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A Modular Approach to Finer Classification of EMG Signals

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ABSTRACT: Electromyography (EMG) is the study of neurological activities of muscle cells and it provides a valuable assistance for diagnosis of various muscular disorders. Physicians visually analyse 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 plays an important role for detecting different muscular disorders. In this paper a modular approach for classification of EMG signals using a classifier module consisting of ANN and Fuzzy Logic is specified. Most of the reported work in this area are on Myopathy and Amyotrophic Lateral Sclerosis (ALS), with minimum analysis for other 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 Normal, Myopathy, Amyotrophic Lateral Sclerosis (ALS), Huntington's disease and Parkinson's disease. EMG signals for this work are taken from the EMGLAB and PhysioNet database. A novel method is used to find out the signal length mathematically. Spectral and temporal features are extracted from the EMG signals. These fundamental features are used in the classification section, where the classifier module classifies these features into its corresponding classes. This work achieved a classification accuracy of about 96.47%.

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]. The recording of neurological activities is known as Electromyogram and the instrument used for recording is known as Electromyograph. When the muscle cells are neurologically activated, an electrical potential is generated and is detected by an Electromyograph. EMG recorded from the muscle cells are used to diagnose neuromuscular disorders in clinical neurology. There are different types of muscular disorders prevailing in our society. Many of them are fatal and should be diagnosed at earlier stages.

EMG signal analysis and classification are done using various methods. They are Fourier Transform, Wavelet Transform [7], Principal Component Analysis, Independent Component Analysis (ICA), Support Vector Machine (SVM) and Artificial Neural Network [2], [3]. Ganesh R. Naik *et al.* proposed a method for diagnosing neuromuscular disorders using Ensemble-Empirical-Mode-Decomposition based ICA method. This method develops a fully automated EMG signal analysis systems [1]. C. J. Gallego Duque *et al.* proposed another method using DWT and k-NN for classification of EMG signals. This method allows proper classification with a small number of features [2]. Kamali *et al.* proposed classification using SVM classifiers for classification of muscular disorders which uses temporal features [3]. Brian D. Bue and James M. Killian proposed a method for predicting the presence of Myopathy from EMG signals [4]. Phinyomark *et al.* proposed a methodology for extracting the information which are hidden in the EMG signal. Redundancy of EMG features in time domain and frequency domain are pointed [5]. Subasi and Abdul Hamit proposed a method using soft computing techniques and combined features for the classification of EMG signals. This method automatically classifies the EMG signals into Normal and Myopathy [6]. Doulah *et al.* proposed a method of wavelet domain feature extraction scheme based on dominant MUAP of EMG signal for neuromuscular disease classification and performance is tested for datasets of two and three class problems [7]. Goen and Anjana proposed a method using SVM. Here Radial Basis Function Neural Network (RBFNN) has been adopted for differentiating the neuromuscular disorders [8]. Artameeyanant *et al.* proposed a method of classification of EMG using weight visibility algorithm with multilayer perceptron neural network [9]. Pattichis *et al.* proposed neural network EMG diagnostic

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models in conjunction with quantitative analysis. It provides an integrated solution to the problem of automated EMG evaluation [10]. M. R. Ahsan *et al.* proposed a method for designing, optimizing and computation of performance of ANN for the EMG signal classification. For training the neural network time and frequency domain features are used [11].

Classification in most methods is done using ANN. Also only minimum work is reported in the analysis of different types of muscular disorders. But this work uses a modular approach for classification of EMG signals using a classifier module consisting of ANN and Fuzzy Logic. This technique is based on extracting spectral and temporal features which represent the hidden information of the EMG signal. The signals from EMGLAB and PhysioNet database are taken for this feature extraction study. Features are extracted from normal EMG signals and the four sets of diseased EMG signals like Myopathy, Amyotrophic Lateral Sclerosis (ALS), Huntington's disease and Parkinson's disease. In this modular approach, classifier module classifies the signal into five classes[8]. Extracted features are given as input to ANN for training and to the trained ANN architecture fundamental features extracted from the test signals are given as input. Output obtained from ANN is fed to fuzzy inference system to obtain fuzzified output and classification of EMG signal is done based on this fuzzy output.

II. MATERIALS

In this study, EMG signals taken from EMGLAB and PhysioNet database are used for the classification of muscular disorders. 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 [4], 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. The signals are in the form of .mat file which can be directly used in the MATLAB for processing. The information regarding the signal is given in .info file. The .info file carries information like sampling frequency, sampling interval, age, samples per signals, record name, type of muscles and number of rows in the signal. 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

A. LENGTH OF EMG SIGNAL

Selection of signal length plays a very important role for determining the quality of features during EMG signal analysis. From various literature surveys it is seen that for EMG signal analysis the commonly used signal length is 2 seconds and there is no information regarding the choice of signal length. So this work uses a novel method to find out the signal length mathematically. The long train Normal EMG signal is broken down into fifty small segments of a common duration starting with 1 second. All features are extracted and the process is repeated for different time periods of the signal. The extracted features are analysed for best consistency. Duration of the signal is increased in steps of 1 seconds and feature extraction is repeated. It is seen that a signal segment of 11 seconds duration is a good fit for the different features and across different diseases.

B. FEATURE EXTRACTION METHODS

This work includes the extraction of spectral and temporal features from the EMG signals during the analysis. 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 Square Integral (SI), Mean Absolute Value (MAV), Variance and Integrated EMG (IEMG).

1. Peak Frequency (PF) : It 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 [5] is computed from the obtained spectrum.

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

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 [5] 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 [5] 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 [5] 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) : It is the sum of absolute values of the EMG signal amplitude and IEMG [5] 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) : It is the mean of absolute values of amplitudes of the EMG signal and MAV [5] 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) : It is the sum of squared values of the EMG signal amplitude and SI [5] 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 : It is the average of squared values of the deviation of the EMG signal and variance [5] 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 [6] of the approximation coefficient is calculated using the formula,

$$WM = \frac{1}{L}\sum_1^L x_i \tag{9}$$

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 [6] of the approximation coefficient is calculated using the formula,

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$$\mathrm{WSD} = \sqrt{\left(\frac{1}{L}\sum_1^L (x_i - x)^2\right)} \qquad (10)$$

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 [2] of the approximation coefficient is calculated using the formula,

$$\mathrm{WE} = \sum_1^L x_i^2 \qquad (11)$$

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 [6] of the approximation coefficient is calculated using the formula,

$$\mathrm{WAP} = \frac{1}{L}\sum_1^L x_i^2 \qquad (12)$$

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

Features from the signals are calculated using the above methods and feature vector for different features are obtained. Features from 60 signals are used as training data.

C. CLASSIFICATION METHODS

Classifier module consisting of ANN and Fuzzy is used for the classification of multiple muscular disorders. ANN is used to model biological neurons using mathematical operations [9],[11]. Neurons are the main processing elements of ANN which functions similar to that of biological neurons. ANN is trained using supervised learning rule. By proper and correct selection of features during training can reduce the error occurring at the ANN output and makes ANN better than other classifiers. ANN consists of three layers - input layer, hidden layer and output layer. Input layer is the layer through which inputs are given to ANN. Number of input neurons in the input layer is equal to the number of features that we are giving as input to ANN. Hidden layer is the layer where all computations are carried out and has no contact with the outside world. Output layer is used to obtain the output and the number of output neurons in output layer is equal to the number of classes in classification. Selection of neural network is done by trial and error method. EMG signal classification is done using pattern recognition network and linear vector quantisation. A total of 75 signals are taken for this selection purpose. 35 signals are used for training the network. 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. Based on these obtained results an inference is made that, pattern recognition neural network gives better classification accuracy than linear vector quantisation network. This work uses pattern recognition network for classifying multiple muscular disorders.

For classification, classifier module consisting of ANN and FIS is used. 60 samples are used as the training set for training ANN. 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. Training of neural network is done using these parameters and the neural network architecture is obtained [10] and using this architecture the classification of test signal is achieved. Obtained neural network architecture is shown in fig 1 below.

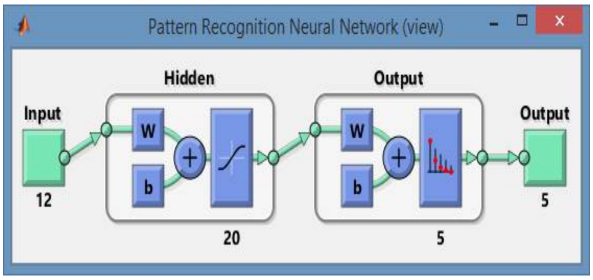

Fig. 1 Neural Network Architecture

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Feature vector from the test signal is given as input to the obtained architecture for ANN and corresponding ANN output is obtained. Obtained ANN output is given to Fuzzy Inference System. Fuzzy logic is based on degrees of truth and its value ranges from 0 to 1. In fuzzy systems, ANN output is used to set the range for membership function where low and high range values are set at the input and output side of membership function respectively. It also consists of rule set which are used to specify the relation between inputs. Different membership functions used in fuzzy are sigmoid, trapezoidal, triangular etc. This work uses trapezoidal membership function because the range of values can be clearly specified at input and output side. Trapezoidal membership function is given by equation 13.

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

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

ANN output with 5 values is given as input to FIS. FIS with 5 inputs, 5 outputs and 5 rules are made. Based on the input, output and rule set given to the fuzzy system a '.fis file' is created. In MATLAB 'evalfis' function is used to evaluate the output from ANN and the .fis file. Using this fuzzy output classification of EMG signals is done. Based on the obtained fuzzy output from FIS, classification of multiple muscular disorder is achieved. Thus classifier module classifies the signals into five classes which includes Normal, Myopathy, Amyotrophic Lateral Sclerosis (ALS), Huntington's disease and Parkinson's disease. FIS and Rule set are shown in fig 2 and Table I respectively.

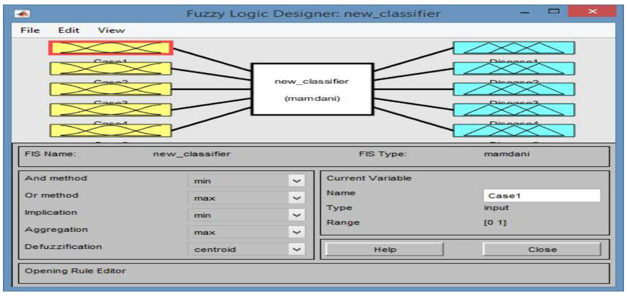

Fig. 2 Fuzzy Inference System

Table I Rule Set

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

IV. RESULT AND DISCUSSION

Spectral and temporal features are extracted from 11 second long EMG signal. The EMG signals includes Normal, Myopathy, ALS, Huntington's disease and Parkinson's disease. Extracted spectral and temporal features are listed in Table II, III and IV 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 module consisting of ANN and fuzzy logic. Test signals are given to classifier module for classification. These fundamental feature vectors from test signal are given as input to ANN which classifies the signal into the group it belongs to. Classification includes detection of common muscular disorders into five classes which includes Normal, Myopathy, ALS, Huntington's disease and Parkinson's disease.

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Table II Spectral Features I

Muscular Disorders	Spectral Features I			
Signals	PF(Hz))	MF(Hz)	TP(mV)	MP(mV)
Normal	4578.1	5927.7	147.4546	5178.8
Myopathy	3898.1	5784.4	117.1632	5697
ALS	2325.9	6054.7	139.5589	4134.4
Parkinson's disease	0.0458	89.1464	6.4074	5076
Huntington's disease	0.087	146.7994	1.1507	8901

Table III Spectral Features II

Muscular Disorders	Spectral Features II			
Signals	WM (mV)	WSD (mV)	WE (mV)	WAP (mV)
Normal	0.2473	150.8182	18.2847	0.8846
Myopathy	0.1134	162.2579	16.4374	0.0995
ALS	0.1706	108.8428	10.2518	0.0472
Parkinson's disease	23.5868	12.8129	0.5502	0.0015
Huntington's disease	38.6628	20.9094	0.9445	0.0012

Table IV Temporal Features

Muscular Disorders	Temporal Features			
Signals	IEMG (mV)	MAV (mV)	SI (mV)	Variance (mV)
Normal	377.342	57.3972	293.4794	0.0012
Myopathy	458.2406	67.8703	307.9908	0.0011
ALS	430.1351	72.4449	325.4598	0.0013
Parkinson's disease	17.2491	280.6063	17.2557	0.0406
Huntington's disease	14.8976	440.4	13.4266	0.0576

Accuracy, sensitivity and specificity are the evaluation parameters used in this work and are shown below by Tables V, VI and VII respectively. Classifier Module gives sensitivity and specificity of 94.95% and 98.67% respectively and

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classification accuracy of 96.47%. Thus the overall classification accuracy achieved by this modular approach is about 96.47%. When compared with literature surveys better classification accuracy is obtained for this modular approach.

Table V Sensitivity of Signals

Sensitivity(%)	**Classifier Module**
Myopathy	100
ALS	100
Parkinson's disease	73.33
Huntington's Disease	73.33

Table VI Specificity of Signals

Specificity (%)	**Classifier Module**
Normal	98.67

Table VII Classification Accuracy

Parameter	**Classifier Module**
Accuracy (%)	96.47

This work is made more user-friendly with the help of Graphical User Interface (GUI). GUI model consists of input parameters (input signal and the corresponding sampling frequency), the graphical display showing the selected input signal, start button which holds the feature extraction and classification module, muscular disorder display showing the classified output and clear button to clear both the displays. GUI Model created for this work is shown in fig 3.

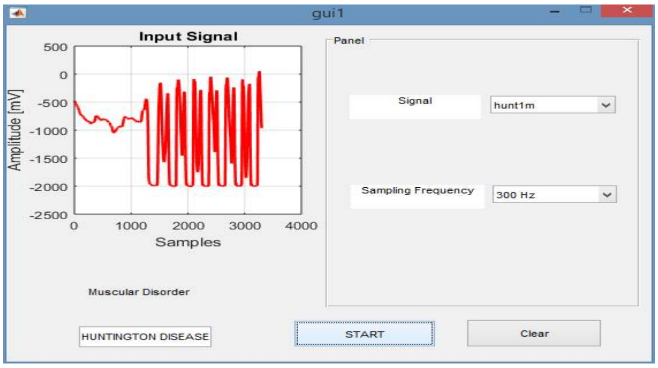

Fig. 3 GUI Model

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V. CONCLUSION

A modular approach for classification of EMG signals using a classifier module consisting of ANN and Fuzzy Logic is specified in this paper. By mathematical computations we arrived at a standard signal length of 11 seconds. Fundamental features like spectral and temporal features are extracted from the EMG signals by applying FFT, wavelets and several mathematical computations on the EMG signals. These features are used to classify multiple muscular disorders. The main challenge to overcome in this paper is the overlapping of features. Quality of the features extracted in this paper is better than those obtained in previous works which includes feature extraction for classification of normal and abnormal signals. ANN and Fuzzy logic is used for classification of EMG signals. This work uses pattern recognition neural network since it gives better classification accuracy than any other neural network. ANN output is given to FIS where the .fis file and ANN output is evaluated using 'evalfis' function and based on this obtained fuzzy output classification of EMG signal is achieved. Classification module classifies the EMG signal into five classes like Normal, Myopathy, ALS, Huntington's disease and Parkinson's disease. When compared with literature surveys better classification accuracy is obtained for this modular approach for the classification of Normal and four muscular disorders. Overall classification accuracy achieved by using this modular approach is about 96.47%. As a future scope this work can be modified by adding another classifier module which classifies the high level classes like ALS and Myopathy into smaller sub-classes.

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