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Review

# Electromyographic models to assess muscle fatigue

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ABSTRACT

Muscle fatigue is a common experience in daily life. Many authors have defined it as the incapacity to maintain the required or expected force, and therefore, force, power and torque recordings have been used as direct measurements of muscle fatigue. In addition, the measurement of these variables combined with the measurement of surface electromyography (sEMG) recordings (which can be measured during all types of movements) during exercise may be useful to assess and understand muscle fatigue. Therefore, there is a need to develop muscle fatigue models that relate changes in sEMG variables with muscle fatigue. However, the main issue when using conventional sEMG variables to quantify fatigue is their poor association with direct measures of fatigue. Therefore, using different techniques, several authors have combined sets of sEMG parameters to assess muscle fatigue. The aim of this paper is to serve as a state-of-the-art summary of different sEMG models used to assess muscle fatigue. This paper provides an overview of linear and non-linear sEMG models for estimating muscle fatigue, their ability to assess power loss and their limitations due to neuromuscular changes after a training period.


**Contents**



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## 1. Introduction

Muscle fatigue occurs in everyday life and can be described as a feeling or sensation of weakness or muscle pain. For physiologists, however, muscle fatigue has a more restricted meaning. Edwards (1981) described muscle fatigue as a "failure to maintain the required or expected force", and Vollestad (1997) described it as "any exercise-induced reduction in the capacity to generate force or power output".

Neuromuscular mechanisms related to fatigue remain to be completely elucidated. Muscle fatigue can arise from many points of the body and can be divided into central and peripheral fatigue. The central factors of fatigue comprise decreases in the voluntary activation of the muscle, which is due to decreases in the number of recruited motor units and their discharge rate. However, the peripheral factors of muscle fatigue include alterations in neuromuscular transmission and muscle action potential propagation and decreases in the contractile strength of the muscle fibers (Boyas and Guevel, 2011). The central components of muscle fatigue were generally described in terms of a reduction in the neural drive command that controls working muscles, which results in a decline in the force output (Gandevia, 2001). It has been suggested that the discharge rate of motor units decreases to match the change in the mechanical state of the muscle during the fatiguing contraction. This mechanism is called "muscle wisdom" (Barry and Enoka, 2007) and was discovered during a number of muscle fatigue studies. Bigland-Ritchie et al. (1983) studied the firing rates of motor unit potentials during isometric contractions. They found that during the first 60 s, mean rates fell from about 27 Hz to 15 Hz. However, not all the motor units appeared to behave in a similar manner. In a more recent study, Fuglevand and Keen (2003) found that electrical stimulation at a declining rate from 30 to 15 Hz evoked a smaller decline in force in the adductor pollicis muscle than electrical stimulation at a constant rate of 30 Hz. These findings suggested that decreases in discharge rate may contribute to force decline during fatiguing contractions. These changes in the discharge rate have been suggested to be protective mechanisms to prevent organ failure if the work was continued at the same intensity (Bigland-Ritchie and Woods, 1984). Therefore, the central model of muscle fatigue is an integrated mechanism that works to preserve the integrity of the system by initiating muscle fatigue through muscle recruitment, before cellular or organ failure occurs (Noakes, 2000). In contrast, peripheral muscle fatigue during physical work is considered an impairment of the peripheral mechanisms from excitation to muscle contraction. Peripheral regulation is, therefore, related to a perturbation of calcium ion movements, an accumulation of phosphate, and/or a decrease of adenosine triphosphate stores (Boyas and Guevel, 2011).

Consequently, the muscle fatigue phenomenon may be explained by several events (central or peripheral) that can occur in any part of the motor command pathway.

During a fatiguing contraction, many biological changes occur, such as increases in metabolite concentrations, changes in muscle fiber conduction velocity (CV), and alterations in the number of motor units that are recruited (Adam and De Luca, 2005). Many of these biological changes are traditionally used to determine the fatigue state of subjects, and these changes can be measured using various techniques. The concentrations of metabolites are obtained by analyzing blood samples or muscles biopsies. In addition, changes in the CV or in the number of recruited motor units or their firing rates can be measured using electromyographic recordings.

Electromyography (EMG) recordings can be divided into two types depending on the place of the recording electrodes; if the electrodes are placed on the skin, the procedure is considered surface electromyography (sEMG), and if the electrodes are inserted in the muscle, it is referred to as intramuscular electromyography. The results obtained from both techniques may differ in some aspects. For example, the evolution of the amplitude of the recording during fatigue differs because the RMS value of intramuscular EMGs decreases, whereas the RMS of the sEMG increases (Stulen and De Luca, 1978). Nevertheless, the two techniques are equally useful for studying muscle fatigue. However, because intramuscular EMG is an invasive technique that can cause discomfort to the subjects, sEMG is more widely used in sports science.

As previously mentioned, there are many techniques that can be used to evaluate muscle fatigue. In this review, we will briefly discuss the study of muscle fatigue using parameters that are extracted from surface electromyographic signals. The sEMG parameters used to evaluate muscle fatigue have been extensively studied in the past (Al-Mulla et al., 2011; Cifrek et al., 2009; Merletti and Parker, 2004). In the following sections, we briefly review the relationship between sEMG signals and muscle fatigue, the different sEMG parameters that have been traditionally used, and their relation to muscle fatigue. In addition, we briefly summarize the linear and non-linear techniques to relate the sEMG parameters to power loss as a measurement of muscle fatigue.

## 2. The influence of muscle fatigue on surface electromyographic (sEMG) parameters

Throughout the literature of the last century, there are many references in which sEMG signals were used to characterize muscle fatigue. In this section, we will briefly summarize the different methods and the difficulties that were found for relating muscle fatigue to changes in sEMG signals.

One of the first researchers to use sEMG techniques to track myoelectric manifestations of muscle fatigue was Piper in 1912 (Piper, 1912). He noticed a progressive "slowing" of the EMG signal during isometric voluntary sustained contractions, which consisted of a shift of the spectral components of the sEMG signals toward lower frequencies. Since then, many authors have used EMG to evaluate muscle fatigue.

The first type of contraction that was studied using these sEMG techniques was isometric or static contractions. sEMG signals during isometric contractions are easier to record than dynamic contractions. During isometric contractions, there is no movement; consequently, there is less movement interference compared to dynamic contractions. However, although the recording of sEMG signals during static contractions is easier, there are other factors that can influence the recording of the signals and therefore complicate their interpretation (Farina et al., 2004). These factors include the attenuation effect of the sEMG signal that is caused by different thicknesses of the subcutaneous tissue layers (for example, fat tissue layer) or the different signal features that can be obtained depending on the placement of the recording electrodes over the muscle (near the tendons or the innervation zones). Another factor of note is the crosstalk, or the electrical activity, of nearby muscles that can be recorded using surface electrodes. This interference signal may be recorded in addition to the sEMG signal of the muscle, even when the muscle is relaxed. This undesired effect can be reduced by ensuring the correct placement of the recording electrodes.

A primary characteristic of sEMG signals that are recorded during isometric contractions, which make the signals easier to analyze, is the changes in the spectral sEMG signal properties that occur during several seconds. Thus, the mean value of the sEMG signal and the correlation between the samples do not depend on time, and therefore, the sEMG signal can be assumed to be stationary (Farina, 2006). Because the EMG signal that is recorded during an isometric contraction can be considered stationary, the traditional frequency-based techniques, such as Fourier transforms or discrete fast Fourier transforms (FFT) can be used to determine changes in the power spectral content of the EMG signals.

Nevertheless, sEMG recordings during dynamic tasks are likely to be more relevant to daily function. Unfortunately, the difficulties in interpreting sEMG signals in static contractions are amplified in dynamic cases. Apart from the factors that influence the sEMG signals that are recorded during static contractions (mentioned above), there are other factors that affect sEMG signals during dynamic tasks that differ from those recording during static conditions (Farina, 2006). During static contractions, the joint angle remains constant. However, during dynamic contractions, the joint angle changes, which causes a shift of the underlying muscle fibers with respect to the recording electrodes. In addition, other effects during a dynamic contraction, such as rapid changes in the recruitment and de-recruitment of motor units and changes in muscle force, cause a faster change in the sEMG signal properties than in a static contraction, in turn producing non-stationarities. Therefore, because the sEMG signal during a dynamic contraction can be assumed to be non-stationary, the traditional frequency techniques may not be appropriate for extracting information, and more complex techniques are needed.

Taking into account that the interpretation of sEMG signal during an isometric contraction is easier than interpretations for dynamic contractions, the conclusions derived regarding fatigue from the former were extended and applied to the latter (Cairns et al., 2005). However, the pattern of neural activation is different during static and dynamic contractions, and the assumption that fatigue-induced changes that are measured during isometric contractions are the same for dynamic contractions is questionable (Cheng and Rice, 2005).

Therefore, researchers began to develop other techniques that provided a way to analyze sEMG signals extracted from dynamic contraction despite the non-stationarities. The new techniques proposed were the time–frequency techniques. Time–frequency techniques allow the study of the spectral content of sEMG signals over time.

Using the techniques mentioned above (the Fourier transform or time–frequency techniques), various sEMG parameters have been obtained for monitoring changes in the sEMG signal due to muscle fatigue. Below, we briefly summarize some of the sEMG parameters that are obtained from the different techniques and the relation to physiological changes due to muscle fatigue. We grouped the sEMG parameters into different subsections (sEMG amplitude-based parameters, spectral parameters, time–frequency parameters or non-linear parameters) according to the technique used to calculate each.

### 2.1. sEMG amplitude-based parameters

This section includes those parameters that quantify the amplitude or magnitude of the sEMG. Two main parameters are used to study sEMG amplitude: the averaged rectified value (ARV) and the root mean squared value (RMS)

$$ARV = \frac{1}{n}\sum_{n}|x_n| \tag{1}$$

$$RMS = \sqrt{\frac{1}{n}\sum_{n}x_n^2} \tag{2}$$

where $x_n$ are the values of the sEMG signal, and n is the number of samples.

Hereafter, we will use the term amplitude to embrace the RMS and the ARV parameters because, although they are calculated in different ways, the results and conclusions drawn from each are similar.

The amplitude of sEMG signals is influenced by the number of active motor units (Moritani et al., 1986), their discharge rates, and the shape and propagation velocity of the intracellular action potentials (Dimitrova and Dimitrov, 2002). Regarding the last point, Dimitrova and Dimitrov (2002) suggested that the amplitude of the sEMG signal is affected by a lengthening of intracellular action potentials (IAP). Using simulations, they found that the lengthening of IAPs could affect the sEMG amplitude depending on the distance of recording position from the fibers. The amplitude of the detected sEMG signal could decrease when the electrodes are placed close to the active fibers but remain almost unchanged at farther distances from the fibers (Dimitrova and Dimitrov, 2002). Moreover, Arabadzhiev et al. (2010) found that this effect could even be more influential on the sEMG amplitude than changes in the number of motor units recruited and their firing rates.

sEMG amplitude has been reported to increase during submaximal isometric contractions (Arendt-Nielsen and Mills, 1988; Lloyd, 1971; Maton, 1981) and to decrease during maximal ones (Moritani et al., 1986; Stephens and Taylor, 1972). In addition, the amplitude during dynamic contractions follows the same behavior. The sEMG amplitude has been observed to increase during submaximal dynamic exercise (Tesch et al., 1990) and to decrease during exercises at maximal levels of voluntary contraction (Komi and Tesch, 1979).

However, it seems that the relation between sEMG amplitude and force differed between protocols. In recent studies, Dideriksen et al. (2010a, 2010b) tested a computational model that simulated changes in sEMG amplitude and muscle force during different fatigue protocols. They showed that during three different isometric protocols at different percentages of the maximal voluntary contraction (MVC), the relations between the amplitude and force were different depending on the fatigue protocol of the given study.

### 2.2. Spectral analysis

This section discusses the frequency analysis that can be performed on the sEMG signal using procedures based on the Fourier transform in order to derive the mean or median frequency and Dimitrov's spectral index of fatigue.

#### 2.2.1. Mean and median frequency

These spectral parameters are traditionally used to quantify the changes in the spectral content of the sEMG signal based on the Fourier transform. However, there are substantial differences in their calculations.

The median frequency is the frequency value that separates the power spectrum in two parts of equal energy

$$\int_{f1}^{Fmedian} PS(f)\cdot df = \int_{Fmedian}^{f2} PS(f)\cdot df \tag{3}$$

where PS($f$) is the sEMG power spectrum that is calculated using Fourier transform, and $f1$ and $f2$ determine the bandwidth of the surface electromyography ($f1$ = lowest frequency and $f2$ = highest frequency of the bandwidth).The mean frequency, however, is obtained as follows

$$Fmean = \frac{\int_{f1}^{f2} f\cdot PS(f)\cdot df}{\int_{f1}^{f2} PS(f)\cdot df} \tag{4}$$

where PS(f) is the sEMG power spectrum calculated using Fourier transform, and f1 and f2 determine the bandwidth of the surface electromyography (f1 = lowest frequency and f2 = highest frequency of the bandwidth).

These spectral parameters are related to changes in muscle fiber conduction velocities and subsequent changes in the duration of the motor unit action potential waveform (Bigland-Ritchie et al., 1981). It has also been shown that higher decrements of mean frequency are related to higher fluctuations of muscle force, which is defined as tremor (Kouzaki et al., 2004).

It has been shown that during static contractions, the mean frequency usually decreases (Arendt-Nielsen and Mills, 1988; Moritani et al., 1986; Naeije and Zorn, 1982; Viitasalo and Komi, 1977). However, during dynamic fatiguing tasks, some authors have found decrements of the mean power frequency (Tesch et al., 1990), whereas others have observed no change during walking exercises (Ament et al., 1996; Arendt-Nielsen and Sinkjær, 1991).

The opposing behavior for the median frequency can be partly attributed to other factors that cause changes in the spectral components. Petrofsky and Lind (1980) found that intramuscular temperature can induce an increase in the spectral content of the sEMG signal, shifting the spectrum toward higher frequencies or increasing the mean frequency. Consequently, during a fatiguing exercise, there are two opposing effects on the spectral components of the sEMG signal: the effects induced by muscle fatigue, which cause a decrease in the mean frequency, and the effects of the increase in intramuscular temperature due to the exercise, which cause an increase in the mean frequency. It is possible that during some types of exercise, such as walking, the two effects compensate each other, and the decrements found in the mean frequency can be smaller or non-significant.

#### *2.2.2. Dimitrov's spectral fatigue index (FInsm5)*

Dimitrov's spectral index was proposed by Dimitrov et al. (2006) and is based on previous indices of peripheral muscle fatigue that are calculated as ratios between sEMG power spectral density content in high and low frequency bands (Basmajian and De Luca, 1985; Chaffin, 1973; Lindstrom et al., 1977; Moxham et al., 1982). They proposed the development of a new set of parameters based on the use of different spectral moments that are quantitative measurements of the shape of a signal. For example, the first moment is related to the mean of a signal, and other moments describe the characteristics of the distribution of the signal, such as the skewness. Dimitrov et al. (2006) suggested that ratios between different spectral moments calculated over the power spectral density that were obtained using the discrete Fourier transform, achieved higher sensitivity under both isometric and dynamic contractions than conventional parameters (mean and median frequency). More precisely, they suggested the use of ratios of moments of order ($-1$) and moments of order 2 and higher.

These moment orders were selected because the spectral moment of order ($-1$) emphasizes the increase in low and ultralow frequencies in the sEMG spectrum due to increased negative after-potentials during fatigue. However, the spectral moments of order 2 and higher emphasize the effect of decreases in high frequencies due to increments in the duration of the intracellular action potentials and decrements in the action potential propagation velocity.

However, the results obtained for the different spectral indices using moments of orders from 2 to 5 showed that the best results were obtained for the spectral index that made use of the moment of the highest order (FInsm5) (Dimitrov et al., 2006). The mathematical equation of FInsm5 is:

$$\mathrm{FInsm5} = \frac{\int_{f1}^{f2} f^{-1} \cdot PS(f) \cdot df}{\int_{f1}^{f2} f^{5} \cdot PS(f) \cdot df} \tag{5}$$

where PS(f) is the sEMG power spectrum calculated using Fourier transform, and f1 and f2 determine the bandwidth of the surface electromyography (f1 = lowest frequency and f2 = highest frequency of the bandwidth).

This parameter was found to increase during fatiguing dynamic contractions, and its sensitivity to map fatigue was higher than the median frequency (Dimitrov et al., 2006).

### *2.3. Time–frequency distributions*

As explained above, the main difference between a dynamic contraction and an isometric or sustained contraction is that during the former, the joint angle and the elongation of the muscles change, which causes a shift of the muscle fibers with respect to the surface electrodes. This shift produces changes in the recording site of the sEMG signal during the contraction and, therefore, increases the non-stationarity of the signal. Therefore, it seems that the parameters based on Fourier transforms (which are explained in Section 2.2) are not appropriate for studying muscle fatigue. To address the non-stationarities of the sEMG signal during dynamic contractions, the use of time–frequency techniques was proposed.

In one set of studies, Bonato and coworkers (1996, 2001a,b) examined the capacity to analyze the sEMG signal of different Cohen class distributions. The Cohen class distributions are a broad set of time–frequency signal analysis techniques that can be written in the following general format

$$C(t,w) = \iint \int x^{*}\left(u - \frac{1}{2}\tau\right) \cdot x\left(u + \frac{1}{2}\tau\right) \cdot \phi(\theta,\tau) \cdot e^{-j\theta t - j\tau w + j\theta x} \cdot dx \cdot d\tau \cdot d\theta \tag{6}$$

where $x$ is the electromyography signal, and is a two-dimensional function called "kernel", which defines the various Cohen class distributions.

The authors concluded that the Choi–Williams distribution, which has an exponential kernel, was the most suitable for analyzing sEMG signals that are recorded during dynamic contractions.

Karlsson et al. (2000) also compared time–frequency distributions. These time–frequency distributions included the short-time Fourier transform, the Wigner–Ville distribution (a Cohen class distribution with kernel = 1), the Choi–Williams distribution and the continuous wavelet transform. The authors concluded that the continuous wavelet transform had the best accuracy and estimation capacity on a simulated data test and, consequently, better accuracy for mapping changes in sEMG signals recorded during dynamic contractions compared with other time–frequency distributions.

#### *2.3.1. Instantaneous mean frequency (IMNF)*

One index of fatigue based on these new techniques is the instantaneous mean frequency (IMNF) (Bonato et al., 2001b), which is calculated over time–frequency and time–scale distributions that are more suitable to address non-stationary sEMG signals. This parameter is a group of values (mean frequencies of each instant of time) that are obtained using an equation for the mean frequency at each instant of time. Therefore, the parameter is affected by the same physiological factors as the mean and median frequency. One of the uses of this parameter is to compare the values that are obtained from different dynamic contractions in fatiguing concentric and eccentric exercise at the same angle (Molinari et al., 2006).

Using time–frequency and time–scale techniques (i.e., Choi–Williams distribution and wavelet distribution), a shift toward lower frequencies (Bonato et al., 1996, 2001b) and, therefore, a decrease in the IMNF over fatiguing dynamic contractions were identified (Bonato et al., 2001b; Molinari et al., 2006).

### 2.3.2. Wavelet spectral parameters

Due to the favorable results obtained using FInsm5 to quantify muscle fatigue, Gonzalez-Izal et al. (2010d) proposed a set of new spectral parameters based on the FInsm5 spectral parameter. These wavelet parameters were obtained from different wavelet bands from the stationary wavelet transform (SWT) which is a version of the discrete wavelet transform without down-sampling. This implies that each approximation and detail of the SWT contains the same number of samples as the input. The wavelet parameters are calculated as ratios of moments of different orders that are obtained for different wavelet bands (WIRM1551, WIRM1M51, WIRM1522), ratios between energies at different scales (WIRE51) or ratios between waveform lengths at different scales (WIRW51). The waveform length is a parameter that measures the changes in amplitude from sample to sample. Therefore, the parameter reflects the features of the sEMG signal as amplitude, frequency and duration of in one formula (Zecca et al., 2002). They were obtained as follows

$$\mathrm{WIRM1551} = \frac{\int_{f_1}^{f_2} f^{-1} D_5^s(f) \cdot df}{\int_{f_1}^{f_2} f^5 D_1^s(f) \cdot df} \tag{7}$$

$$\mathrm{WIRM1M51} = \frac{\int_{f_1}^{f_2} f^{-1} D_{\max}^b(f) \cdot df}{\int_{f_1}^{f_2} f^5 D_1^b(f) \cdot df} \tag{8}$$

$$\mathrm{WIRM1522} = \frac{\int_{f_1}^{f_2} f^{-1} D_5^b(f) \cdot df}{\int_{f_1}^{f_2} f^2 D_2^b(f) \cdot df} \tag{9}$$

where $D_1^s(f)$ and $D_5^s(f)$ are the power spectra of the first and fifth scales, respectively, of the SWT using the sym5 wavelet, and $D_{\max}^b(f)$, $D_1^b(f)$, $D_5^b(f)$, $D_2^b(f)$ are the power spectra of the maximum energy, the first, the fifth and the second scales, respectively, of the SWT using the db5 wavelet. The maximum energy scale in this work was usually scale 4. $f_1$ and $f_2$ are determined by the bandwidth of the signal

$$\mathrm{WIRE51} = \frac{\sum_{i=1}^{N} D_5^2[n]}{\sum_{i=1}^{N} D_1^2[n]} \tag{10}$$

$$\mathrm{WIRW51} = \frac{\sum_{i=2}^{N} |D_5[i] - D_5[i-1]|^2}{\sum_{i=2}^{N} |D_1[i] - D_1[i-1]|^2} \tag{11}$$

where $D_5[n]$ and $D_1[n]$ are the details at scales five and one, respectively, of the SWT calculated using the sym5 wavelet.

Using these spectral moments that are obtained for the high and low frequency bands, the effects of the increases in low frequencies and the decreases in high frequencies due to fatigue, which are explained above in Section 2.2.2, are emphasized more than in FInsm5. To determine the sensitivity of the parameters, the correlation coefficients between the changes in power loss and the changes in these wavelet-based parameters vs. conventional ones were compared. The changes in the wavelet-based parameters (from $R_{\mathrm{WIRM1M51}} = -0.576$ to $R_{\mathrm{WIRW51}} = -0.683$) were more closely related to the changes in force than the conventional parameters ($R_{\mathrm{Fmed}} = 0.435$; $R_{\mathrm{FInsm5}} = -0.518$). In addition, Gonzalez-Izal et al. (2010d) found that after adding Gaussian noise to the sEMG signal, the wavelet-based indices were more robust against noise. This was suggested since higher correlation coefficients between the wavelet-based indices and force than for the conventional parameters, were found at different levels of noise. The authors suggested that this could be related to the fact that the wavelet-based parameters were obtained in narrower bands and, therefore, less noise was computed for their calculations.

## 2.4. Non-linear parameters

Although several parameters based on the use of spectral techniques, such as Fourier transforms, amplitude-based techniques or time–frequency techniques, have been widely used to study sEMG signals recorded during various tasks, Nieminen and Takala (1996) suggested that myoelectric signals could be better modeled as outputs of a nonlinear dynamic system rather than as random stochastic signals. Therefore, the use of non-linear parameters can be more appropriate in extracting information from the sEMG signals.

In this section we will focus on the application of some non-linear parameters for the study of sEMG signals during fatiguing contractions.

### 2.4.1. Entropy

The entropy is a non-linear measurement of the complexity of a signal. There are a number of parameters that can be used to estimate the entropy of a signal. Pincus (1991) developed a parameter called Approximate Entropy (ApEn). This parameter is approximately equal to the negative average natural logarithm of the conditional probability that two sequences that are similar at m points remain similar at the next point within the tolerance $r$. This scenario can be expressed mathematically as:

$$\mathrm{ApEn} \cong -\frac{1}{N-m} \sum_{i=1}^{N-m} \ln\left(\frac{n_i^m}{n_i^{m+1}}\right) \tag{12}$$

where $N$ is the number of samples, m is the length of the vectors to be compared, and $n^m$ is the number of matches of length m that are similar within the tolerance $r$.

However, the ApEn equation counts each sequence as matching itself to avoid the occurrence of $\ln(0)$ in the calculations. This causes the ApEn to be heavily dependent on the record length, and its value is uniformly lower than expected for short records (Richman and Moorman, 2000). To reduce this error, Richman and Moorman (2000) developed a new parameter called Sample Entropy (SampEn) that does not count self-matches. This parameter is defined as the negative natural logarithm of the conditional probability that two sequences that are similar for m points remain similar at the next point, where self-matches are not included in calculating the probability. SampEn is more independent of the record length and is more consistent than ApEn. SampEn can be expressed mathematically as follows:

$$\mathrm{SampEn} = \ln\left(\frac{\sum_{i=1}^{N-m} n_i'^m}{\sum_{i=1}^{N-m} n_i'^{m+1}}\right) \tag{13}$$

where $N$ is the number of samples, m is the length of the vectors to be compared, and $n'^m$ is the number of matches of length m that are similar within the tolerance $r$, excluding the self-matches.

Pincus (2006) suggested the existence of a relationship between the shape of the power spectrum and the entropy. He found that greater entropy corresponded to a broader power spectrum, and smaller entropy corresponded to a peaked power spectrum. As it is mentioned above in Section 2.2.1, due to physiological mechanisms of muscle fatigue, the sEMG power spectrum becomes more peaked and concentrated in lower frequencies. Therefore, it appears that the entropy can be affected by a physiological mechanism similar to that which affects the mean and median power frequency. This result is in accordance with results by Xie et al. (2010), who found that during isometric fatiguing contraction, the entropy and median frequency decrease.

In addition, some authors, including Sung et al. (2007, 2008), have claimed that entropy reveals sEMG characteristics that are not included in the power spectrum. The authors conducted several studies in which subjects were asked to lie in a prone position on a table and suspend their trunks horizontally against gravity (modified Sorensen test). They found that entropy could be useful for differentiating pathologies such as low back pain (LBP), as they found lower entropy values for the patients than for the subjects of the control groups, whereas the mean frequency exhibited significant overlaps between the groups (Sung et al., 2007). The authors attributed this to the fact that a lower signal complexity may be related to pathology. In addition, in other study (Sung et al., 2008), they found that after the modified Sorensen test, the values of the slope of the median frequency were not different between genders, whereas the entropy values were higher for the male subjects than for the female subjects. Therefore, Sung et al. (2008) concluded that entropy can be a useful tool for detecting muscle fatigue in gender differences. They suggested that these differences could be related to potential influences of anthropometric variables.

Other authors (Farina et al., 2008; Troiano et al., 2008) have calculated the entropy between the RMS of different sEMG channels in a multi-electrode sEMG grid. The obtained entropies indicated the degree of homogeneity among activated regions (higher entropy values corresponded to more uniform distributions of amplitude over the grid)

$$Entropy = -\sum_{i}^{N} p^2(i) \cdot \log_2 p^2(i) \tag{14}$$

where $N$ is the number of electrodes, and $p^2(i)$ is the square of the root mean square value at electrode $i$ normalized by the summation of the squares of the N root mean square values of the N electrodes.

Using this approach, Troiano et al. (2008) found that during isometric contractions at different force levels, this entropy value was not related to muscle fatigue (as they could not find any changes), but it increased with muscle force. They suggested that this behavior could be related to increases in MU recruitment and increases in their firing rates. However, Farina et al. (2008) found that during a static contraction with shoulders 90° abducted for the maximum endurance time, the entropy decreases due to fatigue, which implies a less uniform map. In addition, the authors found that the subjects who showed a less uniform map had larger shifts of the center of gravity of the sEMG root mean square map, which suggests that the changes in the spatial muscle activity distribution play a role in the ability to maintain a static contraction.

### 2.4.2. Fractal analysis

A fractal refers to an object or signal that can be split into parts, each of which is (at least approximately) a reduced-size copy of the whole. This property is called self-similarity (Mandelbrot, 1977).

The sEMG signals are the results of the summation of action potentials of different motor units that travel through different tissues and undergo spectral and magnitude compression. In addition, the behavior of the sEMG signal with time that is recorded during isometric contractions exhibits the property that patterns observed at one sampling rate are statistically similar to patterns observed at lower sampling rates. These characteristics suggest that the sEMG signal has self-similarity, and therefore, fractal analysis seems appropriate (Anmuth et al., 1994).

One of the most common fractal parameters used is the fractal dimension (FD), although there are many others. Gitter and Czerniecki (1995) estimated this parameter using a box counting method. A grid of square boxes is used to cover the signal, and the number of boxes that the sEMG waveform passes through is counted. Because the number of the boxes that are counted depends on the alignment of the grid relative to the sEMG signal, the box count should be performed with three different grid alignments relative to the sEMG baseline, and the results of each should be averaged. This procedure is repeated for different sizes of the grid's boxes. When the box size decreases, the number of the boxes that are counted will increase exponentially. However, by plotting the logarithm of the number of boxes counted (log N) vs. the logarithm of the inverse of the box size (log 1/S), the exponential relationship becomes linear. The slope of the interpolation line (estimated using the least mean squared procedure) is the fractal dimension (FD).

It has been suggested that this parameter is related to increases in the synchronization of motor units during muscle fatigue (Mesin et al., 2009; Troiano et al., 2008). However, as with other non-linear procedures, it is difficult to relate the parameter to physiological changes in muscle properties that are a result of muscle fatigue.

Mesin et al. (2009) compared the fractal dimension to other muscle fatigue indexes computed from both synthetic sEMG signals that had different conduction velocity distributions and levels of motor unit synchronization and experimental signals. They found that the fractal dimension was the index that was least affected by conduction velocity changes and most related to the level of synchronism, which suggests that the fractal dimension is a promising index of central fatigue. In addition, Troiano et al. (2008) found that the FD of signals recorded during non-fatiguing contractions is not affected by force levels. However, the FD that is obtained during an isometric contraction at 50% MVC decreases, which indicates that the synchronization level increases because of muscle fatigue. In addition, they found that the FD is a parameter strongly related to endurance time.

Other authors have used different fractal parameters. Gang et al. (2007) studied sEMG signals during isometric contractions and used the area of the multi-fractal spectrum of the sEMG signal as indicator of fatigue. They found that this area increases with fatigue and shows higher sensitivity for muscle fatigue compared to the MDF.

However, some authors have found no relation between the fractal indicators and muscle fatigue. Ravier et al. (2005) obtained the right and left slopes of the plot of the logarithm of the power spectrum of the sEMG signal vs. the logarithm of the frequency. They found that the "right" slope was sensitive to different force levels during isometric contractions of the biceps brachii muscle but insensitive to fatigue. Based on these results, they suggested that this fractal index was a frequency indicator that can complement the information provided by classical frequency parameters (as mean frequency) when studying force during unknown states of fatigue.

### 2.4.3. Recurrence quantification analysis (RQA)

Recurrence quantification analysis (RQA) is a non-linear method based on a graphical method described by Eckmann et al. (1987) to detect deterministic structures in signals that repeat throughout a contraction. This method transforms the single-channel sEMG signal onto a bi-dimensional space (i.e., a sEMG signal vector onto a matrix of ones and zeros) as follows.

First, set of vectors using the sEMG signal vector is created

$$\begin{array}{l|lllll} v_0 & = [s(0) & s(\lambda) & \cdots & s((D-1)\lambda) & ] \\ v_1 & = [s(1) & s(\lambda+1) & \cdots & s((D-1)\lambda+1) & ] \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ v_{N-1} & = [s(N-1) & s(\lambda+N-1) & \cdots & s(K-1) & ] \end{array} \tag{15}$$

where $s$ is the sEMG signal of $K$ samples, $s = [s(0) \quad s(1) \quad \cdots \quad s(K-1)]$, $N$ is defined as $N = k - (D-1)\,\lambda$, $D$ is the embedding dimension of a value equal to 15 (Zbilut and Webber, 1992), and

$\lambda$ is the sample at the first zero of the autocorrelation function of the sEMG signal. Then, a matrix DM is obtained by calculating the Euclidean distance from the $N$ vectors obtained in (15)

$$DM = \begin{vmatrix} d(1,1) & d(1,2) & \cdots & d(1,N) \\ d(2,1) & d(2,2) & \cdots & d(2,N) \\ \cdots & \cdots & \cdots & \cdots \\ d(N,1) & d(N,2) & \cdots & d(N,N) \end{vmatrix} \tag{16}$$

where each element of the matrix $d(i,j)$ is obtained as follows

$$d(i,j) = \sqrt{\sum_{k=0}^{(D-1)\lambda} \left(v_i(k) - v_j(k)\right)^2} \tag{17}$$

where $v_i$ and $v_j$ are vectors calculated in (15), and $D$ and $\lambda$ are defined in (15).

Once the DM matrix is created, each element is replaced by a one if the value exceeds the threshold, termed the radius, or a zero if it does not.

It has been suggested that this procedure can detect increases in the number of deterministic structures produced by increases in force level or during a fatiguing contraction due to the short-term synchronization among MUAP trains or changes in the muscle fiber conduction velocity. However, due to the non-linear nature of this procedure, it is difficult to predict its sensitivity in response to changes in muscle properties (Merletti and Parker, 2004).

Webber and Zbilut (1994) tested the sensitivity of two indexes that were extracted from RQA: %REC and %DET. %REC is obtained as the percentage of "ones" in the matrix with respect to the total number of elements. It quantifies the complexity of the signal itself. %DET is obtained as the percentage of points that form upward diagonal lines with lengths greater than a determined value called "line" with respect to the number of "ones" in the matrix. It quantifies the deterministic structure or how far the time series are from a purely random dynamic system.

These authors (Webber and Zbilut, 1994) compared the sensitivity for detecting the onset of muscle fatigue of the center frequency with the RQA parameters obtained during an isometric contraction of the biceps muscle. The subjects were asked to maintain their forearms in a horizontal position with their elbow bent to 90° and to hold a 1.4 kg weight for 60 s. During this control period, the 95% confident limits for each variable were computed. After the control period, the load was increased to 5.1 kg, and the subjects were asked to maintain their arm position as long as possible. During this period, the onset of fatigue was computed when the variables exceeded the limits that were previously obtained. Skeletal muscle fatigue was indicated by a fall of the center spectral frequency that occurred 74.0 s after the placement of the heavy load. However, %DET was able to detect fatigue in the first 48.8 s after the load was applied, whereas %REC remained relatively unaffected until 145.9 s. These results showed that the RQA is a promising method for detecting muscle fatigue.

Based on this study, other experimental fatigue studies were conducted. %DET and the traditional spectral techniques were found to be highly correlated (Felici et al., 2001), but %DET showed a greater sensitivity to fatigue-induced changes than spectral analysis (Farina et al., 2002). It was found that %DET is sensitive to both conduction velocity and the degree of synchronization changes during fatigue, as with traditional spectral techniques (Farina et al., 2002). This results were in accordance with the results found by Felici et al. (2001), who found an increased %DET in weight lifters but not for the control group during brief maximal efforts. The authors speculated that these results can be related to a higher MU synchronization in people who train.

Morana et al. (2009), have used RQA to study muscle fatigue during a submaximal isometric exercise. They found that %DET was unchanged during the increase in power (due to potentiation), increased when the power decreased and was unchanged despite an increased central command, as reflected by an increased RMS/M (RMS normalized to M-wave area). In light of these results, they suggested that RQA and %DET could be useful for detecting peripheral muscle fatigue.

## 3. Relation between sEMG and power loss (measurement of muscle fatigue)

We previously defined muscle fatigue as "any exercise-induced reduction in the capacity to generate force or power output". Therefore, force, power and torque have been used as direct measurements of muscle fatigue. Some years ago, the measurement of these variables implied important technical difficulties during free daily movements (i.e., cycling or walking). However, currently with the new advances in technology, it is possible to measure mechanical power in several situations, such as using in-shoe foot pressure sensors during walking. In addition, the measurement of sEMG signals during these dynamic daily movements combined with mechanical parameters that can be obtained from new portative systems may be useful for assessing and understanding fatigue.

However, it is not always easy and feasible to relate changes in sEMG signals to muscle fatigue or changes in power, force or torque loss (as a measurement of muscle fatigue). Some authors have found that in some fatigue situations, although the force decreases during muscle fatigue, the sEMG signals are little affected. One study conducted by Baker et al. (1993) found that after 2 min of sustained maximal voluntary contraction exercise and after 15–20 min of intermittent exercise, the force decrease was accompanied by an increase in [Pi] (inorganic phosphate) but no changes in sEMG signals. In addition, Sandiford et al. (2005) found that during fatigue exercises (progressive cycling exercise to fatigue in normoxia and hypoxia) related to a depression of Ca2+ release, the M-wave was unchanged at the point of fatigue. This indicates that there is little or no change in the action potential, and therefore, it is likely that sEMG will not relate to force loss.

Although sEMG signals change due to fatigue, there are other issues to take into account. The main issue when using only the conventional sEMG variables to quantify fatigue is their poor association directly with fatigue (force or power output). After decades of research to find the physiological determinants of various sEMG variables, it is now evident that intra–individual factors, such as muscle anatomy, affect the estimate and alter the association between myoelectric and mechanical variables (Farina et al., 2004). In addition, as previously commented, a recent study by Dideriksen et al. (2010b) demonstrated using simulations that the relation between force and sEMG amplitude during different isometric protocols may change. Therefore, amplitude alone cannot be used to predict the magnitude of a muscle force. Based on the idea that the use of traditional variables alone that are extracted from sEMG signals are not sensitive enough to determine muscle fatigue, many authors have combined various sets of sEMG parameters.

Previous studies (Izquierdo et al., 2009, 2011) have suggested that the main mechanisms responsible for the increased capacity to work with the same relative intensity after short-term strength training are primarily of a peripheral nature. The reason for this assumption is that similar changes in sEMG signals but higher accumulated fatigue and metabolic demand (i.e., blood lactate and ammonia accumulation) were observed after multiple sets of dynamic fatiguing high-power contractions with the same relative load as pre-training (Fig. 1). Therefore, it was suggested that these

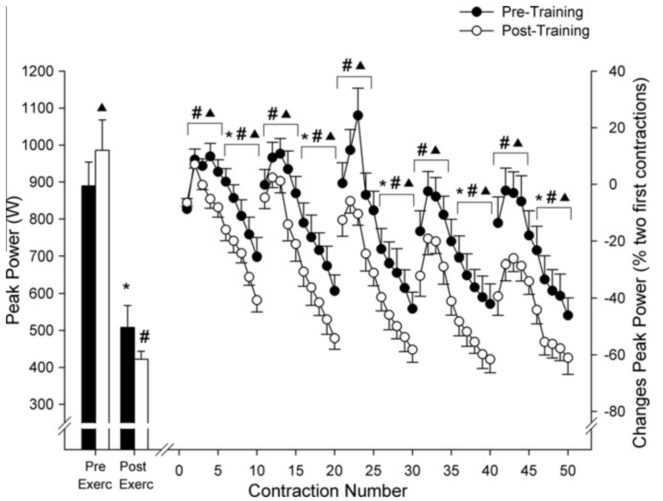


**Fig. 1.** Muscle peak power output (mean ± SE) absolute values (i.e., average value of repetitions 1–5 and 45–50) and percentage changes with respect to the first two repetitions during the five sets of 10 repetitions of the pre-training and post-training loading exercise. *Significant differences ($P < 0.05$) compared with the first five repetitions of the first set during the pre-training loading exercise. #Significant differences ($P < 0.05$) compared with the first five repetitions of the first set during the post-training loading exercise. ▲ Significant differences ($P < 0.05$) between pre-training and post-training loading exercises. From Izquierdo et al. (2011).

metabolic and neuromuscular adaptations caused by resistance training could affect the relationships between the mechanical manifestation of muscle fatigue and electromyographic variables.

Thus, it is clear that sEMG can be useful in tracking muscle fatigue for many reasons (the relationships found between sEMG features and muscle fatigue, and the possibility of recording them in almost any type of situation). Therefore, some studies have examined the relationships between muscle fatigue and sEMG variables and, consequently, the possibility of using sEMG models to accurately track muscle fatigue.

### *3.1. Linear techniques used to estimate muscle fatigue*

The linear techniques that are used to estimate muscle fatigue are based on linear regression, which relates changes in sEMG parameters to changes in power loss (as a direct measurement of muscle fatigue).

Gonzalez-Izal et al. (2010b,d) found that these techniques accurately mapped changes in muscle fatigue using different sEMG parameters (Fig. 2).

More precisely, they found that during a fatiguing contraction that consisted of five sets of 10 leg-presses at 10 RM (i.e., using a load that the subject can only lift 10 times consecutively) the logarithm of FInsm5 accounted for 37% of the performance variance of changes in muscle power output. Moreover, the combination of this parameter and the average (over the observation interval) of the instantaneous mean frequency that was obtained using a

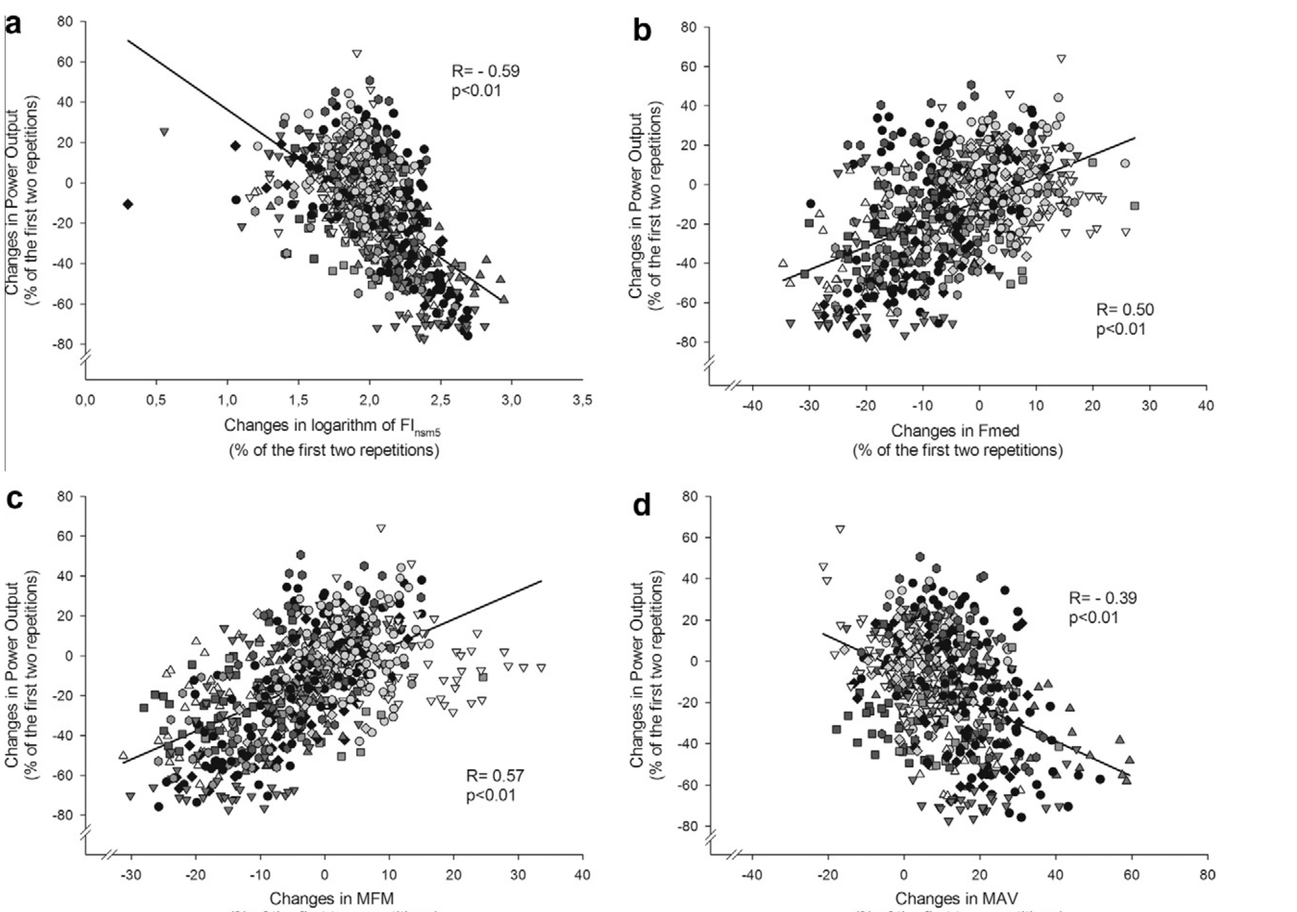


**Fig. 2.** Linear representations of changes in power output (% of the first two repetitions) vs. changes in different sEMG parameters (% of the first two repetitions) for all the subjects (averaged for vastus lateralis and medialis muscles). (a) Changes in power output (%) vs. changes in logarithm of Dimitrov's parameter (log FInsm5) (%). (b) Changes in power output (%) vs. changes in median frequency (Fmed) (%). (c) Changes in power output (%) vs. changes in Mean of the instantaneous mean frequency (MFM) (%). (d) Changes in power output (%) vs. changes in Mean Average Voltage (MAV) (%). From Gonzalez-Izal et al. (2010b).

Choi-Williams distribution (MFM) as a two-factor combination predictor accounted for 44% (Gonzalez-Izal et al., 2010b). In addition, they found that their wavelet-based parameters showed a better accuracy to track changes in power loss (i.e., log-WIRW51 accounted for 46.6% of the variance that was observed in the changes in muscle power) (Gonzalez-Izal et al., 2010d). Therefore, they concluded that these techniques could be useful for tracking muscle fatigue.

### 3.2. Non-linear techniques used to estimate muscle fatigue

The non-linear techniques that are used to estimate muscle fatigue are based on neural networks to relate sEMG parameters to muscle fatigue. The advantage of these techniques compared to the linear methods is that the neural networks can learn the associations between sEMG parameters and muscle fatigue.

The firsts to use these techniques to develop a fatigue index (mapping index) made up of a combination of sEMG parameters using a neural network (a multi-layer perceptron) were MacIsaac et al. (2006). The mapping index (MI) was developed to change linearly over time and was obtained using a combination of different sEMG parameters, which included information about the amplitude and the frequency characteristics of the sEMG signal. The authors found that their MI was more accurate for mapping changes in muscle fatigue during different elbow contractions than unique sEMG parameters (mean frequency or instantaneous mean frequency). They achieved higher signal to noise ratios (SNR), which implies smaller errors between estimated and real parameters, for their MI (7.89 under random condition to 9.69 under static condition) compared to the median frequency (3.34–6.74) and instantaneous mean frequency (2.12–2.63).

Based on this study, Gonzalez-Izal et al. (2010a) proposed a modification of the original technique reported by MacIsaac et al. (2006). They suggested that the original MI may not reflect a direct measure of fatigue during repetitive isokinetic knee extensions, such as force loss, because the original MI assumes a linear progression of fatigue over time, whereas a decrease in maximal voluntary force (which is often assumed to be a direct measure of fatigue) is rarely reported as linear during those dynamic tasks (Gerdle et al., 2000; Komi and Tesch, 1979). To overcome this limitation, Gonzalez-Izal and coworkers (2010a) proposed to use the mechanical force as the objective function that the neural network maps instead of the mapping index, which was considered a priori as changing linearly over time. The two techniques were compared, and the second technique proposed by Gonzalez-Izal and coworkers (2010a) showed better accuracy for mapping changes in muscle fatigue during knee extension tasks ($SNR_{MI} = 4.24$; $SNR_{Force} = 8.07$).

### 3.3. Linear vs. non-linear techniques used to estimate muscle fatigue

Both linear and non-linear techniques provided good results for mapping changes in power or force loss during dynamic exercises based on sets of sEMG parameters. However, there remain some differences between the techniques. The non-linear neural network modifies the weights, and therefore, the relation between sEMG parameters and muscle fatigue is calculated based on a learning procedure. In contrast, for linear techniques, this relationship is assumed to be linear a priori. Moreover, this learning procedure requires more time for computation than the linear model. Gonzalez-Izal et al. (2010c) compared the performance of both techniques to determine which provided a more accurate mapping of power loss using sEMG parameters. They found that although the neural network provided a higher SNR (signal-to-noise ratio), which corresponds to lower error in the power mapping, there were no significant differences between the linear and non-linear approaches (Fig. 3). Therefore, they concluded that due to the lower computational time required by the linear approach, this method was preferable for mapping power changes based on sEMG variables.

### 3.4. Validation of the linear muscle fatigue mapping before and after training

According to the previous works examined, the techniques described here that relate changes in power loss and sEMG parameters can be useful for mapping or estimating muscle fatigue. However, as mentioned above, it has been shown that a short-term strength training period may affect the relationship between sEMG variables and changes in power loss (Izquierdo et al., 2009). Therefore, changes in the training status of the subjects could modify the relationships between the changes in power loss and the changes in the sEMG parameters and could affect the accuracy of the sEMG models for estimating muscle fatigue.

In this respect, Izquierdo and coworkers (2011) compared the linear power mapping models (which related changes in power loss and changes in sEMG parameters or blood metabolites) before and after 7 weeks of training to determine whether the relationships between sEMG variables and power loss were dependent on the training status of the subjects. They compared the changes in power loss, sEMG parameters and blood metabolites during similar protocols before and after training. The fatiguing protocol consisted of subjects performing five sets of 10 leg-presses at 10RM

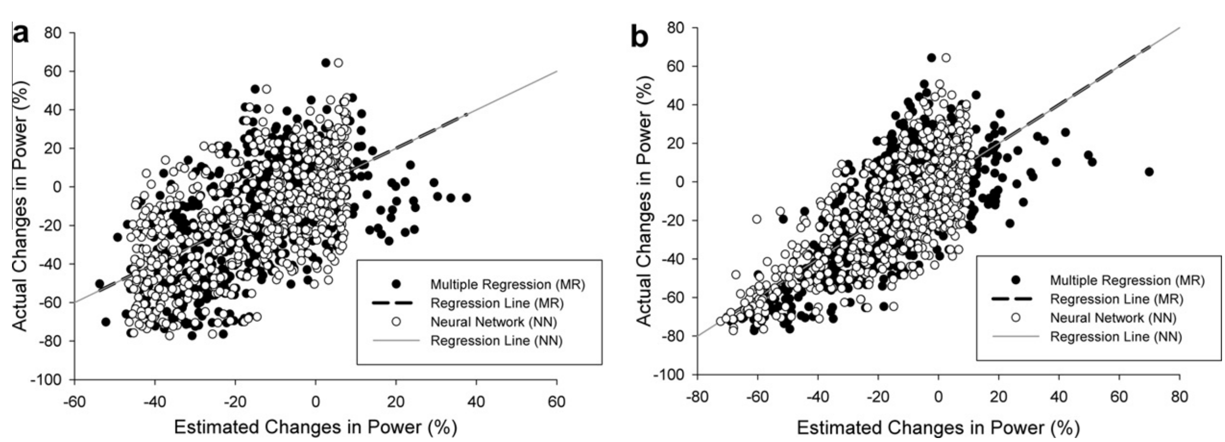


**Fig. 3.** Actual vs. estimated changes in power output obtained for both approaches (linear and non-linear models) using sEMG-based parameters of all the subjects as input variables: (a) average (over the observation interval) of the instantaneous mean frequency and (b) log WIRW51. From Gonzalez-Izal et al. (2010c).

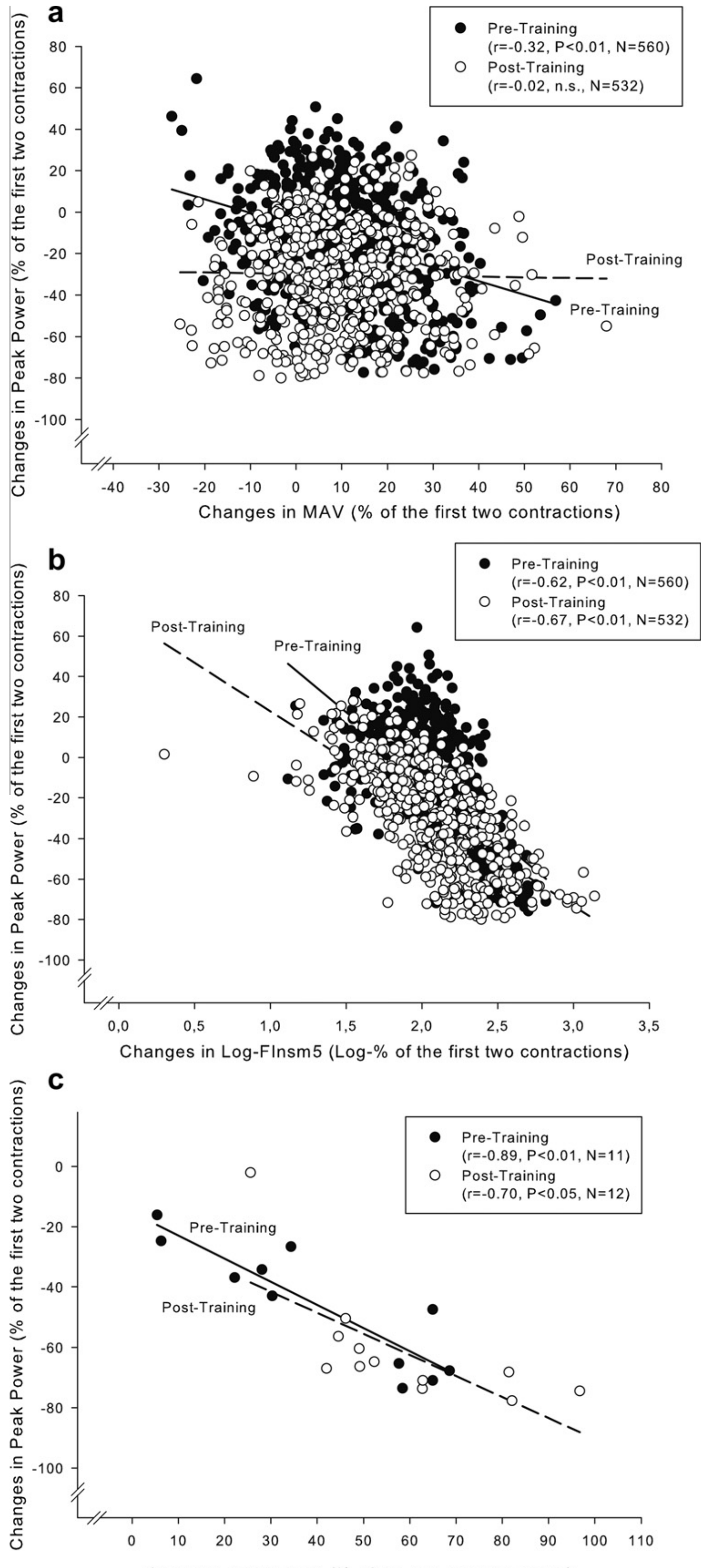


**Fig. 4.** Linear representations of changes in peak power output (% of the first two repetitions) vs. changes in sEMG variables (averaged for vastus medialis and lateralis muscles) (% of the first two repetitions) and blood metabolites (% of the pre-exercise value) for all the subjects during pre- and post-training loading exercises. (A) Changes in power output (%) vs. changes in Mean Average Voltage (MAV) (%). (B) Changes in power output (%) vs. changes in Log-FInsm5 (%). (C) Changes in power output (%) vs. changes in Uric Acid (%). From Izquierdo et al. (2011).

(i.e., using a load that the subject can only lift 10 times consecutively, which was different before and after training due to improvement in the 1RM after the training)). They identified similar changes in the sEMG parameters during the protocol before and after training, and more marked changes in power output and blood metabolites during the protocol after training compared to the pre-training protocol. Therefore, the linear models that related changes in power loss and sEMG parameters were significantly different before and after training, whereas the linear models that related changes in power loss to changes in blood metabolites remained equal (Fig. 4). Thus, Izquierdo et al. (2011) suggested that although the models that relate changes in power loss and sEMG could be useful, they may fail to map muscle fatigue after training.

## 4. Conclusions and further studies

Muscle fatigue is an unpleasant but common experience in daily life. Traditionally, the assessment of muscle fatigue required the measurement of force, power or torque changes. However, the measurement of these variables combined with the measurement of sEMG (which can be measured during all types of movements) during an exercise may be useful to assess and understand muscle fatigue. This paper provides an overview of linear and non-linear techniques that combine various sets of sEMG parameters for estimating muscle fatigue, their ability to assess power loss and their limitations due to neuromuscular changes after a training period.

It could be concluded that the techniques that combine various sets of sEMG variables for estimating changes in force provide useful information about muscle fatigue. However, these models that relate changes in sEMG variables and power loss are significantly different before and after a short-term training period. Therefore, these models may fail to map muscle fatigue after a strength training period. Consequently, more research is needed to develop techniques that combine sEMG variables for estimating changes in force but which are not affected by changes in the training status.

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