Geometric Features based Muscle Fatigue Analysis using Low Frequency Band in Surface Electromyographic signals

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Abstract— **In this study, an attempt has been made to evaluate the applicability of geometric features extracted from the different frequency bands of surface electromyography (sEMG) signals for detecting muscle fatigue condition. For this purpose, sEMG signals are acquired from twenty-five healthy volunteers during isometric contraction of biceps brachii muscle. The nonfatigue and fatigue segments are obtained from preprocessed signals and are separated into low frequency band (LFB: 15-45Hz), medium frequency band (MFB: 55-95Hz) and high frequency band (HFB: 95-500Hz). The analytical representations of these signals are obtained from Hilbert Transform and the features, area and perimeter are extracted from the resultant shape. The results demonstrate that the features obtained from the three bands can differentiate nonfatigue and fatigue conditions with significant difference ($p<0.05$). Among the three bands, LFB achieves high sensitivity of 88% and 84% for perimeter and area feature respectively. However, sensitivity in MFB and HFB is decreased for both the features. It appears that the geometric features associated with LFB signals are more sensitive in detecting fatigue. It is interesting to note that the sensitivity is in acceptable level for low-frequency signals (15-45Hz). However, the study has to be conducted on large population to draw a reliable conclusion.**

I. Introduction

Skeletal muscles are responsible for numerous activities that are performed in our daily life. They play a vital role in control of force and making precise or powerful movements. Muscles consist of fibres that are innervated by α-motor neurons for producing movements [1].

The muscle fibers are divided into slow and fast twitch depending on their speed of contraction and fatiguability. Fast twitch fibers are the primary reason for the generation of high force but they are more prone to fatigue. On the other hand, slow twitch fibers show more resistance towards fatigue and produce less force [1].

Fatigue is a phenomenon that results from the reduction in maximum muscle force during various type of contractions. Examination of muscle fatigue is very essential in rehabilitation, functional electrical stimulation and sports. If left unnoticed, fatigue becomes irreversible and results in muscle impairment [2, 3].

Surface electromyography (sEMG) records the muscle activity with the help of surface electrodes. The sEMG signals are the arithmetic summation of action potentials produced by motor units during various contractions in muscle of interest [4]. The complexity of these signals arises due to the presence of multiple frequency components and its nonstationary variations. This takes place as a result of various physiological factors namely, motor neuron firing rate and conduction velocity [5, 6].

Analyzing sEMG signals by separating its frequency bands have been extensively studied recently. This has been done for finding the possibility of assessing muscle fatigue at low sampling rate. The bands are divided into low frequency band (LFB) with the frequency range of 15-45 Hz, medium frequency band (MFB) ranging from 46-95 Hz, high frequency band (HFB) having frequencies >95 Hz respectively [7, 8].

Recently, geometric features are being used for performing shape analysis in biosignals [9]. They are capable of detecting the hidden structures of time series. It has been applied in various image processing applications and also for seizure detection using electroencephalographic signals [10, 11].

In this work, different frequency bands of sEMG signals are examined for detecting fatiguing contractions of muscle using geometric features.

II. Methodology

A. Experimental Protocol

Twenty-five healthy volunteers took part in the study with written consent obtained prior to the start of experiment. All the participated subjects have no previous history of neuromuscular injuries. This experiment follows the principle of Declaration of Helsinki. The participants are advised to perform isometric contraction after explaining the procedure. They are asked to hold a 6 kg dumbbell load at an elbow angle of 90°. They are advised to inform when they feel first muscle discomfort. The experiment continues until there is a 10° drop of angle or when the subject experiences fatigue. The endurance time is noted for further analysis [8]. The details of the participants are mentioned in Table I.

TABLE I. DEMOGRAPHICS OF PARTICIPANTS

Parameters	***Unit***	***Mean ± SD***
Height	m	1.67 ± 0.22
Weight	kg	70.20 ± 11.89
Age	years	27.12 ± 3.44

B. Signal Acquisition and Preprocessing

The participants are advised to position upright on a wooden platform for electrically isolating from ground. The signals are acquired at 10000 samples per second in bipolar configuration. The Silver-Silver chloride electrodes are positioned on the biceps brachii at an interelectrode spacing of 3cm and elbow as reference. The BIOPAC data acquisition system is used for this process [5].

The recorded sEMG signals are down sampled to 1000Hz during preprocessing. Then, the signals are filtered using 10Hz - 500Hz bandpass filter and 50Hz notch filter respectively for removing high frequency noises, power line interference and other artefacts. The first and last one second segments are obtained from the sEMG signal which represents the nonfatigue and fatigue conditions respectively [6].

The frequency bands are separated from the nonfatigue and fatigue segments. The LFB (15-45 Hz), MFB (55-95 Hz) and HFB (>95 Hz) are obtained from both the segments. For MFB, 55–95 Hz is considered in this work to neglect the dominance of power line interference [8]. These bands are further subjected to Hilbert transform for extracting geometric features.

C. Analytic Signal

Hilbert transform gives the analytical signal $z(t)$ for the filtered input segment $x(t)$ which is expressed in (1).

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

where, H denotes the Hilbert transform. The real and imaginary coefficients obtained from Hilbert Transform are plotted over each other to form an analytical signal representation [13, 14].

D. Geometric Features

The geometric features such as area and perimeter are extracted from the shape formed by connecting the boundary of analytical representation [11, 12].

Area

Area is obtained by summing up the area of triangles formed from centroid and two consecutive boundary points. It is given in (2):

$$Area = \sum_{m=1}^{N} \frac{1}{2} \begin{vmatrix} x_m & y_m & 1 \\ x_{m+1} & y_{m+1} & 1 \\ g_x & g_y & 1 \end{vmatrix} \tag{2}$$

where, N denotes the total boundary points, g_x, g_y are centroid, and x_m, y_m are the boundary points along x and y axes.

Perimeter

The sum of Euclidean distance d_n between the adjacent points in the boundary of the obtained shape. It is expressed as given in Eq. (3).

$$P = \sum_{n=1}^{K-1} d_n \tag{3}$$

where, $d_n = \sqrt{\left(x_{m+1} - x_m\right)^2 + \left(y_{m+1} - y_m\right)^2}$, n = 1, 2, 3,.., N-1, x_m and y_m represents the coordinates of the boundary points in the complex plane.

E. Statistical Significance

The features are found to be normally distributed in all the three bands. The significance of the obtained features is analysed using paired t-test for differentiating the nonfatigue and fatigue conditions ($p<0.05$).

III. RESULTS AND DISCUSSIONS

The sEMG signals of two subjects are depicted in Fig. 1. The subjects are observed to have varied endurance time. Further, their amplitude and frequency characteristics are observed to change across subjects.

The nonfatigue and fatigue segments of Subject 1 are found and the analytical representation for LFB, MFB and HFB are obtained. Fig. 2(a) and 2(b) shows the analytical representation of LFB for nonfatigue and fatigue segments of subject 1 respectively. It is observed to increase in the fatigue condition.

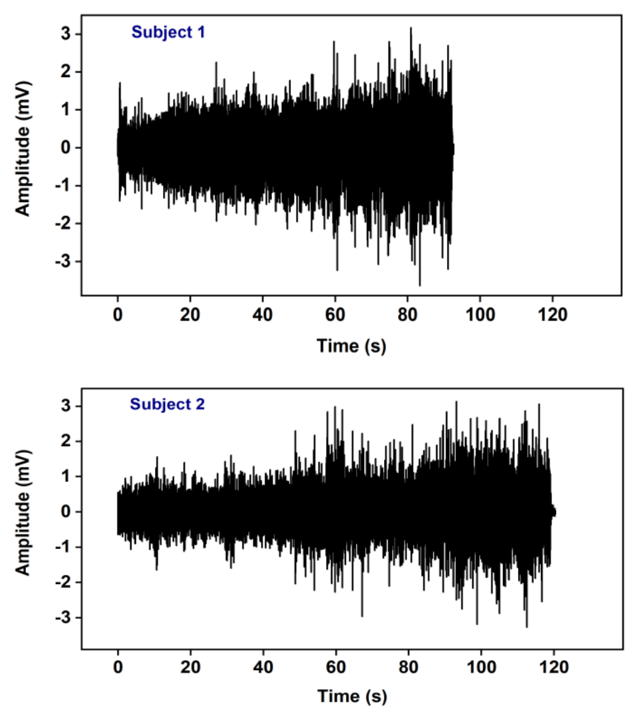
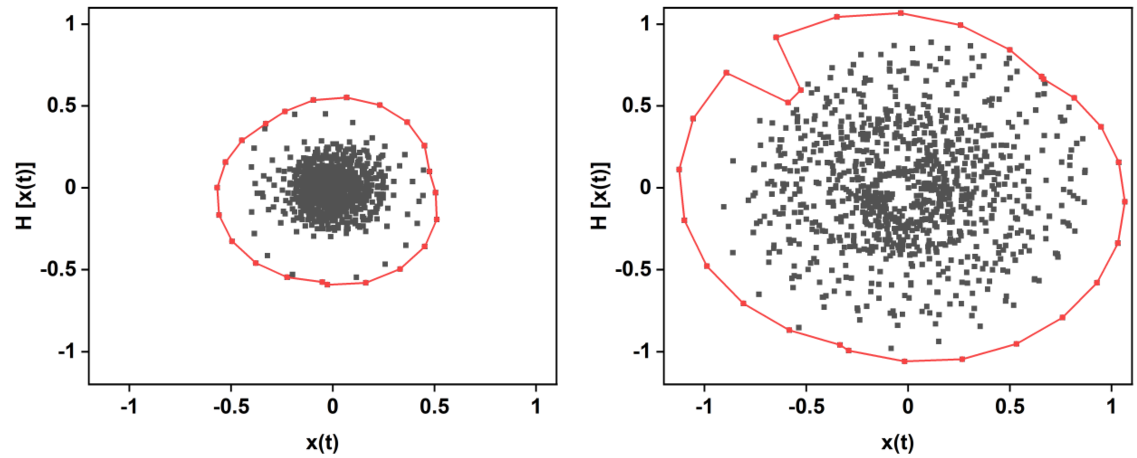
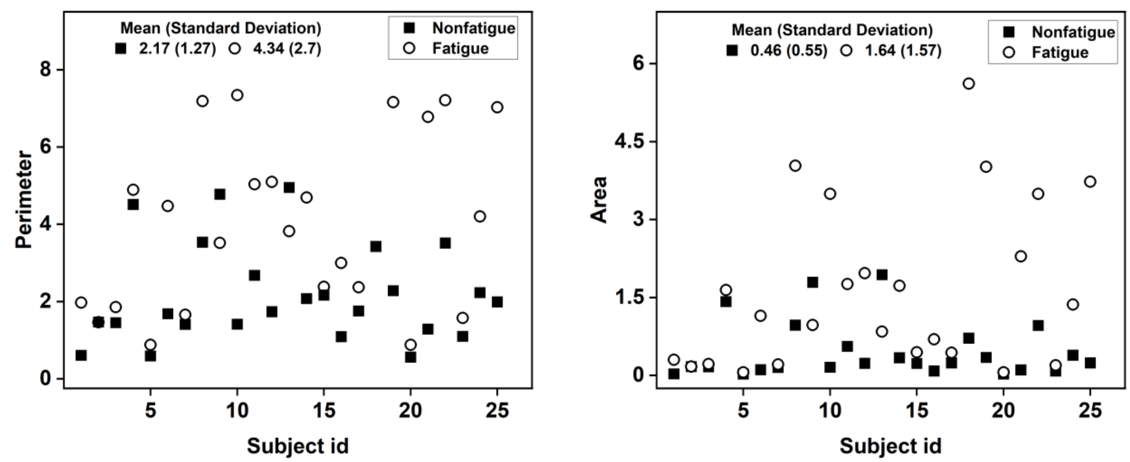


Fig.1. Representative sEMG signals



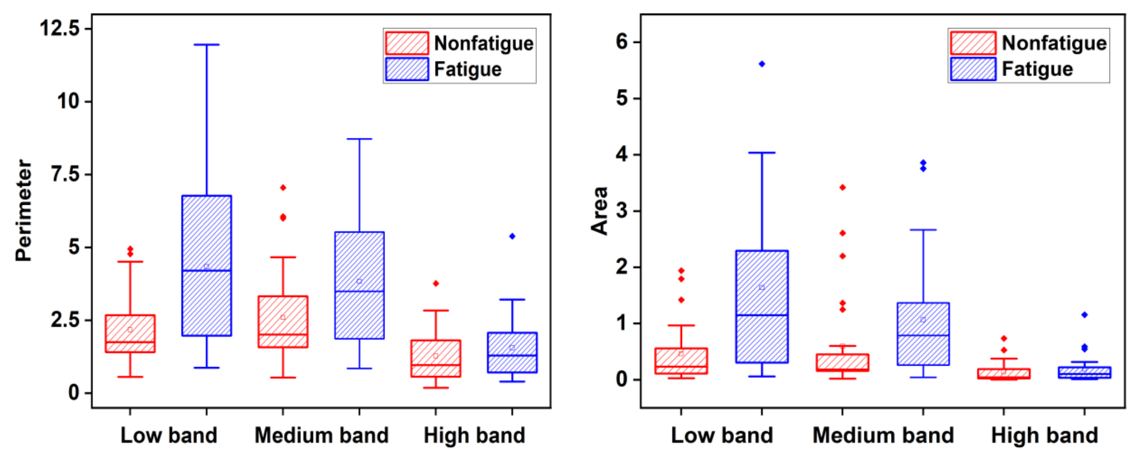
(a) (b)

Fig.2. Analytic representation of Subject 1 (a) nonfatigue and (b) fatigue segment



(a) (b)

Fig.3. Scatter plot showing variation of features in nonfatigue and fatigue in Low frequency band (a) Perimeter (b) Area



(a) (b)

Fig. 4. Box plot showing three frequency band comparison of nonfatigue and fatigue (a) Perimeter and (b) Area

The geometric features namely, area and perimeter are obtained for three bands under both nonfatigue and fatigue conditions. Fig. 3(a) and Fig. 3(b) show the variation of perimeter and area features for LFB across subjects respectively.

The mean value and standard deviation are found to be 2.17 and 1.27 respectively for perimeter feature in nonfatigue condition as seen in Fig. 3(a). However, for fatigue condition, it is found to increase and the values are 4.34 and 2.7. The higher perimeter value indicates the amplitude increase in fatigue conditions. The variations are observed to be high across subjects. It is also found that the sensitivity of the perimeter feature is 88 % in this frequency band. But the sensitivity is reduced to 80% for MFB and it goes further down to 72% for HFB.

Similarly, from Fig. 3(b), the mean value of 0.46 and standard deviation of 0.55 are observed in area feature for nonfatigue condition. It is increased to 1.64 and 1.57 during fatigue condition. The variations are observed to be less when compared with perimeter feature. It is to be noted that this feature corresponding to LFB detects the fatigue condition with sensitivity of 84%. It goes down to 76% and 68% for MFB and HFB respectively.

The band comparison for these two features are given in Fig. 4(a) and 4(b). The increase in perimeter feature for fatigue conditions across three bands is shown in Fig. 4(a). Similarly, Fig. 4(b) illustrates the increase in area feature for fatigue conditions. These features show higher variance in LFB and MFB compared with HFB for both the conditions. It can be seen that the LFB shows better variations between nonfatigue and fatigue conditions for both the features. The HFB shows overlap for nonfatigue and fatigue cases in both the features. The increase in these feature values for the three frequency bands correspond to the amplitude increase in the fatigue conditions which could be due to motor unit synchronization. Further, the LFB is associated with the firing of larger number of slow twitch fibers during fatigue that compensates for the force produced by muscle.

IV. Conclusions

In this study, different frequency bands are analyzed in sEMG signals using geometric features for muscle fatigue detection. The signals acquired from biceps brachii muscle are chopped to obtain nonfatigue and fatigue segments. Then, the LFB, MFB and HFB segments are found and their analytical representations are obtained using Hilbert transform. The shape is formed from the boundary points and geometric features such as area and perimeter are extracted. The results show that these features can differentiate nonfatigue and fatigue conditions under the three bands. But, LFB performs better among the three bands with good sensitivity. The obtained features show significant difference with $p<0.05$. Hence, it appears that the geometric features in LFB is more sensitive in fatigue detection. The results are promising and it could be useful for real time monitoring in workplace and for applications such as rehabilitation.

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