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# Comparison of spectral and entropic measures for surface electromyography time series: A pilot study

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**Abstract—**In a previous study, we reported that the mean square displacement calculated from the surface electromyography (sEMG) signal of low back muscles exhibits a plateaulike behavior for intermediate times 20 ms < $t$ < 400 ms. This property indicates the existence of correlations in the signal for times much longer than the inverse of the median frequency (MF), which is calculated from the power spectrum $1/\langle f \rangle = 1/(100\ \text{Hz}) = 10$ ms, where $\langle f \rangle$ is the MF. This result suggests the use of methods from nonlinear analysis to characterize sEMG time series. In this study, we applied these techniques to sEMG signals and calculated the time-dependent entropy. The results showed that the entropy of physiological time series from nondisabled control subjects is higher than the entropy from subjects with low back pain (LBP). The entropy reveals properties of the sEMG signal that are not captured by the power spectrum. In turn, this suggests a possible benefit of entropy as a tool for the clinical assessment of LBP. Because the two groups of subjects were not matched by age, the physiological origin of the observed differences between groups could be attributed to either LBP, age, or both. Additional studies with larger sample sizes and age-matched subjects are needed to investigate the relationship between LBP and entropy.

**Key words:** clinical assessment, complexity, disability, electromyography, entropy, fatigability, fluctuations, low back pain, nonlinear time series, time correlations.

## INTRODUCTION

Low back pain (LBP) is one of the most common types of musculoskeletal pain [1–2]. The number of physician visits resulting from LBP is second only to cardiovascular problems among chronic disorders. A clinical assessment of LBP is important for physicians to objectively identify subjects with genuine pain and to assess the efficacy of therapeutic interventions. Surface electromyography (sEMG) is a noninvasive tool that might be helpful in the assessment of LBP. The signals recorded during an sEMG test from surface electrodes are the instantaneous algebraic summations of action potentials from muscle fibers. These signals are recorded and then processed with a power spectrum analysis. The median frequency (MF) is defined as the frequency at which the spectrum is divided into two equal parts [3]. The typical MF range is from 70 to 120 Hz [4], which corresponds to a time scale of 10 to 20 ms.

The connection between fatigue and sEMG spectral parameters is the basis for the use of sEMG as an objective and noninvasive method of assessment of back muscle endurance [5–6]. The original study linking LBP with fatigue was presented by De Luca [6]. He found that subjects with LBP have less endurance and thus smaller MF

**Abbreviations:** CSU = Cleveland State University, FFT = fast Fourier transform, LBP = low back pain, MF = median frequency, ODI = Oswestry Disability Index, SD = standard deviation, sEMG = surface electromyography.

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slopes during sustained muscle contractions [4–5,7]. However, contradictory results have been subsequently reported [4,8–9]. Humphrey et al. reported that MF slope is not better than chance in predicting LBP in subjects [8]. Thus, despite considerable efforts, a connection between spectral quantities and musculoskeletal pain and/or dysfunction remains elusive.

Several groups have examined whether other quantities derived from sEMG signals are better indicators for LBP. For example, Ng et al. examined changes in the sEMG amplitude during a sustained contraction [10]. Another study found that amplitude-related characteristics of motor units can help to avoid misleading interpretations of sEMG changes [11]. Ravier et al. pursued a different approach and fitted the sEMG frequency spectrum to $P(f) \sim 1/f^{\alpha}$ behavior, where $P$ is the power of the signal, $f$ is the frequency, and $\alpha > 0$ is an exponent [3]. Such behavior was originally derived for "self-organized" systems such as avalanches [12]. These results were obtained with nonlinear analysis of physiological time series which, in turn, is based on the recent discovery that fluctuations in biological signals are characterized by several time scales and amplitudes [12–13]. Costa et al. suggested that a relatively constant output of a physiological system implies large fluctuations of other system variables [14]. In this manner, the physiological system can adapt to sudden changes in demand and stimulus. The extent of fluctuations in physiological signals can be quantified by entropy calculated from time series.

In our previous study, we reported the results of a nonlinear analysis of sEMG time series from low back muscles [15]. We calculated the mean square displacement $\Delta$ as a function of time $t$. We found that the mean square displacement increases diffusively for short times ($t$ < 30 ms) and then approaches a plateau value. This crossover implies a transition from an absence of correlations in the signal to antipersistence behavior. Similar transitions from short- to long-time behavior have been observed for other physiological time series [16–17]. Because the mean square displacement is related to the entropy $S$ of the signal, $S \sim \ln \Delta$ (where ln denotes the natural logarithm), the plateau value can be used to characterize the sEMG signal [15]. This pilot study examined whether measures of complexity or measures based on the frequency spectrum are better indicators for differentiating between control subjects (nondisabled) and those with LBP. Based on the proposed connection between entropies of physiological time series and disease, we expect that subjects with LBP have lower entropy than control subjects.

## METHODS

### Selection of Subjects

Because of sex differences and variability in electromyographic amplitude and MF, only male subjects were included in this study. Subjects were recruited from a community in Cleveland, Ohio. The subjects in the control group did not report a recent history of LBP based on questionnaires. Subjects with LBP were defined as individuals who reported the continued presence of LBP symptoms for at least 2 months [18]. The characteristics of subjects are shown in **Table 1**. The two groups were matched except for age, with control subjects significantly younger than LBP subjects.

Subjects in the LBP group were eligible to participate if they (1) reported LBP with or without pain referral into the lower limbs, (2) were at least 21 years old, and (3) indicated a willingness to participate in the study. Patients were ineligible to participate if they had (1) overt neurological signs (sensory deficits or motor paralysis); (2) a diagnosed psychological illness that might interfere with the study protocol; (3) difficulty understanding written or spoken English (which precluded them from completing questionnaires); (4) any spinal muscle damage or

**Table 1.**
Summary of control ($n$ = 10) and low back pain (LBP) ($n$ = 10) subjects with selected demographics (Mann-Whitney U test).

| Variable | Control | LBP | $p$-Value |
|---|---|---|---|
| Age (yr) | | | |
| Range | 23–42 | 28–63 | 0.01* |
| Mean ± SD | 30.20 ± 4.91 | 49.70 ± 10.82 | |
| Height (cm) | | | |
| Range | 167–191 | 165–184 | 0.68 |
| Mean ± SD | 177.12 ± 8.62 | 175.25 ± 7.05 | |
| Body Weight (kg) | | | |
| Range | 67–95 | 60–109 | 0.79 |
| Mean ± SD | 77.14 ± 10.27 | 80.81 ± 16.18 | |
| Body Mass Index | | | |
| Range | 22.2–27.3 | 19.7–32.6 | 0.31 |
| Mean ± SD | 24.50 ± 1.73 | 26.17 ± 4.11 | |

*$p$ < 0.05.
SD = standard deviation.

weakness from previous surgery around the trunk, or open abdominal surgery; or (5) spinal fractures and acute neurological symptoms. Volunteers without LBP were eligible to participate if they met the study inclusion criteria. Participants were removed from the study if they asked to withdraw.

Since results from an earlier study indicated the effect of hand dominance on back pain, we used a modified Edinburgh Handedness Inventory to determine the dominant side for activities of daily living [19]. All subjects received information about the purpose and methods of the study and signed a consent form that the Cleveland State University (CSU) Institutional Review Board approved.

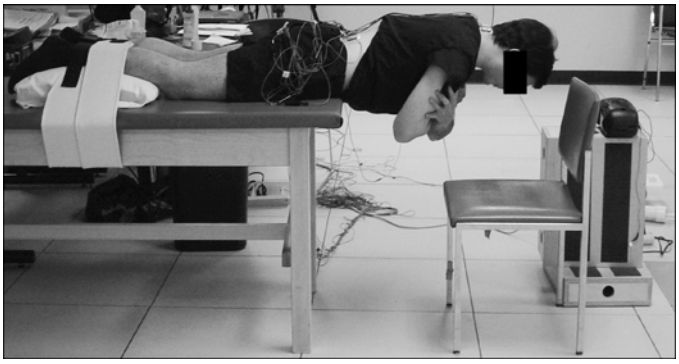

**Figure 1.**
Modified Sorenson test for fatigue measurements. Subjects, with EMG electrodes attached over muscles of low back, lay prone while lifting and holding their trunks off of table until completely exhausted.

### Level of Disability

Patient disability was inferred from self-reported scores on the Oswestry Disability Index (ODI), which was given to each subject during the initial testing sessions. The ODI is one of the most frequently used tools for measuring chronic disability and is presented as a percentage [20–21], where 0 percent indicates no disability and 100 percent indicates the worst possible disability [22]. The mean ODI score for the LBP group was 21.2 ± 3.2 percent, with a range of 16.1 to 23.5 percent (values are shown as mean ± standard deviation [SD] unless otherwise noted). The control group did not report any level of pain or disability.

### Electromyographic Recording

We used the modified Sorenson isometric fatigue test introduced by Mayer et al. [23]. Subjects were asked to lie in a prone position on a table and to sustain their unsupported trunks horizontally against gravity for 1 minute while their lower body was strapped to the table at a 0° angle [24]. The subjects' upper bodies were positioned with their iliac crests at the edge of the table. Their lower bodies were secured at the ankles with seat belt straps. The subjects held their arms across their chests with each hand placed on the opposite shoulder, and they held a horizontal position until exhausted (**Figure 1**). We discontinued the tests once the subjects could no longer maintain a horizontal position level to the table. The subjects were allowed to reposition their upper bodies one time during the tests. Verbal encouragement was given throughout the test for all subjects.

The sEMG electrodes were placed bilaterally over the erector spinae muscles at the lumbar 4–5 level, with a 10 cm distance between electrodes of each pair. We prepared the skin by shaving excess hair and rubbing the skin with alcohol to reduce impedance (typically 10 kΩ). Predetermined landmarks were used as a guideline for electrode placement. The electrodes were placed over the erector spinae muscle parallel to the orientation of the muscle fibers. The electrode sites and the distance of the electrodes were carefully determined for each subject according to Zipp [25]. We collected sEMG data using differential (interelectrode distance of 20 mm with 8 mm diameter), preamplified (gain of 35), silver-silver chloride sEMGs (Therapeutics Unlimited, Inc; Iowa City, Iowa) during the approximately 1-minute testing period. The analog signal was converted digitally at a rate of 1024 Hz (AT-MIO-64E-3, National Instruments, Austin, Texas) and bandpass-filtered at 10 to 400 Hz. We performed data acquisition using AcqKnowledge® software (BIOPAC Systems, Inc; Goleta, California), and analyzed the resulting data in MathCAD (The MathWorks, Inc; Natick, Massachusetts). Standard recommendations of sEMG procedures were followed with regard to myoelectric manifestations of muscle fatigue during sustained contractions [26].

We used fast Fourier transform (FFT) to obtain the frequency spectrum for each 1-second time interval, from which we found the MF. Using linear regression, we then calculated the extrapolated value of the initial MF and the MF slope during the 1-minute testing period.

### Nonlinear Time Series Analysis

We imported sEMG data files into the MathCAD package, which we then used for the subsequent mathematical analysis. The variance of the sEMG signal during 1-second

time intervals was calculated and is shown in **Figure 2** for the control and LBP groups, respectively. The variance remained constant and did not exhibit any significant time dependence during the 1-minute test. However, the variance peaked sharply at the beginning and/or end of the test period for some subjects. Because of this peak, the raw sEMG time series $y_i$ was averaged during a 10 ms moving window: $x_i = (y_i + y_{i+1} + \ldots + y_{i+9})/10$. The reduced time series consisted of approximately 6,000 values $x_i$ (in millivolts), where subscript $i$ equals 0.01 s time increments. As a result, the short-time behavior of the signal ($t < 10$ ms) was averaged.

Since the variance showed no systematic time dependence, the sEMG time series is consistent with a stationary random process. However, more stringent tests are needed for confirmation of these results. The description of the sEMG signal at a random walk (Brownian motion) is based on the interpretation of the signal $x_j$ at time $j$ as random jumps at discrete times. It follows that the sum $X(t) = x_j + x_{j+1} + \ldots + x_{j+t}$ in between times $j$ and $j + t$. The mean square displacement is defined as $\Delta(t) = \langle [X(t) - \langle X(t) \rangle] \rangle$. Here, $\langle\rangle$ indicates the average with respect to the initial time $j$.

The Shannon (information) entropy ($S$) of the time series quantifies the degree of "noisiness" of a signal. After dividing the range of $X(t)$ into 100 equal-sized bins, we determined the probabilities $P_i$ from the histogram. The entropy was calculated as $S = -\Sigma P_i \ln P_i$. Following standard practice, entropy was reported in arbitrary units (dimensionless). If the displacement $X$ follows a Gaussian distribution, the entropy is approximately proportional to the logarithm of the variance; e.g., $S(t) \sim \ln[\Delta(t)]$. **Figure 3** shows the plateaulike behavior, which is followed by diffusive behavior for the control and LBP groups, respectively. This plateau value of $S(t)$ is referred to as entropy.

### Statistical Analysis

We completed statistical analyses using SAS 8.2 (SAS Inc, Cary, North Carolina). Nonparametric data analyses were used, since the data were not normally distributed. We inspected descriptive statistics for sample characteristics and scatter plots of the data to ensure that no outliers existed in the data set. We analyzed the MF, its slope change, and the level of entropy with a Mann-Whitney U test to compare differences between groups. We used the Spearman correlation analysis ($r_s$) to analyze the degree of association between variables. For all statistical tests, type I error rate ($\alpha$) was set at 0.05.

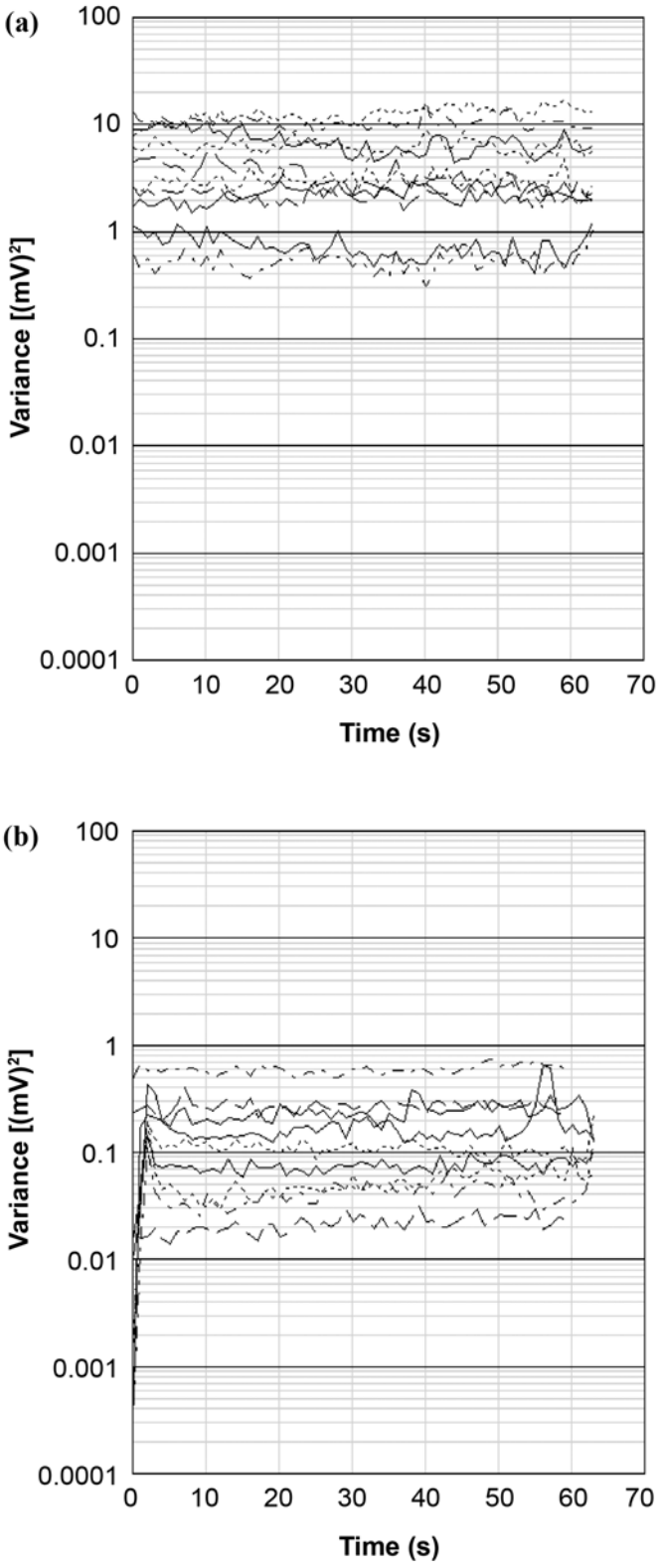


**Figure 2.**
Variance (logarithmic scale) versus time for **(a)** control and **(b)** low back pain groups.

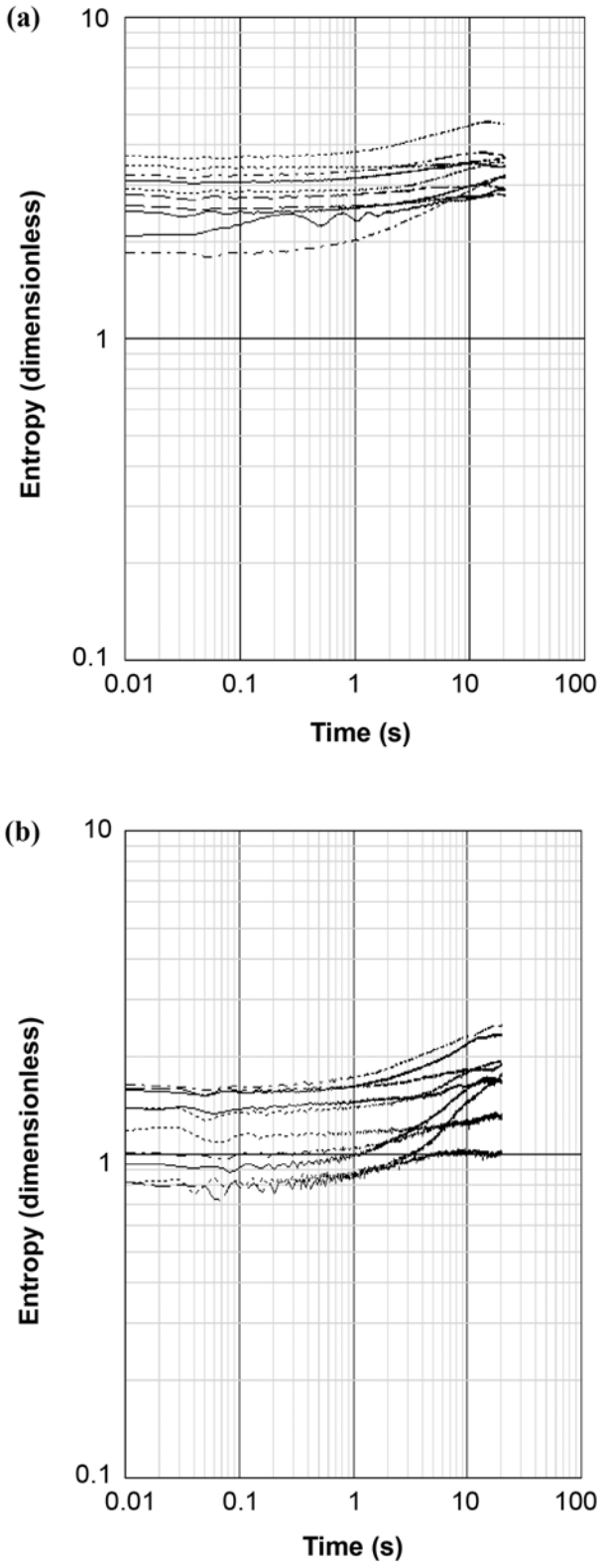


**Figure 3.**
Entropy (logarithmic scale) versus time for **(a)** control and **(b)** low back pain groups.

## RESULTS

**Table 1** indicates the anthropometric data of the two groups. We note that the two groups differ by age ($p < 0.01$). No significant differences were found between groups for height, weight, and body mass index, however. To clarify the age relationship within groups, we analyzed Spearman correlation coefficients ($r_s$). The results for the MF, MF slope, and entropy are summarized in **Table 2**. The mean MF was 98.5 ± 20.0 Hz for the control group and 88.3 ± 29.4 Hz for the LBP group; this difference was not significant ($p < 0.32$). The highest and lowest MFs in this study were found among subjects in the LBP group, and the two distributions completely overlapped (**Figure 4**).

The mean ± SDs of the MF slope for the control and LBP groups were –0.40 ± 0.16 Hz/s and –0.18 ± 0.15 Hz/s, respectively. In **Figure 5**, the distribution of the MF slope

**Table 2.**
Measurement results of median frequency (MF), MF slope, and entropy for control and low back pain (LBP) groups.

| Subjects | MF (Hz) | MF Slope (Hz/s) | Entropy (dimensionless) |
|---|---|---|---|
| Control ($n$ = 10) | | | |
| A | 113.0 | –0.39 | 2.51 |
| B | 82.0 | –0.34 | 2.86 |
| C | 112.0 | –0.63 | 2.75 |
| D | 119.8 | –0.46 | 3.23 |
| E | 102.2 | –0.37 | 2.42 |
| F | 71.4 | –0.32 | 3.68 |
| G | 106.3 | –0.43 | 2.55 |
| H | 97.5 | –0.12 | 1.89 |
| I | 118.3 | –0.62 | 3.08 |
| J | 62.7 | –0.23 | 3.39 |
| LBP ($n$ = 10) | | | |
| A | 121.6 | –0.38 | 0.92 |
| B | 84.5 | –0.29 | 1.32 |
| C | 83.8 | –0.11 | 1.56 |
| D | 147.9 | –0.36 | 1.62 |
| E | 106.2 | –0.21 | 1.39 |
| F | 58.2 | –0.01 | 1.13 |
| G | 59.6 | 0.05 | 0.82 |
| H | 59.2 | –0.02 | 1.00 |
| I | 73.9 | –0.14 | 1.55 |
| J | 87.8 | –0.27 | 0.79 |

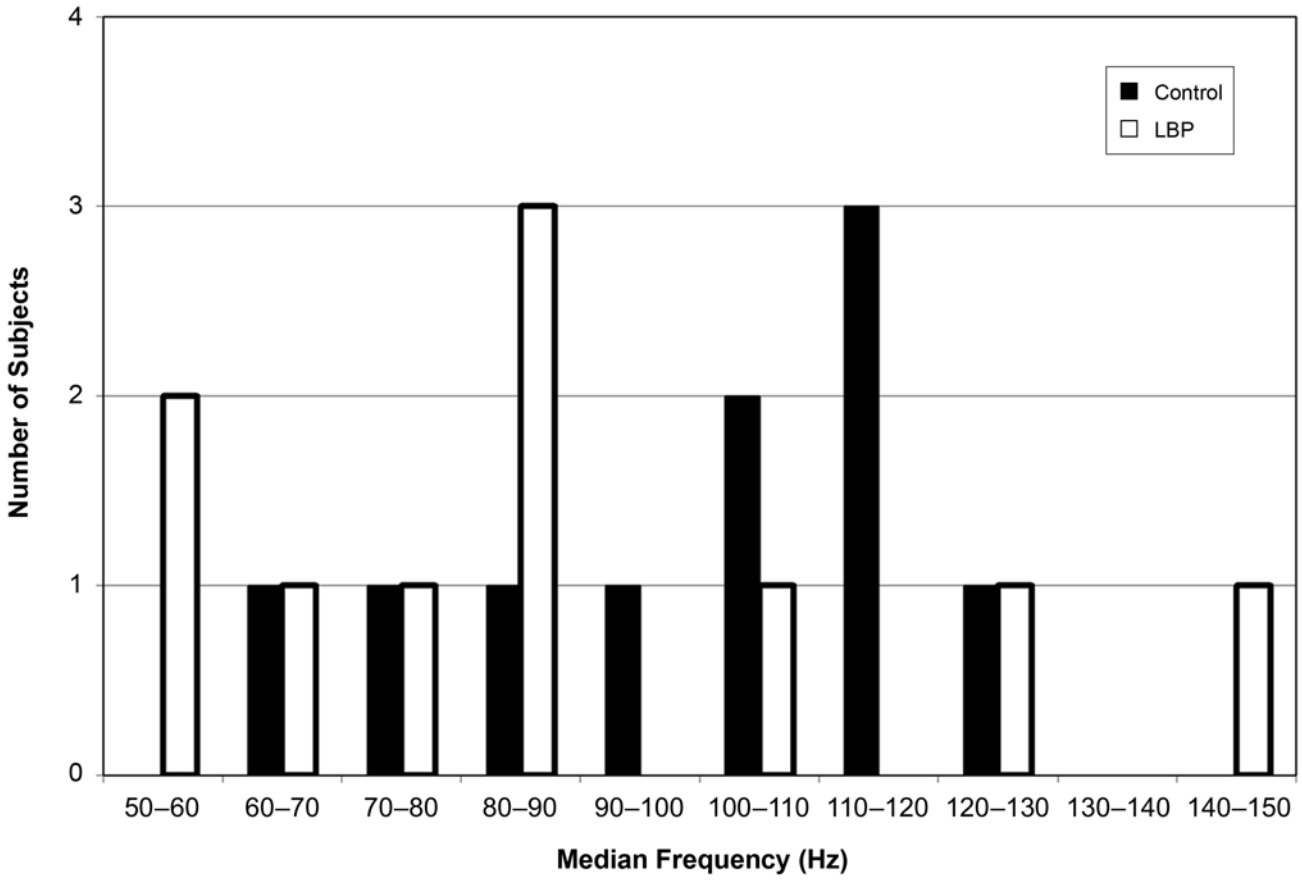


**Figure 4.**
Histogram of median frequency for control and low back pain (LBP) groups.

for the two groups demonstrated significant overlap. Results show that the MF slopes for subjects with LBP tend to be smaller than those for subjects in the control group. A statistical analysis of the MF slopes suggested that this difference was significant ($p = 0.07$).

**Figures 2** and **3** indicate that both the variance and entropy were higher for the control group than for the LBP group. Indeed, the variance and entropy provide the identical ordering of subjects, which suggests that these quantities are related to each other. The histogram of the entropy for the two groups is shown in **Figure 6**. The entropy was significantly higher for the control group ($2.8 \pm 0.5$) than for the LBP group ($1.2 \pm 0.4$) with $p = 0.001$. The distributions demonstrated peaks at $S = 2.75$ and $S = 1.25$ for the control and LBP groups, respectively. The small entropy tail of the distribution for the control group overlaps with the large entropy tail of the distribution for the LBP group.

We then examined whether the entropy of the sEMG signal is related to parameters calculated from the FFT spectrum of the time series. In **Figure 7**, we plotted the MF versus the entropy with open circles representing subjects with LBP and solid circles representing control subjects. The two groups are separated by the vertical line $S = 2.0$, with $S > 2.0$ for the control group and $S < 2.0$ for the LBP group. We conclude that the two groups are differentiated by entropy but not by MF values. A statistical analysis showed no significant correlation between MF and entropy ($r_s = 0.169$, $p > 0.05$). In **Figure 8**, the MF slope versus the entropy was plotted. Of the 10 control subjects, 8 fall within the quadrant $S > 2.0$ and MF slope $< -0.3$, while 8 of the 10 LBP subjects fall within the quadrant $S < 2$ and MF slope $> -0.3$. These results showed that the MF slope and the entropy are weakly correlated; subjects with LBP tend to have larger (i.e., less negative) MF slopes and smaller entropies than control subjects. A statistical analysis yielded $r_s = -0.41$ with $p < 0.04$.

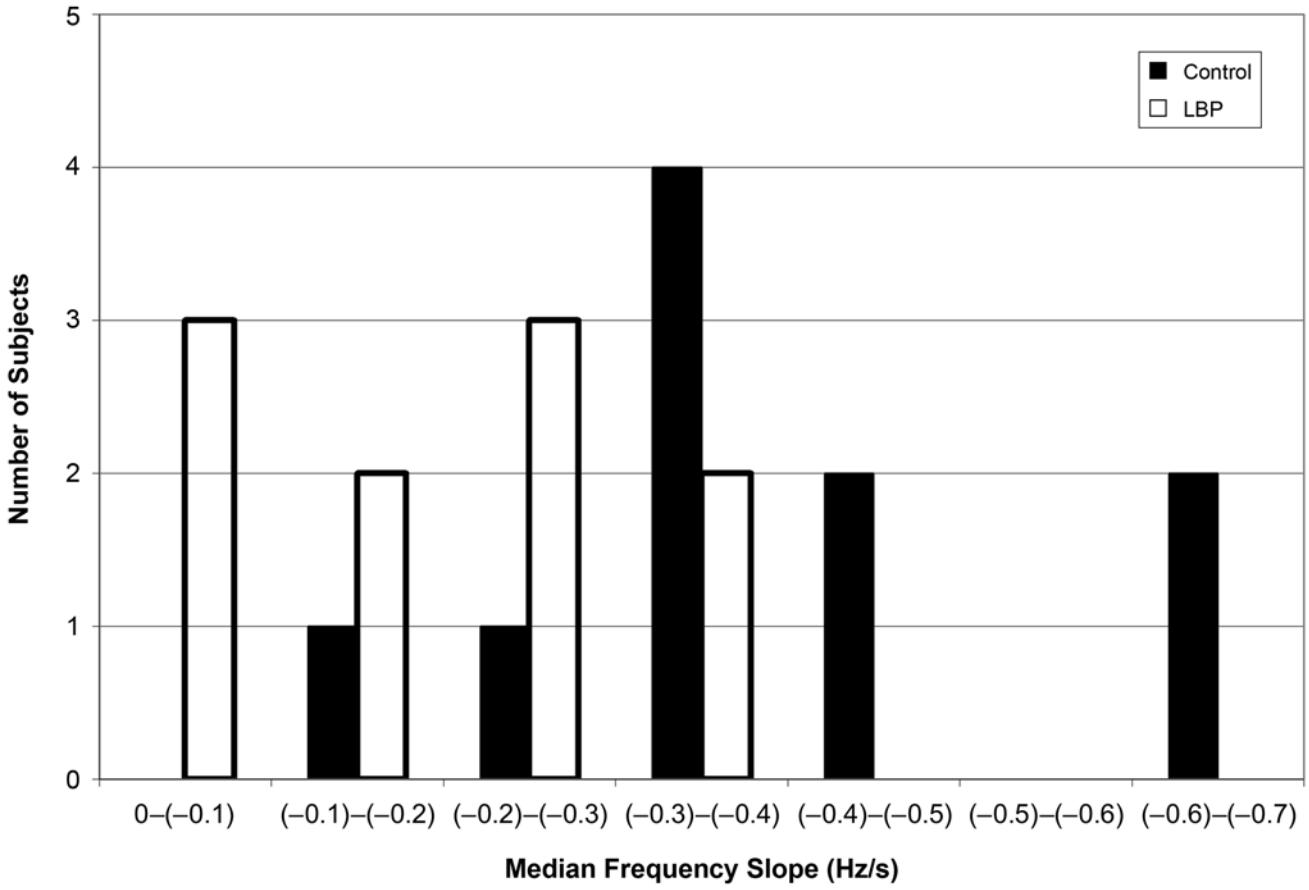


**Figure 5.**
Histogram of median frequency slope for control and low back pain (LBP) groups.

## DISCUSSION

The results of this study indicated that the entropy clearly differentiated the two groups. However, the results of power spectrum analysis based on the distributions of MF and MF slope indicated a significant overlap with contradictory results between the two groups. In this pilot study, we focused on the complexity of the sEMG signal and calculated the entropy of the time series. Our results indicated that the control subjects revealed significantly larger entropy values than the subjects with LBP. Thus, our findings consistently demonstrated a connection between physiological "health" and complexity [14,27–28].

Research in biology and medicine has shown that fluctuations in physiological systems may play a significant role [29–31]. In fractal physiology, the apparent random, or chaotic, signal is observed on different (time) scales. Research has found that the signal looks similar, or self-similar. This means that a single time scale (i.e., 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 nonequilibrium 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 frequency spectrum would be flat $P(f) \sim f^{0}$. 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 an MF. Other studies reported that for physiological systems, a constant "output" requires other variables to fluctuate so that the system can adapt to sudden changes in demand or stimulus [14]. This extent of fluctuations in physiological signals can be quantified by entropy calculated from their time series. Costa et al. suggested that the value of the entropy reflects the adaptability of biological systems [29]; healthy systems are thus expected to have higher values

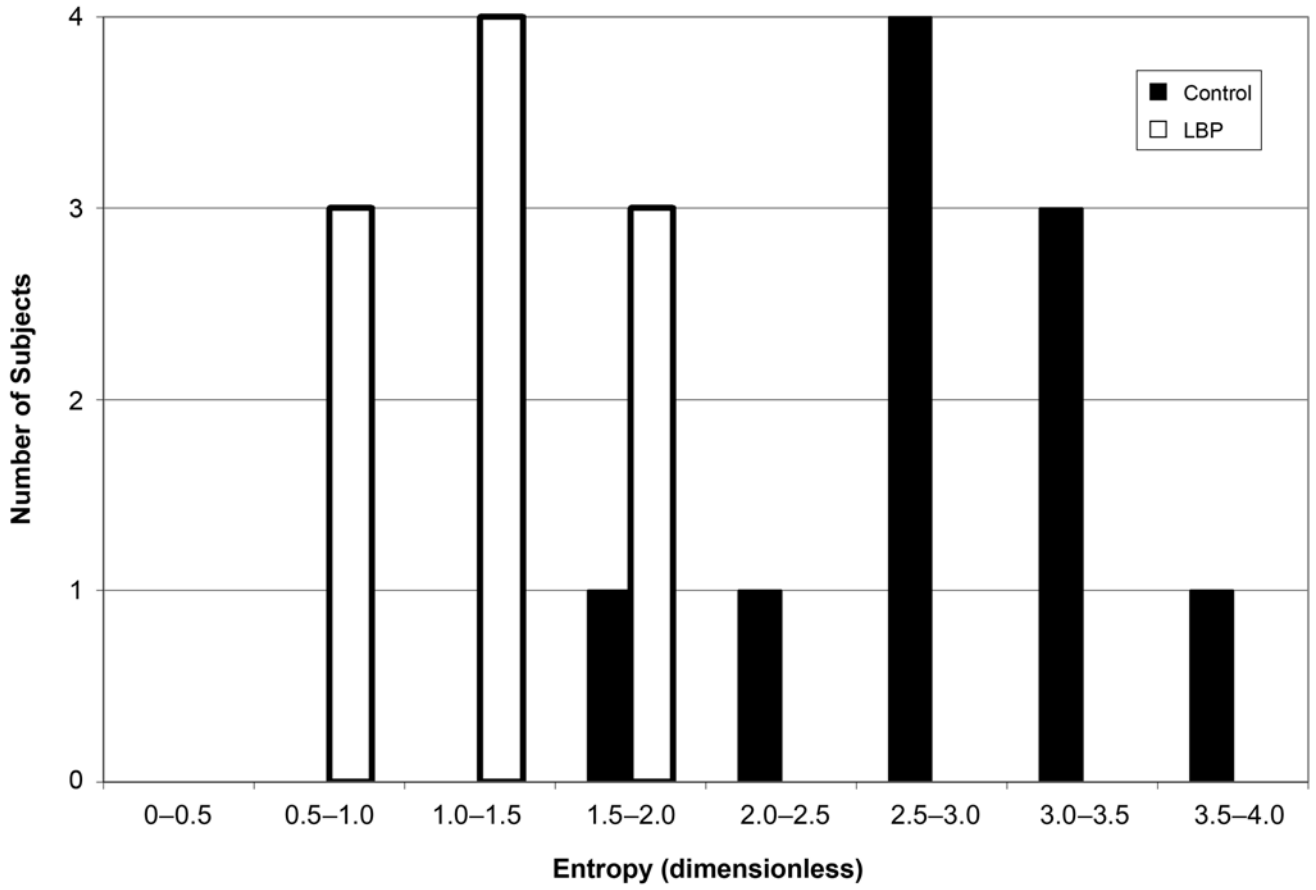


**Figure 6.**
Histogram of entropy for control and low back pain (LBP) groups.

of entropy than unhealthy systems. Nonlinear analysis is used to characterize "hidden" properties of physiological time series. Following this approach, we interpreted the sEMG signal as a 1-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 [14,30]. However, these correlations cannot be explained within a linear model and thus support the use of nonlinear analysis for sEMG time series. This finding 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.

The aim of the study was not to identify the underlying physiological origin of the observed values of entropy. Rather, this pilot study examined whether measures of complexity or those based on the frequency spectrum are better indicators to differentiate between control subjects and those with LBP. In this study, the group of subjects with no history of LBP was referred to as the "control" group and the group with LBP included older subjects with at least a 2-month history of LBP. That is, the two groups differ by both chronological age and history of LBP. Thus, the observed differences could be attributed to LBP, age, or both. We note that the design of the study does not allow for identifying the underlying physiological reason for observed differences between the two groups. Other anthropometric data (height, weight, and body mass index) showed no significant differences between the two groups. Further studies are needed to consider the effects of anthropometric data on spectral and entropic measures for sEMG time series. For example, an interesting study would be the examination

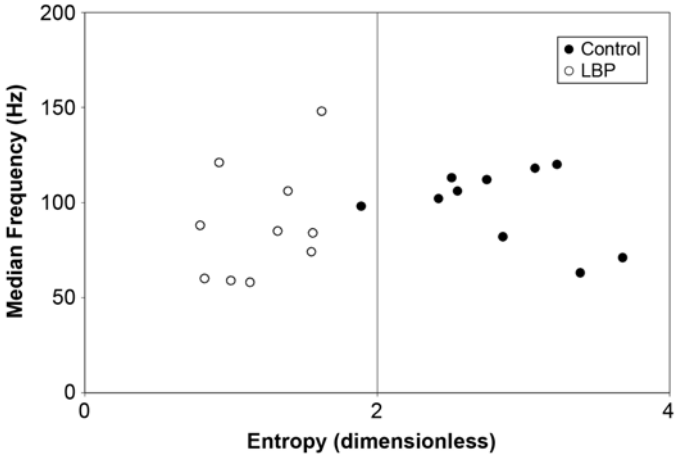


**Figure 7.**
Median frequency versus entropy for control and low back pain (LBP) groups.

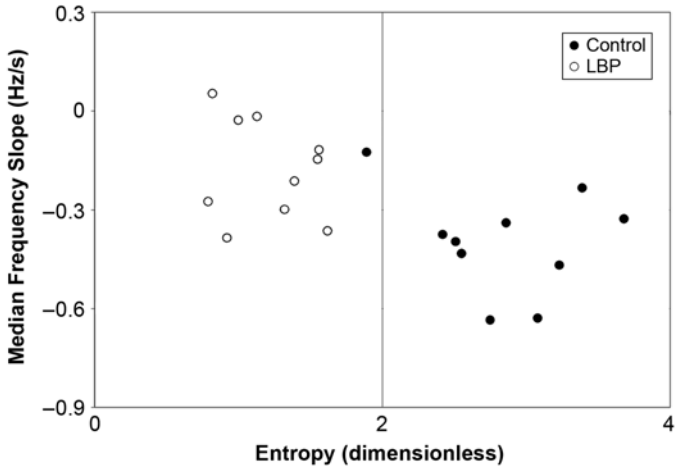


**Figure 8.**
Median frequency slope versus entropy for control and low back pain (LBP) groups.

of the differences in entropy, if any, between the right and left sides of the body [24].

The small sample size of this study is not sufficient to establish a cause-and-effect relationship between complexity measures of sEMG and a clinical diagnosis of LBP. However, future studies should have larger sample sizes and exclude confounding variables reflected in individual variations. Furthermore, this study does not address the reliability of both the spectral and entropic measures of sEMG time series, since the signal was recorded only during a single testing session for each subject.

## CONCLUSIONS

We applied methods from nonlinear analysis to sEMG time series of 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 [14,28,30–32]. The time-dependent entropy of the sEMG signal exhibits a plateaulike behavior that indicates the presence of long-time correlations in the signal.

We found that the plateau value of the entropy was lower for subjects with LBP than for individuals in the control group. This connection might prove useful in a clinical assessment of LBP.

The existence of long-time correlations in the signal explains the large variability in the MF and MF slope obtained from the power spectrum. The entropy clearly differentiated the two groups, whereas the MF and MF slope exhibited significant overlaps between the groups. Further studies are needed to identify the physiological origin of the observed difference in the plateau entropy.

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The authors have declared that no competing interests exist.

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