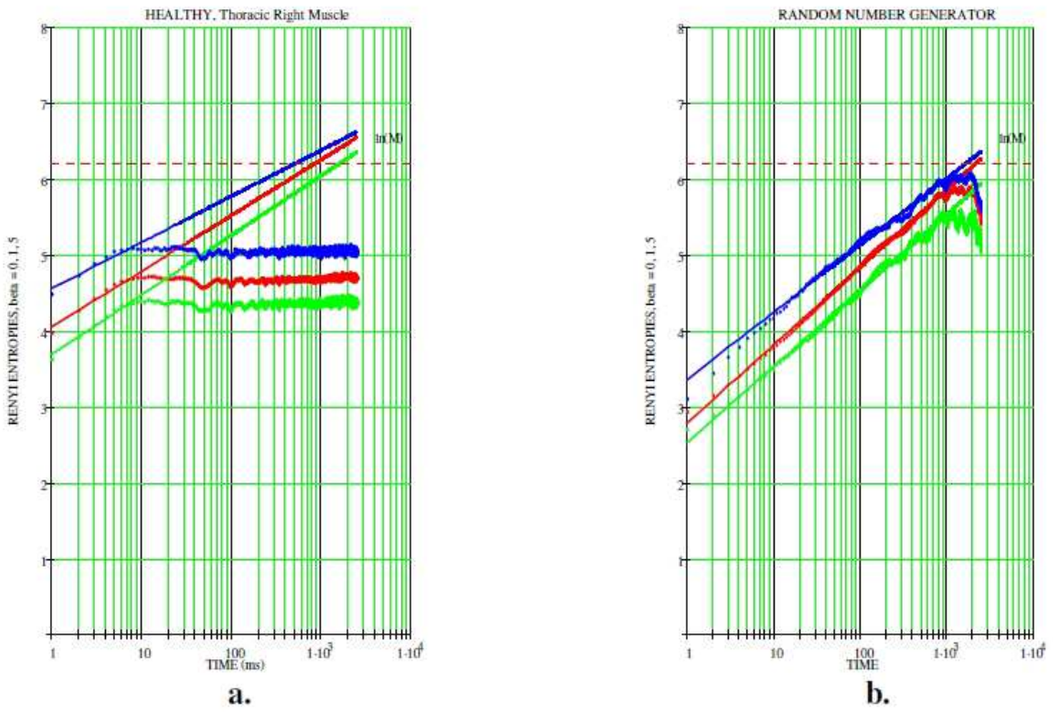


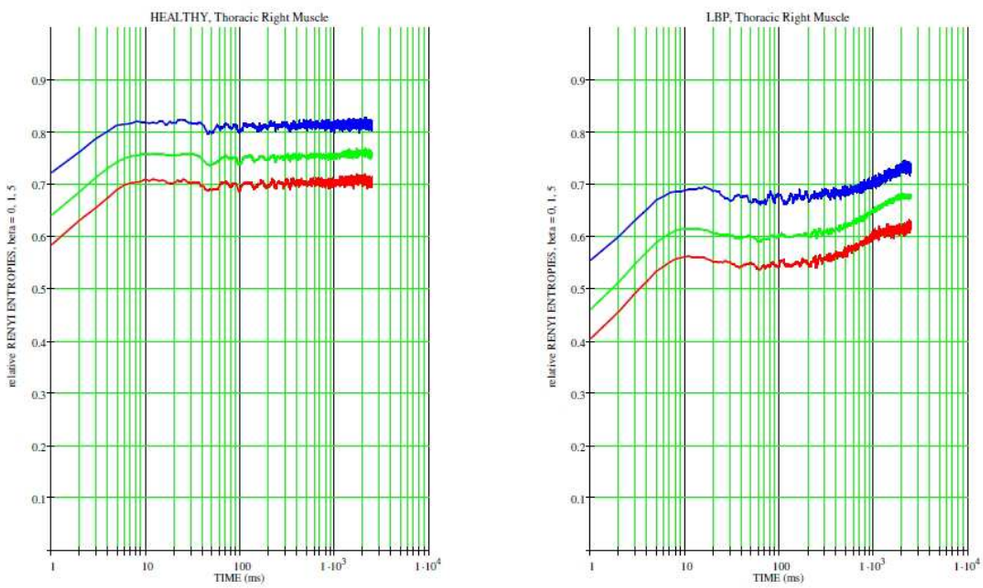
Fig. 1. Entropy vs. ln$t$. Top curve β = 0, middle curve β = 1, bottom curve β = 5. a. Subject without LBP for the right thoracic erector spinae muscle; b. Random number generator.

The entropy plateau corresponds to the Hurst exponent $H \approx 0$. The power spectrum $P(f) \sim f^{\alpha}$ with an exponent $\alpha = 2H + 1 \approx 1$ follows $P(f) \sim 1/f$. Self-organization is generally associated

with $1/f$ noise, and this is the reason why the entropy plateau can be interpreted as a manifestation of self-organization (Buldyrev *et al.*, 2006). Qualitatively similar dependences were observed in the analysis of the erratic motion of the center of pressure of the human body (Collins & De Luca, 1994; Collins & De Luca, 1995). Though the details are not identical (e.g crossover time and slopes are different), we suspect that this type of crossover from large Hurst exponent random walks at short times to small Hurst exponent random walks at long times characterizes organized complex systems. In Figure 1b, the qualitatively different dependence of entropy on time exhibited by time series was generated with a commercial random number generator. The slopes of S versus $\ln t$ for the random number generator data are 0.38, 0.45, 0.44 for $\beta = 0, 1, 5$ respectively. These values are quite close to the Brownian diffusion value $H = ½$. There is no plateau in the random number time series.

This comparison between the EMG data on one hand and random data on the other hand supports the idea that the system responsible for the back muscle signal is complex as opposed to noisy. The time evolution of entropy for EMG data also differs qualitatively from the time dependence of the entropy of chaotically advected tracers: the latter does not exhibit a crossover in time to self-organization, but it does exhibit a substantial dependence of the logarithmic amplitude on the Renyi parameter.

The entropy dependence on time constitutes a potential tool for differentiating between subjects with and without LBP. We show in Figure 2 below, side by side, graphs of the relative entropy $S/\ln(M)$ versus $\ln t$ from four erector spinae (right and left thoracic and right and left lumbar) muscles of a healthy male and a LBP male of the same age. In each case, we computed the entropy using $M = 500$ bins.



a b

Fig. 2. Relative Entropy on lumbar right muscle vs. $\ln t$. Top $\beta = 0$, middle $\beta = 1$, bottom $\beta = 5$; a. Subject without LBP; b. Subject with LBP.

The plateau entropy is consistently higher for the healthy individual than for the LBP individual. A previous pilot study in our lab also demonstrated similar results involving ten

healthy and ten LBP individuals, who were matched by gender, but not by age (Sung *et al.*, 2007b). The question of whether the plateau entropy constitutes a useful diagnostic tool for LBP needs further investigation with large groups of individuals matched by age, gender, body mass index, etc. It is worth emphasizing that Costa et al. and Chialvo argued based on heart time series that pathology is associated with less variability (lower entropy) as indicated in our study (Chialvo, 2002; Costa *et al.*, 2002).

To better understand the entropy time evolution, we show in Figure 3 the histograms used to determine the entropy for the left thoracic muscle of LBP subjects. In Figure 3a, we see the widening of the probability distribution with time corresponding to the entropy increase at short times t < 10 ms. In Figure 3b, the probability distribution is practically stationary corresponding to the entropy plateau at longer times 10 ms < t < 500 ms. In Figure 3c, we show the probability distribution at t = 1000 ms, attempting to understand the increase in entropy apparent for t > 500 ms. We observe the occurrence of two peaks which may correspond to some sort of phase transition. In order to check this hypothesis, we computed the histogram using 66,000 data points rather than the 6,000 points window used in all other computations.

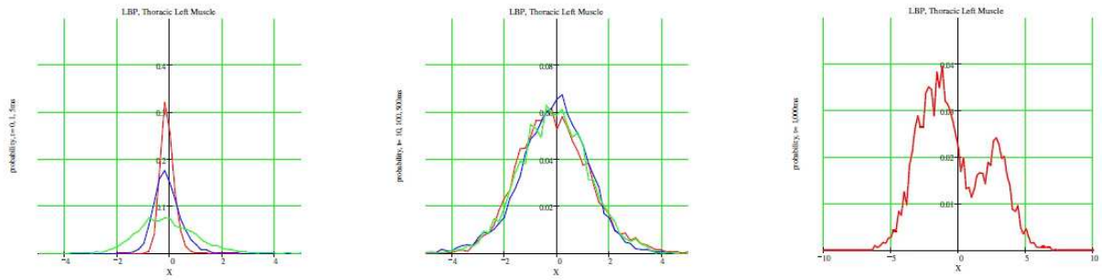


Fig. 3. Probability distributions at short time, intermediate time, and long time for the thoracic left muscle in subjects with LBP at: (a) t = 0, 1, 5ms; (b) t = 10, 100, 500ms; (c) t =1000ms.

We reduced the original time series to 6,000 entries by averaging over 10 consecutive entries of the original time series. We labeled the resulting time series as xn, where the index n ('time') runs from 1 to 6,000. Nonlinear time series analysis assumes that the signal is stationary. To test this assumption, we calculated the mean and variance of 100 data points. The results for the subjects with and without LBP are shown in Figures 4A and 4B, respectively. Clearly, the EMG signal is stationary in both cases. Note that the average of the mean (μ) is nonzero, which reflects an offset in the calibration. For the numerical analysis below, we correct the offset by replacing xn with xn - μ. For nonlinear systems, signals at different times are correlated as shown in a phase portrait where the signal xn+1 at time n+1 is plotted vs the signal xn at time n.

For the subject without LBP (Figure 5A), the phase portrait has a circular shape. This portrait shows that the signals at consecutive times n and n+1 are statistically independent of each other. On the other hand, the phase portrait for the subject with LBP has the shape of an ellipse with the long axis directed along the diagonal (Figure 5B). The elliptical shape along the diagonal indicates the presence of correlations. Physicists have developed several

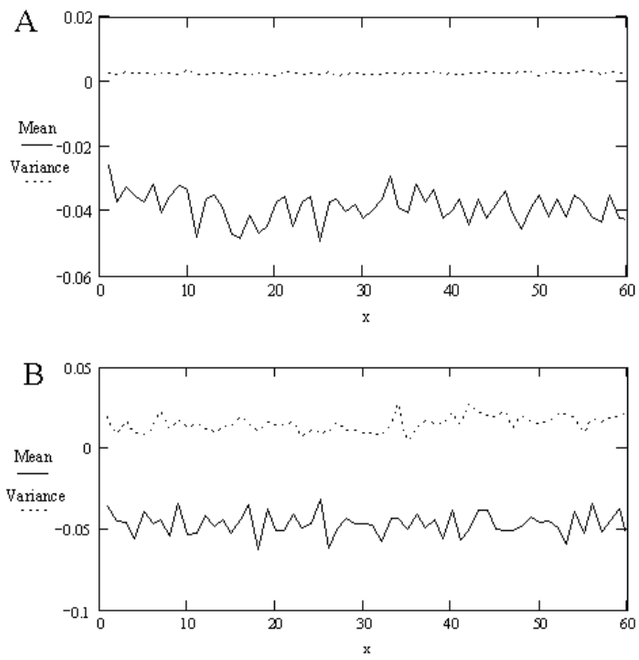
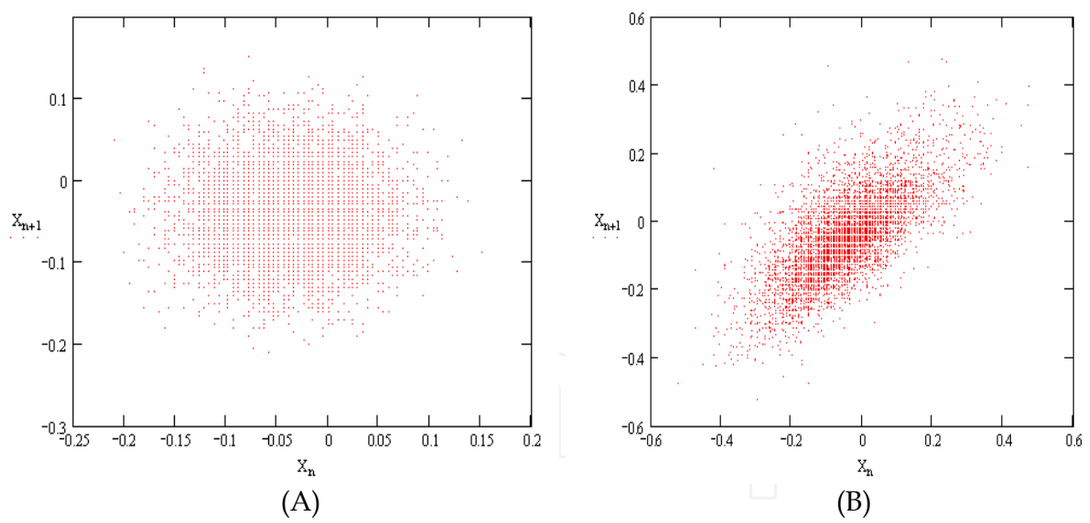


Fig. 4. Mean (solid line) and standard deviation (dashed line) for (A) subjects without and (B) subjects with LBP.



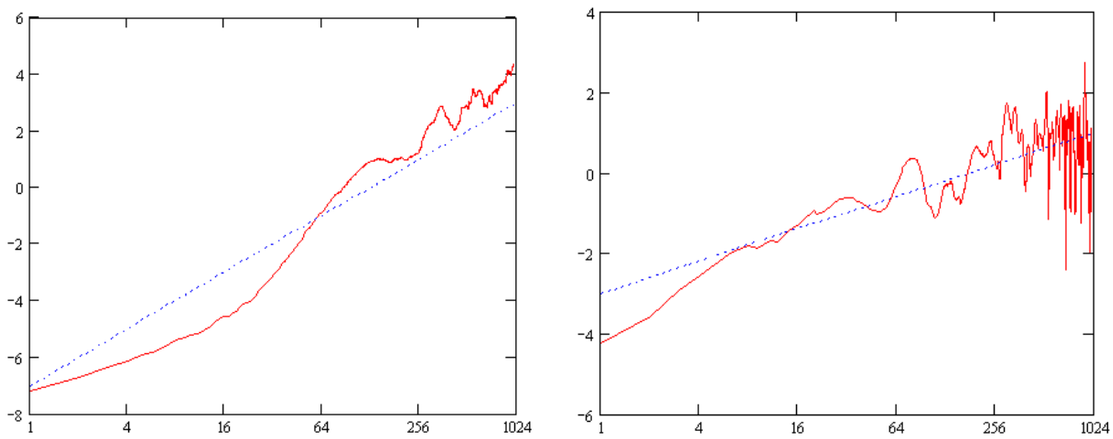
(A) (B)

Fig. 5. Phase portrait of (A) subjects without and (B) subjects with LBP.

methods to quantify the complexity of time series. One method explores the connection with random walks, or Brownian motion (Denny & Gaines, 2000). To this end, we interpret the signal xn as a jump at time n. It follows that the sum $X(t)=xn+xn+1+\ldots+xn+t$ is the displacement between times n and $n+t$. The average is zero $\langle X(t)\rangle=0$. The mean-square displacement is obtained by taking the square and then calculating the average with respect to the initial time n, $\Delta(t) = \langle X2(t)\rangle$. For deterministic motion, $\Delta(t) \sim t2$, while $\Delta(t) \sim t$ is for diffusion. In the general case, we write $\Delta(t) \sim t2h$ so that $0< h < 0.5$ and $0.5 < h< 1$ correspond to sub-

diffusive (negative correlations) and super-diffusive (positive correlations) behavior, respectively. In Figures 6A and 6B, we show the dependence of $\Delta(t)$ vs t in double-logarithmic plots.

A straight line corresponds to power-law behavior, and the Hurst exponent H (Mandelbrot, 1977) is determined by the slope. For the subject without LBP, we find H=0.5, corresponding to diffusive behavior. For the subject with LBP, we have H=0.2, which indicates the presence of long-time correlations in the EMG signal, in agreement with the results from the phase portrait. The mean-square follows (fractional) Brownian motion only for short-times. For long-times, $\Delta(t)$ appears to plateau. The determination of the Hurst Exponent is affected by large statistical fluctuations. In order to get a more reliable estimate of the Hurst exponent, an analysis of the entropy of the time series was undertaken.

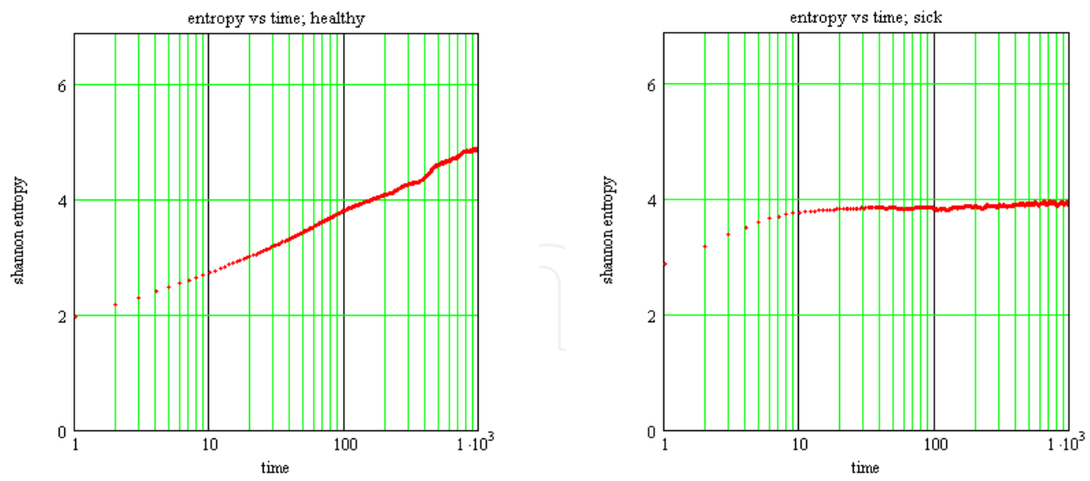


(A) (B)

Fig. 6. Log-log plot Δ*vs. t* for (A) subjects without and (B) subjects with LBP.

One can characterize the complexity of time series by using the information (Shannon) entropy S=-Σpjlogpj, where pj is the probability for outcome number 'j' of a given experiment (Allen *et al.*, 2004; Bezerianos *et al.*, 1995; Bezerianos *et al.*, 2003; Costa *et al.*, 2003). The above equation is the standard formulation of uncertainty as it has the following features: (i) the lowest entropy (S = 0) corresponds to one of the outcomes being certain [i.e. probability one] and the others never occurring [i.e. probability zero]; (ii) the largest value for the entropy, S=ln(M), is achieved when all outcomes are equally likely [all probabilities are equal to each other, pj = 1/M]; and (iii) S is additive over partitions of the outcomes. The results reported here were obtained for M = 1000 bins. The variation of S with t is expected to be logarithmic: $S(t)$~Hln$t$, where H is the Hurst exponent introduced before. The entropic analysis of the time series from the subject without LBP and from the subject with LBP shows significant differences in how fast the entropy saturates.

In addition, there is a difference between the slopes of entropy and time function for subjects without and with LBP (Figure 7). The slopes represent estimates for the Hurst exponent H. In agreement with the variance of displacement analysis presented, there was a difference of the Hurst exponent between the subjects without LBP (H=0.5; Figure 6, A) and subject with LBP (H=0.4; Figure 6, B) were indicated. Note that the value of the exponent H for the LBP subject refers to short-times, while the behavior for long-times is characterized by the value 0.2 quoted before. The difference in the entropy vs time dependence exhibited



(A) (B)

Fig. 7. Shannon entropy versus ln(t) for (A) subjects without and (B) subjects with LBP.

by the healthy and LBP subjects goes beyond the issue of the value of the Hurst exponent. The entropy associated with the LBP subject saturates at very short-times; two orders of magnitude shorter than for the healthy subject. Furthermore, the long time entropy of LBP is lower than for the healthy subject, a result consistent with non-linear analysis of other medical time series (Bezerianos *et al.*, 1995). It is generally observed that injuries result in a decrease in the complexity of biological systems.

In conculsion, nonlinear analysis of time series based on entropy can differentiate between complex biological sources and random sources of the data. While the EMG signal from an erector spinae muscle exhibits an entropy time dependence with a crossover from subdiffusive regime at short times to a self-organization regime (plateau) at longer time scales, time series generated with random number generators do not exhibit the plateau. The Renyi entropy time evolution also differentiates between this complex biological system and deterministic processes (e.g. tracers advection in polymer flows). The presence of the plateau points to the existence of anti-correlations of EMG signals separated in time by at least 0.01 s. Therefore, it is a manifestation of a complex self-organizing system in which individual units interact in a nonlinear fashion such that feedback loops operate over long temporal ranges (Goldberger *et al.*, 2002a).

2.3 Reliability of surface electromyography analysis

The reliability of surface EMG could be different between nonlinear analysis of time series and power spectrum analysis. Our previous study results indicated that the measurement of back muscle fatigability, especially the erector spinae muscle, indicated that the entropy analysis was a more reliable measure than the power spectral analysis (Sung *et al.*, 2008b).

It is well known that the observed EMG signal depends on anatomical factors, such as muscle geometry, subcutaneous fat, gender, and other confounding factors (Lindstrom *et al.*, 1974; Mannion *et al.*, 1997c; Pullman *et al.*, 2000; Roy *et al.*, 1997; Solomonow *et al.*, 1990). As a result, observed quantities from EMG signals show considerable variations even among a group of healthy subjects. A clinical diagnosis of musculoskeletal dysfunction using surface EMG is based on the assumption that dysfunction changes the values of the observed

quantities. This underlying assumption is difficult to prove, however, because the EMG signal prior to an injury is generally not available.

One reliable indicator is MF, which is defined by dividing the area under the spectrum into two equal parts. However, use of the MF has led to contradictory results in muscle fatiguing experiments. It still remains to be seen whether a shift in the MF differentiates the various stages of non-acute LBP. The fatigability of back muscles might predispose individuals to LBP. A number of investigators have attempted to classify LBP via changes in the EMG signal during prolonged contraction of the paraspinal muscles (Lariviere *et al.*, 2002a; Lariviere *et al.*, 2002b; Mayer *et al.*, 1989; Peach & McGill, 1998; Roy *et al.*, 1997; Roy *et al.*, 1990). The MF of the back muscles is typically of the order of 100 Hz and is determined by the propagation of the action potential across the electrodes. That is, the MF reflects the behavior of the EMG signal on short-time scales.

Several studies have suggested that surface EMG power spectrum analysis could be used to evaluate patients undergoing rehabilitation in a non-invasive fashion (De Luca, 1984; Mannion *et al.*, 1998; Merletti *et al.*, 1999). The connection between fatigue and EMG spectral parameters is the basis for the use of EMG as an objective and noninvasive method of assessment of back muscle endurance (De Luca, 1984; Mannion *et al.*, 1997a). The original study linking LBP with fatigue was presented by De Luca (De Luca, 1984) who found that subjects with LBP have less endurance, and thus smaller MF slopes, during sustained muscle contractions (Merletti *et al.*, 1999; Roy *et al.*, 1989). However, contradictory results have subsequently been reported and have shown that MF slope is not better than chance in predicting LBP (Humphrey *et al.*, 2005; Lee *et al.*, 2010; Mannion *et al.*, 2001). Thus, a connection between spectral quantities and musculoskeletal pain/dysfunction remains elusive despite considerable efforts.

In recent studies, we applied methods from nonlinear analysis of time series and found that the time-dependent entropy calculated from the EMG signal shows a distinct plateau-like behavior for intermediate times (Kaufman, 2007; Sung *et al.*, 2005; Sung *et al.*, 2007b). The signal from EMG is the instantaneous algebraic summations of action potentials from muscle fibers, and its power spectrum is obtained from a fast Fourier transform of the signal. Recently, several studies in entropy measurements based on nonlinear time series analysis were published without reporting reliability and validity concerns (Goldberger *et al.*, 2002b; Kaufman, 2007; Sung *et al.*, 2007b). Therefore, it would be valuable to confirm the reliability of measurements for characterizing neuromuscular alterations by investigating differences between the power spectrum analysis and nonlinear time series analysis of entropy measures.

It has been found that the degree of randomness is a characteristic property of time series. Entropy is generally used to quantify the complexity. In particular, entropy is used to characterize non-periodic, random phenomena and indicates the rate of information production as it relates to dynamic systems (Richman & Moorman, 2000). Several research groups have compared entropy values for subjects with and without illness/dysfunction (Chialvo, 2002; Costa, 2002; Goldberger *et al.*, 2002a; Stanley *et al.*, 1992; West, 1990). This concept has been used to differentiate healthy subjects from those with heart disease using electrocardiogram time series as well; it is generally found that disease is associated with a lowering of the entropy. In several papers, we applied these ideas to EMG time series for the low back muscles. We found that subjects with LBP have lower entropies than healthy subjects, which is in agreement with the general finding. The traditional approach of EMG is based within the framework of linear systems for which a given input leads to a well-

defined periodicity. This connection led to the notion of homeostasis, namely that the normal function of physiologic systems operates in a steady state and that fluctuations are suppressed. However, contradictory results have subsequently been reported without clear understanding of the reliability of entropy measures (Humphrey *et al.*, 2005; Sung *et al.*, 2008b).

Our previous studies indicated that the plateau entropy value was consistently higher for the healthy individual than for the LBP individual. However, the question of whether the plateau entropy constitutes a reliable assessment tool for LBP needs further investigation with large groups of individuals matched by age, gender, body mass index, etc. It is important to understand that Costa et al. and Chialvo argued that pathology/dysfunction is associated with less variability (lower entropy), which was consistent with our findings (Kaufman, 2007; Sung *et al.*, 2005; Sung *et al.*, 2007b).

Nonlinear analysis has proved to be useful in the analysis of a variety of physiologic time series such as human heartbeats (Ivanov *et al.*, 1999) and the shapes of red blood cells under flow stress (Korol & Rasia, 2003). Based on these empirical studies, it has been found that the time series from healthy subjects have higher entropy values than the time series from those with pathology/dysfunction. There are also several other studies indicating that traditional approaches to measuring the complexity of biological signals fail to account for the multiple time scales inherent in such time series. Generally, biological time series are complex data that need to be distilled to useful application to assess a pathology/dysfunction. However, no study has investigated the reliability of entropy measures to assess pathology/ dysfunction. In addition, despite much effort, the MF and the MF slope have not shown consistent measurements (De Luca, 1984; Mannion *et al.*, 1998; Merletti *et al.*, 1999; Sung, 2003).

In previous studies, we explored the use of entropy derived from time series as an alternative quantitative measure of EMG signals that can be used in a clinical assessment. We compared the values of the entropy between subjects with LBP and healthy subjects and found that healthy subjects have significantly higher entropies than subjects with LBP (Sung *et al.*, 2007b). However, it is important to examine the between-day variability of entropy, the MF, and the MF slope within the same sample group. In our current study, we compared the values of MF, MF slope, and entropy for two different measurements; and the results indicated the highest correlation for entropy, while the MF slope and MF demonstrated relatively weak correlations.

The results for the right back muscle are illustrated in Figures 8-13 in order to compare values with different measures. The consistent responses of the non-dominant side of the back could be less affected by hand dominance. The histogram of the entropy (Figure 8) demonstrated consistent distributions between pre- and post- measurement entropy values, which are plotted in Figure 9. The points representing the 32 subjects were plotted closely along the diagonal line, indicating that the two measurements reveal a relatively high correlation (R=0.75).

The mean and the standard deviations of the MF slope values for two measurements were analyzed, and the correlations ranged from 0.15-0.18, which does not indicate a significant difference between the MF slopes at two different observations. The intra class correlation coefficients (ICCs) ranged from 0.26-0.30, and the standard error of means (SEM) varied between 0.03 and 0.04, which were not significantly different for the distributions for two different times. Figure 10 compared two measurements of the MF slope for the right back muscle, and the number of subjects repeatedly demonstrated less similar results between

the two measurements. The Pearson correlation coefficients ranged from 0.15-0.18 and were not statistically different. This result confirms the values of the MF slope of the right back muscle for post-measurement, which was plotted versus the values of pre-measurement in Figure 10 and shows no obvious difference. The points representing the subjects were distributed rather broadly, which was reflected in the low correlation coefficient (R=0.18).

The distribution of MF values from post-measurement shifted towards larger values. The correlations ranged from 0.38-0.47 and were statistically significant. Thus, there was a significant correlation between the distributions of the MF values from the measurements at two different times. The ICCs ranged from 0.54-0.64, and the SEM ranged from 3.10-3.60. The Pearson correlation coefficients ranged from 0.38-0.47 and were statistically significant. In Figure 12, two measurements of the MF for the right back muscle are compared, and the number of subjects repeatedly demonstrated less similar results between two measurements. Figure 12 depicts the histograms of the MF values. The two histograms indicated little difference except for two outliers for post-measurement values. Figure 13 depicts the MF values of the right back muscle, and the linear regression analysis yielded R=0.15. The values of MF for the two measurements were more highly correlated than those for the MF slope, although the correlation (R=0.38) was much lower than that for the entropy (Sung *et al.*, 2005).

Overall, the ICC values of entropy for between-day measurements were higher, and the SEM for entropy was lower than the MF and its slope. Therefore, the results of this study indicated that the entropy analysis could provide reliable measurements for muscle fatigability.

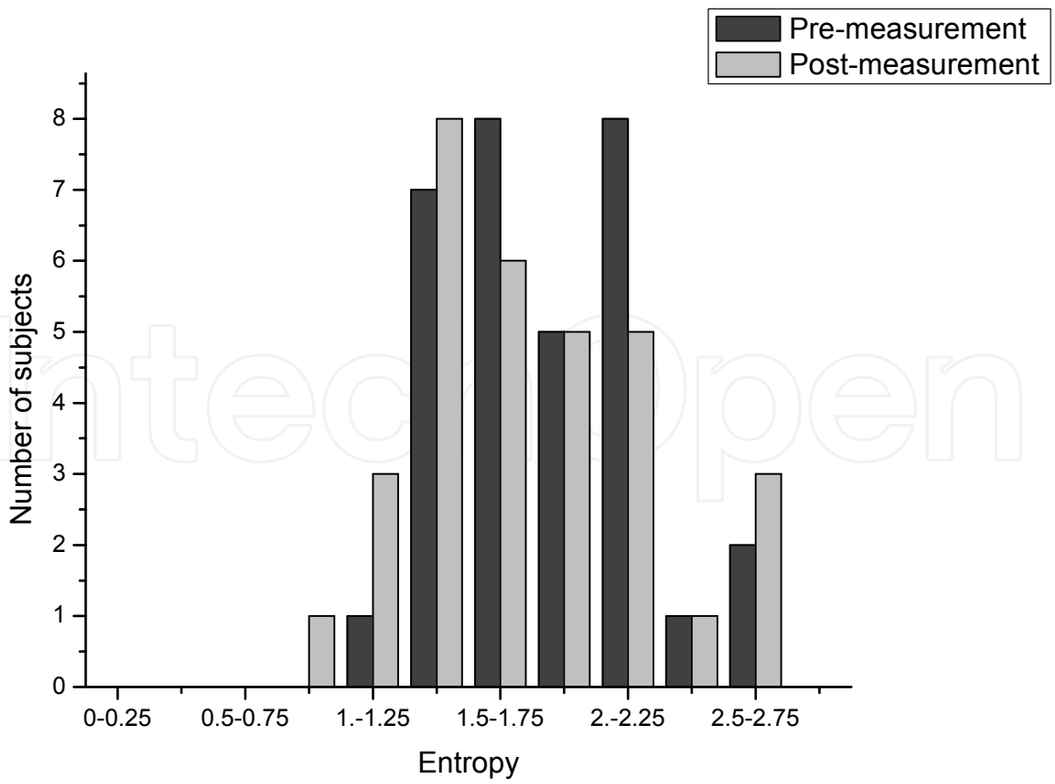


Fig. 8. Histogram of entropy measurements for the right back muscle.

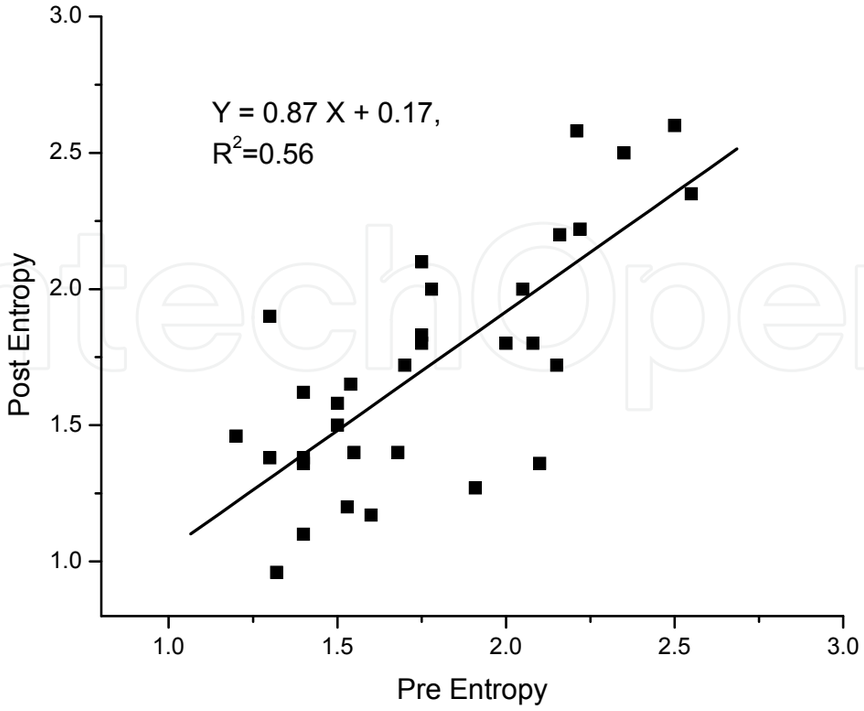


Fig. 9. The entropy values taken at two different measurements for the right erector spinae muscle. The correlation coefficient is R=0.75.

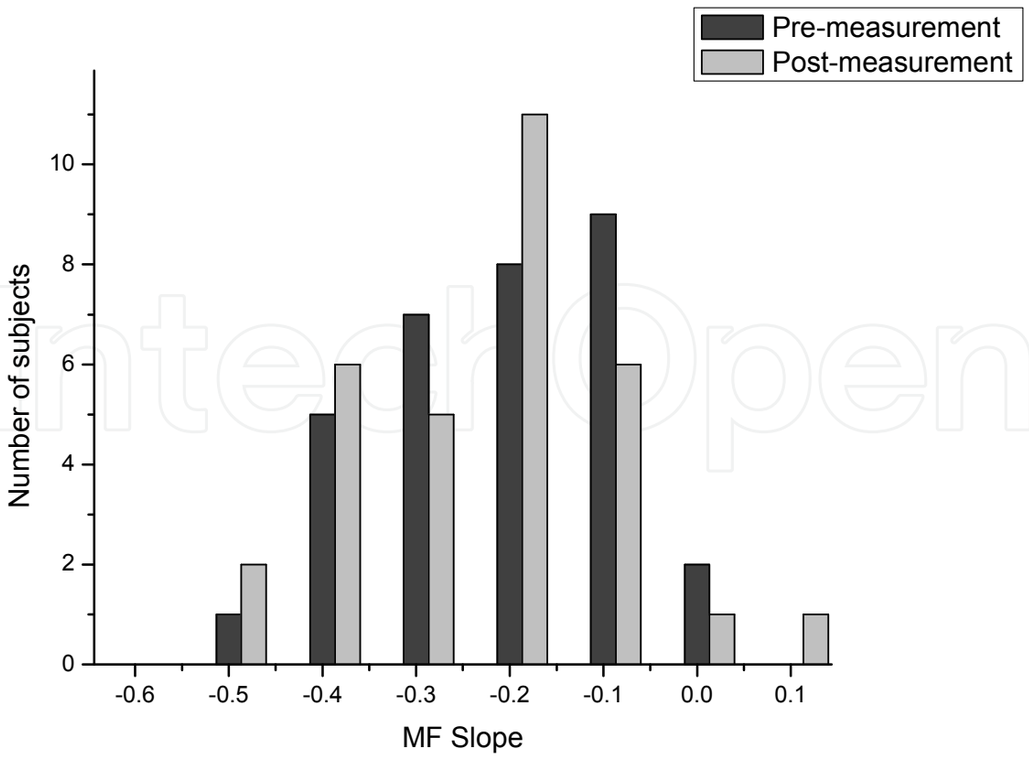


Fig. 10. Histogram of median frequency slope measurements for the right back muscle.

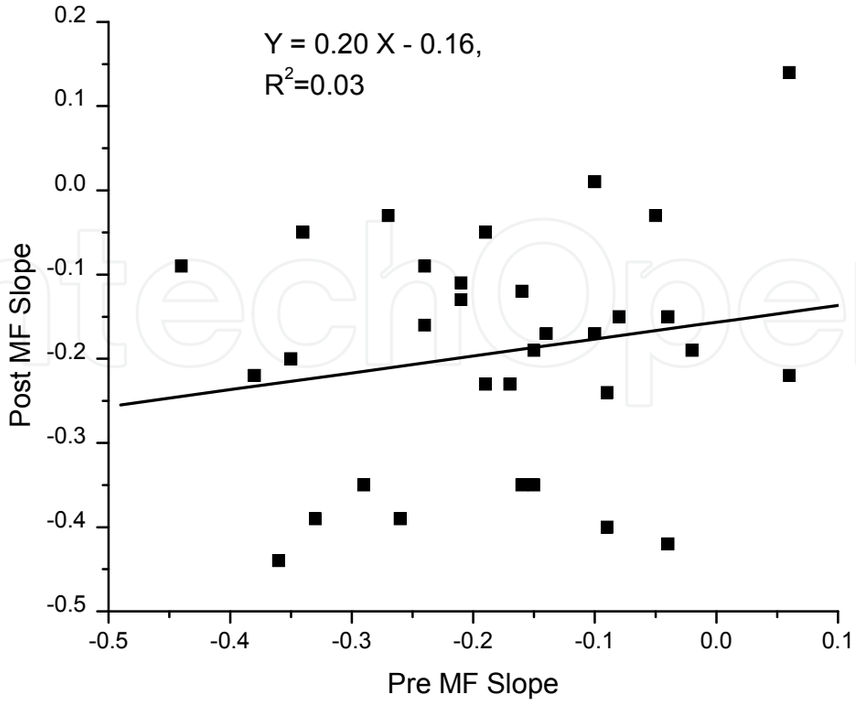


Fig. 11. The median frequency slope taken at two different measurements for the right back muscle. The correlation coefficient is R=0.18.

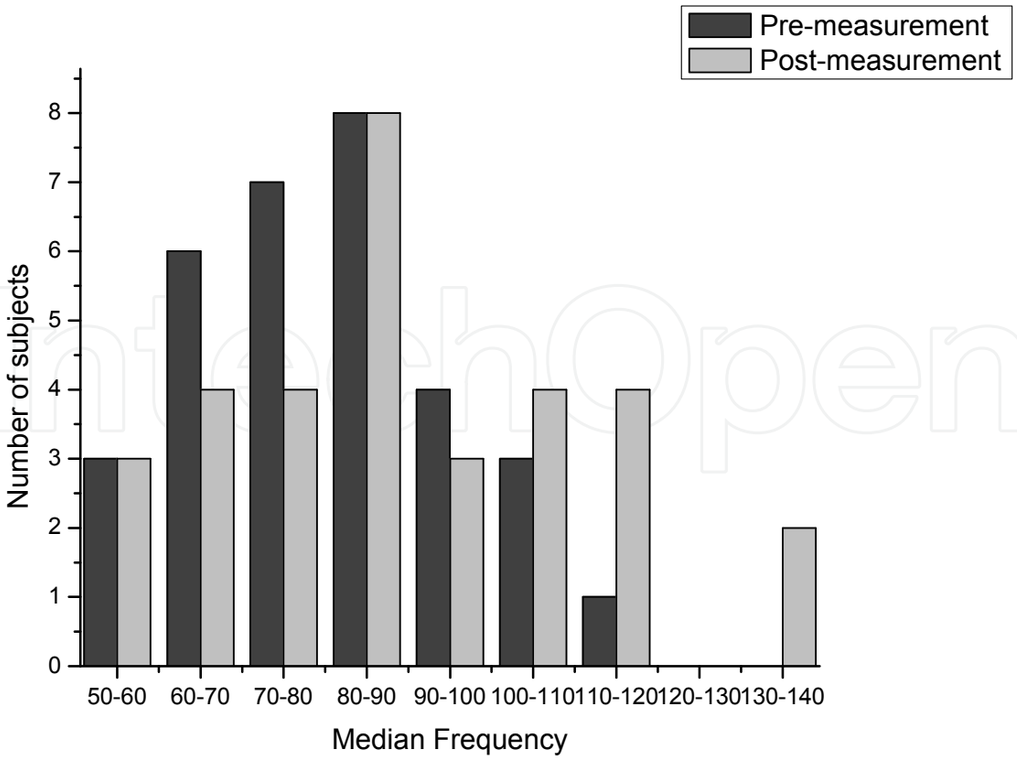


Fig. 12. Histogram of median frequency measurements for the right back muscle.

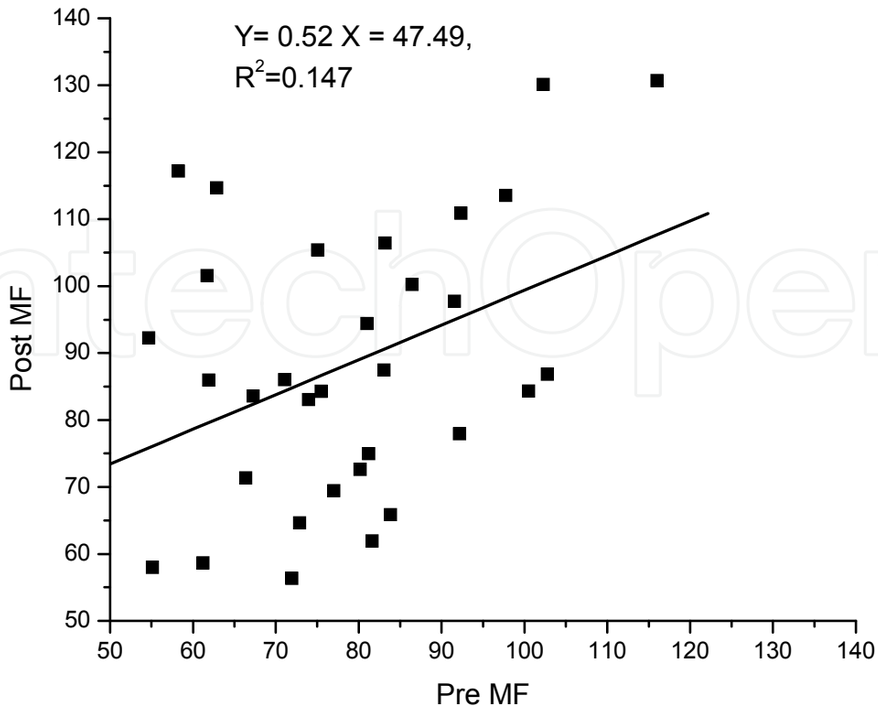


Fig. 13. The median frequency for the right back muscle at two different measurements. The correlation coefficient is R=0.38.

Overall, the entropy measurements for back muscles were more reliable than the power spectrum measures based on between-day reliability. Although there were no significant differences for between-day reliability for both entropy and MF slope, the test-retest reliability based on ICC values was higher for the entropy measure. The results of this study indicated that the complexity of time series analysis is a more reliable measure for the adaptability of biological systems than power spectral analysis.

A clinical assessment of LBP is important to objectively identify subjects with genuine pain and to assess the efficacy of therapeutic interventions. The entropy values from two measurements had the highest correlation, and we concluded that entropy is the most reliable measure from the low back muscles. The correlation of the MF slope and MF also demonstrated weak correlations and were statistically insignificant. Although there is a positive correlation between pain level and MF slope in back muscles, it is possible that the statistical use of correlation coefficients based on several validation studies was poor for reliability studies (Meyer, 1994).

In conclusion, it is important to compare the difference between nonlinear time series and power spectrum analysis regarding the irregularity of signals in biological systems. The quantities derived from nonlinear time series analysis of EMG signals will be compared with power spectrum analysis between subjects with and without musculoskeletal dysfunction/pain.

2.4 Sensitivity of surface electromyography analysis

As reported in our previous studies, the complexity of physiologic time series is a sensitive measure for muscle fatigability (Lee *et al.*, 2010). However, it is necessary to determine

whether the observed Shannon (information) entropy, as compared with MF, was able to differentiate fatigability of the thoracic and lumbar parts of the erector spinae muscle following the intervention. Previously, our lab investigated tools for evaluating back muscle fatigability after spinal stabilization exercises in participants with chronic LBP (Lee *et al.*, 2010; Sung *et al.*, 2005; Sung *et al.*, 2008a; Sung *et al.*, 2010). The results of our previous study indicated that Shannon entropy might be a valuable tool to measure the differences of outcomes following the exercise intervention. The results indicated that the participants' pain levels decreased significantly after 4 weeks of spinal stabilization exercises. The entropy of the EMG signals also decreased and significantly interacted with pain level. The slope of the MF based on power spectrum analysis also decreased but did not demonstrate any interaction with pain level. Therefore, the entropy of the EMG signals might be a useful tool for measuring LBP.

In addition, the results indicated that the entropy clearly differentiated the two groups. However, the results of power spectrum analysis based on complexity of the EMG signal could be calculated with the entropy of the time series. The results indicated that healthy subjects revealed significantly larger entropy values than the subjects with LBP. These findings consistently demonstrated a connection between physiologic "health" and complexity (Costa *et al.*, 2003; Costa *et al.*, 2005; Li & Huston, 2002). Another important finding indicated that the entropy levels of the EMG signals demonstrated significant interactions between muscles and groups following treatment for muscle endurance. However, the MF did not demonstrate this interaction. The significant interaction effect of the entropy between muscles and groups following treatment during the one-minute back extension test supports the characteristics of the recorded signals that occurs with fatigue (Roy *et al.*, 1989). Exercises for graded activity programs can be used to increase trunk muscle endurance and to decrease pain (Jorgensen & Nicolaisen, 1986; Jorgensen & Nicolaisen, 1987). Undoubtedly, other muscles participated in the load sharing during the testing as well as when subjects performed the intervention exercises. The attachment of the lumbar muscles, rather than the thoracic back muscles, results in an effective lever arm for lumbar stabilization. Therefore, the lumbar muscle is more effective in creating a stabilizing moment over the lumbar vertebral segments during the test (Flicker *et al.*, 1993; MacIntosh & Bogduk, 1986).

Research in biology and medicine has shown that fluctuations in physiological systems may play a significant role (Costa, 2002; Goldberger *et al.*, 2002a; Liu *et al.*, 2002). In fractal physiology, the apparent random, or chaotic, signal is observed on different (time) scales. It is found that the signal looks similar, or self-similar. This means that a single time scale (e.g., the period of oscillation) is replaced by a family of time scales. It follows that the single state of the system is replaced by multiple non-equilibrium states that are correlated with each other. If the signal is completely random with no characteristic time scale, it would be modeled by "white noise" and the power spectrum would be flat with $P(f) \sim f0$. In general, the frequency spectrum is fitted to a power law $P(f) \sim 1/f\alpha$, with $0 < \alpha < 2$. In this case, the power spectrum does not define a MF. Other studies reported that for physiologic systems, a constant "output" requires other variables to fluctuate so that the system can adapt to sudden changes in demand or stimulus (Costa *et al.*, 2005). This extent of fluctuations in physiologic signals can be quantified by entropy calculated from their time series.

Nonlinear analysis is used to characterize "hidden" properties of physiologic time series. Following this approach, we interpreted the EMG signal in terms of a one-dimensional

random walk in discrete time. We found that the mean-square displacement increased linearly for short times $t < 20$ ms and is nearly flat for intermediate times 20 ms $< t < 400$ ms. This plateau behavior has been found for other biological systems and implies the existence of correlations in the signal (Costa *et al.*, 2005; Goldberger *et al.*, 2002a). However, these correlations cannot be explained within a linear model, and thus support the use of nonlinear analysis for EMG time series. This may also explain why the MF fluctuates during a sustained contraction, and why the connection between MF slope and LBP has proven elusive despite considerable efforts.

In conclusion, the nonlinear analysis to EMG time series was reviewed for low back muscles. The Shannon entropy is a standard measure of complexity and has been applied in cognitive science research, aging studies, heart failure research, and other fields (Allen *et al.*, 2004; Costa *et al.*, 2003; Costa *et al.*, 2005; Goldberger *et al.*, 2002a; Liu *et al.*, 2002). The time-dependent entropy of the EMG signal exhibits a plateau-like behavior which indicates the presence of long-time correlations in the signal. The plateau value of the entropy was lower for subjects with LBP than for individuals in the control group. This connection might prove to be useful in a clinical assessment of LBP. The existence of long-time correlations in the signal explains the large variability in the MF obtained from the power spectrum. The entropy clearly differentiated the two groups, whereas the MF exhibited significant overlaps between the groups.

3. Conclusion

This chapter covered comprehensive articles comparing the difference between nonlinear time series and power spectrum analysis regarding the irregularity of signals in biological systems. A clinical assessment of pain/dysfunction using EMG should be considered on properties of the signal that change drastically in the presence of pain/dysfunction. A shift in the MF of the spectrum is explained by the change in the velocity of the action potential, and it reflects a quantitative change of the signals. A change in the entropy of the signal also reflects a qualitative change in the physiologic system.

In this chapter, the quantities derived from nonlinear time series analysis of EMG signals was compared with power spectrum analysis between subjects with and without musculoskeletal dysfunction/pain. The fluctuations in physiologic signals can be quantified by entropy calculated from the nonlinear time series. The value of the entropy reflects the adaptability of biological systems; healthy systems are thus expected to have higher values than unhealthy systems. Finally, the distribution of the values of the entropy and power spectrum for a group of subjects with LBP and a group of healthy subjects was discussed.

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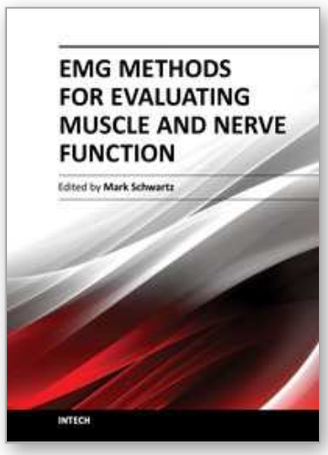

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This first of two volumes on EMG (Electromyography) covers a wide range of subjects, from Principles and Methods, Signal Processing, Diagnostics, Evoked Potentials, to EMG in combination with other technologies and New Frontiers in Research and Technology. The authors vary in their approach to their subjects, from reviews of the field, to experimental studies with exciting new findings. The authors review the literature related to the use of surface electromyography (SEMG) parameters for measuring muscle function and fatigue to the limitations of different analysis and processing techniques. The final section on new frontiers in research and technology describes new applications where electromyography is employed as a means for humans to control electromechanical systems, water surface electromyography, scanning electromyography, EMG measures in orthodontic appliances, and in the ophthalmological field. These original approaches to the use of EMG measurement provide a bridge to the second volume on clinical applications of EMG.

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