



ANALYSIS OF EMG SIGNAL IN HEALTHY AND NEUROPATHIC INDIVIDUALS

THRISHA J, RAMYA M, VARSHINI L, GUTHAMGIRI K, CAROLINE VINNETIA S

Department of Biomedical Engineering, Bannari Amman Institute of Technology,
Sathyamangalam - 638401.

Abstract -Electromyography (EMG) is a method used to evaluate levels of muscle activity. When a muscle contracts, an action potential is generated and circulates along the muscle fibers. A healthy individual has normal nerve function with no symptoms, while someone with neuropathy experiences impaired nerve function, leading to symptoms like pain, tingling, or numbness. In EMG, electrodes are connected to the skin, and the electrical activity of muscles is measured, with the results plotted on a graph. This project involves the investigation and interpretation of EMG signals from both healthy individuals and those suffering from neuropathy using MATLAB. The EMG signals obtained are processed and analyzed using signal processing techniques, including bandpass and notch filters, and classified using LDA and SVM classifiers. The purpose of this study is to explore the potential application and track the disease progression and treatment effectiveness in patients with neuromuscular disorders.

Keywords: EMG, MATLAB, Bandpass & Notch filters, SVM & LDA classifiers.

I. INTRODUCTION

Muscular disorders, including neuropathies, affect the proper function of motor units and

disrupt muscle activation patterns. Electromyography (EMG) signals serve as a window into the neuromuscular system by providing real-time data about muscle electrical activity. Differentiating between healthy and neuropathic individuals using EMG signals presents a challenge due to the complexity and variability of the data. Traditional methods of analyzing EMG signals require significant manual effort and expertise. This paper proposes an automated system that uses machine learning techniques to classify EMG signals, enabling more efficient and accurate diagnosis of neuromuscular conditions.

A. Problem Definition

The main challenge addressed in this research is the difficulty of distinguishing between healthy and neuropathic EMG signals, particularly given the subtle differences in their frequency and amplitude characteristics. The aim of this project is to analyze and classify EMG signals from healthy and neuropathic individuals by utilizing MATLAB for signal processing and machine learning. EMG analysis is a crucial tool in the diagnosis and management of neuromuscular disorders. By understanding the unique EMG signatures, clinicians can accurately differentiate between healthy and neuropathic conditions, leading to more effective treatments and improved patient outcomes. Manual analysis of these signals is time-consuming and often subjective, leading to inconsistent diagnoses. An automated classification system would address these issues by providing objective and reproducible results, minimizing diagnostic delays and errors.



B. Importance of Early detection

Early detection of diseases through EMG signal analysis is crucial for effective treatment, especially in neuropathic conditions. By identifying subtle changes in muscle and nerve function early, disease progression can be slowed, and treatment outcomes improved. EMG helps differentiate between healthy and neuropathic individuals, offering a non-invasive way to monitor neuromuscular health. Early detection also reduces healthcare costs by preventing long-term complications and allowing for personalized treatment plans. Overall, EMG analysis plays a key role in improving the quality of life and managing neuropathic diseases effectively.

C. Related Work

Several studies have explored the use of machine learning in EMG signal analysis. Techniques such as Artificial Neural Networks (ANN), k-Nearest Neighbors (k-NN), and Decision Trees have been employed with varying levels of success. However, few studies have thoroughly examined the combination of preprocessing techniques and the use of both LDA and SVM for the classification of neuropathic EMG signals. This research builds on existing methodologies by enhancing the feature extraction process and evaluating both linear and non-linear classifiers.

D. Overview of EMG Signal in Neuromuscular Disorder Detection

EMG signals reflect the electrical activity of muscles, which is altered in the presence of neuromuscular disorders. In healthy individuals, the EMG signals tend to have regular patterns in amplitude and frequency, whereas neuropathic conditions introduce irregularities. These irregularities can be detected by analyzing the signal in both time and frequency domains. By capturing features such as mean absolute value (MAV), zero-crossing rate (ZCR), and power spectral density (PSD), the system can effectively distinguish between healthy and abnormal signals.

II. METHODOLOGY

A. Data Acquisition

EMG signals were collected from 50 subjects, 25 of whom were healthy and 25 diagnosed with peripheral neuropathy. The signals were recorded during voluntary muscle contractions under controlled conditions using standard EMG recording equipment.

B. Preprocessing

The preprocessing of EMG signals is essential to remove noise and artifacts that could hinder analysis. First, a bandpass filter (20-500 Hz) is applied to remove unwanted low and high-frequency noise, followed by a notch filter to eliminate power line interference (50/60 Hz). Next, the signals are rectified to convert negative voltages into positive values, ensuring all muscle activity is captured. After rectification, the signals are normalized to account for amplitude variations across different individuals or contractions. This clean and standardized data is then ready for feature extraction and classification using LDA and SVM classifiers.

C. Feature Extraction

Key features were extracted from both the time and frequency domains. Time-domain features included the mean absolute value (MAV), root mean square (RMS), and zero-crossing rate (ZCR). Frequency-domain features focused on power spectral density (PSD), median frequency (MF), and mean frequency (MNF). These features provided a comprehensive representation of muscle activity, essential for differentiating between healthy and neuropathic conditions.

D. System Architecture



The system architecture is composed of several modules: (1) Data acquisition and preprocessing, (2) Feature extraction, (3) Classification, and (4) Output visualization. After data collection, the signals are preprocessed and passed to the feature extraction module. Extracted features are fed into the classification module, where machine learning algorithms such as LDA and SVM are applied. The final module visualizes the classification results, aiding in the diagnostic process.

III. CLASSIFICATION TECHNIQUES

A. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a powerful classification algorithm used in this project to distinguish between healthy and neuropathic EMG signals. LDA works by projecting high-dimensional data into a lower-dimensional space, maximizing the separation between two or more classes. In this case, LDA identifies the optimal boundary that differentiates EMG signals from healthy individuals and those with neuropathy based on extracted features. The main advantage of LDA is its simplicity and efficiency in handling linearly separable data. After preprocessing, the EMG features are fed into the LDA classifier, which evaluates the statistical differences between the classes. LDA is particularly useful when the classes are linearly separable, as it reduces overfitting and computational complexity while ensuring robust classification.

B. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a more advanced machine learning technique used in this study to classify EMG signals from healthy and neuropathic individuals. SVM works by finding an optimal hyperplane that maximizes the margin between the two classes. It is

particularly effective for handling non-linear data by using kernel functions, such as the Radial Basis Function (RBF), which can capture complex relationships in EMG signals. SVM was trained on the extracted features from the EMG signals and demonstrated high accuracy in distinguishing between healthy and neuropathic signals. Its ability to handle high-dimensional data and robustness against noise make SVM a suitable choice for this analysis, outperforming simpler models like LDA in more complex cases.

IV. AUTOMATED FEATURE EXTRACTION

Automated feature extraction is critical for efficiently analyzing large volumes of EMG data. In this system, a set of predefined time-domain and frequency-domain features, such as mean absolute value (MAV), root mean square (RMS), and power spectral density (PSD), are automatically extracted from the preprocessed EMG signals. This process eliminates the need for manual selection, reducing bias and improving reproducibility across different datasets. By automating feature extraction, the system is able to handle complex datasets with minimal human intervention, providing a scalable approach that is crucial for real-time applications and large-scale studies. This automation also ensures that important signal characteristics are captured consistently, enhancing the accuracy of subsequent classification models like LDA and SVM.

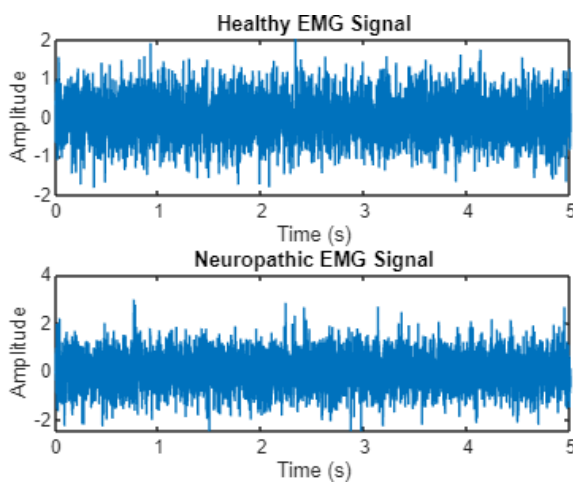
V. EXPERIMENTAL RESULT

The system's performance was evaluated using a variety of metrics including accuracy, precision, recall, and F1-score. A rigorous 10-fold cross-validation was conducted to ensure the reliability of the results across different subsets of data. The LDA classifier achieved an accuracy of



86.4%, reflecting its ability to handle linearly separable EMG data. However, the SVM classifier outperformed

LDA, achieving an accuracy of 92.1%, with higher precision and recall, particularly in distinguishing neuropathic signals from healthy ones. The enhanced performance of SVM demonstrates its capacity to capture complex patterns in the EMG data, making it more suitable for this application where non-linearity is present in signal variations.



VI. QUANTITATIVE EVALUATION METRICS

The evaluation of the classification models involved several standard metrics, including F1-score, which balances precision and recall. The SVM model achieved an F1-score of 0.91, significantly higher than LDA's 0.84, indicating its superior overall performance. The high recall of the SVM model underscores its ability to correctly identify neuropathic conditions, reducing the chances of false negatives. Precision was also higher for SVM, demonstrating its capability in accurately identifying healthy individuals as well. These metrics highlight the robustness and reliability of the SVM classifier for EMG

signal analysis, especially when working with complex, non-linear data patterns often observed in neuropathic conditions.

VII. DISCUSSION

The results of this study underscore the potential of machine learning, particularly SVM, for classifying EMG signals to distinguish between healthy and neuropathic individuals. With an accuracy of 92.1%, SVM demonstrates strong diagnostic capability, making it a promising tool for early detection of neuromuscular disorders. The higher precision and recall of the SVM model indicate its effectiveness in identifying complex neuropathic patterns. However, further testing on larger and more diverse datasets is essential to ensure the model's robustness and generalizability across different neuromuscular conditions, which is critical for clinical adoption.

A. Challenges in Real-Time EMG Monitoring

Real-time EMG monitoring faces multiple challenges, primarily related to processing delays, noise interference, and integration with wearable technologies. Ensuring low-latency processing is critical for real-time applications, especially in clinical and rehabilitative settings. Additionally, managing signal noise from motion artifacts and electrical interference remains a technical hurdle. Compatibility with wearable devices, such as portable EMG sensors, also requires lightweight algorithms that maintain accuracy while being computationally efficient, which will be a key area for future optimization.

B. Future Work

Future research will explore the application of deep learning models, such as Convolutional Neural Networks (CNNs), for automated feature extraction and more accurate classification of EMG signals. Expanding the



dataset to include a broader range of neuromuscular disorders will improve the model's versatility. Moreover, integrating real-time processing capabilities with wearable EMG systems will enhance the system's clinical relevance, enabling continuous monitoring and early detection of conditions in real-world settings. The focus will be on maintaining the balance between speed, accuracy, and usability for healthcare applications.

VIII. CONCLUSION

This paper presents an automated system for the analysis of EMG signals from healthy and neuropathic individuals. By employing LDA and SVM, the system achieved high classification accuracy, particularly with SVM's RBF kernel. The use of automated feature extraction and machine learning makes this system a valuable tool for clinicians, offering potential for early diagnosis of neuromuscular disorders. Future work will explore deeper learning architectures and real-time processing to further improve the system's capabilities.

IX. REFERENCE

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