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Utility of traditional and alternative EMG-based measures of fatigue during low-moderate level isometric efforts

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Abstract

Traditional electromyographic (EMG) measures (e.g., amplitude, mean and median frequencies of the power spectra) have demonstrated inconsistent abilities in monitoring localized muscle fatigue at relatively low effort levels. In the present study, several alternative EMG-based fatigue indices were evaluated, derived using a logarithmic representation of the power spectrum, the fractal dimension of the raw signal, and a Poisson distribution fit to the power spectrum. These methods, along with traditional approaches, were applied to EMG data obtained from three separate experiments. In the first two experiments, 24 participants performed sustained isometric shoulder abductions and torso extensions at 30% of maximum voluntary strength (MVC). In the third experiment, another group of 12 participants performed similar shoulder exercises at 15% and 30% MVC, with repeatability assessed at 15% MVC. Both traditional and alternative EMG measures were analyzed for their 'utility', in terms of sensitivity to fatigue, variability, repeatability, and predictive ability. Results demonstrated that parameters derived from fractal analysis and the Poisson distribution demonstrated high utility. These alternative approaches appear promising as fatigue indices for low level isometric tasks.

Keywords: Electromyography; Muscle fatigue; Low level isometric contraction; Fractal; Utility

1. Introduction

Surface electromyography (EMG) has widely been used to detect the occurrence and development of muscle fatigue (De Luca, 1997). Consistent changes in traditional EMG measures, including root mean square (RMS), the median (MdPF) and mean (MnPF) power frequencies, have been documented especially for relatively high effort levels (e.g., (Duchene and Goubel, 1993)). In contrast, these measures have yielded inconsistent patterns during sustained contractions at lower level efforts. While increasing RMS or decreasing MdPF and MnPF have been found in the majority of reports, contradicting and non-conclusive patterns have also frequently been observed (Farina et al., 2006; Hagberg, 1981; Hägg and Ojok, 1997; Öberg et al., 1994). Given that many occupational and rehabilitation tasks and activities of daily living are characterized by muscle contraction at low-moderate effort levels, further study is warranted for obtaining EMG measures sensitive to fatigue in such conditions (i.e. fatigue indices).

1.1. Alternative EMG-based fatigue indices

Several alternative EMG-based fatigue indices have been proposed as complementary to the traditional measures, including changes in quartile or decile frequencies (Linssen et al., 1993), mode frequency (frequency at the highest spectrum peak; (Hägg, 1992)), and half-width (spectral width at half maximum amplitude; (Nargol

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et al., 1999)). Such indices represent single spectral values (Merletti and Lo Conte, 1997). Other proposed indices are obtained from changes in certain frequency ranges such as a low frequency band (Dolan et al., 1995; Maisetti et al., 2002), mid-frequency region (Lowery et al., 2000), and ratio of EMG power between high and low frequency bands (Allison and Fujiwara, 2002; Moxham et al., 1982). However, the reliability and sensitivity of these indices for fatigue assessment at low level efforts have not been confirmed. Furthermore, some indices have produced inconsistent results when applied in different studies (Kumar et al., 2001).

Recently, non-linear concepts (e.g. complexity, self similarity, and dimensionality) have been employed in deriving alternative EMG-based fatigue indices. Such concepts are of interest since EMG signals demonstrate high complexity, and mechanisms underlying the generation of EMG signals (as well as other biological signals) seem to be non-linear in nature. We applied logarithmic transformations of the EMG power spectra to generate several fatigue indices based on changes in lower and higher frequency components (Yassierli and Nussbaum, 2003). The same method was recently reported by other investigators (Ravier et al., 2005), and considered to be related to a fractal approach. Note that fractal characteristics of EMG signals have also been previously described (Anmuth et al., 1994; Gitter et al., 1991; Gupta et al., 1997). Our preliminary investigation indicated that such fractal behavior might be limited to a certain frequency range, and that a fractal-based fatigue index had sensitivity comparable to the traditional EMG measures (Nussbaum and Yassierli, 2003).

1.2. Criteria for comparison among EMG-based fatigue indices

By what criteria should an EMG-based fatigue index be evaluated? This issue has been addressed using diverse approaches in previous studies. An index should obviously reflect muscle fatigue development within muscles (Merletti et al., 1991), although the entire physiological fatigue process appears too complex to be described by a single index (Hägg, 1991). In addition, an index should have low variability, more specifically in terms of the temporal consistency of changes (e.g. do the data closely follow an underlying trend), for example based on the residual (root-mean-square) error from linear regression within trials (Nussbaum, 2001). Some authors have also suggested that a better EMG index should be reliable (e.g., (Dolan et al., 1995)). Reliability (a.k.a. repeatability) is generally defined as the ability to achieve similar results (e.g. rates of EMG change) on repeated trials. Unfortunately, repeatability for slopes of MnPF was reported to be lower at low-level contractions (i.e. 10–30% MVC) compared to repeatability at 50–70% MVC (Rainoldi et al., 1991).

Since changes in EMG measures with respect to time are frequently linear, and a significant correlation between rates of EMG change and endurance time has been reported (Hagberg, 1981; van Dieën et al., 1993), some investigators have employed initial subsets of EMG data to predict and extrapolate early trends in the EMG data to a complete endurance test (Maisetti et al., 2002; van Dieën et al., 1993). This ability, namely predictive ability, could also be considered as an additional evaluation criterion. Predictive ability appears to be beneficial in practice, such as for task evaluations, for several reasons. First, participants can avoid the very strenuous parts of an endurance test. Second, it minimizes some influences of motivational factors at the end of strenuous voluntary exercises. Third, it reduces the length of prolonged exercise tests. In summary, a good EMG-based fatigue index should be: (1) sensitive to fatigue; (2) consistent in terms of temporal changes; (3) repeatable; and (4) predictive.

1.3. Purpose of the study

The main objective of this study was to develop alternative EMG-based fatigue indices for prolonged isometric contractions at low-moderate level efforts, and further to investigate their utility in comparison to the traditional measures which have demonstrated a lack of utility (e.g., less sensitive to fatigue or less reliable). Note that the term 'utility' was proposed in this study to comprehensively encompass all the aforementioned criteria: sensitivity, variability, repeatability, and predictive ability. Results were expected to provide improved EMG-based methods in muscle fatigue assessment, particularly for occupational tasks (our applied interest), many of which are predominantly characterized by low-moderate level contractions.

2. Methods

2.1. Experimental protocol

Three experiments (A, B, and C) were conducted focusing on sustained isometric contractions, and surface EMG signals obtained were analyzed. In each experiment, participants were screened for injuries or musculoskeletal disorders (in the prior 12 months), and only those with moderate levels of self-reported daily physical activities were included. Informed consent, using procedures approved by the Virginia Tech Institutional Review Board, was obtained prior to the experiment. Detailed procedures for experiments A and B can be found elsewhere (Yassierli, 2005), and are briefly summarized below. In all experiments, efforts were made to ensure that participants were comfortable, and non-threatening verbal encouragement was provided. All postures and fixture configurations were recorded and maintained across days.

2.1.1. Experiment A

A total of 24 young adults (age: 21.7 ± 1.9 years old; gender balanced) performed isometric endurance tests involving shoulder abduction efforts of the dominant arm at 30% of maximum voluntary contraction (MVC) with the arm fixed (via straps) horizontally. Each participant was comfortably stabilized in a seated position in a dynamometer (Biodex^{TM} System 3 Pro Medical System, Shirley, New York, USA). Following a brief warm up, each participant was instructed to perform pre-fatigue MVCs. All recorded torques were corrected for gravitational effects on the participant's arm and dynamometer attachment. After a brief practice and rest period, each participant was asked to maintain the exertion level at

30% MVC within ±5% of the target torque until exhaustion. Torque feedback was displayed on a computer screen located directly in front of the participant. Immediately after cessation of the exercise, each participant was instructed to perform a post-fatigue MVC with the same postures and instructions used for pre-fatigue MVCs.

2.1.2. Experiment B

A group of 24 young adults (age: 21.5 ± 1.2 years old; gender balanced) performed isometric endurance tests involving torso extension efforts at 30% MVC. The procedures (pre-fatigue MVCs, endurance test, and post-fatigue MVC) were similar to those in experiment A. Each participant stood upright with their hips and knees strapped to a fixture. A force plate (OR6, Advanced Mechanical Technology Inc., Massachusetts, USA) was placed underneath the fixture, and torques exerted at the L5/S1 level were estimated from the recorded forces and relative distance to the force plate (Granata et al., 1996).

2.1.3. Experiment C

Another group of 12 participants (age: 18.1 ± 3.6 years old; gender balanced) were recruited to perform isometric endurance tests involving shoulder abduction efforts at 15% and 30% MVC. To allow for examining repeatability, two replications were conducted at 15% MVC. The three sessions were performed in a random order, on separate days, and with at least 2 days rest between each. Procedures used in this experiment in general were similar to those employed for experiment A, with the differences only related to the arm posture. Here, the arm was abducted 20°, instead of horizontal. The former posture minimized the effect of arm mass on contraction levels, which was necessary in order to obtain the low workload level for weaker participants. In this experiment, ratings of perceived discomfort (RPD) were collected every 30 s throughout the endurance test using a modified version of Borg's CR-10 scale (Borg, 1990). The scale was continuous, ranging from 0–10 in which 0 means ''no discomfort at all'' and 10 corresponds to ''extremely strong (almost maximal)'' discomfort.

2.2. Dependent measures

The primary dependent measures were changes in EMG-based fatigue indices (described below). Other dependent measures obtained were endurance time, rate of MVC decline, and rate of RPD increase. Endurance time was determined as the time during which torque was maintained within the target. Rate of MVC decline (%/min) was computed as percentage reduction in MVC (post–pre-fatigue divided by pre-fatigue MVC), and divided by individual endurance time. Rate of RPD increase (units/min) was determined as the slope from a linear regression fit.

2.3. Surface EMG signal acquisition and processing

During shoulder abductions (experiment A and C), a pair of Ag/AgCl electrodes (inter-electrode distance of 2.5 cm) were located over the muscle belly of the middle deltoid (Hermens et al., 2000). During torso extensions (experiment B), four pairs of the electrodes were placed bilaterally over the paraspinal muscles at the L1 and L4/L5 levels, specifically targeting the longissimus thoracis and the multifidus muscles, respectively (Hermens et al., 2000). EMG signals were recorded continuously using an EMG amplifier system (Measurement System Inc., Ann Arbor, MI, USA). Raw signals were pre-amplified (x100) near the electrode site and hardware filtered at 10–500 Hz. Raw EMG was sampled at 2048 Hz, while EMG RMS was obtained in hardware (110 ms time constant) and sampled at 128 Hz. MnPF and MdPF were obtained from the power spectral density (PSD) of 2-s subsamples, using 50% overlapping, a Hanning window, and Fast Fourier transform (FFT). EMG RMS was low-pass filtered using software (Butterworth, zero phase-lag, 4th order, 3 Hz cutoff). Each 1-s sample of RMS taken during endurance tests was averaged and normalized (nRMS) against maximum RMS values obtained during pre-fatigue MVCs. In addition to these traditional processing methods, several alternative processing methods were applied to the same EMG signals as described below.

2.3.1. Frequency-band method

The PSDs were further processed using the Frequency-band method (Allison and Fujiwara, 2002; Dolan et al., 1995). For each PSD (from each 2-sec subsample), the sum of the power within 10–45 Hz bandwidth (LF_{Band}) was calculated as a percentage of the total power. This particular bandwidth was chosen based on previous studies of similar muscle groups (Allison and Fujiwara, 2002; Dolan et al., 1995).

2.3.2. Logarithmic power frequency

Each PSD was transformed into a logarithmic function and normalized using total power. Three new parameters (Yassierli and Nussbaum, 2003) were derived (Fig. 1): peak frequency (*Peak*), slope of lower frequency (LFslp), and slope of higher frequency (HFslp). The first parameter was defined as the frequency with highest log amplitude obtained from a polynomial curve fit over the 10–200 Hz bandwidth. The latter two parameters were derived from slopes of a linear regression fit over two frequency ranges: 10–45 Hz for the lower frequency slope and 90–150 Hz for the higher frequency slope. These selections were based on preliminary data processing in which *Peak* ranged within 50–85 Hz and data within the ranges selected demonstrated linear trends.

2.3.3. Fractal analysis

Two methods were used for fractal analysis: dispersion analysis (DA) and detrended-fluctuation analysis (DFA). In the first method (DA), the fractal dimension (D) was determined based on the relative dispersion of consecutive windows (a detailed algorithm can be found in Bassingthwaighte and Raymond (1995); Chau (2001)). Raw EMG were divided into 2-s overlapping subsamples as above. For each window, D was derived from lower and higher frequency components of the signals, namely D_{LF} and D_{HF}, using band-pass filtering (Butterworth, zero phase-lag, 4th order) of 10-F_{Peak} Hz and F_{Peak}-200 Hz, respectively. F_{Peak} was determined, from above, as the *Peak* from a logarithmic PSD. Prior to applying DA, raw EMG signals were full-wave rectified (converted to absolute values). Group sizes ranged from 10 to 100 and 5 to 50 points, respectively, for the lower and higher frequency components, determined based on the sampling rate and filtering used.

In the second method (DFA), an algorithm proposed earlier (Iyengar et al., 1996) was used to yield fractal scaling (α). Similar to the procedures used for DA, raw EMG were divided into overlapping 2-s subsamples. For each, α_{LF} and α_{HF} were computed to represent lower and higher frequency behaviors. The signals were band-pass filtered using software (Butterworth, zero phase-lag, 4th order) into 10-F_{Peak} and F_{Peak}-200 Hz, respectively, for α_{LF} and α_{HF}.

2.3.4. Poisson-fit methods

As previously mentioned, changes in the shape of EMG PSD have received little attention as a fatigue index. Assuming that all frequency

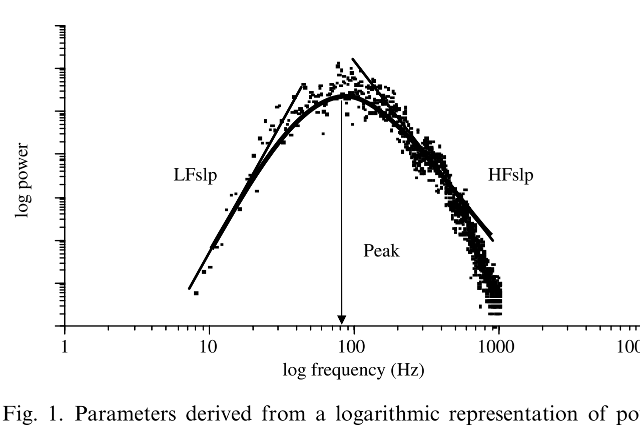

Fig. 1. Parameters derived from a logarithmic representation of power spectral density: Peak, LFslp, and HFslp.

components provide useful information towards characterizing fatigue development, quantifying changes in the shape of the PSD may be meaningful. The Poisson distribution is a discrete distribution that may be useful for describing the distribution of the EMG PSD. This distribution is commonly used to model the number of random occurrences within a given time interval (Eq. (1)).

$$P_\lambda(k) = e^{-\lambda}\lambda^k/k!, \quad k = 0, 1, 2, \ldots \tag{1}$$

Here λ, indicating the average value, represents the shape parameter (Fig. 2). A graphical method, a Poissonness plot (Hoaglin, 1980), can be used to diagnose how well a set of data fit a Poisson model. Briefly, using a logarithm transformation, Eq. (1) can be manipulated to:

$$\log(x_k) + \log(k!) = k\log(\lambda) + \log(N) - \lambda \tag{2}$$

Thus, λ can be estimated as the slope of $\log(x_k) + \log(k!)$ versus k if a relatively linear relationship exists (Hoaglin, 1980). To apply this method to EMG signals, the PSDs from each 2 sec subsample were divided into segments of 10 Hz frequency bands (k), and the sum of the power within each band ($k = 1..19$) was computed and normalized to total power (Fig. 3a). Finally, λ was calculated from the slope (for example in Fig. 3b, $\lambda = 10^{0.91} = 8.13$).

2.4. Analysis

Linear regression (justified based on data inspection) was employed to quantify temporal changes of each derived parameter, including nRMS, MnPF, and MdPF from the traditional approaches, and LF_{Band}, *Peak*, LFslp, HFslp, D_{LF}, D_{HF}, α_{LF}, α_{HF}, λ from the alternative methods. The resultant regression slopes were used as fatigue indices. For experiment B, fatigue indices were determined as mean values of the bilateral torso muscles, for both longissimus thoracis (B1) and multifidus (B2), justified by initial analyses that indicated no significant bilateral differences.

For each experiment, the utility of the derived EMG parameters were compared based on sensitivity, variability, repeatability, and predictive ability using the following procedures.

1. Sensitivity to fatigue development was determined based on the proportion of trials within an experiment that yielded significant linear changes over time (increasing or decreasing trend within a trial). In addition, sensitivity to force (exposure) level was determined by comparing indices (slopes) in experiment C at 15% and 30% MVC. Here, omega squared (ω^2) was computed (ranging from 0 to 1) as a measure of relative treatment magnitude (Keppel, 1991).
2. Variability was calculated as the residual (root-mean-square) error from linear regression within trials. Since the units of measure should be comparable, a transformation was done to yield centered and standardized data (Newsom et al., 2003). Centering provides zero mean, while standardizing results in a unit standard deviation. Differences in variability among indices were tested using ANOVA; separate ANOVAs were conducted for each experiment. Post-hoc analyses were conducted using Tukey's HSD Test.

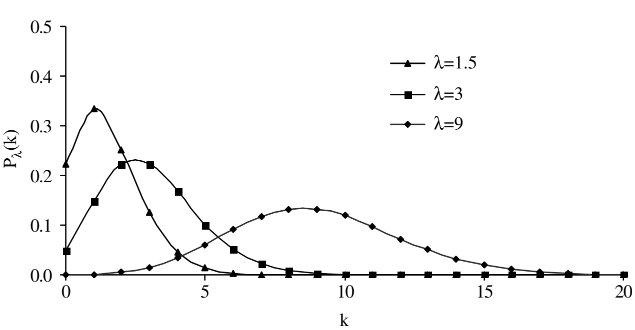

Fig. 2. The mean and shape indicator of a Poisson distribution (λ).

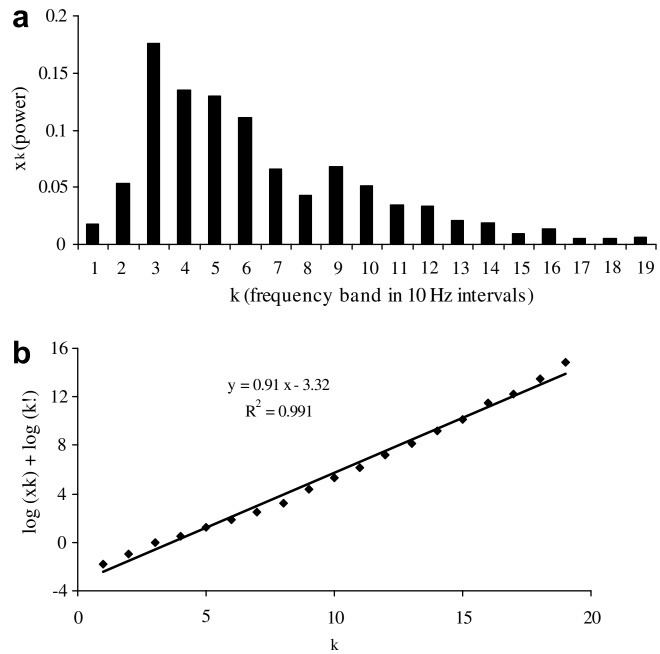

Fig. 3. EMG power spectral density after grouping into 10-Hz intervals (a) and a Poissonness plot taken from subsets of EMG (b).

3. Repeatability of EMG slopes was determined from the repeated exercises performed at 15% MVC (experiment C). Repeatability was assessed using intra-class correlations (ICC) (Elfving et al., 1999).
4. Predictive ability was tested by comparing fatigue indices (slopes) estimated from shorter fixed periods, specifically one-half and one-fourth of the mean endurance time across participants, to slopes obtained during the full exercise period. This ability was also quantified using ICC.

Correlation analysis was conducted between pairs of all dependent measures. Correlations between the EMG- and RPD-based indices were only available for experiment C. For all statistical tests, significance was concluded if $p \leqslant 0.05$.

3. Results

3.1. Non EMG measures

Summary results pertaining to pre-fatigue MVC, endurance time, rates of MVC decline and RPD increase are described in Table 1.

3.2. EMG-based measures

3.2.1. Sensitivity

Sensitivity to fatigue for the EMG indices varied depending on the muscles investigated (Table 2). For the shoulder exercises (experiments A and C), significant positive linear changes were observed for α_{LF} and LF_{Band} across all participants and trials. While decreasing trends were expected for MnPF and MdPF changes, some of the data showed non-significant changes or increasing trends. For the torso (experiment B), sensitivity of λ was comparable to MnPF and MdPF. Sensitivity of an index

Table 1
Summary of non-EMG dependent measures (mean ± S.D.)

	A (30% MVC)	B (30% MVC)	C at 15% MVC	C at 30% MVC
MVC (Nm)	64.5 ± 20.7	257.1 ± 63.6	55.4 ± 19.6	
Endurance time (min)	1.5 ± 0.4	4.7 ± 2.5	7.8 ± 2.7	2.4 ± 0.6
MVC decline (%/min)	10.7 ± 5.6	4.6 ± 4.3	3.4 ± 1.7	8.0 ± 5.4
RPD increase (unit/min)	NA	NA	1.4 ± 0.7	3.6 ± 1.2

Note: A, B, and C represent experiments described in the text.

was overall higher for B2 than B1. Across experiments, the least sensitive fatigue index was RMS.

Sensitivity to fatigue at different force levels (ω^2) also differed between indices. Among the alternative indices, fractal scaling at low-frequency components (α_{LF}) was the most sensitive index, followed by λ and LF_{Band}. In comparison to the traditional indices, ω^2 of α_{LF} was considerably higher than RMS, somewhat greater than MnPF, but slightly lower than MdPF.

Table 2
Sensitivity of EMG-based fatigue indices

Index	Proportion of time-dependent changes (−/0/+)				ω^2
	A	B1	B2	C	C
RMS	29/8/63	35/10/54	33/25/42	33/3/64	0
MnPF	100/0/0	90/8/2	94/6/0	92/6/3	0.71
MdPF	100/0/0	81/15/4	92/6/2	92/3/6	0.76
LF_{Band}	0/0/100	4/21/75	2/25/73	0/0/100	0.66
Peak	100/0/0	75/19/6	85/13/2	97/3/0	0.64
LFslp	96/4/0	50/44/6	58/38/4	97/3/0	0.26
HFslp	8/0/92	15/25/60	4/27/69	31/11/58	0.03
D_{LF}	71/29/0	50/48/2	48/48/4	72/25/3	0.36
D_{HF}	88/13/0	38/54/8	44/48/8	72/19/8	0.22
α_{LF}	0/0/100	2/27/71	0/15/85	0/0/100	0.74
α_{HF}	0/0/100	6/15/79	4/10/86	3/6/92	0.64
λ	100/0/0	88/8/4	92/8/0	97/0/3	0.69

Note: A, B, and C represent experiments. In B, averages from bilateral longissimus thoracis (B1) and multifidus (B2) muscles are reported, respectively. Proportions were determined as the percentages of slopes that were significantly positive (+), negative (−), or non-significant (0).

Table 3
Variability and repeatability among EMG-based fatigue indices

Index	Variability					Repeatability (ICC)
	A	B1	B2	C-15%	C-30%	C
RMS	0.72	0.81	0.84	0.72	0.68	0.69
MnPF	0.25	0.61	0.53	0.66	0.2	0.87
MdPF	0.18	0.72	0.63	0.58	0.23	0.90
LF_{Band}	0.34	0.82	0.81	0.61	0.22	0.98
Peak	0.22	0.77	0.78	0.51	0.2	0.87
LFslp	0.69	0.94	0.91	0.53	0.59	0.91
HFslp	0.63	0.92	0.90	0.91	0.78	0.70
D_{LF}	0.86	0.97	0.95	0.96	0.85	0.60
D_{HF}	0.82	0.96	0.96	0.9	0.8	0.93
α_{LF}	0.23	0.79	0.81	0.43	0.16	0.88
α_{HF}	0.25	0.74	0.69	0.64	0.4	0.76
λ	0.23	0.71	0.62	0.48	0.25	0.84

Note: A, B, and C represent experiments. In B, averages from bilateral longissimus thoracis (B1) and multifidus (B2) muscles are reported, respectively.

3.2.2. Variability

Variability was significantly different among indices (Tables 3 and 4). Variability was relatively higher for experiment B, and this difference was observed consistently for all indices. For experiment C, a lower effort level was generally associated with higher variability. Overall, variability was comparable among α_{LF}, α_{HF}, MnPF, MdPF, and λ. Among the traditional indices, MnPF had slightly and significantly lower variability than MdPF and RMS. Among the alternative indices, higher variability was observed for those derived from the logarithmic-power frequency and dispersion analysis (fractal).

3.2.3. Repeatability and predictive ability

As shown in Table 3, repeatability was highest for LF_{Band}, followed by D_{HF} and LFslp. The least repeatable measure was HFslp, followed by D_{LF} and RMS. Predictive ability using half of the estimated endurance time was typically better than that using one-fourth, with a difference in ICC magnitudes over a range of 30–60% (Table 5). Predictive ability of the indices varied between the two exercises. For the shoulder efforts, RMS and LF_{Band} demonstrated the highest predictive ability. For the torso, MnPF, λ, and α_{HF} were among the most predictive. Results from experiment C showed that the lower effort level was associated with higher ICC values.

3.3. Correlations among measures

Coefficients of correlation (r) between EMG parameters, endurance time, and rates of MVC decline are shown in Table 6. With the exception of HFslp and RMS, EMG-

Table 4
Results of post-hoc analysis on variability of EMG indices

	Experiment A					Experiment B					Experiment C					
MnPF					1					1				3	2	1
λ				2	1				2						2	1
α_{LF}				2	1			3								1
MdPF				2	1				2					3	2	1
Peak				2	1		4	3							2	1
α_{HF}				2	1			3	2					3	2	
LF_{Band}				2			4							3	2	1
LFslp			3			5							4	3		
RMS		4	3				4					5	4			
HFslp			3			5					6	5				
D_{HF}	5	4				5					6	5				
D_{LF}	5					5					6					

Note: Indices not connected by same number are significantly different. Lower numbers corresponds to lower variability.

Table 5
Predictive ability (ICC) of EMG-based fatigue indices

Index	Based on 1/2 of estimated Endurance time					Based on 1/4 of estimated Endurance time				
	A	B1	B2	C-15%	C-30%	A	B1	B2	C-15%	C-30%
RMS	0.64	0.83	0.88	0.91	0.87	0.12	0.24	0.50	0.86	0.49
MnPF	0.58	0.90	0.90	0.68	0.22	0.22	0.59	0.57	0.36	0.18
MdPF	0.63	0.81	0.87	0.64	0.45	0.24	0.53	0.55	0.39	0.22
LF_{Band}	0.78	0.93	0.92	0.84	0.57	0.49	0.29	0.61	0.83	0.55
Peak	0.56	0.93	0.84	0.68	0.40	0.17	0.61	0.41	0.36	0.23
LFslp	0.65	0.66	0.78	0.72	0.52	0.23	0.33	0.32	0.29	0.17
HFslp	0.10	0.75	0.74	0.55	0.33	0	0.27	0.35	0.23	0.10
D_{LF}	0.53	0.58	0.70	0.61	0.62	0.06	0.13	0.20	0.27	0.33
D_{HF}	0.33	0.58	0.81	0.89	0.63	0	0	0.13	0.47	0.10
α_{LF}	0.66	0.93	0.80	0.65	0.21	0.27	0.63	0.43	0.50	0.15
α_{HF}	0.50	0.82	0.88	0.80	0.20	0.18	0.56	0.55	0.49	0.23
λ	0.56	0.90	0.91	0.73	0.42	0.19	0.55	0.66	0.46	0.28

based fatigue indices had a good correspondence with endurance time and rates of RPD (absolute r greater than $\sim$0.5). Correlations for MnPF, MdPF, peak, λ, α_{LF}, and α_{HF} appeared to be comparable. Similar good correlations were observed between the majority of EMG indices and rates of MVC decline. High correlations were observed for MnPF, MdPF, peak, λ, α_{LF}, and α_{HF}, all of which had an absolute $r > 0.93$.

4. Discussion

The main purpose of this study was to determine the utility of several EMG-based fatigue indices in the context of low-moderate level isometric contractions. Previous studies have focused on relatively high contraction levels which are relatively uncommon in many occupational and daily activities. In the present study, indices were determined from changes in traditional (RMS, MnPF, MdPF, and LF_{band}) and alternative (Peak, LFslp, HFslp, λ, D_{LH}, D_{HF}, α_{LF}, and α_{HF}) EMG parameters. The utility of the indices was evaluated based on several criteria which have been employed separately in previous studies. Results of this study suggested that several alternative EMG indices can be used to monitor fatigue development, yet their utility varied in terms of sensitivity, variability, repeatability, and predictive ability. Among the alternative indices evaluated here, those derived from fractal analysis and Poisson distribution were found to have promise for future EMG-based assessments of localized muscle fatigue.

4.1. Traditional measures

Overall, utility of MnPF and MdPF seemed to be similar. A slightly higher fatigue sensitivity of MnPF (based on time-dependent changes) was probably due to fatigue-associated PSD shifts being accompanied with changes in its shape (Merletti et al., 1992). However, MdPF was found to be more sensitive to effort level (ω^2), but had higher variability than MnPF. The latter is in agreement with earlier results (Nussbaum, 2001). Previous studies have shown that both MnPF and MdPF might be insensitive to fatigue during low level efforts (e.g. (Öberg et al., 1994; Thorn et al., 2002), and similar results were observed here. Some trials showed nonsignificant linear changes (i.e., initial decrease followed by an increasing trend) and even increasing linear changes. A reason for this, as has been postulated

Table 6
Correlations among EMG-based fatigue indices, as well as with endurance time, rates of MVC decline, and rates of RPD increase

	RMS	MnPF	MdPF	LF_{Band}	λ	Peak	LFslp	HFslp	D_{LF}	D_{HF}	α_{LF}	α_{HF}
Endurance time	ns	0.70	0.70	−0.54	0.64	0.67	0.48	ns	0.52	0.55	−0.65	−0.64
MVC decline	0.25	−0.65	−0.65	0.41	−0.65	−0.64	−0.36	ns	−0.52	−0.53	0.60	0.64
RPD increase	0.42	−0.82	−0.84	0.76	−0.87	−0.84	−0.50	ns	−0.65	−0.71	0.84	0.83
RMS		−0.24	ns	ns	−0.23	ns	ns	ns	0.05	−0.33	ns	ns
MnPF			0.99	−0.73	0.95	0.95	0.50	ns	0.70	0.76	−0.93	−0.96
MdPF				−0.73	0.93	0.96	0.50	ns	0.75	0.74	−0.93	−0.95
LF_{Band}					−0.75	−0.68	−0.48	−0.30	−0.58	−0.57	0.73	0.68
λ						0.95	0.49	ns	0.66	0.77	−0.95	−0.98
Peak							0.50	ns	0.76	0.75	−0.99	−0.97
LFslp								−0.24	−0.37	−0.36	−0.51	−0.44
HFslp									ns	ns	ns	0.25
D_{LF}										0.56	−0.74	−0.68
D_{HF}											−0.70	−0.79
α_{LF}												0.96

Note: ns = non-significant.

(Hägg and Ojok, 1997), is that such spectral indicators are oversimplified methods for detecting changes in motor unit behaviors during prolonged low level effort, since such efforts have been shown to be fairly complex, including combinations of decreasing firing rate, de-recruitment of motor units, motor unit rotation, and recruitment of larger motor units with larger action potentials (Jensen et al., 2000; Kamo, 2002). Increasing trends in MnPF or MdPF may be due to the effect of the latter (recruitment of larger motor units) which tends to be more dominant than the first three behaviors (Hägg and Ojok, 1997).

RMS seemed to be inferior compared to other parameters, and demonstrated inconsistent performance as a fatigue index. This result is in agreement with previous findings which have shown inconsistent RMS changes throughout contractions (e.g., Hagberg, 1981). The relatively high predictive ability associated with this index should be interpreted with caution, since its sensitivity and variability were poor, and no significant correspondence was observed with endurance time. LF_{Band} appeared to be the best index in terms of repeatability and predictive ability, but its sensitivity was slightly lower than MdPF, MnPF, and α_{LF}. This finding agrees with earlier evidence (Maisetti et al., 2002), that changes in 6–30 Hz frequency band computed from the first 15–30 s of knee extensor contractions had a better correspondence with endurance time than RMS, MnPF and MdPF. Note that the appropriate frequency band is still unknown since the PSD shape highly depends on the muscle investigated, subject characteristics, and experimental protocols (e.g. electrode type and placement).

4.2. Fractal analysis

A number of methods have been proposed to characterize the fractal dimension of physiological signals (e.g., (Schepers et al., 1992)). If the EMG signal is assumed to be a roughly Gaussian random process (Stulen and De Luca, 1981), then Dispersion analysis (DA) seems to be more appropriate in characterizing its fractal dimension (Caccia et al., 1997; Eke et al., 2000). DA computes the relative dispersion of the signals by determining the ratio of the standard deviation over the mean. Since raw EMG signals tend to have a zero mean, it was necessary to rectify the raw EMG signal to apply this method. As a result, the $1/f^{\alpha}$ pattern of power spectra might have been disturbed. To address this possible error-inducing artifact, alternative methods were also applied in our preliminary analyses (not reported here) by shifting the raw signal by 10 V (i.e., mean = 10 V) or by computing the relative dispersion as $\mathrm{RD}(m) = \mathrm{SD}(m)$, instead of $\mathrm{RD}(m) = \mathrm{SD}(m)/\bar{x}$. However, both approaches produced similar results, in which inconsistent plots of $\log \mathrm{RD}(m)$ versus $\log m$. were obtained.

In this work, another computation method (i.e. DFA) was employed that, to our knowledge, had not been applied to EMG signals. Using DFA, the original raw EMG signal can be maintained. This method was initially applied for heartbeat signals to identify age-related disruptions (Iyengar et al., 1996). Results of the present study showed that DFA produced a more sensitive, more repeatable, and less variable fatigue index than DA.

Fractal characteristics of EMG signals have recently been documented (Gupta et al., 1997; Nieminen and Takala, 1996), and similar phenomena were observed in this study. In general, changes over time in fractal parameters (the fractal dimension and fractal scaling) with fatigue were consistently found in this study. It has been suggested that a fractal dimension in the range $1.0 < D < 1.5$ indicates the presence of long-range positive correlations, while a dimension in the range $1.5 < D < 2.0$ shows the existence of long-range negative correlations, and $D = 1.5$ suggests a random, uncorrelated signals (Bassingthwaighte and Raymond, 1995). Our observation of decreasing D associated with fatigue (starting value ~1.2–1.3) could be interpreted as evidence of increasing long-range positive correlations (vs. pure randomness). This can also be inferred as lowered dimensionality of the signals with fatigue (Nieminen and Takala, 1996) that may reflect a decreased ability of the physiological control system to perform motor control functions as fatigue increases. Pertaining to the fractal scaling, an α value of 0.5 indicates white noise, and an α of 1.5 corresponds to Brownian noise or a random walk (Iyengar et al., 1996). The increases in α associated with fatigue (starting value ~1.2–1.4) found here could be explained as an increasing short term correlation in EMG signals, probably due to increasing motor unit synchronization.

Previous research has noted that fractal characteristics may be limited to a certain frequency range (Nussbaum and Yassierli, 2003). These findings are supported by the profile of the power spectral density; if the PSD is plotted using log–log axes, the higher frequency components show a $1/f^{\alpha}$ pattern, a common sign of fractal behavior. In the present work, both components of lower and higher frequency of signals were investigated since a similar, though inverse, pattern was also observed for the lower frequency components. The results suggested that both lower and higher frequency components of the EMG signal demonstrated, to some extent, fractal characteristics, yet their utility differed across muscles (e.g. α_{LF} seemed to be more sensitive than α_{HF} for the shoulder exercises, not for the torso). This may suggest a muscle-dependency for the frequency range exhibiting fractal behavior, since both muscles (shoulder and torso) are morphologically different (Mannion et al., 1997; Manta et al., 1996). This hypothesis remains to be investigated in future studies.

It is not clear why fractal indicators (i.e. α_{LF} and α_{HF}) resulted in high utility, especially for the shoulder efforts, though several reasons are plausible. First, one advantage of this method is that it focuses on either lower or higher frequency signal components. Changes due to a decrease in conduction velocity and an increase in motor unit synchronization mainly affect the shape of PSD in the lower-frequency range, and recruitment or decruitment of motor units would, to some extent, influence power in middle to higher frequency band (Hägg, 1991). These behaviors are expected to occur mainly during sustained contractions at low level efforts, and observations on either extreme of the frequency spectrum may be advantageous. Second, fractal methods such as DFA view signals using a completely different approach in comparison to 'normal' PSD measures, such as MnPF, MdPF, or LF_{Band}. Using fractals, complexity and dimensionality of the signals were analyzed, and theoretically, fatigue is associated with an increase in signal complexity and a reduction in signal dimensionality. Further study is warranted to investigate whether fractal approaches are similarly applicable for different exercise types (e.g. dynamic effort) and why the fractal indicators demonstrated lower utility for the paraspinal muscles.

4.3. Logarithmic-power frequency and Poisson-fit methods

The methods of Logarithmic-power frequency and Poisson-fit were inspired from a common observation that fatigue is associated with compression of the PSD toward lower frequencies (De Luca, 1984; Hägg, 1992). Both methods were expected to facilitate detecting changes in PSD shape using simple geometrical approaches. The results showed that they indeed provided additional information on changes in EMG signals due to fatigue. Logarithmic-power frequency was initially proposed by Yassierli and Nussbaum (2003), with an expectation that the parameters resulting from this method would be less sensitive to noise, sampling rate, and frequency resolution than other existing fatigue indices. Among the three parameters proposed using this method, Peak appeared to have a better utility. Note that Peak may be more reliable than mode-frequency (discussed in De Luca, 1984; Hägg, 1991), since Peak is derived from a "smooth" PSD in a log-log scale. In general, Peak was found to decrease with fatigue as PSD shifted toward lower frequencies. An increase in Peak, although the overall trend was to decrease, may be a sign of newly recruited motor units (Hägg, 1991). This phenomenon might not be detected by MnPF or MdPF since increases in lower frequency component due to fatigue and in higher frequency component due to recruitment of larger motor units may cancel out each other.

As previously reported (Yassierli and Nussbaum, 2003), LFslp and HFslp tend to have high variability. Similar results were obtained here. Overall, LFslp seemed to have better utility than HFslp, but their overall utilities were less than those for MnPF and MdPF. Lower sensitivity may be due to complex motor unit behaviors associated with fatigue, as previously mentioned, that affect power in the low and/or high frequency components. Although the data for both low- and high-frequency components can visually be fitted to a line, this approach needs further investigation (here, the chosen frequency bands were 10–45 and 90–150 Hz). Note that the selection of cut-off ranges of the lower and higher frequency bands have varied in previous studies. For example, for lower frequency content: 5–30 Hz (Dolan et al., 1995), 20–40 Hz (Hägg, 1991), 15–45 Hz (Allison and Fujiwara, 2002), and for higher frequency content: 130–238 Hz (Bigland-Ritchie et al., 1981) or above 95 Hz (Allison and Fujiwara, 2002). Physiological interpretations for each bandwidth are still unknown. It is worth noting that the same Logarithmic-power frequency method used here was also recently documented (Ravier et al., 2005). In their study, and in line with the results here, the resulting parameters were found to be less sensitive to fatigue in comparison to MdPF, but more sensitive to force level.

High utility was found for the index derived from a Poisson distribution. However, fatigue may result in compressions of the PSD with or without an associated shape change (Merletti et al., 1992). This may explain why the utility of λ was not actually superior. Nevertheless, utility of λ was found to be at least similar to MnPF. This index seems promising due to its ability to detect changes in PSD shape and its lower noise sensitivity.

4.4. Limitations

A main limitation of this study is related to the model used to fit time-dependent changes in EMG parameters during the isometric contractions. Linear trend analysis was used, an approach that has been suggested by others (Nussbaum, 2001; van Dieën et al., 1993). However, fatigue-related data have also been reported to follow an exponential trend (Merletti et al., 1991) or a sequence of rapid change and plateau (Gerdle and Fugl-Meyer, 1992). Here, a linear model greatly simplified the analysis, and inspection of the data indicated that the assumption of linear trends was reasonable for all parameters. Another limitation relates to the exercises performed, which were limited to shoulder abduction and torso extension. Furthermore, 30% MVC efforts are still relatively high in comparison to many common tasks and activities. Further study is thus needed that employs similar methods for lower exercise levels and for different muscles, considering that motor unit behaviors may vary depending on contraction level and muscle morphology.

4.5. Conclusions

Fatigue is a complex process, and multiple EMG indices may be needed to characterize the development of local fatigue. Previous studies have suggested that motor units demonstrate complex behaviors during maintenance of prolonged low-effort contractions. Since the commonly used spectral indicators (MnPF and MdPF) have been considered overly simplistic to accurately represent these behaviors, several alternative indices were employed in this investigation and the utility among the indices was compared. In general, parameters derived from fractal analysis and a Poisson distribution demonstrated high utility, suggesting the potential application of these methods as fatigue indices.

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