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Classification of Electromyography Signal for Identifying of Nerve Muscles Disorder using ANFIS

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Abstract

The Electromyography signal indicates the electrical activity and comprehensive analysis of muscles. Electromyography uses electrodes to measure the electrical activity of the heart. Extracting Electromyography(EMG) signals is a noninvasive process that opens the door to new possibilities for the application of advanced signal processing and data analysis techniques in the diagnosis of heart diseases. With the help of today's large database of Electromyography (EMG) signals, a computationally intelligent system can learn and take the place of a Neurologist. Detection of various abnormalities in the patient's Nerve to identify various Neuromuscular Disorder can be made through an Adaptive Neuro-Fuzzy Inference System (ANFIS) preprocessed by subtractive clustering. ANFIS combines both neural networks and fuzzy logic principles; it can capture the benefits of both in a single framework. Various types of neuromuscular disorders are classified: Amyotrophic lateral sclerosis (ALS),Charcot-Marie-Tooth disease, Multiplesclerosis, Muscular dystrophy, Myasthenia gravis, Myopathy, Myositis, including polymyositis and dermatomyositis, Peripheral neuropathy. The goal is to detect important characteristics of an EMG signal to determine if the patient's Neuromuscular is normal or irregular.

Keywords: ANFIS, Neuromascular Disorder, EMG,Signal Processing.

1. INTRODUCTION

Electromyographic (EMG) signal analysis plays a major role in the diagnosis of neuromuscular diseases, such as amyotrophic lateral sclerosis (ALS) and myopathy. Neuromuscular diseases changes, the shape and characteristics of the motor unit action potentials (MUAPs) and firing patterns of the motor unit (MU) are affected. There are numerous neuromuscular disorders that influence the spinal cord, nerves or muscles. Early finding an diagnosis of these diseases by clinical examination is crucial for their management as well as their anticipation through prenatal diagnosis and genetic counseling

This information's are also valuable in research, which may lead to the understanding of the nature and eventual treatment of these diseases The parametric extraction that used from EMG signals is one of the important steps to determine the feature vector. Feature selection provides the indications for choosing the best feature for classification based on several criteria. This is the reason why feature extraction plays an important role in Adaptive Neuro-Fuzzy Inference System (ANFIS) is a type of neuro-fuzzy classifier and is one of many areas of study in Computational Intelligence (CI). for the classification purpose.

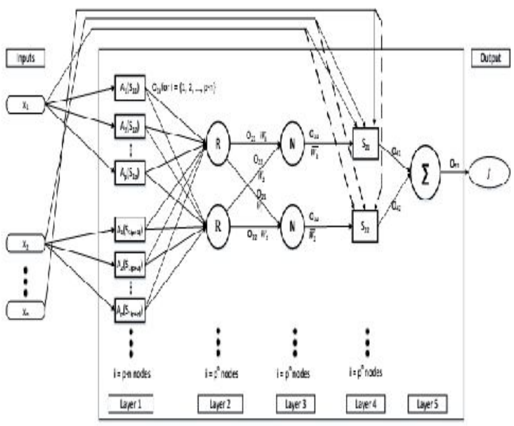

Figure 1 n-input first-order Sugeno Adaptive Neuro-Fuzzy Inference System (ANFIS)

An ANFIS, as mentioned combines the FIS with neural networks to tune the rule-based fuzzy systems. Two common FIS structures can then be applied: Sugeno or Mamdani. The Sugeno method is chosen in this thesis because it is computationally efficient, works well with linear techniques, works well with optimization and adaptive techniques, and it is well suited to mathematical analysis. The advantage of Mamdani is that it's intuitive and well suited to human input. The disadvantage of Mamdani is it's computationally expensive because another set of parameters is added to increase human interpretability. The Sugeno ANFIS has the premise part of the fuzzy rule as a fuzzy proposition and the conclusion part as a linear function. There are five layers of the structure discussed below and shown in Figure 1. A rectangle represents an adaptive node. Assuming a Sugeno fuzzy model, fuzzy-if-then rules are applied.. A first-order Sugeno ANFIS structure is used in order to output a linear function. A zero-order Sugeno ANFIS structure would output a constant parameter.

2. LITERATURE REVIEW

The study of EMG signal and its classification is an interesting topic, which has lots of scope for research. The EMG signal has been detected for various reasons in the past [10]. This area of research has been vastly explored in the last few decades. Researchers and clinicians had great difficulties [11, 12] in converting the raw EMG signal into usable signals - 6 - that can provide sufficient information about the subject. This is primarily due to the fact that technology at that time, especially in terms of hardware and software, was still unable to handle the uncertainties involved in the measurement of the myosignals. Different methods to decrease the range of pick-up and thereby potential crosstalk have been proposed. Some of them include using electrodes of smaller surface area, choosing smaller bipolar spacing and employing mathematical differentiation. Control of assistive devices and exoskeletons using EMG signals has been the focus for many researchers. Given the complexity of EMG signals for specific motion tasks, motion detection and EMG - 7 - classification is a challenging task. Many approaches to achieve efficient control using EMG signal classification had been considered, and they could generally be classified into the following main categories: (1) Neural Network (2) Fuzzy logic (3) Hybrid Fuzzy-Neural approaches and (4) Wavelet based. In 1990, Kelly et al.,[15] described some early work done to explore the application of neural networks to myoelectric signal analysis. Hopfield algorithm was used to compute the time series parameters of the moving average signal model. The performance of two algorithms, namely the Hopfield and Sequential Least Squares algorithm were compared and it was concluded that Hopfield was two to three times faster than the latter based on a typical EMG data. In 1991, SpechT [16] used neural network to discriminate hand motions for EMG-Controlled Prostheses. Here the neural network was used to learn the relation between EMG signal's power spectrum and the motion task desired by the handicapped subject. Hudgins et al., [17] analyzed the EMG signals for controlling multifunction prosthesis. Features were extracted from several time - 8 - segments of the myoelectric signal to preserve pattern structure. These features were then classified using an artificial neural network. They observed that the performance of their system enhanced due to the neural network's ability to adapt to small changes in the control patterns. Kiguchi et al. developed a fuzzy controller to control the elbow and shoulder joint angles of the exoskeleton based on the moving average value of EMG signals from arm and shoulder muscles and the generated wrist force [20]. Nearly 50 fuzzy IF-THEN control rules were designed based on the analyzed human subject's elbow and shoulder motion patterns in the pre-experiment. In 2003, the same group proposed an improved version known as the fuzzy-neuro controller and implemented a back-propagation learning algorithm for the controller adaptation. Desired joint angle and impedance of the exoskeletal system were outputs from this controller. Fuzzy logic was also used to detect the onset of EMG and to classify user intention in a multifunction prosthesis controller [1]. The fuzzy logic system did the EMG classification and based on the classification results, the controller executed the corresponding prosthesis functions. M.Clerc [3] proposed a heuristic fuzzy logic approach for multiple EMG pattern recognition in a multifunctional prosthesis control. Basic signal - 10 - statistics such as mean and standard deviation were used for membership function construction

3. PROPOSED SYSTEM

3.1. Anfis of EMG Signal

Figure 2 shows an overall approach to classification. In this case, a raw signal is first preprocessed. This means the signal is filtered and annotated. Filtering involves both a low pass and high pass filter. The low pass filter filters out unwanted noise such as power noise. Power noise is around 60 Hz. The high pass filter is used to detrend or center the signal on a base-level of zero volts in order to later extract the true amplitude of the various parts of the signal. For example, the amplitude of the wavefrom an EMG signal can be extracted and compared with the other wave amplitudes. inputs of the system consist of characteristics of the signal. Characteristics can either be annotated or calculated. Input features are composed of both temporal and amplitude characteristics of an EMG.

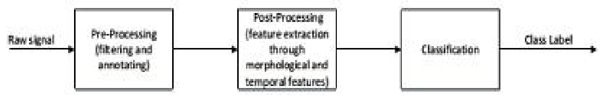

Figure 2 Process of classification

3.2. Extracting inputs features

It is necessary to annotate the signal to extract the features. The MIT-BIH website, collectively known as Physionet, holds multiple tools for analyzing and annotating various heart signals (most being EMG records). This EMG classification is based off the Arrhythmia Database . In order to begin preprocessing the EMG records of the database, the signal files had to be downloaded from Physionet's 'Physiobank Automated Teller Machine', this machine allows for a graph of each signal from 10 second-length signals to the full 30 minute-length signals. The full 30 minutelength signals were chosen for a complete analysis of each patient's record. For the purpose of analyzingthe signal in MATLAB, data ('.dat'), header ('.hea'), and annotation ('.atr') files for each record needed to be downloaded.

A MATLAB toolbox, called the Physionet Waveform Database (WFDB) toolbox, is specialized for analyzing the EMG signals. It can be downloaded from the Physionet website. This toolbox consists of functions that annotate the signal and specialized algorithms for detecting various points of an EMG signal. One of the annotation functions allow for classifying each mascular signal as normal or abnormal as determined by two cardiologists. Several records could not be simulated under the toolbox. Preprocessing MATLAB functions, some from the WFDB toolbox

3.3. Program Flow

Figure3 shows a program flowchart for classification of the EMG record(s). The program starts with choosing which EMG record(s) to classify. Normalization of the input features from the EMG signals was done through the subtractive clustering algorithm. The signal was detrended and cleansed of noise through a high and low pass filter for preprocessing.

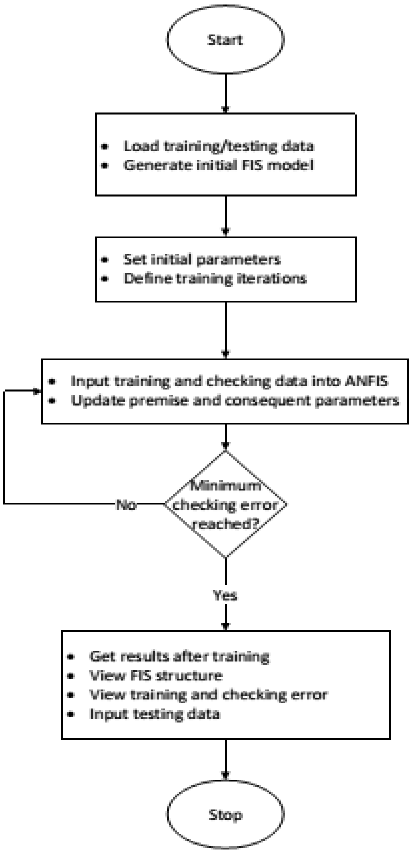

Figure 3 Flowchart of classification

Since the ANFIS has one output, the output vector is created. Each output index of the vector is assigned to a specific mascular signal type. For example, normal signala would be defined as '1' and other would be defined as '0'

3.4. Performance Evaluation Method

Accuracy, sensitivity, and specificity can be used as performance measurements to evaluate the effectiveness of a classifier. All three measurements include mascular signal that define true positive, true negative, false positive, and false negative. Let *TP* represent the true positive mascular signal classified. Let *TN* represent the true negative mascular signals classified. Let *FP* represent the false positive mascular signal classified. Let *FN* represent the false negative mascular signals classified. Let *N* represent the total number of mascular signal being classified. The three performance measurements can then be

Accuracy (%)= TP+ TN / N *100%
Sensivity(%)= TP/ TN +FN *100%
Specificity(%)=TN/ TN +FP *100%

4. RESULT AND DISCUSSION

Figure. 3 (a) to (c) show the different EMG signals.

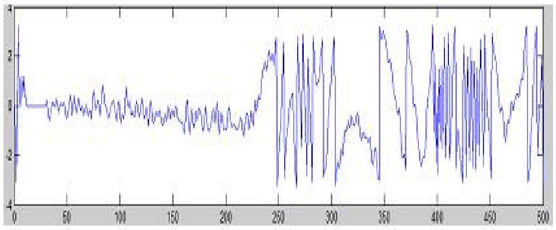

Figure 3a. Myopathy EMG signals

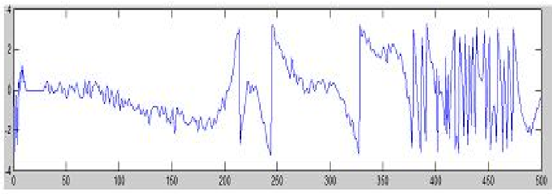

Figure 3b. NeuropathyEMG signals

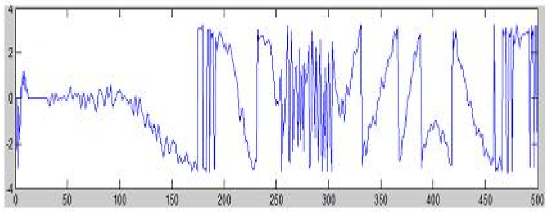

Figure 3a. Healthy EMG signals

To obtain best classification, five different methods from feature extraction were used as the input of the training. They are Autoregressive, Root mean square, Mean absolute value, Zero crossing and Waveform length. The resultof accuracy for each testing group based from each feature extraction is used to compare with other results

5. CONCLUSION

ANFIS architecture is successfully developed for identification of EMG signals. The Sugeno ANFIS is useful tool to classify the EMG signals with three different groups such as healthy, myopathy and neuropathy. The future work could use all these feature extraction technique with other classification methods such as Hybrid Classification Each has different advantage and its limitation. All these techniques can be explored further.

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