

# Electromyography Analysis For Prediction Of Neuromuscular Disorders

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**Abstract-** The electromyographic (EMG) signal generated in muscle fibers has been the topic under substantial research in the immediate past years as it provides a fairly large amount of information for assessment of neuromuscular diseases particularly amyotrophic lateral sclerosis (ALS) and also many Neuro-muscular diseases. Besides this, the design of an accurate and computationally efficient diagnostic system remains a challenge due to variation of EMG signals taken from different muscles with different levels of needle insertion. This study offers a complete framework for accurate classification of EMG signals which includes denoising by empirical mode decomposition (EMD), feature extraction from both the time and frequency domains and classification by logistic regression (LR) and support vector machine (SVM). The presented work efficiently discriminates between the EMG signal of healthy subjects and patients with Nervous disease independent of which muscle is used for EMG signal acquisition and what insertion level of needle is. Accuracy of 95.1% is attained using LR classification technique. Performance evaluation measures such as sensitivity, specificity, F-measure, total classification accuracy and area under ROC curve (AUC) are used to validate the performance of both classifiers. These results show the competence of the proposed diagnostic system for classification of EMG signals. Moreover, the proposed method can be applied in clinical applications for diagnoses of neuromuscular diseases.

**Keywords-** Electromyography, EMG, Nuclear disorders prediction, Butterworth filter

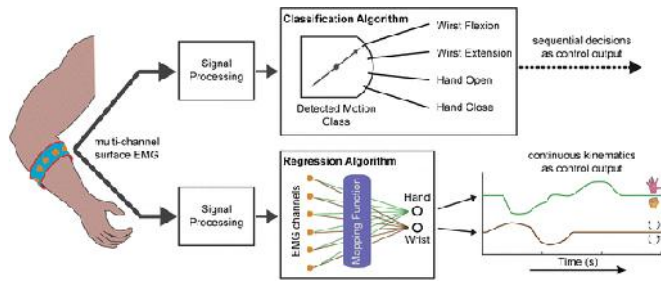
## I. INTRODUCTION

In electromyography, a needle is inserted into a muscle, and electrical activity of rest and contracting phase of the muscle is recorded. Normally, resting muscle is electrically silent. As contraction increases, the amount of muscle action potentials increases, forming an interference pattern. Denervated muscle fibers are recognized by increased activity with needle insertion and abnormal spontaneous activity electrode units are recruited during contraction, producing a reduced interference pattern. Surviving axons branch to innervate adjacent muscle fibers, enlarging the

impulse generation unit and producing giant muscle action potentials. In muscle disorders, individual fibers are affected without relation to their motor units; thus, amplitude of their potentials is diminished, but the interference pattern remains full.

[1] Qualitative EMG analysis mainly depends on subjective visually and expert advice may lead to misinterpretations. Qualitative EMG analysis can't give data for comparison and classifying EMG disorders. To overcome this, computer-based EMG algorithms have been proposed. The literature has shown a combination of classification techniques with extracted feature sets for diagnosis of muscular disorders. Applied classification techniques like conventional bipolar EMG method, linear and matrix electrode array. The highly investigated EMG Parameters are muscle fiber conduction velocity, Motor Unit Size, frequency spectrum and entropy. Pattichis et al. used a wavelet transform for extracting EMG features and applied different neural networks for EMG classification. The Time domain approach has been implemented for analysis and classification of the EMG signals.

[2] Abdulhamit et al. proposed an autoregressive system and wavelet neural network to extract different features of EMG. Katsis et al. applied SVM, Decision Tree (DT) and RBFN for EMG classification. In a combined technique of parametric power spectral and features extraction through WT is used for EMG signal analysis using neuro-fuzzy classifiers. The results of classification accuracy are between 72% to 86% in all such proposed methods. To improve classification accuracy, a quality research is needed in this particular area which will give more than 90% of accuracy. Support Vector Machine (SVM) and Artificial Neural Network (ANN) classifiers are implemented here. Both the classifiers having great predictive power are effectively implemented for medical diagnostic decision support systems. Several researchers have shown their research interest in integrating the prediction of several systems often results in a classification accuracy that is higher than that of individual systems.



**II. EXISTING SYSTEM**

Recent trend have seen a move toward evidence-based medicine to inform the clinical decision-making process with reproducible findings from high-quality research studies. There is a strong need for objective, quantitative measurement tools to increase the reliability and reproducibility of studies evaluating the efficacy of healthcare interventions, particularly in the field of physical and rehabilitative medicine. Surface electromyography is a non-invasive measure of muscle activity that is widely used in research.

This is under-utilized as a clinical tool in rehabilitative medicine. Other types of electrophysiological signals are commonly recorded by healthcare practitioners, however, EMG analysis has yet to successfully transition to clinical practice.

Thus reliable extraction of information requires knowledge of the appropriate methods for recording and analyzing sEMG and an understanding of the underlying biophysics. They are generally not covered in sufficient depth in the standard curriculum for physiotherapists and kinesiologists to encourage a confident use of sEMG in clinical practice.

In addition, the common perception of sEMG as a specialized topic means that the clinical potential of sEMG and the pathways to application in practice are not apparent.

**Disadvantages:**

1. Can be Applicable for superficial Muscular Diagnosis only.
2. Only one Dimensional analysis of impulse signals is insufficient for the Analysis of the disorders

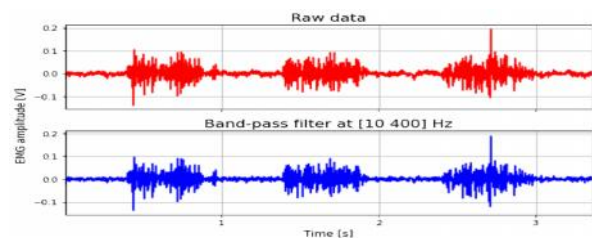
**III. PROPOSED SOLUTION**

In the proposed system, the presented work efficiently discriminates between the EMG signal of healthy subjects and patients with Nervous disease independent of which muscle is used for EMG signal acquisition and what

insertion level of needle is. Performance evaluation measures such as sensitivity, specificity, F-measure, total classification accuracy and area under ROC curve are used to validate the performance of implemented classifiers. The applied LR classification technique shows superlative performance with a classification accuracy of 95.1%. These results show the competence of the proposed diagnostic system for classification of EMG signals. Moreover, the proposed method can be used in clinical applications for diagnoses of neuromuscular disease. This enables the user to have the ability to not only stay informed and updated but that too by using one of the most sought-after technologies in the world right now. The proposed system will reduce the amount of human effort required by the user to perform previously and will offer a more exciting way of getting informed.

**3.1 Signal Filtration**

Any bioelectrical signal is contaminated by noise, be it from other electrical sources in the human body, from external sources, or by the own process of measurement. To get rid of part of this noise, we can apply a band-pass filter to only pass signals with frequencies in the desired range. A common choice for filtering EMG data it's the Butterworth filter with zero lag



**3.2 Butterworth filter**

A common filter employed in biomechanics and motor control fields is the Butterworth filter. This filter is used because of its simple design, it has a more flat frequency response and linear phase response in the pass and stop bands, and it is simple to use.

The Butterworth filter is a recursive filter (IIR) and both a and b filter coefficients are used in its implementation. Let's implement the Butterworth filter. We will use the function butter to calculate the filter coefficients:

```
butter(N, Wn, btype='low', analog=False, output='ba')
```

Where N is the order of the filter, Wn is the cutoff frequency specified as a fraction of the Nyquist frequency (half of the sampling frequency), and btype is the type of filter

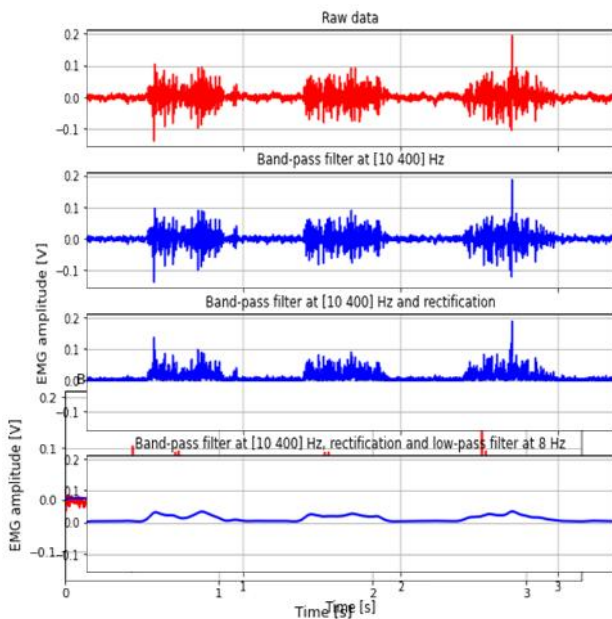
(it can be any of {'lowpass', 'highpass', 'bandpass', 'bandstop'}, the default is 'lowpass'). See the help of butter for more details. The filtering itself is performed with the function lfilter:

```
lfilter(b, a, x, axis=-1, zi=None)
```

Where b and a are the Butterworth coefficients calculated with the function butter and x is the variable with the data to be filtered.

### 3.3 Linear envelope

A common process of the EMG signal is to calculate an activation level of the signal, a process called linear envelope. The linear envelope consists in two steps: the signal is full-wave rectified by computing the absolute value of the signal; then the rectified signal is low-pass filtered with a cutoff frequency typically at the range of 3 to 8 Hz, depending of the contraction muscle characteristics and the specific application for the linear envelope processing. This last step can also be reproduced with a moving average of the rectified signal with a moving window of 100 to 200 ms of duration. Alternatively, instead of the two previous steps, a moving root mean square (RMS) with a moving window of 100 to 200 ms of duration is applied to the original signal.



### 3.4 Onset Detection:

A common operation in the analysis of EMG data is to select the period of muscle activation based on the amplitude of the EMG signal. Of course this can be done manually by showing the EMG signal on a window and the expert user manually selects the events with mouse clicks, but

a lot of research has been conducted to propose automatic methods to perform this task.

## IV. EXPERIMENTS & OUTPUT

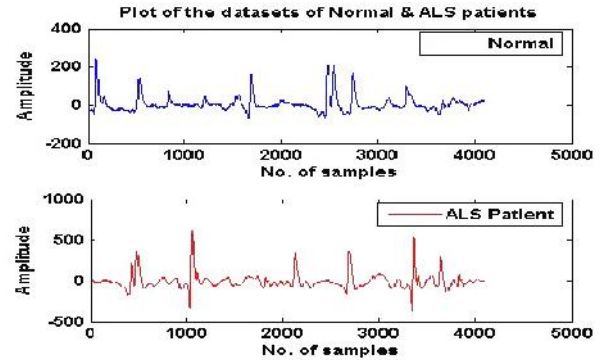
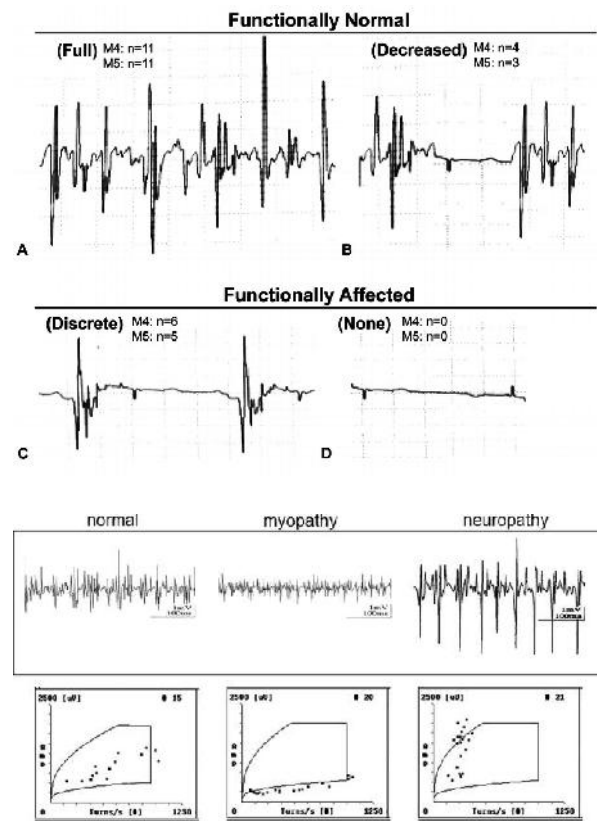
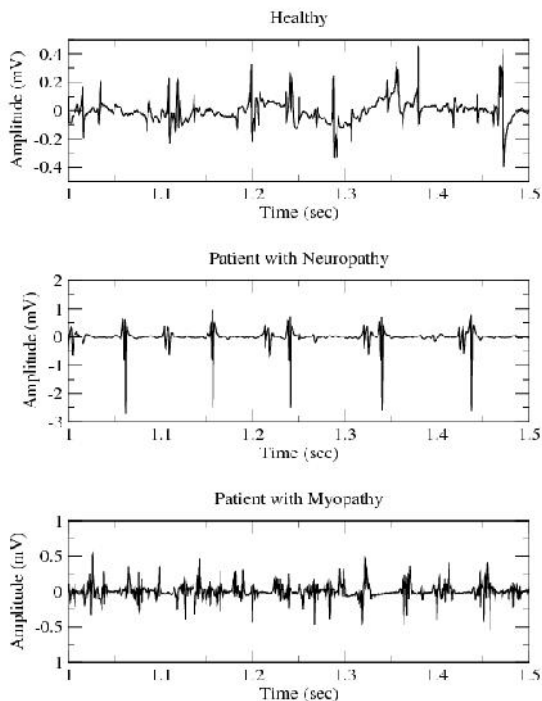


Figure 9. EMG data pattern of a normal person and the ALS patient.



- [2] Konrad P (2006) **The ABC of EMG: A Practical Introduction to Kinesiological Electromyography**. Noraxon U.S.A., Inc.



## V. CONCLUSION

Disease classification has important clinical applications. The present paper describes a new approach to deal with Neuromuscular disease classification based on AI and ANN. The results show that this has achieved high accuracy classification suitable for clinical applications. Hence, it represents an appropriate solution for the analysis of EMG signals and its use for diagnosis purposes. We can also see the effectiveness of the method used for surface EMG segmentation, named FM-ALED and the interest of voting rule on the performances of the proposed diagnostic system. However, we are aware that the fact a classifier showing 100% correct classification may be a manifestation of inadequate testing. We have achieved testing with many combinations of features and parameters on a dataset of only 17 (9 + 8) patients in ICPRAM 2021 - 10th International Conference on Pattern Recognition Applications and Methods 292 in order to find the best configuration. Our procedure is motivated by the relative limited dataset, which could be increased for example by the use of data augmentation methods.

## REFERENCES

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