Understanding the effect of window length and overlap for assessing sEMG in dynamic fatiguing contractions

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Understanding the effect of window length and overlap of periodograms for assessing surface electromyography in dynamic fatiguing contractions: a non-linear dimensionality reduction and clustering.

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ABSTRACT

Short-time Fourier transform (STFT) is a helpful tool to identify muscle fatigue with clinical and sports applications. The choice of STFT parameters by the examiner may affect the estimation of myoelectrical manifestations of fatigue. Here we determine the effect of window length and overlap selections on the frequency slope and the coefficient of variation from EMG spectrum features in fatiguing contractions. We also determine whether combinations of parameters may affect frequency slopes and task failure outcomes. Eighty-eight healthy adult men performed one-leg heel-rise until exhaustion. A factorial design of 50, 100, 250, 500, and 1000 ms window length with 0, 25, 50, 75, and 90% of overlap was used. The frequency slope was non-linearly fitted as a function of task failure, followed by dimensionality reduced and clustered. The STFT parameters elicited five patterns. A small window length produced a higher slope frequency for the peak frequency ($P<0.001$). The contrary was found for the mean and median frequency ($P<0.001$). A larger window length elicited a higher slope frequency for the mean and peak frequencies. The largest frequency slope was found for a window length of 50 ms without overlap. A combination of window length of 250 ms with 50% of overlap increased the slope frequency without a higher dispersion. The choices for STFT parameters can reduce sensitivity to task failure introducing non-linear distortion in the electrical manifestation of fatigue. On the other hand, STFT parameters that increase the slope frequency can help a dichotomous classification of fatigue.

Keywords: electromyography; methods; muscle activation; Fourier; gastrocnemius medialis; fatigue.

1. Introduction

Muscle fatigue is characterized by a reduction in the maximal capacity to generate force or power output (Vøllestad, 1997). It can be assessed by reductions in maximal force or time until task failure (Enoka and Duchateau, 2008). Although these assessments provide information when fatigue is installed, evaluating changes in muscle's electrophysiological properties extracted from electromyography time-series helps identify fatigue or non-fatigue status (Merletti et al., 1990). The myoelectric manifestations of muscle fatigue are indirectly related to reduced motor unit firing rate (Mettler and Griffin, 2016) and a concomitant decrease in muscle fiber conduction velocity (Rampichini et al., 2020). This information can be obtained by analyzing different spectral patterns using short-time Fourier transform (STFT) (Karthick et al., 2016).

The variation in the EMG spectrum in the function of time can be estimated by applying the Fourier transform to signal segments, also known as the STFT and periodogram (Cifrek et al., 2009; Jeon et al., 2020). The STFT provides time-localized frequency information when frequency components of a signal vary over time. For example, the window length is related to the resolution, where a large length provides higher frequency resolution but lower time resolution. In comparison, a short length provides higher time resolution but lower frequency resolution (Jeon et al., 2020). The windowing choice can result in data loss by overlapping (Jeon et al., 2020). The STFT is widely used for frequency tracking over time (Zhang et al., 2020), being of particular interest in assessing biological signals and supporting decisions between fatigue or no-fatigue status (Cifrek et al., 2009; Rampichini et al., 2020).

The features median, mean, and peak frequencies extracted from the electromyography periodogram are commonly used to quantify myoelectric manifestations of muscle fatigue (Cifrek et al., 2009, 2000; Merletti et al., 1990; Rampichini et al., 2020; Shair et al., 2017). These descriptors estimate the changes in the sum of motor units action potential trains (MUAPT) in response to fatigue when the spectrum shifts towards lower frequencies (Cifrek et al., 2009, 2000; Eken et al., 2019; Martinez-Valdes et al., 2016; Rampichini et al., 2020). Applying regressions methods to the myoelectric manifestations of muscle fatigue frequency parameters over time allows determining the frequency slope during a muscle contraction (rate of change of frequency in time) (Merletti et al., 1990). More negative slopes represent a larger left shifting of the spectrum (also known as compression of the spectrum), which is associated with higher muscle fatigue status (Ament et al., 1993; Cifrek et al., 2009, 2000; Eken et al., 2019; Merletti et al., 1990). However, this approach has limitations due to the low sensitivity for the motor unit's discharge rate (Rampichini et al., 2020), EMG amplitude cancelation (Cifrek et al., 2009; Rampichini et al., 2020), frequency leakage (Tan and Jiang, 2019), and time-frequency resolution problems verified when

STFT outcomes are compared to more complex techniques like wavelets (Cifrek et al., 2009; Costa et al., 2010; Waly et al., 1996), in addition to certain physiological information that is in the periodograms and still could be accessed (Costa et al., 2010). Previous studies using bipolar and high-density EMG recordings found high variability in the chosen window length for analysis of isometric and dynamic contractions (Ament et al., 1993; Angelova et al., 2018; Cifrek et al., 2009, 2000; do Espírito Santo et al., 2018; Falla et al., 2017; Guzmán-Venegas et al., 2015; Hawkes et al., 2018; Hegyi et al., 2019; Hill et al., 2018; Jordanic et al., 2016; Jordanić et al., 2017; Watanabe et al., 2018; Zhu et al., 2017). Most of these studies did not provide details about the window overlap (do Espírito Santo et al., 2018; Hawkes et al., 2018; Hill et al., 2018; Lark et al., 2019). The effects of window length and overlap have mainly been studied for isometric contractions (Xie and Wang, 2006; Zhang et al., 2010), but its effects remain unclear for dynamic muscle contractions. The recognition of adequate parameters is essential to avoid bias (Jordanic et al., 2016; Waly et al., 1996). Most importantly, these parameters must accurately predict failure during dynamic fatiguing tasks (Cifrek et al., 2009). However, an improper selection of window length and overlap might worse the sensitivity of EMG parameters to assess fatigue during dynamic contractions.

Continuous wavelet transform and STFT can provide similar muscle fatigue estimations, but considerably higher variability is found for STFT outcomes (Costa et al., 2010). We hypothesize that specific STFT parameters can more precisely estimate muscle fatigue while others may suffer a distortion being low sensible to muscle fatigue. The non-linear dimensionality reduction technique uniform and the manifold approximation and projection (UMAP) combined with the clustering technique density-based spatial clustering of applications with noise (DBSCAN) has provided evidence to efficiently capture latent information of raw data (McInnes et al., 2018). We considered that this approach might facilitate understanding distorted and non-distorted manifestations of muscle fatigue affected by parameters selection for the STFT. Also, considering that the gastrocnemius medialis muscle is highly susceptible to fatigue during dynamic contractions (Ament et al., 1993), we considered this muscle a good model to investigate the effects of the STFT parameters on surface EMG outcomes in response to muscle fatigue. Therefore, we determine the effects of STFT window length and overlap parameters on the frequency slope and coefficient of variation from median, mean, and peak frequencies from EMG data from the gastrocnemius medialis recorded during a fatiguing protocol until task failure. We also determine which clusters of STFT parameters affect the relationship between the frequency slope and task failure.

2. Material and Methods

2.1. Study design

The study had two factors (window length and overlap) and five levels for window length (50, 100, 250, 500, and 1000 ms) and overlap (0, 25, 50, 75, and 90%). The sample included 88 healthy untrained men of age 22 ± 2 years, height 172.4 ± 2.5 cm, and body mass 71 ± 6 kg. The eligible participants were male adults, university students, with age between 18 and 25 years old, and not enrolled in regular physical activity. They were self-reported as healthy, without a life history of injury to the lower extremities, no history of cardiovascular or metabolic alterations, no skin allergy, chronic pain, or cognitive impairments. Participants were orientated to avoid alcohol intake and any physical exercise and keep their regular daily routine in the 48 h before the experiment. The participant was excluded if they reported alcohol intake, physical exercise, or sleep alteration in the night before the experiment. This study was approved by the local institutional ethics committee IRB 23032019. All participants signed an informed consent form, agreeing to participate in the study.

2.2. Sample size

A sample size of 80 participants was *a priori* estimated considering a difference for factorial ANOVA with two factors (window length and overlap) and five levels for each one, using the F-test family distribution, an alpha error of 5%, the statistical power of 80% (four times the alpha error). We considered that the EMG differences could require a small (0.01) to medium effect size (0.06) due to intrinsical variability and decided for an arbitrary η^2 of 0.025. Furthermore, eight additional participants were included to anticipate possible losses (10% of estimation). The sample size estimation was performed using G*Power software version 3.1.9.2. (Kiel University, Germany).

2.3. Fatigue protocol

Participants performed the one-leg heel-rise test on a plane surface, until exhaustion (Figure 1). During the test, they were allowed to touch two fingers over the wall to help keep the balance (De la Fuente et al., 2018). Each participant was familiarized with the task one week before data collection. For data collection, after performing a 10 min warm-up pedaling at 60 rpm on a cycle ergometer (535U, SportsArt, USA) without external load, the participants performed the one-leg heel-rise test. They continuously lifted their heels as high as possible at a rhythm of 45 bpm following auditory feedback provided by a metronome (Google, USA). Task failure was defined as the point where participants could no longer lift the heel. Constant visual supervision and verbal encouragement were given to each participant to control the heel's lift. The criteria to finish the test were the drop of the cadence or the exhaustion of volunteers, defined as the incapacity to lift the heel from the floor.

***** Figures 1 near here please *****

2.4. Data acquisition and processing

Muscle activation was recorded continuously during the performance of the one-leg heel-rise test by a wireless EMG sensor placed on the skin over the gastrocnemius medialis (Delsys inc., USA). The skin was shaved and cleaned with alcohol before the electrode placement according to SENIAM guidelines (Hermens et al., 2000). The EMG signals were acquired using a Trigno^{TM} electromyography amplifier (Delsys Inc., Boston, USA) and with an Avanti sensor (Delsys Inc., Boston, USA), and an inter-electrode distance of 10 mm (De Luca et al., 2012). Data were collected with a 16-bit analog-digital converter card (Vicon Motion Systems, Oxford, UK) and sampled at 4 kHz, analog bandpass filtered (20±5–450±50 Hz), CMRR > 80 dB, resolution of 168 nV/bit, basal noise of < 0.75 μV, with hardware amplification of 1000 V/V. All data were recorded using the software Nexus 2.0 (Vicon Motion Systems, Oxford, UK).

2.5. Data processing and analysis

The EMG signals were zero mean-centered, zero-padded to equal the length of the window used. They were filtered by a zero-lag four order bandpass Butterworth filter with a passband between 20 and 450 Hz. The Teager-Kaiser energy operator threshold-based method was used to detect the individual EMG muscle contractions bursts during the heel test (Solnik et al., 2010), see Figure 1. The operator was defined by $\Psi\big[x[n]\big] = x[n]^2 - x[n+1]x[n-1]$, where de $x[n]$ is a time series at sample n. Rest EMG signals used for the Kaiser energy operator threshold-based were extracted while standing and analyzed for 500 ms.

The STFT provides time-localized frequency information when frequency components of a signal vary over time (Jeon et al., 2020; Karthick et al., 2016). Hence, the discrete-time form of the STFT used in this study is defined by $X_{(m,\omega)} = \sum_{n=-\infty}^{\infty} x[n]\, w[n-mR]\ e^{-j\omega n}$. The STFT was evaluated at sample time m, $x[n]$ was each EMG burst time-series at sample time n, $w[n]$ was a rectangular window function, and R was the hop size that determines the amount of overlap. For the window length, $w[n]$, the parameters used were 50, 100, 250, 500, and 1000 ms. The overlap, R, was 0, 25, 50, 75, and 90% (Figure 1). Although there are many options for selecting the shape of the window function, we used a rectangular one as a fixed and controlled factor. The effect of the window type on myoelectric manifestations of fatigue is outside the scope of our study, and these limitations have been addressed in a previous publication (Tan and Jiang, 2019). Finally, as $X_{(m,\omega)}$ is a complex quantity, the assessment of fatigue was performed using the STFT's magnitude $2^{*}|X_{(m,\omega)}|$ (Karthick et al., 2016). As a result, a Fourier transformation was determined for each contraction burst, which allowed the extraction of median, mean, and peak frequencies (frequency features) from each spectrum varying the length of $w[n]$ and R, see Figure 1.

The three frequency features combined with the five window lengths and the five overlaps resulted in 75 time series containing variation of the median, mean, and peak frequencies obtained from each EMG burst (Figure 1). We applied a linear regression to this data that expressed the rate of change in frequency ($Hz.s^{-1}$) during the motor task (Horita and Ishiko, 1987; Priego-Quesada et al., 2019), see Figure 1. From the same 75 time series, the coefficient of variation, defined as the ratio between standard deviation and mean and expressed as a percentage, was obtained for each frequency feature.

To find the window length and overlap that minimizes the over- and sub-estimation (outliers) of the coefficient of variation and frequency slope, we estimated the centroid of the plane formed by the ratio between the frequency slopes and the coefficient of variation. This ratio reflects the capability to estimate the variation of a frequency feature over the time normalized by its dispersion. The centroid was the sum of the dot product between the ratio of the coefficient of variation/frequency slope and the factor level (1, 2, 3, 4, or 5), divided by the total sum of the ratio of the coefficient of variation/frequency slope, expressed as the number of window and overlap (Jordanic et al., 2016).

Finally, to understand the sensitivity to the task failure for all combinations of window length and overlap, we obtained the curve patterns from the relationship between the frequency slope and the number of heel rise repetitions until task failure. These patterns were fitted using the non-linear least squared method with the model $y = a\,e^{bx} + c\,e^{dx}$, where y is the frequency slope for each combination of window length, overlap, and frequency features (a total of 75 models), x is the number of repetitions until task failure for each participant, and *a, b, c,* and *d* are model parameters (Merletti et al., 1990). Hence, one curve was fitted for each combination of window length, overlap, and frequency features. Therefore, if a heterogenic curve pattern for all combinations exists, there would be only one pattern. In contrast, if different patterns exist, different combinations would produce different patterns from the same sample.

The implementation was made using functions associated with the signal processing toolbox, mainly fft, next2power, filtfit, or butter. We also used basic math functions like image, surf, abs, linspace, median, fix, size, find, sum, polyfit, std, mean, repmat, or exp. The non-linear fitting was made through the curve fitting tool, including the non-linear model previously described. All computations were performed using Matlab 2020a (Matworks Inc., USA).

2.6. Non-linear dimensionality reduction and clustering

We performed a non-linear dimensionality reduction to capture the latent data characteristics using the uniform manifold approximation and projection (UMAP) algorithm (McInnes et al., 2018). It determined the pattern from the relationship between the frequency slope and the heel-rise repetitions until failure for all parameters, features, and participants. The UMAP approximates a high-dimensional structure (all relationships between the slope and the number of heel rise repetitions until failure) into a low dimensional (probability projection of the raw data) by creating a fuzzy topological structure using the gradient of the binary cross-entropy as the loss function. The weights are the probability of the existence of 0-simplex (most low dimensional connection) or 1-simplex, which is a topographic representation of the connection or not between neighbors (McInnes et al., 2018). The weight between neighbors was modeled as $w = e^{-d(x_i - x_j) - \rho_i / \sigma}$, being ρ_i the distance from i-th data points to its first nearest neighbor (Oskolkov, 2019). The binary cross-entropy was modeled as $\sum_{je \in E} \left[w_h(e) \log\left(\frac{w_h(e)}{w_l(e)}\right) + (1 - w_h(e)) \log\left(\frac{1 - w_h(e)}{1 - w_l(e)}\right) \right]$. The input to the UMAP was the set of 75 patterns, each one represented by the fitted curve evaluated for x between 1 and 88, that is a time series that involved a dimension of 88 heel rise task failure. The algorithm reduced these 75 curves of dimension 88 into 75 points of dimension 3 to understand how the families of the pattern are projected into a tridimensional UMAP space. The parameters used for the UMAP algorithm were: Euclidean metric, number of neighbors set to 7, learning rate set to 1, local connectivity set to 1, repulsion strength set to 1, and minimal distance equal 0.5 (Meehan et al., 2020).

After UMAP embedded the latent data structures in a tridimensional domain, a density-based spatial clustering of applications with noise (DBSCAN) was applied. DBSCAN groups data based on the density of the space. Then we determined the clusters or families of parameters related to its capacity to identify muscle fatigue and labeled the families of the pattern (clusters). The parameter for DBSCAN was an epsilon set to 5. Finally, the mean of the data was used to summarize the behavior for each cluster. The estimations were obtained using the Matlab software 2020a (Mathworks, Inc., USA).

2.7. Outcomes

The study outcomes were the frequency slope ($Hz.s^{-1}$) and the coefficient of variability (%) for the 75 possible combinations of the frequency manifestations of muscle fatigue, the number of heel rises repetitions to the failure, the clusters of STFT parameters (label of the cluster), and the patterns obtained from the relationship between the frequency slope and task failure ($Hz\ s^{-1}$ no. of $repetitions^{-1}$).

2.8. Statistic analysis

Results are described as mean, standard deviation, percentage, proportions, and coefficients. The Shapiro-Wilk test confirmed the normality of data distribution. Homoscedasticity and sphericity assumptions were confirmed using the Bartlett and Mauchly tests, respectively. To determine the within and between groups effects and interactions, we conducted a two-way ANOVA with five levels for window length (50, 100, 250, 500, and 1000 ms), and five levels for overlap (0, 25, 50, 75, and 90%) with a Tukey post-hoc test, considering a significance level set at .05. The proportion between myoelectric manifestations for each cluster was obtained using an adjusted-χ^2 test with confidence of 99%, 10 K samples for Monte Carlo simulation, and 0.5 references of the proportions. To compare proportions, we used the Pearson's-χ^2 test for a contingency table of 3 x 5. All data were analyzed considering a significance level set at .05 using the trial SPSS software (IBM, USA).

3. Results

Window length showed a main effect for the frequency slope and coefficient of variation ($p < 0.001$, Figure 2). The multiple comparisons showed that the smallest window lengths (50, 100, and 250 ms) elicited the larger frequency slopes for peak frequency ($p < 0.001$) while larger window lengths (1000 and 500 ms) elicited larger frequency slopes in the median frequency ($p < 0.001$). The larger window length (1000 ms) elicited larger frequency slopes for mean frequency ($p < 0.001$). The multiple comparisons showed that the smaller window length (50 and 100 ms) elicited a small coefficient of variance for peak frequency ($p < 0.001$). The larger window lengths (500 and 1000 ms) elicited the smaller coefficient of variation in the median frequency ($p < 0.001$). The smaller window lengths (50, 100, and 250 ms) elicited the smaller coefficient of variance for mean frequency ($p < 0.001$).

Overlap showed a main effect for the coefficient of variation ($p < 0.001$, Figure 2), but no effect was found for frequency slope ($p = 0.1584$). The multiple comparisons showed that the smaller overlap (0%) elicited the smaller coefficient of variance for peak frequency ($p < 0.001$). The overlap of 25% elicited a small coefficient of variance for peak frequency ($p < 0.001$). The smaller overlap (0%) elicited the smaller coefficient of variance for mean frequency ($p < 0.001$). Interaction between window length and overlap was found for the coefficient of variation ($p < 0.001$) and frequency slope ($p < 0.001$).

***** Figure 2 near here, please *****

A 50 ms window length without overlap (0%) resulted in the minimal value for the plane 'frequency slope - coefficient of variation' (Figure 2). A 250 ms window length and a 50% overlap were the nearest parameters to the location of the centroids for the plane 'frequency slope - coefficient of variation' (Table 1).

***** Figures 3 and Table 1 near here please *****

Task failure occurred after 39.6 ± 13.3 heel-rise repetitions (median 45; range 18 to 63 repetitions). The R-squares for the relationship between the frequency slope and the number of heel rise repetitions until failure are summarized in Table 2. There were 5 clusters of STFT parameters projected by the non-linear reduction dimensionality technique into the UMAP domain. The projections differentiated between them by clustering (Figure 3 and Table 2). The central cluster found was the fifth (Table 2). The frequency features conformed to each cluster are described in Table 3. The relationship between the frequency slope and task failure patterns is summarized in Figure 3.

***** Table 2 and 3 near here please *****

4. Discussion

Here we show that STFT parameters definitions affect the frequency slope of myoelectrical manifestations of fatigue estimated from the median, mean, and peak frequencies recorded from gastrocnemius medialis. The window length and overlap directly influenced the relationship between slope frequency and task failure, distorting the manifestations of muscle fatigue depending on the parameters selected for the STFT.

The endurance capacity varied among the participants, most likely due to different levels of neuromuscular adaptations to fatigue between the individuals (Walton et al., 2002). An early or delayed task failure may depend on participant tolerance to fatigue. It helps to understand the different sensitivity patterns for the relationship between slope frequency and task failure. In particular, the fitted series in each cluster with dissimilar slope frequency and dispersion demonstrates how the STFT parameters change the frequency manifestation of muscle fatigue. For instance, the fitted cluster shows a higher electrical frequency slope for an earlier task failure in cluster 1, which is consistent with individuals with poor tolerance to fatigue. This behavior was not observed in other clusters obtained by different STFT parameters. Even other clusters show an opposed behavior, although the time series of the task failure contained in the cluster indicates muscle fatigue.

It is expected that the electrical manifestations allow the classification between fatigue and non-fatigue status. The opposed results between some clusters suggest that STFT parameters may introduce non-linear distortion in the electrical manifestation of fatigue. Here, we found that a window length of 50 ms with 0% overlap of the peak frequency resulted in a higher frequency slope. However, it is essential to consider that a small window length elicits a high risk of hiding the muscle fatigue or overestimate it. This confusion may result of of noise (outliers) that increase the dispersion and will affect the regression outcomes. Hence, we recommended the treatment of the outliers before applying the regression, in addition to the attention during data collection. STFT parameters may easily influence frequency slopes, but it is worthy of mentioning that the frequency slope per se does not reflect the entire fatigue process (Ament et al., 1993; González-Izal et al., 2010; Horita and Ishiko, 1987; L. Wang et al., 2018). Frequency slopes mainly reflect the global electrophysiological processes accompanying fatigue installation, which is dependent on central and peripheral motor unit properties. Moreover, non-physiological phenomena from the target muscle, such as cross-talk and volume conduction, may also influence the frequency slope (Farina et al., 2014). Therefore, the use of the frequency slope as an index of fatigue requires caution.

Fourier methods have been validated to analyze EMG signals when slow changes exist in the time domain (Farina et al., 2014; Srhoj-Egekher et al., 2011). Nevertheless, some complexities exist related to muscle fatigue as neuromuscular action potentials suffer morphological, amplitude, frequency, or spatial distribution changes (Martinez-Valdes et al., 2020). These complexities affect both time and spectrum domain characteristics (Rampichini et al., 2020). In this regard, Fourier methods allow to measuring the spectrum left-shift (because there is variance between periodograms). On the other hand, it may lead to misinterpretation of the physiological phenomenon due to fixed resolution problems (Cifrek et al., 2009; Singh et al., 2017; Srhoj-Egekher et al., 2011). In these cases, the wavelets are suggested due to its time-resolution adaptations during the convolution (Costa et al., 2010). However, Fourier decomposition method generating a set of a small number of bands derived from empirical decomposition mode has been proposed as a better method for non-linear behavior in comparison to a

STFT or wavelet method (Singh et al., 2017). It might be helpful for biomechanical applications using machine and deep learning.

When we compared window lengths of 50 ms, 100 ms, and 250 ms, the largest slopes were found considering the peak frequency. In contrast, the mean and median frequencies generated the highest frequency slope, with windows of 500 ms and 1000 ms. It suggests a negative covariance between the frequency components and the number of heel-rise repetitions, explaining the largest negative frequency slope obtained after the linear regression analysis (Cifrek et al., 2009). An improper parameter definition may result in statistical bias. For instance, the statistical type I error is induced when contractions are not performed to fatigue, and a negative frequency slope is found (Krzywinski and Altman, 2013). On the other hand, considering that the median and mean frequencies show small frequency slopes, this could be associated with an under-estimation, resulting in a higher probability of statistical type II error (Krzywinski and Altman, 2013).

The largest dispersion found for the peak frequency is in agreement with a previous report (Srhoj-Egekher et al., 2011) and expressed a large spread of data for the mean compared to the peak and median frequencies. This behavior also means that the sum of squares is large. Therefore, to avoid the statistical type II error when the peak frequency is used, a larger number of samples is needed compared to the mean and median frequencies (Krzywinski and Altman, 2013). Peak frequency may be affected by a small number of samples despite its better capacity to generate a more negative frequency slope, as found here.

Larger overlap increased dispersion of data for peak and mean frequencies. Median and peak frequencies showed similar behavior, except for the 0% overlap showing the highest dispersion. As we discussed for selecting window length, we need to be careful with the sample size to avoid statistical type II error due to increased data dispersion (Krzywinski and Altman, 2013). Finally, the centroid method used here tends to smooth small or large values in the intensity- dispersion plane, acting as a low-pass filter. However, this does not guarantee the best sensitivity to predicting task failure and could be considered a conservative selection of parameters (250 ms with 50% overlap).

We acknowledge the limitation of windowing and overlapping being set only in a forward manner. Another limitation was our incapacity to consider metabolic markers of peripheral fatigue to estimate fatigue intensity and correlate these parameters with different stationary parameters from the EMG signals.

5. Conclusions

STFT parameters can reduce sensitivity to task failure introducing non-linear distortion in the electrical manifestation of fatigue. In opposition, STFT parameters that increase the slope frequency could be useful for a dichotomous fatigue classification.

Conflict of interests

The authors declare no conflicts of interest.

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Figure legends

Figure 1. **Experiment design.** The figure shows the heel-rise test where the time series of the electromyography signal (x [n]) is wirelessly transmitted, collected to be zero men centered, and filtered. Then, each burst is identified using the Taeger-Keiser Operator (TKO). On each burst, a windowing manipulating the length and the overlap (R) of the window (w [n]) is performed. From each segmented signal, the Fast Fourier Transform is applied, and the magnitude is obtained. From each segmented signal, the frequency features mean, median, and peak can be extracted during the time t of the motor task, which lasted until the failure. Finally, the frequency slope (FS) is extracted from linear regression, and the dispersion of data measured as the coefficient of variance also is obtained.

Figure 2. **STFT parameters behavior during the heel-rise test.** The figure shows how the frequency slope obtained by linear regression and normalized respect for its dispersion behaves regarding the window length and overlap for the mean, median, and peak frequency. Main effects for window length ($p < 0.0001$), overlap ($p < 0.0001$), and interaction between have existed ($p < 0.0001$). The lowest value was found for the combination of 50 ms and overlap of 0% using the peak frequency, and the centroid for the three planes is located at 250 ms with 50% of overlap. For the same motor task performed until exhaustion, different manifestations of muscle fatigue depending on STFT parameters existed.

Figure 3. **Non-linear dimensionality reduction and clustering for the relationship between slope frequency and the task failure (number of maximal heel rises obtained by the sample).** The figure shows the fuzzy projection of the UMAP algorithm into a tridimensional domain measured in weights. The dots indicate the projected families of STFT parameters, and the gray ellipsoid shadow delimits the recognized cluster by DBSCAN algorithm. Each dot cluster is expanded, showing the pattern of sensitivity to task failure as graphs; the black line of these graphs illustrates the cluster's mean pattern.