Indian Journal of Fundamental and Applied Life Sciences ISSN: 2231-6345 (Online)
An Open Access, Online International Journal Available at http://www.cibtech.org/jls.htm
2014 Vol. 4 (4) October-December, pp.49-54/Azadbakht et al.
Research Article

INVESTIGATION OF CHAOTIC DYNAMICAL BEHAVIORS IN UPPER LIMB ELECTROMYOGRAM SIGNALS

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ABSTRACT
In this paper we investigate the complexity and chaos in the electromyogram signals of skeletal muscles. Several papers in the literature have studied the statistical features of these biological signals for feature extraction and signal characterization but no study has been made on the complexity and chaotic dynamics of such the signals. However we have used two features as approximate entropy as the complexity feature and largest Lyapunov exponent of the signal as the chaotic feature to model the EMG signals dynamical behavior. It is shown that complex features can characterize the dynamics of recorded EMG signals as well as statistical signals and in some cases they perform better. For the classification task of these signals, three classifiers will be employed and compared in terms of MSE of modeling and classification rate and it is demonstrated that fuzzy neural networks are superior to the other classifiers used. Modeling capabilities of complex and chaotic features imply that electromyogram signals show nonlinear complex behavior in their dynamics and this complexity is delivered from the nature of these biological signals.

Keywords: *Electromyogram Signals; Statistical Features; Complex Features; Chaos; Classification*

INTRODUCTION
Electromyography (EMG) is the study of the electrical activity of the muscle and is a valuable tool in the assessment of neuromuscular disorders. EMG signals have been widely used and applied as a control signal in numerous man-machine interface applications and have also been deployed in many clinical and industrial applications (Pandey and Mishra, 2009; Rafiee *et al.*, 2011; Phinyomark *et al.*, 2012).
Feature extraction is a method to extract the useful information that is hidden in surface EMG signal and remove the unwanted EMG parts and interferences (Zardoshti-Kermani, 1995; Boostani and Moradi, 2003). Some features are robust across different kinds of noises; consequently, intensive data pre-processing methods shall be avoided to be implemented (Phinyomark *et al.*, 2009). In addition, appropriate features will directly approach high classification accuracy (Oskoei and Hu, 2008). Three properties have been suggested to be used in quantitative comparison of their capabilities that include maximum class separability, robustness, and complexity (Zardoshti-Kermani, 1995; Boostani and Moradi, 2003). Although many research works have mainly tried to explore and examine an appropriate feature vector for numerous specific EMG signal classification applications (e.g. Zecca, 2002), there have a few works which make deeply quantitative comparisons of their qualities, particularly in redundancy point of view (Bremen, 2001).
Several statistical and frequency based features have been introduced and defined in the literature (Pandey and Mishra, 2009; Rafiee *et al.*, 2011; Phinyomark *et al.*, 2012; Zardoshti-Kermani, 1995; Boostani and Moradi, 2003). Due to the complexity in the nature of the biological signals, it has been shown that some of them as ECG and EEG signals exhibit non-linear complex dynamic behavior. This complexity in the several publications has been interpreted as chaotic dynamics and then the signals have been characterized in chaotic domain. Therefore, the researchers have followed such the features to model the dynamics of biological signals. EMG signals, like some other biological signals shown nonlinearity and complexity in their dynamic behavior. In this paper, we aim to analyze samples of EMG signals in this point of view.

In order to distinguish deterministic chaos, several important invariants are proposed such as Lyapunov exponent (Liu *et al.*, 2003), correlation dimension (Keller & Sinn, 2010), Kolmogorov entropy (Keller and Sinn, 2010). Aiming to study more comprehensively the dynamics of a chaotic system, the Lyapunov exponents should be estimated. Before the introducing of chaos theory, the concept of Lyapunov exponents existed long and was expanded to describe the stability of linear as well as non-linear systems. Lyapunov exponents are described as the logarithms of the absolute value of the eigenvalues of the linearized dynamics averaged over the attractor. This definition comprises both discrete and continuous systems (Tsonis, 1992). A negative value of the exponent indicates a local average rate of convergence, while a positive value indicates a local average rate of divergence.
Considering the problem of optimally selecting the embedding dimension and time delays which are of preliminaries of Lyapunov exponents estimation, we use the embedding theorem proposed by Takens (1981) which guarantees a solution, and the proposed method of Albano *et al.*, (1988) in which the earliest time τ at which the autocorrelation drops to a fraction of its initial value is set as the delay time.
Approximate Entropy (ApEn) is a statistic that can be used as a measure to quantify the complexity (or irregularity) of a signal. It was first proposed by Pincus (1991). For more details on calculation of the ApEn value of a time series, the readers are referred to reference “Approximate entropy as a measure of system complexity” written by Pincus (1991). Nonetheless, a short description is given as follows.
In this paper we follow this assumption that electromyogram signals show chaotic dynamical behavior and the extracted chaotic features from the EMG signals can model the dynamic of this biological system. Therefore, referring to the work of Razjouyan *et al.*, (2012) largest Lyapunov exponents of the EMG signals are estimated and the method of Pincus (1991) will be employed to calculate the approximate entropy of the signals. It should be noted that these two features refer to the chaoticity and complexity of the system, respectively.

MATERIALS AND METHODS

Dataset

A data acquisition system including PowerLab, 16sp and Dual BioAmp manufactured by ADInstruments Ltd. and software Chart V5.0 with sampling rate adjusted at 2kHz, recording signal amplitude 2mV, primary low-pass filter 1 with cut-off frequency 500Hz and primary high-pass filter 2 with cut-off frequency 0.3Hz is used for surface EMG signal recording. Data are outputted in txt or excel format which are readable in MATLAB for data processing. MATLAB 7.0 software installed on a Laptop with 2.2GHz Core2Dual CPU is used for signal processing.

Totally 40 signal samples of 30 second duration have been recorded from some normal young subjects aged between 18 and 22 satisfying the conditions of having enough rest and appropriate nutrition, having no considerable physical activity before the test, no sedative drug use for at least 24 hours before the test, with no bone fracture and musculoskeletal disorder close to the test and no pain should be sensed during the tests by the subjects.

All individuals give their consent to the test and to publishing the results of the test. EMG signals have been recorded from the biceps, triceps and quadriceps muscles in the isometric contraction state, maximum voluntary contraction and dynamic contraction.

A preprocessing filtering process is then applied to the recorded signals. A window consisting of 20,000 samples (10 seconds) is made cut off for each signal to be processed and analyzed.

Feature Extraction Method

Feature extraction, which is the step to measure features or properties from the input data, is essential in the pattern recognition system design. The goal of the feature extraction is to characterize an object to be recognized by measurements whose values are very similar for objects in the same category, and very different for objects in different categories. Computational complexity and class discrimination are two main factors for determining the best feature set.

Table 1: Extracted features of the recording EMG signals. (k: sample number and N: total number of samples)

Item	Features name	Features definition	Description
1	Integration of absolute of EMG signal	$IEMG = \sum_{k=1}^{N} \lvert emg_k \rvert$	Related to muscle activity
2	Mean Absolute Value of the signal	$MAV = \frac{1}{N} \sum_{k=1}^{N} \lvert emg_k \rvert$	Related to muscle contraction points
3	Root Mean Squared of the signal	$RMS = (\sqrt{\sum_{k=1}^{N} emg_k^2)/N}$	Related to muscle contraction indication with constant force before starting the muscle fatigue
4	Wave Length of the signal	$WL = \sum_{k=1}^{N-1} \lvert emg_{k+1} - emg_k \rvert$	-
5	Difference Absolute Mean Value of the signal	$DAMV = \frac{1}{N-1} \sum_{k=1}^{N-1} \lvert emg_{k+1} - emg_k \rvert$	Mean of WL
6	Variance of the signal	$VAR = \frac{1}{N-1} \sum_{k=1}^{N} emg_k^2$	Related to the signal power
7	Zero Crossings of the signal	$ZC = \sum_{k=1}^{N} sgn(-emg_k emg_{k+1})$ $sgn(x) = \begin{cases} 1\ if\ x > 0 \\ 0\ otherwise \end{cases}$	For measuring the frequency shift and showing the number of signal sign varying
8	Wilson Amplitude of the signal	$WAMP = \sum_{k=1}^{N} f(\lvert emg_k - emg_{k+1} \rvert)$ $f(x) = \begin{cases} 1\ if\ x > threshold \\ 0\ otherwise \end{cases}$	An indication of the action potential firing of the motional unit and therefore the muscle contraction level
9	Cepstrum Coefficients of the signal	$c_1 = a_1$ $c_n = -\sum_{k=1}^{N} (1 - k/N) a_k c_{N-k} - a_N$ CC= $(c_1\ c_2\ \ldots\ c_N)$	Containing information about the power spectrum of the signal and belonging to the static features
10	Simple Square Integral of the signal	$SSI = \frac{1}{N} \sum_{k=1}^{N} \lvert emg_k \rvert 2$	An indication of energy of the signal
11	Conduction Velocity of the signal	$CV = (\frac{1}{N-1} \sum_{k=1}^{N} emg_k^2)$	Similar to RMS feature
12	Mean Absolute Value Slope of the signal	MAVS=MAV(i+1)-MAV(i)	Related to muscle contraction variations

A set of features are listed in Table 1 along with their descriptions. These features have been used in several literatures either a set of them or all of them. However most of these features are statistical features defined to express the statistical behavior of the signal. The primary purpose of this work is to

show whether the chaotic features can demonstrate the signals behavior as well as these statistical features.
To analyze the characterizing ability of a feature it should be assessed in a classification task. Classification of two or more groups of signals will be based on the defined and extracted features and however the classification rate will show the effectiveness of the features used. In this paper three classifiers commonly used in the literature for the task of clustering and classification are used. A three layer Feed forward neural network with one hidden layer and 20 neurons in the hidden layer, a five layer fuzzy neural network with two Gaussian shaped fuzzy membership function for each input node and fuzzy C-means. Since the classifiers used in this paper have been widely used in the literature, for more details on the structure of them and the method of action the readers are referred to the related references (Zardoshti-Kermani, 1995; Boostani and Moradi, 2003; Phinyomark *et al.*, 2012).

RESULTS AND DISCUSSION

Results

For the sake of comparison, two features from the list given in Table 1 are selected randomly and also from the chaotic domain, largest Lyapunov exponent and approximate entropy of the signal are chosen. Features are used to discriminate the states of contraction for the muscles. Hence we have three classes of signals as class 1: isometric contraction state, class 2: maximum voluntary contraction and class 3: dynamic contraction state. The comparisons are made between two sets of features one set consists of two selected features from Table 1 and another set consists of the two chaotic features and also between the three classifiers. As noted before, all implementations are executed by MATLAB 7.0 software installed on a 2.2GHz processor.
For evaluating the classifier, Mean Squared Error is used which is the most common criterion defined as below

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y}_i) \tag{1}$$

where y_i and $\bar{y}_i$ are real and desired outputs of the network, respectively, and N is the total number of samples. In our simulations the output values will be class labels. MSE of the training process shows the trainability of the system and MSE of the testing samples indicates the system's modeling capability. In the results MSE of the testing is only shown.

Table 2: Classification results of the three classifiers and two sets of features, MSE and C.R results are average values over the samples and classes respectively

Classifier	Features	# of Classes	# of Samples	Ave. MSE	Ave. C.R
Feed Forward Neural Network	Statistical features	3	40	0.023	~94%
Feed Forward Neural Network	Chaotic features	3	40	0.012	~96%
Fuzzy Neural Network	Statistical features	3	40	0.014	~96%
Fuzzy Neural Network	Chaotic features	3	40	0.008	~97%
Fuzzy C-means	Statistical features	3	40	0.041	~88%
Fuzzy C-means	Chaotic features	3	40	0.037	~91%

True classification rate is defined as the rate of true assigned samples to their classes to the whole number of samples as below

$$C.R = \frac{\sum_{i,j} S_i^j}{\sum_i \sum_j S_i^j} \tag{2}$$

In which C.R refers to the achieved classification rate, the numerator and denominator of the fraction refer to the true assigned samples and total number of samples respectively.

Discussion

The results of sample classification over the three classes of contraction states for EMG signals of normal subjects are shown in Table 2. It can be seen that among the three classifiers used in our experiments the fuzzy neural network with two Gaussian-shaped fuzzy membership functions for each input node yields the best classification rates and also the lowest MSE values averaged over the samples. Among the two other classifiers, feed forward neural network with one hidden layer and 20 neurons in the hidden layer performs better that fuzzy C-means both in classification rate and MSE of testing.

It can also be seen from the Table 2 that for the two feature sets of statistical and chaotic features, the chaotic features set which consists of largest Lyapunov exponent and approximate entropy describes the signals behavior better. This superiority is interpreted as the features characteristics in signals dynamics modeling. Therefore it can be inferred from the results given in Table 2 that by a fuzzy neural network we can model the dynamics of EMG signals with chaotic features better than the statistical features and this issue demonstrates the nonlinear complex dynamics of these biological signals.

Conclusion

Three classifiers as feed forward neural network, fuzzy neural network and fuzzy C-means were used to model the dynamics of electromyogram signals recorded from biceps, triceps and quadriceps muscles in the isometric contraction state, maximum voluntary contraction and dynamic contraction. A preprocessing filtering process was first applied to the recorded signals and a number of windows consisting of 20,000 samples (10 seconds) were made cut off for each signal to be processed and analyzed. It was shown that among the classifiers used in our experiments, fuzzy neural network with two Gaussian-shaped fuzzy membership functions for each input node yields the best classification rates and also the lowest MSE values averaged over the samples. It was also demonstrated that for the same number of features, chaotic features characterize the signals better than the statistical features. This issue illustrates the chaos in the dynamics of these biological signals which motivate us to follow this issue in the future in processing and analyzing EMG signals with more complicated chaotic features as correlation dimension, Lyapunov spectrum and other types of entropies like Kolmogorov entropy.

ACKNOWLEDGMENT

The authors state that this project has been supported financially by Borujerd branch, Islamic Azad University, Borujerd, Iran.

Conflict of Interest

None declared.

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