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AN IMPROVED METHOD TO DETECT COMMON MUSCULAR DISORDERS FROM EMG SIGNALS USING ARTIFICIAL NEURAL NETWORK AND FUZZY LOGIC

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ABSTRACT

Electromyogram (EMG) is a common technique to monitor neurological activities of muscle cells. Physicians visually examine lengthy EMG records to arrive at appropriate diagnosis. This is a time consuming process. At the same time we cannot rule out the possibility of missing some minutiae details of EMG. Thus automated analysis of EMG signals are important for the detection of different muscular disorders. This work is a technique for automated feature extraction and classification of EMG signals, to detect common muscular disorders into five high level categories which includes Myopathy, Amyotrophic Lateral Sclerosis (ALS), Huntington's disease and Parkinson's disease. EMG signals for this work are taken from the EMGLAB and PhysioNet databases. Both temporal and spectral features are used in this work. Length of the EMG signal is selected for optimal performance. Artificial neural network (ANN) and Fuzzy logic are used for classification. Use of Fuzzy logic in conjunction with ANN is seen to provide improved classification accuracy.

Keywords: EMG, Myopathy, ALS, Huntington's disease, Parkinson's disease, ANN, Fuzzy Logic.

I. INTRODUCTION

Electromyography is a common method for monitoring the neurological activities generated from the muscle cells [1]. When the muscle cells are neurologically activated, an electrical potential is generated and is detected by EMG. There are different types of muscular disorders prevailing in our society. Many of them are fatal and should be diagnosed at earlier stages. So we take EMG of a patient to detect the problem. Physicians may visually analyse EMG signals to arrive at appropriate conclusion. This is a time consuming process and at the same time we cannot rule out the missing minutiae details of EMG. This calls for automated analysis of EMG signals.

Various methods for the analysis of EMG signals are reported. These methods are Fourier Transform, Wavelet Transform [2], Principal Component Analysis, Independent Component Analysis (ICA), Support Vector Machine (SVM) and Artificial Neural Network [3], [4]. Each of the reported methods use only a small subset of the diverse characteristics features of EMG signals. This paper includes all the features which show the diverse characteristics of EMG signals. This study is based on extracting spectral, temporal and wavelet features which represent the hidden information of the EMG signal. The signals from EMGLAB and PhysioNet databases are taken for this feature extraction study. Features are extracted from normal EMG signals and the four sets of diseased EMG signals. These features are used for the classification of muscular disorders into five classes [5]. Firstly ANN is trained by giving the extracted features as input. Once training is completed neural network architecture is formed and by using the created network, testing of signals can be done. Output obtained from ANN is fed to fuzzy inference system to obtain improved classification accuracy.

II. MATERIALS

Data collection plays an important role in this work. Signals are taken from EMGLAB and PhysioNet database. These EMG signals includes 75 signals belonging to Normal with a sampling frequency of 23438Hz, 75 signals belonging to Myopathy with a sampling frequency of 23438Hz [6], 75 signals belonging to ALS with a sampling frequency of 23438Hz, 15 signals belonging to Parkinson's disease with a sampling frequency of 300Hz and 20 signals belonging to Huntington's disease with a sampling frequency of 300Hz. Other details of the signals are also available in the database. Designing tools used in this work are MATLAB, Neural Network (NN) toolbox, Fuzzy Inference System (FIS) toolbox and Guide (GUI) toolbox. MATLAB is the programming tool used to implement this work and NN is used for classification and FIS is used to improve the classification. The final work is made user friendly with GUI.

III. METHODS

3.1. Length of EMG signal

Choice of the length of EMG signal for analysis is an important factor which decides the quality of the features that are extracted from the signal. In the literature, no detail is available on choosing the length of an EMG signal for analysis. In many cases, a 2 second EMG signal is used for analysis. It is observed that the quality of the extracted features, in many cases, depend on the length of the EMG signal. A novel method to choose the length of the EMG signal for analysis is proposed.

A long train of normal EMG signal of a single person is the base for this work. The signal is broken down into fifty small segments of a common duration starting with one second. All features are extracted. This is repeated for different time periods of the signal. The extracted features are analyzed for best consistency. The consistency of a feature is evaluated in terms of its variance in the experimented signal segments. Duration of the signal is increased in steps of one second and feature extraction is repeated. It is seen that a signal segment of 11seconds duration is a good fit for the different features and across different diseases.

3.2. Features and their Extraction Methods

Quality of extracted features is very important in the automated analysis of muscular disorders. Spectral features included in this work are Peak Frequency (PF), Mean Frequency (MF), Total Power (TP), Mean Power (MP), Wavelet Mean (WM), Wavelet Standard Deviation (WSD), Wavelet Energy (WE) and Wavelet Average Power (WAP). Temporal features included in this work are Integrated EMG (IEMG), Mean Absolute Value (MAV), Squared Integral (SI) and Variance.

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1.Peak Frequency (PF) :- Peak frequency [7] is the frequency corresponding to the maximum amplitude in the spectral domain. The EMG signal is first subjected to a fourth level Daub 4 wavelet decomposition. An N - point FFT is applied on the signal and we get the amplitude and frequency in spectral domain and PF is computed from the obtained spectrum.

$$PF = \max(P_j),j = 1,2, \dots,M \tag{1}$$

where P_j is the spectral amplitude at the FFT point j.

2. Mean Frequency (MF) :- It is the ratio of sum of frequency multiplied with EMG spectral power to the sum of spectral power. An N - point FFT is applied on the signal and we get the amplitude and frequency in spectral domain. To obtain the power take the square of the FFT samples and MF [7] is given by,

$$MF = \frac{\sum_1^M f_j \times P_j}{\sum_1^M P_j} \tag{2}$$

where P_j is the EMG spectral power and M is the length of the signal.

3. Total Power (TP) :- An N - point FFT is applied on the signal and we get the amplitude and frequency in spectral domain. To obtain the power take the square of the FFT samples and TP [7] is calculated from the formula,

$$TP = \sum_1^M P_j \tag{3}$$

where P_j is the EMG spectral power and M is the length of the signal.

4. Mean Power (MP) :- It is the average power of the EMG power spectrum. An N - point FFT is applied on the signal and we get the amplitude and frequency in spectral domain. To obtain the power take the square of the FFT samples and MP [7] is given by,

$$MP = \frac{1}{M}\sum_1^M P_j \tag{4}$$

where P_j is the EMG spectral power and M is the length of the signal.

5. Integrated EMG (IEMG) :- IEMG [7] is the sum of absolute values of the EMG signal amplitude and is calculated using the given formula,

$$IEMG = \sum_1^N |x_i| \tag{5}$$

where x_i is the EMG signal and N is the length of the EMG signal.

6. Mean Absolute Value (MAV) :- MAV [7] is the mean of absolute values of amplitudes of the EMG signal and is calculated using the given formula,

$$MAV = \frac{1}{N}\sum_1^N |x_i| \tag{6}$$

where x_i is the EMG signal and N is the length of the EMG signal.

7. Squared Integral (SI) :- SI [7] is the sum of squared values of the EMG signal amplitude and is calculated using the given formula,

$$SI = \sum_i^N x_i^2 \tag{7}$$

where x_i is the EMG signal and N is the length of the EMG signal.

8. Variance :- Variance [7] is the average of squared values of the deviation of the EMG signal and is calculated using the given formula,

$$Variance = \frac{1}{N-1}\sum_i^N x_i^2 \tag{8}$$

where x_i is the EMG signal and N is the length of the EMG signal.

9. Wavelet Mean (WM) :- The EMG signal is subjected to a fourth level Daub 4 wavelet decomposition and wavelet mean [8] of the approximation coefficient is calculated using the formula,

$$WM = \frac{1}{L}\sum_{1}^{L} x_i \qquad (9)$$

where x_i is the wavelet coefficients and L is the length of the wavelet coefficients.

10. Wavelet Standard Deviation (WSD) :- The EMG signal is subjected to a fourth level Daub 4 wavelet decomposition and wavelet standard deviation [8] of the approximation coefficient is calculated using the formula

$$WSD = \sqrt{\left(\frac{1}{L}\sum_{1}^{L}(x_i - x)^2\right)} \qquad (10)$$

where x_i is the wavelet coefficients and L is the length of the wavelet coefficients.

11. Wavelet Energy (WE) :- The EMG signal is subjected to a fourth level Daub 4 wavelet decomposition and wavelet energy [3] of the approximation coefficient is calculated using the formula,

$$WE = \sum_{1}^{L} x_i^2 \qquad (11)$$

where x_i is the wavelet coefficients and L is the length of the wavelet coefficients.

12. Wavelet Average Power (WAP) :- The EMG signal is subjected to a fourth level Daub 4 wavelet decomposition and wavelet average power [8] of the approximation coefficient is calculated using the formula,

$$WAP = \frac{1}{L}\sum_{1}^{L} x_i^2 \qquad (12)$$

where x_i is the wavelet coefficients and L is the length of the wavelet coefficients.

3.3. Classification Methods

ANN together with fuzzy is used for classification of multiple muscular disorders. Type of classifier used is ANN to model neural biology using mathematical operations[9], [10]. It consists of neurons which are the processing elements with performance similar to biological neurons. ANN consists of three layers input layer, hidden layer and output layer. Supervised learning rule is used to train ANN. Error occurring at the ANN classifier output can be reduced by proper feature selection during training. This makes the ANN better than any other classifier.

The extracted 12 features are fed to the input layer through input neurons (number of input neurons=12), the hidden layer consists of 20 hidden neurons and the output layer consists of 5 neurons. 65% of the samples are used for training and 15% for validation and 20% for testing. Training of neural network is done using these parameters and the neural network architecture is obtained [11]. Using the obtained architecture testing is done.

3.3.1. Selection of neural network

Classification of muscular disorders using pattern recognition network and linear vector quantisation is done. Training is done using 35 signals out of 75 signals. Pattern recognition network classifier correctly classifies 71 signals out of 75 signals whereas the linear vector quantisation network correctly classifies only 55 signals out of 75 signals.

An inference is made based on correctly classified signals and finally concluded that pattern recognition neural network gives better classification accuracy than linear vector quantisation network. So this paper uses pattern recognition network for classifying multiple muscular disorders. Obtained architecture for classification of five classes is shown in Fig.1. given below.

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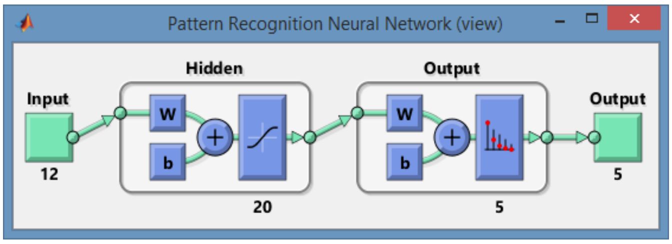

Fig 1: Neural Network Architecture

3.3.2. Fuzzy Logic

Output from ANN is given to the FIS for improving the classification accuracy. Fuzzy logic approach is used for computations based on degrees of truth. Fuzzy logic values ranges between 0 and 1. The logic for using fuzzy with ANN is that, in fuzzy the range of input from ANN and output from fuzzy can be specified with the help of membership function whereas ANN classifies the signals based on its output. Also fuzzy can interpret the relation between inputs by generating rule sets. A fuzzy inference system with 5 inputs, 5 outputs and 5 rules is made by using fuzzy logic toolbox. Different types of membership functions used in fuzzy are sigmoid membership function, trapezoidal membership function, triangular membership function etc. This work uses trapezoidal membership function at the input and output side. Trapezoidal membership function is used because the range of parameters at input and output side can be defined very clearly. The equation is given by,

$$f(a;w,x,y,z) = \begin{cases} 0\,; & a \le w \\ \frac{a-w}{x-w}\,; & w \le a \le x \\ 1; & x \le a \le y \\ \frac{z-a}{z-y}\,; & y \le a \le z \\ 0\,; & z \le a \end{cases} \tag{13}$$

where a is the input, w, x, y and z are the parameters specifying the range.

By using fuzzy inputs, fuzzy outputs and the fuzzy rules, a fis file is created with the extension .fis. Based on the obtained output from the fuzzy inference system classification of muscular disorders is done. The rule set is shown in the Table I given below. Once the fuzzy inference system is generated the output is evaluated using 'evalfis' function in MATLAB. This function evaluates the output from artificial neural network and the .fis file. Fuzzy logic designer is shown in Fig.2 below.

TABLE 1

FUZZY LOGIC RULES

Rules				
2	1	1	1	1
1	2	1	1	1
1	1	2	1	1
1	1	1	2	1
1	1	1	1	2

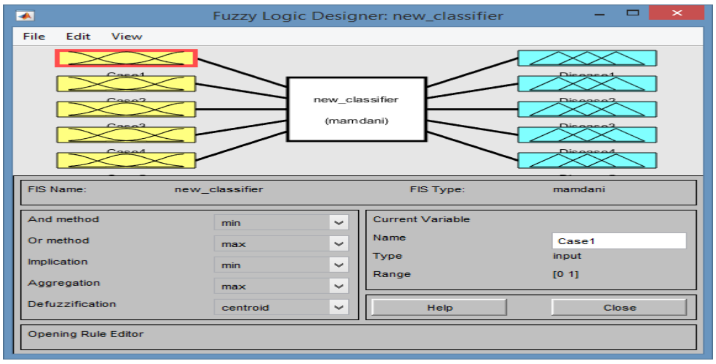

Fig 2: Fuzzy Logic Designer

IV. RESULTS AND DISCUSSION

From the EMG signal of selected signal length we extract the spectral and temporal features. The EMG signals include Normal, Myopathy, ALS, Huntington's disease and Parkinson's disease. Extracted spectral and temporal features are listed in Table II and III respectively. These obtained fundamental features gives a better result than those obtained in previous works which includes classification of signal into normal and abnormal disease. These features are fed to the classifier section which includes ANN and fuzzy logic.

TABLE II SPECTRAL FEATURES

Muscular Disorders	**Spectral Features**							
Signals	**PF (Hz)**	**MF (Hz)**	**TP (mV)**	**MP (mV)**	**WM (mV)**	**WSD (mV)**	**WE (mV)**	**WAP (mV)**
Normal	4578.1	5927.7	147.5	5178.8	0.2473	150.81	18.28	0.885
Myopathy	3898.1	5784.4	117.16	5697	0.1134	162.25	16.43	0.099
ALS	2325.9	6054.7	139.55	4134.4	0.1706	108.84	10.25	0.047
Parkinson's Disease	0.0458	89.15	6.4074	5076	23.58	12.813	0.55	0.0015
Huntington's Disease	0.087	146.8	1.1507	8901	38.66	20.91	0.945	0.0012

TABLE III TEMPORAL FEATURES

Muscular Disorders	**Temporal Features**			
Signals	**IEMG (mV)**	**MAV (mV)**	**SSI (mV)**	**VARIANCE (mV)**
Normal	377.342	57.39	293.48	0.0012
Myopathy	458.24	67.87	307.99	0.0011
ALS	430.13	72.44	325.46	0.0013
Parkinson's Disease	17.44	280.606	17.255	0.0406
Huntington's Disease	14.89	440.4	13.426	0.0576

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Classifier is tested with the signals taken from the databases. Features obtained from the EMG signals are given as the input feature vector to the ANN. Based on the extracted features from the test signal the classifier decides the class to which the signal belongs to. The paper uses two methods, method 1 includes classification using ANN and method 2 includes ANN together with fuzzy logic for classification of test signals into their corresponding classes. The performance evaluation of classifier is done using three parameters sensitivity, specificity and accuracy shown below by Tables: IV, V and VI respectively. Sensitivity gives the percentage of correct detection of diseased condition. Specificity gives the percentage of correct detection of normal condition.

TABLE IV SENSITIVITY OF SIGNALS

Sensitivity(%)	ANN	Fuzzy with ANN
Myopathy	98.66	100
ALS	100	100
Parkinson's Disease	66.67	73.33
Huntington's Disease	55	55

TABLE V SPECIFICITY OF SIGNALS

Specificity(%)	ANN	Fuzzy with ANN
Normal	97.33	98.67

TABLE VI ACCURACY

Parameter	ANN	Fuzzy with ANN
Accuracy (%)	93.46	94.61

The sensitivity, specificity and accuracy measures are calculated for both methods. First method (ANN) gives sensitivity and specificity of 91.89% and 97.33% respectively. Second method (Fuzzy with ANN) gives sensitivity and specificity of 92.97% and 98.67% respectively. Classification accuracy obtained for ANN is 93.46% and for Fuzzy with ANN is 94.61%. Thus Fuzzy with ANN gives an improved accuracy of about 94.61% than using ANN alone.

V. CONCLUSION

The paper describes the suitable method for extracting fundamental features from different EMG signals. By mathematical computations we arrive at a standard signal length of 11 seconds. FFT, Wavelets and several mathematical computations are used for extracting time domain and frequency domain features respectively from the EMG signal. The target is to classify multiple muscular disorders using these features. The main challenge to overcome in this paper is the overlapping of features. Quality of features extracted in this paper is better than those obtained in previous works. These extracted good features are used for the classification of muscular disorders. By several computations we arrived at pattern recognition neural network since it gives better classification accuracy than any other neural network. Output from ANN is fed to FIS. Based on the output from FIS the test signal is classified into their corresponding high level classes. Fuzzy logic gives an improved classification accuracy of about 94.61% when combined with ANN. As a future scope the work can be modified by classifying the high level classes like ALS and Myopathy into smaller sub-classes.

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