# EFFECTS OF CONDUCTION VELOCITY AND SPECTRAL COMPERSSION ON FRACTAL PARAMETERS OF MYOELECTRIC SIGNALS

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**Abstract**-Myoelectric signals undergo spectral compression during muscle fatigue, which is largely due to an underlying mechanism of decreasing muscle fiber conduction velocity. To examine the effects of spectral compression and changes of the conduction velocity on the fractal parameters of the myoelectric signals, we evaluate fractal indicators extracted from the power spectrum in this context. In this study, the myoelectric signals are simulated using a structural model. Fractal indicators are computed using a novel general power spectrum method. We have previously showed that these indicators are capable of sensing force and joint angle independently. These experimental results show fractal indicators provide measures independent from spectral compression, further demonstrating the potential of this form of myoelectric fractal analysis.

## I. INTRODUCTION

The surface myoelectric signal (MES) provides a noninvasive measure of neuromuscular activities and electrical behavior of the muscle, and is widely employed in biomedical and rehabilitation engineering applications [1]. One important application of the surface MES is in studying muscle fatigue [1-4]. It is a well established that the MES interference pattern (IP) undergoes changes during sustained muscular contractions; in particular, muscular fatigue is related to a compression of the MES power spectrum density (PSD) towards lower frequencies [5]. There are many factors which contribute to this PSD compression such as decreasing firing rate of the active motor units (MUs), changes in synchronization of MUs and their recruitment strategies, and decreasing muscle fiber conduction velocity (CV) [5-6]. It is generally well accepted that the dominant underlying mechanism leading to the PSD compression is the decreasing CV. The true nature of this decrease is not yet fully understood; however, it has been suggested that this might be caused by the accumulation of metabolic byproducts such as lactic acid which causes a decrease in membrane excitability and the muscle fiber CV [6]. When the CV is decreased, the observed MU action potentials (MUAPs) expand along the time axis, which causes the frequency content of the MES to shift towards lower frequencies. This spectral compression can be conventionally monitored using a single characteristic frequency, such as the first spectral moment, mean frequency (MNF), 50$^{th}$ percentile frequency, or median frequency (MDN), which is the index most commonly used to track muscle fatigue [7-8].

Recently, alternative approaches have been employed for fatigue monitoring. For example, calculating the mean shift in all percentile frequencies (i.e. from the 5$^{th}$ to 95$^{th}$ percentile frequency) [9], dividing the PSD into a series of frequency bands [10], and the spectral distribution technique [11], which is a method for detecting small variations in the shape of two arbitrary signals. While these new techniques provide a more comprehensive indication of PSD compression, significant improvement compared to single characteristic frequencies is not clear.

In recent years, techniques developed for the analysis of nonlinear and chaotic systems have been also applied to MES in context of muscular fatigue by a few authors [12-13]. In [12] multi-fractal characteristics of MESs based on generalized entropy and *Renyi* dimensions is examined in the presence of muscle fatigue and it is shown that the *Renyi* dimensions show a general pattern caused by the fatigue; however, results of this study are debatable mainly because the *Renyi* dimensions of this approach are calculated based on the *Hausdorff* definition of dimension, with a single slope computed in a bi-logarithmic plot. We have shown in [14] that this is not an efficient way of dealing with MESs because they show more general self-affine characteristics compared to ideal random scaling fractals (RSFs); therefore, the classic power law may not be appropriate. In [13] the $1/f^{\alpha}$ behavior of the MES PSD is examined, with a partitioning algorithm. The MES PSD is divided into two low and high frequency regions with respect to the peak of the PSD and each portion is modeled by a single line in the form of an ideal RSF. The slope of each line is considered as a fractal indicator. The authors conclude that these spectral slopes are not sensitive to muscle fatigue mainly because they are not changed in a bi-logarithmic plot when a spectral compression occurs (i.e. $1/f^{\alpha} \rightarrow 1/(\beta f)^{\alpha}$). This piece-wise $1/f^{\alpha}$ approach, applicable to the partitioned power spectrum of MES, is potentially accurate computationally; however, there is some confusion in this methodology. Firstly, considering MES PSD compression to be uniform, as discussed by [13], may be too simplistic and is in contrast with non-uniform PSD compression reported by [9] and [10]. Secondly, this partitioning criterion is not necessarily the optimal method for partitioning the power spectrum. Thirdly, high and low frequency indicators (i.e. spectral slopes) are computed separately and how they are related to each other is vague. Fourthly, approximating the curve of the MES power spectrum with two lines as it is done in this approach is not highly efficient, nor representative of the true power spectrum.

In this paper, we will examine effects of conduction velocity and spectral compression on fractal parameters of simulated MESs, which are extracted using a more sophisticated fractal analysis method; namely, the general power spectrum method (GPSM), as introduced in [14]. The results are compared to the piece-wise $1/f^{\alpha}$ approach.

## II. METHODS AND MATERIALS

### A. Simulations

Simulated MESs enables the analysis of the effects of CV on fractal parameters in isolation, removing confounding effects of other physiological changes. MESs were simulated using a general purpose structural model-based simulator [15]. In this simulator, single fiber action potentials (SFAPs) are summed and tissue filtered to compose a MUAP, and MUAPs are summed to produce the surface MES. Ten sets of MESs were generated for each CV value, which ranged from 4.5 to 6 m/s in steps of 0.1 m/s. Simulations were based on a sustained isometric moderate contraction of the *biceps brachii* and were carried out for bipolar electrodes 5 mm apart. The simulation parameters were used considering the available literature [16] and summarized in Table I.

Table 1: Simulation Parameters

| | |
|---|---|
| Source Duration | 3 msec |
| Num. of Fibers in MU | 40 |
| Distance from Innervation Zone to Electrode | 35 mm |
| Length of Fiber | 210 mm |
| Termination Dispersion | 1 mm |
| Innervation Zone Dispersion | 1 mm |
| Depth of MU | 25 mm<br>σ = 2.5 mm |
| Num. of MU | 50 |
| Firing Rate | 20 Hz<br>σ = 3 Hz |
| Sample Rate | 20 kHz |

### B. Processing

The PSD shape is greatly influenced by the PSD estimation method; thus, special care should be taken since the GPSM is sensitive to the PSD shape. The amplitude of the MESs was normalized before PSD estimation. The PSD of the MES was estimated using Welch's method [17]. The ergodicity and pseudo-stationary features of MESs make them well suited for such a time slice averaging PSD estimation algorithm. For averaging, a Hamming window with a temporal width of 512 samples was applied, with a 50% overlap between windows. Fractal indictors were computed using two methods: the Piece-Wise $1/f^{\alpha}$ Approach and the GPSM.

Piece-Wise $1/f^{\alpha}$ Approach: A random scaling fractal exhibits self-affinity and its PSD shows $1/f^{\alpha}$ behavior [18]. This behavior represents fractal properties of the signal's structure; that is, as we zoom into the signal by changing the scale, the distribution of amplitudes remains the same, subject to scaling with a single level dimension, which represents the complexity of the structure. The PSD of a RSF could be approximated by a single line and the slope of that line in a bi-logarithmic plot is related to the fractal dimension through a linear transformation and could be held as a fractal indicator (FI). In piece-wise $1/f^{\alpha}$ approach, the peak value of the MES PSD is used to partition the PSD into two regions. Each partition is modeled by one line and the bi-logarithmic derivatives are considered as FIs. These left slope and right slope, correspond to the low and high frequency partitions, respectively.

General Power Spectrum Method: There are noise-type signals which exhibit more general fractal behavior and show non-linear PSD behavior. In [14] we have introduced an irrational power law as Eq. (1) which is capable of representing almost any stochastic signal with some degree of self-affinity.

$$\hat{P}(f) = c\left|\frac{f}{f_0}\right|^{2g} \Bigg/ \left(\left(\frac{f}{f_0}\right)^2 + 1\right)^{q+g} \tag{1}$$

In Eq. (1), $c$ is a scaling factor, $f_0$ is the characeteristic frequency, $q$ is the high frequency indicator, and $g$ is the low frequency indicator of the PSD. A signal with such PSD is also self-affine in a more general way; that is, as we zoom into the signal the probability distribution of amplitudes remains the same, subject to scaling with a single level complexity factor related to $q$ and $g$, and the characteristic frequency of the distributions is also scaled. These parameters could also be held as FIs which contain textural information. This method provides a fairly accurate and precise representation for MES PSD as shown in Fig. (1).

Statistical analysis was performed using an ANOVA with a significance level $\alpha_T = 0.05$.

## III. RESULTS

In this section, all the plots show the mean and the standard deviation of the results, averaged for all ten sets of the simulated MESs. Fig. (2), shows a high correlation between the MDN and the CV. MDN is also significantly affected by the CV ($p < 0.001$).

Fig.(3) and Fig. (4), show that the spectral slopes extracted of the piece-wise $1/f^{\alpha}$ approach are correlated with CV and are significantly affected ($p < 0.001$). Fig. (5) and Fig. (6), show insignificant changes caused by the CV on the GPSM high (q; $p=0.096$) and low frequency (g; $p=0.066$) indicators. Finally, Fig. (7), shows that the GPSM characteristic frequency ($f_0$; $p<0.001$) is highly correlated and significantly affected by the CV.

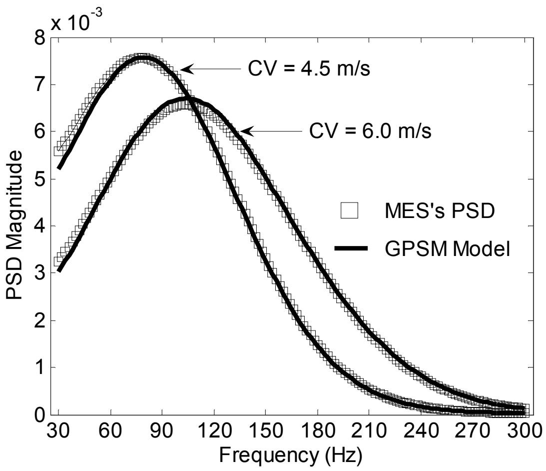

Figure 1: MES PSD and its model using GPSM for two different values of CV. Compression towards lower frequencies is noticeable when CV is decreased.

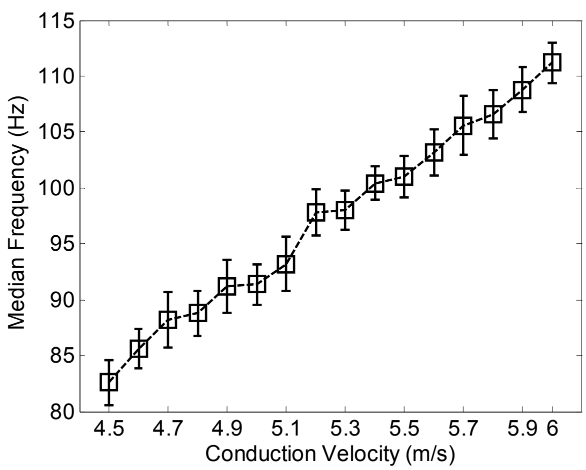

Figure 2: Median frequency vs. CV

## IV. DISCUSSION

Results show that spectral slopes extracted using the piece-wise $1/f^{\alpha}$ approach are sensitive to changes of the CV which is in contrast to the results of [13]. This could be explained by the fact that the spectral compression is not uniform, mainly because of the tissue filtering effects; however, the PSD estimation criteria and the variability of the estimated slopes from the human subject data may be masking this sensitivity, causing the contrast in results.

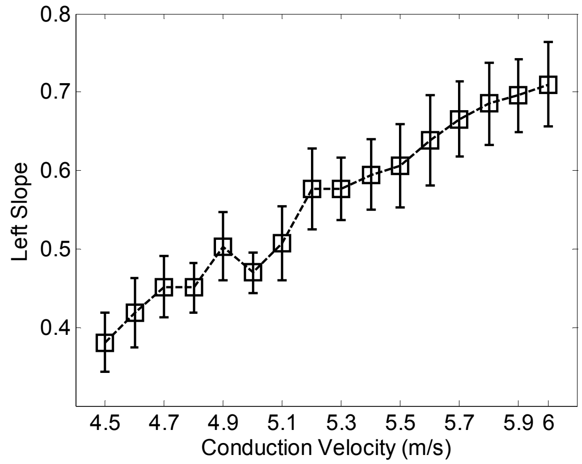

Figure 3: Piece-wise $1/f^{\alpha}$ method's left slope vs. CV

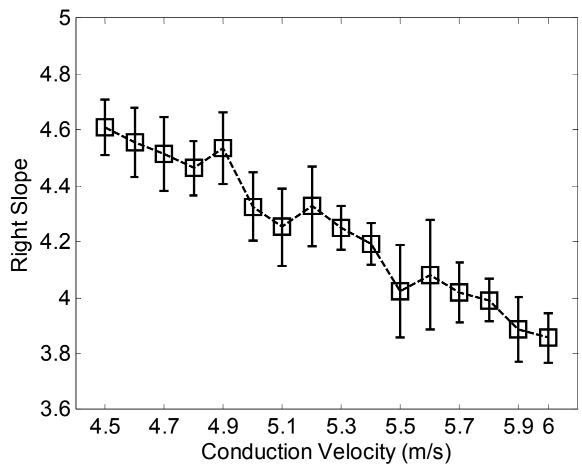

Figure 4: Piece-wise $1/f^{\alpha}$ method's right slope vs. CV

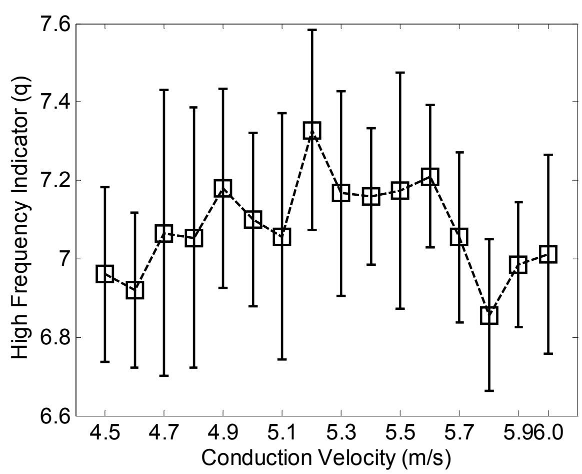

Figure 5: GPSM's high frequency indicator (*q*) vs. CV

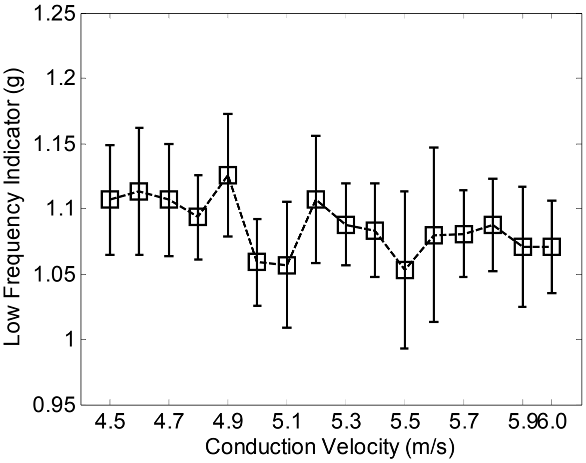


Figure 6: GPSM's low frequency indicator (*g*) vs. CV

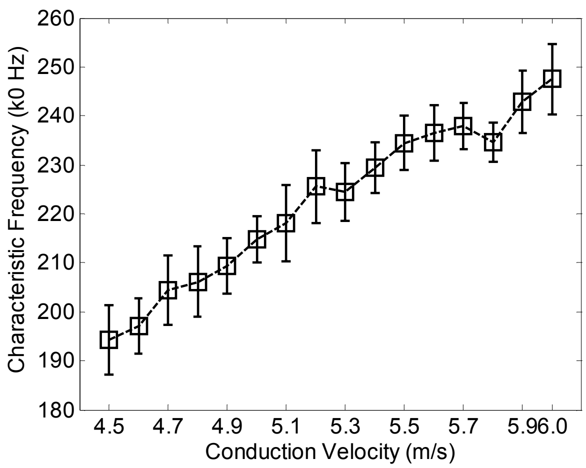


Figure 7: GPSM's characteristic frequency ($f_0$) vs. CV

On the other hand, the high and low frequency indicators achieved by the GPSM are insensitive to spectral compression when CV is decreased up to 75% of its initial value. This could be explained by the fact that the distribution of the SFAPs is not changing when the CV is changed, they are only scaled and their characteristic frequency is altered.

## V. CONCLUSIONS

In this paper GPSM was evaluated in context of muscle conduction velocity and spectral compression. The FIs obtained by this method are insensitive to CV. This is interesting because these parameters are sensitive to force and joint angle [14]. This suggests that these FIs could be used as a measure for force and joint angle independent of fatigue. It was also demonstrated that the spectral slopes extracted by piece-wise $1/f^{\alpha}$ are sensitive to non-uniform spectral compression of the MESs when CV is changed.

These results are encouraging and motivates further research into the GPSM, in the context of muscular fatigue; this will include experimental work involving human subjects.

## ACKNOWLEGMENTS

The authors would like to acknowledge the assistance of the Natural Sciences and Engineering Research Council (NSERC) of Canada, in the form of a Discovery Grant #262474-03.

## REFERENCES

[1] R. Merletti and P.A. Parker, *Electromyography:Physiology, Engineering and Non-Invasive Applications*. New Jersey: IEEE Press, 2004.

[2] C. J. De Luca, "Myoelectric manifestations of localized muscular fatigue in humans," *CRC Crit. Rev. Biomed. Eng.*, vol. 11, pp. 251–279, 1984.

[3] A. J. Lloyd, "Surface electromyography during sustained isometric contractions," *J. Appl. Physiol.*, vol. 30, pp. 713–719, 1971.

[4] D.T. MacIsaac, K.B. Englehart, P.A. Parker and D.R. Rogers, "Fatigue estimation with a multivariable myoelectric mapping function," *IEEE Trans. Biomed. Eng.,* vol. 53, pp.694-700, 2006.

[5] F. B. Stulen and C. J. De Luca, "Frequency parameters of the myoelectric signal as a measure of muscle conduction velocity," *IEEE Trans. Biomed. Eng.*, vol. BME-28, pp. 515–523, 1981.

[6] G. M. Hagg, "Interpretation of EMG spectral alterations and alteration indexes at sustained contraction," *J. Appl. Physiol.*, vol. 73, pp. 1211-1217, 1992.

[7] R. Merletti and L. L. Conte, "Advances in processing of surface myoelectric signals: Part 1," *Med. Biol. Eng. Comput.*, vol. 33, pp. 362–372, 1995.

[8] L. R. L. Conte and R. Merletti, "Estimating EMG spectral compression: Comparison of four indices," *18th Annu. Intl. Conf. IEEE EMBS*, Amsterdam, Netherlands, p. 5.7.2-5.7.5, 1996.

[9] R. Merletti and L. R. L. Conte, "Surface EMG signal processing during isometric contractions," *J. Electromyogr. Kinesiol.*, vol. 7, pp. 241–250, 1997.

[10] P. Dolan, A. F. Mannion, and M. A. Adams, "Fatigue of the erector spinae muscles," *Spine*, vol. 20, pp. 149–159, 1995.

[11] H. Rix and J. P. Malenge, "Detecting small variations in shape," *IEEE Trans. Syst. Man Cybern.*, vol. SMC-10, pp. 90–96, 1980.

[12] T. Ehtiati, W. Kinsner, and Z.K. Moussavi, "Multifractal characterization of the electromyogram signals in presence of fatigue," *IEEE Proc. Elec. Com. Eng.*, vol. 2, pp. 866-869, 1998.

[13] P. Ravier, O. Buttelli, R. Jennane and P. Couratier, "An EMG fractal indicator having different sensitivities to changes in force and muscle fatigue during voluntary static muscle contractions," *J. Electromyo. Kinesiol.*, vol. 15, pp. 210-221, 2005.

[14] M. Taebinejad, A.D.C. Chan, A. Miri and R. Dansereau, "Fractal analysis of myoelectric signals: a novel pwer spectrum-based method, " submitted to *IEEE Trans. Biomed,* Dec 2006.

[15] N. Jiang, "Modelling of motor unit innervation process correlation and motor unit common drive in human skeletal muscles," M.Sc.E. Thesis, University of New Brunswick, Fredericton, New Brunswick, Canada, 2004.

[16] J. V. Basmajian and C. J. De Luca, *Muscles Alive*, 5th ed. Baltimore, MD: Williams and Wilkins, 1985.

[17] H. Monson, *Statistical digital signal processing and modeling*. Wiley, 1996, pp. 287-295.

[18] M.J. Turner, J.M. Blackledge and P.R. Andrews, *Fractal geometry in digital imaging.* London: Academic Press, 1998, pp. 31-62, 80-99.