Algorithm of detection and alert of muscle fatigue in paraplegic patients, by Digital Signal Proccesing of Surface Electromyogram

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Abstract—This work propose a detection and alert algorithm for muscle fatigue in paraplegic patients undergoing electrotherapy sessions by means of surface electromyographic (SEMG) signal processing. The procedure is based on a mathematical chaotic model instead of real signals and a continuous Wavelet Transform. Finally quantification of results was obtained through Total Wavelet Entropy TWE values observed during electrical stimulation. These steps allow obtaining an implementable and practical alert and detection algorithm for muscle fatigue.

Keywords-Wavelet Trasform, Total Wavelet Energy; Chaos; SEMG.

I. INTRODUCTION

Paraplegia deprives individuals of movement and sometimes sensitivity. Paraplegic patient should attend sessions of electrotherapy, not to regain mobility but to avoid muscles to suffer other damage due to lack of movement. However, if fatigue is sustained more than necessary during therapy, the muscle can also be damaged. The therapy main drawback is lack of equipment to identify accurately when to stop the stimulation as each patient reacts differently to electrical stimulation therapy.

The present work proposes a detection algorithm for muscle fatigue in paraplegic patients undergoing electrotherapy sessions by means of surface electromyographic (SEMG) signal processing. Most of researches focused in this kind of signal work with Fourier Transform FT [1], although literature shows that SEMG signal has been characterized as chaotic [2], [3]. In section II, a mathematical chaotic model (that emulates real SEMG signals) is proposed. In section III A, is presented an identifying method based on pattern recognition technique and the continuous Wavelet Transform. This is applied to the chaotic model in order to extract signal features as was done in [4]. The results quantification is obtained through Total Wavelet Entropy TWE observed during electrical stimulation. Numerical results obtained from the TWE show that SEMG signal energy grows over time i.e. as the patient becomes fatigued (as presented in section III B). This data can raise the threshold of fatigue that will alert when electrical stimulation should be stopped. In this sense, in section V, an algorithm design of detection and alert of fatigue is proposed. Finally, in section V main conclusions of the work are presented.

II. METHODS

In following subsections the main tools and methods used in the proposed recognition algorithm are briefly described.

A. *Chaos.*

Chaotic systems apparently show a sequence of disorderly or random facts. But in fact there are rules that determine their behavior. The sensitivity to initial conditions suggests that, no matter how close are two states with each other, the evolution of both, subject to the same law of evolution, can be completely different. The existence of deterministic laws but unpredictability at the same time is perhaps the most striking feature of chaos. Topological Transitivity indicates that the system will evolve over time so that any given region or open set of its phase space will eventually overlap with any other given region. Chaotic systems are characterized by following topics: Sensitivity to initial conditions, irregular behavior (not predictable for long periods of time), not correlated signs, wide bandwidth [9].

B. *Wavelet Trasnform.*

Before explaining the characteristics of signal analysis using Wavelet Transform WT, it is noteworthy that a wavelet is a time-limited signal whose average value is zero. Comparing Wavelets with sinusoidal functions (which are the basis of Fourier analysis), it is possible to note that the main difference between then is that sinusoidal signals are no time-limited, since they extend from $-\infty$ to ∞ [6].

Wavelet analysis represents a logical next step to Short-time Fourier Transform STFT: a technique using windows with regions of variable size. Wavelet analysis allows the use of large intervals of time, in those segments, that require more precision in low frequency, and smaller regions where information is required in high frequency. Similarly to FT, signal analysis using

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WT decomposes the signal, displaced (in time) and scaled (in frequency), into versions of the original wavelet, known as mother wavelet. One of the main advantages provided by WT is its ability to analyze localized areas of large signals [5], [6]. Since range of frequencies that corresponds to each signal is known, it is possible to group them and make a graph in three dimensions, being the axis: time, frequency and amplitude. Thus, it is possible to observe what frequencies occur at what time.

C. *Continuous Wavelet.*

There are two kinds of WT, Continuous Wavelet Transform CWT and the Discrete Wavelet Transform. CWT is optimal for purposes of extracting intuitive characteristics [5]. Therefore, for SEMG signal analysis in coordinate time-scale was applied CWT, due to the aforementioned attributes.

As first step, the wavelet function which will be the Mother Wavelet should be chosen. This function will serve as a prototype for all windows that are used in the process. There are a significant number of families of Wavelet functions. After selecting the mother wavelet, equation (1) is applied along the signal with a scale factor determined then, the scaling factor should be varied in (2) in order to reduce or enlarge the size of windows. Apply (1) again along the signal, and repeat these steps until attain the amount of information required for analyzing the same.

$$c(\tau, s) = \int_{-\infty}^{\infty} f(t)\psi^{*}_{\tau,s}(t) \qquad (1)$$

$$\psi^{*}_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right) \qquad (2)$$

D. *Total Wavelet Entropy.*

Total Wavelet Entropy TWE is based on the principle of Entropy Shannon [7], defined as:

$$S_{wt} = -\sum\left[p_j \ln p_j\right] \qquad (3)$$

Where, p_i is the probability distribution or Relative Wavelet Energy (RWE), at a given scale. Then, the total wavelet entropy is defined as:

$$TWE = \frac{-\sum\left[p_j \ln p_j\right]}{\ln N} \qquad (4)$$

Where N is the maximum scale used in the analysis. This measure indicates the level of energy contained in the signal

III. CHAOTIC SIGNAL GENERATOR.

This section presents the Chaotic Signal Generator of Surface Electromyographic signals and its validation. This step emulates data acquisition stage.

A. *Chaotic Signal Generator.*

Chaotic signal generator has been based on the chaotic model of logistic map (see appendix), which has been modified according to the characteristics of the Surface Electromyogram (SEMG) signal of a paraplegic patient shown in [1]. For this purpose Matlab®7.1 was used.

In order to perform the signal generator, time segment of the logistic map was divided in three parts. Each part was affected by arithmetic operations as (5), (6) and (7) shown. Each f_{s1} is the scale factor that modifies each interval of logistic map. Notice that $f_{s1} \neq f_{s2} \neq f_{s3}$. Finally, a constant value of parameter "r" was used; this value works in the greatest chaotic region.

$$x_{i+1}=rx_i(1-x_i)+f_{s1} \quad \text{For} \quad 1 < i < n/6 \qquad (5)$$

$$x_{i+1}=rx_i(1-x_i)+f_{s2} \quad \text{For} \quad n/6 < i < n/4 \qquad (6)$$

$$x_{i+1}=rx_i(1-x_i)+f_{s3} \quad \text{For} \quad n/4 < i < n \qquad (7)$$

The main characteristics of signal generator developed in this work are similar to real signals as highlighted bellow:

a) Signal duration. The signal generated during 350 sec, emulates the signal of a patient which has reached maximum fatigue at time of 350 sec. It is an assumption because each patient may become fatigued at different times due to external and internal factors to the muscle.

b) Time behavior. As can be observed in fig.1. SEMG signal amplitude tends to increase over time. This feature can also be noticed in reconstruction of face portraits [2] and [3], as the attractor increases its range at different time intervals. Such amplitude increases due the increment in number of motor units activated by the fatigue and due other phenomenas: fire growth rate, impaired excitation-contraction and synchronization of motor unit recruitment. According to several studies based in real signals [2], it has been defined that this increase in amplitude is more important and faster when the greater the effort.

B. *Validation of Chaotic signal generator.*

In subsection A was proposed a chaotic signal generator to emulate the SEMG signal of a paraplegic patient when muscles are stimulated by electrotherapy, A generated temporal data example is presented in fig.1 (where a initial condition of x_0 =0.71 is used).

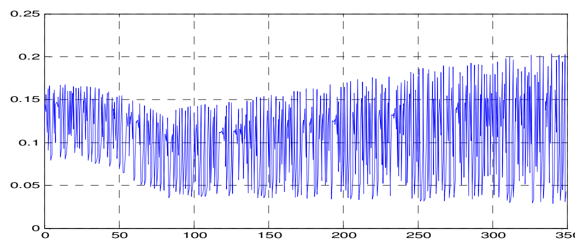

Figure 1. Chaotic Generator of SEMG signal

The model based data shows that signals obtained from signal generator could classified as chaotic through the following criteria:

- *Sensitivity to little variations in initial conditions:* it has observed that varying initial condition in just one hundredth, the generated signal is totally different, but maintaining similar trajectories.

- *Strange attractor*: reconstruction of phase space result in a strange attractor, which tends to grow at passage of time, as can be seen in fig.2. Attractor shows fractals that is a typical characteristic of chaotic systems.
- *Correlation dimension*: it has a value not integer ($\approx$ 0.51), this indicates that the signal has a strange attractor and therefore is a chaotic signal, as was previously observed.

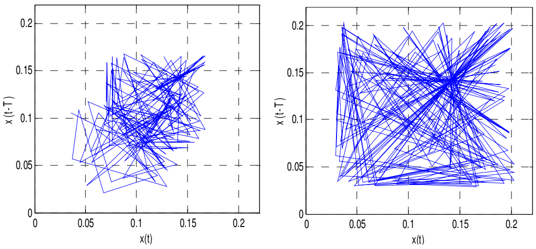

Figure 2. Phase Portrait of SEMG signal
a. From 0 to 87.5 sec. b. From 262.5 to 350 sec.

IV. WAVELET TRANSFORM APPLICATION.

After obtaining signal generator, CWT should be applied in order to extract signal characteristics. Finally, features observed graphically, through CWT portrait, are quantified by application of TWE.

A. *Continuous Wavelet Transform*

Daubechies4 (db4) was chosen as a mother wavelet. Then, the WT of the signal should be calculated. To perform calculation Matlab®7.1 and its commands to calculate the CWT were used.

Results obtained are shown in fig.3, where, in color scale, values of the coefficients from dark brown (lowest coefficient values), to white (highest coefficient values) are presented.

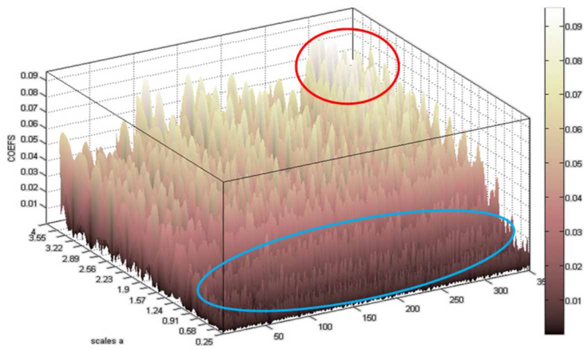

Figure 3. Continuous Wavelet Transform

For low scales (high frequencies) it can be seen that the passage of time do not undergo in significant changes in coefficient values, for better observation this area has been highlighted with a blue circle (Fig.3). Frequencies above 500 Hz are not be taken into account for the analysis in case of real signals as the frequency range of SEMG signals goes from 20 to 500 Hz [8]. This analysis also shows that wavelet coefficients values grow over time on high scales (low frequencies) as highlighted with a red circle in Fig.3. It should be noticed that as the fatigue increases (over time), the concentration of coefficients at low-frequencies increases proportionally. This feature supports analysis obtained through the Fourier Transform, which indicates that because of increased fatigue over time, there is a decrease in the Mean Frequency and Median.

As the WT is applied to the SEMG signal, and a direct proportional increase in signal power and muscle fatigue is observed, a pattern recognition method could be proposed determining thresholds values for fatigue phenomena. To realize this procedure, in this work an energy indicator known as Total Wavelet Entropy is used [7].

B. *Total Wavelet Entropy.*

Wavelet Entropy (TWE) values, for a SEMG signal sequence divided in eight parts are presented in fig.4 (for an initial condition of x_0=0.71). CWT and this indicator were calculated for many different initial conditions several times. Both of them present the same feature: an increment over time.

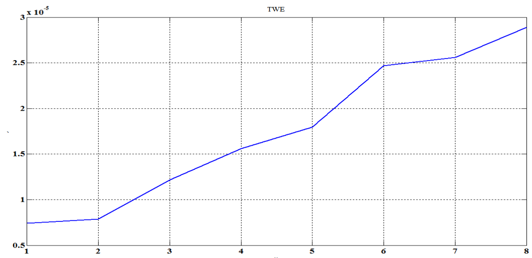

Figure 4. Total Wavelet Entropy

TWE was compared with other indicators of energy. These indicators are known as Shannon Entropy and Relative Wavelet Energy (RWE) [9]. For the type of signals used in this work, TWE presents the best results in terms of overlapping (main feature in pattern recognition methods).

V. PROPOSED ALGORITHM

After observing and analyzing all results, the algorithm detection and alert of fatigue proposed in this work, consists of:

A. Data acquisition.

B. Calculation of the CWT (each 25 sec).

C. Calculation of the TWE (of wavelet coefficients each interval).

D. Calculation of growth percentage of TWE in 25 sec intervals (in relation to the first 25 sec).

Where:

A: A chaotic signal generator of non-variable complexity, from a scaled logistic map, emulates data acquisition step. This generator provides different signals that emulate the behavior of electromyographic signals obtained from paraplegic patients undergoing electrotherapy sessions. These signals vary according to the initial condition, which permits simulate signals from different patients.

B: CWT calculation helped to show graphically the behavior of the signal in frequency domain. Calculation of CWT every 25 sec is suggested to meet the minimum requirements of quantity of data, which is possible to work, and medical requirements that safeguard the health of the patient.

C: To quantify increment of energy TWE has been chosen because it has provided better results than other two quantifiers of wavelet energy.

TABLE 1. Thresholds of Fatigue

Alerts	Ok	Alert 1	Alert 2	Alert 3
% Growth	1%-136%	137%-199%	200%-280%	281%
Meaning	**Without fatigue**	**Initial fatigue**	**Transition**	**Maximum fatigue**

D: Alert levels are defined, as shown in Table 1, based on the percentage growth of TWE. Electrical stimulation should be stopped at Alert 2.

The proposed algorithm is validated in Matlab® platform considering several tests and different initial conditions working at the most chaotic region of logistic map. As table 1 presents, all results obtained returns four main thresholds of fatigue from reported growth rates.

VI. CONCLUSIONS AND FUTURE WORKS

The main purpose of this work was to improve "one of the most important drawbacks in physiotherapy which is referred to electrotherapy dosage". The results verify that traditional procedures concentrate more attention on the type of signal applied instead of the type of signals that the patient receives. Studies conducted so far on muscle fatigue has been made based on FT and calculation of mean and median frequency, these are statistical methods whose use is controversial , as reported by medical studies.

The main contribution of this work is the pattern recognition procedure proposed by means of the CWT feature. This tool has permitted to indentify a direct relationship between fatigue increment and wavelet energy increment at low frequencies. This characteristic was quantified by means of TWE. Numerical results have permitted to obtain thresholds of fatigue shown in Table 1. It is suggested stopping stimulation before patient allows Maximum fatigue. Implementation of the algorithm will be important to both the patient, because it prevents the muscle achieve maximum fatigue during electrotherapy, and the therapist, giving adequate information about when electrical stimulation should be stopped. As a future work, the algorithm would be implemented on a Digital Signal Processor using a development kit and data acquisition devices. Hardware and software requirements are obtained through this study, to implement the detection algorithm taking into account criteria for acquisition, preparation, pre-filtering and sampling period of the electromyographic signal. Software requirements are MatLab®7.1 that must have the processor library signals to be used (Texas Instruments, Analog Device). Code Composer Studio (TM) for digital processors Texas Instrument. Hardware requirements are: Operational amplifier configuration with CMRR (for pre-amplification stage) INA128, protection and reference circuits, high-pass filter, amplifier, low pass filter, and a development platform for DSP (which sampled the signal with a rate sampling of 1200Hz) also a Pentium 3 CPU that supports the program MatLab 7.1 and Code Composer Studio (TM) to load the DSP program.

Finally, it is worth noting that Wavelet Transform is useful for different applications in addition to the biomedical ones. CWT is helpful to identify characteristics of a great variety of signals.

VII. ACKNOWLEDGMENTS

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APENDIX

Logistic map equation is described by:

$$x_n = rx_n\left(1 - x_n\right)$$

When r<1 equilibrium point is zero.
For 1<r<3 there are one equilibrium point.
For 3<r<4 there are more than one equilibrium points.
When r>4 this system is not observable.

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