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Neuromuscular Disease Detection by Classification of EMG Signals using Statistical Features Set

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ABSTRACT

Electromyography (EMG) signaling is the electrical expression of neuromuscular activation, which is the access to physiological processes that help muscles to produce energy foractivities. EMG has non-fixed features. For classification of EMG signals there two issues. One is feature selection, the other is design of classifier. In the detection of EMG diseases, the first and most important step is feature extraction. In this paper, the features include mean, standard deviation and variance is used to classify the signal for normal and two different abnormalities, which occurs under neuropathy and myopathy. For the classification design problem, we apply the Probabilistic neural network classification to classify signals as mentioned above. From the experimental results, the PNN classification showed 87.52% average accuracy to classify the EMG signals of healthy, myopathy and neuropathy subjects.

Key Words: FCM, LDA, MUAP, PCA, PNN, SWT.

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INTRODUCTION

Electromyography (EMG) signal is a biomedical signal that measures electrical currents produced in a muscle during its action that reflects neuromuscular activity. Electromyographic Signal (EMG) provides an important source of information for the diagnosis, treatment and management of neuromuscular disorders. Neuromuscular diseases change, shape and symptoms of motor unit action (MUAPs). The MUAPs found in myopathic patients are characterized by very high content, peak-to-peak height and neuropathic MUAPs patients are poly-phasic, low frequency, high frequency than normal MUAPs. EMG can be recorded with two types of electrodes namely a non-invasive electrode called a wire or an electrode needle and a non-invasive electrode called a surface electrode [1]. The use of lotions and creams on the skin for 24 hours is avoided before the recording of EMG Muscle diseases are distinguished mainly by their therapeutic appearance. In the early 1990's the long-term differentiation of disease was based on genetic injury tissue and was also classified on the basis of cell trauma. Myopathy and Amyotrophic lateral sclerosis (ALS) are two major muscle disorders and 20,000 Americans have ALS, and an estimated 5,000 Americans are diagnosed with the disease each year. Myopathy is a disease of the skeletal muscle that is not the cause of neurological disorders [2] [3]. These diseases cause the skeletal or voluntary muscles to become weak or weak.

In diagnosing muscle diseases, there are two main factors, namely feature selection and classification design. In general, methods of feature selection can be divided into two types: measurement of classification accuracy and evaluation using statistical criteria. The selection of the best features will be investigated based on the proposed statistical criterion method. For this purpose, we evaluate the various features that are widely used in the identification of EMG diseases. The results of this evaluation and the proposed statistical method can be widely used in EMG applications such as EMG robots and prostheses control or EMG diagnosis of neurological and muscular diseases.

Various features have been found in the literature [4]. For example, time domain features are Mean, Standard deviation, variance, Mean Absolute Value, Modified Mean Absolute Value, Integrated EMG, Root Mean Square, Simple Square Integral, Waveform Length and Variations. The amplitude and timing and frequency domain characteristics of the surface EMG signals depend on the time and intensity of the muscle contraction. When the patient maintains a low level of muscle contraction, individual MUAP can

be easily detected. As the intensity of contraction increases, more motor units overlap different MUAPs, creating an interference pattern that neurophysiologist cannot reliably identify different MUAP structures [5]. The methods described in [6], [7] use wavelet-domain properties derived from multi-level decomposition using a filter-bank structure, which only has the analysis bank with the dubies 4 wavelet filter, and often time domain features such as zero cross-rate, twist-amplitude Ratio, Root-Mean-Square (RMS) value and Autoregressive (AR) coefficient are used [8], [9]. Several classification methods have been reported in [6], [10], such as fusion classification, multi-classification, and an SVM that provides such opportunities for each class. Current EMG signal decomposition methods successfully decompose EMG signals the signals into "approximations" and "details" at different scales.[9].
Due to the different noise and artifacts present in EMG signals, the required information is compounded within the raw EMG signals. However, if raw EMG signals are used as input in the EMG classification, the efficiency of the classification decreases. To improve the performance of the classification, researchers are using a variety of EMG features as input to the classification. To achieve the performance of classifier at optimal level, the characteristics of the EMG feature space (e.g., maximum class segmentation, visibility and computational complexity) must be considered [11].

MATERIAL AND METHODS

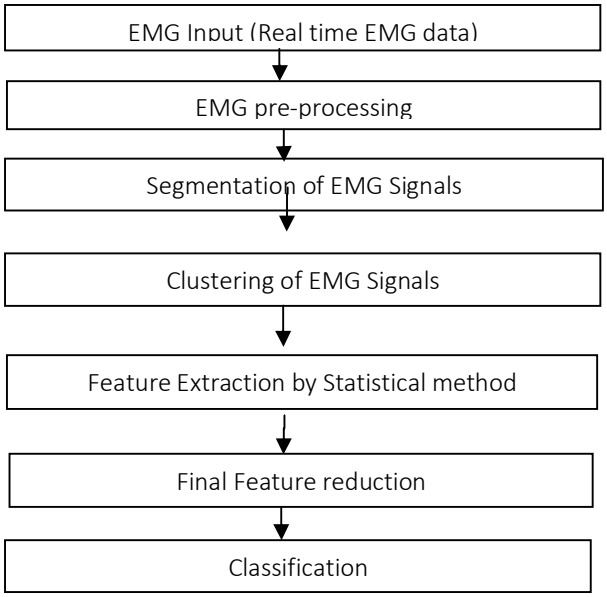

Figure 1.Block diagram of proposed work for neuromuscular disease classification.

DATA COLLECTION

The Real time EMG data set is taken from the Department of Computer Science, University of Cyprus. The standard concentric needle electrode was used to acquire the signal from NOR, MYO and MND subjects for duration of 5 seconds. All the EMG signals were acquired from the biceps brochii muscle at up to 30% of the maximum voluntary contraction (MVC) level under isometric conditions.

DENOISING OF EMG SIGNAL

After enforcing wavelet transform, we will be predisposed to left with a group of the high frequency sub bands wave coefficients. These high frequency sub bands include the information contained by the data set. Enough small details are eliminated from the data without affecting the required features of data set. Additionally, these small details are often related to noise; consequently, by putting those coefficients to zero, we are basically killing the noise. This turns into the fundamental theory in the back of thresholding-set all frequency sub band coefficients lower than a defined threshold to zero and reconstruct the information set by using the usage of inverse wavelet transformation of those coefficients.

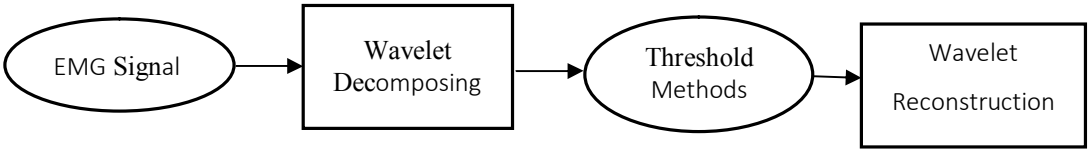

Fig. 2 Block diagram of denoising process

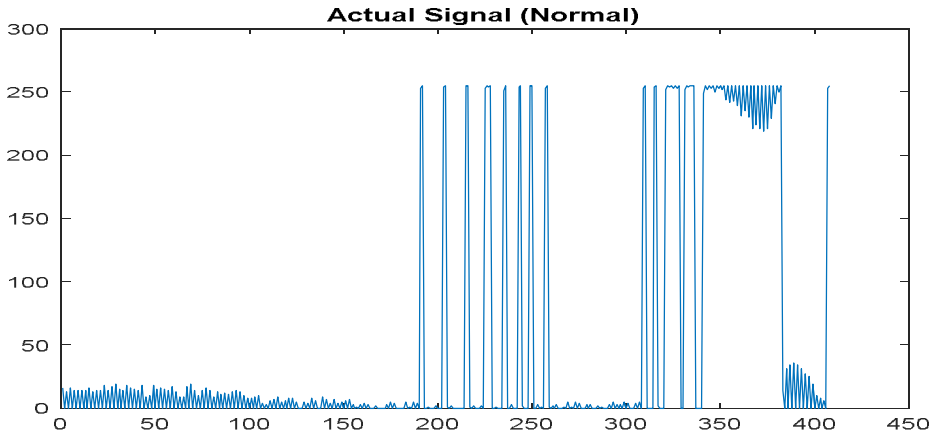

Fig.3 Raw EMG signal of Normal Subject

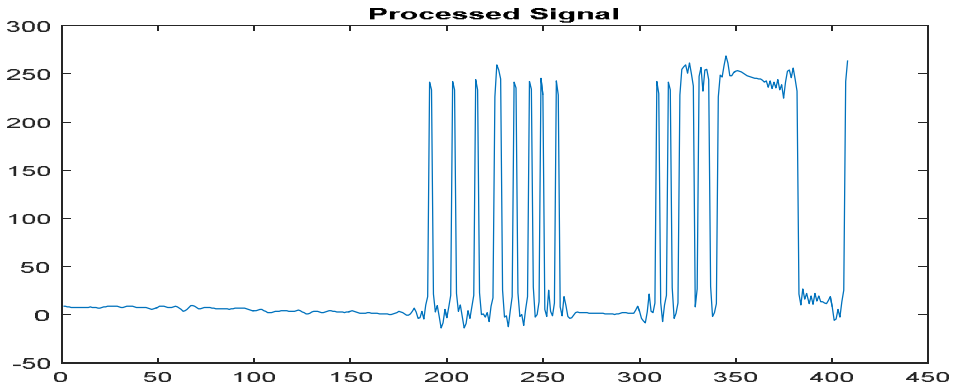

Fig4. Denoised version of Normal Signal

SEGMENTATION OF DENOISED SIGNAL

In SWT at each level high and low pass filter are applied to the data. It does not modify the filter at each level, by padding them with zeros. It is more complex to compute the data with this technique. The selection of subsets of the positions "n" and scales "m" of the mother wavelet $\Psi(t)$ [12–14] is as follows:

$$\psi_{mn}(t) = 2^{\frac{m}{2}} \psi(2^m t - n) \quad \text{..... (1)}$$

Positions and dyadic scales (nand m are integers) are based on powers of two. Wavelet for any function is shaped through dilation of $\Psi(t)$ with a coefficient 2^m (from (1)) resulting in the translated interval on a grid proportional to 2^{-m} . By correlating the actual signal with wavelet function of various sizes, the details of the signal are acquired at several scales. This hierarchical scheme known as multiresolution decomposition, which separates the signals into "approximations" and "details" at different scales. The SWT retains the property that a translation of actual signal does not necessarily suggest a translation of the corresponding wavelet coefficient.

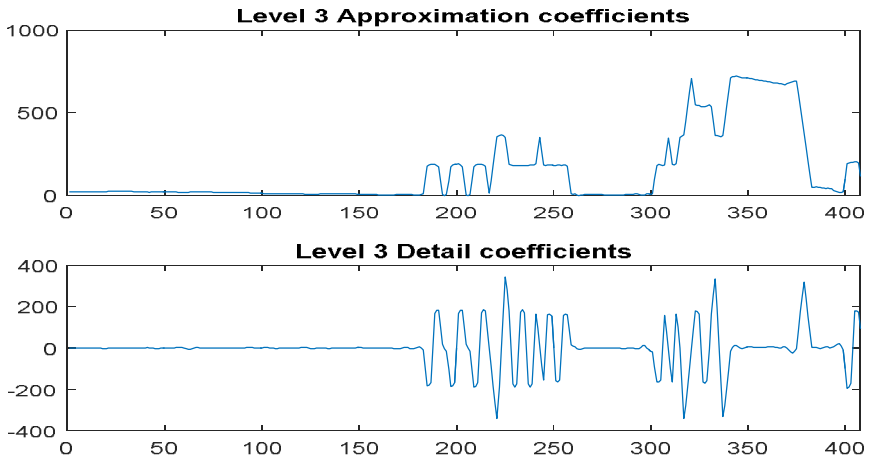

Fig5. Detailed and approximate coefficients of signal

CLUSTERING OF SEGMENTED EMG SIGNALS

For the purpose of data reduction clustering algorithms have been used. Taking the Centre of the cluster apart from each member in that cluster can resolve the problem. In FCM method, a fuzzy membership is assigned to every data point according to their distances corresponding to each cluster Centre. After each iteration, membership and cluster centers are updated by using the formula [15]:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} (d_{ij} / d_{ik})^{(2/m-1)}} \quad \text{..... (2)}$$

$$v_j = \frac{\left(\sum_{i=1}^{n} (\mu_{ij})^m x_i \right)}{\left(\sum_{i=1}^{n} (\mu_{ij})^m \right)}, \forall j = 1, 2, 3 \ldots\ldots c \quad \text{..... (3)}$$

Where 'μ_{ij}' represents the membership of i^{th} data to j^{th} cluster centre. 'v_j' represents the j^{th} cluster centre. 'c' represents the number of cluster centre. 'n' is the number of data points. 'm' is the fuzziness index m € [1, ∞]. 'd_{ij}' represents the Euclidean distance between i^{th} data and j^{th} cluster centre.

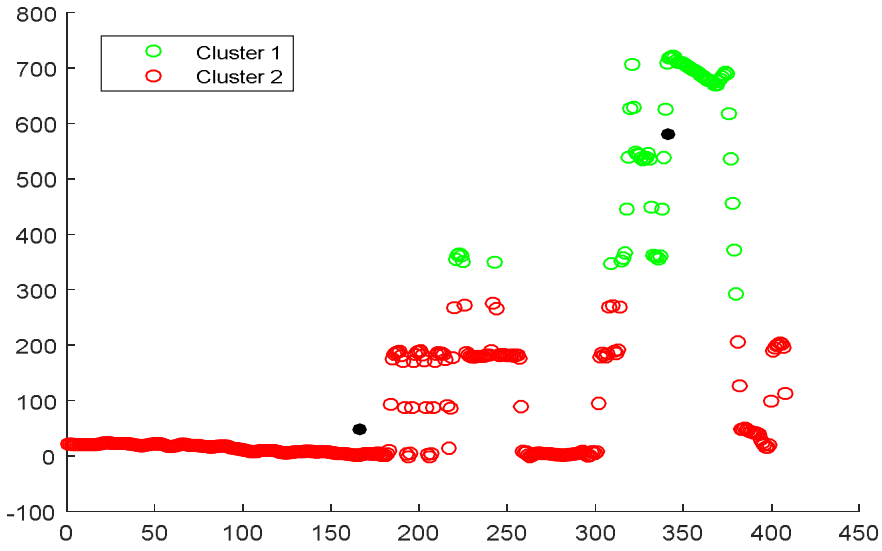

Fig.6 Signal clustered representation of normal signal

The objective of fuzzy c-means algorithm is to minimize:

$$J(U,V)=\sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{ij})^{m}\,\|x_i-v_j\|^2 \quad \text{..... (4)}$$

Where, $'\|x_i-v_j\|'$ is the Euclidean distance between i^{th} data and j^{th} cluster center.

FEATURE EXTRACTION AND REDUCTION

The following features are commonly used to identify muscle isometric contractions of the muscle brachii and can be calculated using the algorithm in the MATLAB tool:

Mean(μ):Mean is given by average sum of wavelet coefficients.

$$\mu=\frac{1}{N}\sum_{i=1}^{N}A_i \quad \textbf{..... (5)}$$

StandardDeviation: In statistics and probability theory, standard deviation shows how much variation or "dispersion" exists from the average (mean, or expected value).

$$S=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|A_i-\mu|^2} \quad \text{..... (6)}$$

Variance: In statistics, variance is a measure of variability. It is calculated by taking the average of squared deviations from the mean.

$$V=\frac{1}{N-1}\sum_{i=1}^{N}|A_i-\mu|^2 \quad \text{..... (7)}$$

The above-mentioned features are extracted using the MATLAB code for healthy, myo and neu EMG signal and are given in table 1:

TABLE 1: VALUES OF FEATURES EXTRACTED FROM PROCESSED SIGNAL

Cluster number	Features	Values
Cluster 1	Mean	572.74
	Standard Deviation	141.75
	Variance	20094.98
	Mean of Peaks	631.19
	Standard Deviation of Peaks	131.86
	Variance of Peaks	17387.55
Cluster 2	Mean	54.97
	Standard Deviation	75.57
	Variance	5711.67
	Mean of Peaks	98.80
	Standard Deviation of Peaks	99.72
	Variance of Peaks	9944.91

The EMG feature vectors of healthy, myopathy and neuropathy patients are statistically analyzed, both vectors computed using the identical function extraction algorithm and firmware setup. The device is designed with the aid of taking numerous cases of different training and testing data sets. Furthermore, the samples used in the training session will not be used in the test session. There is no overlap of the training set in the test set or vice versa.

In the present study, a feature reduction of EMG was performed by using PCA and LDA fusion structure for the purpose of classification, which is based on a number of criteria explained in the following sections. PCA can predict feature vectors from a high-dimension space onto a low-dimension, and make the variance of data maximum in the low-dimension space. A set of orthogonal basis denoted by A $(a_1, a_{2,} a_{3,} \ldots\ldots\ldots, a_m)$, is obtained, and it can project n-dimension random variables X= (X1, X2, …, Xn) for

m(m<n)-dimension random variables Y=(Y1, Y2,…,Ym)T achieving dimensionality reduction meanwhile retaining the maximum information.

$$Y = A^T X \quad \text{…….. (8)}$$

LDA reduce the vector dimension by projecting high-dimension vectors onto an optimal discriminant space to extract class information and ensures the largest between-class distance and the smallest within-class distance in projected vectors. To get a new sample Y, sample X can be projected onto the LDA optimal discriminant space, as the following equation

$$Y = W^T X \quad \text{…….. (9)}$$

For the PCA+LDA projection scheme, the matrices A and W can be sequentially obtained in the training stage, and then a sample X can be projected onto the PCA+LDA combination projected space to obtain a new sample Y, as the following equation

$$Y = A^T W^T X \quad \text{…….. (10)}$$

CLASSIFICATION METHOD

Artificial neural network techniques are the trending for classification of 1-D and 2-D signals. In literature, classification of EMG signals is done by using various techniques such as Support vector machine (SVM), principal component analysis (PCA), feed forward network at different layers (FFNN), back propagation neural network (BPNN), Logistic Regression (LR), probabilistic neural network (PNN), multilayer perceptron neural network (MLPNN), etc. [16,19].

PROBABILISTIC NEURAL NETWORK (PNN):

Multiclass problems can suitably handle by single PNN. This is opposite to the so-called one-against-the rest or one-per-class approach taken by some classifiers, such as the SVM, which decompose a multiclass classification problem into dichotomies and each chotomizer, has to separate a single class from all others [17].

TABLE2: CONFIGURATION SETUP OF CLASSIFIER WITH ITS VALUES

Sr no	Parameters	Values
1	**PNN**- Ist Layer Neuron Type	Radbas neurons
2	**PNN**- 2nd Layer Neuron Type	Compet neurons
3	**PNN**-Spread of radial basis function	0.1

In PNN architecture many interlinked processing units or neurons are organized by successive layers. The input layer simply distributes the input to the neurons in the pattern layer it does not perform any computation. On receiving a pattern x from the input layer, the neuron x_{ij} of the pattern layer computes its output is given by [18],

$$\phi_{ij} = \frac{1}{(2\pi)^{\frac{d}{2\sigma^d}}} \exp\left[\frac{-(x-x_{ij})^T(x-x_{ij})}{2\sigma^2}\right] \quad \text{…….. (11)}$$

Where d denotes the dimension of the pattern vector x, is the smoothing parameter, and x_{ij} is the neuron vector.

RESULT AND DISCUSSION

The brachial biceps muscles were used in this work because they were the frequently investigated in the different patient groups. For the purpose of detecting the EMG diseases from the given EMG data, 66 EMG datasets of 22 normal, 19 myo and 25 MND subjects are used. 408 samples of each dataset are selected in frame for feature extraction. In this paper raw data is preprocessed and denoised using wavelet. two types of experiments have done. In next phase segmentation is done for feature extraction using discrete wavelet transform. From each frame, detailed and approximate coefficients are used for features extraction. The results presented are computed using the 'sym4' type mother wavelet. These coefficients values are clustered by using Fuzzy C mean clustering which results in two clusters by assigning fuzzy membership to each value around the center. Mean, Standard deviation and variance are prominent feature set used for classification of EMG signals. To reduce the dimensionality of prominent features PCA and LDA.

TABLE3: PCA AND LDA BASED FEATURE REDUCTION

Sr No.	Actual Features	PCA Features	LDA Features
1	572.74	-4006.06	0.0245
2	141.75	-4437.05	0.0060
3	20094.98	15516.16	0.8624
4	631.19	-3947.62	0.02709
5	131.86	-4446.95	0.00565
6	17387.55	12808.74	0.7462
7	54.97	-4523.84	0.00235
8	75.57	-4503.23	0.0032
9	5711.67	1132.86	0.245
10	98.8	-4480.00	0.004240
11	99.72	-4479.08	0.00428
12	9944.91	5366.10	0.42

The classification performance was evaluated for EMG datasets (normal, myopathy and neuropathy subject). In the experiment different cases are considered by taking different ratios of training and testing data set. The average accuracy obtained from PNN classifier 87.52%, as shown in table 4.

TABLE4: PNN BASED CLASSIFICATION RESULTS

Phases	Data set taken for training and testing (%)	Accuracy (%)	Average Accuracy (%)
1	60-40	87.778	87.524
2	40-60	87.366	
3	70-30	87.333	
4	80-20	87.143	
5	90-10	88	

CONCLUSION

From the discussion above, these different types of EMG signals (both normal and abnormal) can be clearly identified by the methods described above, using the cost-effective automated classification design, which can be used as a time-efficient approach. Based on the features discussed the results of PNN shows variation in accurate classify healthy, myo and neuropathy EMG signals by changing ratio of training and testing data sets. Classification accuracy depends on the specificity of the characteristics of different classes. The PNN classification showed remarkable accuracy as the error was less than 0.05 in each case and the average classification accuracy was found to be 87.52% for healthy, myo and neuropathy EMG signals.

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