Analysis of Biceps Brachii Muscles in Dynamic Contraction Using sEMG Signals and Multifractal DMA Algorithm

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***Abstract*—In this work, an attempt has been made to analyze surface electromyography (sEMG) signals in dynamic contraction using multifractal detrending moving average algorithm (MFDMA). The signals are recorded from biceps brachii muscles of twenty two healthy participants using a standard experimental protocol. The recorded sEMG signals are pre-processed and normalized by dividing the time axis into six equal segments. The first segment and sixth segment are considered as nonfatigue and fatigue conditions for analysis. The signals are subjected to MFDMA and verified to test multifractal properties of biceps brachii muscles using scaling exponent, generalized Hurst exponent and multifractal spectrum in both nonfatigue and fatigue conditions. Each multifractal spectrum is characterized by calculating three features namely peak exponent (PEV), degree of multifractality (DOM) and mean multifractal spectral exponent (MSE). The variation of multifractal spectral features in fatigue conditions are analyzed using ANOVA and Tukey test. The results of scaling exponent function and generalized Hurst exponent function indicated multifractal characteristics for sEMG signals in dynamic contractions. DOM increased from 0.56 to 0.96 and MSE increased from 0.54 to 0.75 in nonfatigue and fatigue conditions respectively. It appears that this method is useful in analyzing fatigue and nonfatigue conditions associated with muscle mechanics using non-invasive sEMG recordings. This study can be useful in field of clinical studies, rehabilitation, prosthetics control and sports medicine.**

***Index Terms*—surface EMG, biceps brachii, multifractal, detrending moving average algorithm, muscle fatigue, dynamic contractions**

I. Introduction

Biceps brachii muscles are commonly known as biceps and located in the upper arm of human body. The biceps run along the anterior side of humerus bone from the shoulder joint to elbow joint. This muscle is normally a two headed muscle and has a spindle shape. The two heads of the biceps muscle vary in length and help in various functioning of upper limbs. The biceps muscles are responsible for supination of proximal radius (forearm action for using key), flexion of humerus joint (dumbbell curl exercise) and stabilizing the shoulder joint movement. The muscles in human body are composed of muscle fibers that are innervated by alpha motor neuron. The alpha motor neuron together with muscle fibers is known as motor unit. Muscle tissue is broadly grouped into slow-twitch and fast-twitch muscle fibers. The slow-twitch fibers have higher endurance, higher resistance to fatigue and lower ability to generate rapid force. The fast-twitch fibers have lower endurance, lower resistance to fatigue but higher ability to generate rapid force. The biceps muscle has about 46% of slow-twitch fibers and 54% of fast-twitch fibers [1]. In the case of heavy intense repetitive action such as dumbbell curl exercise, muscle fibers are involved in contraction process for sustaining force generation. Prolonged repetitive action can lead to muscle fatigue [2]. Surface electromyography (sEMG) is a non-invasive method of recording electrical activity of muscles [3]. The intense variation of sEMG signals during dynamic contraction increases the complexity of signal analysis due to varying recruitment levels of slow-twitch and fast-twitch muscle fibers, nonlinear motor unit recruitment and synchronization of motor units [4]. The sEMG signals are analyzed using time [5], frequency [6], [7] and time-frequency domain techniques [8]. The statistical property of signals are assumed to be constant in traditional methods and muscular system is considered to be linear [9], [10]. In time and frequency domain analysis, the physiological signals are also considered linear. The time-frequency domain techniques address the nonstationary aspect of the signal but still considers the system to be linear [10]. The characteristics of nonlinear systems can be estimated better with measures such as entropies, correlation and fractal dimension [11].

The fractal system is represented by a scale invariant non integer parameter known as fractal dimension [12]. There is a growing acceptance of physiological signals, generated by complex self-similar system, may have fractal structure [13], [14]. A fractal refers to a signal that can be split into parts that is a reduced-copy of whole [15]. There are two types of fractal behavior in most of time series, namely monofractal and multifractal. Monofractals are homogenous and characterized by single scaling property for the entire signal. Multifractal signals are characterized by numerous scaling properties

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for the entire signal. Multifractal signals are intrinsically more complex and inhomogeneous as compared to monofractal signals [15].

The detrended fluctuation analysis (DFA) was proposed for analyzing DNA sequences that was suitable for monofractal scaling properties [16]. Based on a generalization of DFA, the multifractal detrended fluctuation analysis (MFDFA) is introduced for the multifractal characterization of non-stationary time series [15]. Multifractal analysis using moving average was first proposed to estimate Hurst exponent of self-affinity signals [17]. The detrending moving average (DMA) method was later developed considering second order difference between original signal and moving average function [18]. The DMA method was extended to multifractal detrending moving average (MFDMA) to analyze multifractal time series and surfaces [19]. Muscle fatigue analysis in isometric contraction was reported for biceps brachii muscle using fractal analysis, and it was found that fractal area increased during fatigue condition [20]. The detrended fluctuation analysis method was proposed for tracking muscle fatigue using Hurst exponent over time [21]. The analysis of sEMG signal for muscle fatigue is not analyzed using MFDMA in available literature for biceps brachii muscle.

The aim of the present study was to analyze dynamic sEMG signals in nonfatigue and fatigue conditions. sEMG signals are recorded from biceps brachii muscles while performing standard experimental protocol and subjected to nonlinear analysis using multifractal detrending moving average techniques. Two standard features were extracted from multifractal spectrum. A new feature is proposed in this study and compared with standard features. These three features are further analyzed in nonfatigue and fatigue condition for understanding the sEMG signal characteristics.

II. Methodology

A. Subjects

Twenty two normal healthy volunteers {Age=21.04 (±0.84); Weight=68.22 (±12.36); Height=170.99 (±6.42); Gender=18 Males and 2 Females} without any history of neuromuscular skeleton disorder participated in this study. The subjects were asked to take complete rest for at least 12 hours before the experiment. A written consent form approved by the institute review board is taken from each participant before the start of exercise. The participants were given training without load before conducting the experiment. Each participant is requested to perform full dumbbell curl exercise in upright position with forearm in supine position and using their dominant hand with 6 kilograms dumbbell. The participants are asked to maintain speed of curl at their comfortable pace. Signals are acquired for the entire course of exercise till exhaustion. No encouragement was provided during the exercise to avoid any potential confounding effect on exercise performance. The experiment was stopped when the participant was unable to lift the dumbbell and exhausted.

B. Skin Preparation and Instrumentation

Ag-AgCl disc-type disposable surface electrodes, 1 cm diameter, were placed on the belly region of triceps brachii muscle. The skin was cleaned with alcohol and cotton prior to the experiment. A differential electrode configuration is used, with an inter-electrode distance of 3cm [5]. The reference electrode is placed at the proximal end of the elbow. The subjects stood on a wooden platform to electrically isolate them from ground. The electrodes were placed on the belly region of triceps brachii as per SENIAM standards in bipolar configuration. The reference electrode was placed on elbow region. The sampling frequency was set as 10KHz and sampled using Biopac MP36 system (Gain 1000; 24 bit ADC; CMRR 110db). The signals are filtered using band-pass filter (10 Hz to 400Hz) after removing 50Hz power signal noise. To ease the computation, the signals are down sampled offline at 1000 samples per second for further analysis.

C. Multifractal Detrending Moving Average Algorithm

Multifractal detrending moving average is designed for analyzing multifractal time series [19].

Step 1: Let the sEMG time series be represented as $x(t)$, where t = 1, 2, 3,…., N. Then the cumulative sums for the sequence is represented as

$$y(t) = \sum_{i=1}^{t} x(i)\,, t = 1, 2\,, 3 \ldots \mathrm{N} \tag{1}$$

Step 2: Next, the moving average function is computed in a moving window, and represented as

$$\tilde{y}(t) = \frac{1}{n} \sum_{k=-[(n-1)\theta]}^{[(n-1)(1-\theta)]} y(t-k)\,, \tag{2}$$

where n is window size, $[(n-1)(1-\theta)]$ is largest integer not greater than x, and $[(n-1)\theta]$ is smallest integer not smaller than x, and θ is position parameter with value varying in between 0 and 1. If θ = 0, 0.5 and 1 then it corresponds to backward moving average (BMA), centered moving average (CMA) and forward moving average (FMA) respectively. The moving average function is calculated over past values of $n-1$ in the case of BMA, and future values of $n-1$ in the case of FMA.

Step 3: Detrend the signal series by removing $\tilde{y}(i)$ from $y(i)$ to get residual sequence $\varepsilon(i)$ using the below equation

$$\varepsilon(i) = \tilde{y}(i) - y(i) \tag{3}$$

where $n-(n-1)\theta \le i \le N-(n-1)\theta$

Step 4: The residual series is divided into M disjoint segments with same size n where $M = \frac{N}{n} - 1$. Each segment can be represented as ε_v such that $\varepsilon_v(t) = \varepsilon(l+i)$ for $1 \le i \le n$ and $l = (v-1)n$. The root-mean square function $F_v(n)$ with segment of size n can be calculated as

$$F_v^2(n) = \frac{1}{n}\sum_{i=1}^{n} \varepsilon_v^2(i) \quad (4)$$

Step 5: The q th order overall fluctuation function is determined as follows

$$F_q(n) = \left\{ \frac{1}{M} \sum_{v=1}^{M} F_v^q(n) \right\}^{1/q} \quad (5)$$

For q is a real value and not equal to zero. When $q = 0$, then the fluctuation function is given according to L'Hospital rule.

Step 6: The power-law function can be determined by varying the segment size n for fluctuation function as

$$F_q(n) \sim n^{h(q)} \quad (6)$$

The multifractal scaling exponent is given as

$$\tau(q) = qh(q) - D \quad (7)$$

where D is the fractal dimension of geometric support of multifractal measure [15]. The singularity strength function and multifractal spectrum are obtained using Legendre transform [22], and represented as

$$\alpha(q) = \frac{d\tau(q)}{dq} \quad (8)$$

$$f(q) = q\alpha - \tau(q) \quad (9)$$

D. Data Analysis and Flow Chart

The three features are measure from the multifractal spectrum.

- Peak Exponent (PEV) is the value of exponent when spectrum is at peak or PEV = α when $f(q) = 1$
- Degree of multifractality (DOM) is the distance between maximum exponent and minimum exponent in multifractal spectrum, DOM = $\alpha_{\max}$ - $\alpha_{\min}$
- A new feature, mean multifractal spectral exponent, is computed from the multifractal spectrum based on power spectral analysis feature, mean power frequency. This feature uses both singularity function and exponent, and represented as weighted average

$$\text{MSE} = \frac{\sum f(q).\alpha(q)}{\sum f(q)}$$

E. Statistical Analysis

The experimental analysis of four multifractal features are expressed as mean (standard deviation), and compared using one-way analysis of variance (ANOVA) and Tukey's post hoc test for nonfatigue and fatigue conditions. All analyses were carried out using OriginPro 8.5 software package. The differences were considered significant at $p<0.05$ and highly significant at $p<0.005$.

III. Results and Discussion

A. Surface Electromyography Signals

The representative sEMG signals recorded from biceps brachii muscles during dynamic contractions for three different participants are shown in Fig. 1. There is a steady burst of sEMG signals with increase and decrease of strength. These burst represents the flexion and extension of each curl. The number of curls, duration of curl and speed of curl action varied across the participants. The amplitude of sEMG signals ranged from ±1.5 volts in Subject A to ±5 volts in Subject B and C. This variation is based on individual's performance, anthropometry data and muscle characteristics. The sEMG signals are recorded until task to failure. The task to failure in this dynamic contraction protocol varied from 19 seconds to 93 seconds.

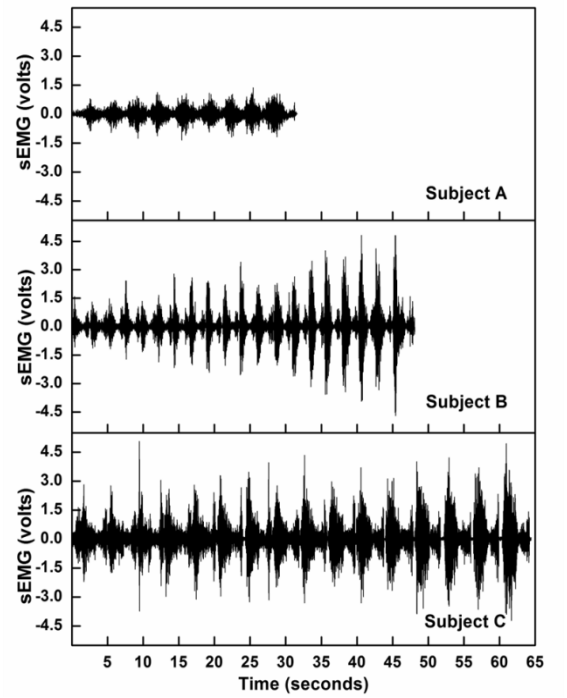

Figure 1. sEMG signals of biceps brachii muscle from three subjects (A, B and C)

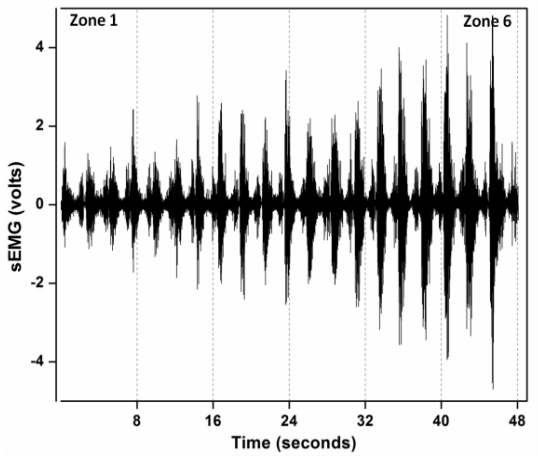

Figure 2. sEMG signal of subject B divided into six equal segments with zone 1 and zone 6

B. Non-Fatigue and Fatigue Conditions of sEMG

The task to failure in this study had a wide spread from a low of 19.3 seconds to high of 93.8 seconds. The task to failure is the instance where the subject is unable to perform the experiment and stops the curl exercise. This is due to onset of fatigue and the muscles in the region of upper arm are unable to continue generation of forces. In order to analyze the fatigue condition in a varied task to failure set of data, the sEMG signals are divided into different segments of equal length. The study in earlier work was done with three segments [23] and six equal segments [24]. Increasing the number of segments can help in quantifying the sEMG characteristics in spatial domain but it also increases the computational complexity. Hence, in this study, the sEMG signal was divided into six equal segments (Zone 1 to Zone 6). This is represented in Fig. 2 for subject B. The first segment (Zone1) is taken as nonfatigue condition and sixth segment (Zone 6) is taken as fatigue condition. The nonfatigue and fatigue signals for subject B is shown in Fig. 2. The signals in fatigue condition are clearly showing increased amplitude, but the pattern varied for different subjects. It is also observed that there is also a reduction in number of curls during fatigue zone, in some cases, due to inability of the muscles to sustain force. The segmented zones varied from 3.2 seconds to 15.64 seconds. The nonfatigue and fatigue segments are subjected to multifractal detrending moving average algorithm for further analysis.

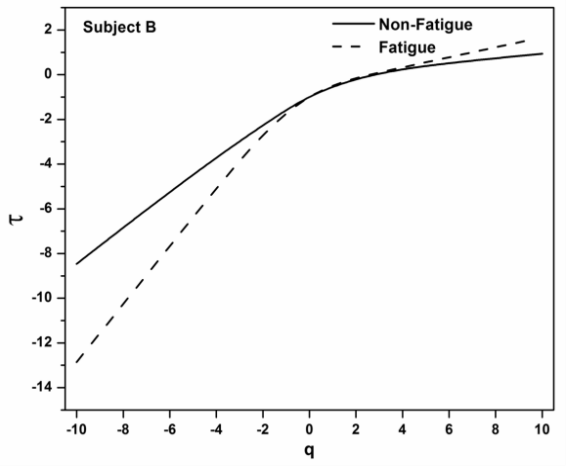

Figure 3. Scaling exponent function variations for nonfatigue and fatigue conditions of sEMG signal in Fig. 2

C. Multifractal Analysis

The scaling exponent τ (q) for sEMG signals during dynamic contraction for nonfatigue and fatigue conditions are represented in Fig. 3. In both the cases, the scaling exponent function is appearing to be nonlinearly varying for negative and positive values of order of fluctuation (q). The linear variation of scaling exponent is an indication of mono fractal nature of time series. Based on this nonlinear variation of scaling exponent for both nonfatigue and fatigue series, the sEMG signal may be considered having multifractal behavior. For nonfatigue conditions, the scaling exponent ranges from -8 to 1, as compared to -13 to -2 for fatigue conditions. The larger variation in scaling exponent range of nonfatigue may be due larger components of higher amplitude and increase in lower frequency components due to motor unit action potential synchronization. This may result in increase of higher amplitude fluctuations and lower amplitude fluctuations during fatigue conditions. The negative order of fluctuations is found to have distinctly different values (-13 and -8) for fatigue and nonfatigue condition. This may be due to increase of smaller amplitude fluctuations in synchronization during fatigue than in nonfatigue condition. This may contribute in shifting the scaling exponent function to higher negative values during negative order of fluctuations in fatigue conditions.

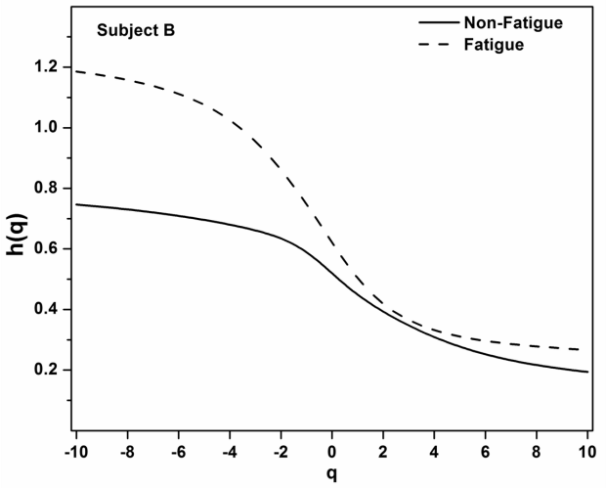

Figure 4. Generalized hurst exponent for nonfatigue and fatigue conditions of sEMG signal in Fig. 2

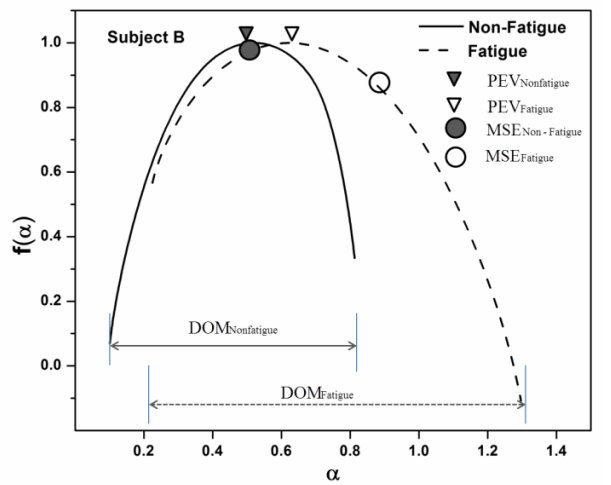

Figure 5. Multifractal spectrum with features in nonfatigue and fatigue conditions of sEMG signal in Fig. 2

The generalized Hurst exponent was estimated for both nonfatigue and fatigue signals, and plotted for different order of fluctuations. The generalized Hurst exponent variations with q is represented in Fig. 4 for the representative sEMG signal in Fig. 2, for both nonfatigue (thick line) and fatigue condition (dashed line). In the case of nonfatigue signal, the Hurst exponent varied from 0.75 to 0.2, and in the case of fatigue signal, the Hurst

exponent varied from 1.2 to 0.3. It is observed from Fig. 4 that the variation of fatigue signal is more prominent than nonfatigue signal. This may be due to increase in different type of fluctuations, comprising of high amplitude and low amplitude in fatigue condition. The behavior of high amplitude fluctuations may be different from low amplitude fluctuations, and thus this is reflected as a variation of generalized Hurst exponent in Fig. 4. The positive order ($q>0$) is representation of high amplitude fluctuations and negative order ($q<0$) is representation of low amplitude fluctuations. It is also reported than mono fractal time series has a constant Hurst exponent [15]. If the sEMG signal has uniform behavior for various amplitude fluctuations then Hurst exponent would be a nearly constant value for different order of fluctuations. Thus, it may be inferred that sEMG signals are having multifractal characteristics using generalized Hurst exponent analysis, in both nonfatigue and fatigue condition. The degree of multifractal nature is higher in fatigue condition as compared to nonfatigue condition.

The multifractal spectrum is computed for nonfatigue and fatigue conditions. This is represented in Fig. 5. The fatigue signal has a broad concentration (α=0.2 to α=1.3) and nonfatigue signal has a relatively narrow concentration (α=0.1 to α=0.8). The changes in the spectrum may be due to presence of different levels of scale invariance. The peak exponent for nonfatigue segment ($PEV_{Nonfatigue}$) and fatigue segment ($PEV_{Fatigue}$) for the representative signal is found to be 0.43 and 0.63 respectively. The left and right extremes of the spectrum represent rare exponent and smooth exponent values of time series. The rare exponent is an indication for positive order of fluctuation ($q\rightarrow\infty$) and smooth exponent is an indication for negative order of fluctuation ($q\rightarrow-\infty$). In this study, the order of fluctuation is analyzed for q ranging from -10 to 10. The degree of multifractality is also represented in Fig. 5 for both nonfatigue ($DOM_{Nonfatigue}$) and fatigue segments ($DOM_{Fatigue}$). The DOM value is found to be 0.7 and 1.1 for nonfatigue and fatigue segment. The reduction in DOM for nonfatigue is due to closer range concentration of spectrum as shown in Fig. 5. The narrow concentration of spectrum is an indication of lower scale invariance and broader concentration is an indication of greater scale invariance. The changes to scale invariance are based on presence of high amplitude and low amplitude fluctuations in the time series. In fatigue condition, it is reported that there may be a reduction in conduction velocity and synchronization of motor unit action potentials [25]. This may result in an increase of higher and lower amplitude fluctuation signals. This can be correlated to the reduction of mean frequency and median frequency in sustained fatigue condition as reported in previous work [2], [26].

The new feature mean multifractal spectral exponent (MSE) is computed for nonfatigue and fatigue. This feature is derived from power spectral analysis feature mean power frequency. This feature uses the weighted average of spectrum at various values of exponent and provides a weighted average. The $MSE_{Nonfatigue}$ is found to be lower than $MSE_{Fatigue}$ as in the case of peak exponent. The variation of MSE is found to higher than PEV feature in this study. The MSE and PEV for sEMG signal in fatigue and nonfatigue conditions are represented in Fig. 5.

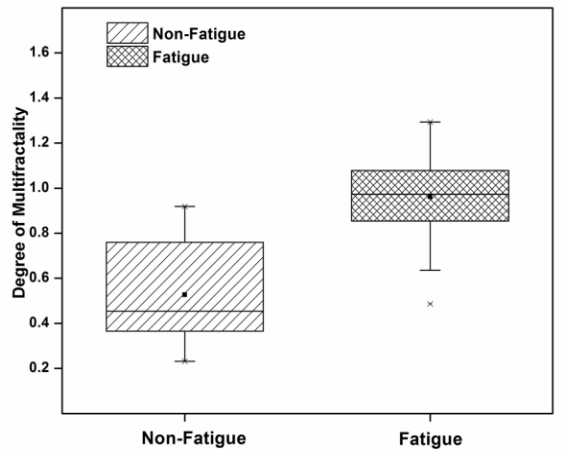

Figure 6. Box plot of $DOM_{Nonfatigue}$ and $DOM_{Fatigue}$

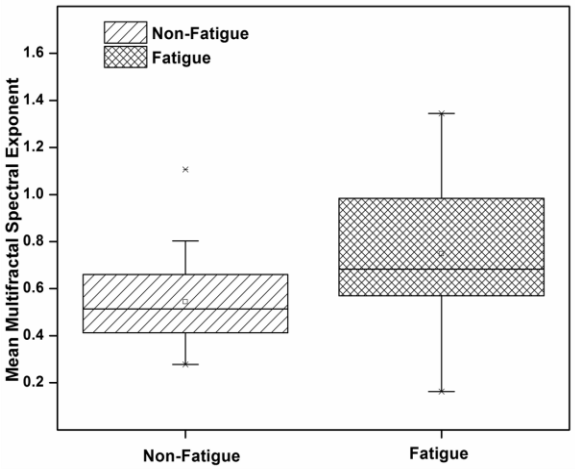

Figure 7. Box plot of $MSE_{Nonfatigue}$ and $MSE_{Fatigue}$

The mean and standard deviation for three features, PEV, DOM and MSE is given in Table I for nonfatigue and fatigue condition. The results of ANOVA and Tukey test are shown in Table II and Table III respectively. The DOM feature is found to be statistically highly significant (3.77E-8) and MSE is statistically significant (0.008) in this study. However, the PEV feature was not found to be significant for biceps brachii muscle in nonfatigue and fatigue conditions. The box plot is represented for DOM and MSE in Fig. 6 and Fig. 7 respectively.

TABLE I. MULTIFRACTAL SPECTRAL FEATURES MEAN, STANDARD DEVIATION AND MEAN ERROR IN NONFATIGUE AND FATIGUE

Features	Non-Fatigue		Fatigue	
	Mean (Std Deviation)	SE of Mean	Mean (Std Deviation)	SE of Mean
PEV	0.384 (±0.11)	0.024	0.408 (±0.14)	0.031
DOM	0.526 (±0.21)	0.044	0.961 (±0.22)	0.047
MSE	0.544 (±0.18)	0.039	0.749 (±0.29)	0.062

TABLE II. ANOVA ANALYSIS OF MULTIFRACTAL SPECTRAL FEATURES

Features	Mean Square	F Value	Prob > F
Peak Exponent (PEV)	0.0063	0.367	0.548
Degree of Multifractality# (DOM)	2.083	45.029	3.77E-8
Mean Multifractal Spectral Exponent* (MSE)	0.046	7.598	0.008

*Statistically significant; # statistically highly significant

TABLE III. MULTIFRACTAL SPECTRAL FEATURES COMPARISON USING TUKEY'S PROCEDURE IN NONFATIGUE AND FATIGUE

Features	Diff between Mean	Standard error of Mean	Prob	Sig
Peak Exponent (PEV)	0.024	0.039	0.547	0
Degree of Multifractality (DOM)	0.435	0.065	5.297E-8	1
Mean Multifractal Spectral Exponent (MSE)	0.204	0.074	0.0086	1

Sig equals 1 indicates that mean difference is significant
Sig equals 0 indicates that mean difference is not significant

IV. CONCLUSION

Surface EMG signals are complex nonlinear signal and their complexity increasing during intense dynamic contractions. The biceps brachii muscles play role of agonist and antagonist during flexion-extension action respectively. The sustained force generation in this action is followed by muscle fatigue and leading to task-to-failure. The dynamics of bicep brachii muscle vary during curl exercise and thereby resulting in nonlinear variations in sEMG signals. In this study, sEMG signals are recorded from biceps brachii muscle with 22 participants. The signals are pre-processed and segmented into six equal zones. The first segment and last segment are considered as nonfatigue and fatigue condition. The multifractal detrending moving average algorithm is applied for these two segments to derive scaling exponent function, generalized Hurst exponent and multifractal spectrum. Two standard features, peak exponent and degree of multifractality are computed for nonfatigue and fatigue condition. A new feature, mean multifractal spectral exponent is introduced and compared with peak exponent. In certain cases, the spectral component is shifted toward right due to dominance of larger fluctuations. However the peak is towards the middle of spectrum. In these cases, the new feature MSE appears to provide distinct values between nonfatigue and fatigue conditions. The results of scaling exponent and generalized Hurst exponent confirmed the multifractal nature of sEMG in both nonfatigue and fatigue condition. The ANOVA results of multifractal spectral features are found to be statistically significant in fatigue condition (Degree of multifractality p=5.297E-8; Mean multifractal spectral exponent p=0.0086).

The results using multifractal analysis with MFDMA technique on sEMG signals provide a method to study the underlying muscular system dynamics in nonfatigue and fatigue condition. The biceps brachii muscles exhibit nonlinear interactions in dynamic contraction. The sEMG signal is found to be characterized by a range of fractal exponent with varying scales in nonfatigue and fatigue condition. The scaling exponent function and generalized Hurst exponent function indicate the influence of higher amplitude and lower amplitude fluctuation during fatigue condition. This method of multifractal detrending moving average method may be a good tool to assess sEMG signals during dynamic contractions due to its ability to discriminate between nonfatigue and fatigue conditions. sEMG signals exhibit complex dynamics and therefore multifractal detrending moving average spectrum analysis may prove to yield useful insights into the varying dynamics.

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