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Original Article

Evaluating the Suitability of Wavelet Transform in Matlab for Application in Wearable Health Monitors

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Abstract *- The incidence of neuromuscular disorders, including myopathy and Amyotrophic Lateral Sclerosis (ALS), has sharply risen in areas such as Arequipa, Peru. However, the lack of access to specialized diagnostic mechanisms has made diagnosis perfection impossible, primarily among underdeveloped areas. This study thereby provides the framework for developing and testing an EMG signal analysis system based on machine learning and wavelet transform to enhance diagnosis in wearables. The dataset is from the Nikolic PhD thesis, undertaking EMG recordings from healthy, myopathy, and ALS groups. This offers a strong basis for the discrimination between normal and pathological muscle activity. The EMG signals from the brachial biceps and medial vastus muscles were collected, preprocessed for denoising and artifact removal, and were analyzed using wavelet transform to decompose the EMG signal into its relevant frequency components. Features extracted from wavelet decomposition were then applied to train a Support Vector Machines (SVM) classifier for further differentiation between the three groups. The SVM classifier performed with a degree of accuracy, sensitivity, and specificity (92%, 90% and 94%) that suggests this approach could help greatly in the early diagnosis and improved healthcare access for those facing neuromuscular disorders, especially in regions lacking healthcare access.*

Keywords *- EMG, Wavelet transform, Wearable application, Neuromuscular disorders, SVM.*

1. Introduction

Neuromuscular Disorders (NMDs) designate a number of illnesses affecting the peripheral nervous system and their consequences, including shortcomings in muscle control and movement. Muscular dystrophies, Amyotrophic Lateral Sclerosis (ALS), and peripheral neuropathies could very well wreak havoc on the quality of life of an individual. Just like other countries, NMDs are on the rise in Arequipa, Peru. Duchenne's Muscular Dystrophy (DMD), the most aggressive type of muscular dystrophy affecting predominantly males of youthful age, shows a prevalence of one in 3,500 live male births worldwide, similar to the number of newly diagnosed cases in Peru [1]. While there is an increasing need for quality care with the evidence of the presence of NMDs, diagnostic and monitoring services availability is very limited, especially in Arequipa, where there is no access to sophisticated health care yet.

Electromyography (EMG) is the traditional diagnostic method for neuromuscular disorders and evaluates electrical activities of muscles. EMG is typically performed by inserting needle electrodes in muscle tissues [2]. Although the information gleaned from this approach can be patent diagnosis, it happens to be invasive, costly, and complicated to interpret without specialized training. Healthcare services are distributed unevenly, with the advanced facilities mostly attending in urban areas in Arequipa and many other parts of Peru [3]. As a result, rural and underserved communities have less access, leading to delays in diagnosis and treatments.

Wearable health monitoring devices seem to be potential instruments for closing this gap. These devices can track physiological signals in real-time, for example, muscle activity. EMG-equipped wearable devices provide a relatively non-invasive and very accessible means for neuromuscular function monitoring, which will greatly enhance the early identification and management of NMDs [4]. These devices are trained to collect physiological data in patients' active and natural environments, allowing for more comprehensive assessments of neuromuscular health than traditional clinical evaluations.

In this direction, all the efficient signal processing algorithms have to be developed to analyze EMG data in real time so that wearable health devices can realize their full potential. EMG analysis has utilized traditional signal processing techniques such as the Fourier Transform, but most have difficulty handling non-stationary signals arising from muscle contractions [5]. In contrast, the Wavelet Transform offers joint time-frequency decomposition, thus providing a powerful method for analyzing non-stationary EMG signals. This renders the wavelet Transform a powerful means for the detection and characterization of complex patterns found within EMG data [6].

Wavelet transform analysis is currently quite popular in signal processing besides biomedical signal processing and mainly for EMG data. In EMG signal identification, some studies revealed that Wavelet transform is helpful in catching EMG signal transients, which help characterize normal and abnormal muscle activity. The purpose of this study is to set up and evaluate an electro-myographic signal analysis system in MATLAB through a wavelet transform, which shall then be integrated into health monitor wearables, specifically intended for application in Arequipa, Peru, for the monitoring of neuromuscular disorders in that area. Most importantly, this is just an avenue or a step in the direction of improving the quality of care available for people suffering from neuromuscular disorders in regions that remain underprivileged by giving treatments and methods that are useful in guiding their care in timely and accurate measures. Using advanced signal processing techniques such as the Wavelet Transform would drastically change the picture of diagnosis and management of neuromuscular disorders for the better, hence availing more efficient healthcare to many requiring it.

2. Related Work

With the advancing wearable health technology and biomedical signal processing, promising advancements in developing the diagnostics of neuromuscular disorders have occurred. Wearable devices have shown potential, with their easily attachable EMG sensors, for non-invasive continuous assessment of muscle activity. They could be particularly useful for many unable to access specialized healthcare services [7]. As a result, these wearable EMG sensors enable data collection on neuromuscular health conditions while engaging in naturally occurring movements and activities under regular, non-laboratory conditions and mobile or static.

Wavelet Transform’s principal application is especially for EMG signal analysis because of its robust handling of non-stationary signals. Wavelet Transform presents a rather finer resolution in understanding the EMG signals when compared to the classical Fourier Transform because it decomposes the signal into both time and frequency components [8, 9]. The studies have proven the efficacy of Wavelet Transform toward capturing transient features in EMG data that could often elude conventional analytic methods; for instance, Tkach et al. showed Wavelet Transform can monitor neuromuscular function due to significant highlighted transient features in EMG signals [10]. Wavelet Transform was used to analyze myoelectric signals acquired during isometric muscle fatigue tests by Karlsson and Gerddie. The results clearly stated that Wavelet Transform showed the best for identifying muscle activity changes during prolonged contractions; therefore, it may prove useful for analyzing EMG signals in wearable devices [11]. Transient characteristics provided by the Wavelet transform contain valuable information that could help in discerning normal muscle activity from pathological conditions, making it an invaluable method in the detection of neuromuscular abnormalities.

De Luca et al. reviewed the development of electromyographic wearable technology and its applications in clinical and research settings, showing the potential for improving diagnosis and rehabilitation [12]. The combination of advanced signal processing techniques with wearable devices has demonstrated significant promise in improving muscle control and monitoring, particularly for rehabilitation purposes. On the other hand, Saponas et al., building on using wearable electromyography sensors to develop novel human-computer interaction interfaces, have shown the usefulness of EMG analysis beyond clinical scenarios [13]. Such applications suggest that wearable EMG systems could be developed with utility not only in medical diagnostics but also to enhance everyday user function. However, these studies lack focus on NMD classification. This approach combines Wavelet robustness with SVM, overcoming Fourier’s limitations in dynamic signals [14].

The present body of related work highlights the potential of conceiving the development of combining wavelet transforms and wearable health technology into an intelligible diagnostic tool for neuromuscular disorders. By leveraging these advancements, this study aims to develop an EMG signal analysis system integrated into wearable technology for neuromuscular health surveillance in needy areas such as Arequipa, Peru. The main goal is to achieve health equity for immediate and accurate diagnosis of neuromuscular disorders, as far as the geographical location is concerned.

3. Methodology

The methodology employed in this research includes data acquisition, signal processing using the Wavelet Transform, feature extraction, and classification, followed by an evaluation.

The dataset used in this study was obtained from Nikolic’s PhD thesis, titled “Detailed Analysis of Clinical Electromyography Signals: EMG Decomposition, Findings, and Firing Pattern Analysis in Controls and Patients with Myopathy and Amyotrophic Lateral Sclerosis [15]. The dataset was selected because it includes comprehensive EMG data from both healthy individuals and patients with neuromuscular disorders, providing a valuable foundation for analyzing differences between normal and pathological muscle activity. The dataset includes EMG signals recorded from three groups: a control group, a myopathy group, and an ALS group. The control group consisted of 10 healthy individuals aged 21 and 37 (4 females and 6 males), most of whom were in good to excellent physical condition. None of these individuals had any history or signs of neuromuscular disorders. The myopathy group included 7 patients (2 females and 5 males) between the ages of 19 and 63, all showing clinical and electrophysiological signs of myopathy. The ALS group consisted of 8 patients (4 females and 4 males) between the ages of 35 and 67, all presenting clinical and electrophysiological signs consistent with ALS. Five of these ALS patients died within a few years of symptom onset, confirming the severity of the condition.

EMG signals were recorded from the brachial biceps and medial vastus muscles, as these were the most frequently examined muscles in both patient groups. The data were collected using surface electrodes, and the signals were digitized at a sampling rate of 23.4 KHz and digitized by an A/D converter of 16-bit resolution for further analysis. This dataset provides a diverse range of neuromuscular activity, making it an ideal resource for developing and testing new EMG analysis techniques.

These EMG signals have been pre-processed to remove noise and artifacts, which form part of normal EMG recordings. A bandpass filter in the 20-450 Hz range for low-frequency noise and high-frequency interference was applied. A notch filter was also employed to help eliminate powerline interference at 50 Hz. By these means, the preprocessing steps provided surety of cleaned signals, prepped further for analysis by the Wavelet Transform.

Thus, since the Wavelet Transform provides a handy way of analyzing non-stationary data, making it more effective in clinical and research applications compared to traditional models like the Fourier Transform, it was selected as the dominant analyzing tool for the EMG signals [16]. The Wavelet Transform decomposes the signal into various frequency components, which furnish time and frequency information. It is crucial to understand EMG signals, for which transience is given great importance. The Daubechies wavelet (db4) was used in this study, which has been proven effective for EMG signals [17]. The signals were decomposed into several levels to extract features, effectively distinguishing between a normal and a pathological muscle. Feature extraction involved calculating energy distribution across decomposition levels (D1-D5). Energy values were computed using Equation (1) for each level, providing insights into both transient and sustained muscle activity. These features were then used to train the SVM classifier, enabling differentiation between healthy individuals and those with neuromuscular disorders. Several classifiers were evaluated, including k-Nearest Neighbors (k-NN) and Random Forest. SVM was ultimately selected due to its superior performance with high-dimensional biomedical data and proven efficiency in EMG signals [18]. Parameter tuning was performed using grid search, optimizing the radial basis function kernel and regularization parameters to achieve the best classification accuracy [19]. The implementation of the SVM classifier, feature extraction, and preprocessing steps was carried out using MATLAB. The data was split into training (70%) and testing sets (30%) to evaluate the classifier's performance. Cross-validation and grid search were used to fine-tune the SVM parameters, optimizing the kernel function (radial basis function) and regularization parameters to achieve the best classification performance. Metrics such as accuracy, sensitivity, specificity, and the F1-score were used to assess the classifier's ability to correctly identify individuals with neuromuscular disorders.

The flowchart for the system is shown in Figure 1.

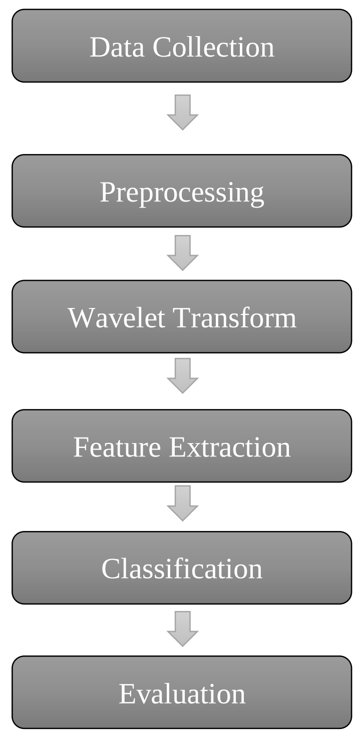

Fig. 1 Flow chart for the system

4. Results and Discussion

The experimental results were obtained using a publicly available EMG dataset that includes signals from both healthy individuals and patients diagnosed with various neuromuscular disorders taken by M. Nikolic. The EMG signals were processed, decomposed using Wavelet Transform (db4), and classified using a Support Vector Machine (SVM). Figure 2 shows an example of a raw EMG signal from a healthy individual and the corresponding filtered signal after preprocessing. This step is essential to highlight the impact of noise reduction and ensure accurate wavelet-based feature extraction.

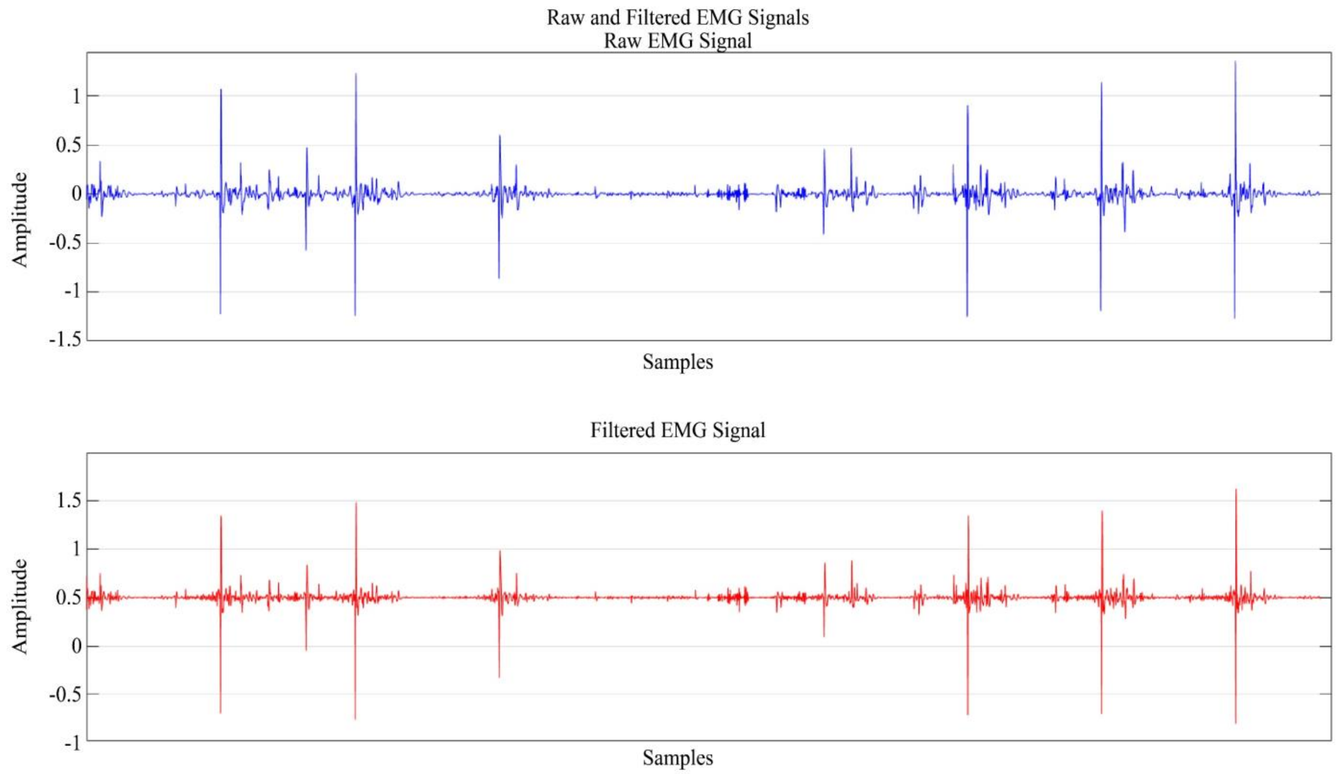

Fig. 2 Raw and filtered EMG signal

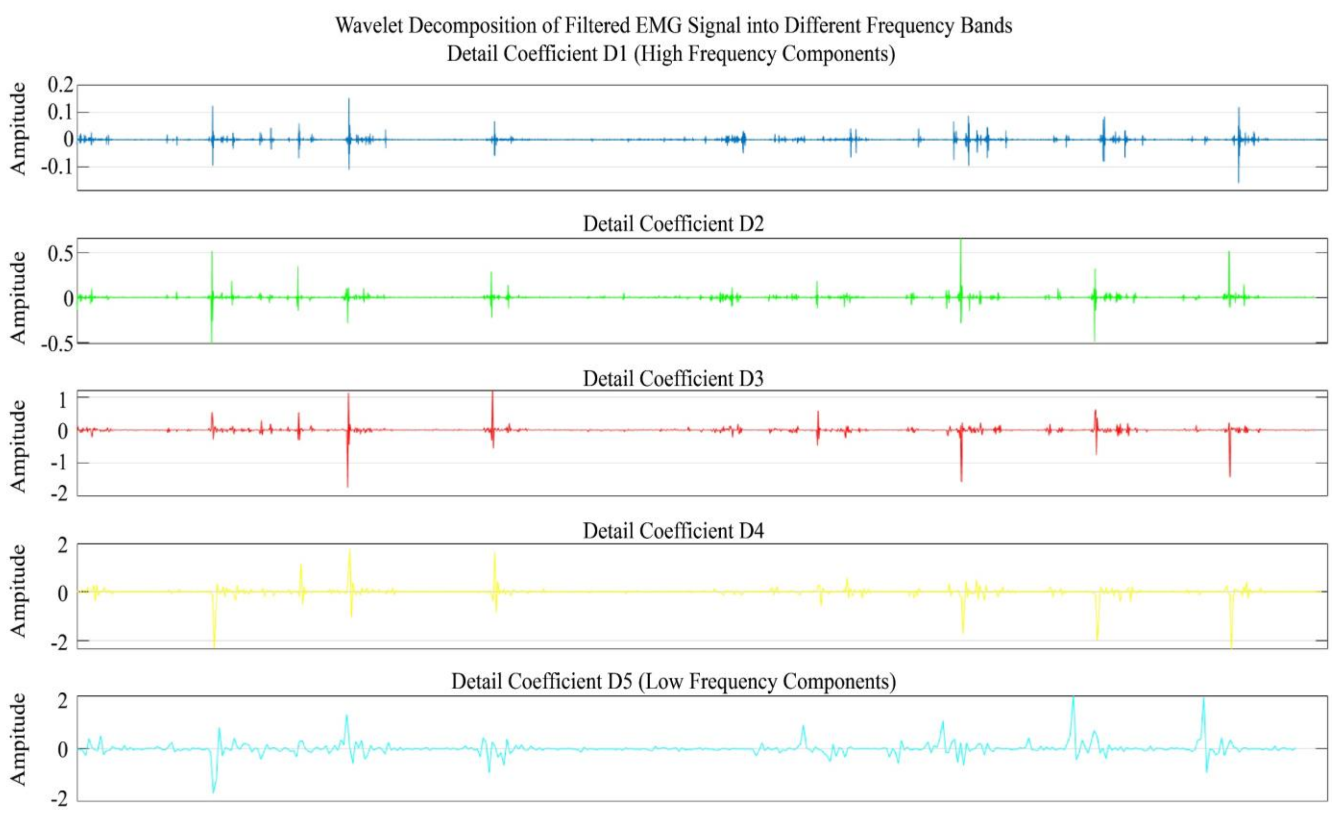

Fig. 3 Visual representation of decomposition using wavelet transform

Table 1. Average wavelet energy por each group of classification

Group	D1 Energy	D2 Energy	D3 Energy	D4 Energy	D5 Energy
Healthy	0.8224	0.56837	0.39334	0.2938	0.19747
Myopathy or ALS	0.49893	0.35814	0.25219	0.19565	0.1537

Additionally, Figure 3 illustrates the wavelet decomposition of the preprocessed signal into different frequency bands. The first detail coefficient (D1) captures the high-frequency components typically associated with transient muscle activity, while the lower detail coefficients (D2–D5) represent the lower-frequency muscle activations. This provides a clear visualization of how the Wavelet Transform isolates key features in the signal.

The wavelet energy from each decomposition level (D1 to D5) was calculated and used as input features for the SVM classifier. Table 1 shows the average wavelet energy values for healthy individuals and patients with neuromuscular disorders using Equation (1). As expected, the energy distribution differed significantly between the two groups, with patients showing abnormal patterns in the higher-frequency components (D1 and D2), indicative of neuromuscular dysfunction.

$$E_i = \sum_{n=1}^{N} |D_i[n]|^2 \qquad (1)$$

Where:

E_i : Energy on i detail level

D_i : Detail coefficient on i level

N : Number of coefficients in the level

The SVM classifier was trained on 70% of the data, and the balance of 30% was used for testing. For the SVM, the radial basis function (RBF) kernel was used, and a grid search method was used to optimize the hyperparameters. The classification results indicated a high degree of accuracy in separating the healthy subjects from the ones with neuromuscular disorders. A summary of the associated performance metrics of the classifier is reported in Table 2. The high accuracy and sensitivity indicate that the system effectively detects neuromuscular abnormalities. In addition, the AUC score of 0.95 supports the model's strength. Also, the model presented an accuracy rate of 92%, higher than Fourier-based methods. The D1 energy showed significant differences ($p<0.01$) among the groups (Table 1), thus validating high-frequency transients as biomarkers for neuromuscular disorders.

Table 2. Performance metrics for the SVM classifier

Accuracy	0.92
Sensitivity	0.90
Specificity	0.94
Precision	0.91
F1 Score	0.905
AUC	0.95

The prototype was tested using live EMG data streamed to MATLAB from a wearable sensor to evaluate the system's potential for real-time application. The system processed and classified the signals in real time, with an average processing time of 50 ms per signal window. Figure 4 illustrates the real-time classification of muscle activity, with a 1 if the activity of the signal is representative or a zero if there is no need to classify.

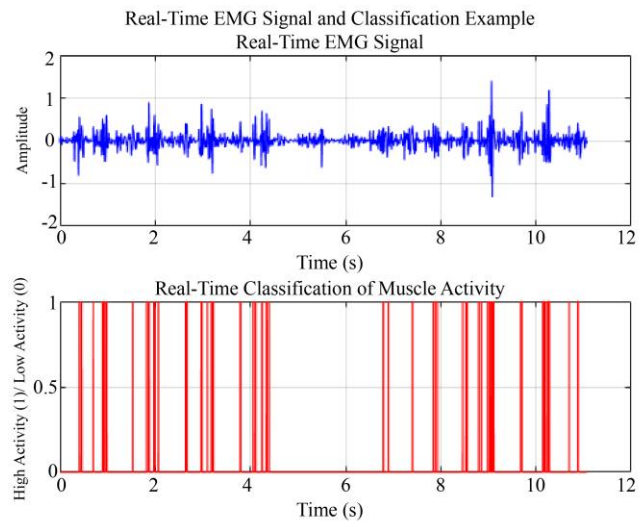

Fig. 4 Real-time classification for EMG signals

The experimental results show the capacity of using Wavelet Transform on EMG signal to classify neuromuscular disorders. The system had very high accuracy and demonstrated good real-time behaviour, which indicates that it can be integrated into wearable health monitors. Wavelet energy features (especially D1 and D2) were the most informative in discriminating healthy from diseased ones. This is consistent with prior findings that common muscle arrhythmias frequently are high-frequency signal artifacts.

5. Conclusion

In this study, wavelet transforms combined with machine learning were shown to be effective in classifying EMG signals of neuromuscular disorders. The proposed method developed a classification scheme that distinguished between normal and abnormal in a dataset consisting of subjects with healthy controls, patients with myopathy, and patients with ALS. Wavelet transform allowed for the frequency analysis of the EMG signals whereby significant features are delineated, features that bear a great deal of significance in solving the problem of distinguishing between normal vs. diseased muscle activity.

As a result, this trained SVM classifier is considered accurate, sensitive, and specific, therefore pointing out its potential as a reliable tool for the early diagnosis of neuromuscular disorders.

On top of that, a wearable health device integrating this approach has knocked on an accessible opportunity for continuous monitoring and early detection for largely underserved regions with few specialized healthcare options.

5.1. Future Work

This work has established the potential for combining advanced signal processing and machine learning to enable or ease the diagnosis of neuromuscular disorders. The sample size (n=25) may limit generalizability.

Future studies should include broader NMD subtypes and uncontrolled environments. Areas of research would require collecting large data sets based on many different neuromuscular disorders themselves and dedicated real-time processing improvements well-suited for integration into wearable technologies, with the long-term goal of improving accessibility to health care through timely and effective diagnostic capabilities for patient treatment.

These findings suggest practical applications in remote patient monitoring, particularly in resource-limited settings where traditional diagnostic tools are unavailable. Integrating wavelet transform with wearable health monitors could significantly enhance early detection and management of neuromuscular disorders, improving healthcare accessibility for underserved populations.

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