Detection and Alert of muscle fatigue considering a Surface Electromyography Chaotic Model

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Abstract. This work proposes a detection and alert algorithm for muscle fatigue in paraplegic patients undergoing electro-therapy sessions. The procedure is based on a mathematical chaotic model emulating physiological signals and Continuous Wavelet Transform (CWT). The chaotic model developed is based on a logistic map that provides suitable data accomplishing some physiological signal class patterns. The CWT was applied to signals generated by the model and the resulting vector was obtained through Total Wavelet Entropy (TWE). In this sense, the presented work propose a viable and practical alert and detection algorithm for muscle fatigue.

1. Introduction
Paraplegia deprives individuals of movement and sometimes sensitivity. Paraplegic patient should attend sessions of electro-therapy, 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. Most of researches, focused in this kind of signal, work with Fourier Transform FT, as we can see in [1], [2], [3] and [4] although recently literature shows that SEMG signal has been characterized as chaotic [5], [6]. The present work proposes a detection algorithm for muscle fatigue in paraplegic patients undergoing electro-therapy sessions by means of surface electromyographic (SEMG) signal processing considering a chaotic model approach of SEMG. In section 2, the main definitions related to Wavelet Transform and chaos theory, which are used throughout the work, are presented. In section 3 is presented a chaotic model that emulates the electro-therapy process. Section 4 describes the pattern recognition technique, based on a continuous Wavelet Transform, proposed in this work. Aiming to exhibit the main functionalities of the proposed methodology, several numerical results are presented in section 5. Finally, in section 6, the main conclusions of the work are presented.

2. Nonlinear Chaos theory and Wavelet Transform
Nonlinear chaos theory and wavelet transform are applied in modeling of an electro-therapy process. In the following sections the main tools and methods used in the proposed recognition algorithm are briefly described.
2.1. Logistic Map
In this section is briefly described the logistic map, which is the basis of the proposed chaotic generator. The logistic map equation is represented by (1) [7]:

\[ x_{n+1} = rx_n(1 - x_n) \]  

Where parameter \( r \) defines the complexity of the system by means of the following relations [7]:
When \( r < 1 \) the equilibrium point is zero.
For \( 1 < r < 3 \) there is one equilibrium point.
For \( 3 < r < 4 \) there are more than one equilibrium points.
When \( r > 4 \) the system is not observable.

2.2. Chaos Theory
Chaotic systems are used to modeling sequences of disorderly or random events by means of inherent rules that determine some characteristics of their behavior [7]. The sensitivity to initial conditions suggests that, the evolution of two states, in the same neighborhood, 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. Chaotic systems are characterized by the following topics: Sensitivity to initial conditions, irregular behavior (not predictable for long periods of time), not correlated signs and wide bandwidth [8].

2.3. Wavelet Transform
A wavelet is a time-limited signal whose average value is zero. Comparing Wavelets with sinusoidal functions (basis of Fourier analysis), it is possible to note that the main difference between them is that sinusoidal signals are no time-limited, since they extend from \(-\infty\) to \(+\infty\) [1]. Wavelet analysis represents a logical next step to Short-time Fourier Transform STFT, more precisely, it considers windows with regions of variable size [8]. Wavelet analysis allows the use of large intervals of time in those segments that require more precision in low frequency, and smaller intervals of time in regions where information is required in high frequency. Similarly to FT, signal analysis using WT decomposes the signal, displaced (in time) and scaled (in frequency), into versions of the original wavelet, known as Mother Wavelet. Since the range of frequencies that corresponds to each signal is known, it is possible to group them to make a graph in three dimensions, being the axis: time, frequency and wavelet coefficients. Thus, it is possible to observe what frequencies occur at what time. An important advantage provided by WT is its ability to analyze localized areas of large signals [9], [8].

2.4. Continuous Wavelet Transform.
There are two types of WT, Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT). CWT is optimal for purposes of extracting intuitive characteristics [9], therefore, in this work, CWT is applied for SEMG signal analysis in coordinate time-scale. Equation (2) describes WT, as equation (3) represents the Mother Wavelet, which displacement and scaling depends on \( \tau \) and \( s \), respectively.

\[ C_{(\tau,s)} = \int_{-\infty}^{+\infty} f(t) \psi^*_{\tau,s}(t) \, dt \]  
\[ \psi^*_{\tau,s}(t) = \frac{1}{\sqrt{|s|}} \psi \left( \frac{t - \tau}{s} \right) \]
To analyze a signal by means of WT the next steps must be followed [8]:

1° 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.

2° After selecting the mother wavelet, equation (2), is applied along the signal with a scale factor determined (constant).

3° Then, the scaling factor should be varied in (3) in order to reduce or enlarge the size of windows.

4° Equation (2) should be applied again along the signal.

5° Repeat steps 3 and 4 until attain the amount of information required for the analysis.

2.5. Total Wavelet Entropy.
Total Wavelet Entropy (TWE) is based on the principle of Shannon Entropy. TWE is defined in (4), [10]:

\[ S_{wt} = -\sum_{n=0}^{n} p_j \ln p_j \]  \hspace{1cm} (4)

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

\[ TWE = \frac{S_{wt}}{\ln N} \]  \hspace{1cm} (5)

Where N is the maximum scale used in the analysis. This measure indicates the level of energy contained in the signal [10].

3. Chaotic Signal Generator.
This section presents the Chaotic Signal Generator proposed for Surface Electromyographic signals and its validation. It must be noticed, that this stage has the main goal of simulate data acquisition stage.

3.1. Chaotic Signal Generator.
The chaotic signal generator is based on the chaotic model of the logistic map, which has been modified according to the characteristics of the Surface Electromyogram (SEMG) signal of a paraplegic patient.

To perform the signal generator, the time segment of the logistic map was modified in order to obtain characteristics of SEMG signal showed in [5]. The most important considerations, in order to develop the Chaotic Generator are listed following.

- The main variables considered are \( r \) and \( x_0 \), system complexity and initial condition, respectively.
- A constant value of \( r \) is used in the suggested model, aiming minimal variations of SEMG signals complexity, [5] [6].
- \( r \) must be greater than 3.89 once there is a non chaotic region near from this value [7], and simultaneously it must be less than 4 because from this value the system is not observable. The value \( r = 3.99 \) is selected for all numerical simulations.
- Initial condition value varies from 0 to 1.
- Changing initial condition value, SEMG signals of different paraplegic patients, or the same patient at different sessions, are simulated.
The time segment of the logistic map was divided in three parts to perform the signal generator.

Summarizing, the time segment of the logistic map was divided in three parts where \( f_{s1} \) is the scale factor that modifies each interval of logistic map \((f_{s1} \neq f_{s2} \neq f_{s3})\). Aiming to guarantee the process convergence in the greatest chaotic region, and considering several initial conditions, a constant value of parameter \( r \) was used in this work. Equations (6), (7) and (8) presents the proposed chaotic model of the SEMG signal generator based on the modified logistic map:

\[
\begin{align*}
\text{for } 1 < i < \frac{n}{6} & \quad x_{i+1} = rx_i(1 - x_i) + f_{s1} \\
\text{for } \frac{n}{6} < i < \frac{n}{4} & \quad x_{i+1} = rx_i(1 - x_i) + f_{s2} \\
\text{for } \frac{n}{6} < i < n & \quad x_{i+1} = rx_i(1 - x_i) + f_{s3}
\end{align*}
\]  

(6) (7) (8)

The main characteristics of the signal generated by the proposed model, are similar to real physiological signals as highlighted bellow:

- **Signal duration.** The signal generated, during 350 sec, simulates the signal of a patient which has reached maximum fatigue at time of 350(s). It is a plausible assumption considering that each patient could became fatigued at different times due to external and internal factors to the muscle [11].

- **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, as presented in [5] and [6], since the attractor increases its range at different time intervals. This amplitude increases due the increment in number of motor units activated by the fatigue and due other physical phenomenas. According to several studies based in real physiological signals, [12],[11] and [5], it has been defined that amplitude increases faster when the greater the effort.

Assuming an initial condition \( x_0=0.71 \), a generated temporal data example is presented in Fig.1.

![Figure 1. Chaotic Generator of a emulated SEMG](image-url)
3.2. Validation of the proposed Chaotic Signal Generator.

The model based data shows that signals obtained from chaotic generator could be validated as chaotic through the following criteria [7]:

- **Sensitivity to little variations in initial conditions**: varying initial condition by 0.01, the generated signal is totally different, but maintain similar trajectories.

- **Strange attractor**: reconstruction of the phase space results in a strange attractor, which tends to grow at passage of time, as can be seen in Fig.2.

- **Correlation dimension**: the correlation dimension presents a non integer value ($\approx 0.51$), this indicates that the signal has a strange attractor and therefore is a chaotic signal, as was previously observed.

![Figure 2. SEMG signal Phase Portraits, generated at four intervals of time](image)

4. Wavelet Transform based analysis.

Once emulated a statistically uncorrelated group of signals, CWT should be applied in order to extract the main characteristics. Then, features observed through CWT portrait, are quantified applying TWE.

4.1. Continuous Wavelet Transform.

Initially, the Daubechies4 (db4) function is selected as a mother wavelet. Applying the CWT transform is verified that all signals presents the same characteristics. As an example, results obtained for a signal with an initial condition $x_0 = 0.71$ are shown in Fig.3. Values of the coefficients are represented in color scale, from dark brown (lowest coefficient values), to white (highest coefficient values).

For low scales (high frequencies) it can be observed that the passage of time do not undergo in significant changes in coefficient values, as highlighted with a blue line in Fig.3. This analysis also shows that wavelet coefficients values grow over time on high scales (low frequencies), as highlighted with a red circle. Accordingly, as the fatigue increases over time, the concentration of coefficients at low-frequencies increases proportionally. This feature supports previous 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 [12].
As a direct proportional increase in signal power and muscle fatigue are observed, by means of CWT, a pattern recognition method could be proposed to determine thresholds values for fatigue phenomena. In order to realize this procedure, in this work a Total Wavelet Entropy is applied. This function enables summarizes the pattern characteristics in the Wavelet frequency analysis [13]

4.2. Total Wavelet Entropy.
Continuous Wavelet Transform and Total Wavelet Entropy (TWE) were calculated for several signals. Both of them present the same feature: an increment over time, in low frequencies. Total Wavelet Entropy values obtained, from five different signals are presented in Fig.4 and these values were calculated at eight different intervals of the SEMG signal sequence. It could be observed that TWE values increase over time for those five signals, tests realized in several signals presents the same pattern.

![Figure 3. Continuous Wavelet Transform](image)

![Figure 4. Total Wavelet Entropy](image)
5. Resume of the Proposed Algorithm.

The algorithm detection and alert of fatigue proposed in this work, can be summarized in the following steps:

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, that simulates data acquisition step. This generator provides several signals that emulate the behavior of electromyographic signals obtained from paraplegic patients undergoing electro-therapy sessions. These signals vary according to the initial condition, which permits simulate signals from different patients.
B: CWT shows the signal behavior in frequency domain. CWT should be calculated every 25 sec.
C: To quantify increment of energy the TWE function has been chosen, as it provides better results than other two quantifiers of wavelet energy [14].
D: Alert levels are defined based on the percentage growth of TWE, as shown in Table 1. Electrical stimulation should be stopped at Alert 2.

| Alerts | % Growth | Meaning       |
|--------|----------|---------------|
| OK     | 1% -136% | Without Fatigue |
| Alert 1| 137%-199%| Initial Fatigue |
| Alert 2| 200%-280%| Transition     |
| Alert 3| ≥ 281%  | Maximum Fatigue |

The proposed algorithm is validated in Matlab® 7.1 platform, considering several tests, 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.

6. Conclusions

The purpose of this work consists in improve one of the most important drawbacks in physiotherapy which is referred to electro-therapy dosage. The Chaotic Signal Generator provides the enough quantity of data to realize this work. The main contribution of the work consists in the pattern recognition procedure proposed, by means of the CWT. This tool has permitted to identify 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 as shown in Table 1 and enable stopping stopping stimulation before patient allows maximum fatigue. Implementation of the algorithm will be important to both the patient, since it prevents the muscle achieve maximum fatigue during electro-therapy, 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.
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