USING TIME LAG AND FRACTAL DIMENSION TO QUANTIFY PHYSIOLOGICAL FATIGUE

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Abstract: Most studies of EMG signals are based on either the analysis of their stochastic parameters in the time domain or in the frequency domain. In this paper, from the analysis of the muscle behaviour (i.e. contraction and extension movements) during a controlled repetitive exercise activity, it is proved there are two main parameters of the EMG signal: lag time and fractal dimension, based upon chaotic behaviour, that could be used as fatigue indicators. With this goal in mind, two software applications were developed with LabVIEW®´s programming features. These applications allow for the estimation of these two parameters after signals have been captured.

Introduction

Surface electromiography is a non invasive very useful method to study normal muscle behaviour as well as muscle myopathies. Furthermore, surface electromyiographic signal analysis has been shown to be a powerful tool to quantify physiological fatigue.

Lineal methods, until now, have been widely used to analyze and characterize biomedical signals, but they are beginning to reach their limits of utilization [1]. In reference to electromyography, specifically in the analysis and utilization for quantifying fatigue, several lineal techniques are commonly used. For example, shifting the mean power frequency (MPF) toward lower frequencies and increasing the root mean square (RMS) of the time signal. Today there is a tendency to use methods in order to get a whole characterization of EMG signals. With this goal in mind, Horjth developed a parameter set, which initially was utilized to describe the EMG signals changes in the temporal domain, but is now demonstrating it's effectiveness in power spectral evaluation of surface recorded EMG signals. Nevertheless, all these analytical methods have several limitations. For example, the increase of fatigue not only produces a frequency shift, but also changes shape, an aspect which this method is unable to quantify.

This sensibility to the spectral shape has been proved with the RMS parameter and after that, other variants of it that have been used. Everything seems to prove poor consistency of these methods with the analysis of signals generated by complex and non lineal living creatures. Recent experimental results have shown that complex systems -- and more precisely in deterministic chaos – This discovery opens up new points of view of the investigation. Using these kinds of techniques to analyze temporal series could be a promising alternative [2].

Unfortunately, tools used for characterizing non lineal systems are very different from lineal systems, mainly when it comes to try to approximate complex to lineal systems. In addition, parameters that describe non lineal processes – and are used to identify and classify them – do not have an interpretation as clear as the lineal descriptor.

In addition, although the first investigations concluded that this class of signal is random in nature, but not chaotic, other later dated papers [3], have proved it to have a chaotic behaviour. In fact, non lineal characterization of EMG signals has been used to distinguish several myopathies [4] and more recently other attempts to quantify physiological fatigue from signals recorded off an isometric contraction of the trapezius muscle [5], [6].

Materials and Methods

To extract quantitative information about the dynamic of observed EMG signals when they are working as a chaotic system, the first step to delineate some of the underlying dynamic is the construction of the process phase space. Phase space includes a set with all probable states that could be reached by certain types of systems. Each state is represented by a point in a D dimensional space, where the coordinates are corresponding with value of the state variables. When time increases, those states describe a trajectory. For dissipative systems the trajectory converges to a subset with lower dimension, for chaotic systems, this subset is called an attractor. Taken's Theorem determines how to construct an attractor of dynamic system from only knowledge of one dimensional time sequence behaviour of the system. Then, from a recorded signal:

$$\Gamma(n) = \{x(t_1), x(t_2), ..., x(t_n)\} \quad (1)$$

The theorem says that if we are able to observe this time serial then the geometric structure of the multivariate dynamics can be unfolded in a space made out of new vectors D dimensional. Furthermore, it is admitted that

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the behavior of the original temporal series Γ(n) is due to the interaction with the rest of variables (D-1), then important information in Γ(n) has to contain properties of the D-dimensional system. It is possible to construct a D-dimensional set of points from a variable Γ(n), in the following way

$$\Gamma(n,D) \equiv \{x_i = (x(t_i), x(t_i+\tau), \ldots, x(t_i+(D-1)\tau))\} \tag{2}$$

Where τ > 0 is in integer called time lag and D is called embedding dimension. The points of the new space are constructed by the xi coordinates and integer multiples of the same lag $x(t_i+j\tau)$. Of course, correlation between two consecutive points will be a function of the time lag value; the higher it is, the lower the correlation will be. That leads one to think that there is a relation between set Γ(n,D) and the unknown set:

$$\Gamma(D) = \{x_i = (x_1(t_i), x_2(t_i), \ldots, x_D(t_i))\} \tag{3}$$

If the last dynamic system is chaotic – in addition it has a low dimension attractor—the system properties will be reproduced without ambiguity at the reconstructed attractor. Furthermore, it will be possible to reconstruct the whole system only from temporal recorded series. Needless to say, it is necessary to estimate the time lag and embedding dimension in order for the reconstruction of the unknown system.

First at all, to estimate the time lag the suggestion of Fraser [10] is used, determining average mutual information, IM:

$$\sum_{x(n),x(n+\tau)} P(x(n), x(n+\tau)) \log_2 \left[\frac{P(x(n), x(n+\tau))}{P(x(n))P(x(n+\tau))} \right] \tag{4}$$

The first minimum of the average mutual information is chosen. Mutual information could be considered as a nonlinear generalization of the autocorrelation function that permits calculating when the values x(n) and x(n+τ) are so sufficiently independent form each other as to be useful as coordinates of the time lag vector, but not independent enough as not to be connected at all.

Chaotic systems often exhibit fractal structures. Then, a characterization of the chaotic signals estimating their fractal dimension (Df) is possible. Fractal dimension is a characteristic of the geometrical figure of the attractor and a function of how attractor points are distributed in the phase space. Fractal dimension is invariant and independent of changes in initial conditions and coordinate system. So, it is possible to be evaluated in the reconstructed phase space made out of time delay vectors.

An efficient form to estimate fractal dimension is to calculate the Hurst exponent. The Hurst exponent for temporal series is related to fractal dimension by:

$$Df = 2 - H \tag{5}$$

The Hurst exponent, H, is a self-similarity parameter, 0<H<1, that measures the long range dependence in a time series. For H=0.5 the behaviour is Gaussian, however in the cases where H<0.5 represents anti-persistent behaviour and if H>0.5 is a fractional Brownian motion with increasing persistence strength when H is higher, it is a long memory process.

There are several methods to estimate the Hurst exponent, one of the most popular is R/S analysis, it can be found in Weron [11]. Previously, this method is not any assumption about probability distribution, therefore it is suitable to be used for nonlinear stochastic systems.

The time series with N points, is divided into windows of n elements, with or without overlapping, we have chosen non overlapping windows, there will be d windows, where dxn=N. For each window m:

1. Mean Em{x}is calculated.
2. Standard deviation σm{x}is calculated.
3. Data are normalized by subtracting the mean:

$$z_{i,m} = x_{i,m} - E_m\{x\} \text{ para i} = 1,\ldots,\text{n} \tag{6}$$

4. New values are created by adding up the data points:

$$y_{i,m} = \sum_{j=1}^{i} x_{i,m} \text{ para i} = 1,\ldots,\text{n} \tag{7}$$

5. Range, Rm, is calculated by subtracting the maximum value from the minimum value:

$$R_m = Max\{y_{1,m},\ldots y_{n,m}\} - Min\{y_{1,m},\ldots y_{n,m}\} \tag{8}$$

6. Range, Rm/Sm is calculated by dividing the range into the standard deviation:

$$(R/S)_n = \frac{1}{d}\sum_{m=1}^{d} R_m / S_m \tag{9}$$

7. Length is increased. Steps 1 to 7 are repeated
8. Hurst exponent is calculated by using a linear regression line with log(n) as the independent variable. and $\log(R/S)_n$, as the dependent variable.

In order to minimize program execution time, two powered lengths series have been chosen.

In order to verify the techniques described, first, the EMG signals were recorded from trapezius and biceps of 12 subjects with ages between 23 and 26 years, all male with weights between 72 Kg. and 80 Kg. The first six subjects (Group 1) had normal muscular structure,

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the last six subjects (Group 2) had a better muscular condition.

The trapezius muscle election as one of the muscles where EMG signals were recorded was mainly motivated because this muscle would support the most severe effort at the test proposed. It was elected as well because of its easy accessibility, good SNR and low contamination with other artifacts. Besides, it was recorded EMG biceps muscle. Results recorded off biceps – muscle with a little muscular activity at the test designed -- could be easily correlated with the results from trapezius muscle.

The exercise was developed in a gymnastic machine chosen ad hoc. Subjects had to do successive contraction and extension movements under a controlled effort with two different fixed rhythms. Three subjects from each group performed exercise for 40 minutes (Exercise A) and 20 minutes (Exercise B). Data registration was implemented using Ag-AgCl passive surface electrodes, to reduce inter-electrode impedance , the skin underlying the electrode was cleaned with alcohol swabs prior to electrode placement. A platform for biopotencials acquisition BIOPAC-MP100 and software tools to data biomedical exchange in European Standard Format EDF [9], developed by EIMED. Signals were low pass filtered, the upper frequency cut-off was chosen 1 KHz. Gain was adjusted to allow maximum amplification without saturation of the analog to digital converter. Sample frequency was fs=2 KHz. Once signals were recorded, samples were segmented with 10 s duration.

Results

Several interesting results are shown using algorithms developed with LabVIEW® programming. It is possible to verify the turn of the attractor trajectories at the phase space of the data segments when time lag is reached --On the other hand, when several phase spaces of different segments are represented, and those segments belong to distinct time series, as the muscle becomes more fatigued, new objects appear and the number of trajectories increases (Fig. 1).

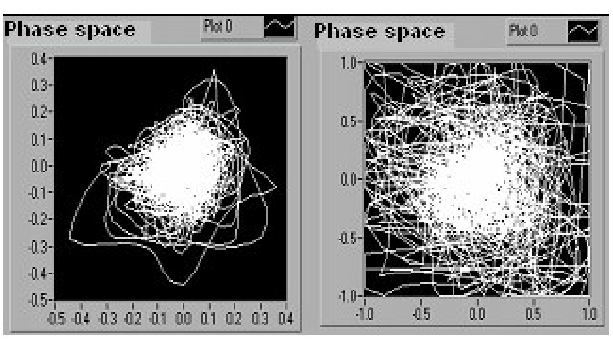

Figure 1. Phase space diagram. Left: Non fatigue; Right: Fatigued

Because of that, these features could be used as alternative indexes for fatigue.

From the mutual average information representation time lag is calculated. In order to do it, the first minimum of the mutual average information is calculated. Fig. 2. shows mutual information for a segment belonging to subject Group A who did exercise B.

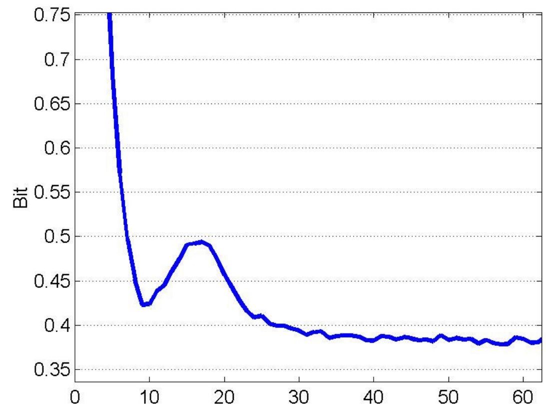

Figure 2. Mutual Information.

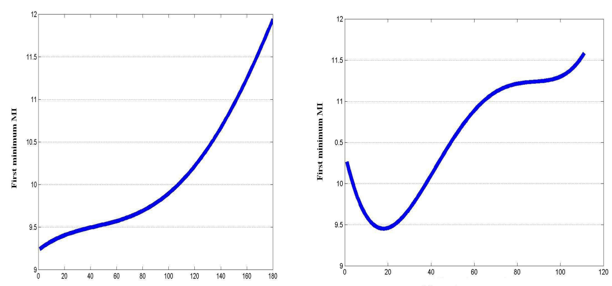

Figure 3: Time lag evolution.
Left: Exercise A (Hard); Right: Exercise B (Soft);

On other hand, Fig. 3 shows a polynomic interpolation of the time lag during exercise B for a subject belonging to Group 1. Time lag always increases for subjects who belong to Group 1. The longer the exercise the more time lag increases. The same figure shows time lag evolution for a subject belonging to Group 1 who did exercise B, time lag increases when the test goes on, when same subject performs exercise B, time lag increases as well, but not so much because of the more reduced time of the exercise. Very interesting results are proved for the subjects belonging to Group 2 who perform exercise B, (Fig .4) because time lag remains almost constant; that could be caused by their muscle structure and excellent fitness. To summarize, the exercise performed by this subject was unable to produce any kind of fatigue.

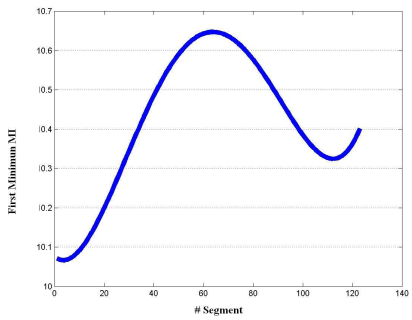

Figure 4: Time lag evolution. Group 2 and exercise B

After calculating time lag, fractal dimension of the same time series was estimated. Hurst Exponents were estimated with non overlapping windows, 16384 samples each. Fig. 5 shows fractal dimension for one of the subjects during the whole test. It is possible to verify as fractal dimension decrease when fatigue appears, so it could be used as fatigue indicator as well.

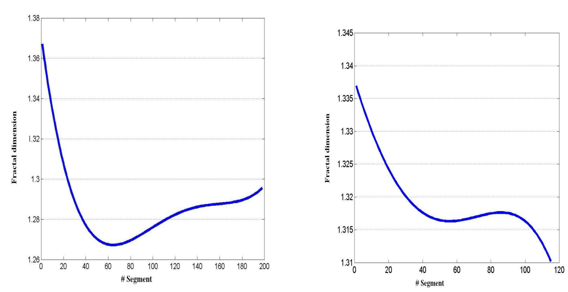

Figure 5. Fractal Dimension.
Left: Group 1- Exercise A; Right: Group B- Exercise B

Table 1 shows an average variation of time lag and fractal dimension from the beginning of the exercise to the end for all groups and exercises performed.

Table 1: Variation of time lag and fractal dimension

Variation (%)	Group 1 Exercise A	Group 1 Exercise B	Group 2 Exercise A	Group 2 Exercise B
τ	30	12	5	3
Df	10	8	4	2

Discussion

The algorithms implemented allow us to estimate Hurst exponent and lag time without any a priori assumption on the stochastic process and on the probability distribution of the random variables entering the test.

We have reported preliminary results concerning the time lag and fractal dimension of EMG temporal series. We calculated both parameters in order to quantify physiological fatigue. The ability of the techniques to perform such analysis is proved by the increasing of the time lag and decreasing of the dimension fractal.

These results have to be considered as an encouraging starting point for an automatic estimation. Time lag could be considered a good resolution estimator. Experimental data indicate a little poor sensitivity of the fractal dimension to the presence of fatigue.

Hurst exponent exceeds 0.5 in all subjects, that shows a long-time memory effect. EMG temporal series have a persistent behaviour, like most natural phenomena.

If the scaling exponent reveals the complexity, we may say that the complexity of the EMG pattern in fatigued condition is decreased. If the muscle reaction to a muscular activity is well defined then it could be hypothesized that fractal dimension will decrease.

Conclusions

Non lineal methods are efficient alternatives to the characterization and classification of EMG signals because of the unique nature of that kind of signal.

The characterization of the EMG permits quantifying physiological fatigue by using two related parameters: time lag and fractal dimension, both of them could be estimated in real time. Further studies in larger populations are needed to confirm those results.

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