EMG Signal Classification for Neuromuscular Disorder using Soft-Computing Techniques

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***Abstract*: This paper represents the implementation of EMG classification of recorded signals from bicep muscles. The signals are collected from various patient group like normal, mayopathic and nueropathic during muscles contraction and analyzed the Electromyography using soft computing techniques that is by analyzing the time domain parameter and frequency domain parameters of a motor unit action potential (MUAP) and the symptoms of a patient. Surface electromyography (SEMG) is a complex signal, which is controlled by the nervous system and is depend on the anatomical and physiological properties of muscles. Surface electromyography Electrode (Surface electrode) at the surface of the skin collects signal from different motor units at a time, which may generate interaction of different signals. These signals get corrupted by noise while traveling through different tissues. These noises are either biological i.e. motor artifacts or environmental noises. These signals are tested by using MUAP data or normal muscle data as well as neuromuscular disease and myopathic disease. Specialists diagnose the neuromuscular diseases using visual inspection of the recorded Electromyography (EMG) of the patients and compare their shape and key points to the standard ones. This recorded signal is then processed to extract some predefined features as input to the soft computing technique. The time and frequency based extracted features are use to train the diagnosis system.**

***Keywords*: Surface electromyography (SEMG), Motor unit action potential (MUAP), Radial basis function network (RBFN), k-Nearest neigbour (k-NN), Support Vector Machine (SVM), Partical Swarm Optimization (PSO)**

I. INTRODUCTION

Skeletal or voluntary muscles constitute the principal organ of locomotion. There are more than 600 separate muscles in the human body, which constitute 40% of weight in the adults [6]. EMG can be defined as a signal that records the electric activities generated by the depolarization of muscle cells during muscle contraction, and the nerve impulses that initiate the depolarization of the muscle. The EMG signals is a type of neural signal which find its application in various applications, such as: diagnoses of neuromuscular diseases, rehabilitation through controlling assistive devices like prosthetic orthotic devices and for human computer interfacing.

Myopathy is also known as the dysfunction of muscles. Though this paper uses a particular muscle set – biceps brachii (BB), but myopathy isn‟t localised only to this area. This paper concentrates only on this muscle set. BB, or simply biceps, falls under the category of skeletal muscles. These are connected to the bones located in the upper forearm of the body. This muscle set is responsible for the two actions, namely – elbow flexion and forearm supination. For EMG recordings, both these actions were performed by the subjects.

Myopathy causes weakening of muscles it affects. Cramping, stiffness, fatigue, pain, spasms, atrophy etc., as shown in Fig. 1, are some general symptoms of this disease. BB along with other central muscles, like that of thighs and shoulders are often affected by this disease. Diagnosis of this disease is necessary so as to avoid permanent disability or paralysis in some cases. Myopathy can be detected by physicians using several techniques, of which one includes reading the aforementioned general symptoms. Other techniques include blood testing, neurological testing, biopsy, studying family disease history, EMG recording etc.

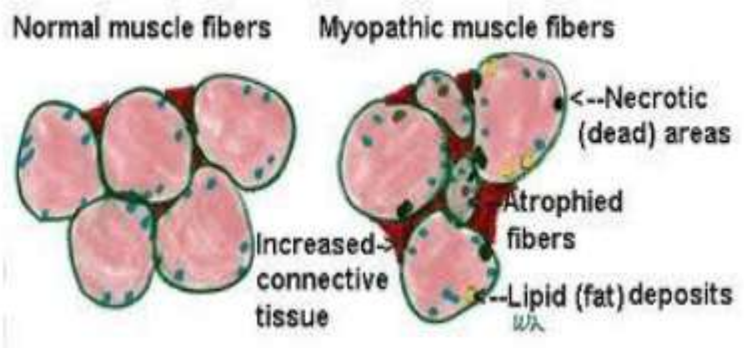

Fig. 1 Structure of Muscle fibres (Normal versus Myopathic)[1]

Electromyograph records muscular activity of a patient. And the recording is known as EMG. Surface and needle electrodes are the two ways of recording an EMG. The quantitative analysis of EMG signals also provides an important source of information for the diagnosis of neuromuscular disorders. However, there are a numbers of physiological processes which may complicate the interpretation of the recorded EMG signal. A large variation in EMG signals can be observed, having different signatures depending on age, muscles activity, motor unit paths, skin-fat layer and gesture style. Compared to other biosignals, EMG signal contains complicated types of noise that are caused by inherent equipment and environment noise, electromagnetic radiations, motion artifacts and the interaction of different tissues. Sometimes it is difficult to extract useful features from the residual muscles of an amputee or disabled. This difficulty becomes more critical when it is resolving multiclass classification problems. To maximize the classification accuracy, many researchers have studied various types of different statistical and learning algorithm-based classifiers. Beside this, number of researchers have attempted to extract more information from the EMG signals to help the classifiers for better classification of user's intended motion. A variety of signal features representing both amplitude and spectral property have been used to supplement the information given to the classifier and have been shown to increase classification accuracies.

II. THE EMG DECISION SUPPORT SYSTEM

In the case of difficult pattern recognition problems, the combination of the outputs of multiple classifiers using for input multiple feature sets extracted from the raw data, can improve the overall classification performance. In the case of noisy or of a limited amount of data, different classifiers often provide different generalisations by realising different decision boundaries. Also, different feature sets provide different representations of the input patterns, containing different classification information. Selecting the best classifier or the best feature set is not necessarily the ideal choice, since potentially valuable information contained in the less successful feature sets or classifiers may not be taken into account. The combination of the results of the different features and the different classifiers increases the probability that the errors of the individual features or classifiers may be compensated by the correct results of the rest [5]. Furthermore according to Perrone [6] the performance of the combiner is never worse than the average of the individual classifiers, but not necessarily better than the best classifier. Also, the error variance of the final result is reduced making the whole system more robust and reliable. The use of a confidence measure by weighting the individual classification results before combining can further improve the overall performance.

III. DATA ACQUISITION AND PRE-PROCESSING

Data has been generated for Normal, Myopathic and Neuropathic subjects using the simulator published as: Hamilton-Wright A, Stashuk DW. Physiologically based simulation of clinical EMG signals. IEEE Trans Biomed Eng, 52: 171-183, 2005. Myopathic/Neuropathic data has been simulated for fibre/motor unit involvement.All this data are collected form surface electrode. The recording arrangement is shown in figure below

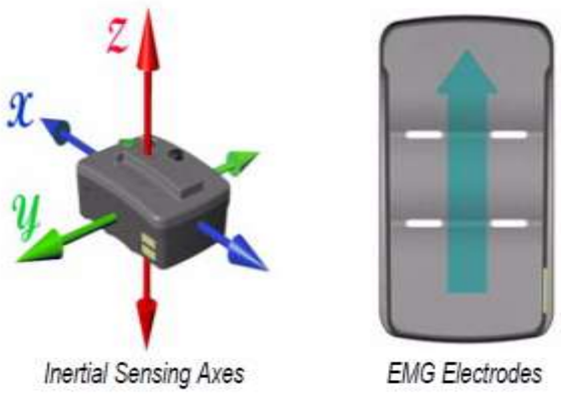

Fig.2 Arrangement multichannel recording system **surface electrode**

Segmentation:

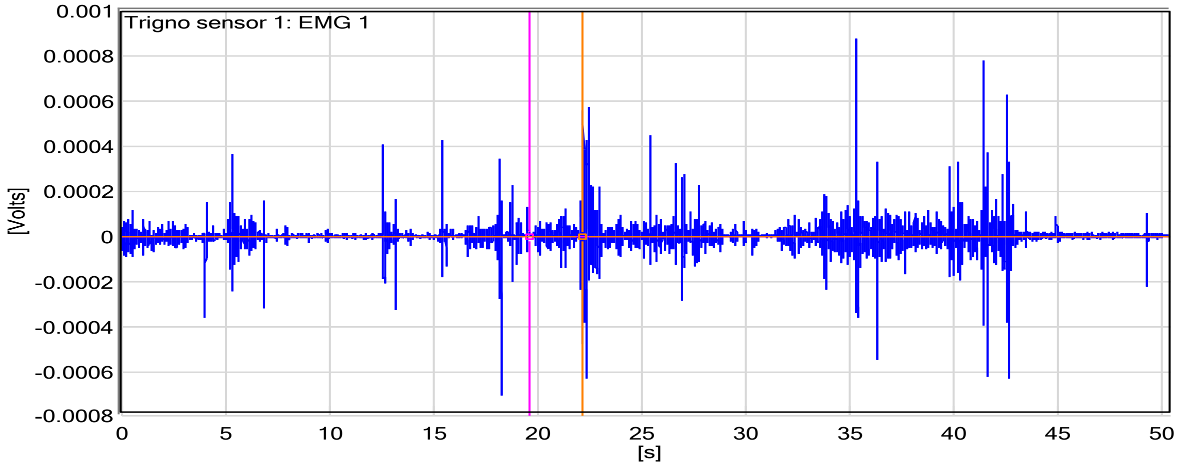

Fig.3 Raw Surface electromyogram (SEMG) signal

The EMG signal cut into segments of possible MUAP waveforms to eliminate areas of low activity [2]. The segmentation algorithm basically calculates a threshold depending on the maximum value and the mean absolute value of the whole EMG signal, The Threshold T is calculated as:

If maxi {xi}> $(30 \div L)$ $\left| xi \right| li=1$ then $(5 \div L)$ $\left| xi \right| li=1$

else maxi{xi}/5

Clustering:
In this technique the Euclidian distance is used to identify and group similar MUAP waveforms [3]. The group average is continuously calculated and is used for the classification of MUAPs using a constant threshold.

IV. FEATURE EXTRACTION

The time domain, AR parameters and correlation dimension features are calculated. The time domain parameters are computed from the MUAP waveforms: Spike duration: measured from the first to the last positive peak. Amplitude: Amplitude difference between minimum positive and maximum negative peak. Area: Rectified MUAPs integrated over the calculated. The autoregressive (AR) model a current signal x(n) is described as linear combination of previous samples x(n- k) weighted by a coefficient . A common strategy to calculate the AR coefficients is to use the Burg's algorithm. It provides an iterative and fast method to figure out the parameters of the AR-model adaptively. We have used this method in our work to find the AR coefficients a0 to a2 of a 3rd order AR model.

1. RMS and logRMS

The root mean square (RMS) value of each channel was calculated to create a 2-D feature vector. It has been argued that the response time of the control system should not introduce a perceivable delay. In the same set of data if the signal functions in a continuous f (t), which is set in the T1 ≤t ≤T_2can measure RMS of continuous functions from the equation (1)

$XRMS$= 1$T2-T1$ [(t)]12$T2T1$ .... (1)

Similarly, the log-transformed feature space, demonstrates a more uniform scattering of points compared to the untransformed RMS features of an able-bodied participant [12]. That shown by equation (2)

$XRMS$=log .... (2)

2. Centroid of Frequency

The frequency centroid is a measure used in digital signal processing to characterise a spectrum. It indicates where the centre of mass of the spectrum. The spectral centroid is the barycentre of the spectrum. It is computed considering the spectrum as a distribution which values are the frequencies and the spectrum of frequency [10].That shown by equation (3)

$\mu = \int x.p(x)\delta x$ .... (3)

3. Standard Deviation

The standard deviation of EMG signal can calculate by the sample of signal that shown by equation (4)

$$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$ .... (4)

CONCLUSION

In order to classify the clustered MUAPs into NOR, MYO and MND classes, a SVM classifier is employed. RBFN ork-NN or SVM can be used for the classification of EMG signals. The overall classification rate for RBFN is 87.3% For k-NN is 92% and for SVM is 95.25%. Statistically, SVM is a better classifier compared to RBFN and k-NN according to the classification rate achieved in the experiments. Nonetheless, BPNN still has its own advantages which beat against RNN. In the experiment, it was verified that the SVM classifier showed benefit in the selection of parameters. This demonstrates that the SVM classifier can be valuable for the capture and expression of knowledge useful to a clinician. These results provide encouragement to develop and evaluate the SVM method for quantifying the level of involvement of a neuromuscular disorder.

V. FUTURE WORK

One of the SVM tools will be developed for online classification of EMG signal for muscular diseases. With the help of neuromuscular human expertise the classified result will be verified for different pathologies. The optimization of neuromuscular disorder will be done by using particle Swarm Optimization (PSO) or Genetic Algorithm (GA) for estimating the better result of classification of different muscular disease.

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