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Manifestation of Fatigue in Myoelectric Signals of Dynamic Contractions Produced During Playing PC Games

Mohammadreza Asghari Oskoei, Huosheng Hu and John Q. Gan

Abstract—**This paper investigates manifestation of fatigue in myoelectric signals during dynamic contractions produced whilst playing PC games. The hand's myoelectric signals were collected in 26 independent sessions with 10 subjects. Two methods, spectral analysis and time-scale analysis, were applied to compute signal frequency and least-square linear regression was used to model the trend of frequency shift. Non-parametric statistical methods were employed to analyze experimental results, which indicates significant decline in signal frequency as a manifestation of fatigue in long-term muscle activities.**

I. Introduction

Muscle fatigue is a subjective feeling whose quantitative assessment is very complex, not unique and sometimes controversial. It influences muscle activity particularly on long-term operation, and has a direct impact on myoelectric signals (MES). This phenomenon plays an important rule when a myoelectric control system is used as a user interface, because MES patterns are gradually changing in long-term operation and the controller has to adapt itself based on the changes [1], [2].

Fatigue is a concept determined by two dimensions, psychological and physiological. In physiology, fatigue is usually defined as the loss of voluntary force-producing capacity during exercise, and is not necessarily accompanied by self-perceived fatigue, which is known as psychological concept. An important problem in interpreting changes during fatiguing contraction is that it is not always clear whether a change is a direct result of the exhaustion or whether it is an adaptation [3]. Fatigue has mostly been studied at the peripheral level (i.e. in the muscle tissue) rather than the central level (i.e. central nervous system).

Myoelectric signals provide useful information about peripheral fatigue. Manifestation of fatigue can be studied by means of signal amplitude, signal frequency and muscle conduction velocity (CV). Fatigue has mostly been studied in sustained contraction, while the muscle length and tension are hold constant. During non-maximal voluntary sustained contraction, signal amplitude usually increases considerably due to the recruitment of extra motor units and increasing in firing rate of motor units. Both are mechanisms to cope with the declining force output. In contrast, during high and maximal voluntary sustained contraction, the amplitude usually declines. Furthermore, in sustained contraction, the muscle CV decreases with fatigue due to the change in the metabolic of cellular environment, and this phenomenon is reflected as a shift to the lower frequencies of signal spectrum. Hence, signal frequency is known as the main manifestation of fatigue in MES under static conditions.

During unconstrained contraction however, when the muscle length and/or tension are free to vary, characteristic frequency measurements are influenced by factors other than fatigue. Geometrical factors, which indicate the relative position of active and detectable motor units, significantly change the signal frequency spectrum that may incorrectly attribute to physiological factors. High degree of nonstationarity of signal is the other main problem in dealing with unconstrained contraction. Moreover, MES, indeed, may suddenly change its spectral properties due to different limb states, and this may be difficult to investigate with classical spectral techniques. Time-scale methods, particularly wavelets and Cohen's class, are introduced to cope with signals' nonstationarity and sudden changes. Furthermore, direct measurements of muscle CV are difficult to attain accurately during unconstrained contraction, possibly because of muscle innervations zone migration and/or end-effects.

Karlsson et al. [4] applied different time-scale methods to analyze MES during dynamic contraction, and found out that continuous wavelet transform (CWT) provides more accurate estimation comparing with short-time Fourier transform (STFT), Wigner-Ville distribution, and Choi-Williams distribution. Farina et al. [5] proposed a technique for detection and processing of muscle CV during dynamic contraction, and showed CV decline reflecting muscle fatigue. Bonato et al. [6] applied Cohen's class time-scale transform for assessing muscle fatigue during cyclic dynamic contractions. It was assumed that the non-physiological factors contributing the MES non-stationarity during dynamic contractions could be constrained and isolated for cyclic dynamic contractions.

Georgakis et al. [7] showed that average instantaneous frequency (AIF) outperforms the conventional mean and median spectrum frequency in fatigue analysis of sustained contraction. Finally, MacIsaac et al. [8] presented a mapping

M. Asghari Oskoei, PhD Candidate, Dept. of CES, University of Essex, UK, URL: http://privatewww.essex.ac.uk/~masgha/, Email: masgha@essex.ac.uk
H. Hu, Professor, Dept. of CES, University of Essex, Colchester CO4 3SQ, UK, URL: http://cswww.essex.ac.uk/staff/hhu/ , Email: hhu@essex.ac.uk
J.Q. Gan, Reader, Dept. of CES, University of Essex, Colchester CO4 3SQ, UK, URL: http://dces.essex.ac.uk/staff/jqgan/, Email: jqgan@essex.ac.uk

Fig. 1 - A user, with MES electrodes on his forearm, drives the car of PC game using hand gestures

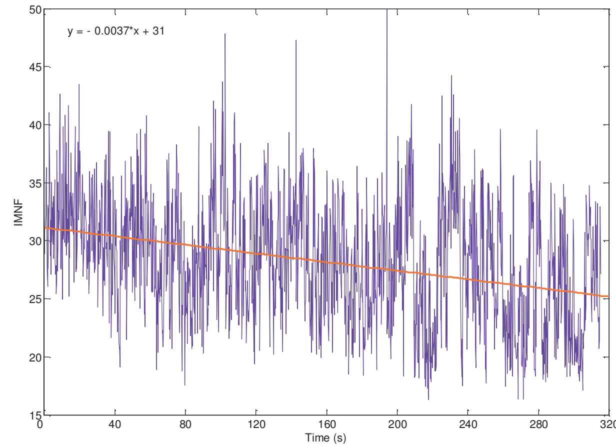

Fig. 2 - IMNF of a channel of MES and its least-square linear regression during a session

function that maps multiple MES time domain features to fatigue estimation for dynamic contractions. This function is tuned by artificial neural networks (ANN), and is capable to use in real time applications.

This paper conducts a statistical study on the wide range of hand motion-based activities during a relatively long-term of playing PC games by different subjects. Section II briefly outlines some background information and the methods adopted in this research. Implementation and experimental results are presented in Section III. Finally, a brief conclusion and future extension are given in Section IV.

II. Background and Methodology

A. Spectral Features

Mean and median frequencies are the most commonly used spectral features in MES analysis. The mean frequency (MNF) is the average frequency of the power spectrum and is defined as its first-order moment

$$MNF = \frac{\int_0^\infty \omega P(\omega) d\omega}{\int_0^\infty P(\omega) d\omega} \tag{1}$$

where P(ω) is the power spectrum density (PSD) of MES and ω is the frequency variable. The median frequency (MDF) is the frequency at which the spectrum is divided into two parts of equal power. Involving zero-order moments of PSD, it mathematically defined by:

$$\int_0^{MDF} P(\omega) d\omega = \int_{MDF}^\infty P(\omega) d\omega = \frac{1}{2}\int_0^\infty P(\omega) d\omega \tag{2}$$

These two features are mostly applicable in sustained contraction, where the MES is a quasi-stationary signal, and provide basic information about how the power spectrum changes with time [9]. They are employed in this paper to be compared with other features. In calculating both, the recorded signals are segmented into consecutive disjoint segments with the length of 200ms and then PSD estimation takes place, followed by computation of the spectral features (MNF or MDF). Thus, the time course of the MDF or the MFN is obtained. From this, the initial value, the fall rate, and the confidence interval of these spectral variables are usually calculated, since they physiologically can represent manifestation of fatigue [3], [10]. These parameters are estimated by fitting a least-square regression line to the features. Both linear and curvilinear regression can be used, and the parameters serve as fatigue indices (intercept and slope of a linear regression) [7].

B. Time-Scale Features

The MES in dynamic conditions, in which the muscle force, length, and position of body segments change, is a non-stationary signal. Therefore, time-scale techniques (e.g. wavelet transforms) play a key rule in signal analysis. A wavelet transform (WT) enables local analysis to be performed, i.e., to analyze a localized area of a larger signal. Wavelet analysis reveals data aspects that other techniques miss, such as trends (main aim of this work), breakdown points, discontinuities in higher derivatives, and self-similarity. Continuous wavelet transform (CWT) is defined as

$$CWT(s,\tau) = \int x(t) \Psi^*_{s,\tau}(t) dt \tag{3}$$

where s represents the scale parameter, τ represents translation parameter (time shifting), $x(t)$ is the MES, and the basic function $\Psi_{s,\tau}$ is obtained by scaling the mother wavelet Ψ at time τ and scale s:

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-\tau}{s}\right) \tag{4}$$

The scalogram (corresponding to periodogram or PSD in spectral analysis) of signal is defined as the square of CWT and then the mean scale of signal in WT is obtained by

$$MNS = \frac{\int_0^{\tau 1}\int_0^{s1} s\left|CWT(s,\tau)\right|^2 ds d\tau}{\int_0^{\tau 1}\int_0^{s1} \left|CWT(s,\tau)\right|^2 ds d\tau} \tag{5}$$

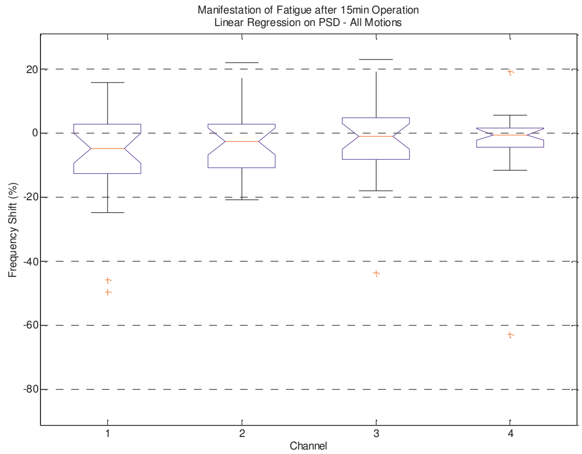

Fig. 3 - Estimated frequency shift (%) of four-channel MES after 15min operation, computed based on spectral features, for all motions

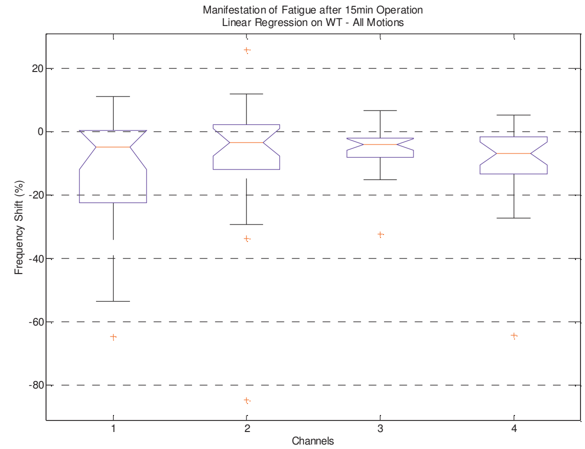

Fig. 4 - Estimated frequency shift (%) of four-channel MES after 15min operation, computed based on time-scale features, for all motions

The inverse of mean scale (MNS), which is proportional to the signal frequency, is known as instantaneous mean frequency (IMNF) [6], and used in this paper as the MES feature to analyze manifestation of fatigue in dynamic contractions. Linear regression, as described in spectral features, is applied to this feature to evaluate the signal trend in time-scale domain. By comparing three well-known wavelet families, including Duabechies (db), Symlet (sym), and Coiflet (coif), the former with order 5 (i.e. db5) is used as the mother wavelet in this study.

C. MES Data Collection

Fatigue usually happens in long-term continuous muscle activities. Hence, four-channel MES data were collected during playing PC games, in which the subject's hand randomly and continuously changes among five hand states. The hand states [2] were to drive a virtual car in an environment with random obstacles, and MES were collected from four locations on a forearm (i.e., biarticulate wrist flexor, and triarticulate and biarticulate wrist extensor muscles), using bipolar active electrodes (Biometrics Ltd SX230). An active electrode has a pre-amplifier with gain 1000, which can differentiate between a small signal of interest and much larger interference signals that are present on the skin. Signals are passed through a band-pass filter with a cut-off frequency 10-450Hz, and a notch filter used to remove unwanted line-frequencies (50/60Hz). Signals were sampled at 1000Hz using a 12-bit A/D converter.

III. Experiments and Results

A. Experiments

Ten subjects, four healthy (2 male and 2 female) and six unhealthy (5 male and 1 female, with a hand motor disability or lack of full control on their hands), took part in our experiments and conducted totally 26 sessions. Each session was comprised of playing a PC game, and subjects had to drive a car in a route, in which obstacles randomly appeared, until they felt fatigue. They were encouraged to gain as highest score as possible.

The car, in the associated PC game, was controlled by the subject's hand gestures (Fig. 1). Motion commands applied to drive the car were Go Forward, Turn Right, Turn Left, Go Backward, and Stop. A myoelectric control system (MCS) with the core of SVM classifier [1],[2] was employed to drive the car based on subject's hand motions. Since the car was manipulated based on forearm muscle myoelectric signals, each subject had to keep a constant level of muscle contraction for each hand state. These levels were defined during MCS training process. Hence, the level of muscle contraction for each hand state was approximately constant.

The time of a session depends on subjects, and on average, each one took about 10min. The recorded signals of each session were segmented into consecutive disjoint segments with the length of 200ms (200 samples) and then the mentioned frequency features (i.e., MNF, MDF, and IMNF) were calculated. As expected, the frequency features were extensively fluctuating (Fig. 2) due to the change in hand states (i.e., level of muscles contraction), geometric factors, signal non-stationarity, and other physiological factors. Despite unpredictable fluctuations, MES frequency features decline significantly in all sessions and all channels, and this fact was found out by applying statistical analysis on the linear regression of the features in each session.

To have a comparable estimation about the change in signal frequency, the percentage of frequency shift after 15min is computed by estimation based on applied linear regression. The confidence interval and delta error of estimations are calculated and illustrated. Wilcoxon rank-sum and Kruskal-Wallis [1] are two non-parametric statistical analysis methods that were applied to the results of 26 sessions to find meaningful difference or similarity over observations with certain significance (0.05). The results are illustrated in box-plots, in which the median and confidence intervals of the observations are shown.

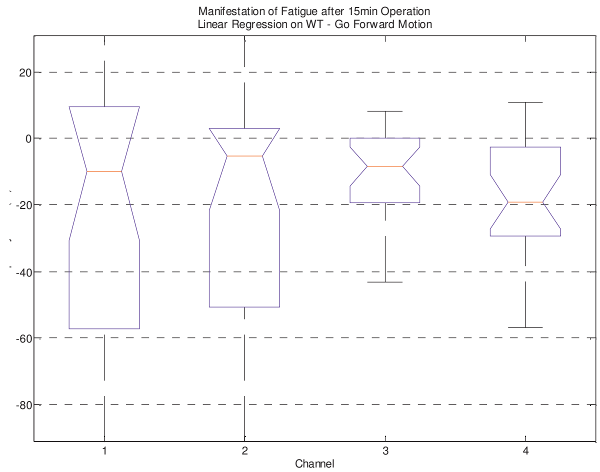

Fig. 5 - Estimated frequency shift (%) of four-channel MES, computed based on time-scale features, for Go Forward motions

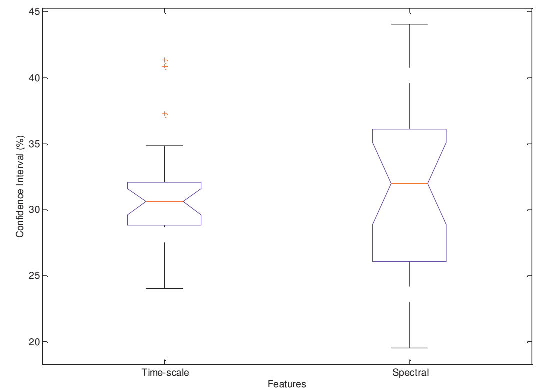

Fig. 6 - Confidence interval (%) of estimation by linear regression applied on time-scale and spectral features

B. *Results*

Fig. 3 and Fig. 4 illustrate frequency shifts in four-channel MES after 15min operation, including all motions in each session, obtained based on spectral and time-scale features, respectively. Fig. 5 shows shift of frequency for only one motion (i.e., Go Forward command). As it seen, the averages of frequency shifts of four channels are significantly negative. The average decline of frequency, with the probability of 95%, is about -5%. This means, there is a gradual frequency decline in the entire MES signal among the observations. Regarding to the theories mentioned in the first section, the most probable factor that can justify this fact is the fatigue. Because the other factors, such as geometric factors, may shift frequency features but not necessarily in negative direction.

Comparison of results in Fig. 3 and Fig. 4 shows that the time-scale features demonstrate frequency decline better than the spectral features. Fig. 5 implies more extensive frequency shift when we consider particular hand motion rather than combination of hand motions. This means that by omitting frequency shifts emanated from changes in hand state and focusing on individual hand state, frequency decline would be more remarkable. Fig. 6 shows the confidence interval (%) of estimations applied on two types of features (i.e. spectral and time-scale features). As it shown, there is no significant difference between accuracy of the two estimations.

IV. Conclusion and Future work

MES patterns gradually change in long-term muscle activities, and this can affect the performance of MCS in long-term operation. This paper studies the trend of frequency shift in hand's MES collected from 26 independent sessions with 10 subjects, in which different subjects were playing a PC game. The rate of frequency shift can show the manifestation of fatigue in dynamic contractions. Two methods, spectral and time-scale, were used to calculate signal frequency, and linear regressions were applied to find the trend of frequency shift. Non-parametric statistical methods were used to evaluate the results and extract scientifically meaningful conclusion.

Experimental results show that there is a significant decline in signal frequency after a while of operation, and existing theories justify it by most probable factor, i.e., the fatigue in the muscles. The rate of shift in MES frequency can be used to apply adaptive schemes in MCS to make a stable performance in long-term operation. The future research will focus on adaptive schemes to cope with time-related changes in MES patterns.

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