International Journal on Recent and Innovation Trends in Computing and Communication
Volume: 3 Issue: 12

ISSN: 2321-8169
6799 - 6801

Comparison between kNN and SVM for EMG Signal Classification

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Abstract— This paper shows an approach for EMG signal processing and classification as a tool to classify neuromuscular disorder. EMG signal classification is an emerging field of science and engineering providing efficient way for diagnosing neuromuscular disorder. Several techniques have been suggested for classification of EMG signals.This paper shows an approach for EMG signal processing and classification based on discrete wavelet transform as a tool to extract important information such as approximate and detail coefficients. Present work shows the comparison of kNN (k-Nearest Neighbours) and Support vector machine.

Keywords— *Electromyography (EMG), Motor unit Action Potential (MUAP)Discrete wavelet transform (DWT), Amyotrophic Lateral Sclerosis (ALS), k-Nearest Neighbours (kNN), support vector machine(SVM)*

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I. INTRODUCTION

Biomedical signals are collection of electrical signals which are generated from any organ of the human body through depolarization cell. Electromyography (EMG) is a technique for analysis and recording of electrical activities produced from skeletal muscles fibbers. There are many applications of EMG signals in biomedical field. Major interests lie in the field of clinical as well as biomedical engineering for diagnosis. EMG is used as a diagnostic tool for identifying neuromuscular disorders of patient. Earlier finding and diagnosing this disease was a difficult for their analysis through clinical counselling. The skeleton muscles composed of several thousands of muscles fibbers which are connected to the axon or motor neuron which generates the electrical activity in the muscles as shown in figure 1.

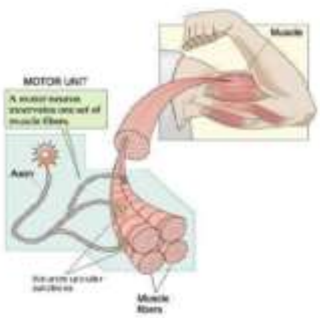

Fig 1.Muscles Composed of several thousand Muscles fibbers

Traditionally neurophysiologist and medical professionals used to access the MUAPs information from their shapes and pattern using oscilloscope [2]. But MUAPs from different motor neurons leads to overlap creating interference pattern and it is difficult to detect individual MUAP shapes perfectly due to overlapping. For this reason a number of computer based EMG signal analysis algorithm has been developed. In this work wavelet based classification scheme have adopted to classify myopathy, ALS and healthy patient signals. An unsupervised pattern classification of EMG signal using neural network is presented in [3].In this proposed work discrete wavelet transform (DWT) is used for feature extraction. EMG signal decomposition through wavelet transform is very efficient for long-term intramuscular electromyogram (EMG) signals. The decomposition software EMG-LODEC (Electromyogram Long-term Decomposition) is especially designed for multichannel long-term recordings of signals of slight muscle movements. A wavelet-based, hierarchical cluster analysis algorithm estimates the number of classes [motor units (MUs)], distinguishes single MUAPs from superposition and sets up the shape of the template for each classof neuromuscular disorder [4].

II. METHADOLOGY

EMG signal classification involves following steps, which involve reading EMG signal from raw EMG data, Feature extraction, Classification using kNN or SVM. The block diagram of proposed method shown in figure 2.

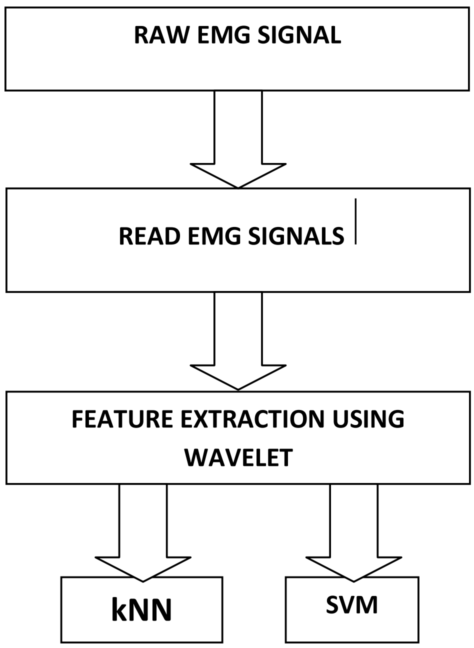

Fig 2. Block diagram of proposed work.

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III. DISCRETE WAVELET TRANSFORM

It is basically impossible to apply any classification method directly to the EMG signals, because of the large amount and the high dimension of the examples necessary to describe such a big variety of clinical situations having lakhs of samples. A set of algorithms from signal conditioning to measurements of average wave amplitudes, durations, and areas, is usually adopted to perform a quantitative analysis and description of the signal and a parameter extraction [6].

Discrete wavelet transform (DWT) is a powerful time-frequency approach which has been applied to multiple biomedical engineering signal processing applications, such as EMG. But discrete Fourier transform (DFT) which is less useful and less applicable in non-stationary signals, localized only in frequency domain and having issues with time frequency resolution. At the same time DWT is able to provide the time and frequency information at the same time, thus giving a time and frequency representation of the signal [7]. The wavelet function is shown below

$$\mathbf{X(a,b)} = \frac{1}{\sqrt{b}}\int_{-\infty}^{\infty}\mathbf{x(t)}\Psi\left(\frac{t-a}{b}\right)\mathbf{dt} \qquad (1)$$

The EMG Signal data afterreading are passed through two convolutions functions; each creates an output stream that is half the length of the original input signal. These convolutions functions are high or low pass filters; one half of the output is produced by the low-pass filter function equation (2).

$$\boldsymbol{y_1[k] = \sum_n x(n)h_0[2k-n]} \qquad (2)$$

And the other half is produced by the high pass filter function equation (3).

$$\boldsymbol{y_2[k] = \sum_n x(n)h_1[2k-n]} \qquad (3)$$

IV. K NEAREST NIEGHBOUR

A more general version of the nearest neighbour technique bases the classification of an unknown sample on the "votes" of k of its nearest neighbour rather than on only it's on single nearest neighbour. The k-Nearest Neighbour classification procedure is denoted by k-NN. If the costs of error are equal for each class, the estimated class of an unknown sample is chosen to be the class that is most commonly represented in the collection of its K nearest neighbour's sample. Among the various methods of supervised statistical pattern recognition, the Nearest Neighbour is the most traditional and powerful one; it does not consider a priori assumptions about the distributions from which the training examples are Arranged. It involves a training set of all cases of classification. A new sample is classified by calculating the Euclidean distance to the nearest training case, the sign of that point then determines the classification of the sample. The k-NN classifier extends this idea by taking the k(considered any odd number) nearest points and assigning the sign of the majority. It is common to select k small and odd to break ties (typically 1, 3 or 5). Larger k values help reduce the effects of noisy points within the training data set, and the choice of k is often performed through cross- validation. In this way, given a input test sample vector of features x of dimension n.

$$q(x,y) = \sqrt{\sum_{j=1}^{n}\left(x_j - y_j\right)^2} \qquad (4)$$

The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples as 1,2 or 3 class. In the classification phase, k is a user-defined constant, and an unlabelled vector (a query or test point) is classified by assigning the label which is most frequent among the k training samples nearest to that query point. Usually Euclidean distance is used as the distance metric.

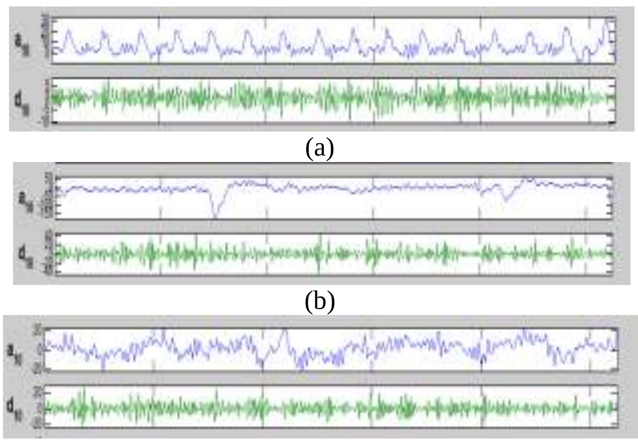
V. SUPPORT VECTOR MACHINE

SVM is a binary classifier An approach to solve this problem was to build three different SVMs one for each emotion and choose the class which gives the highest output score. If the highest output score was negative, a testing sample could not be classified through SVM. Based on this approach, different experiments with different kernel functions were performed during this research. Kernel employed polynomial is given by[9]

Kp(X,Y) = (X.Y+1)p (5)

Where p is the order of the polynomial, Classifier employs Kphave polynomial decision function, polynomial functions whose orders ranged from 2 to 3 respectively. Radial basis functions whose gamma values ranged from 2 to 6 respectively.

VI. RESULT AND DISCUSSION



(a)

(b)

(c)

Fig 5. (a) Healthy after 10 level decomposition (b) ALS after 10 level decomposition(c) Myopathy after 10 level decomposition

Figure 5 shows the EMG signal after 10 level of decomposition. The signal had 2,56,633 samples and after 10 level decomposition the overall samples are reduced to 263 samples for each signals. Healthy, Myopathy and ALS patient signals are passed through discrete wavelet transform and is shon respectively as (a), (b),and (c) in figure 5.kNN and SVM classifier produces different results. Where a randomized data sets of three classes are used. Since this data sets are randomized before input to kNNand SVM classifier each group have different samples. Out of 150 samples these classifier have different classification accuracy. The classification accuracy are tabulised in table I as shown below

TABLE I.
Overall performance Comparison kNN and fNN

Classifier	True (%)	False
kNN	82%	18%
SVM	92.33%	8%

VII. CONCLUSION

The kNN and SVM classifiers were used to classify three classes of EMG signal where the feature of wavelet were used as input. The kNN technique able to classify upto 82% accuracy, whereas SVM classifier can classify this data with an accuracy of 92.33%. This demonstrates that SVM can be efficiently used for such classification purposes. This result encouragement to develop and evaluate SVM method for quantifying the level of contribution of a neuromuscular disorder.

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