Multiscale Feature Based Analysis of Surface EMG Signals under Fatigue and Non-fatigue Conditions

Navaneethakrishna M and Ramakrishnan S
Non Invasive Imaging and Diagnostics Laboratory

*Abstract***— In this work, an attempt has been made to differentiate sEMG signals under muscle fatigue and non-fatigue conditions using multiscale features. Signals are recorded from biceps brachii muscle of 50 normal adults during repetitive dynamic contractions. After prescribed preprocessing, each signal is divided into six segments out of which first and last segments are considered in this analysis. Multiscale RMS (MSRMS) and Multiscale Permutation Entropy (MSPE) are computed for each subject in the time scales ranging from 1 to 50. The median values of the MSRMS and MSPE are calculated for further analysis. The results show an increase in amplitude for sEMG signals under fatigue condition. MSRMS values are found to be significantly higher in fatigue. An approximately constant difference in MSRMS value between fatigue and non-fatigue condition is observed over the entire time scale with a negative slope. Further, the median of MSRMS values for each subject is able to distinguish fatigue and non-fatigue conditions. Similar analysis on MSPE showed significant difference between fatigue and non-fatigue cases and lower values of MSPE is observed in fatigue. It is also observed that the median value of MSRMS and MSPE are able to distinguish these conditions. t-test for MSRMS, MSPE and their median value show high statistical significance. It appears that this method of analysis can be used for clinical evaluation of muscles.**

I. Introduction

Muscle fatigue is a neuromuscular condition in which muscle fails to produce required force [1]. Although muscle fatigue occurs in normals, it is also experienced in certain abnormal conditions, such as Parkinson's disease [2], endocrine disturbances [3], Guillain–Barré syndrome, Pompe disease and immobilization [4]. Recent researches suggest that the analysis of fatigue can help in diagnosis of the progression of neuromuscular disorders [5]. Analysis of muscle fatigue also plays a vital role in the fields of ergonomics, sports medicine [6] and rehabilitation [7].

The sEMG signals are widely used to study the behavior and dynamics of muscles in fatigue conditions. Various signal processing methods based on time, frequency, time-frequency distributions are employed in muscle fatigue assessment. The time domain features, such as root mean square value, average rectified value and frequency domain features namely median frequency, mean frequency and peak frequency have been used in fatigue analysis. Also, time-frequency method based features, such as instantaneous median frequency, mean frequency and spectral moments are used [8 - 10].

Frequency and time-frequency methods are limited in single time scale analysis [11]. Multiscale analysis is a technique, which transforms the time domain signal into different time scales by down-sampling or coarsegrain method [12]. Similar to the theory of wavelets, multiscale analysis includes subtle details of time series at different time scales. It facilitates the isolation of brief events in discrete time scales [13]. Wu et al. (2013) has applied multi-scale sample entropy, multiscale permutation entropy, multi-scale root-mean-square and multi-band spectrum entropy for ball bearing defect diagnosis [12].

Studies conducted by Gao et al. (2007) on monkey's neuronal activity suggests that the use of multiscale methods for the spiking pattern analysis would bring out the inherent distribution of energy at different time scales [14]. Features extracted from temporal structure of signals are important in differentiating normal and pathological conditions [15]. Goldberger et al. and Costa et al. have reported that analysis of signals in terms of several time scale components provides information about the complexity of physiological variable [11, 16]. It has been shown by Cashaback et al. (2013) that multiscale Shannon entropy analysis of sEMG signals under fatigue conditions is able to quantify the complexity associated with the physiological variable [15].

In this work an attempt is made to study the dynamic behavior of sEMG signals of biceps brachii in fatigue and non-fatigue conditions. The signals are analyzed using multiscale RMS (MSRMS) and multiscale permutation entropy (MSPE). The median of the MSRMS and MSPE are calculated. These features are further used to differentiate sEMG signals under fatigue and nonfatigue conditions.

II. Methods

A. Signal Acquisition and Experimental Protocol

In this study, sEMG signals from 50 healthy volunteers with no history of neuromuscular disease are recorded. The subjects were informed about the study and a written consent was obtained. Ag-AgCl surface electrodes are fixed on the bulk of the biceps brachii muscle after skin preparation. The inter electrode distance is kept as 3 cm. The electrodes are connected to Biopac MP36 system (24 bit resolution, CMRR 110 db) in bipolar configuration. The signals are acquired at a sampling rate of 10 KHz.

Navaneethakrishna M is with the Indian Institute of Technology Madras, Chennai, 600036 India (e-mail: kmakaram@ yahoo.com).
Ramakrishnan S is with the Indian Institute of Technology Madras, Chennai, 600036 India (e-mail: sramki@ iitm.ac.in).

The subjects are made to stand erect on an insulated platform. Each participant is requested to perform the biceps curl exercise using their dominant hand. The subjects are free to select the cycle frequency and encouraged to continue the experiment until they are unable to lift the load again [8].

B. Preprocessing

The acquired signals are preprocessed offline with a band pass filter of range 10 Hz – 400 Hz and a 50 Hz notch filter [8]. To normalize the time axis the signal is divided into six equal segments. The first segment corresponds to the signal after the start of dynamic contraction and the last segment is the signal acquired before task failure. These two segments are considered for the study as they indicate non fatigue and fatigue segments respectively.

C. Multiscale Root Mean Square

Multi-scale RMS is the RMS of the signal at multiple time scales. In this method the input signal is converted to a new time series of reduced length based on the coursegrain formula. A moving average based scale reduction is performed on the signal to give a new time series of the length N/t_s where N is the length of signal and t_s is the time scale. The new time series is split into 250ms windows and the RMS value is calculated. This is performed for compensating non-stationarity of the signal. The mean of the RMS (mRMS) value is calculated and is used for analysis [12, 17].

Also, the median value of mRMS across different time scales is computed and is used for further analysis.

The coursegrain acts as a moving average filter without overlap. This is calculated using the expression given

$$y_j^{t_s} = \frac{1}{t_s} \sum_{i=(j-1)t_s+1}^{jt_s} x_i \tag{1}$$

where, $y_j^{t_s}$ is the associated time series at scale t_s, x is the original time series and j=1,2,…N/t_s.

Root mean square value provides the energy related information and is calculated as follows,

$$RMS = sqrt\left(\frac{1}{n}\sum_n x(t)^2\right) \tag{2}$$

where, n is length of the series and $x(t)$ is the time series.

D. Multiscale Permutation Entropy

Similar to the MSRMS the coarsegrain time series is constructed and to that newly computed time series permutation entropy is computed [12].

The permutation Entropy (PE) is computed as follows,

$$P(\pi) = \frac{\#\{X_i^m \ has\ type\ \pi, i|1,2,\ldots,N-m+1\}}{N-m+1} \tag{3}$$

$P(\pi)$ represents the relative frequency for the permutation π
X_i^mIs the order-m segment of the time series

$$PEn(S,m) = -\sum_{i=1}^{m!} p(\pi_i)\log(p(\pi_i)) \tag{4}$$

E. Statistical Analysis

The statistical significance (paired t-test) of the RMS and PE at each time scale is found out using MATLAB. The median value across time scale is calculated for analyzing the distribution of energy values across all subjects.

III. Results and Discussion

Figure 1 shows a representative sEMG signal recorded from biceps brachii muscles during curl exercise. Depending on the subjects endurance limit the signal duration is observed to vary between 30 s to 90 s. The fatigue and non-fatigue zones are not distinguishable due to the complex nature of the signal. This may be due to the derecruitment of several motor units and non linear firing patterns.

For consistent analysis, among the six uniform segments, the zones under fatigue and non-fatigue conditions are considered and are shown in Fig.2 and Fig. 3 respectively. An individual observation on both the zones does not give enough information on fatigue and non-fatigue conditions. However, on close observation among most of the subjects, it is observed that the amplitude of the signals under fatigue cases is comparatively high. This may be due to increased firing rate of motor neurons and recruitment of more motor units.

Fig. 4 shows the MSRMS value of the representative signal shown in Fig. 1.

The obtained energy variations across the time scale are able to differentiate fatigue and non-fatigue conditions. It is found that the difference between the MSRMS values of fatigue and non-fatigue condition is maintained approximately constant throughout the time scale. The same trend is observed with all the subjects considered in this study.

The reduction in magnitude with respect to time scale is observed in both the cases. This may be attributed to the fact that the energy is proportional to the number of samples considered in that time scale.

To quantify MSRMS values across the time scale, the median values are considered for each subject pertaining to fatigue and non-fatigue conditions and are shown in Fig. 5.

The median values of MSRMS are low in all non-fatigue case whereas the same in fatigue are high despite the dispersion in the data values. Further, the spread in the non-fatigue data are found to be low whereas the spread is high in fatigue case which can be due to the varying degree of force produced by the subjects.

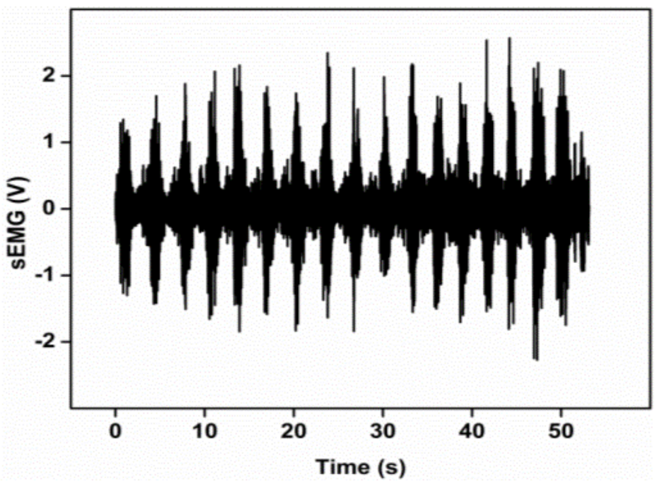

Figure 1. sEMG obtained under dynamic contractions

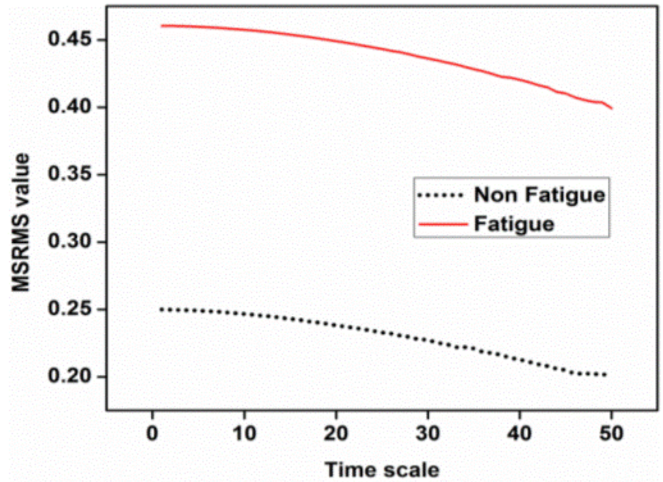

Figure 4. Representative variation of MSRMS with Time Scale

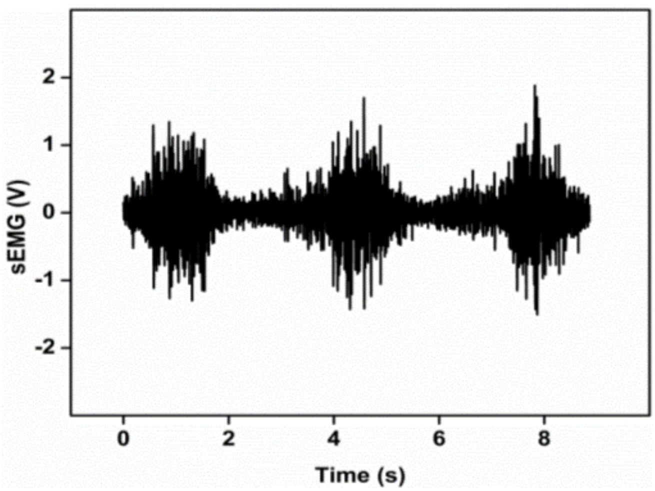

Figure 2. Representative Non-fatigue signal

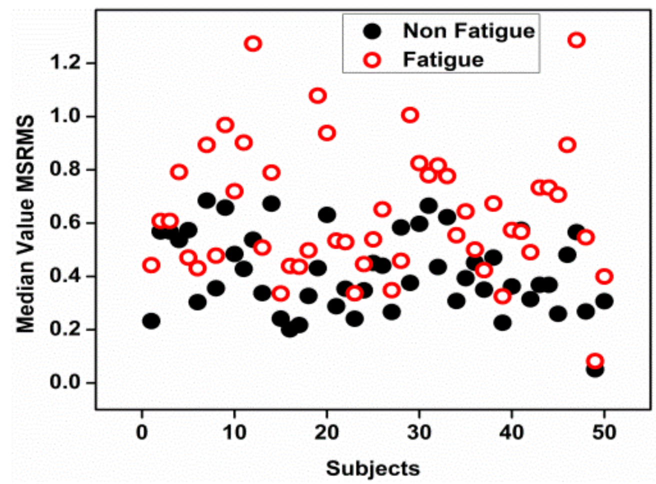

Figure 5. Variation of MSRMS Median values

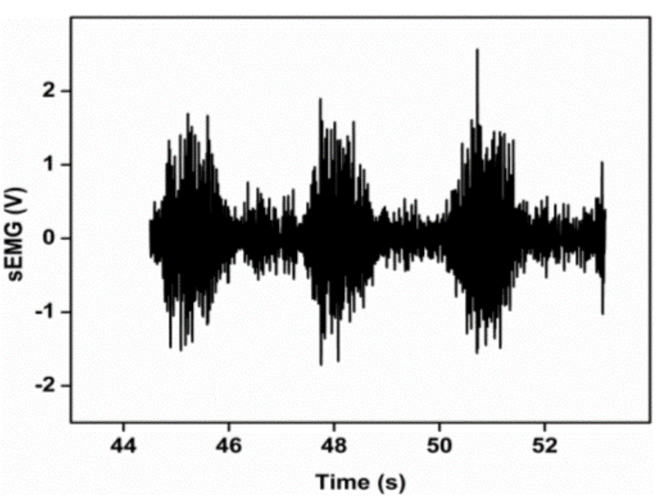

Figure 3. Representative Fatigue signal

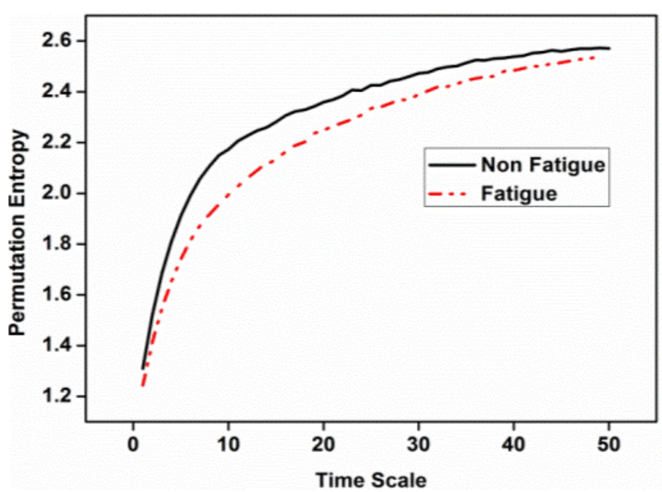

Figure 6. Variation of MSPE with Time Scale of the representative signal

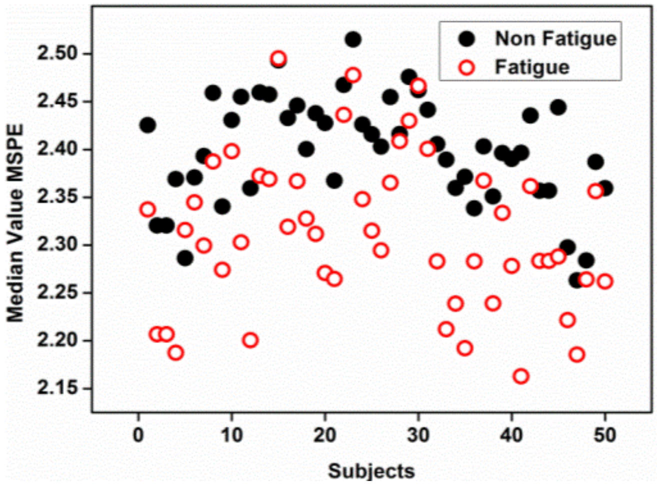

Figure 7. Variation of MSPE Median values among the considered subjects

The MSPE gives the variation of the permutation entropy based on time scale. There is a sharp increase in the PE value in the initial time scale and later on the values become a constant. Further it can be seen that the entropy value of the non-fatigue is higher which may be due to the reduction in complexity in the fatigue case.

For further analysis the median value of MSPE across subject are computed and is shown in Fig. 7. It found that in most of the subjects the median value is higher in non-fatigue. It is also observed that the fatigue median value has more variance.

The calculated mean and standard deviation of median values of MSRMS are found to be significantly reduced in non-fatigue condition. The inverse is true for the median values of the MSPE. The calculated P-value of the median of MSRMS and MSPE show that they are highly significant ($p < 0.0001$). The median value is found to be comparatively consistent in non-fatigue condition.

IV. Conclusion

The sEMG signals varies largely in fatigue conditions due to several factors, such as recruitment of fast twitch muscle fibers, nonlinear motor unit recruitment, synchronization of motor units, recruitment and de-recruitment of active motor units in the vicinity of recording electrodes and the movement of innervation zone [18]. It may be due to anthropometric variations, such as muscle size and muscle mass.

In this work, the sEMG signals in fatigue and non-fatigue conditions are analysed using multiscale parameters, such as MSRMS and MSPE. The results show a significant variation in the values of MSRMS and MSPE in the two zones. Median of MSRMS and MSPE are also able to differentiate the output conditions. The t-test scores for both of these features are found to be highly statistically significant ($p < 0.0001$). It appears that this method is useful for the identification of fatigue in various clinical conditions.

References

[1] 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.

[2] Falup-Pecurariu, "Fatigue assessment of Parkinson's disease patient in clinic: specific versus holistic.," J. Neural Transm., vol. 120, no. 4, pp. 577–81, Apr. 2013

[3] Greig and D. A. Jones, "Muscle physiology," Surg., vol. 28, no. 2, pp. 55–59, Feb. 2010.

[4] J. M. de Vries, M. L. C. Hagemans, J. B. J. Bussmann, A. T. van der Ploeg, and P. A. van Doorn, "Fatigue in neuromuscular disorders: focus on Guillain-Barré syndrome and Pompe disease.," Cell. Mol. Life Sci., vol. 67, no. 5, pp. 701–13, Mar. 2010.

[5] N. A. M. E. Van der Beek, M. L. C. Hagemans, A. J. J. Reuser, W. C. J. Hop, A. T. Van der Ploeg, P. A. Van Doorn, and J. H. J. Wokke, "Rate of disease progression during long-term follow-up of patients with late-onset Pompe disease.," Neuromuscul. Disord., vol. 19, no. 2, pp. 113–7, Feb. 2009.

[6] L. Ma, D. Chablat, F. Bennis, W. Zhang, B. Hu, and F. Guillaume, "A novel approach for determining fatigue resistances of different muscle groups in static cases," Int. J. Ind. Ergon., vol. 41, no. 1, pp. 10–18, 2011.

[7] J. H. Song, J. W. Jung, S. W. Lee, and Z. Bien, "Robust EMG pattern recognition to muscular fatigue effect for powered wheelchair control," J. Intell. Fuzzy Syst., vol. 20, no. 1, pp. 3–12, Jan. 2009.

[8] 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, no. 6, pp. 2652–2659, May 2014.

[9] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," Expert Syst. Appl., vol. 39, no. 8, pp. 7420–7431, Jun. 2012.

[10] P. Bonato, G. Gagliati, and M. Knaflitz, "Analysis of myoelectric signals recorded during dynamic contractions," IEEE Eng. Med. Biol. Mag., vol. 15, no. 6, pp. 102–111, 1996.

[11] L. Goldberger, L. A. N. Amaral, J. M. Hausdorff, P. C. Ivanov, C. K. Peng, and H. E. Stanley, "Fractal dynamics in physiology: alterations with disease and aging.," Proc. Natl. Acad. Sci. U. S. A., vol. 99 Suppl 1, no. 90001, pp. 2466–72, Feb. 2002.

[12] S. D. Wu, C. W. Wu, T. Y. Wu, and C. C. Wang, "Multi-Scale Analysis Based Ball Bearing Defect Diagnostics Using Mahalanobis Distance and Support Vector Machine," Entropy, vol. 15, no. 2, pp. 416–433, Jan. 2013.

[13] Mugler and A. Mahadevan, "Multiscale Signal Processing with Discrete Hermite Functions," in Multiscale Signal Analysis and Modeling SE - 11, X. Shen and A. I. Zayed, Eds. Springer New York, 2013, pp. 257–274.

[14] J. Gao, Y. Cao, W. W. Tung and J. Hu, Multiscale Analysis of Complex Time Series: Integration of Chaos and Random Fractal Theory, and Beyond , Wiley-Interscience; 1 edition, 2007, p. 368.

[15] J. G. A. Cashaback, T. Cluff, and J. R. Potvin, "Muscle fatigue and contraction intensity modulates the complexity of surface electromyography.," J. Electromyogr. Kinesiol., vol. 23, no. 1, pp. 78–83, Feb. 2013.

[16] M. Costa, A. L. Goldberger, and C. K. Peng, "Multiscale entropy analysis of complex physiologic time series.," Phys. Rev. Lett., vol. 89, no. 6, p. 068102, Aug. 2002.

[17] S. Thongpanja, A. Phinyomark, F. Quaine, Y. Laurillau, B. Wongkittisuksa, C. Limsakul, and P. Phukpattaranont, "Effects of Window Size and Contraction Types on the Stationarity of Biceps Brachii Muscle EMG Signals," in *Proceedings of the 7th International Convention on Rehabilitation Engineering and Assistive Technology*, 2013, pp. 44:1–44:4.

[18] D. R. Rogers and D. T. MacIsaac, "EMG-based muscle fatigue assessment during dynamic contractions using principal component analysis," J. Electromyogr. Kinesiol., vol. 21, no. 5, pp. 811–818, 2011.