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Multifractal analysis of surface EMG signals for assessing muscle fatigue during static contractions*

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Abstract: This study is aimed at assessing muscle fatigue during a static contraction using multifractal analysis and found that the surface electromyographic (SEMG) signals characterized multifractality during a static contraction. By applying the method of direct determination of the $f(\alpha)$ singularity spectrum, the area of the multifractal spectrum of the SEMG signals was computed. The results showed that the spectrum area significantly increased during muscle fatigue. Therefore the area could be used as an assessor of muscle fatigue. Compared with the median frequency (MDF)—the most popular indicator of muscle fatigue, the spectrum area presented here showed higher sensitivity during a static contraction. So the singularity spectrum area is considered to be a more effective indicator than the MDF for estimating muscle fatigue.

Key words: Muscle fatigue, Surface electromyographic (SEMG) signals, Multifractal, Static contraction
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INTRODUCTION

Surface electromyographic (SEMG) signals can be monitored noninvasively by using electrodes on the skin surface. They are the summation of all motor unit action potentials (MUAP) within the pick-up area of the electrodes, so they provide information on the neuromuscular activities of the examined muscle (Englehart *et al*., 1999). In addition, these signals depend on anatomical and physiological properties of the contracting muscle (de Luca, 1979). SEMG signals have been widely applied to functional electrical stimulation (FES) (Frigo *et al*., 2000), control system for powered prostheses (Hudgins *et al*., 1993) and clinical diagnosis (Abel *et al*., 1996), and also for muscle fatigue assessment (Karlsson *et al*., 1999; Sparto *et al*., 2000; Georgakis *et al*., 2003; Kim *et al*., 2005; Xie and Wang, 2006). Muscle fatigue is any exercise-induced reduction in the ability of a muscle to generate force or power (Gandevia, 2001) and can be evaluated by monitoring the time course of characteristic variables of the SEMG signals. The systematic study of muscle fatigue assessment can provide insight into the physiology of the muscle under investigation as well as into the mechanisms of fatigue (Georgakis *et al*., 2003).

During static contractions, various parameters extracted from the SEMG signals have been studied to assess muscle fatigue. Masuda *et al*.(1999) evaluated the muscle fiber conduction velocity (MFCV) by the cross-correlation method and found that the MFCV during the static contraction significantly decreased during exercise. Merletti and Lo Conte (1997) and Inbar *et al*.(1986) extracted some time-domain parameters such as the average rectified value (ARV), root mean square value (RMS) and zero crossing rate (ZCR) to monitor the muscle fatigue. Due to the stochastic nature of the raw SEMG signals, Kim *et al*.(2005) used autoregressive (AR) models to extract the first AR model coefficients for quantifi-

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cation of trunk muscle fatigue. A single characteristic frequency such as the median frequency (MDF) or mean frequency (MNF) of the power spectral density (PSD) is currently the most popular method of estimating fatigue (Lindstrom *et al*., 1977; Stulen and de Luca, 1981). Georgakis *et al*.(2003) and Xie and Wang (2006) proposed the averaged instantaneous frequency (AIF) and mean frequency based on Hilbert-Huang transform respectively with application to muscle fatigue analysis and obtained steadier results than the widely used MNF and MDF. In addition, time-frequency transform has also received considerable attention as a new mathematical approach for processing the SEMG signals. In this way, Sparto *et al*.(2000) used wavelet and short-time Fourier transform (STFT) for detection of back muscle fatigue. Recently nonlinear tools have been widely applied to SEMG signal analysis for capturing the entire information content of these signals (Gitter and Czerniecki, 1995; Gupta *et al*., 1997; Sbriccoli *et al*., 2001; Ravier *et al*., 2005; Hu *et al*., 2005). Webber *et al*.(1995) investigated the changes of the percent determinism (%DET) in the course of muscle fatigue using recurrence quantification analysis (RQA) and observed that the %DET measure performed significantly better than the MDF. Here we will further investigate the nonlinear dynamic behavior of SEMG signals during static contractions.

There is evidence that physiological signals generated by complex self-regulating systems may have a fractal structure. Ivanov *et al*.(1999) reported that time series of healthy human heartbeats show multifractal character. They also uncovered the loss of multifractality for a life-threatening condition, i.e., congestive heart failure. The multifractal singularity spectrum was then used to distinguish adults having coronary heart disease from healthy adults (Wang *et al*., 2003a; 2003b). Our work showed that SEMG signals are characterized by multifractality during static contractions. In order to quantitatively analyze the multifractal spectrum, the area of the spectrum stated in (Wang *et al*., 2003a; 2003b) is computed. It was found that the area of the multifractal spectrum of the SEMG signals significantly increased during muscle fatigue. This could then be used as an assessor of muscle fatigue and is more sensitive than the MDF.

MATERIALS AND METHODS

Subjects and data acquisition

Twelve normal, right-handed subjects were informed of the content and risk of the experiment in advance and gave written consent to voluntarily take part in this experiment. In the course of the experiment they were all in a good physical condition and none of them had a history of neuromuscular disorders. During isometric constant force contractions, the subject sat in front of a table with the elbow joint being in a position of 90° of elbow flexion. The elbow flexion force was measured by a wrist belt attached to a dynamometer. Prior to the experiment, the maximum voluntary contraction (MVC) forces were measured three times to calculate the average MVC, which was used as the reference value. Then each subject was instructed to sustain a 60% of their elbow flexion MVC for 50 s. The skin of each subject was prepared by gentle abrasion and cleansing with alcohol. The SEMG signals were recorded by a pair of bipolar Ag/AgCl disc electrodes (5 mm in diameter) with conductive paste and the electrodes had a center-to-center spacing of 20 mm. The electrode pair was located over the biceps brachii on the skin surface of the right forearm of each subject. The reference electrode was an Ag/AgCl disc electrode and was placed on the top side of the wrist. Differential amplifiers with bandpass filters of 10~500 Hz were used to reduce the effects of high frequency noises and low frequency motion artifacts. The sampling frequency was 1 000 Hz.

Multifractal analysis

We used the method to compute the $f(\alpha)$ spectrum developed by Chhabra and Jensen (1989), which was mathematically precise and could be easily applied for analysis of real experimental data where the underlying dynamics are unknown (Yamaguti and Prado, 1995; Jensen *et al*., 1987; Chhabra and Jensen, 1989; Chhabra *et al*., 1989; Cuevas, 2003; Wang *et al*., 2005). The idea was to focus on the fact that $f(\alpha)$ was simply the dimension of the measure-theoretic support of a particular measure. It is suggested that the experimental measure should be covered with boxes of size l and that the probability $P_i(l)$ in each of these boxes should be computed, subsequently constructing a one-parameter family of normalized measure $\mu(q)$ where the probabilities in the boxes of size l are

$$\mu_i(q,l)=\frac{[P_i(l)]^q}{\sum_j [P_j(l)]^q}. \tag{1}$$

As in the definition of the generalized dimension D_q (Chhabra and Jensen, 1989), the parameter q provided a microscope for exploring different regions of the singular measure. For $q>1$, $\mu(q)$ amplified the more singular regions of the measure; for $q<1$, it accentuated the less singular regions; and for $q=1$, the measure $\mu(1)$ replicated the original measure. Consequently the Hausdorff dimension of the measure-theoretic support of $\mu(q)$ is given by

$$\begin{aligned} f(q) &= -\lim_{N\to\infty}\frac{1}{\ln N}\sum_{i=1}^{N}\mu_i(q,l)\ln\mu_i(q,l) \\ &= \lim_{l\to 0}\frac{1}{\ln l}\sum_i \mu_i(q,l)\ln\mu_i(q,l). \end{aligned} \tag{2}$$

In addition, the average value of the singularity strength $\alpha_i=\ln(P_i)/\ln l$ with respect to $\mu(q)$ could be computed by evaluating:

$$\begin{aligned} \alpha(q) &= -\lim_{N\to\infty}\frac{1}{\ln N}\sum_{i=1}^{N}\mu_i(q,l)\ln P_i(l) \\ &= \lim_{l\to 0}\frac{1}{\ln l}\sum_i \mu_i(q,l)\ln P_i(l). \end{aligned} \tag{3}$$

Eqs.(2) and (3) provide a relationship between a Hausdorff dimension f and average singularity strength α as implicit functions of the parameter q. They also provide an alternative definition of the singularity spectrum, which could be used to compute the $f(\alpha)$ curve directly from experiment without the intermediate Lengendre transform of the $\tau(q)$ curve (Halsey *et al.*, 1986).

In order to quantitatively analyze the multifractal spectrum, the area of the spectrum S (which is included by the curve) was computed. The area of the spectrum S is defined by

$$S=\int f\mathrm{d}\alpha. \tag{4}$$

The explanation of S is as follows: f and α constructed a 2D phase space of the measure. Any singularity strength α and matching fractal dimension f of the measure determined the corresponding point in this space. Therefore, the integral of f and α included total information of the measure (Wang *et al.*, 2003a; 2003b).

RESULTS

In this analysis, the SEMG data from each 50 s contraction was segmented into subsequent signal epochs of 1 s. Two adjacent epochs overlap each other by half a second. The amplitudes of all the samples were normalized into a coordinate scale. The way to normalize the given signal $s(t)$ is to center it at zero mean and scale it to unit standard deviation:

$$s_{\text{normalize}}(t)=\frac{s(t)-mean[s(t)]}{std[s(t)]}, \tag{5}$$

where $mean[s(t)]$ is the mean value of the given signal and $std[s(t)]$ is the standard deviation of the signal.

The SEMG signals obtained during the start epoch (t=0~1 s) and end epoch (t=49~50 s) from Subject 2 are displayed in Fig.1. Examples of the singularity spectrum, calculated from two epochs mentioned above, are presented in Fig.2. It could be seen that the entire spectrum exhibits the typical single-humped shape, which is a characteristic of multifractal signals. The area of the singularity spectrum of the end epoch is significantly larger than that of the start epoch. It is generally accepted that more and more motor units might be recruited during the fatigue process in order to compensate for the inability of the activated muscle fibers and to maintain their force generation (Garland *et al.*, 1994). This means that the activity of the nervous system of the body is strengthened during a static contraction. Wang *et al.*(2003a) reported that a subject's ECG multifractal singularity spectrum is controlled by his nervous system. In the same way, we can deduce that a subject's SEMG multifractal singularity spectrum is also controlled by his nervous system. In addition, the large area of the SEMG multifractal singularity spectrum reflects the strengthened activity of the nervous system of the body in the process of muscle fatigue.

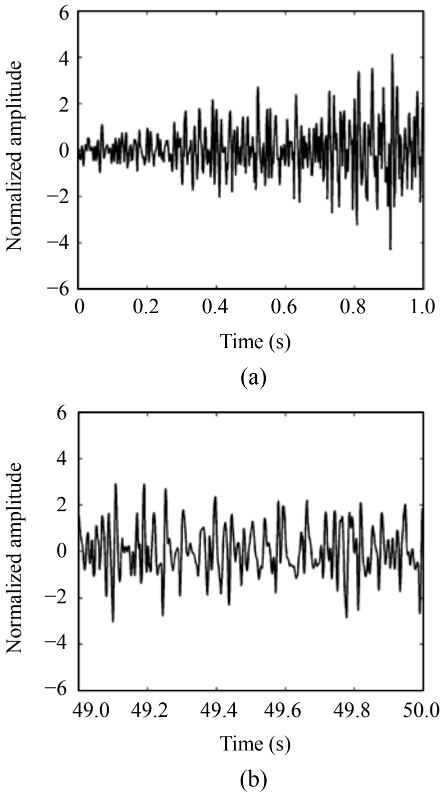

Fig.1 The SEMG signals at the start epoch (a) and end epoch (b) during a static contraction from Subject 2

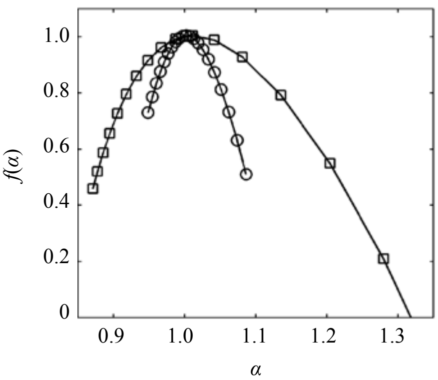

Fig.2 The singularity spectrum of the SEMG signals at the start epoch (○) and end epoch (□) during a static contraction from Subject 2

For monitoring the change of the singularity spectrum area of the SEMG signals over time, the singularity spectrum was first estimated for each epoch according to Eqs.(1)~(3). Then a value for the area of the spectrum was computed. Subsequently, the area parameter was normalized by the value of its first epoch and a least-square error linear regression was fitted to each normalized parameter over the period of 50 s contraction to obtain the slope. Generally speaking, the slope in the linear regression analysis signifies the rate of change in a response variable for one unit of change in a predictor variable. Thus the slope can be used to represent the sensitivity of the normalized parameter in quantification of muscle fatigue during a static contraction. The larger the slope is, the higher is the sensitivity. Also, the large sensitivity can facilitate estimating muscle fatigue. Fig.3 illustrates the typical results on Subject 2 (*slope*=0.0311). The results of other subjects showed similar trends. It was found that the area of the multifractal spectrum of the SEMG signals significantly increased during muscle fatigue. Therefore the area could be used as an indicator for assessing muscle fatigue.

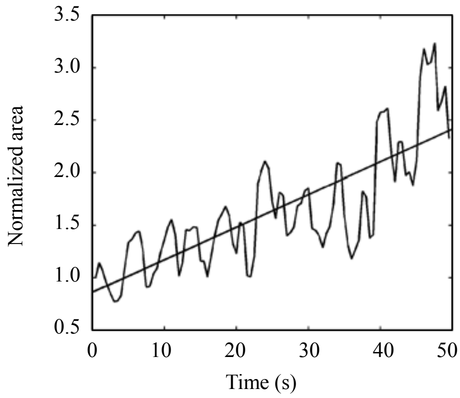

Fig.3 Time courses of the normalized area of the singularity spectrum of the SEMG signals during a static contraction of Subject 2

DISCUSSION

In order to further discuss the effectiveness of the proposed method, we compared it with other methods. The normalized MDF was employed in this comparison and monitoring this fatigue indicator is considered to be currently the most popular method for estimating fatigue (Deangelis *et al*., 1990). To facilitate the effectiveness comparison, the SEMG data obtained from Subject 2 was applied to this method once again. Firstly, the PSD of each epoch was estimated by the AR model, and the AR model of the tenth order was selected for this research using Akaike Information Criterion (AIC) (Muthuswamy and Thakor, 1998). The MDF was then calculated from the PSD. Subsequently, the MDF was normalized by the value of its first epoch and a linear regression was fitted to each normalized MDF to obtain the slope. Fig.4 shows the time course of the MDF of Subject 2 (*slope*=−0.0087). Table 1 gives the slopes of the singularity spectrum area and MDF of the SEMG signals for each subject.

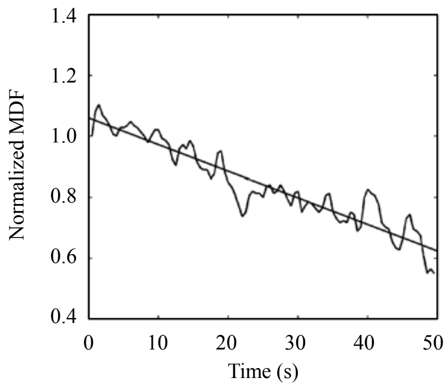

Fig.4 Time courses of the SEMG MDF normalized by the value of the first data point during a static contraction from Subject 2

Table 1 The slopes of the singularity spectrum area and MDF for each subject

Subject	Slope	
	Area	MDF
1	0.0315	−0.0081
2	0.0311	−0.0087
3	0.0208	−0.0006
4	0.0115	−0.0042
5	0.0320	−0.0088
6	0.0454	−0.0067
7	0.0260	−0.0071
8	0.0110	−0.0052
9	0.0466	−0.0127
10	0.0406	−0.0072
11	0.0136	−0.0018
12	0.0214	−0.0021
Mean	0.0276	−0.0061

When we compared the performance of the two fatigue indicators, the absolute value of the slopes of the singularity spectrum area and MDF for each subject was first computed and then a one-way ANalysis of VAriance (ANOVA) was used (Englehart *et al.*, 1999; Castillo-Valdivieso *et al.*, 2002). Since we used 12 subjects, the degrees of freedom were 1 and 22 for the *F*-test. The slope of the singularity spectrum area is significantly higher than that of the MDF (p=0.000008). In addition, we know that the normalized parameter producing large slope can explain the course of muscle fatigue more sensitively. Therefore the sensitivity of the singularity spectrum area is higher than that of the MDF. In conclusion, the singularity spectrum area is a more effective indicator than the MDF for estimating muscle fatigue.

CONCLUSION

We have reported that the SEMG signals characterized multifractality in the process of muscle fatigue and that the area of the SEMG singularity spectrum significantly increased along with muscle fatigue. Hence the spectrum area could be used as an indicator for assessing muscle fatigue. Compared with MDF—the most popular indicator for assessing muscle fatigue, the singularity spectrum area presented here showed higher sensitivity during a static contraction. With the merits mentioned above, this method will also provide a new idea for analyzing other nonstationary physiological signals and be easily generalized to other applications.

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