A Method to Differentiate Fatiguing Conditions in Surface Electromyography Signals using Instantaneous Spectral Centroid

S. Edward Jero, K. Divya Bharathi, and S. Ramakrishnan

Abstract— **The nonstationarity measure of surface Electromyography (sEMG) signals provide an index for muscle fatigue conditions. In this paper, a new framework has been proposed for the analysis of sEMG signal using Instantaneous Spectral Centroid (ISC). The novelty of the proposed work is use of topological signal processing method to quantify the nonstationarity of sEMG signal. For this, the signals are recorded from the biceps brachii muscles of 25 healthy subjects in isometric contraction. The analytical signals corresponding to nonfatigue and fatigue segments are computed using Hilbert Transform. Further, topological features such as center of gravity (CoG), triangular area function (TAF) and ISC are calculated from the geometrical representation of a transformed signal. The result indicates the increase of TAF in fatigue condition and the significant right shift of CoG in *x*-axis for 80% of subjects. Importantly, the ISC estimate is decreased by 17% upon fatiguing for 84% of subjects. The obtained results show statistical significance with $p < 0.05$. It is observed that the shape parameters are varied in accordance with the changes observed in global characteristics of sEMG signals during muscle fatigue. The preliminary results show that the topological features are able to quantify the nonstationarity in sEMG signal. Therefore, the proposed method can be used as a fatigue index for diagnosing various neuromuscular disorders.**

Clinical Relevance – **This method can be used to establish metrics of muscle fatigue for the benefit of physicians especially in the field of fitness, sports, pre and post-surgery surveillance and rehabilitation.**

I. Introduction

Fatigue is the state when the muscles fail to produce the essential force for a brief period of time. It is due to the sustained contraction of the muscle or the chemical imbalances of metabolites in the muscle fibers. It affects the physiology such as motor unit recruitment and conduction velocity. Permanent impairment of muscles may occur if the contraction continues even after reaching the fatigue state and it is irreversible. Therefore, muscle fatigue analysis is important in fitness, sports, and pre and post-surgery surveillance [1]. The surface Electromyography (sEMG) signal is the superposition of the action potentials generated by the motor units which provide the information associated with fatiguing conditions. Usually, the amplitude and frequency components of sEMG signal are analyzed for the extraction of biomarkers to detect the onset of fatigue condition [2]. The recent signal processing methods can be used to extract the insights of sEMG signal characteristics for the interpretation of fatigue condition.

In time domain, root mean square and average rectified value features are widely used to differentiate the nonfatigue (NF) and fatigue (FG) conditions. However, the lack of frequency information in these features may limit their usability in muscle fatigue analysis. On the other hand, spectral changes are studied using the frequency domain features such as mean and median frequency for characterizing the progression of fatigue [3]. Frequency domain analysis has a prior assumption that the signals are stationary in nature. Time Frequency Representation (TFR) namely, short time Fourier transform, Hilbert transform, continuous wavelet transform and Wigner Ville distribution are also applied for the analysis of sEMG signals. Significantly, TFR provides better understanding of sEMG signals compared with time domain and frequency domain features [4].

Recently, signal processing methods are used to extract the topological features from biosignals. It provides the shape description of a signal. Commonly, the boundary points of a shape are obtained from the polar coordinates of (i) an analytical signal and (ii) Fourier descriptors of the signal [5,6]. The major classifications of shape features are: (i) 1D function (ii) spatial interrelation feature (iii) moments (iv) shape transform domains and other methods. The most common shape-based features include axis of least inertia, center of gravity, eccentricity, bending energy, circularity ratio, rectangularity, elliptic variance and convexity [7]. However, the feasibility of muscle fatigue analysis using topological features is the challenging task which is not explored.

In this work, several topological features are proposed to calculate the muscle fatigue index and quantify the nonstationarity in sEMG signals. The shape representation of a signal is obtained from the analytical signal of sEMG. Then, the instantaneous frequencies of the signals are computed followed by the extraction of features.

II. Related work

The widely used method for the analysis of nonstationary time series is Hilbert Transform which provides the analytical signal. Hilbert marginal spectrum based muscle fatigue analysis has been reported in [8,9]. They used several entropy based measures for fatigue index estimation from the marginal

S. Edward Jero, K. Divya Bharathi and S. Ramakrishnan are with the Indian Institute of Technology Madras, Chennai 600036, India (e-mail: edwardjero@gmail.com, divyak0593@gmail.com, sramki@iitm.ac.in).

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spectrum. The dynamics of nonlinear and complex nature of Electroencephalography (EEG) signals has been characterized using topological features in [10]. They represented the EEG signal in phase space followed by the extraction of features. They reported an accuracy of 97% using topological features for EEG signal classification. Further, shape based parameters such as centroid and area are obtained from the closed boundary in the polar plane [11]. They calculated the features directly from the Fourier coefficients of the boundary function. However, the topological features are not explored in sEMG signal for muscle fatigue analysis.

The remainder of this paper is structured as follows: Section III describes the proposed method. The results are discussed in section IV followed by the conclusion.

III. PROPOSED METHOD

The proposed work aims to estimate muscle fatigue index using topological features. Various steps followed in this approach are: (i) sEMG signal acquisition (ii) Hilbert transform based shape description of sEMG signal (iii) computing envelope of sEMG in polar plane and (iv) topological feature estimation. The framework for analyzing muscle fatigue using topological features is given in Fig. 1.

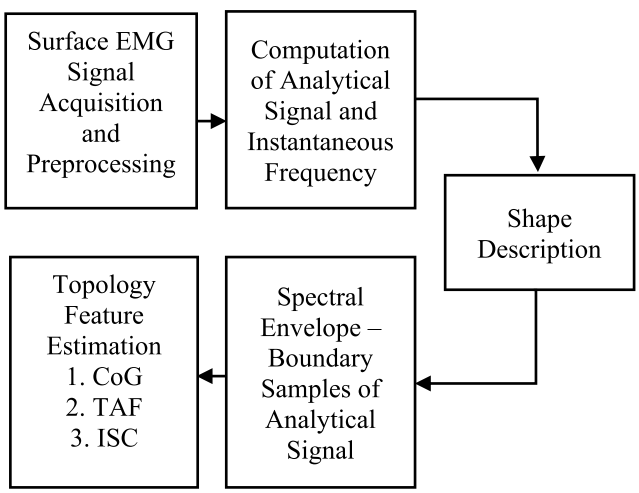


Figure 1. Proposed Topology Feature based Framework

A. Experimental Protocol

sEMG is acquired using BIOPAC data acquisition system at the sampling frequency of 10000 Hz. The electrodes are positioned in bipolar configuration on biceps brachii muscle belly and bony part of elbow is used as reference. Alcoholic wipe is used for skin preparation. Electrical isolation is provided by means of wooden platform. The subjects are asked to hold a 6 kg dumbbell at an elbow angle of 90° and monitored for 10° drop or verbal input confirming the fatigue condition [8]. In this experiment, isometric contraction protocol (ICP) is used to acquire signal from 25 healthy adult volunteers with their informed consent. Table I gives the demographic information of the subjects.

During preprocessing, the recorded sEMG signals are down sampled to 1000Hz. Next, high frequency noises, power line interference and other artefacts are removed from sEMG signal using 20Hz - 500Hz bandpass filter and 50Hz notch filter respectively. The first and last one second segments chopped from the sEMG signal represent the NF and FG conditions respectively. Further, these segments are considered for the extraction of topological features.

TABLE I. DEMOGRAPHIC DETAILS

Parameters	***Unit***	***Mean ± SD***
Weight	kg	70.20 ± 11.89
Height	m	1.67 ± 0.22
Body Mass Index	kg/m^2	23.29 ± 3.9
Age	years	27.12 ± 3.44

B. Analytical Signal Computation

Hilbert transform provides the analytical signal $z(t)$ for the NF and FG segment $x(t)$ as expressed in (1).

$$z(t) = x(t) + iH\left[x(t)\right] \qquad z(t) = a(t)e^{i\theta(t)} \tag{1}$$

where, $H[x(t)]$ is the Hilbert transform of $x(t)$. The amplitude $a(t)$, phase angle $\theta(t)$ and the instantaneous frequency (InsFreq) w of the obtained Hilbert coefficients are calculated using (2), (3) and (4) respectively.

$$a(t) = \sqrt{x^2(t) + H^2\left[x(t)\right]} \tag{2}$$

$$\theta(t) = arctan\left(\frac{H\left[x(t)\right]}{x(t)}\right) \tag{3}$$

$$w(t) = \frac{d\theta(t)}{dt} \tag{4}$$

The shape description of sEMG signal is obtained from the polar coordinates (a, θ) as given in (2) and (3). Then, the envelope of a signal is constructed from boundary points. The instantaneous frequencies of the boundary points are used for topology feature estimation.

C. Center of Gravity of Analytical signal

The Center of Gravity (CoG) is obtained from the shape formed by the envelope of the analytical signal using (5).

$$g_x = \frac{1}{N}\sum_{m=1}^{N} x_m \ , \ g_y = \frac{1}{N}\sum_{m=1}^{N} y_m \tag{5}$$

where, x represents the NF or FG segment of sEMG signal and y is an analytical signal of x, N is number of data points.

D. Triangular Area Function

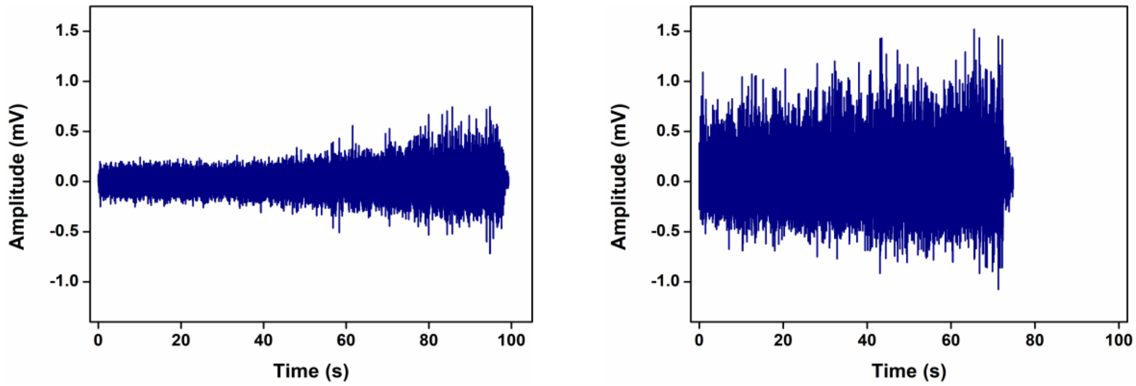
Triangular area function (TAF) is obtained by summing up the area of triangles formed from CoG and two consecutive boundary points. It is given in (6):

$$TAF = \sum_{k=1}^{N} \frac{1}{2} \begin{vmatrix} x_k & y_k & 1 \\ x_{k+1} & y_{k+1} & 1 \\ g_x & g_y & 1 \end{vmatrix} \tag{6}$$

where, N represents the number of boundary points.

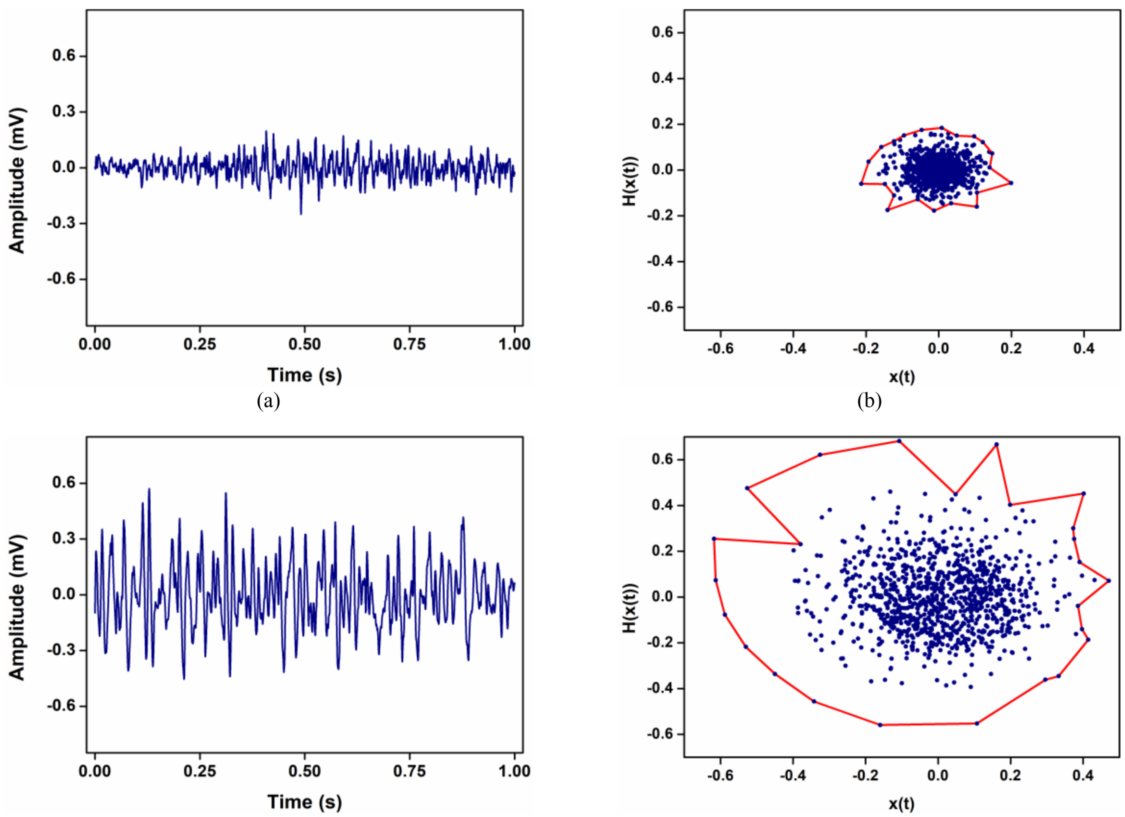
E. Instantaneous Spectral Centroid

The measure of Instantaneous Spectral Centroid (ISC) is obtained by evaluating the spectral centroid using the InsFreq found from Hilbert transform and its magnitude.



(a) (b)

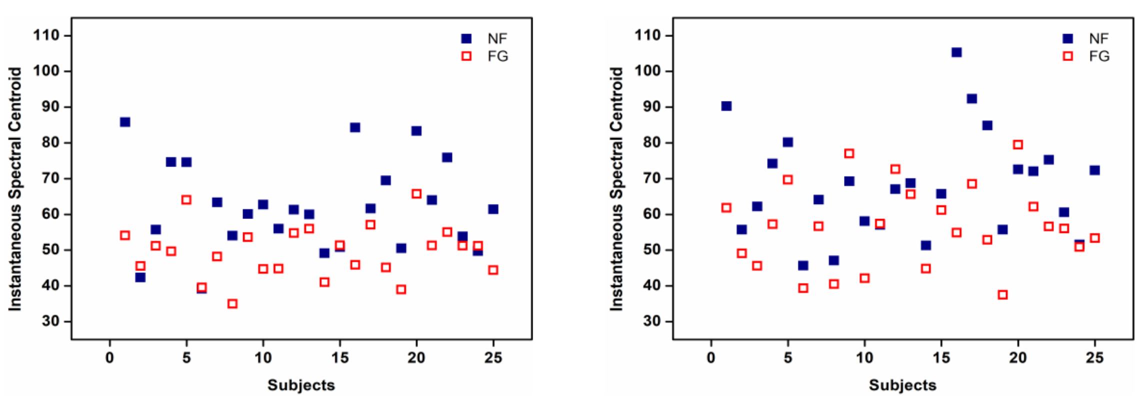
Figure 2. Representative sEMG signal of (a) Subject 1 (b) Subject 2



(a) (b)

(c) (d)

Figure 3. (a) NF segment of Subject 1 and (b) its shape representation (c) FG segment of Subject 1 and (d) its shape representation



(a) (b)

Figure 4. Instantaneous Spectral Centroid using (a) All the samples (b) Boundary samples

$$ISC = \frac{\sum_{k=1}^{N} w_k |H_k|}{\sum_{k=1}^{N} |H_k|} \tag{7}$$

where, w_k and $|H_k|$ denote InsFreq and magnitude of InsFreq respectively. In this study, the performance of InsFreq based spectral centroid feature in differentiating NF and FG condition is compared using all the analytical signal samples and the boundary samples.

IV. Results and Discussion

The representative signals of two subjects are depicted in Fig. 2(a) - 2(b). It can be observed that the amplitude increases towards fatigue and the variations in endurance time can be seen among subjects.

Figure 3(a) and 3(c) show the NF and FG segments of signal 1 respectively and their corresponding analytical signals are given in Fig. 3(b) and 3(d). The boundary points obtained from the analytical signal are connected which gives the shape representation of signals. It is clearly visible that the area of the shape formed by the envelope of FG segment is found to be higher than the NF segment. This can be due to the increase in amplitude of sEMG signal during fatiguing.

The values of TAF and CoG for two representative subjects are given in Table II. For subject 1, TAF is found to be ten times higher in FG compared with NF. For subject 2, TAF is increased by 1.3 times in FG segment. Hence, it can be seen that the changes in amplitude of sEMG signal is reflected in TAF feature. Similar changes are observed for NF and FG segments in 80% of subjects. It appears that TAF can be interpreted as the amplitude of sEMG signal.

TABLE II. TAF and CoG for two representative subjects

	TAF		CoG	
	NF	FG	NF	FG
Subject 1	0.095	0.947	0.00048	0.001
Subject 2	1.343	1.711	-0.004	-0.0025

The x-coordinate of CoG for NF and FG segments of two representative subjects are given in Table II. The values show that the CoG increases in FG segment. That is, CoG is right shifted by a certain factor in the x-axis. It is to be noted that the x-coordinate corresponds to the real part of the analytical signal which can be directly related with the amplitude of sEMG signal. The right shift in CoG upon fatiguing condition denotes the increase in amplitude of sEMG signal.

Figure 4(a) shows the ISC estimates of 25 subjects obtained using all the analytical signal samples in NF and FG segments. In the same way, ISC estimated using the samples of the envelope is depicted in Fig. 4(b). It is observed that ISC is decreased for 84% of subjects upon fatiguing conditions in both the cases. The ISC of the representative subject 1 and 2 is decreased by 59% and 7.89% during fatiguing condition when ISC is estimated using all the samples. On the other hand, ISC is decreased by 46% and 34% for FG segment compared with NF segment, when ISC is estimated using the boundary samples of envelope. This high value in NF segment may be due to the presence of high frequency components and vice versa. These features are found to be statistically significant with p value < 0.05. It appears that ISC can be used as a fatigue index estimator for sEMG signals.

V. Conclusion

For this study, twenty-five sEMG signals of biceps brachii muscle are recorded from healthy volunteers using ICP. The signal shows higher amplitude towards cessation time as a consequence of motor unit synchronization upon fatiguing conditions. First, the analytical signals of NF and FG segments are obtained using Hilbert Transform. The envelope of the signals in polar plane and the boundary points are obtained. Then, ISC is estimated using InsFreq of all the analytical signal samples and boundary samples. In addition, CoG and TAF features are estimated. The insight of this study is that the topological features CoG and TAF are connected with the amplitude of the signals. On the other hand, ISC directly reflects the decrease in frequency of sEMG signals for fatigue condition. The results show statistical significance with $p < 0.05$. It appears that the topological signal processing method can be applied for muscle fatigue analysis. The proposed method can be extended to analyze the sEMG signals of other skeletal muscles.

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