Interpretation of Muscle Fatigue Using Temporal and Spectral Moments of EMG Signals

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Abstract: - In this study, we aim to evaluate the muscle fatigue in human arms by using surface electromyography (EMG) signals. EMG signals are recorded from biceps and triceps muscles of healthy subjects while they are seated on a special experimental chair. The aim of this experimental set-up is to apply a force to arm tip to cause an isometric muscle contraction and, over time result in muscle fatigue. Then, median frequency, temporal and spectral moments are calculated to characterize EMG signals. In conclusion, muscle fatigue can be successfully characterized in 93 % of the subjects by using both median frequency and spectral moments or in 94 % of the subjects by using both median frequency and time moments.

Key-Words: Muscle fatigue, Electromyography Signals, High Order Statistical Moments, Neuromuscular diseases.

1 Introduction

When a muscle cannot maintain the sustained contraction against a certain force level, this condition points out the onset of muscle fatigue. In many biomechanical studies, it is pursued to determine the fatigue by using electromyography (EMG) signals, which mean that bioelectrical activity of the muscle fibers [1], but none of them is capable of characterizing the fatigue in a quantitative manner. Dimitrova and Dimitrov [2] aimed to point out the pitfalls and possible fallacies in the interpretation of amplitude and spectral characteristics of experimental results from a theoretical point of view and to analyze possible reasons for EMG changes with fatigue. They concluded that theory does not predict a linear relation between the characteristic frequencies (maximum, mean and median) and muscle fibre propagation velocity. Georgakis et al. [3] proposed the averaged instantaneous frequency as an alternative method for the frequency analysis of surface electromyography in the study of muscle fatigue during sustained, isometric muscle contractions. They showed that results from performance analysis using experimental EMG signals demonstrate the low variability of the proposed frequency variable. Ravier et al. [4] compared force and fatigue effects on the EMG during short (about 3 sec.) isometric contractions at different strength intensities and during a sustained isometric contraction until exhaustion. 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 quan-

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titatively 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 noninvasive. 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 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 $x(t)$ is performed via calculating the area under the signal after rectification [1];

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

Since the rectified value is always positive, $I\{|x(t)|\}$ 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]:

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

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, 3, 5]. 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]:

$$\int_0^{\omega_{med}} P_x(\omega) d\omega = \int_{\omega_{med}}^{\infty} P_x(\omega) d\omega \tag{3}$$

$$\omega_{mean} = \frac{\int_0^{\infty} \omega P_x(\omega) d\omega}{\int_0^{\infty} P_x(\omega) d\omega} \tag{4}$$

Here $P_x(\omega)$ is the power spectrum, ω_{med} and ω_{mean} are the median and mean frequencies of the EMG signal respectively. De Luca [6] prefers the median frequency instead of the mean frequency, because it is less sensitive to noise, less sensitive to signal aliasing, and most cases it is more sensitive to the biomechanical and physiological factors that occur within the muscles during sustained contractions.

2 Experimental Set-Up

The EMG measurements are carried out at Istanbul University, Istanbul School of Medicine, Department of Neuroscience. Signals are recorded from 26 healthy male and female subjects during isometric contraction on their dominant 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, as shown in Fig. 1, 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

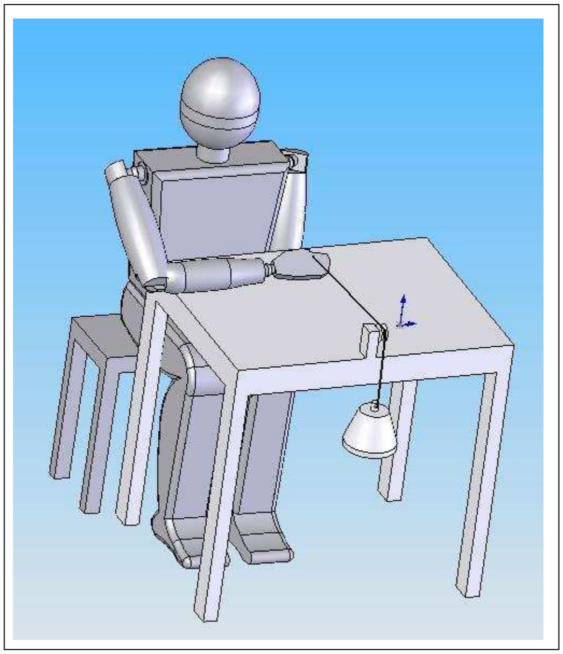

Fig. 1. Position of the subjects during experiments.

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 Analysis of EMG Signals Using Time and Frequency 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 [7, 8, 9, 10] 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 [3, 5] 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 [11]. 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 [12, 13, 14]. 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 [12]. 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 [12, 13, 14]. Temporal and spectral moments of a signal $x(n)$ are given by [12]

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

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 [15, 16, 17, 18]. These changes can be used to describe the fatigue of target muscles [19, 20, 21, 22]. 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 [2, 3]. 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.

According to our approach, muscle fatigue cannot be detected;

1. in 19 % of the recordings, using only median frequency;
2. in 26 % of the recordings, using only time moments;
3. in 23 % of the recordings, using only spectral moments;
4. in 6 % of the recordings, using both median frequency and time moments;
5. in 7 % of the recordings, using both median frequency and spectral moments;
6. in 22 % of the recordings, using both time moments and spectral moments.

In conclusion, muscle fatigue can be successfully characterized in 93 % of the subjects by using both median frequency and spectral moments, or in 94 % of the subjects by using both median frequency and time moments. Fig. 2 shows the EMG signals, which are recorded from biceps brachii and triceps muscles during isometric contraction. Figures 3, 4, and 5 give median frequency, temporal moment and spectral moment changes during fatigue acquired from above EMG data.

5 Conclusions

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.

References:

[1] J.V. Basmajian, C.J. DeLuca, *Muscles Alive: Their Functions Revealed By Electromyography*, Williams and Wilkins, Los Angeles, 1985.

[2] N.A. Dimitrova, G.V. Dimitrov, “Interpretation of EMG changes with fatigue: facts, pitfalls, and fallacies,” *J. Electromyography and Kinesiology*, Vol. 13, 2003, 13-36.

[3] A. Georgakis, L.K. Stergioulas, G. Giakas, “Fatigue Analysis of the Surface EMG Signal in Isometric Constant Force Contractions Using the Average Instantaneous Frequency”, *IEEE Trans. on Biomedical Eng.*, Vol. 50, 2003, No. 2, 262-265.

[4] P. Ravier, O. Buttelli, R. Jennane, P. Couratier, “An EMG fractal indicator having different sensitivities to changes in force and muscle fatigue during voluntary static muscle contractions,” *Journal of Electromyography and Kinesiology*, Vol. 15, 2005, 210-221.

[5] D. Farina, M. Gazzoni, R. Merletti, “Assessment Of Low Back Muscle Fatigue By Surface EMG Signal: Methodological Aspects,” *J. Electromyography and Kinesiology*, Vol. 13, 2003 319-332.

[6] C. J. De Luca, “The use of surface electromyography in biomechanics,” *Journal of Applied Biomechanics*, Vol. 13, No. 2, 1997, 135-163.

[7] R.B. Unsal Artan, A. Akan, L.F. Chaparro, “ Higher Order Evolutionary Spectral Analysis,” *ICASSP*, Bursa, 2005.

[8] C.L. Nikias, A.P. Petropulu, *Higher Order Spectra Analysis*, Prentice-Hall, New Jersey, 1993.

[9] C. L. Nikias, J. M. Mendel, “Signal Processing with Higher Order Spectra,” *IEEE Signal Processing Magazine*, pp. 10-37, July, 1993.

[10] C. L. Nikias, M. R. Raghuveer, “Bispectrum Estimation: A Digital Signal Processing Framework,” *J.Proceedings of the IEEE*, pp. 869-891, July, 1987.

[11] S. Kay, *Modern Spectral Estimation: Theory and Application*, Prentice-Hall, 1988.

[12] A. Akan, R.B. Unsal, “Time-Frequency Analysis and Classification of Temporomandibular Joint Sounds,” *J. Franklin Institute*, Vol. 337, No 4, 437-451, July 2000.

[13] Y.Z. Arslan, M.A. Adlı, A. Akan, “Inverstigation of the Relationship Between EMG Signals and the Forces Applied to Human Arms,” *Fourth Int. Conf. on Electrical and Electronics Engineering*, Bursa, 2005.

[14] Y.Z. Arslan, A. Akan, M.A. Adlı, “Estimation of The Human Arm Tip Forces By Using EMG Signals,” *The 3rd European Medical and Biological Engineering Conference EMBEC’05*, Prague, 2005.

[15] C.J. DeLuca, “Physiology and mathematics of myoelectric signals,” *IEEE Trans. on Biomed. Eng.* 26 (1979) 313-325.

[16] L. Lindstrom, R. Magnusson, “Interpretation of myoelectric power spectra: A model and its applications,” *Proc. IEEE*, 65 (1977) 653-662.

[17] R. Merletti, M. Knaflitz, and C.J. DeLuca, “Myoelectric manifestations of fatigue in volunatry and electrically elicited contractions,” *J. Appl. Physiol.* 68 (1990) 1657-1667.

[18] R. Merletti, L. Lo Conte, “Advances in processing of surface myoelectric signals, Part 1,” *Med. Biol. Eng. Comp.* 33 (1995) 362-372.

[19] C.J. DeLuca, “Myoelectric manifestations of localized muscular fatigue in humans,” *Crit. Rev. Biomed. Eng.*, vol. 11, pp. 251-279, 1984.

[20] R. Merletti, C.J. DeLuca, “Myoelectric manifestations of muscle fatigue during voluntary and electrically elicited contractions,” *J. Appl. Physiol.*, vol. 69, pp. 1810-1820, 1990.

[21] J. Duchene, F. Goubel, “Surface electromyogram during voluntary contraction: Processing tools and relation to physiological events,” *CRC Crit. Rev. Biomed. Eng.*, vol. 21, pp. 313-397, 1993.

[22] R.H. Edwards, “Human muscle function and fatigue. Human muscle fatigue: physiological mechanisms,” *Pitman Medical, London (Ciba Foundation symposium 82)* 1981, pp. 1-18.

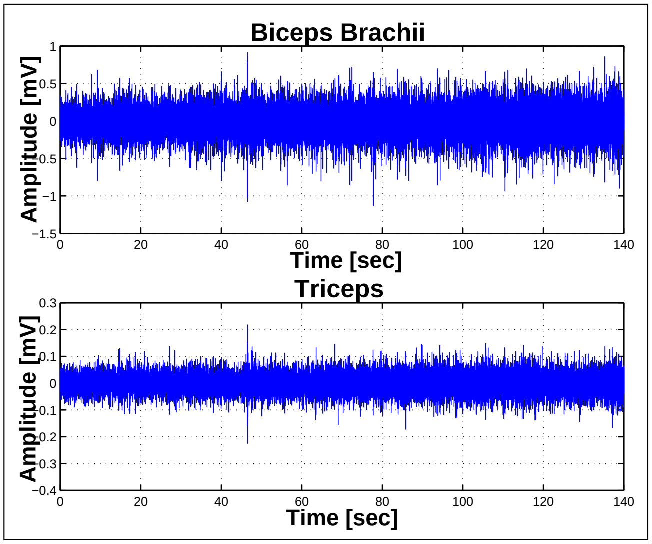

Fig. 2. Examples of EMG signals recorded from biceps brachii and triceps muscles

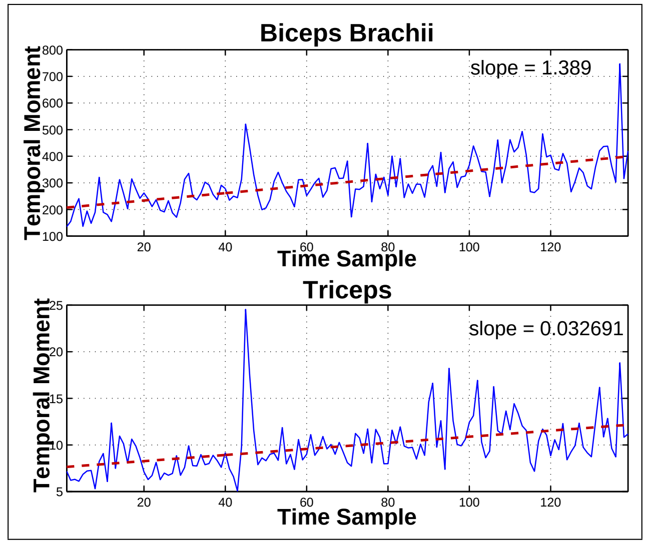

Fig. 4. Change in the temporal moments during fatigue.

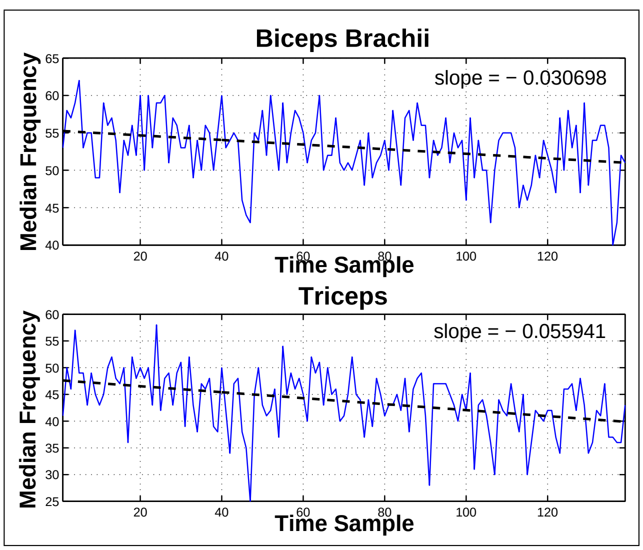

Fig. 3. Change in the median frequency during fatigue.

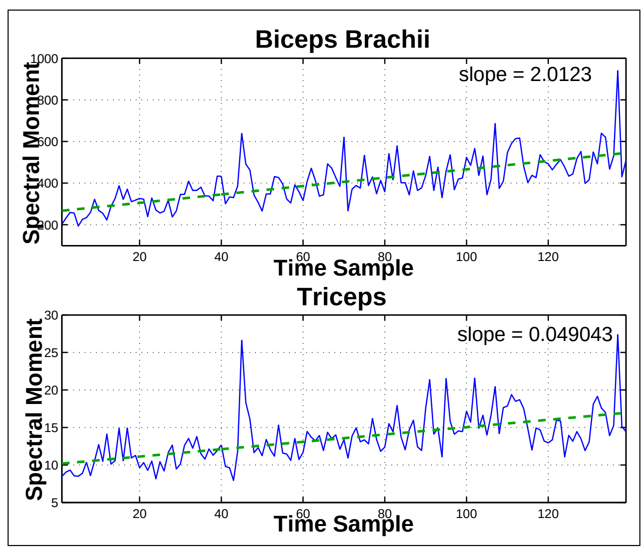

Fig. 5. Change in the spectral moments.