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Analysis of muscle fatigue conditions using time-frequency images and GLCM features

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Abstract: In this work, an attempt has been made to differentiate muscle non-fatigue and fatigue conditions using sEMG signals and texture representation of the time-frequency images. The sEMG signals are recorded from the biceps brachii muscle of 25 healthy adult volunteers during dynamic fatiguing contraction. The first and last curls of these signals are considered as the non-fatigue and fatigue zones, respectively. These signals are preprocessed and the time-frequency spectrum is computed using short time fourier transform (STFT). Gray-Level Co-occurrence Matrix (GLCM) is extracted from low (15–45 Hz), medium (46–95 Hz) and high (96–150 Hz) frequency bands of the time-frequency images. Further, the features such as contrast, correlation, energy and homogeneity are calculated from the resultant matrices. The results show that the high frequency band based features are able to differentiate non-fatigue and fatigue conditions. The features such as correlation, contrast and homogeneity extracted at angles 0°, 45°, 90°, and 135° are found to be distinct with high statistical significance ($p < 0.0001$). Hence, this framework can be used for analysis of neuromuscular disorders.

Keywords: gray-level co-occurrence matrix; short time fourier transform; surface electromyography; time-frequency image.

1 Introduction

Muscle fatigue is a time-related progressive impairment of maximal force generating capacity of the muscles. It arises due to sustained or intense contraction, Parkinson's disease, carcinoma, endocrine disturbances, malnutrition and immobilization [1]. Repeated fatigue may lead to irreversible impairment of muscles. Hence, it is necessary to analyse fatigue conditions for the clinical diagnosis of muscle disorders. Surface electromyography (sEMG) is a non-invasive technique which is commonly used to analyse muscle fatigue [2].

sEMG is a complex bio-electric signal which represents the contraction of the muscle in the body. It offers useful information to understand the human movement which helps in the assessment of muscular activation and internal loads on muscles, tendons, and other tissues. These signals are random, non-stationary and multi-component in nature [3].

The main component of fatigue analysis is the identification of prominent features of the signal [1]. Various methods have been proposed in the literature based on the extraction of sEMG features in the time [4], frequency [5], and t-f domain [2, 3, 6]. The time domain features contain amplitude, rhythmicity and entropy information. The frequency domain features includes spectrum normalized power, frequency sub-band powers and mean frequency. In the t-f domain, the features are extracted from the time-frequency representation of sEMG signals and are capable of characterizing the non-stationary and multi-component nature of sEMG signals [3]. These include instantaneous frequency and sub-band energies.

Recently, time-frequency spectrum computed from the EEG signals is considered as images and the features extracted are used for the automatic detection of epileptic seizure in EEG data [7–12]. These features includes Haralick features [8], texture features such as first order moment, second order moment [10], GLCM [7, 10, 12], texture feature coding method [4] and local binary pattern [7, 9] and Histogram features such as mean, variance, skewness and kurtosis [11].

In this work, sEMG signals are recorded from biceps brachii muscles in bipolar configuration. These signals are represented in t-f domain using the spectrogram of STFT. The corresponding images obtained are subdivided into three images based on the frequency bands and converted into 8- bit grayscale images. Finally, GLCM texture features are extracted and sEMG signals are analysed.

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2 Methodology

Signals are acquired from 25 normal subjects with no history of neuromuscular problems. The experiment is carried out on the biceps. Ag–AgCl disc-type disposable surface electrodes are placed on the belly of the muscle in differential electrode configuration, with the distance between the electrodes equal to 3 cm. The reference electrode is placed at the proximal end of the elbow. The subjects are made to stand on a wooden platform to provide isolation. The subjects perform repetitive flexion and extension of the elbow with a 6 kg load until they experiences fatigue [3]. These signals are recorded at a sampling rate of 1000 Hz. The sEMG signals corresponding to the first and the last curls are used in this study.

2.1 STFT spectrogram

STFT is a commonly used method for spectrogram image formation [2]. Each signal is divided into smaller segments and subjected to discrete fourier transform (DFT). The spectrum values from each segment are stacked side-by-side to form the spectrogram image. The spectrogram shows dominant frequency information against time where the frequency components are equally spaced along the vertical axis with constant bandwidth.

By definition, STFT spectrogram is the normalized, squared magnitude of the STFT coefficients. STFT coefficients for a signal is calculated as [7]

$$X(n, \omega) = \sum_{m=-\infty}^{\infty} x[m]w[n-m]e^{-j\omega n} \tag{1}$$

where $x[m]w[n-m]$ is a short time part of input signal $x[m]$ at time n.

The frequency range of sEMG varies from dc to 10 kHz with the dominant frequency content lying in the range of 50–150 Hz [3]. Each spectrogram is divided into three subimages corresponding to the dominant frequency bands as follows: Low frequency band (15–45 Hz), Medium frequency band (46–95 Hz) and High frequency band (96–150 Hz).

2.2 GLCM features

The sub images are converted into 8-bit grayscale images and the texture features are extracted. GLCM is a method to analyse the texture images which estimates image properties related to second-order statistics [10]. This corresponds to a directional pattern counter with a specific distance d and angle θ between neighbouring pixel pairs for grayscale images [7]. The distance parameter d is set to 1 and the angle parameters θ are 0°, 45°, 90°, and 135°. The corresponding displacement vectors are [0 1], [−1 1], [−1 0] and [−1 −1]. The features such as contrast, correlation, energy and homogeneity are extracted and the formula is given below:

$$\text{Contrast} = \sum_{i,j} |i-j|^2 p(i,j) \tag{2}$$

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \tag{3}$$

$$\text{Energy} = \sum_{i,j} p(i,j)^2 \tag{4}$$

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{5}$$

where p(i, j) is the intensity value of the pixel at point (i, j), μ and σ represents the mean and standard deviation.

Contrast is a measure of the intensity variation between a pixel and its neighbour over the whole image. Correlation explains the relation between a pixel and its neighbour over the whole image while energy is the sum of squared elements in the GLCM. Homogeneity calculates the closeness of the distribution of elements in the GLCM to its diagonal.

3 Results and discussion

The representative sEMG signals recorded during the experiment is shown in Figure 1.

The amplitude and frequency components of the recorded signals are found to be subject dependent. The amplitude is observed to be higher in fatigue condition. This may be due to the participation of more motor units during the contraction. Similar variations are observed in most of the cases.

The spectrogram of sEMG signals has been represented as a t–f image. Figure 2 shows the spectrogram of sEMG signals for non-fatigue and fatigue conditions. The colormap represents the strength of the magnitude of sEMG signals. The variations in the spectral components are associated with physiological parameters such as random firing rate, motor unit recruitment patterns, muscle fibre conduction velocity and volume conductor effects.

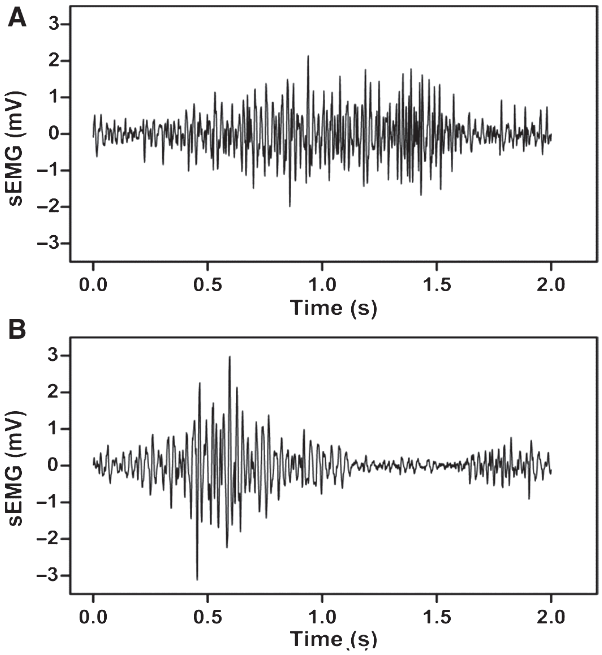

Figure 1: Typical sEMG signals. (A) Non-fatigue and (B) Fatigue conditions.

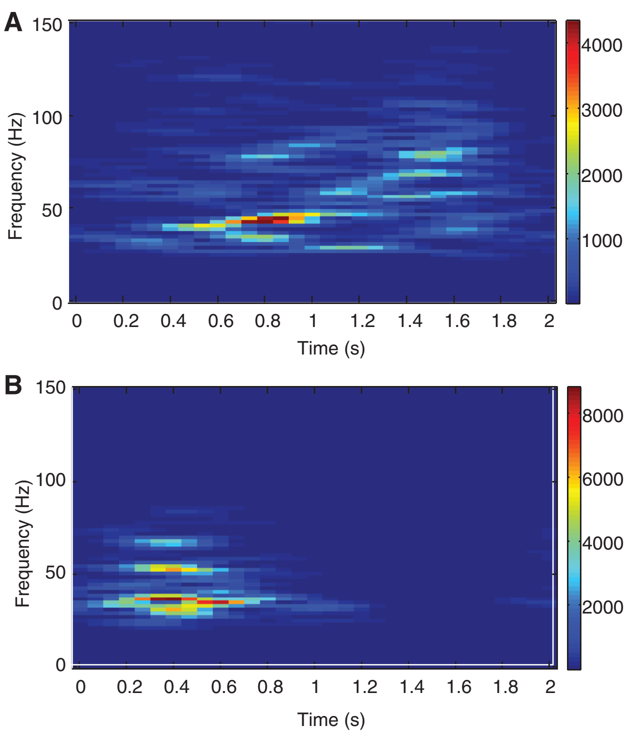

Figure 2: Spectrogram of sEMG signals. (A) Non-Fatigue and (B) Fatigue.

A reduction in the frequency components is observed in fatigue condition and this may be due to the synchronisation of motor units.

Table 1: Average value of features extracted from t-f images.

Features		Non-fatigue	Fatigue	p-Value
Contrast	0	6.1236	4.5720	0.0588
	45	59.5267	40.9858	0.0265
	90	53.8319	36.7704	0.0287
	135	59.4551	41.0085	0.0270
Correlation	0	0.9959	0.9957	0.8075
	45	0.9627	0.9638	0.2671
	90	0.9665	0.9677	0.2209
	135	0.9627	0.9637	0.2961
Energy	0	0.4098	0.5906	<0.0001
	45	0.3972	0.5821	<0.0001
	90	0.4000	0.5843	<0.0001
	135	0.3972	0.5821	<0.0001
Homogeneity	0	0.9494	0.9670	0.0033
	45	0.8758	0.9219	0.0003
	90	0.8899	0.9312	0.0003
	135	0.8758	0.9218	0.0003

It is observed that, during non-fatigue conditions, the texture pattern exhibits brighter pixels with more variations compared to fatigue conditions. In order to discriminate between these texture patterns, GLCM features are employed. The t-f images are converted to 8-bit grayscale images. For each of these images, the angle parameter is varied from 0° to 135° with a 45° increment. Thus four GLCMs are obtained for each image. Features such as contrast, correlation, energy and homogeneity are extracted for each angle thereby constructing a 16-dimensional feature vector for each image. The average value of these features is shown in Table 1. The class discrimination ability of the feature sets is quantified using t-test. It is observed that only the energy feature calculated from all the angles is distinct with high statistical significance ($p < 0.0001$).

Figure 3 shows the 8-bit grayscale sub-image representation of t-f images. For each of these sub-images, the GLCM features are extracted. Due to the non-uniform nature of the sEMG spectrograms, this local feature extraction gives better results than global features.

The average value of the features extracted from the high frequency band is shown in Table 2. Among the three frequency bands considered, the high frequency band is able to discriminate non-fatigue and fatigue conditions. The three features namely correlation, energy and homogeneity extracted from this band in all the four angles is found to be highly significant ($p < 0.0001$). There is a greater value of energy for fatigue condition compared to non-fatigue condition indicating reduction in the action potential of the muscles. The higher correlation for non-fatigue condition indicates normal muscle activity.

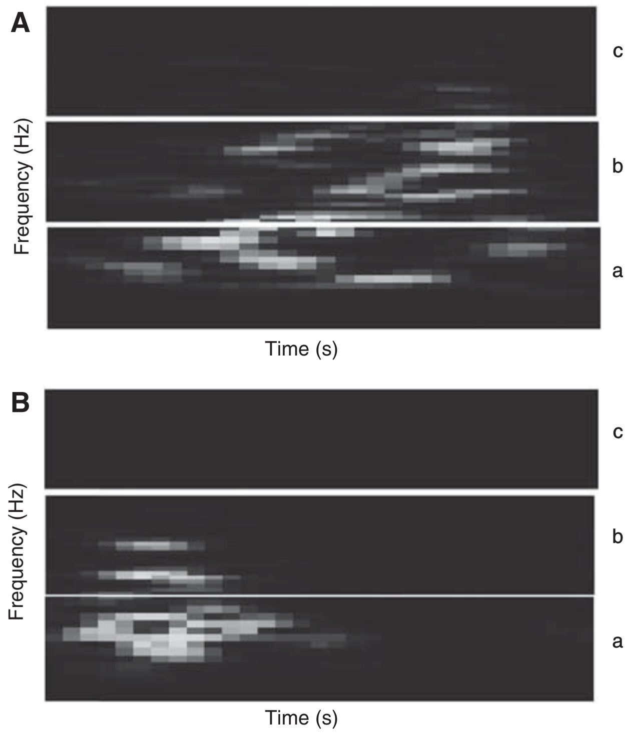

Figure 3: Grayscale sub-images: (A) Non-fatigue and (B) Fatigue sEMG signals corresponding to frequency-bands (a) low (15–45 Hz), (b) medium (46–95 Hz), (c) high (96–150 Hz).

Table 2: Average value of the features in the high frequency band.

Features		Non-fatigue	Fatigue	p-Value (less than)
Contrast	0	5.8881	7.0186	0.1355
	45	20.3979	11.5909	0.001
	90	15.9509	5.9354	0.001
	135	20.3952	11.5927	0.001
Correlation	0	0.9679	0.7277	0.0001
	45	0.9303	0.6082	0.0001
	90	0.9557	0.8403	0.0001
	135	0.9302	0.6084	0.0001
Energy	0	0.6386	0.9216	0.0001
	45	0.6292	0.9199	0.0001
	90	0.9679	0.7277	0.0001
	135	0.9303	0.6082	0.0001
Homogeneity	0	0.9557	0.8403	0.0001
	45	0.9302	0.6084	0.0001
	90	0.6386	0.9216	0.0001
	135	0.6292	0.9199	0.0001

4 Conclusion

In this work, second order texture statistics have been used to analyse muscle non-fatigue and fatigue conditions after mapping the sEMG signals into a 2D grayscale image. The time-frequency spectrum of the signals is computed using STFT. Each spectrum is divided into three frequency bands such as low, medium and high. GLCM features such as contrast, correlation, energy and homogeneity are calculated for different angles from these sub-images. The visual results suggest that the non-fatigue and fatigue conditions have different spectral patterns. The features calculated from the sub band images carry more information than the whole spectral images. The texture features namely correlation, energy and homogeneity calculated from the high frequency sub images gives significant results compared to other frequency sub images ($p < 0.0001$). Hence, it appears that time-frequency images based texture features could be used for analysis of neuromuscular disorders.

Author's Statement
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