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New Wavelet Indices to Assess Muscle Fatigue during Dynamic Contractions

González-Izal M., Rodríguez-Carreño I, Mallor-Giménez F, Malanda A, Izquierdo M

***Abstract*—**The purpose of this study was to evaluate and compare new indices based on the discrete wavelet transform with another spectral parameters proposed in the literature as mean average voltage, median frequency and ratios between spectral moments applied to estimate acute exercise-induced changes in power output, i.e., to assess peripheral muscle fatigue during a dynamic fatiguing protocol. 15 trained subjects performed 5 sets consisting of 10 leg press, with 2 minutes rest between sets. Surface electromyography was recorded from vastus medialis (VM) muscle. Several surface electromyographic parameters were compared to detect peripheral muscle fatigue. These were: mean average voltage (MAV), median spectral frequency (Fmed), Dimitrov spectral index of muscle fatigue (FInsm5), as well as other five parameters obtained from the discrete wavelet transform (DWT) as ratios between different scales. The new wavelet indices achieved the best results in Pearson correlation coefficients with power output changes during acute dynamic contractions. Their regressions were significantly different from MAV and Fmed. On the other hand, they showed the highest robustness in presence of additive white gaussian noise for different signal to noise ratios (SNRs). Therefore, peripheral impairments assessed by sEMG wavelet indices may be a relevant factor involved in the loss of power output after dynamic high-loading fatiguing task.

***Keywords*—**Median Frequency, EMG, wavelet transform, muscle fatigue.

I. INTRODUCTION

SURFACE electromyography (sEMG) is an non-invasive tool which provides valuable information about neuromuscular function. Recording of sEMG signals has been used during recent years in sports research area as a complement to the strength data to assess local muscle fatigue. Isometric tests have been applied by other researches to assess muscle fatigue due to the stationarity of the sEMG signals under these conditions [1], [2]. Traditional temporal parameters as mean or root mean square, and spectral parameters as the mean or median frequency calculated over the power spectral density obtained from the Fourier transform have been applied to quantify muscle fatigue in maximal voluntary contractions before and after isokinetic [3] and isotonic dynamic exercises [4]-[7]. Besides ratios between high frequency and low frequency bands have been also applied to isometric contractions to estimate fatigue [8]-[11]. Fatigue assessment is more relevant to daily function, that is why researchers have recently focused on procedures to estimate fatigue during dynamic instead of isometric contractions. However the sEMG signal becomes non-stationary under these conditions and the traditional parameters decrease in sensitivity to show the amplitude and spectral shifts of the power spectral density, and therefore new parameters are needed to assess muscle fatigue. As suggested by Dimitrov [12], ratios between different spectral moments calculated over the power spectral density obtained using the fast Fourier transform presented a much higher sensitivity under both isometric and dynamic contractions. Otherwise, time-frequency processing techniques are more suitable to deal with non-stationary sEMG signals, as the discrete wavelet transform (DWT). The DWT has been successfully applied to detect biological events [13], in the analysis of electromyographic (EMG) and electrocardiographic (ECG) recordings [14]-[17], electroencephalographic (EEG) signals for analysis of epileptic activity [18], or event-related potentials [19]. Moreover they have been also applied in feature extraction from sEMG signals as a source for controlling assistive devices [20]-[23]. Some authors have applied DWT to analyze muscle fatigue during isokinetic contractions [24] or estimating power spectrum of sEMG signals during dynamic contractions [25], [26]. The new five indices proposed make use of the DWT. They have been calculated as ratios of spectral moments and other features between two different wavelet scales, reflecting low and high frequency components of the signals. In this work, we compare the performance of MAV, Fmed, Dimitrov and wavelet indices to assess muscle fatigue during dynamic contractions by Pearson correlation coefficients and we measure the goodness-of-fit of their regressions. Besides, we analyze the behavior of the above parameters with signals with different SNRs.

González-Izal, M. is with the Studies, Research and Sport Medicine Center, Government of Navarre, and with the Department of Electric and Electronic Engineering, Public University of Navarre, Spain (corresponding author to provide phone: + 34 948 292623; fax: + 34 948 292636; e-mail: gonzalez.38546@e.unavarra.es).
Rodríguez-Carreño I. is with the Faculty of Economics and Business, University of Navarre, Spain (irodriguezc@ unav.es).
Mallor-Giménez, F. is with the Department of Statistics and Operations Research, Public University of Navarra, Spain (mallor@unavarra.es).
Malanda A is with the Department of Electric and Electronic Engineering, Public University of Navarre, Spain (malanda@unav.es)
Izquierdo M is with the Studies, Research and Sport Medicine Center, Government of Navarre, Spain (mikel.izquierdo@ceimd.org).

II. MATERIAL

A. Experimental design

Fifteen physically active men (age, 34.2 ± 5.2 yr; height, 177.3 ± 5.6 cm; body mass, 73.1 ± 6.4 kg) (mean ± SD) volunteered to participate in the study.

The protocol consisted of 5 sets of 10 repetition maximum leg press (10RM) (i.e. the heaviest load that could be correctly pressed only 10 consecutive times using the correct technique) with 120 s of rest between sets. Each trial was performed on a bilateral leg extension exercise machine (i.e. leg press action in a sitting position) (Technogym, Gambettola, Italy). The trial began with a knee angle of 90º and a hip angle of 45º, and finalized when subjects extended their legs to achieve a knee angle of 180º and a hip angle of 90º. Muscle power output of the leg extensor muscles was measured during the concentric phase of leg press.

B. Surface Electromyography (sEMG)

sEMG activity during the extension actions of the leg muscles was recorded from the vastus medialis (VM) of the right leg by pairs of bipolar surface electrodes (Blue Sensor N-00-S, Medicotest) with a distance between the electrode’s centres of 20mm.

EMG signals were recorded at a sampling rate of 1kHz with a Muscle Tester ME3000 (Mega Electronics Ltd) (bandwidth of 8-500Hz / 3dB and a common mode rejection ratio > 100dB). To facilitate and normalize the analysis, the knee movement was divided into 4 intervals of 22.5º. The parameters analyzed in the present study corresponded to the first interval of the movement of the dynamic contractions (from 90º to 112.5º of knee movement), where the VM had its maximal activation.

III. METHODS

A. EMG parameters

Eight parameters were used to analyze the relative changes in power output to quantify muscle fatigue: the mean average voltage, the median frequency, the spectral parameter proposed by Dimitrov and another five new indices proposed by the authors based on the discrete wavelet transform (DWT).

A.1. Mean Average Voltage(MAV)

MAV was calculated after a full-wave rectification and filtered by a moving root-mean-squared filter with a time constant of 50ms, as the integrated EMG divided by the integration time.

A.2. Median frequency (F_{med})

F_{med} was calculated numerically from the following equation:

$$\int_{f_1}^{F_{med}} PS(f)\cdot df = \int_{F_{med}}^{f_2} PS(f)\cdot df \qquad (1)$$

where *PS(f)* is the EMG signal power spectrum calculated using Fourier Transform, $f_1=8\ Hz$ and $f_2=500\ Hz$ (determined for the bandwidth of the surface electromyograph).

A.3. The spectral parameter proposed by Dimitrov (F_{Insm5})

This parameter was designed to overcome the low sensitivity of the median frequency [1]:

$$FI_{nsm5} = \frac{\int_{f_1}^{f_2} f^{-1} PS(f)\cdot df}{\int_{f_1}^{f_2} f^{5} PS(f)\cdot df} \qquad (2)$$

where *PS(f)* is the EMG power spectrum calculated using Fourier Transform and $f_1=8\ Hz$ and $f_2=500\ Hz$.

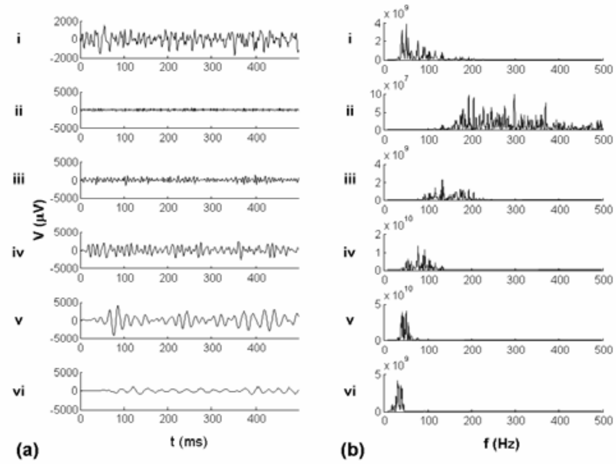

Fig 1. (a) sEMG original signal (i) and wavelet details at scales 1 to 5 (ii-iv). (b) Power spectrum using fast Fourier transform for original sEMG signal (i) and wavelet details at scales 1 to 5(ii-iv).

A.4. New wavelet indices proposed to quantify muscle fatigue.

The DWT is a transformation into a wavelet basis space. This time-frequency wavelet representation is performed by repeatedly filtering the signal with a pair of filters.

Specifically, the DWT decomposes a signal into an approximation signal using a low-pass filter h[*n*] and a detail signal using a high-pass filter *g*[*n*]. Both low-pass and high-pass filters are synthesized from the wavelet function $\psi(t)$ and the scaling function $\varphi(t)$, respectively. The approximation signal is subsequently divided into new approximation and detail signals. This process is carried out iteratively producing a set of approximation signals at different detail levels (scales) and a final gross approximation of the signal. The detail D_j and the approximation A_j at level *j* can be obtained by filtering the signal with *h* and *g*, respectively:

$$D_j[n] = \sum_{k=0}^{L-1} g[k] A_{j-1}[k] \qquad (3)$$

$$A_j[n] = \sum_{k=0}^{L-1} h[k] A_{j-1}[k] \qquad (4)$$

where $A_0[n]$, n = 0,1,…N-1 is the original EMG sequence. If we focus on the detail signals, their processing using the DWT can be considered as a filter bank [27]. This can be observed in figure 1, where the discrete Fourier transforms of the first five details (using the wavelet symlet 5) of a 500 ms EMG signal are shown.

The DWT was calculated using the Mallat's algorithm [28]. We tried different wavelet functions $\psi(t)$ to calculate the wavelet indices and finally we chose the symlet 5 (sym5) and the Daubechies 5 (db5), which experimentally yielded the best results.

Five different indices were calculated using the DWT:

1. *Wavelet indices ratios between moments at different scales*. Three parameters were calculated from spectral moments:

(a) *Wavelet index of ratio between moment -1 at scale 5 and moment 5 at scale 1 (WIRM1551).* This parameter was calculated as:

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

where $D_5(f)$ and $D_1(f)$ are the power spectra calculated using Fourier Transform of the five and first scales respectively of the DWT using the wavelet sym5, and $f_1=8$ *Hz* and $f_2=500$ *Hz.*

(b) *Wavelet index of ratio between moment -1 at maximum energy scale and moment 5 at scale 1 (WIRM1M51).*

$$WIRM1M51 = \frac{\int_{f_1}^{f_2} f^{-1} D_{\max}(f) \cdot df}{\int_{f_1}^{f_2} f^{5} D_1(f) \cdot df} \tag{6}$$

where $D_{max}(f)$ and $D_1(f)$ are the power spectra calculated using Fourier Transform of the maximum energy and first scales respectively of the DWT using the wavelet db5, and $f_1=8$ *Hz* and $f_2=500$ *Hz.* The maximum energy scale in this work was usually scale 4.

(c) *Wavelet index of ratio between moment -1 at scale 5 and moment 2 at scale 2 (WIRM1522).*

$$WIRM1522 = \frac{\int_{f_1}^{f_2} f^{-1} D_5(f) \cdot df}{\int_{f_1}^{f_2} f^{2} D_2(f) \cdot df} \tag{7}$$

where $D_5(f)$ and $D_2(f)$ are the power spectra calculated using Fourier Transform of the five and second scales respectively of the DWT using the wavelet db5, and $f_1=8$ *Hz* and $f_2=500$ *Hz.*

(d) *Wavelet index of ratio of energies at scales 5 and 1 (WIRE51):*

$$WIRE51 = \frac{\sum_{i=1}^{N} D_5^2[n]}{\sum_{i=1}^{N} D_1^2[n]} \tag{8}$$

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

2. *Wavelet index ratio between square waveform lengths at different scales (WIRW51)*. Waveform length is a parameter that measures the cumulative changes in amplitude from time sample to time sample over the whole signal. Waveform length effectively encapsulates the amplitude, frequency, and duration of the EMG signal in one simple formula [29]. The index was calculated as:

$$WIRW51 = \frac{\sum_{i=2}^{N} \left| D_5[i] - D_5[i-1] \right|^2}{\sum_{i=2}^{N} \left| D_1[i] - D_1[i-1] \right|^2} \tag{9}$$

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

B. *Statistical analysis*

Changes in percentage between each variable (sEMG-based parameters and peak power) and the averaged of the values of the first two contractions were calculated. Those percentage changes which did not follow a normal distribution were log-transformed. ANOVA tests were used to calculate the significant differences in groups of 5 contractions (average of the values of the parameters recorded in 5 consecutive contractions). Pearson correlation was used to analyze the relationship between changes in peak power and sEMG-based parameters. The $p<0.05$ was used to establish statistical significance.

To measure the goodness-of-fit of the regressions of the sEMG parameters, we used the residual values of their regressions. The lower the variance of the residuals is, the better the regression of the parameters. Levene's test was applied to reject the equality of the variances of the residual values of the regressions. Then, to find significant differences among the regressions, we took the square root of the absolute value of the residuals, SRARs (its mean coincide with the variance of the residuals), applied them Box-Cox transformation to obtain normal distributions and finally applied a one-way ANOVA. Moreover, the Duncan's test was applied to find subgroups of equivalent regression models.

C. *Behaviour of the sEMG parameters with noise.*

By adding zero-mean white Gaussian noise, we made a series of sets of our sEMG signals with different SNRs. We calculated all the parameters and obtained their Pearson correlation coefficients, which were plotted against SNRs.

TABLE I
CORRELATION BETWEEN SEMG PARAMETERS AND POWER OUTPUT

	MAV	Fmed	Log-FInsm5	Log-WIRM1551	Log-WIRM1M51	Log-WIRW51	Log-WIRE51	Log-WIRM1522	Peak Power
MAV		-0.486**	0.576**	0.474**	0.680**	0.515**	0.502**	0.467**	-0.506**
Fmed			-0.537**	-0.517**	-0.602**	-0.564**	-0.560**	-0.579**	0.435**
Log-FInsm5				0.787**	0.884**	0.727**	0.742**	0.638**	-0.518**
Log-WIRM1551					0.765**	0.945**	0.964**	0.917**	-0.635**
Log-WIRM1M51						0.719**	0.719**	0.610**	-0.576**
Log-WIRW51							0.994**	0.955**	-0.683**
Log-WIRE51								0.961**	-0.674**
Log-WIRM1522									-0.650**
Peak Power									

* Significant correlation coefficients $p<0.05$
** Significant correlation coefficients $p<0.01$

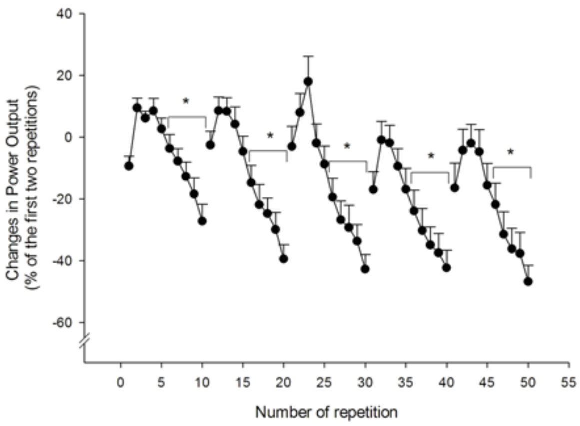

Fig 2. Changes in Peak Power (mean ± standard error) during the 5 sets of 10 repetitions.

IV. RESULTS

A. Peak Power Output

Muscle peak power output of the last repetitions of each set was significantly lower ($p<0.05$) than that recorded during the first two repetitions (Fig 2).

B. sEMG indices

The values of the wavelet indices and FI_{nsm5} significantly increased ($p<0.05$) during the last five repetitions of each set and the first ones of the 3rd, 4th and 5th set compared to the values of the first five repetitions of the 1st set (Fig 3c, 3d, 3e, 3f, 3g, 3h). The MAV and Fmed values of the last 5 repetitions of each set were significantly ($p<0.05$) higher and lower (respectively) than that recorded during the first five repetitions of the 1st set (Fig 3a, 3b).

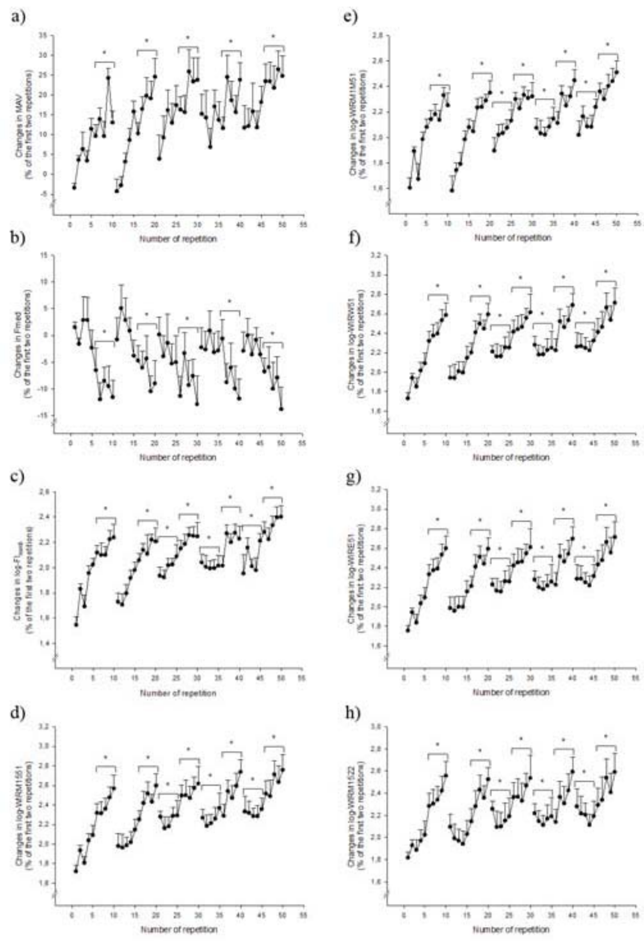

Fig.3. Changes in sEMG parameters (mean ± standard error) during the 5 sets of 10 repetitions. a) Average MAV b) Median frequency c) Logarithm of Dimitrov's index (FI_{nsm5}) d) Logarithm of WIRM1551 e) Logarithm of WIRM1551 f) Logarithm of WIRW51 g) Logarithm of WIRE51 h) Logarithm of WIRM1522.

C. Relationships between sEMG-based parameters and Peak Power Output

Pearson correlation analysis revealed that the new wavelet indices showed greater correlations values [log-WIRM1551 (R= -0.635; p<0.01); log-WIRM1M51 (R= -0.576; p<0.01); log-WIRW51 (R= -0.683; p<0.01); log-WIRE51 (R= -0.674; p<0.01) and log-WIRM1522 (R= -0.650; p<0.01)] with peak power than the other sEMG indices [MAV (R= -0.506; p<0.01), log-FI_{nsm5} (R= -0.518; p<0.01) and Fmed (R=0.435; p<0.01)] (Table 1).

Stepwise multiple linear regression analysis with muscle power changes as a dependent variable and the individual values of the different sEMG parameters obtained during the fatiguing dynamic protocol as independent variables showed that the log-WIRW51 as a single parameter predictor accounted for 46.6% of the performance variance of changes in muscle power, and the log-WIRW51 and MAV, as a two factor combination predictor, accounted for 49.8% of the performance variance of changes in muscle power, respectively.

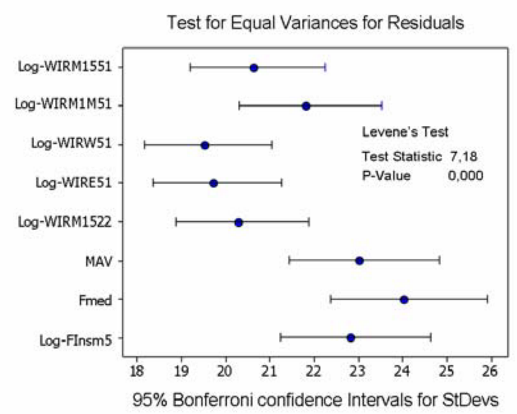

Fig. 4. Levene's test. 95% Bonferroni confidence intervals for variances of the residuals of the regressions of the parameters.

Levene's test was significant (p<0.001) over the residuals, therefore the regressions can not be assumed equal. Fig. 4 shows the confidence intervals of the distributions of residuals for each parameter. It can be appreciated that the wavelet indices are most similar among them and different from the rest of parameters.

Significant differences (p<0.05) were obtained using one-way ANOVA (Dunnet T3, N=686 values) from the SRARs among the regressions of Fmed and all the wavelet indices and between MAV and log-WIRW51. Therefore, wavelet indices are significantly better than traditional parameters as MAV and Fmed.

Fig. 5 shows the mean of SRARs for each sEMG parameter and the four different homogeneous subgroups formed by Duncan's test. The subgroups are formed by the parameters whose regressions could be considered equivalents. The first subgroup involves only the wavelet indices and in the second and fourth subgroups wavelet indices are present too.

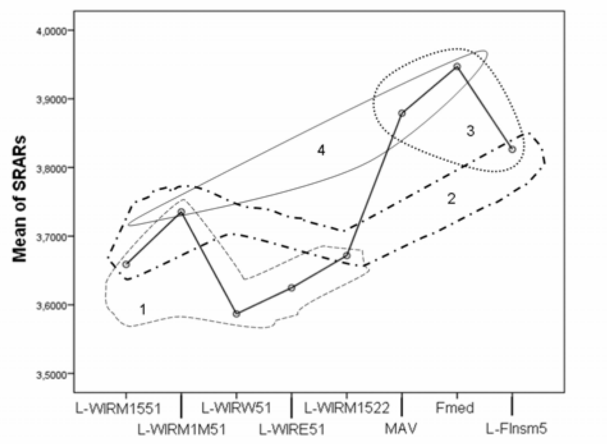

Fig.5. Mean of SRARs and homogeneous subgroups formed by Duncan's test.

D. Comparison of the automatic methods with different levels of noise

In Fig. 6 we plot the Pearson correlation coefficients of the relative changes of all the indices used to estimate power output against different SNRs. The first two upper graphics corresponds to MAV and Fmed parameters. The next below is log-FI_{nsm5}, and the rest of the parameters are the new wavelet indices. It can be appreciated that wavelet indices are more robust against noise than the rest of the parameters, as their Pearson correlation coefficients are greater in the whole range of SNRs. These results can be explained as white additive Gaussian noise disturb the whole power spectrum of the sEMG signals, that is why log-FI_{nsm5} is more affected by noise. Otherwise, wavelet indices are calculated in specific bands, therefore less noise is present in their values. Specifically, the best performance is achieved by log-WIRM1522, as this parameter makes use of wavelet scale 2, which has less and lower frequency content than wavelet scale 1, and therefore is less disturbed by noise.

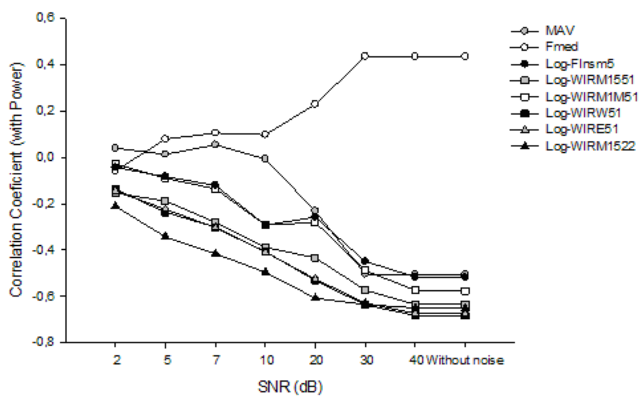

Fig. 6. Correlation coefficient between sEMG parameters and peak power with different SNR values.

V. DISCUSSION

In agreement with previous works, this study in dynamic fatiguing exercise led to major muscle fatigue, as there was a shift of EMG power spectrum to lower components in amplitude and frequency.

Fatigue-related decreases in muscle voluntary activation to maintain a given muscle power output (i.e. dynamic task failure) have been exclusively assessed by the measurement of the EMG signal during maximal voluntary isometric contractions [12]. During dynamic contractions, however, several factors, as the change in the number of active motor units, changes in force/power though the range of motion, and others [12], [24] and [25], may increase the non-stationarity of the sEMG signal.

Therefore, the traditional parameters based on the fast Fourier transform, as mean or Fmed during dynamic contractions may not reflect muscle fatigue.

A powerful time frequency technique as the DWT is more suitable to deal with non-stationary signals, as it has been shown in this work. Applying ratios of moments as Dimitrov and coworkers to different wavelet scales or other features as wavelength waveform outperforms the correlations with muscle power output, yielding better results than traditional parameters as MAV or recent as Log-FInsm5. Specifically, the log-WIRW51 can be considered as a sensitive index to assess muscle power fatigue after multiple sets of dynamic fatiguing high-power contractions, accounting for 46.6%-49.8% of the performance variance of changes in muscle power output. Moreover, the changes in muscle power output can be explained using a regression model based only on the wavelet indices. On the other hand, these indices behave more robustly in presence of noise than other parameters.

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