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Investigation of Muscle Fatigue Using Temporal and Spectral Moments

UMUT GÜNDOĞDU[1], ALAATTİN SAYIN[1], AYDIN AKAN[1], YUNUS ZİYA ARSLAN[2]
ELİF KOCASAY ORHAN[3] MEHMET BARIŞ BASLO[3]

Istanbul University
[1] Department of Electrical and Electronics Engineering, Avcilar, 34320, Istanbul, Turkey

[2] Department of Mechanical Engineering, Avcilar, 34320, Istanbul, Turkey
[3] Istanbul Faculty of Medicine, Department of Neuroscience, Capa, 34093, Istanbul, Turkey

Abstract: - When a muscle cannot maintain the sustained contraction against a certain force level, this situation points out the onset of muscle fatigue. In many bio-mechanical studies, it is pursued to determine the fatigue by using electromyography signals, but none of them is capable of characterizing the fatigue in a quantitative manner. The need for determination of a fatigue index from the point of view of quantitative evaluation is derived from the use in physiotherapy exercises. In this study, EMG signals are recorded from biceps and triceps muscles during isometric contraction from 12 healthy subjects. Then, median frequency, and temporal and spectral moments, which are characterizing features of EMG signals are calculated. It is concluded that using higher order temporal and spectral moments for determining the muscle fatigue improves the performance compared to using only change in the median frequency.

Key-Words: - Muscle fatigue, EMG Signals, Spectral and Temporal Moments, Neuromuscular diseases.

1 Introduction

The signals recorded during electromyography show bioelectrical activity of the muscle fibers. Analysis of the EMG signals is one of the methods for the qualitative evaluation of human skeletal muscle fatigue [1].

Most of the neuromuscular diseases are progressive in nature and therefore cause increasing amounts of functional loss. The degree of functional loss as well as the progression rate change depending on the type of the disease. Although routine EMG investigation gives so many clues for the diagnosis of these neuromuscular diseases, it does not measure muscle weakness quantitatively. However, most of the time, patients seek medical attention because of increasing amount of weakness rather than the diagnosis which is already known. The only method to report this weakness is clinical muscle power testing that gives results depending on physician's skills. From this point of view, it is reasonable to assume that the EMG signals recorded from the muscles of the patients may reveal the degree of weakness quantitatively after the proper signal processing. Repeated EMG recordings and detection of fatigue threshold over time, would be the quantitative measure for increasing amounts of weakness. Besides, using surface electrodes for EMG signal recording will make this investigation non-invasive. It is also possible to repeat measurement as many times as needed without giving any trouble to the patient.

The final common pathway for motor performance is a functional unit called *motor unit*. This unit includes lower motor neuron, its axon and all muscle fibers innervated by this particular axon. Lower motor neuron depends on the upper motor neuron for its function. During steady contraction (isometric contraction), target muscles get fatigue by physical and biochemical manner. Because of the fatigue, it is expected to have less and less amounts of power from the muscle under investigation during sustained isometric contraction. However, human body tries to compensate this *fatigue effect* by modulating the firing frequency of motor units under the commands of upper

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motor neuron drive. This compensation causes to more synchronous firing of motor units leading to an increase of the amplitude of EMG signal. At the same time, synchronous firing causes grouping of motor unit discharge which can be seen as an increase of low frequency sinusoidal contributors of raw EMG data.

In electromyography, one of the most common techniques for extracting features used to classify the signal is integration [1]. Integration of a signal $m(t)$ is performed via calculating the area under the signal after rectification [1];

$$I\{|m(t)|\} = \int_0^t |m(\tau)| d\tau \tag{1}$$

Since the rectified value is always positive, $I\{|m(t)|\}$ is a function of time which is always positive. Similar to above, a time varying integrated rectified value can be calculated under a time window [1]:

$$I\{|m(t)|\} = \int_t^{t+T} |m(\tau)| d\tau \tag{2}$$

If the integration duration, T is selected long enough, equation (2) will characterize the variation of the signal smoothly with respect to time. On the other hand, analysis of EMG signals in frequency domain renders some specific frequencies (i.e. mean and median frequencies) observable. Fast Fourier Transform techniques are very common methods for obtaining power spectral density (PSD). Three parameters of PSD contain very fundamental knowledge about frequency distribution of the signal. These are the mean frequency, the median frequency and the bandwidth of the spectrum and frequently used to obtain a fatigue index from EMG signals in fatigue research [1, 2, 3]. Median frequency is the frequency value that divides the spectrum into two equal parts. Mean frequency is the average frequency of the power spectrum. Median and mean frequencies are defined as [1, 3]:

$$\int_0^{f_{med}} S_m(f) df = \int_{f_{med}}^{\infty} S_m(f) df \tag{3}$$

$$f_{mean} = \frac{\int_0^\infty f S_m(f) df}{\int_0^\infty S_m(f) df} \tag{4}$$

Here $S_m(f)$ is the power spectrum, f_{med} and f_{mean} are the median and mean frequencies of the EMG signal respectively.

2 Measurement Set-Up

The EMG measurements are carried out at Istanbul University, Istanbul School of Medicine, Department of Neuroscience. Signals are recorded from 12 healthy male subjects during isometric contraction on their right arms. The aim of this experimental set-up is to apply a force to arm tip to cause a muscle contraction and in time result in muscle fatigue. While the muscles are contracted EMG signals are gathered from biceps and triceps muscles simultaneously.

The position of the arm is fixed parallel to the floor, and forces are applied to the hand while keeping this position unchanged. The forces are chosen such that they cause a tiredness at the muscle, i.e., about 30-40 % of the maximum voluntary contraction. The recordings are repeated four times for each subject, to have enough signals and to provide unbiased measurements. The forces are applied using a simple pulley system and perpendicular to the arm tip.

In our experiments, considering the isometric contraction of the arm parallel to the ground, we record EMG signal form the most actively contracted muscles i.e., biceps brachii and triceps that are also opposite of each other (agonist-antagonist muscle pair) and durations of the recordings are 140 seconds.

During EMG recordings, electrodes are required to tightly contact the muscle surface. For a healthy signal acquisition, a conducting gel is applied between muscle and electrode surfaces. Furthermore, electrodes are placed exactly at the center of the muscles (muscle belly) to minimize cross-talk effect. After recording, EMG signals are filtered between 10 Hz and 500 Hz and then sampled at 5 kHz.

3 Representation of EMG Signals by Higher Order Moments

Power Spectral Density of signals gives valuable information for the characterization of deterministic and random stationary signals. Power spectrum of a signal shows the distribution of power among signal frequency components. This information is only sufficient for Gaussian and linear processes and it does not show any phase relations between frequency components. However, there are non-Gaussian and non-linear processes in practical situations, such as biomedicine, oceanography, sonar, radio astronomy and sunspot data where power spectrum may not give enough information. In such cases, higher than second order statistics of the signal are used for detection of non-Gaussian and non-linear properties of the signal. Higher Order Spectra (HOS), also known as Polyspectra, is defined [4, 5, 6, 7] as the Fourier transform of higher order statistics of a stationary signal. HOS of a signal can be defined in terms of its moments and cumulants. Moments can be very useful in the analysis of deterministic signals whereas cumulants are of great importance in the analysis of random signals.

In this paper, we propose a different approach from the ones in the literature [2, 3] where we use higher order time and frequency moments of the signal together with median frequency for characterizing fatigue by using the EMG signal. First, in order to calculate statistical moments, the power spectra, $P(\omega)$ of EMG signal segments are estimated by using periodogram approach [8]. The periodogram estimate of the power spectral density of a random signal $x(t)$ with a time duration of T is given by:

$$P_x(\omega) = \frac{1}{T}|X(\omega)|^2 \tag{5}$$

where $X(\omega)$ denotes the Fourier transform of $x(t)$. In statistical mean, periodogram estimate converges to power spectrum of random process. In our implementation, Discrete Fourier Transform (DFT) is used to calculate periodogram estimate of windowed signals. EMG signal $x(n), 0 \leq n \leq N-1$ is first multiplied by a sliding window to generate segments of the signal:

$$x_m(n) = x(n)w(n - mL) \qquad m = 0, 1, \cdots \tag{6}$$

where L is the amount of window shift which is taken as $1/4$ of the effective window length. Using short-time segments to analyze the frequency content of EMG signal allows us to track the time-variations in the signal due to change of force better than taking the whole spectrum. Then the DFT, $X_m(\omega_k)$, of the short-time signal $x_m(n)$ is calculated, and the power spectral estimate is obtained as:

$$P_m(\omega_k) = \frac{1}{N}|X_m(\omega_k)|^2. \tag{7}$$

$P_m(\omega_k)$ contains enough information to characterize the EMG signal and it is also used in previous studies [9, 10, 11]. However, for a signal of length N, it is required to calculate an N sample power spectral estimate, which means very large number of features and a high computational burden. Especially, because of the long durations of the EMG recordings taken to observe the fatigue in muscles, this situation introduces the capacity problem. Instead of the whole power spectrum, using a few features extracted from it will be a computational advantage [9]. In our proposed method, after power spectrum estimation for the segments of EMG signal, higher order time and frequency moments are calculated and used as the characterizing features, besides the median frequency. Higher order moments carry the higher order statistical information of a random signal [9, 10, 11]. Temporal and spectral moments of a signal $x(n)$ are given by [9]

$$\begin{aligned} < n^i > &= \sum_n n^i \, P(n) \qquad i = 0, 1, 2, ... \\ < \omega_k^j > &= \sum_k \omega_k^j \, P(\omega_k) \qquad j = 0, 1, 2, ... \end{aligned} \tag{8}$$

respectively. Here $P(n) = |x(n)|^2$ is the energy density in time and $P(\omega_k) = |X(\omega_k)|^2$ is the energy density in frequency where $X(\omega_k)$ is the discrete Fourier transform of $x(n)$.

The frequency domain analysis of a stochastic and non-stationary signals such as EMG, does not reveal the time domain variations of the signal. Hence in our implementations, EMG signals are windowed into 1 sec. segments, then power spectrum and median frequency of each segment are calculated. In this way, the short-time signal in these segments are assumed stationary and then frequency distribution calculation which has the number of sliding window is carried out.

4 Results

The measured EMG signals of a muscle which is contracted under constant strength and position show increase in amplitude of signals and decrease in the components of high energy level frequency with time [12, 13, 14, 15]. These changes can be used to describe the fatigue of target muscles [16, 17, 18, 19]. For random signals such as EMG, power spectral density can be estimated either by classical (i.e. Periodogram, etc.) or by modern parametric or nonparametric (i.e., AR, ARMA, Burg, Capon, etc.) methods. However, the mean and median frequency values of the nonstationary EMG signals might be failed to determine muscles' fatigue [3, 20]. In addition these values unable to determine fatigue threshold and classification in people who are specific age, gender and body mass index. On the other hand, the window width chosen to process signals can alter the mean and median frequency values [3]. Therefore, the reliability of frequency analysis only for fatigue evaluation is still being controversial.

In this study according to this approach, muscle fatigue cannot be demonstrated by using;

1. only median frequency, in 25 % of the recordings;
2. only time moments, in 26 % of the recordings;
3. only spectral moments, in 20 % of the recordings;
4. both median frequency and time moments, in 7 % of the recordings;
5. both median frequency and spectral moments, in 7 % of the recordings;
6. both time moments and spectral moments, in 20 % of the recordings.

In conclusion, muscle fatigue can be successfully characterized in 93 % of the subjects by using both median frequency and spectral moments or both median frequency and time moments. Fig. 1 shows the EMG signals, which are recorded from biceps brachii and triceps muscles during isometric contraction. Fig. 2 depicts fatigue related median frequency time moment and spectral moment changes calculated from EMG signals shown in Fig. 1.

5 Concluding Remarks

In this study, EMG signals were recorded in order to determine the fatigue of the arm muscles while they were contracting against a fixed load under isometric condition. Then, the median frequency, temporal and spectral moments of short-time EMG segments are calculated. Median frequency is known to be one of the characterizing features of EMG signals. Our simulation results showed that using only median frequency to determine fatigue is not sufficient. Therefore, employing temporal or spectral moments together with median frequency, which are also extracted from the signal as features, might improve the performance of fatigue analysis.

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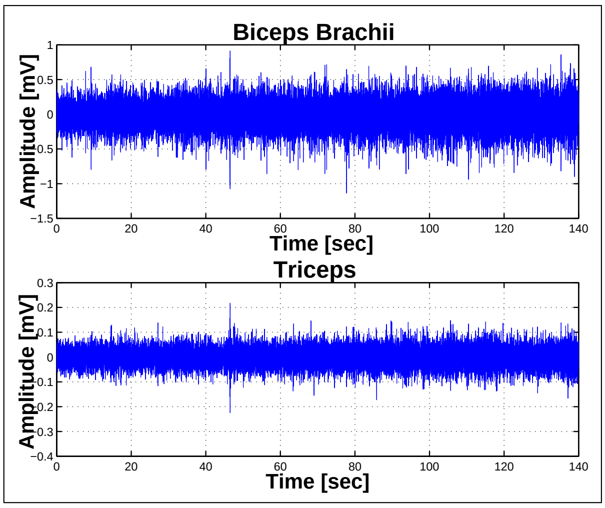
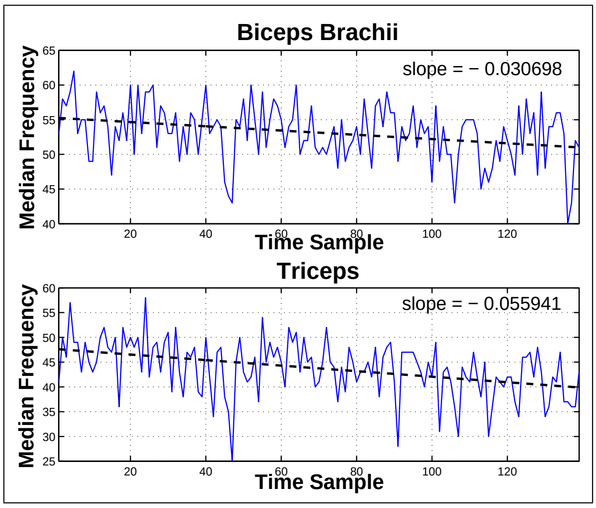
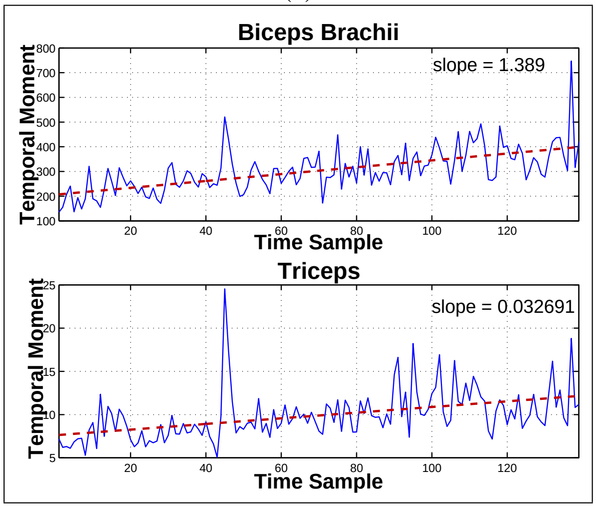


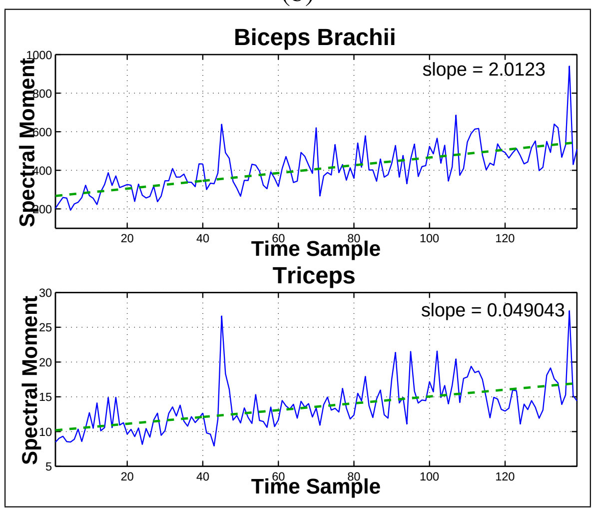
Fig. 1. Examples of EMG signals recorded from biceps brachii and triceps muscles



(a)



(b)



(c)

Fig. 2. a) Change in the median frequency, b) change in the temporal moments c) change in the spectral moments with fatigue.