35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Exercise Muscle Fatigue Detection System Implementation via Wireless Surface Electromyography and Empirical Mode Decomposition

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Abstract—**Surface electromyography (sEMG) is an important measurement for monitoring exercise and fitness. A wireless Bluetooth transmission sEMG measurement system with a sampling frequency of 2 KHz is developed. Traditional muscle fatigue is detected from the median frequency of the sEMG power spectrum. The regression slope of the linear regression of median frequency is an important muscle fatigue index. As fatigue increases, the power spectrum of the sEMG shifts toward lower frequencies. The goal of this study is to evaluate the sensitivity of empirical mode decomposition (EMD) quantifying the electrical manifestations of the local muscle fatigue during exercising in health people. We also compared this method with the raw data and discrete wavelet transform (DWT). Five male and five female volunteers participated. Each subject was asked to run on a multifunctional pedaled elliptical trainer for about 30 minutes, twice a week, and there were a total of six recording times for each subject with a wireless EMG recording system. The results show that sensitivity of the highest frequency component of EMD is better than the highest frequency component of DWT, and raw data.**

I. Introduction

Muscle fatigue is thought of as a loss of required or expected force and has been an attractive research issue for a long time. The nature of muscle fatigue and its relation to muscle activity have been studied[1]. Spectral parameters such as the mean frequency (MNF) and the median frequency (MF) derived from the sEMG power spectrum are widely used to detect static and dynamic muscle contractions [2]. The Fourier transform is one of methods used to obtain the power spectrum of a signal. However, within the analysis window, the signal must be stationary or exhibit a periodic frequency; otherwise, the resulting spectrum will make little sense. Dimitrova et al. proposed new spectral indices of muscle fatigue (FInsmk) that perform better than the traditional MNF and MF[3]. Wavelet-based spectra and derived spectrum features have been used to compare the traditional power spectrum–derived MNF and MF performance for fatigue quantification.

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Recently, a novel nonstationary and nonlinear signal processing technique has been proposed, known as empirical mode decomposition (EMD). EMD was introduced by Huang, and it has been widely used for nonlinear signal analysis[4]. The principle of EMD is based on a decomposition derived from the data, and EMD is useful in the analysis of nonlinear and nonstationary time series signals. With an iterative decomposition of signals, EMD separates the full signal into ordered elements with frequencies ranging from high to low in each intrinsic mode function (IMF) level. The filter bank-like property of EMD has been widely applied in many fields, such as to the sound analysis of an infant crying to assess a newborn's pain [5] and classification of ship-radiated underwater sound [6]. Weather-related issues are the main application for EMD scholars [7]. Another major application of EMD is biomedical signal analysis [8-9]. The decomposed IMFs were further extracted with the power or entropy approach to analyze the nonstationary biosignals for noise reduction and for feature extraction[10]. The main topics of concern for EEG—the detection of epileptic seizure [11] and evoked potential extraction [12] have been investigated by EMD with impressive results. Heart rate signal analysis is another major application of EMD. Reconstructions of selected IMFs of heart beat intervals were used for noise filtering [13], feature extraction for discrimination from local anesthesia [14], fetal heart rate monitoring [15], and ventricular fibrillation detection [16]. Modulation of respiratory sinus arrhythmia between respiratory and heart beat signal is also achieving promising results. EMD had been applied to extract the MNF of sEMG as a muscle fatigue index [17]. Srhoj et al. have extracted the MF from selected IMFs of sEMG recorded over quadriceps muscles during cyclic dynamic contractions [18]. Their results showed that HHT-derived spectral and linear regression parameters were consistent and more reliable than those obtained with the short-time Fourier transform and the wavelet transform.

To reduce the nonstationary problem of the long EMG segment, this study investigates the EMD performance for muscle fatigue spectrum estimation and compares it with discrete wavelet transform (DWT) and EMD. The MFs were used as fatigue indices during dynamic contractions. There were 10 volunteers who joined this experiment; they ran in a multifunctional pedaled elliptical trainer. A self-designed wireless device was used to record the sEMG signal of the vastus lateralis in the left leg of each volunteer. Each subject performed six experiments in three weeks. Furthermore, the comparison of the different decomposition methods revealed that the IMF 1 component of EMD was best for evaluating muscle fatigue.

II. Methods

A. sEMG recording and subjects

A wireless sEMG recording device developed by the authors was worn on the left lateral waist of the subject to measure the sEMG signal. The gain of the device is 1000, and the bandwidth is 30 Hz to 1000 Hz to avoid the aliasing problem. This device is based on the microcontroller MSP430-F5438 as the core structure, which is a 12-bit analog-to-digital converter with a sampling rate of 2000 Hz. The digital EMG signal is transferred by a Bluetooth chip to a remote server. A Visual Basic-based interface system is used to display and store the digital EMG data in real time [19].

There were ten volunteers involved (5 male and 5 female), with ages ranging from 19 to 27 years. Subjects were required to run in a multifunctional pedaled elliptical trainer (Johnson E8000). We measured the vastus lateralis of the left leg. The surface electrodes used for the EMG recording were Ag/AgCl with a 10 mm diameter on self-adhesive supports. The bipolar electrodes were placed over the midline of the muscle belly between the motor point and the myotendinous junction, and the inter-electrode distance was 5 cm. The electrode arrangement ensured negligible crosstalk between adjacent muscles. The positions of the electrodes for each subject were recorded, and the electrodes were placed at the same position in the subsequent experiments.

B. Experimental procedure for evaluating muscle fatigue

The muscle fatigue experiment is based on the following procedures.

Step 1: The subjects are required to wear the wireless sEMG device. Alcohol is used to clean the surface, and electrolytic gel is smeared on the electrodes to decrease the contact impedance. Athletic tape is used to fix the electrodes and so avoid movement of the electrodes. Before data collection, a consent form was signed by each subject.

Step 2: There are three load levels in the multifunctional pedaled elliptical trainer, L2, L4 and L6, with L2 being light and L6 being heavy. The speed range of L2 is 55-60 steps per minute (SPM) for males and 50-55 SPM for females. The speed range of L4 is 60-70 SPM for males and 55-65 SPM for females. The subjects are required to run at their maximum speed until exhaustion for L6, which has a faster speed range than L4. A ten minute session is required for both L2 and L4. The average duration for L6 was also approximately 10 minutes. In the pre-experiment, the subjects tested the speed range and chose the most appropriate speeds for the L2 and L4 levels, separately, and ran at their maximum speed for the L6 level. These speeds were recorded for every subject. In the experiments, the subjects ran at their self-selected speeds during the experimental procedure.

Step 3: Each subject was recorded twice a week at the same time, and there were a total of six recording times for each subject.

C. EMD algorithm

The EMD algorithm used in this study comprised the following steps [4]:

Step 1: Extrema (maxima and minima) of the signal, $x(t)$, are identified.

Step 2: Upper and lower envelope of the extreme point is developed.

Step 3: Mean function of the upper and lower envelope, $m(t)$.

Step 4: Difference signal $d(t)=x(t)-m(t)$.

Step 5: If $d(t)$ becomes a zero-mean process, then the iteration stops, and $d(t)$ is a first IMF (IMF1), called $c_1(t)$; otherwise, go to step 1 and replace $x(t)$ with $d(t)$.

Step 6: Residue signal $r(t)=x(t)- c_1(t)$.

Step 7: Replace $x(t)$ with $r(t)$ and repeat the procedure from steps 1 to 6 to obtain the second IMF (IMF 2), called $c_2(t)$. To obtain $c_n(t)$, continue steps 1 to 6 after n iterations. The process is stopped when the final residual signal $r(t)$ is obtained as a monotonic function.

Now, the original signal can be represented as:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r(t)\,. \quad (1)$$

Often, we can regard $r(t)$ as c_{n+1}(t).

D. Discrete wavelet analysis

Assuming the raw sEMG signal is $x[n]$, the DWT decomposition involves the following filtering process:

$$A_j[n] = \sum_{k=-\infty}^{\infty} A_{j-1}[k] \cdot h[2n-k], \quad (2)$$

$$D_j[n] = \sum_{k=-\infty}^{\infty} A_{j-1}[k] \cdot g[2n-k], \quad (3)$$

where $A_0[n]= x[n]$ and $A_j[n]$ and $D_j[n]$ indicate the coarse and detailed sequences, respectively, after the jth decomposition. The variable $h[n]$ represents the half-band low-pass filter, and $g[n]$ represents the half-band high-pass filter. The original signal is decomposed from the high-frequency component to the low-frequency component as a combination of $A_j[n]$ and $D_j[n]$. For example, if the decomposition level is 5 (j=5), then the original signal can be represented as:

$$x[n]=D_1[n]+D_2[n]+D_3[n]+D_4[n]+D_5[n]+A_5[n]. \quad (4)$$

E. Muscle signal processing

The recorded sEMG is divided into segments, and a Fast Fourier Transform is performed. Each segment's MF is extracted. The *MF* is defined as the frequency at which the accumulated spectrum energy is half of the total spectrum energy, as shown in equation (5):

$$\int_0^{MF} p(f)df = \int_{MF}^{\infty} p(f)df = \frac{1}{2}\int_0^{\infty} p(f)df\,. \quad (5)$$

The sEMG segment window size is 30 seconds, and the step size is 15 seconds. There is one MF for each sEMG segment. A further linear regression analysis is applied to the *MF* series during the three stages of the muscle fatigue examinations. The linear regression equation is defined as:

$$y = Ax + b, \tag{6}$$

where y is estimated as the *MF*, x is the time interval, A is the regression slope and b is the bias. The greater the muscle fatigue, the smaller the slope [20]. We also used the correlation coefficient (R) to represent the stability of sEMG in terms of muscle fatigue. It is well known that the MF shifts toward lower frequencies as a muscle fatigues. Parameter R and A were used as indexes of the muscle fatigue.

$$R = \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}} \tag{7}$$

F. Statistics

In this study, the SIGMAPLOT software package was used to conduct the data analysis. Descriptive statistics were applied to subjects' personal information and muscle fatigue parameters (regression slope, A, and correlation coefficient, R). The data were represented as the mean (standard deviation). Statistical testing of the muscle fatigue parameters obtained from the raw data and the different decomposition methods was performed using t-tests. The significance level for the p value was set at 0.05.

III. Results

DWT and EMD were used to decompose the sEMG signal. The lower IMF and the lower wavelet detail function both correspond to higher-frequency components. Table 1 shows the analysis results of one experiment for the raw data and the decomposed signals of the other two methods for the entire 30 minute experiment. The MF slope of the raw sEMG is -0.012 Hz/s. For the DWT decomposition, the absolute MF slope of the first detail component is larger than the rest of the decomposition (D_1, slope = - 0.03 Hz/s). This is also true for EMD: the absolute MF slope of the first IMF is significantly larger than that of the other IMFs (IMF1 of EMD, slope = - 0.049 Hz/s. In the following analysis, only the D_1 component of the DWT and the IMF1 component of the EMD were chosen for further MF estimation and regression analysis. The absolute MF slope of the raw data and the high-frequency components of the three methods is EMD (0.049 Hz/s) > DWT (0.030 Hz/s) > raw EMG (0.012 Hz/s). Figure 1 shows the MF distributions of the raw data, the D1 component of the DWT, and the IMF1 components of the EMD during a complete experiment.

TABLE I. TYPICAL REGRESSION RESULTS FOR THE RAW DATA AND THE DECOMPOSED SIGNALS OF THE DWT AND EMD,

	Slope Hz/s	**Coefficient**	**MF (Hz)**
Raw	-0.012	0.859	269.6 (5.8)
DWT, D_1	-0.030	0.894	665.7 (14.5)
D_2	-0.001	0.365	344.6 (1.4)
D_3	-0.001	0.218	184.6 (1.3)
EMD	-0.049	0.865	474.0 (24.5)
IMF1			
IMF2	-0.025	0.874	269.7 (12.4)
IMF3	-0.010	0.813	167.7 (5.1)

TABLE 2. STATISTICAL RESULTS OF THE MF SLOPE OF THE RAW DATA AND THE DECOMPOSITION METHODS WITHIN THE THREE LEVELS AND FOR THE ENTIRE EXPERIMENT. THE DATA ARE REPRESENTED AS THE MEAN (SD).

Level	RAW (n=60)	DWT (n=60)	EMD (n=60)
L2	-0.0164* (0.0144)	-0.0232* (0.0176)	-0.0456* (0.0356)
L4	-0.0125* (0.0100)	-0.0209* (0.0157)	-0.0362* (0.0302)
L6	-0.0193* (0.0154)	-0.0276* (0.0264)	-0.0501 (0.0503)
All	-0.0197* (0.0128)	-0.0296* (0.0153)	-0.0594* (0.0364)

SD is standard deviation, ALL represents the entire experiment, P<0.05*;

In Table 2, the MF slope of the raw data is also significantly different from the highest-frequency components of the other two decomposed methods. The ranges of the absolute MF slope value are also EMD> DWT> raw EMG within the three loading levels and the complete experiment.

IV. Discussions and Conclusion

In Table 1, the absolute MF slope of the highest-frequency component of the different decomposition methods is significantly larger than the rest of the decomposition. The results show that the intrinsic information about muscle fatigue could be embedded in the high-frequency portion of the sEMG. Therefore, in this study, we only used the highest-frequency component of the different decomposition methods to evaluate the muscle fatigue. In this study, we hypothesized that health subjects run a fixed speed with the different load in muscle activity as fatigue progressed. From the results, EMD has been proven to quantify the electrical manifestations of muscle fatigue at the local muscle being better than the DWT and raw data. The reason could be that EMD suits the nonlinear signal decomposition of the intrinsic mode function. Although EMD acted as a filter-bank, there was no strict bandwidth restriction with the IMF. The frequency range of each IMF level is adaptive, depending on the raw signal content. The DWT decomposition is based on the successive filtering of the symmetric half-band high-pass and low-pass filters. The frequency range of the more detailed component is nearly twice that of the adjacent less detailed component. The EMD approach can extract major high-frequency components in the first IMF level with better adaptation than wavelet transforms. Although the MF of the D_1 component of the DWT is larger than the IMF 1 component of the EMD, the absolute MF slope of the IMF 1 component of the EMD is larger than the D_1 component of the DWT with the time course of fatigue.

Finally, we used our designed wireless device to record the sEMG and quantify the electrical manifestations of muscle fatigue at the local muscle. We found that the intrinsic fatigue information of the sEMG could be embedded in the high-frequency component. Two decomposed methods, DWT and EMD, were used to extract this component. The preliminary results revealed the potential of EMD for sEMG signal processing.

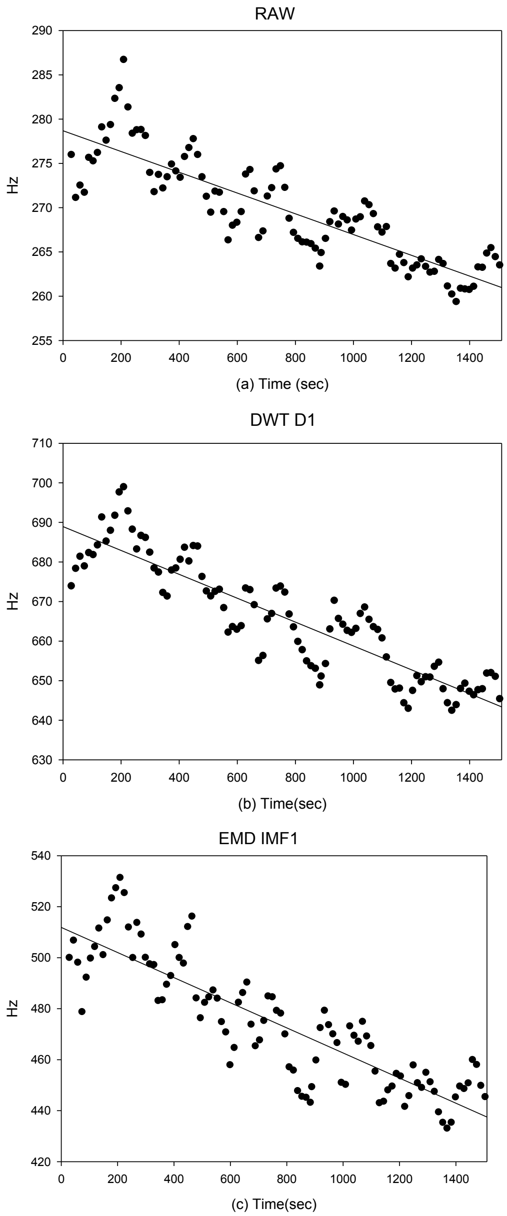

Figure 1. The distribution of MF during a complete experiment, (a) Raw data, (b) D_1 of DWT, (c) IMF1 of EMD.

Acknowledge

This research is in part funded by the National Science Council (Taiwan) with the grant number NSC 100-2221-E-324-013-MY2, NSC 101-2221-E-214 -001

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