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Classification of EMG using Lyapunov and Hurst Exponent

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ABSTRACT: An electromyogram (EMG) measures the electrical activity of muscles at rest and during contraction. Nerve conduction studies measure how well and how fast the nerves can send electrical signals. EMGs have large variation and nonstationary properties. There are two issues in the classification of EMG signals. In EMG's diseases recognition, the first and the most important step is feature extraction. In this paper, six non-linear features have been used to classify EMG signals of isometric contraction for two different abnormalities under Neuropathy and Myopathy. From the experimental results, Lyapunov exponent and Hurst exponent is the best feature with higher accuracy comparing with the other features, whereas features like Capacity Dimension, Correlation Function, Correlation Dimension, Probability Distribution & Correlation Matrix are useful augmenting features.

KEYWORDS: Hurst exponent, Lyapunov exponent, Myopathy.

I. INTRODUCTION

Movement and position of the limbs are controlled by the electrical signals travelling forward and backward between Muscle fibers, Peripheral and Central Nervous System [1],[2]. Conscientious Registration and interpretation of these muscle electrical potential is called as Electromyogram (EMG).

Due to the emanation of Pathological condition in motor system, whether in spinal cord, the motor neuron, the muscle or the neuromuscular junction the characters of electrical potentials generated during the contraction and relaxation of muscles changes [4]. Careful registration and study of electrical signals in muscles thus can be valuable aid in discovering and diagnosis abnormalities not only in muscles but also in the motor system as a whole [3][6]. A more quantitative approach emerged, where features such as potential duration, peak-to-peak amplitude, and number of phases were measured on the paper records and compared with a set of normal data gathered from healthy subjects of all ages.

EMG is recorded with the help of two types of electrodes EMG can be recorded by two types of electrodes which are an invasive electrode called as wire or needle electrodes and a noninvasive electrode called as surface electrode [26]. Use of lotions and creams on skins for 24 hour is avoided prior to EMG recording. EMG is a main nerve diagnostic tool used in Electro diagnostics medicine and in clinical neurophysiology. EMG test collect information about injured nerves, damaged nerves and muscle disorders leading to symptoms like numbness stinging, burning pain and weakness. EMG test is a valuable diagnostics tool which provides a real map for physicians which will help to evaluate locate and treat neuromuscular disorders. Muscle diseases are mainly categorized by their clinical appearance. At the beginning of 1990's long lasting classifications of disease were based on the genetic abnormalities muscle and further it is also classified on the basis molecular abnormalities [27-28].

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Myopathy is a main muscular disorders . Myopathy is diseases of skeletal muscle which are not the cause of nervous disorder. These diseases cause the skeletal or voluntary muscle to become weak or weakest. Myopathy is usually degenerative, but they are sometime caused by drug side effects, chemical poisonings, or a chronic disorder of the immune system.

This paper we are trying to introduce and explain chaotic dynamics, in biomedical systems. A brief description of Chaos parameters and some other nonlinear parameters for the classification of various diseases are as given below [11], [12].

EMG classification is one of the most difficult pattern recognition problems because there usually exists small but numerous variations in EMG features, which leads to difficulty in analyzing EMG signals. In muscles diseases recognition, there are two main points, namely *feature selection* and *classifier design*. In general, the methods of feature selection can be divided into two types: the measure of classification accuracy and the valuation using statistical criterion. After that the selection of the best features based on the proposed statistical criterion method is investigated [29].

For this purpose, we evaluate different kinds of features that have been widely used in EMG diseases recognition. The results of this evaluation and the proposed statistic method can be widely used in EMG applications such as control of EMG robots and prostheses or the EMG diagnosis of nerve and muscle diseases[7],[8],[9].

II. DATA SELECTION

A. Experimental Protocol

The EMG signals were recorded under usual conditions for MUAP analysis. The recordings were made at low (just above threshold) voluntary and constant level of contraction. A standard concentric needle electrode was used. The EMG signals were recorded from bicep brachii of bicep. The high and low pass filters of the EMG amplifier were set at 2 Hz and 10 kHz for 11msec duration with sampling frequency of 10 kHz [5].

III. PROPOSED METHOD

In this paper, we describe each of the following steps involved for the classification of the acquired EMG signal. These steps are: (A) Base line shift for accurate estimation of parameters. (B) Butterworth band pass Filter for attenuating low frequency noise (DC Offset Voltage) & high frequency noise (instrumental noise). (C) Notch filter for removing DC power line interference [22]. (D) Various parameters/features calculation.

A. Base Line Shifting

Generally human being produces static current which will interfere while recording EMG signal. Due to this problem EMG signal shifts upper side from the base line. This defect occurs due to the muscle tension, body movement or some environmental noise [23-25]. For removing this problem, base line of EMG is shifted to zero line. This will optimize the result .

B. Butterworth Filter

Butterworth filters are one of the most commonly used digital filters in motion analysis. They are fast and simple to use. Since they are frequency-based, the effect of filtering can be easily understood and predicted. Choosing a cutoff frequency is easier than estimating the error involved in the raw data in the spline methods. This section contains pages related to Butterworth digital filters: low-pass, band-stop, etc.

C. Notch Filter

A notch filter is a band-stop filter with a narrow stopband (high Q factor). . A notch filter is used to remove 50 HZ power line interference since its a significant noise appears during EMG acquisition..

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D. Feature Extraction & Calculation

1. Lyapunov Exponent

It is measure of rate of separation of infinitesimally close trajectories for dynamical system. It gives the rate of exponential divergence from perturbed initial conditions. It is a measure of the rate at which nearby trajectories in phase space diverge [19]. Chaotic orbits have at least one positive Lyapunov exponent. For periodic orbits, all exponents are negative. It is zero near bifurcation. In general there are as many exponents as there are dynamical equations. Only the most positive exponent is calculated here. Its unit is bits per sample. Thus a value of +1 means separation of nearby orbits doubles on the average in the time interval between data samples. The displayed error is estimated from 2.5 times the standard deviation of the slope divided by the square root of the number of trajectories followed [20-21].

2. Hausdorff Dimension

It is also known as Capacity dimension. It is calculated successively dividing the phase space with embedding dimension D into equal hypercubes that are occupied with data points with respect to the log of the normalized linear dimension of hypercubes.

3. Correlation Dimension

It is a method to determine the dimension of space occupied by sets of random points [10], [11]. It provides a good measure of the complexity of the dynamics, i.e. of the number of active degrees of freedom. With each pass through the data, a new data point is taken and a hyperdimensional sphere of embedding dimension d and radius r is centered on that point. The fraction of subsequent data points in the record within that sphere is then calculated for various values of r , and a plot is made of the log this number with the log of the radius. The correlation dimension is a characteristic of the underlying invariant measure μ . In a certain sense it characterizes how smoothly μ is distributed over the attractor: if μ is a point measure, then $\alpha = 0$, and if μ is absolutely continuous with respect to Lebesgue measure, then α equals the topological dimension d of X . These are two boundary cases, in general $0 < \alpha < d$.

4. Correlation Matrix

Singular Value decomposition begins with the correlation matrix which is a two dimensional matrix formed by putting the value of the correlation function with $\tau=0$ along the diagonal and putting of the value of the correlation function with $\tau=1$ to the right and left filled [13]. The Eigen values are determined.

5. continuous Probability density Function

It shows the probability of occurrence of certain data values. We can specify a number of bins between 2 and 128 into which data points are sorted according to their value. The bins all have the same width and are spread uniformly between the lowest and highest data value [12].

$$F(x) = F(x) = \int_{-\infty}^x f(t) dt$$

6. Hurst Exponent

It is referred to as the "index of dependence," and is the relative tendency of a time series to either strongly regress to the mean or 'cluster' in a direction. The Hurst exponent is used as a measure of the long term memory of time series, i.e. the autocorrelation of the time series. Where a value of $0 < H < 0.5$ indicates a time series with negative autocorrelation (e.g. a decrease between values will probably be followed by an increase), and a value of $0.5 < H < 1$ indicates a time series with positive autocorrelation (e.g. an increase between values will probably be followed by another increase). A value of $H=0.5$ indicates a true random walk, where it is equally likely that a decrease or an increase will follow from any particular value (e.g. the time series has no memory of previous values) [17].

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$$E \left[\frac{R(n)}{S(n)} \right] = Cn^H \text{ as } n \rightarrow \infty$$

where

$\left[\frac{R(n)}{S(n)} \right]$ is the rescaled range.

$E[x]$ is the expected value.

n is the time of the last observation

(e.g. it corresponds to X_n in the input time series).

C is a constant.

IV. RESULT AND DISCUSSION

We are classifying EMG signals for differentiating different diseases from the normal. Our classification uses features which has described above. So we are spotting some of the features which produce demarcation between different subjects [14].

- (i) The Lyapunov exponent is one of the most prominent features because it shows great variation between three groups. The table is given below [7].

TABLE1. CALCULATED LLE_s OF DIFFERENT GROUPS
LYAPUNOV EXPONENT

DATA	MYASTHENIA GRAVIS (MG)	MYOPATHY	NORMAL
1	1.0196	1.0085	1.047
2	1.0238	1.0069	1.292
3	1.0225	1.0086	1.24
4	1.0188	1.0073	1.064
5	1.0194	1.0089	1.22
6	1.0206	1.009	1.097

- (ii) Capacity Dimension is also a good feature for classifying different diseases from normal patient. The table is given below [15], [16].

TABLE2. CALCULATED CAPACITY DIMENSION OF DIFFERENT GROUPS
CAPACITY DIMENSION

DATA	MYASTHENIA GRAVIS (MG)	MYOPATHY	NORMAL
1	2.942	2.044	1.262
2	2.862	2.266	1.716
3	2.983	1.985	1.871
4	2.205	1.965	1.883
5	2.11	1.933	1.986
6	2.947	1.937	1.575

- (iii) Correlation Dimension of the signal can be successfully used to measure dimension of space occupied by sets of random points [10], [11].

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TABLE3. CALCULATED CORREALTION DIMENSION OF DIFFERENT GROUPS

CORRELATION DIMENSION			
DATA	ALS	MYOPATHY	NORMAL
1	2.241	1.976	2.067
2	2.154	1.928	1.912
3	2.036	2.05	2.087
4	2.423	2.143	2.043
5	2.277	2.064	2.082
6	2.139	1.991	2.115

(iv) Probability Distribution Function is same as histogram. In the histogram of normal, number of samples is uniform in middle region whereas histogram of Myopathy forms a bell shaped figure. But histogram of normal patient forms an inverted bell shaped figure [18].

TABLE4. CALCULATED HURST OF DIFFERENT GROUPS

HURST COMPONENT			
DATA	MYASTHENIA GRAVIS	MYOPATHY	NORMAL
1	0.63	0.8	0.61
2	0.67	0.87	0.73
3	0.76	0.87	0.8
4	0.85	0.88	0.67
5	0.86	0.72	0.82
6	0.82	0.88	0.7

(v) The next feature which is used for classification is Hurst Exponent whose table is given below [17].

V. CONCLUSION

In this present study we are analyzing the different class of EMG signals considering some of the best non-linear features. Based on the above features we can state that LLE and Hurst exponent are the best to distinguish the EMG signals. As per the authors the techniques used is a cost effective and time effective approach for analyzing the EMG signals. In future we will use machine expertise system for classifying the EMGs for detecting the diseases.

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