MULTI-SCALE ANALYSIS OF MYOELECTRIC SIGNALS: ASSESSMENT OF LONG-RANGE DEPENDENCIES AND FRACTAL-SCALING-BREAK

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Abstract In this paper we propose a novel methodology for structure-function-based multi-fractal analysis of myoelectric signals. This methodology provides multi-scale information about the geometry of the myoelectric interference pattern. Specifically, it provides insight into the fractal characteristics of sampled myoelectric signals with assessment of long-range dependencies and fractal-scaling-break properties of this signal. Power spectrum and structure-function-based methods are also integrated in this work, presenting a unified framework for multi-scale analysis of myoelectric signals. Results of an experiment for comparison of myoelectric signals to strict mathematical fractional Brownian motion are provided. The novel methodology provides insight into the myoelectric signal's renewal process. The results also show a great potential for applications to clinical diagnosis and fatigue studies.

I. INTRODUCTION

The surface myoelectric signal (MES) can be readily measured but the complex nature of this signal (i.e. sensitivity to recording conditions and non-stationary), challenges extracting precise characterizing information.

Previously, random fractal theory for analysis of MES power spectrum as a mono-fractal, in [1, 2], in the form of strict self-affinity and in [3, 4, 5], in the form of multi-scale self-affine power-laws has shown unique properties, which could be used for better understanding myoelectric dynamics and to complement conventional measures [3, 4, 5].

Power spectrum-based methods are very informative in terms of understanding the statistical nature of the myoelectric dynamics; however, these methods require a spectral representation. Non-parametric power spectrum estimation has associated difficulties with temporal resolution and phase information of the time series. Moreover, it is not possible to comment on multi-fractality of a signal solely based on the power spectrum; the power spectrum-based methods provide a measure of dominant complexity [5].

This motivates computing a fractal indicator (FI) in the spirit of a power-law scaling exponent by exploiting the actual time series, similar to structure-function-based analysis [6], to enhance the power spectrum-based FIs.

The conventional structure-function-based analysis is limited for the noise types; the bounded amplitude of a noise type does not exhibit a power-law scaling regime and the estimated power-law scaling exponent is saturated around zero [6]. We propose a novel methodology in which this difficulty of conventional methods is resolved and that is applicable to MESs. A discussion for integration of multi-scale power-law power spectrum method to this methodology is also presented for further insight into the multi-scale analysis of MESs. The methodology is evaluated with simulated fractional Brownian motion and experimental MESs to study the renewal process and fractal characteristics of these noise types.

II. METHODS

A. Long memory and fractal analysis:

1. Power spectrum method:

Assume we are given a random process $\{ X_i,\ i = 1,2,...,N \}$, which denotes a finite sampled temporal signal, that has a $1/f^{\alpha}$ power distribution. Treating the signal as a mono-fractal, the power spectrum might show persistent or anti-persistent characteristics; that is the slope of the $1/f^{\alpha}$ power-law is extended from a memory-less series with no range dependencies (i.e. anti-persistent) to a long-range dependent process with a highly persistent distribution. This type of analysis is well suited for exact processes which show a $1/f^{\alpha}$ power distribution in its strict mathematical sense, similar to fractional Brownian motion. This notion could be extended to a wider class of self-affinity with multiple scales for different frequency ranges. Multi-scale power-laws outperform simple single-scale self-affine routine when applied to MESs. Interested readers are referred to [5] for a complete discussion on power spectrum-based MES analysis.

2. Structure-function method:

The autocorrelation of the random process X could also be used for assessment of range dependency and memory of a fractal time series with $1/f^{\alpha}$ power-law. Consider a correlation measure from two non-overlapping segments of the random process X in this form,

$$Z^{(q)}(m) = \left\langle \left| X_{i+m} - X_i \right|^q \right\rangle \propto m^{\zeta(q)} \qquad (1)$$

In Eq.(1), $Z^{(q)}(m)$ is a time averaged autocorrelation taken from all possible pairs of { $X(i+m)$,$X(i)$ }. It is examined whether there exists a power-law scaling between $\xi(q)$ and $Z^{(q)}(m)$ for different values of the scaling factor q. This approach allows focusing on different aspects of the signal using different q denoting small and large emphasize of absolute increments of the random process. Consider the approximating power-law in this form,

$$H(q) = \zeta(q)/q \qquad (2)$$

where $H(q)$ is an a power-law scaling exponent similar to Hurst exponent. Eq.(1) could be re-written in this form,

$$F^{(q)}(m) = \left\langle \left| X_{i+m} - X_i \right|^q \right\rangle^{1/q} \propto m^{H(q)} \qquad (3)$$

When $H(q)$ is a constant function of q (i.e. $F^{(q)}(m)$ has a constant slope on a log-log scale), the process is a mono-fractals; otherwise, the process has multi-fractal characteristics. This methodology is similar to fluctuation analysis for q = 2 [6].

B. A novel random walk-based analysis:

For noise types the structure-function method might result in erroneous and saturated results. This could be explained by the bounded fluctuations of a temporal noise type; that is, larger number of samples in such time series will not necessarily result into larger fluctuations [9].

A solution to this limitation is constructing a temporal random walk by integrating the signal in this form,

$$Y_k = \sum_{i=1}^{k} X_i \qquad (4)$$

In Eq.(3), Y is a random walk, based on the random process X (after removal of mean). The random walk is expected to show a stronger correlation persistency; therefore, its fractal properties could be more accurately characterized.

After integration of X, Y is expected to show increased amplitude with evolution of time. This is a result of increased fluctuations with evolution of time and suggests that even due the mean value of all the samples is zero different sample ranges might possess non-zero averages (similar to non-zero mean of a sine wave in its half periods). If this characteristic is not well-satisfied it suggests that the time series is pseudo-stationary; that is, arbitrary successive samples are likely to have a zero mean. In this case we propose random walk integration with more emphasis on the spikes of the random process X (after removal of mean) in this form,

$$Y_k^P = \sum_{i=1}^{k} \left| X_i \right|^P \qquad (5)$$

In Eq.(3), Y^P is a random walk, based on the random process X. The mean value of all sample ranges will be nonzero, as we are concerning ourselves with the absolute values; the parameter P controls the amount of magnification on the peak values and spikes in the time series. In this paper, P = 2 was used.

E. Experiment:

Through comparison of MESs to fractional Brownian motion we seek to address two issues: 1) whether MESs are exhibiting pseudo-stationary dynamics or the renewal process is stationary; and 2) whether these dynamics are mono- or multi-fractal. MESs used in this experiment are a subset of 5 subjects from the dataset used in [7]; MES were collected from the right *biceps* under static conditions.

The fractional Brownian motion was simulated by fractional filtering of the white noise's FFT [6], with a fractional order of 0.5 (anti-persistent). All data, sampled at 1024 Hz, were divided into 5 sec segments.

The structure-function method is applied to all data in the form of Eq.(3). The conventional integration of Eq.(4) is also compared to the proposed approach in Eq.(5).

III. RESULTS AND DISCUSSIONS

A. Simulated fractional Brownian motion:

Figure 1 shows the results of applying Eq.(3) to a typical simulated fractional Brownian motion. The zero slope value is not valid because it is does not agree with the known fractional filter order which is 0.5. This is consistent with the bounded amplitude of the simulated data and limitation of structure-function-based analysis for noise-types. Figure 2 shows the results after integration according to Eq.(4). The random walk representation resembles a clear linear power-law scaling regime (i.e. high degree of fractality). A least squares linear regression could be used for accurately estimating the power-law scaling exponent (i.e. linear slope). The slope for higher orders is very close to 0.5 (i.e. negligible changes) implying multi-fractality of the time series is not very strong which is consistent with mono-fractal characteristics of the simulated data. The average estimated linear for 5 sets of simulated data was H = 0.49 with a negligible standard deviation of σ = 0.01 for q = 2. Using the novel integration procedure similar results is obtained;

the mirroring of negative values does not affect the power-law scaling regime.

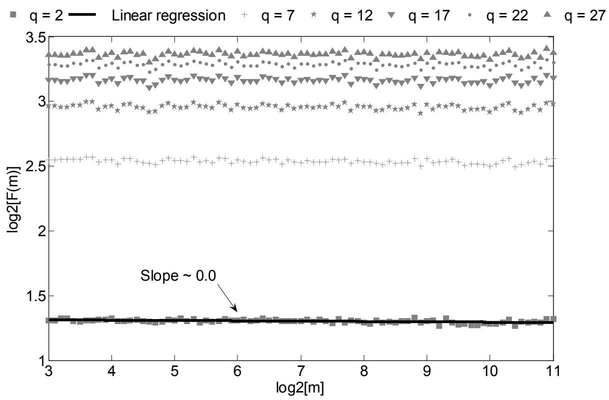

Figure 1: Analysis of simulated fractional Brownian motion before random walk integration. The slope is not informative.

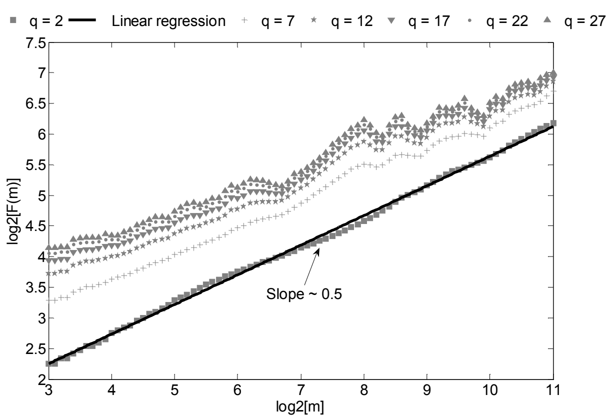

Figure 2: Analysis of simulated fractional Brownian motion after random walk integration. The slope accurately characterizes the time series.

B. Myoelectric signals:

Figure 3 shows the results of applying Eq.(3) to a typical sample of MES. Figure 4 shows the results after integration according to Eq.(4). The linear slope could not be used for accurately estimating the power-law scaling exponent as it is still saturated around zero. This suggests that the increments of MESs are not stationary like fractional Brownian motion; pseudo-stationary properties results into saturation of the linear slope around zero. Figure 5 shows the results after applying the novel random walk construction methodology of Eq.(5). Mirroring the negative values in space (i.e. taking the absolute values) and emphasizing the spikes masks pseudo-stationary related difficulties. Figure 5 resembles a power-law scaling regime which is very much linear for lower orders. Figure 5 suggest multi-fractal characteristics at short-range scales because the linear slope is significantly varying with different orders. This could be explained by the fact that for small time scales, there is a stronger dependency between successive random walk samples and multi-fractality hints properties beyond a simple mono-fractal randomness characteristic as seen in simulated fractional Brownian motion; this also suggest that a single power-law scaling regime denoting a dominant complexity fractal dimension is not adequate for characterizing the signal. For larger time scales an average statistics is quantified which resemble a mono-fractal random process similar to simulated fractional Brownian motion. Meanwhile, it is probable that random like recruitment strategies are resulting into an anti-persistent mono-fractal with a linear slope close to 0.5. The average estimated linear slope for 5 sets of recorded data was H = 0.46 with a negligible standard deviation of σ = 0.05 for q = 2.

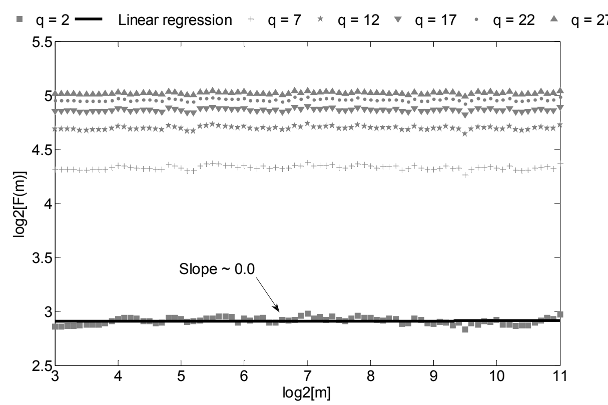

Figure 3: Analysis of MES before random walk integration. The slope is not very informative. This segment of the signal has been collected from the first 5 sec of data of subject 1 during a static contraction.

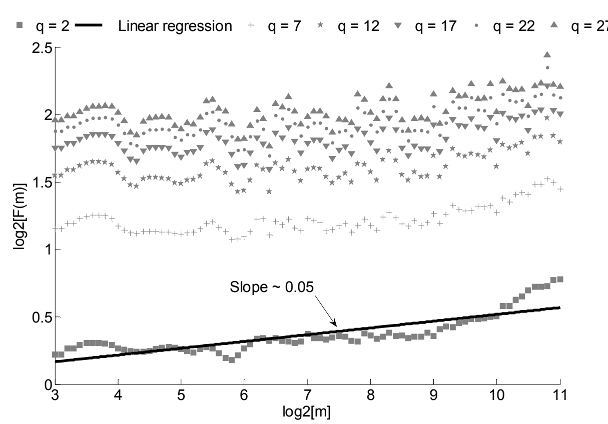

Figure 4: Analysis of MES after random walk integration. The slope is not very informative. This segment of the signal has been collected from the first 5 sec of data of subject 1 during a static contraction.

C. Comparison with power spectrum method:

The MES power spectrum is not well-defined by strict self-affinity, but it could be accurately approximated by a multi-scale power-law [4, 5]. A multi-scale power-law provides two FIs and a fractal-scaling-break at which each FI is asymptotically independent from the other. The general power spectrum method presented in [5] represents a mono-fractal with one fractal-scaling-break. This is consistent with Figure 5 in which the MES is showing mono-fractality after a fractal-scaling-break. The novel structure-function methodology provides a unique representation for MESs through which multi-fractal characteristics could be also taken into account to complement the power spectrum-based FIs.

III. CONCLUSIONS

Results of this work demonstrate that MES exhibit: 1) pseudo-stationary dynamics and conventional random walk analysis is not applicable; and 2) that these dynamics are both mono- and multi-fractal and the nature of combination depends on a fractal scaling break similar to multi-scale power spectrum method [5]. Pseudo-stationary properties of MESs do not allow conventional structure-function-based analysis. A novel methodology for tackling this problem is proposed which resolves the difficulties of conventional random walk integration technique. This new methodology could be potentially used for estimation of fatigue and clinical diagnosis. Preliminary results of our research demonstrate potential for employing this methodology. Figure 6 shows an example in the presence of localized muscular fatigue during static contractions. With decreasing conduction velocity more time dependency and memory in the MES dynamics are seen as the single motor unit action potentials are longer and extended to more samples. The slope represents a persistent time series and implies a greater synchrony among the motor units which is reflected in the form of long-range dependency.

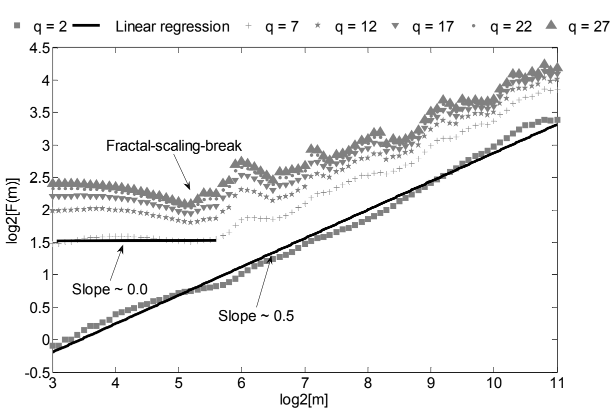

Figure 5: Analysis of MES after random walk integration using novel methodology. The slope accurately characterizes the time series. This segment of the signal has been collected from the first 5 sec of data of subject 1 during a static contraction (MDN ~ 123 Hz).

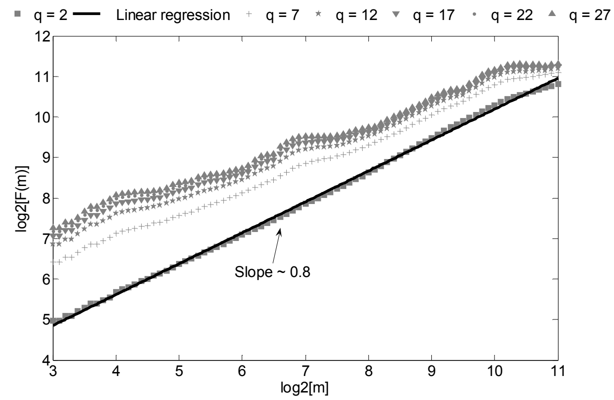

Figure 6: This segment of the signal has been collected 500 sec after the start of static contraction from subject 1(MDN ~ 43 Hz). After random walk integration samples exhibit a high degree of mono-fractality which is also highly persistence (slope = 0.8) compared to non-fatigued case (slope = 0.5).

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