Analysis of Progression of Fatigue Conditions in Biceps Brachii Muscles Using Surface Electromyography Signals and Complexity Based Features

P. A. Karthick, Navaneethakrishna Makaram and S. Ramakrishnan

Abstract— **Muscle fatigue is a neuromuscular condition where muscle performance decreases due to sustained or intense contraction. It is experienced by both normal and abnormal subjects. In this work, an attempt has been made to analyze the progression of muscle fatigue in biceps brachii muscles using surface electromyography (sEMG) signals. The sEMG signals are recorded from fifty healthy volunteers during dynamic contractions under well defined protocol. The acquired signals are preprocessed and segmented in to six equal parts for further analysis. The features, such as activity, mobility, complexity, sample entropy and spectral entropy are extracted from all six zones. The results are found showing that the extracted features except complexity feature have significant variations in differentiating non-fatigue and fatigue zone respectively. Thus, it appears that, these features are useful in automated analysis of various neuromuscular activities in normal and pathological conditions.**

I. Introduction

Muscles are made up of motor units. A motor unit consists of an alpha motor neuron and it innervated into its associated muscle fibers. Muscles are responsible for regulation of force output for precise and powerful movements, locomotion, and other daily activities [1]. Electromyography (EMG) is a technique, used to record the electrical activity of skeletal muscles [2]. Two types of signal acquisition methods are exist in practice namely surface electromyography (sEMG) and needle electromyography. The sEMG is a non-invasive technique where electrodes are placed over the skin. It is used in the area of myo-electric control, sports biomechanics and ergonomics [3-5]. Needle electromyography is an invasive technique, and it is widely used in clinical research and studies.

Muscle fatigue is a neuromuscular condition in which the muscle is unable to maintain the force [6, 7]. This condition can also be caused due to some abnormalities such as neuropathy, myopathy and Parkinson disease [8-10]. Also it is experienced due to endocrine disturbance, carcinoma malnutrition and immobilization [5]. Fatigue analysis plays considerable importance in the field of rehabilitation and kinesiology [11]. Fatigue study is carried out by imaging techniques, muscle biopsy and sEMG signal analysis. The sEMG signal analysis is most widely used techniques in fatigue analysis [12].

The sEMG signal exhibits non-linear and non-stationary property. It is a complex signal and depends on several neuromuscular system parameters such as firing rate, muscle fiber types, motor unit types, anisotropic nature of muscles, muscle crosstalk's and volume conductor effects. It also relies on detection system parameters such as gain, common mode rejection ratio and signal to noise ratio of data acquisition system and ambience. Daily activities such as walking and running are based dynamic contraction of muscles. In dynamic contractions, the degree of non-stationarity and randomness increases due to change in muscle length and movement of innervation zones with respect to electrode [1].

Various time domain, frequency and time-frequency domain and its features have been used in muscle fatigue assessment and classification [13]. Time domain features such as root mean square, average rectified value and frequency domain features such as mean frequency, median frequency and peak frequency have been used in EMG signal processing [13]. Time-frequency based features such as instantaneous frequency, instantaneous median, mean frequencies have been employed in muscle fatigue assessment [14].

Entropy is a feature that describes the irregularity of time series [15]. The entropy based features are widely used in areas such as EEG and speech signal processing where the signals are non stationary and complex [16]. Recently McBride et al, have used spectral and complexity features namely activity, mobility, complexity, sample entropy and other similar parameters to discriminate EEG signals under various normal and abnormal conditions [17]. Also Bachiller et al have used spectral entropy and quantified the regularity of EEG signal [18]. However these complexity features are not been explored in sEMG signals under dynamic contractions of muscles.

In this work, sEMG signals are recorded during dynamic contractions of biceps brachii muscles. Five complexity based features are extracted from the recorded signal for further analysis.

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II. METHODS

A. Experimental protocol and Signal Acquisition

Fifty healthy volunteers with no history of neuromuscular disorder performed the experiment. The subjects are informed about the nature of the experiment and an informed consent is taken from each subject before the start of the experiment. The subjects are asked to perform biceps curl exercise involving the flexion and extension of their dominant hand with 6-kilogram weights. The exercise is continued until task failure. After the necessary skin preparation, Ag-AgCl surface electrodes in bipolar configuration are placed on the bulk of biceps brachii muscle for the acquisition of the signal with an inter-electrode distance of 3 cm.

The Biopac MP36 acquisition system with sampling rate of 10 KHz and a gain of 1000 is used to record a signal. First muscle discomfort (FMD) time is identified from verbal communication of subjects and recorded [12].

B. Preprocessing

The acquired signal is downsampled to 1000 Hz. Then the signals are preprocessed with a band pass filter (10-400Hz) and 50Hz notches filter to remove unwanted noise [12]. The muscle endurance time and FMD are found to be subject dependent. In order to normalize, the dynamic signals are split into six equal segments and are used for further analysis. The first segment are considered as non-fatigue zone and the last segment is corresponds to fatigue zone.

C. Complexity features:

The complexity features such as activity, mobility, complexity, sample entropy and spectral entropy are extracted in all six zones for further analysis.

Activity:

It is a measure of the squared standard deviation of the amplitude or variance. The activity or variance in time domain can be considered as surface of power spectrum in frequency domain.

$$\text{Activity}=\sigma_0 \tag{1}$$

Mobility:

It is defined as the square of root ratio of the variance of first time derivative of signal to variance of the signal. It is can be considered as the time domain approximation of mean frequency.

$$Mobility = \sqrt{\left(\frac{\sigma_1}{\sigma_0}\right)} \tag{2}$$

Where σ_1= variance of first time derivative of signal, σ_0 is variance of signal

Complexity:

It is a measure of excessive details with reference to the softest possible curve shape, the sine wave, this corresponding to unity. It is expressed as the ratio of the mobility of slope of signal to the mobility of the signal. Due to the non-linear calculation of standard deviation this parameter will quantify any deviation from the sine shape as an increase from unity.

$$Complexity = \sqrt{\frac{\sigma_2}{\sigma_1} - \frac{\sigma_1}{\sigma_0}} \tag{3}$$

Sample entropy (SampEn):

It is the negative natural log of the conditional probability that time series of length *N*, having repeated itself within a tolerance of *r* for *m* data points, will also repeat itself for *m* + 1 points excluding self-matches. Sample entropy can then be defined mathematically by given below.

$$\text{SampEn} = -\ln\left(\frac{N_{m+1}^{m}}{N^{m}}\right) \tag{4}$$

Where N_m is the number of matches of length m and Nm m+1as the subset of Nm that also matches for length m + 1. Here m = 2 and r = 0.2 times the standard deviation of the signal.

Spectral Entropy:

Spectral entropy (SE) is used to quantify the global regularity of the signal [18]. For example, a white noise having uniform spectrum has high SE value whereas narrow band power spectrum having less frequency components provides low SE value. The spectral entropy of the signal is calculated from power spectral density and it is given by

$$SE^{(i)} = -\frac{1}{\log(L)} \cdot \sum_{i=1}^{n} PSD_n^{(i)} . \log\left[PSD_n^{(i)}\right] \tag{5}$$

Where, L is the number of spectral components in the sEMG spectrum, PSD is a power spectral density, i is a time instant of the window and n is the number of segments.

The windowing is performed to account for the non-stationarity of the signal. A sliding window technique is applied and the time evolution of PSD is evaluated. The powers spectral density measures the spectral properties of the signal. In order to represent it as probability density function it is normalized and is used in eq.5.

The normalization of PSD is performed as given by

$$PSD_n^{(i)} = \frac{PSD^{(i)}}{\sum_{i=1}^{L} PSD^{(i)}}$$

III. RESULTS AND DISCUSSION

The statistical demographic details of the participants in this study are shown in Table 1.

Table 1
Demographics of subjects

Parameter	Unit	Mean ± SD
Age	Years	27.12 ± 3.44
Weight	kg	70.20 ± 11.89
Height	m	1.67 ± 0.22
Body mass index	kg/m^2	23.29 ± 3.9

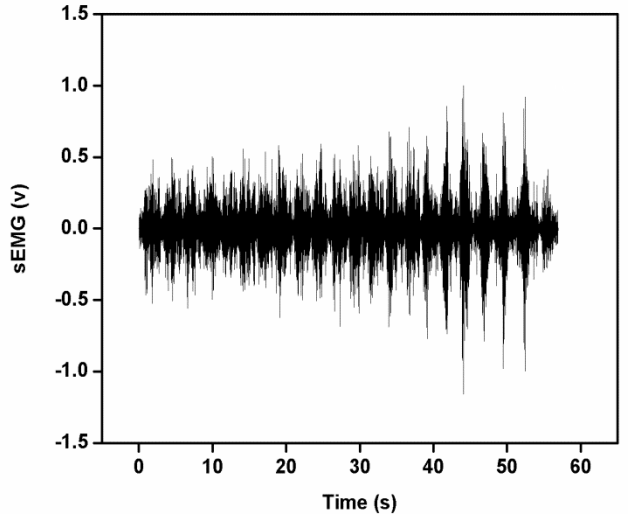

Figure 1. Representative recorded sEMG signal Intensity

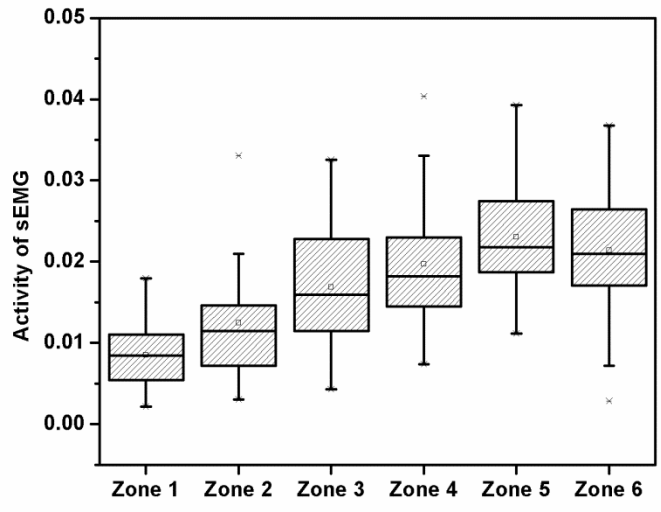

Figure 2. Activity of sEMG signals in all zones

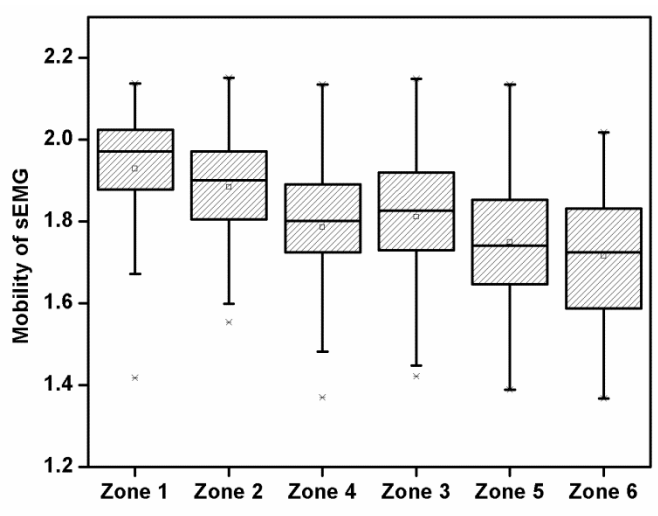

Figure 3. Mobility of sEMG signals in all zones

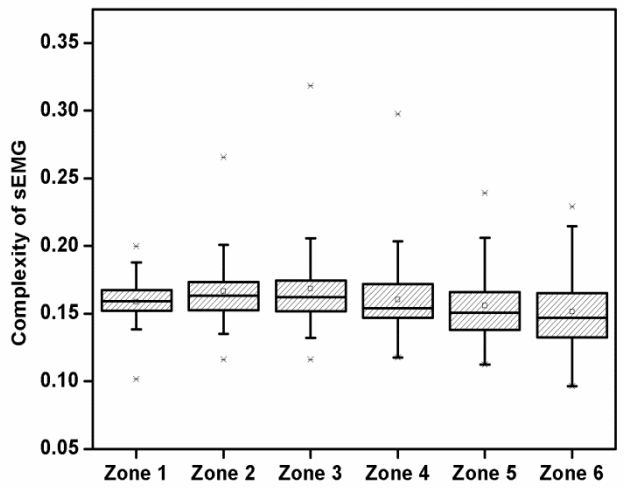

Figure 4. Complexity of sEMG signals in all zones

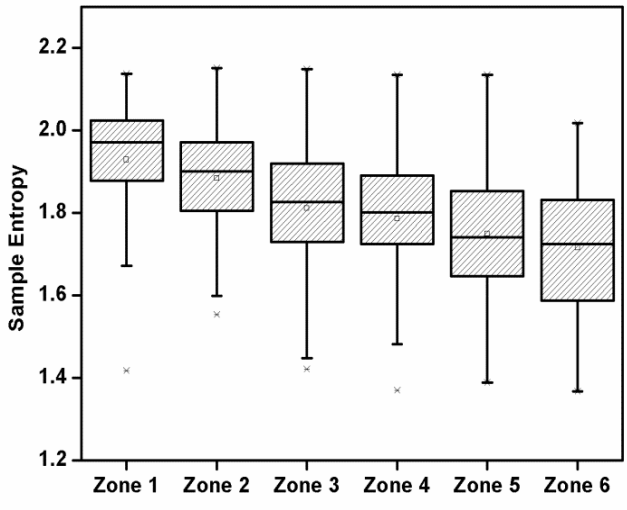

Figure 5. Sample Entropy of sEMG signals in all zones

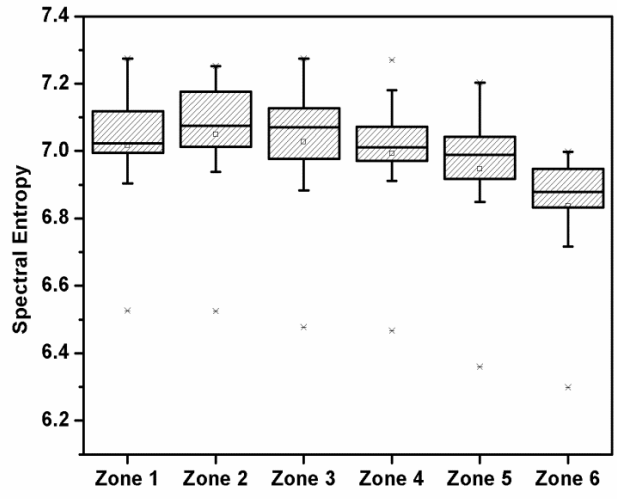

Figure 6. Spectral Entropy of sEMG signals in all zones

The sEMG signal recorded during dynamic contractions is shown in Figure 1. The amplitude and frequency component variations are observed and it is different among subjects. These signals are complex and nonlinear signal with low signal to noise ratio. This is due to the dependency of physiological parameters and the acquisition procedures.

The activity feature of sEMG signals are calculated for all zones and the corresponding box plot is shown in Figure 2. It is found to increase progressively from non-fatigue zone to fatigue zone. This is an indication of variation in non-stationarity of sEMG signal. This may be due to the reduction of motor units firing rate leading to synchronization of motor units. The mean of activity in non-fatigue zone is 0.009 and increased to 0.021 during fatigue as shown in Figure 2.

The mobility feature of sEMG signals is plotted for all zones and it is shown in Figure 3. This parameter is an indication of frequency variance of signal obtained in time domain. It is found to be decreasing from non-fatigue zone to fatigue zone. It can be considered as mean frequency [19]. The decrease in mobility parameter is due to reduction in conduction velocity and firing rate of motor units. Figure 4 shows the variation in complexity feature in all zones. It is associated with the change in frequency. However, this parameter is of less significant.

Sample entropy is found to be decreasing from non-fatigue to fatigue zone as shown in Figure 5. Higher value of SampEn is an indication of higher complexity. In fatigue zone, there may be a reduction in number of motor units participating in contraction. The SampEn is lower in fatigue zone due to this reduction. The smaller values of SampEn are also an indication of increasing self-similarity. This may be also due to reduction in degree of non-stationarity of sEMG signal in fatigue zone.

Spectral entropy parameter is found to reduce progressively as shown in Figure 6. The reduction in SE is associated with higher regularity. This may be due to lesser conduction velocity and firing rate in fatigue zone. The SE parameter is found to be distinct between non-fatigue and fatigue zone. The statistical t-test performed between the adjacent zones for all features has shown significant difference ($p<0.01$) in most cases.

IV. Conclusion

The sEMG signals are highly complex and non-stationary. In this study, the variation of time and frequency complexity features associated with progression of muscle fatigue is analyzed. The sEMG signals are recorded for fifty healthy subjects and divided into six equal epochs. The complexity features such as activity, mobility, complexity, SampEn and SE are extracted from all zones. The results are indicating that features such as mobility, sample entropy and spectral entropy are progressively decreasing during dynamic contraction. The mean value of mobility, SampEn, SE is lower in fatigue conditions. Further the mean value of activity is higher in fatigue conditions. All features except complexity provides clear demarcation for all six zones. Thus this method of analysis can be used in automated analysis of sEMG in varied clinical conditions.

References

[1] R. Merletti and P.A. Parker, Electromyography, physiology, Engineering and Non-invasive applications, IEEE Press in Biomedical Engineering, 2004.

[2] M. B. I. Reaz, M.S.Hussain and F. Mohd Yasin, “Techniques of EMG signal analysis: detection, processing, classification and applications," Biological Procedures Online, vol.8, pp. 11-35, 2006.

[3] G. Filligoi and F. Felici, “Detection of hidden rhythms in surface EMG signals with a non-linear time-series tool,” Med Eng Phy, vol. 21, no. 6, pp. 439–448, Jul. 1999.

[4] C. Falup-Pecurariu, “Fatigue assessment of Parkinson’s disease patient in clinic: specific versus holistic,” J Neural Transm, vol. 120, no. 4, pp. 577–581, Apr. 2013.

[5] A.G.Carolyn and A.J.David, “Muscle physiology,” Surgery, vol.28, no.2, pp. 55–59, 2010.

[6] S. Boyas and A. Guével, “Neuromuscular fatigue in healthy muscle: Underlying factors and adaptation mechanisms,” Ann Phys Rehabil Med, vol. 54, no. 2, pp. 88–108, Mar. 2011.

[7] N. A. Dimitrova and G. V. Dimitrov, “Interpretation of EMG changes with fatigue: facts, pitfalls, and fallacies,” J Electromyogr Kinesiol, vol. 13, no. 1, pp. 13–36, Feb. 2003.

[8] F. Monti, S. Mezzaroba, A. Accardo, L. Ferigo, M. Millevoi, A. De Michiel, and G. Pizzolato, “Quantitative sEMG analysis of gait in Parkinson’s patients with Freezing in {ON},” Clin. Neurophysiol., vol. 119, Supplement 1, no. 0, pp. S47 – S48, 2008.

[9] F. Spolaor, Z. Sawacha, G. Guarneri, A. Avogaro, E. Carraro, A. Venturin, R. Ferrari, A. Munari, S. Masiero, and C. Cobelli, “Dynamic {EMG} patterns in neurological pathologies: Comparison between chronic stroke and diabetic neuropathy,” Gait Posture, vol. 30, Supplement 1, no. 0, p. S44 –, 2009.

[10] M. J. Zwarts, G. Drost, and D. F. Stegeman, “Recent progress in the diagnostic use of surface {EMG} for neurological diseases,” J. Electromyogr. Kinesiol., vol. 10, no. 5, pp. 287–291, 2000.

[11] Slupik, Anna; Bialoszewski, Dariusz; Korabiewska, Izabela, “The Effect of Kinesiology Taping and Muscle Fatigue on Movement Control in the Shoulder Joint”, Int J Rehabil Res, pp. 32-41, 2009.

[12] G. Venugopal, M. Navaneethakrishna, and S. Ramakrishnan. “Extraction and analysis of multiple time window features associated with muscle fatigue conditions using sEMG signals,” Expert Syst Appl, vol.41, pp.2652–2659,2014.

[13] A. Phinyomark, P. Phukpattaranont and C. Limsakul, “Feature reduction and selection for EMG signal classification,” Expert Syst Appl, vol.39, pp.7420–7431, 2012.

[14] P.Bonato , S.H.Roy, M .Knaflitz, .CL.D.Luca. Time-frequency parameters of the surface myoelectric signal for assessing muscle fatigue during cyclic dynamic contractions, IEEE Trans on Biomed.Engg, vol.48, pp. 765-775, 2001.

[15] S.D. Wu, Chiu-Wen Wu, Tian-Yau Wu, and Chun-Chieh Wang, Multi-Scale Analysis Based Ball Bearing Defect Diagnostics Using Mahalanobis Distance and Support Vector Machine, Entropy, vol. 15, pp.416-433, 2013.

[16] Misra, H. Ikbal, S.; Bourlard, H. Hermansky, H. Spectral entropy based feature for robust ASR Acoustics, Speech, and Signal Processing. Proceedings. (ICASSP '04). IEEE International Conference on Acoustics, Speech and Signal Processing, vol.1, May 2004.

[17] J.C.McBridea, X.Zhaoa, B. Nancy, et al, Spectral and complexity analysis of scalp EEGcharacteristics for mild cognitive impairment andearly Alzheimer’s disease, Comput Meth Prog Med, vol.114, pp. 153–163, 2014.

[18] A. Bachiller, A. Díez, V. Suazo, C. Domínguez, M. Ayuso, R. Hornero, J. Poza, and V. Molina, “Decreased spectral entropy modulation in patients with schizophrenia during a P300 task,” Eur. Arch. Psychiatry Clin. Neurosci., pp. 1–11, 2014.

[19] C.Vidaurrec, N.Krämerc, B.Blankertzc and A.Schloglb," Time Domain Parameters as a feature for EEG-based Brain–Computer Interfaces," Neural Networks, 2009, vol..22, pp.1313-1319.