Evaluating EMG Signal Characteristics for Differential Diagnosis of Myopathies to Prohibit Contractures

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Abstract: **Neuromuscular disorders, such as myopathy are a major cause of muscle weakness, fatigue and dysfunction. Electromyography (EMG) is a diagnostic tool used to identify muscle disorders based on the analysis of electrical signals from the muscles. This study based on EMG-signal analysis to differentiate between healthy individuals and myopathic patients using the software MATLAB. The methodology involves preprocessing of the bio signals through statistical analysis, Root Mean Square (RMS), peak detection, envelope analysis, Power Spectral Density (PSD), cross-correlation, and coherence analysis. Publicly available EMG datasets from PhysioNet were used for healthy individuals and myopathic patients sampled at 1kHz. Unlike other works that use machine learning and classification for this purpose, the approach in this research paper does not contain classification, which makes the analysis more interpretable and reproducible. The results show a clear difference between the healthy and myopathic signals including reduced amplitude, decreased peak distribution, lower RMS values, and lower spectral power in myopathic signals, indicating reduced muscle activity and neuromuscular efficiency in myopathic patients. These findings reveal that the use of complex algorithms for signal detection does not achieve the same sensitivity as MATLAB scripts; as a result, the interpretation of the signal's properties is straightforward, and there are no components such as deep learning.**

Keywords: **Electromyography (EMG), Myopathy Detection, MATLAB, Biomedical Signal Analysis, Clinical Neurophysiology.**

INTRODUCTION

EMG, or Electromyography, is a critical tool in rehabilitation and neurology, used to record and analyze the electrical activity produced by muscles, assessing muscle function [1]. Myopathy is a term for a group of conditions associated with muscle weakness and atrophy [2]. It refers to a group of neuromuscular disorders characterized by primary muscle fiber dysfunction, leading to muscle weakness, fatigue, and progressive loss of function.

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It has been a substantial public health concern: while the exact prevalence varies by geographical region and the subtype of the condition, recent research reports that 7 to 40 per 100,000 individuals worldwide are affected by genetic and developmental myopathies [3,4]. In some regions, particularly where genetic forms such as Duchenne muscular dystrophy are prevalent, it may reach 1 in 3,500 to 5,000 male births [5]. Its impact on quality of life can be severe, affecting the ability to walk, stand, or walk up steps, and, in the case of respiratory muscles, the capacity to breathe, and impacting the quality of life in daily work and routine (lifting weights, holding items, and remaining fit) because of exhaustion and constraint [6].

As a result, many patients require assistive devices, such as wheelchairs and ventilators, which can limit their quality of life. In a recent 2020 Neurology survey, nearly 60% of people diagnosed with the disease reported severe work limitations, and 30% were unable to maintain employment [7].

Myopathy is frequently diagnosed using black-box techniques, which are traditional design paradigms closely connected to prior learning, and do not fully understand [8]. Several recent investigations have explored different EMG signal analysis methods and different EMG signal processing computational algorithms. Although deep learning models, such as long-short-term memory networks, have been used to classify myopathic signals with high accuracy [9], they suffer from interpretation and computational complexity, as well as data dependence. This research features the significance of computational approaches for processing of EMG based bio- signals. In that context, MATLAB-based signal processing [10], which does not utilize deep learning technologies, may be a transparent, interpretable, and reproducible tool for EMG signal processing.

The novelty of this paper lies in its focus on a MATLAB-based, non-AI EMG signal analysis study that gives priority to interpretability and clinical relevance. The key contributions of this work include an analytically transparent methodology appropriate for small datasets and clinical settings, a critical assessment of traditional signal processing techniques against complex computational methods, and a systematic comparison of healthy and myopathic EMG signals.

LITERATURE REVIEW

A systematic review of previous studies reveals that machine learning has been mostly applied in EMG signal classification. Tannemaat et al. explored the use of automated Myopathy Detection using Artificial Neural Networks (ANN) with high accuracy but faced issues with data dependency and clinical interpretation [11]. Deep learning methods were implemented in another study for EMG pattern recognition. However, issues concerning feature extraction complexity and tremendous computations for the model were problematic [12]. Hybrid feature extraction was proposed using support vector machines (SVM) but required high computation and particular training sets [13]. Furthermore, withholding feature selection for EMG-based Myopathy detection was discussed in another study, but the issue of standardizing the dataset was highlighted [14].

Selvaraj et al. conducted more studies to look at how different myopathy detection feature selection problems are approached in EMG signal processing and found out that one of the signal processing features, that is, just statistical and spectral traditional methods of analysis, had the same results as machine learning with no excessive computation, unlike other EMG methods [13]. Another study presented a different approach to myopathy classification diagnosis feature extraction. This approach, however, relied on having plenty of training data [15]. Another publication demonstrated noise filtering and tedious methods for data collection and the positive outcomes [16]. This review points out towards the clear gap between methodological complexity and clinical usability and the significance of simplest software tools for the processing of bio signals for diagnostic purpose. This study addresses this gap by applying classical EMG analysis techniques using MATLAB demonstrating their efficiency without depending on artificial intelligence or classification-based models.

METHODOLOGY

This study aimed to analyze the EMG signals from normal and myopathic individuals using MATLAB. The first step of this study was the data capture phase, during which EMG signals were extracted from standard datasets and transferred to MATLAB. After that, preprocessing steps, including cleaning noise and normalization, were performed to maintain a quality standard of data. Similar pre-processing techniques were used in prior studies on EMG signal processing. For feature extraction, different methods including statistical calculations, RMS techniques, peak extraction, envelope detection, PSD calculation, and cross- correlation were used. The signals were also compared in terms of their characteristics, and this was made possible through MATLAB, which facilitated visualization and interpretation of the data by making it graphically easier. The PhysioNet repository, a reputable platform for physiological signal databases, is openly accessible and provided the EMG recordings used in this investigation (https://archive.physionet.org/cgi- bin/atm/ATM). Two datasets were chosen: emg_myopathym.mat, which represented electromyographic signals from a subject with myopathy, and emg_healthym.mat, which represented electromyographic activity from a healthy individual. Every dataset includes 40,000 samples of a single-channel EMG signal. A typical sampling frequency of 1,000 Hz was used for the analysis. However, particular acquisition information like electrode placement and sampling frequency were not specifically included in the data. EMG signals on PhysioNet are normally captured under standardized settings. To help doctors in the diagnosis of neuromuscular illnesses, these datasets were utilized to extract significant features and conduct a comparison analysis that sought to distinguish between myopathic patterns and healthy muscle activity. Given Figure 1. depicts the steps involved in accessing the information from the EMG and its categorization into a Normal or myopathic bio signal.

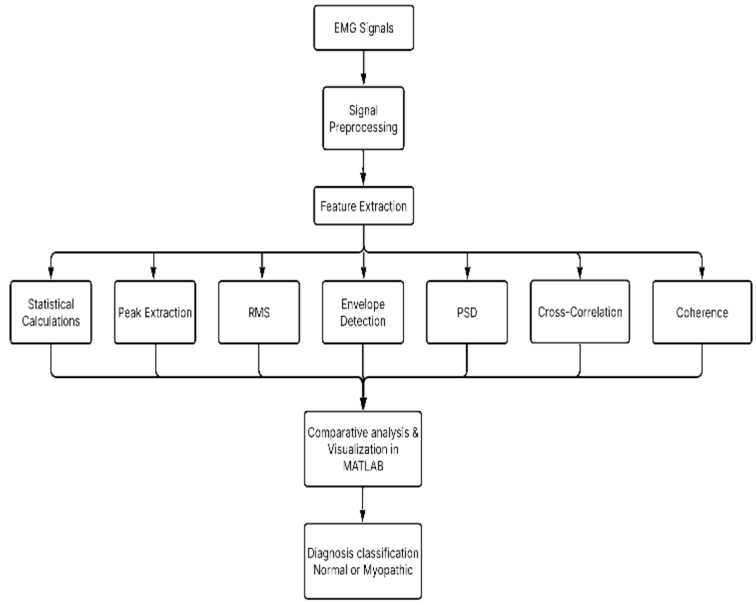

Fig. 1. Block Diagram of the steps involved in evaluating EMG signals

RESULTS AND OUTPUTS

The MATLAB approach generated outputs for further processes that were particularly important. The statistical analysis showed that the myopathy signals had a smaller mean and variance when compared to the healthy signals. Similar results were previously noted by Singh et al. [13], who observed lower statistical readings in myopathic EMG signals. The peak detection analysis demonstrated that the myopathy signals had severely reduced peaks suggesting a lower degree of muscle contractions. The myopathy signals also had significantly lower Root Mean Square (RMS) values, which suggested lower muscle activity. Moreover, the myopathy signals had a lower power in the highest frequencies, which suggested muscle wasting, corresponding to the findings from Belkhou et al. [15]. Last, with cross-correlation and coherence analysis, different patterns among normal and myopathy signals were observed, which is the achievement of the MATLAB analysis.

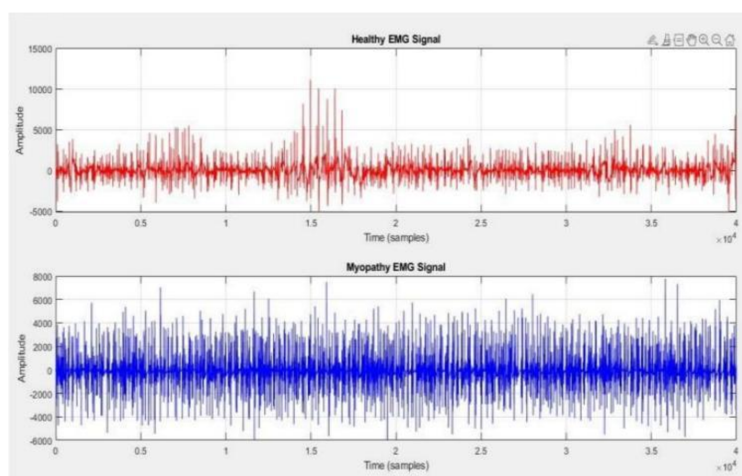

Fig. 2. Healthy Vs Myopathic EMG Graphs

Figure 2 exhibits comparison between healthy and myopathic EMG graphs. Myopathic and healthy muscles exhibit clear differences when comparing their EMG signals. A healthy EMG signal displays strong contractions with coordinated muscle movements having an amplitude of the order of ±10,000, whereas myopathy EMG signal is characterized by lower amplitude range of living with insufficiently sharp peaks around ±8,000, which reflect a less consistent and weak muscle activity. Results highlight that muscle performance was reduced which is representative by conditions of myopathic that is predictable and linked with transformed signal outlined and low amplitude.

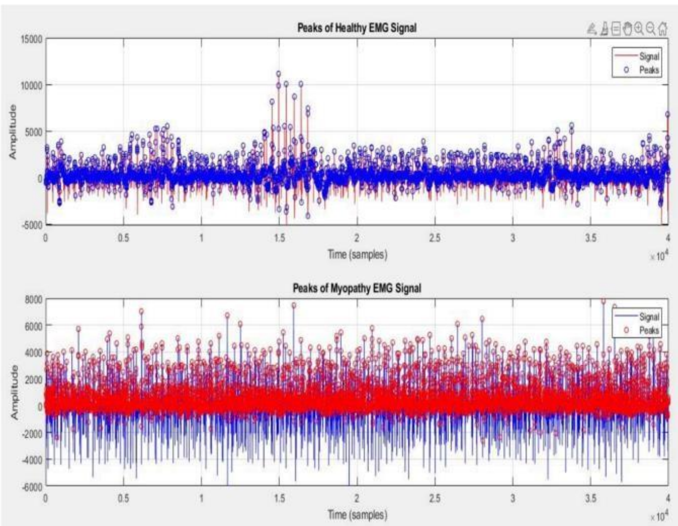

Fig. 3. Peaks of Healthy vs Myopathic EMG Graphs

Figure 3 represents the diversity in the activity of muscles through analysis of muscle signals. Those entities that are healthy or more fit EMG signal represents periodicity and peaks with greater amplitudes by signifying vigorous and steady contraction, whereas, myopathic EMG signal represents uneven peaks with minor magnitude, that shows varying and insufficient muscle fibers contractions. In particular this defines the irregular functioning of muscles in myopathy.

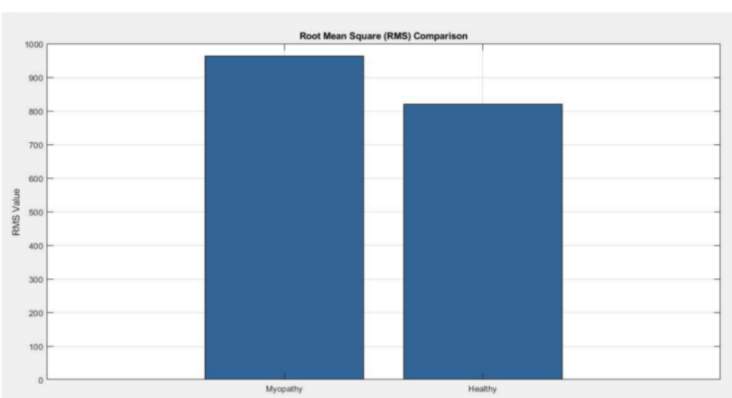

Fig. 4. RMS Comparison of Healthy and Myopathic EMG Graphs

The Root Mean Square (RMS) bar chart in Figure 4, highlights the difference of muscle activity between myopathy patients and healthy individuals. The myopathy patients have a higher RMS value around 1000 which may indicate high signal variations or different physiological response. Whereas the healthy individuals have a smaller RMS value around 800 which may indicate less variable muscle activity. The comparatively high RMS in myopathy patients shows wide fluctuations of the signal, supporting its use for the diagnosis of neuromuscular abnormalities.

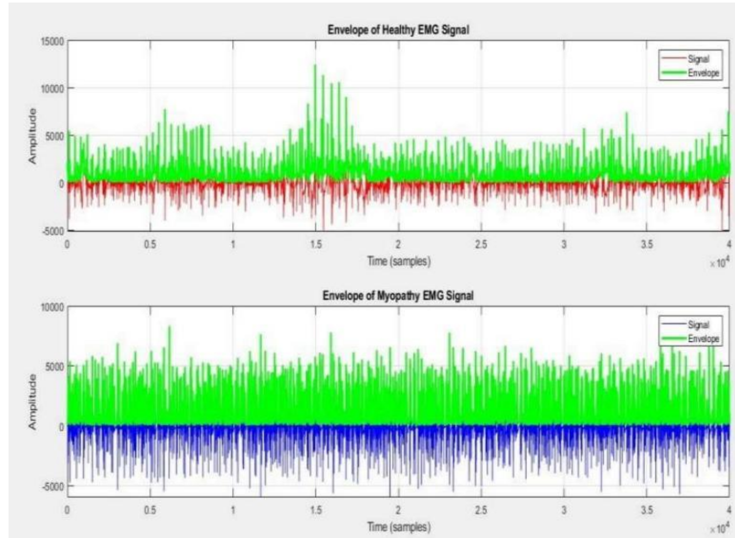

Fig. 5. Envelope Comparison of Healthy and Myopathic EMG Graphs

Figure 5 is the envelope analysis of EMG signal, highlight the muscle activity differences related to myopathic and healthy situations. The dynamic range of the healthy signals of EMG (0-15,000) represents more prominent and even oscillations. In this scenario, the EMG signal of myopathy with amplitude rang of 0-10,000 retains lesser oscillations and smooth envelope, suggesting weaker muscle contractions. The results disclose the reduced in muscle function that represents the presence of myopathy.

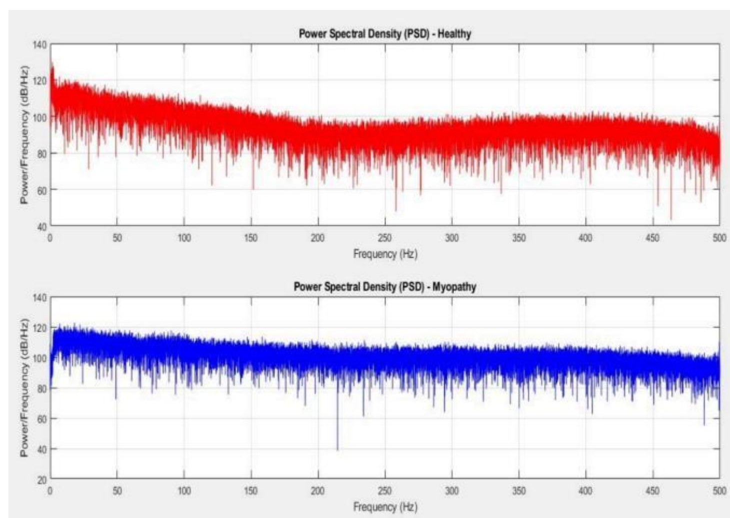

Fig. 6. PSD Comparison of Healthy and Myopathic EMG Graphs

In Figure 6, the Power Spectral Density (PSD) analysis shows the difference in the functional characteristics of the muscles between healthy individuals and myopathic patients. The PSD analysis of myopathic patients displays low levels of fluctuations and power compared to the PSD analysis of healthy individuals which displays higher peaks range of variability. These differences indicate the reduced efficiency in neuromuscular response for people suffering from myopathy.

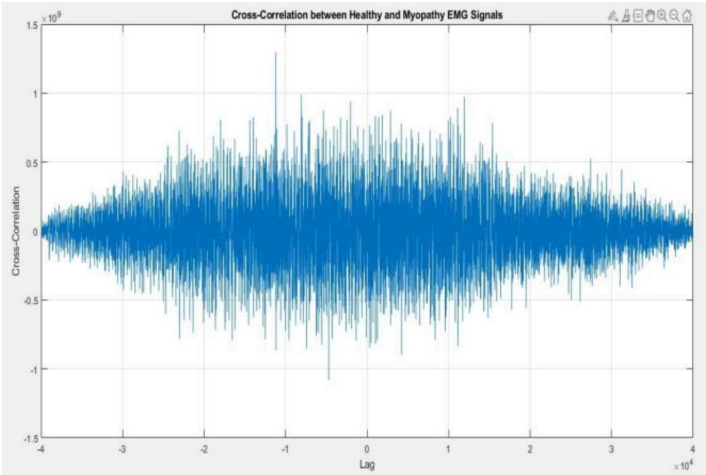

Fig. 7. Cross-Correlation Between Healthy and Myopathic EMG Signals

Cross-correlation analysis is used in Figure 7 to measure similarity between healthy and myopathic EMG signals at each of the lagged positions. In the representation above, positive spikes show the correlation of the data and negative spikes indicate how similar the data is. Concurrently, positive spikes at zero lag indicate high similarity whereas the alterations at other lags suggest altered muscle activity because of myopathy. These findings provide a significant advancement in our understanding of neuromuscular physiology for biomedical applications.

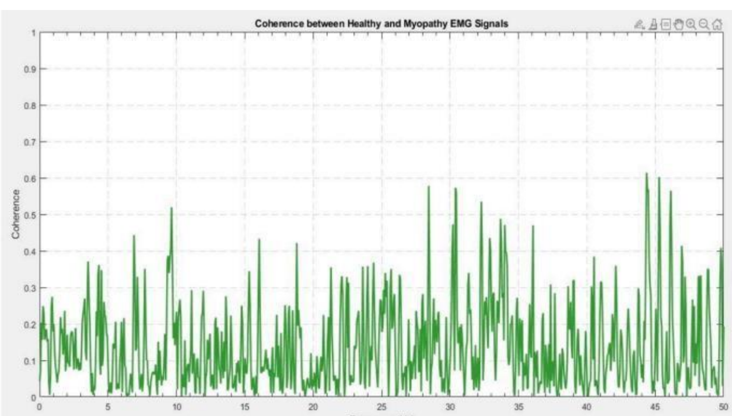

Fig. 8. Coherence Between Healthy and Myopathic EMG Signals

Figure 8 shows the analysis of coherence between healthy and myopathic EMG signals were achieved by the frequency domain i.e. (0-50Hz). The coherence is characterized by a range of 0 to 1, determining the correlation at varying frequencies. The inconstant coherence level of the graph represents the variability in low frequencies muscle activity presence. This identifies the etiology of myopathy and its effect on neuromuscular function.

DISCUSSION

Compared to other traditional methods that rely on machine learning, the MATLAB analysis remains unmatched. Machine learning models like ANN-based approach by Tannemaat et al., showed accurate results but required extensive training datasets and faced issues in the clinical interpretability [9]. Likewise, Torres-Castillo et al. highlighted that models using deep- learning approaches require computationally intensive feature extraction [10]. In contrast, MATLAB has the advantage of transparency. While machine learning works as a black-box system, MATLAB functions as an interpretable tool providing information regarding signal processing and signal properties to clinicians and researchers which is straightforward, logical, and can be analyzed directly. Additionally, unlike machine learning, which relies on large training sets, MATLAB- based analysis works well independently of datasets, which is ideal for smaller sample sizes, as also noted in the study by Fuglsang-Frederiksen [12]. Moreover, MATLAB works in real-time, and because it is less computationally demanding than deep learning algorithms, it can be more efficiently utilized, which is a major advantage over deep learning models as specified in the comparative studies on EMG feature extraction [11]. The last feature that requires optimization is clinical usability. This is because the output from MATLAB is more easily interpretable by medical practitioners without the need for AI-generated classifications.

This comparative analysis of healthy and myopathic EMG signals using MATLAB offers a valuable advantage. Based on these observations, we developed a model which is able to differentiate between normal and myopathic EMG patterns. This model has the potential to be combined into rehabilitation clinics, allowing clinicians to enter real-time EMG signals to recognize whether they represent healthy muscle activity or myopathy. This enables early detection and improves diagnostic operations.

CONCLUSION

The key findings of our research is to determine the worth of MATLAB that it deals with signal processing of EMG for the diagnosis of myopathic conditions. In divergence to Artificial Intelligence, machine learning toolkit in MATLAB is very precise, computationally efficient and interpretable. The results represents that conventional methods in signal processing have not lost their value in clinical diagnosis and biomedical research.

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