Nonlinear surface EMG analysis to detect changes of motor unit conduction velocity and synchronization

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Farina, Dario, Luigi Fattorini, Francesco Felici, and Giancarlo Filligoi. Nonlinear surface EMG analysis to detect changes of motor unit conduction velocity and synchronization. J Appl Physiol 93: 1753–1763, 2002. First published August 9, 2002; 10.1152/japplphysiol.00314.2002.—Amplitude and frequency content of the surface electromyographic (EMG) signal reflect central and peripheral modifications of the neuromuscular system. Classic surface EMG spectral variables applied to assess muscle functions are the centroid and median power spectral frequencies. More recently, nonlinear tools have been introduced to analyze the surface EMG; among them, the recurrence quantification analysis (RQA) was shown to be particularly promising for the detection of muscle status changes. The purpose of this work was to analyze the effect of motor unit short-term synchronization and conduction velocity (CV) on EMG spectral variables and two variables extracted by RQA, the percentage of recurrence (%Rec) and determinism (%Det). The study was performed on the basis of a simulation model, which allowed changing the degree of synchronization and mean CV of a number of motor units, and of an experimental investigation of the surface EMG signal properties detected during high-force-level isometric fatiguing contractions of the biceps brachii muscle. Simulations and experimental results were largely in agreement and show that 1) spectral variables, %Rec, and %Det are influenced by CV and degree of synchronization; 2) spectral variables are highly correlated with %Det (R = 0.95 in the simulations and −0.78 and −0.75 for the initial values and normalized slopes, respectively, in the experimental signals), and thus the information they provide on muscle properties is basically the same; and 3) variations of %Det and %Rec in response to changes in muscle properties are significantly larger than the variations of spectral variables. This study validates RQA as a means for fatigue assessment with potential advantages (such as the higher sensitivity to changes of muscle status) with respect to the classic spectral analysis.

The surface electromyographic (EMG) signal presents smaller bandwidth with respect to the intramuscular EMG, because the tissues separating the muscle fibers and the recording electrodes act as low-pass filters (15, 28). This determines low-spatial selectivity, which hinders the separation of the contributions of different motor units (MUs). For this reason, past research efforts in the surface EMG field were mainly devoted to the development of processing techniques in time and frequency domain, which gave indications about the global EMG activity, without aiming at an analysis at the single MU level. Although, recently, techniques for noninvasive assessment of single MU properties have been proposed and refined (4, 6, 8), their applicability is still limited by the need of complex detection systems, to low-contraction levels, and controlled laboratory conditions for signal recording. Thus the extraction of global information from the surface EMG signal remains of paramount importance in many applications, such as sport and occupational medicine, rehabilitation, and basic and applied physiology.

Spectral analysis and amplitude estimation are usually performed from single differential signals (3) to obtain indications about the physiological processes occurring during sustained voluntary contractions. In addition to the efforts devoted to the technical issue of estimating amplitude and spectral variables in a reliable way (12, 32, 41), many studies were focused, in the past, on the clarification of the relationships between these global variables and the underlying physical processes, to extract information of physiological interest from the global analysis of the surface EMG signal. It has been clearly established that the rate of change of spectral variables and conduction velocity (CV) during a sustained contraction is indicative of muscle fatigue (31) and may be correlated with MU type (39, 43). It has also been shown, both theoretically (28, 41) and experimentally (2), that, during fatiguing contractions, CV and mean (MNF) or median spectral frequency (MDF) of the surface EMG signal are highly correlated; MNF and MDF reflect mainly the CV changes of the active MUs. However, the comparison of the percent
rate of CV and MNF and MDF decrease showed that, although being the main contribution to spectral compression, CV is not the only determinant of changes of the characteristic spectral frequencies. A higher decrease of MNF and MDF with respect to CV was indeed observed in a number of past studies (refer, for example, to Ref. 31 and, recently, to Ref. 30). To explain these results, changes in MU CV distribution spread, increase of the depolarization zone length, or increase in MU short-term synchronization has been suggested (31), although with no direct evidence. Among these factors, recent results indicated a major role of MU synchronization (25, 45). However, the ability of surface EMG spectral analysis as an indicator of MU short-term synchronization is still under debate.

On the basis of the above considerations, nonlinear analysis of surface EMG signal has been exploited (35, 42). Recurrence quantification analysis (RQA), described by Eckmann et al. (5), is a technique for the detection of state changes in drifting dynamic systems that does not necessitate any a priori constraint on data size, stationarity, and statistical distribution (18). RQA has been used recently in a number of experimental studies (17, 23, 42), showing its potential in detecting changes in surface EMG due to fatigue. Webber et al. (42) tested the sensitivity of different indexes extracted from RQA. These authors indicated that subtle changes in surface EMG can be detected by the percentage of determinism (%Det), which reflects the amount of rule-obeying structure in the signal dynamic, and the percentage of recurrence (%Rec), which reflects the current state of the system. Furthermore, under particular experimental conditions, it was speculated (16, 18) that %Det should be more sensitive than spectral analysis to MU short-term synchronization, because it reveals embedded determinisms in an apparently stochastic signal. However, none of these studies has investigated in depth details which EMG signal parameters are indeed reflected by EMG variables extracted by RQA. For this reason, it is difficult to interpret experimental results, in particular when they are compared with those obtained by spectral analysis.

In this work, we focused on two phenomena, the MU CV change and the degree of short-term synchronization, which clearly have an impact on surface EMG spectral variables. The theoretical derivation of the effects on RQA of mean MU CV and MU short-term synchronization and its relationship with classic spectral EMG analysis are difficult because of the complexity of the surface EMG generation and detection system. A modeling approach is, on the other hand, feasible and may be useful for the interpretation of experimental results.

The aims of this work were thus 1) to investigate the effect of MU short-term synchronization and mean CV on EMG variables extracted from linear and nonlinear analysis, 2) to assess whether some variables of RQA and spectral analysis provide indications on the same neuromuscular system parameters or whether they have different sensitivity to variations of such parameters, and 3) to analyze advantages and limitations of the linear and nonlinear approach for assessment of changes in the surface EMG signals, as a consequence, for example, of fatigue, pathological conditions, or training. The study is performed on the basis of a simulation model, which allowed separate investigation of different muscle parameters. The modeling results are used to interpret experimental findings obtained from the biceps brachii muscle during voluntary isometric contractions.

METHODS
Linear and Nonlinear Surface EMG Analysis

Spectral surface EMG variables. Classic spectral variables computed from the surface EMG signal are MNF and MDF. The estimates of these variables depend on the additive noise and the estimators adopted (12); on anatomical, physical, and detection-system parameters (9); and on the number, size, type, and firing rates of the active MUs (10). In the present study, these variables have been computed from synthetic and experimental surface EMG signals with well-known algorithms (for a recent review, see Ref. 12). In particular, the periodogram-based spectrum estimation was obtained from adjacent nonoverlapping signal epochs of 1 s.

RQA. For the mathematical details about RQA, the reader can refer to a recent review by Filligoi and Felici (18), here summarized in the APPENDIX. The procedure is based on embedding EMG data in an N-dimensional Euclidean space. Recurrence maps are built from signal epochs, and quantification indexes are extracted from these maps (refer to the APPENDIX). Among these indexes, %Rec and %Det will be investigated in this study.

Simulation Model

Generation of MU action potentials. A model previously developed for the simulation of the surface EMG signal (13) was used in this study. The model simulates synthetic MU action potentials (MUAPs) generated by finite-length fibers and detected by surface electrodes with physical dimensions. The volume conductor is an anisotropic medium representing the muscle and two-layered isotropic media representing fat and skin tissues (15) (Fig. 1C). The transmembrane current density was described as indicated by Rosenfalck (37). The fixed-model parameters (such as the conductivities of the subcutaneous layers) are the same as reported in a previous study (10).

The simulated signals were detected by a single differential system with electrodes 5 mm long and 1 mm thick. The interelectrode distance was 20 mm. The detection probe was located in the middle between the centers of the innervation zone and the tendon region of a number of MUs with a mean semilength (in both directions) of 65 mm. The detection volume of the system was defined as suggested by Farina et al. (10) on the basis of a threshold in the energy of the surface MUAPs. The contributions to the surface EMG signal of the MUs out of the detection volume were neglected. The number of MU fibers was uniformly distributed between 50 and 450, and the MU fiber density was 20 fibers/mm² (19). The MU territory was circular, and the fiber density in the muscle was 200 fibers/mm². Thus the fibers of different MUs could be intermingled. The surface-recorded MUAPs were obtained as the sum of the action potentials generated by the muscle fibers belonging to each specific MU. Sixty-five MUs were
simulated in each trial. This value was selected so that the total number of simulated fibers was similar to that of a real muscle in the detection volume (10).

**Firing rates.** The simulated signals corresponded to a full recruitment of the MUs in the detection volume. To obtain the distribution of firing rates, it was assumed that the generated force was that corresponding to the recruitment threshold of the highest threshold MU in the simulated set. The MU recruitment threshold was computed with the exponential rule suggested by Fuglevand et al. (19) and recently applied by Farina et al. (10). Recruitment of MUs was assumed to take place at up to 80% of the maximal force, simulating a muscle that recruits MUs almost until the maximum contraction level, as is the case of the biceps brachii (26). The firing rates were inversely related to the recruitment threshold (34), with a minimum of 8 pulses/s at the recruitment and a maximum of 35 pulses/s. The standard deviation of the interpulse interval was fixed for all MUs to 15% of the mean interpulse interval (Gaussian distribution).

The 65 MUs had a Gaussian distribution of CV with a standard deviation of 0.3 m/s. The mean value of the distribution was varied between 3 and 5 m/s to investigate its effect on the EMG variables. The distribution of CV was truncated at 2 and 7 m/s, which are the extremes of the experimentally observed values. The smallest MUs had the lowest CV (1), and the recruitment order followed the size principle (21), with the small and low CV MUs recruited at the beginning of the contraction (and thus having higher firing rate).

**Generation of the firing patterns.** The firing patterns of the active MUs were first generated independently (no synchronization) on the basis of the calculated mean firing rates and interpulse interval variability (Fig. 1A). After this step, some firing instants were moved to create the desired level of firing synchronization (Fig. 1B). In particular, the synchronization level was defined by two parameters, indicating the percentage of firings in each train synchronized with other firings (%F) and the number of firings synchronized together for each synchronization event [expressed as a percentage of the total number of MUs (%M)]. Given %F and %M, for each train, the preset number of MUAPs was synchronized with others by moving their firing instants. The MUAPs to be synchronized were moved to have their firing instants at a distance described by a Gaussian random variable with 0 mean and 2-ms standard deviation.

In summary, after the generation of the independent firing patterns, the steps followed to induce MU synchronization were as follows: 1) compute the number \( N_m \) of firings of different MUs synchronized in each synchronization event as \%M of the total number of MUs; 2) consider the first MUAP train generated and compute the number \( N_r \) of its firings, which should be synchronized with others as %F of the total number of firings of the train; 3) select randomly the \( N_r \) firings among those of the train; 4) for each of the \( N_r \) firings (reference firings), select randomly the \((N_m - 1)\) MUs, of which one firing should be synchronized with the reference firing; 5) select, for each of the \((N_m - 1)\) MUs, the firing closest to the reference firing; 6) move the selected firings in a position obtained as the realization of a Gaussian random variable with mean value of the reference firing position and standard deviation of 2 ms; and 7) repeat the operations described in steps 2–6 for all of the selected firings and for all of the MUAP trains. Once a firing has been shifted, it cannot be moved in subsequent operations. This procedure has been proposed by Yao et al. (45) and was validated by those authors by comparison of synchronization indexes proposed by Yao et al. (45) and was validated by those authors by comparison of synchronization indexes proposed in the past in simulated and experimental signals.

Figure 1 shows the representative firing patterns generated with and without MU synchronization and an example of the generated signal. Figure 2 shows examples of simulated signals with three levels of MU synchronization. The cross-histograms of two randomly selected firing patterns in the set are also reported.

**Simulation modalities.** In each simulation, all of the 65 MUs were active, with firing patterns computed as described above on the basis of their recruitment threshold, size, CV, and degree of synchronization. In the simulations, the two parameters describing MU synchronization (%F and %M)
were always set equal to reduce the number of parameters describing central changes. The values chosen were in the range between 0% (no synchronization) and 25% (very high synchronization) at steps of 5%. For each of these synchronization levels, the distribution of CV had a mean from 3 to 5 m/s at steps of 0.5 m/s.

To take into account the variability of the results, depending on the locations of the MUs in the detection volume, the MUs were placed randomly in the muscle. For each physiological condition, 50 synthetic signals were generated. For each of the 50 signals in the same set, the positions of the MUs in the muscle were randomly selected (with uniform distribution in the detection volume), whereas the firing patterns (with synchronization), CV distribution, and number of fibers for each MU were fixed for the entire set. Thus, in each physiological condition, 50 anatomic conditions were tested, describing a basic source of variability between subjects. The simulated signals were all 5-s long, with a sampling frequency of 1,024 Hz and noise free. In total, 1,500 synthetic signals (corresponding to 5 CV values, 6 synchronization levels, and 50 signals for each condition) were generated.

Experimental Protocol

Subjects. Ten healthy male volunteers (age, mean ± SD: 27.4 ± 5.2 yr; body mass, 72.3 ± 4.7 kg; stature, 174.3 ± 6.1 cm) participated in the study. No subject had known symptoms of neuromuscular disorders. The study was approved by the local ethics committee, and written, informed consent was obtained from all participants before inclusion.

Electrophysiological and mechanical recordings. The torque of the elbow flexor muscles was measured with a modular brace, which incorporates two independent torque meters (model TR11, CCT Transducers, Torino, Italy), on each side of the brace. The force signal was digitized by a 12-bit analog-to-digital converter and sampled at 1,024 Hz.

A linear array of electrodes (silver bar electrodes, 5 mm long, 1 mm diameter, 10 mm interelectrode distance) was applied between the two tendon regions of the long head of
the biceps brachii muscle. A reference electrode was applied at the wrist. Before electrode placement, the skin was slightly abraded with abrasive paste and cleaned with water. The optimal orientation of the array was determined by visual inspection of the EMG signals in a few trials at the beginning of the experimental session. The array was held in place by elastic straps, which did not obstruct blood flow. The EMG signals were amplified and band-pass filtered (3 dB bandwidth = 10–500 Hz), sampled at 1,024 Hz, and converted in digital form by a 12-bit analog-to-digital converter.

General procedures. Subjects were seated comfortably and performed isometric contractions with the arm placed in the isometric torque brace with the shoulder angle at 90° flexion and the elbow angle at 120°. Measurements were performed on the right (always dominant) biceps. The hand was maintained halfway between pronation and supination. Maximal voluntary elbow flexion contraction was measured during three successive trials with 2 min of recovery in between. The greatest value was assumed as the maximal voluntary contraction (MVC) for the elbow flexion. After the determination of the MVC, 5-min rest was given to the subjects. After the MVC assessments, the subjects performed an 80% MVC isometric contraction of the elbow flexors lasting 10 s. Subjects held the contraction, matching a torque target by visual feedback. Each subject repeated the experimental session on 2 different days separated by more than 1 day.

Experimental data processing and statistical analysis. From the 15 single differential signals detected by the 16 electrodes of the array spaced by 10 mm, we computed the 14 single differential signals detected by electrodes spaced 20 mm. This was achieved by summation of consecutive single differential signals, as described in Ref. 11. The location of the main innervation zone was assessed by visual inspection of the multichannel EMG signals, and only the channels distal with respect to the innervation zone were considered for further analysis. From these signals, we selected that corresponding to the minimal variability of spectral EMG variables with respect to adjacent locations, as suggested in Ref. 30. From this channel, EMG variables from linear and nonlinear analyses were computed. Thus the signals used for subsequent analysis were detected by a single differential system, with electrodes spaced 20 mm, placed between the innervation zone and the distal tendon region, and providing the minimal variability of spectral variables to shifts of the recording system in that muscle zone.

%Det, %Rec, and spectral variables were estimated from the selected signals from adjacent nonoverlapping epochs of 1 s. For each EMG variable, the first-order regression lines were computed from the values obtained during the 10-s-long contractions. The slope of EMG variables was defined as the slope of the regression line and the initial value as the intercept of the regression line. Normalized slopes, defined as the slopes divided by the initial values, were expressed in percentages per second.

The experimental data were analyzed by using two-way repeated-measures ANOVA, followed by post hoc Student-Newman-Keuls pairwise comparisons, when required. Threshold for statistical significance was set to \( P = 0.05 \). Data are presented as means ± SD.

RESULTS

Simulated Signals

Figure 3 shows simulated signals with different mean values of CV distribution and degrees of synchronization level. The recurrence plots and the power spectra are also shown. The difference between the two recurrence maps in the two physiological conditions is evident (see also APPENDIX). In particular, a higher number of rule-obeying structures in the signal is clearly shown by a higher regularity of the recurrence map.

Figure 4 shows %Det and MNF as functions of mean CV and synchronization, normalized with respect to the highest mean CV simulated and to the lowest synchronization level. MDF led to results similar to those for MNF. Assuming, for example, decreasing mean CV (31) and increasing synchronization (25) during fatigue, these plots can be interpreted as indicative of the changes in linear and nonlinear variables during fatiguing contractions with normalization with respect to the initial values. Note that, for both CV and synchronization level changes, %Det shows greater relative changes with respect to MNF. The percent increase of %Rec for CV decreasing from 5 to 3 m/s was 130%. The percent increase of %Rec for the degree of synchronization increasing from 0 to 25% was 73%.

The average nonnormalized values of %Det for 0% synchronization level and 3 m/s CV were 28.09 ± 12.31 and 22.93 ± 8.71%, respectively. For %Rec, they were 3.10 ± 0.88 and 3.52 ± 1.25%, respectively. The average values for the two conditions were 97.72 ± 16.27 and 101.34 ± 10.90 Hz for MNF and 94.77 ± 16.12 and 97.89 ± 11.46 Hz for MDF, respectively.

Figure 5 shows the scatterplot between %Det and MNF. For CV decreasing and increasing degree of synchronization, %Det shows greater relative changes with respect to MNF. The percent increase of %Rec for CV decreasing from 5 to 3 m/s was 130%. The percent increase of %Rec for MNF and MDF, normalized with respect to the mean values computed over all of the simulation set (\( n = 1,500 \)). A high correlation was found between the two variables in the simulated conditions (linear regression analysis, \( R = -0.95 \), \( P < 0.001 \)). MDF showed very similar results, with a correlation with %Det resulting in \( R = -0.93 \) (\( P < 0.001 \)). Changes in MNF or MDF corresponded to opposite changes in %Det, as already observed in Fig. 4. However, the normalized changes in %Det are almost twice those of the normalized MNF and MDF.

%Rec showed a decrease with CV increasing and an increase with decreasing degree of synchronization, as %Det. However, the correlation with spectral variables was weaker than for %Det (\( R = -0.74 \) for MNF and \( R = -0.72 \) for MDF), although statistically significant (\( P < 0.001 \)).

Experimental Signals

All subjects were able to maintain the selected force level constant for the time interval of the contraction within ±5% MVC. For all of the subjects, a statistically significant (linear regression analysis, \( P < 0.001 \)) decrease in MNF and increase (\( P < 0.001 \)) in %Det and %Rec was observed during the fatiguing task. As for the simulated signals, MNF and MDF showed very similar results; thus only those from MNF analysis are reported in the following paragraph.

The mean MNF, %Det, and %Rec slopes (absolute values) were 2.03 ± 0.55 Hz/s, 2.32 ± 1.04%/s, and 0.27 ± 0.18%/s, respectively. The mean MNF, %Det,
and %Rec initial values were 73.15 ± 8.34 Hz, 35.15 ± 9.31%, and 3.63 ± 1.04%, respectively. The normalized slopes (absolute values) were 2.66 ± 0.66%/s, 7.50 ± 5.05%/s, and 8.41 ± 7.32%/s, for MNF, %Det, and %Rec, respectively.

A two-way (three EMG variables, MNF, %Det, and %Rec, and 2 days) ANOVA of the normalized slope was significant for the EMG variable ($F_{9.38}$, $P < 0.01$) and not for the day. The post hoc Student-Newman-Keuls test disclosed pairwise differences ($P < 0.01$) between MNF normalized slopes and the normalized slopes of both %Det and %Rec.

The initial values and normalized slopes of MNF and %Det were significantly correlated. For the initial values, the correlation coefficient was $R = -0.78$ (linear regression analysis, $P < 0.001$), whereas for the normalized slopes it was $R = -0.75$ ($P < 0.001$). The correlation between MNF and %Rec was significant ($P < 0.05$), although, as for the simulations, much lower than that between MNF and %Det ($R = -0.55$ for the initial values and $R = -0.46$ for the normalized slopes). Figure 6 reports the scatterplots between MNF and %Det initial values and normalized slopes.

**DISCUSSION**

Although RQA is being used in many studies on muscle assessment, surprisingly, it was not clearly known what information it provides. Mean CV and short-term synchronization were the two phenomena investigated in this work, because they have been proven to affect surface EMG spectral features during fatigue assessment. In this study, we were interested in analyzing the information that is extracted by RQA from the surface EMG signals and to compare this with that obtained by classic spectral analysis.

We followed a simulation approach proposed in a previous study for addressing the issue of MU recruitment strategies (10). The main advantage of this approach is to take into account a number of anatomic conditions, thus avoiding results biased by a particular location of the MUs in the muscle.

**Simulation of the MUAPs**

The simulation of the MUAPs was performed with a number of simplifications, which have been discussed already in previous works (9, 10, 13) and which are related to the choices of the simulation parameters.
most of them not exactly known in practice. Different choices for these parameters probably would not affect the general conclusions drawn in this study, which are mostly related to the statistical properties of the MU firing patterns and to the relationships between CV and surface MUAPs. Another limitation of the physical model used for the generation of the surface MUAPs is the description of the subcutaneous layers and of the muscle as infinite parallel layers (13, 15). Other models may be better in this respect, as, for example, the approach followed by Kleine et al. (25), who assumed a cylindrical volume conductor, which probably simulates the arm better (40). Again, we do not think our main conclusions would be different by assuming a different volume conductor shape. Moreover, the agreement with the experimental results indicated that the modeling was accurate enough to clearly interpret the experimental findings.

**Simulation of the MU Firing Patterns**

The assumed correlation among MU size, firing rate, and recruitment threshold is a consequence of the size principle (21), which has been validated in a number of previous studies. The association among CV, MU size, and firing rate is based on the results reported by Andreassen and Arendt-Nielsen (1), who indicated a relationship between CV and twitch MU properties and thus proposed CV as an additional size principle parameter. The correlation between firing rate and CV was also directly shown by Farina (6) using intramuscular and surface EMG techniques for assessing control and conduction properties of single MUs (7).

Some previous studies aimed at the simulation of MU short-term synchronization. Hermens et al. (22) shifted the firings of independently generated firing patterns to create synchronization of all of the firings of MU pairs. The complete synchronization of MU firings was also assumed by Weytjens and van Steenberghe (44) for their analytic derivation of the power spectrum of the surface EMG signal. This simplification implies that the two synchronized MUs have the same mean firing rate. Yao et al. (45) proposed a method to introduce synchronization in a pool of MUs, again based on the shift of MU firings. This approach was validated by the analysis of classic indexes of synchronization (36) applied to the simulated signals and was adopted in the present study, although with a different model of MUAP generation and different simulation modalities. Recently, Kleine et al. (25) proposed a different approach based on the model suggested by Matthews...
(29), which described the afterhyperpolarization after a firing as an exponential function on which membrane noise is superimposed. The noise was then divided into a common and an individual part to simulate different degrees of synchronization. However, when comparing the synchronization level introduced by their method with that introduced by Yao et al. (45), these authors concluded that similar results were obtained (25); thus the choice of one of the two models is probably not critical in the context of this study.

**Effect of CV on Linear and Nonlinear EMG Analysis**

The effect of muscle fiber CV on spectral features of the EMG signal is well known from past studies (2, 31). Theoretically, neglecting the effects of the firing statistics on spectral features, the relative change of CV and MNF or MDF are equal if 1) no MUAP shape change occurs (only scaling), 2) the MU pool is stable (10), and 3) all of the MUs have the same CV. In our simulations, condition 3 was not met, to better approximate experimental signals. However, it was shown (Fig. 4) that the relative changes of MNF (MDF provided the same results) and CV are similar also in this condition. Direct interpretation of the plots of Fig. 4 in terms of changes occurring in CV during fatigue is, however, rather critical, because in real cases it is not known how the distribution of CV changes independently on the mean value, that is, how the relative weight of large and small MUs changes with fatigue.

The dependence of %Det and %Rec on CV was not previously known, because the only results in this respect came from experimental fatigue studies in which a number of phenomena occurred and could not be separated from each other. The finding that the two variables extracted from the recurrence maps are changing with CV, as the spectral variables, clarifies that CV is a parameter strongly affecting nonlinear surface EMG analysis. The result can be explained by observing that the number of recurrent structures identified depends on the duration of the segments in the EMG signal, which repeat in time with almost the same shape, i.e., on the duration of the MUAPs. CV is directly related to the duration of the surface MUAPs if the length of the depolarized zone is constant during time, as assumed in the simulations. Thus, the higher CV is, the smaller is the duration of the surface MUAPs. From this point of view, %Det and %Rec detect changes in the frequency content of the signal, a conclusion important for the interpretation of experimental findings. From our results, it clearly appears that there is no possibility of separating the changes due to CV and to the degree of synchronization by using %Det or %Rec.

**Effect of MU Synchronization Level on Linear and Nonlinear EMG Analysis**

The effect of the degree of synchronization on the spectral frequencies of the surface EMG signal was investigated in some previous works. Weytjens and van Steenberghe (44) extended the derivations of Lago and Jones (27) on the effect of MU firing statistics on the surface EMG power spectrum to the case of dependent firings and showed that cross-terms arise that increase the energy of the signal mostly at low frequencies. Hermens et al. (22) validated this analytic observation by a simulation model, and similar results were shown, more recently, by Yao et al. (45) and, with the inclusion of the electrode location variability, by Kleine et al. (25). Our results are in line with these previous studies and confirm the role of synchronization in determining MNF and MDF patterns during fatigue.

%Det and %Rec also depended on MU synchronization, exhibiting an increase for increasing degree of synchronization. This study is the first that clearly shows that these EMG variables increase with an increasing level of MU short-term synchronization; the result is in agreement with the expectation that a higher number of deterministic structures in the signal should be detected by RQA. In previous studies, this dependence was suggested, but, in experimental investigations on muscle fatigue, it was not possible to separate changes of MU synchronization and CV. Felici et al. (16), for example, reported RQA analysis on a group of weight lifters, assuming that a higher degree of synchronization should occur with fatigue in this group with respect to a control group of sedentary...
persons. They reported a higher rate of change of %Det in the weight lifters with respect to the control group during sustained isometric contractions, but it was not possible to attribute this difference exclusively to the different change in MU synchronization degree, because CV was also changing.

Correlation Between Variables Extracted from Linear and Nonlinear Analysis

One of the main results of this study is the observed high correlation between %Det and MNF (or MDF) in all of the simulated conditions. The regression analysis reported in Fig. 5 shows a correlation coefficient between the two variables close to one. This result indicates that, as spectral variables, %Det also reflects physiological phenomena of interest in muscle assessment. Indeed the %Det changes found in previous studies could not be explained on a physiological basis before the present study.

As it always happens in simulation studies, the crucial point is the validation and the extension of the results to experimental paradigms. We designed a simple fatigue protocol, and we assumed that, during the muscle contractions performed by the subjects, phenomena similar to those simulated occurred. The contraction level was selected to exclude recruitment of MUs during fatigue, because it corresponded to almost the maximal level at which MUs are recruited in the biceps brachii muscle. The simulation results were largely in agreement with the experimental findings. We found, indeed, a highly significant correlation between MNF and %Det in the experimental signals also, in agreement with the simulation predictions. Webber et al. (42) already showed a correlation between the rates of %Det and MNF change on 12 subjects who performed fatiguing contractions. We also observed high correlation between initial values. Thus, although many factors of variability among subjects were not included in the simulations for limiting the computational effort (differences of subcutaneous layer thickness, variability in the orientation of the detection system with respect to the fibers, length of the fibers, etc.) and within the limitations of the model used, as mentioned above (see Simulation of the MUAPs), the model results were still a valid tool for interpreting the experimental signals.

For both the simulations and the experimental signals, %Rec resulted in poorer correlation with spectral variables with respect to %Det. Thus interpretation of %Rec changes from the surface EMG signals may be less direct than that of %Det changes.

The observed larger changes in %Det and %Rec in response to fatigue than those in MNF were predicted by the simulation analysis. Webber et al. (42), in their experimental study, indicated an even higher difference between the normalized rate of change in MNF and %Det (changes in %Det were approximately five times larger than those in MNF). The discrepancy of the latter result with those of our study is probably due to the different experimental setup used (for example, interelectrode distances were different).

Implications for Fatigue Assessment

The present results show that the two linear and nonlinear tools tested provide similar indications about CV and MU synchronization changes, two mechanisms that affect surface EMG signal features during fatigue. The claimed higher sensitivity of %Det to MU synchronization than to other fatigue-related changes was not confirmed, and thus RQA cannot be used to separate MU synchronization changes from other factors. During fatigue, in nonpathological conditions, %Det is highly correlated to spectral variables. This is in agreement with previous experimental studies in which RQA and spectral analysis always provided the same indications of muscle fatigue (16, 17, 42), although a correlation between variables obtained with the two tools was reported for experimental data only by Webber et al. (42). The results suggest that no new information is extracted by RQA with respect to that provided by classic spectral analysis. However, another important finding of the present study is that the sensitivity of RQA to muscle changes is higher than that of spectral variables. This was already suggested by Webber et al. and has been demonstrated in the present study on a large set of simulation conditions (including a number of anatomic configurations). From the above considerations, RQA seems promising for detection of muscle changes due to fatigue or other factors and could allow a better separation among groups of subjects and/or muscles.

Conclusions

The main conclusions of this work are as follows. 1) Spectral variables, %Det, and %Rec are influenced by CV and the degree of synchronization; thus none of them can be used to separate the two effects during fatiguing contractions. 2) Spectral variables and %Det are highly correlated, and thus the information they provide on muscle properties is similar. The correlation between %Rec and spectral variables is much poorer than that for %Det, although %Rec, like %Det, is similarly sensitive to changes in muscle properties. These results are confirmed by both simulation and experimental findings and are particularly important for the correct interpretation of linear and nonlinear variables when comparing muscles or subjects. 3) Relative variations of %Det (and %Rec) in response to changes in muscle properties are significantly larger than relative variations of spectral variables. Thus nonlinear analysis of the surface EMG signal is a technique more sensitive than spectral analysis for the assessment of muscle fatigue and can be used for more detailed noninvasive muscle assessment.

The application of RQA to surface EMG still needs, however, research efforts in determining its sensitivity to other factors of variability between subjects and muscles, such as the thickness of the subcutaneous layers, the orientation of the detection system, the
interelectrode distance, the electrode location, the recruitment of MUs, the additive noise, and so on. Whereas the influence of all of these parameters on spectral variables has been analyzed in many past publications (see, for examples, Refs. 9–12, 14, 20, 24, 33, 38, 47), there is a complete lack of this information for RQA.

APPENDIX

RQA

Although RQA has been described in detail in some past works, it is necessary in the context of this study to recall the basic principles of this technique. Given the surface EMG signal samples \( s(m) \) \( (m = 0, \ldots, M) \), the following steps have been followed to compute the recurrence maps and the relative indexes.

Embedding procedure. From the surface EMG, vectors representing the states of the system are extracted. To do this, data are lagged by an integer number \( \lambda \) of samples (“time delay”), which defines the time distance between two uncorrelated samples. Selection of \( \lambda \) is performed on individual time series; in the present study (simulated and experimental data), \( \lambda \) values ranged between 3 and 6.

The space dimension (phase space), referred to as embedding dimension, has been selected in the present study as 15 (according to Ref. 18). The following set of D-dimensional vectors \( \mathbf{v}(n) \) is extracted from the original myoelectric time series

\[
\mathbf{v}(1) = \{s(1) \ s(\lambda + 1) \ \cdots \ s[(D - 1)\lambda]\}
\]

\[
\mathbf{v}(2) = \{s(2) \ s(\lambda + 2) \ \cdots \ s[(D - 1)\lambda + 1]\}
\]

\cdots

\cdots

\cdots

\mathbf{v}(N) = \{s(N) \ s(N + \lambda) \ \cdots \ s[N + (D - 1)\lambda]\}
\]

where \( N = M - (D - 1)\lambda \).

Distance matrix \( \mathbf{DM} \). The states of the dynamic system under consideration are represented by the vectors \( \mathbf{v}(n) \) defined in Eq. 1. To define the recurrences between the states, their closeness should be quantified. To do so, the most commonly used metric is the Euclidean distance \( d \)

\[
d(i,j) = \sqrt{\mathbf{v}(i) - \mathbf{v}(j)}^2 (2)
\]

where \( < > \) indicates the summation of the elements of the argument vector.

To make the results of the analysis independent of the energy of the observed signal, the values adopted in RQA are normalized with respect to the average distance \( d_{av} \) between vectors

\[
d_{av} = \frac{1}{N(N - 1)/2} \sum_{i=1}^{N} \sum_{j=i+1}^{N} d(i,j)
\]

where the denominator represents the number of possible distances \( d(i,j) \).

The collection of the normalized distances provides a symmetric matrix, indicated as distance matrix \( \mathbf{DM}(N \times N) \)

\[
\mathbf{DM} = \begin{bmatrix}
d(1,1) & d(1,2) & \cdots & d(1,N) \\
d(2,1) & d(2,2) & \cdots & d(2,N) \\
\vdots & \vdots & \ddots & \vdots \\
d(N,1) & d(N,2) & \cdots & d(N,N)
\end{bmatrix}
\]

Recurrence map \( \mathbf{RM} \). The recurrences between the states are evaluated from the matrix \( \mathbf{DM} \). A recurrence occurs if the distance \( d(i,j) \) is smaller than a threshold (referred to as radius \( R \)), i.e., if \( \mathbf{v}(i) \) and \( \mathbf{v}(j) \) fall within a sphere of radius \( R \) centered at \( \mathbf{v}(i) \). The comparison of the distances in \( \mathbf{DM} \) with \( R \) provides the recurrence map \( \mathbf{RM} \) as the collection of the pixels \( b(i,j) \), defined as follows

\[
\begin{align*}
d(i,j) \leq R & \quad \rightarrow \quad \text{pixel } b(i,j) = \text{ON} \\
& \quad \rightarrow \quad \text{pixel } b(i,j) = \text{OFF}
\end{align*}
\]

The value of \( R \) was always set, in accordance with Ref. 46, smaller than 10% of the normalized mean distance (its value was adjusted depending on the data set). Because \( \mathbf{RM} \) is symmetric, for the computation of the quantitative indexes of the recurrence map, only the upward or downward portion of it is considered.

Quantification of the recurrence map. Often nonlinear plots contain subtle patterns that are difficult to detect by simple visual inspection. Thus quantitative descriptors that emphasize different features of the map have been proposed (42). Pixels ON are defined as recurrent (Re) if they share local neighborhoods in higher dimensional space (42). The percentage of plot occupied by Re points is defined as \%Rec. The percentage of Re forming lines parallel to diagonal is defined as \%Det. Lines are constituted by two or more points that are diagonally adjacent with no intervening white spaces. Thus \%Det is defined as \%Det = \( L / \text{Re} \times 100 \), where \( L \) is the number of points forming lines.

Figure 3 shows examples of recurrence maps computed from simulated signals. The presence of diagonal structures can be clearly observed for the two simulated signals shown. \%Det and \%Rec quantify this difference, as it appears from Fig. 3.

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REFERENCES


