WAVELET DECOMPOSITION METHOD BASED AUTOMATED DIAGNOSIS OF MUSCLE DISEASES

MURUGESWARI[1], VIJAYARAJ[2]

[1]Post Graduate Student Government College of Engineering, Tirunelveli
[2]Professor, Dept. of Electronics and Communication Engineering, Government of Engineering, Tirunelveli

---

Abstract - *The skeletal muscle tissues in the human body produce complex, irregular, and non-stationary electrical signals known as electromyograms or electromyography (EMG) signals. The clinical diagnosis of a variety of neuromuscular disorders, including myopathy and neuropathy, is frequently carried out using EMG signals. To stop the progression of these diseases and, at the same time, lessen patient suffering, early detection of these neuromuscular and neurodegenerative disorders is essential. An innovative method for the advancement of human-computer interaction is hand gesture recognition based on electromyography (EMG) signals, which enables the computer to recognise and understand the user's intent and respond appropriately. In this proposal, the wavelet decomposition technique is proposed for automated muscle disease diagnosis using EMG signals. A Hilbert transform-based method is used to choose the best methods for feature selection. The formation of the analytical signal is facilitated by the Hilbert transform. The analytical signal is helpful for band-pass signal processing in the communications industry. Here, a correlation matrix for each independent variable that serves as an input to the system is used as the feature set. Convolutional neural networks (CNN), a powerful classifier, is employed, and results are correctly predicted. Simulation software created with MATLAB is used to carry out this project.*

Key Words*: EMG-*Electromyography, CNN-Convolutional Neural Networks.

1. INTRODUCTION

The use of electromyography (EMG) signals is a cutting-edge strategy for the advancement of human-computer interaction, a vast field whose goal is to implement user-friendly interaction tools and human-computer interfaces (HMIs). The demand for intelligent devices that can operate in real time under severe power, size, and cost constraints and extract information from sensor data is what drives this field's research. Robot communication and industrial robot control, game or mobile interfaces, interactions for virtual worlds, sign language recognition, rehabilitative services, and control of poly-articulated prostheses are just a few of the many applications for HMIs with EMG-based intuitive control. The electromyography (EMG) signal, which is a key indicator of the muscular activity, is the bio potential produced by the passage of ions through the membrane of the contracting muscle fibres. Instruments that are invasive or non-invasive can be used to collect EMG data. Invasive techniques use wire or needle electrodes that pierce the skin to the targeted muscle. On the other hand, surface electromyography (sEMG) is a non-invasive method that makes use of skin-surface electrodes [1].

One of the most promising approaches in the HMI field is to base gesture recognition on sEMG signal analysis, since non-invasiveness is a prerequisite for many different types of HMIs. The creation of solutions based on a strong recognition approach represents an open challenge in HMI design. On the one hand, commercial systems based on the EMG-based interaction paradigm became available as a result of the implementation of devices showing high recognition capabilities in controlled environments. On the other hand, reliability issues like motion artefacts, postural and temporal variability, and problems brought on by sensors that are repositioned after each use continue to restrict the use of EMG-based HMIs in many real-world scenarios [2].

1.1 EMG-BASED HMIS AND GENERALIZATION ISSUES

The electromyogram (EMG), a key indicator of muscular activity, is the bio potential signal resulting from muscular activity. The surface EMG (sEMG) signal is generated when it is sensed using non-invasive surface electrodes. A promising method for implementing non-intrusive EMG-based Human-Machine Interfaces is the processing of sEMG signals. The state-of-the-art today, though, must deal with difficult problems. Numerous factors, including subject differences, user adaptation, fatigue, and the variability introduced by the refocusing of electrodes during each data collection session, have a significant negative impact on the sEMG signal. These problems limit the long-term usability and dependability of the EMG analysis-based devices. These variability factors can be modelled in the machine learning framework using the idea of data sources, or information subsets drawn from various distributions. Machine learning on EMG data is a difficult task because it requires identifying multiple sources [3]. The goal is to implement classifiers with good inter-source generalisation, for example in inter-posture, inter-session, or inter-subject scenarios. As of right now, within-subject cross-validation has much more accurate classification than leave one-subject-out cross-validation (LOSOCV) [4].

1.2 MACHINE LEARNING TECHNIQUES

Only properly represented text can be understood by a computing machine in its general form. As a result, in order to instruct a machine, the text of the reviews must be converted into the appropriate format. Again, the machine comprehends or learns a specific set of data called training data and then predicts the other set of data, i.e., the untrained or testing data, based on the learning of training data. Machine learning methods (MLTs) support both learning and prediction.

The following can be used to explain the various MLT types:

- **Unsupervised MLT:** This type of MLT does not have a labeled dataset. Thus, while analysis of these reviews, clustering approach is considered, which makes a group of similar types of the elements into a cluster. Various different evaluation parameters are considered to check the performance of these techniques

- **Semi-supervised MLT:** In this type of approach, a small size of label dataset is present, where the size of the unlabeled dataset is large. Thus, using the small size labeled dataset, this approach makes an attempt to label the whole dataset. The small labeled dataset is trained and based on these values a small size of the unlabeled dataset is predicted. These predicted data are added to the already labeled dataset until the total data is labeled [5].

1.3 ELECTROMYOGRAPHY (EMG)

Electromyography is referred to as EMG. It is the research of electrical signals in muscles. A different name for EMG is myoelectric activity. The term "muscle action potential" refers to the electrical signals that are carried by muscle tissue similarly to how nerves do. The information contained in these muscle action potentials can be captured using surface electromyography (EMG). There are two main concerns that affect the fidelity of the EMG signal when it is detected and recorded. The signal-to-noise ratio comes first. Specifically, this is the energy to noise signal energy ratio in EMG signals. Electrical signals that are not a desired component of the EMG signal are generally referred to as noise. The distortion of the signal is the other problem, so the relative importance of any frequency component in the EMG signal shouldn't be changed. Invasive electrodes and non-invasive electrodes have both been used to collect muscle signal. A composite of all the muscle fibre action potentials occurring in the muscles beneath the skin is the signal obtained when EMG is obtained from electrodes mounted directly on the skin. Intervals between these action potentials are random. The EMG signal could therefore be positive or negative voltage at any given time. On occasion, wire or needle electrodes inserted directly into the muscle are used to record the nerve impulses of individual muscle fibres [6].

1.4 THE ORIGIN OF EMG

Francesco Redi's documentation from 1666 served as the impetus for the development of EMG. According to the document, the electric ray fish's highly specialised muscle produces electricity. In 1773, Walsh was able to show that the muscle of eel fish could produce an electrical spark. A. Galvani's "De Viribus Electricitatis in Motu Musculari Commentarius," which was published in 1792, demonstrated how electricity could cause muscle contractions. Dubios-Raymond discovered that it was also possible to record electrical activity during a voluntary muscle contraction six decades later, in 1849. Marey, who also coined the term "electromyography," made the first recording of this activity in 1890. An oscilloscope was used by Gasser and Erlanger in 1922 to display the electrical signals coming from muscles. The myoelectric signal is stochastic, so its observation could only provide a rough understanding of the situation. From the 1930s through the 1950s, the ability to detect electromyography signals steadily improved, and researchers started using improved electrodes more frequently for the study of muscles. In the 1960s, surface EMG was first used clinically to treat more specialised disorders. The first users of sEMG were Hardyck and his researchers in 1966. In the early 1980s, Cram and Steger introduced a clinical method for scanning a variety of muscles using an EMG sensing device [7].

It wasn't until the middle of the 1980s that electrode integration techniques had advanced enough to enable batch manufacturing of the necessary compact and light-weight amplifiers and instruments. There are currently several suitable amplifiers on the market. Early in the 1980s, cables that produce artefacts in the desired microvolt range were made accessible. The characteristics of surface EMG recording have improved over the previous 15 years of research. In clinical protocols, exterior electromyography has become more frequently used in recent years to document from superficial muscles, while intramuscular electrodes are only used for deep muscle [8].

EMG can be applied in a wide variety of situations. Clinically, EMG is used to diagnose neurological and neuromuscular issues. Gait laboratories and clinicians skilled in biofeedback or ergonomic evaluation use it for diagnostic purposes. EMG is employed in a wide range of research settings, such as biomechanics, motor control, nerve and muscle physiology, movement disorders, postural control, and physiotherapy [9].

1.5 TYPES OF MUSCLE TISSUE

The three different types of muscle tissue are skeletal, smooth, and cardiac. Cardiac muscle cells are found in the heart's walls, where they can be seen as being striped (or striated) and controlled by an involuntary process. Except for the heart, smooth muscle fibres are found in the walls of hollow visceral organs (such as the liver, pancreas, and intestines), are spindle-shaped, and are also controlled involuntarily. Muscles that are connected to the skeleton contain skeletal muscle fibres. They appear striated and are controlled voluntarily [10].

2. PROPOSED SYSTEM

This study suggests using wavelet transform to automatically diagnose muscle diseases from EMG signals. The wavelet decomposition process was applied to the EMG signal in the proposed work. In its application domains, wavelets decomposition is used to increase the precision of hand movement recognition. The HT is employed to represent the EMG signal analytically. The complex plane plot of

The analytical signal obtained using the Hilbert Transform is used to calculate the features (HT). To categorise the EMG signal into the appropriate classes, the classifier is fed these features as input. Figure 2.1 shows the proposed algorithm's block diagram. The correlation matrix approach, which is used to compute the distances by setting up a complex plane plot, is used to select the appropriate IMFs for features for feature selection. The CNN classifier stage receives the data at this point. The CNN algorithm is used to enhance model functionality and boost accuracy.

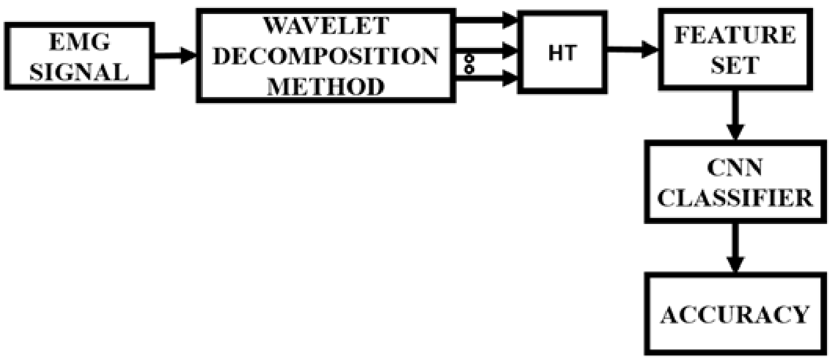

Figure 2.1 Block Diagram for Proposed System

2.1 EMG SIGNAL

The electrical currents created in muscles during their contraction, which represent neuromuscular activities, are measured by the biomedical signal known as the EMG. Muscle activity is always under nervous system control. This signal is frequently a function of time and can be described in terms of its amplitude, frequency, and phase.

2.2 WAVELET DECOMPOSITION

This technique generates an approximation coefficient subset and a detail coefficient subset from the original EMG signal by passing it through a low-pass and high-pass filter, respectively. The toolbox of multiscale signal processing techniques has more recently included wavelet decompositions. They offer a complete image representation and perform scale- and orientation-based decomposition, in contrast to the Gaussian and Laplacian pyramids. Each t-f image representation of the EEG signals undergoes wavelet decomposition to produce diagonal (D), vertical (V), and horizontal (H) components. These components are stored as images and used for feature extraction.

2.3 HILBERT TRANSFORM

The Hilbert transform of u can be thought of as the convolution of u (t) with the function h (t) = 1/π t, known as the Cauchy kernel. Because $^1/_t$ is not integral across t = 0, the integral defining the convolution does not always converge. Instead, the Hilbert transform is defined using the Cauchy principal value (denoted here by p.v.). Explicitly, the Hilbert transform of a function (or signal) $u(t)$ is given by

$$\mathrm{H(u)(t)} = \frac{1}{\pi}\, p.v \int_{-\infty}^{+\infty} \frac{u(T)}{t-\tau}\, d\tau \quad (2.1)$$

Provided this integral exists as a principal value. This is precisely the convolution of u with the tempered distribution p.v. 1/π t. alternatively, by changing variables, the principal value integral can be written explicitly as

$$\mathrm{H(u)(t)} = \frac{1}{\pi}\, p.v \int_{-\infty}^{+\infty} \frac{u(T)}{t-\tau}\, d\tau \quad (2.2)$$

When the Hilbert transform is applied twice in succession to a function u, the result is:

$$\mathrm{H\big(H(u)\big)(t)} = -\mathrm{u(t)} \quad (2.3)$$

Provided the integrals defining both iterations converge in a suitable sense. In particular, the inverse transform is H. This fact can most easily be seen by considering the effect of the Hilbert transform on the Fourier transform of u (t).

For an analytic function in the upper half-plane, the Hilbert transform describes the relationship between the real part and the imaginary part of the boundary values. That is, if f(z) is analytic in the upper half complex plane {z : Im{z} > 0}, and u(t) = Re{f (t + 0·i)}, then Im{f (t + 0·i)} = H(u)(t) up to an additive constant, provided this Hilbert transform exists.

2.4 FEATURE SET – CORRELATION MATRIX

This section explains the covariance matrix descriptor's basic idea. A collection of local feature vectors form the foundation of the feature covariance matrix. Given that there are typically few hand gesture training samples, it offers a concise representation of a hand gesture video segment and is very helpful for classifying hand gestures. With minimal storage and processing requirements, the feature covariance matrix can offer a classification representation that is significantly discriminative.

In contrast to a vector space, a collection of covariance matrices of a certain size typically forms a closed convex cone. As a result, learning classifiers using traditional machine learning algorithms based on these feature covariance matrices is not appropriate. However, the matrix logarithm can be used to map the convex cone of covariance matrices into the vector space of symmetric matrices, offering a way to take advantage of the body of knowledge already present in machine learning algorithms. Suppose that C's Eigen decomposition is as follows:

$$\mathrm{C} = VDV^T \quad (2.4)$$

Where the columns of V are orthonormal eigenvectors and D is the diagonal matrix of nonnegative eigenvalues. Then, we define

$$\log(C) := V\widetilde{D}V^T \quad (2.5)$$

Where $\widetilde{D}$ is a diagonal matrix acquired from D.

2.5 CONVOLUTIONAL NEURAL NETWORKS

In recent years, the fields of semantic segmentation and radar imaging have seen significant advancements in convolutional neural networks (CNNs). In-depth learning methods like CNNs were developed specifically for image recognition and classification. A variety of real-world applications have made use of CNN. This network was developed and is similar to multi-layered neural networks. The biological neural networks used in speech recognition, image processing, and other applications are the same as CNNs. With remarkable accuracy, CNNs can be trained to classify images, identify objects in images, and even predict the next word in a sentence.

Instead of manually analysing the MRI images, a CNN-based algorithm will assist medical professionals in their treatment role to hasten the healing process. Examples of CNN include face recognition, image categorization, and other computer vision applications. It is similar to the basic neural network. CNNs also have learnable parameters, like weights and biases, like neural networks do. Despite their complexity in terms of resources and expertise, CNNs offer in-depth findings.

2.6 CNN CLASSIFIER

The process of feature extraction uses a convolution tool to separate and pinpoint the distinctive qualities of an image for analysis. The feature extraction network consists of many pairs of convolutional or pooling layers. a fully connected layer that uses the output of the convolutional process and classifies the image using the previously extracted features. The goal of this CNN feature extraction model is to extract as few features from a dataset as possible. It creates new features by combining the features of an initial set of features into a single new feature. Three different types of layers make up the CNN: fully-connected (FC), pooling, and convolutional layers.

2.6.1 CONVOLUTIONAL LAYER

This is the first layer that is used to extract the various features from the input photos. At this layer, a mathematical operation called convolution is performed between the input image and a filter with the dimensions MxM. By sliding the filter over the input image, the dot product is obtained between the filter and the elements of the input image in relation to the filter's size (MxM).

CNN's convolution layer moves the output to the following layer after performing the convolution operation on the input. Convolutional layers in CNN are very helpful because they ensure that the spatial relationship between the pixels is preserved.

2.6.2 POOLING LAYER

After a convolutional layer, a pooling layer is frequently applied. The primary objective of this layer is to reduce the size of the convolved feature map in order to reduce computational costs. Using fewer links between layers and independently modifying each feature map, this is accomplished. Depending on the mechanism used, there are different kinds of pooling operations. It is essentially a summary of the features that a convolution layer produced.

Usually, the FC Layer and the Convolutional Layer are connected by the Pooling Layer. By making the characteristics extracted by the convolution layer more general, the CNN approach enables the networks to recognize the features on their own. This helps a network's computations run more efficiently.

2.6.3 FULLY CONNECTED LAYER

Weights and biases are included in the Fully Connected (FC) layer, which connects the neurons between two layers. A CNN Architecture's final few layers are frequently positioned before the output layer. This flattens the input image from the layers beneath and provides it to the FC layer. The standard operations on mathematical functions are then performed on the flattened vector through a few more FC layers. At this point, the classification process begins to take place. Two layers are connected because two fully connected layers perform better than one connected layer. The need for human oversight is reduced by these CNN layers.

3. RESULT AND DISCUSSION

The simulation results are examined using a software MATLAB/SIMULINK. The MATLAB is a high performance language for technical computing integrates computation, visualization and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. The simulation analysis was completed by using the same scenarios of the experimental set-up just to improve the concept verification.

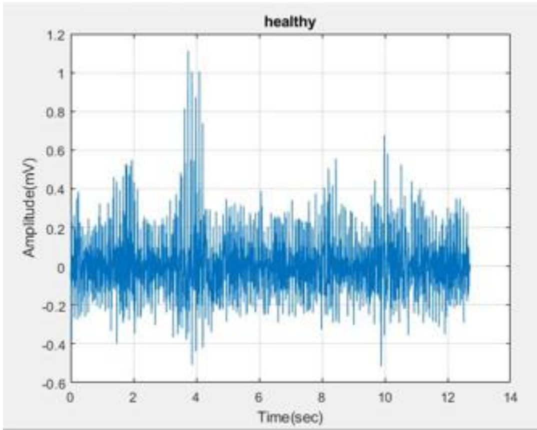

Figure 3.1 Healthy signal

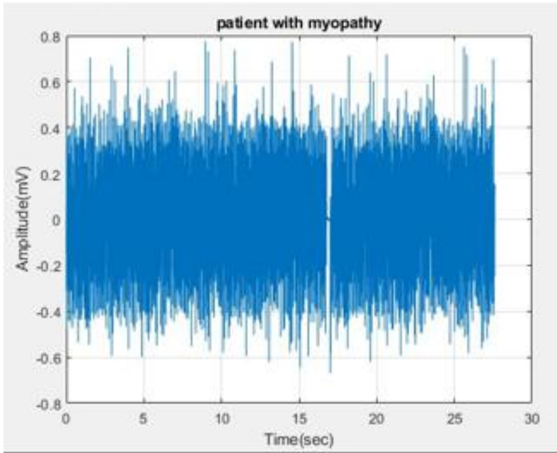

Figure 3.2 Patient with Myopathy

Figure 3.2 Displays the Myopathy Patient.

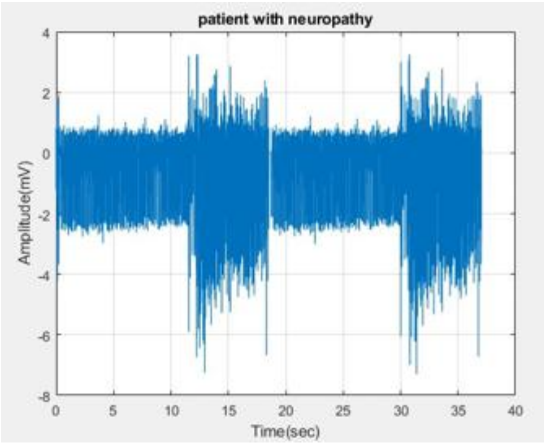

Figure 3.3 Patient with Neuropathy

Figure 3.3 describes a person who has Neuropathy.

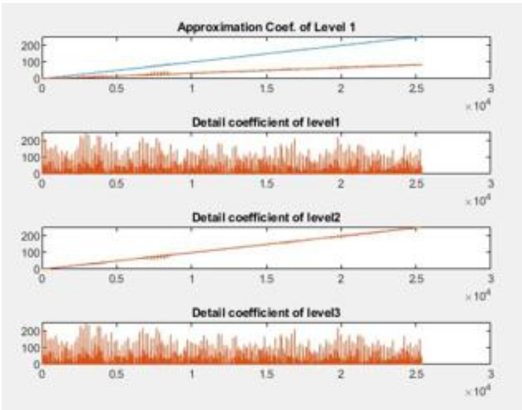

Figure 3.4 Wavelet Decomposition of Healthy EMG Signal

Wavelet Decomposition Of Healthy EMG Signal Is Shown In Figure 3.4.

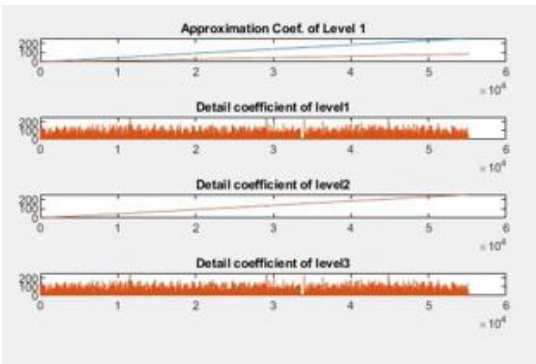

Figure 3.5 Wavelet Decomposition of Patient with Myopathy.

Figure 3.5 shows a patient with myopathy's wavelet decomposition.

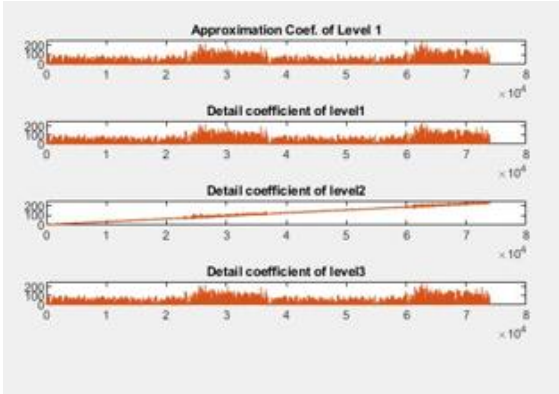

Figure 3.6 Wavelet Decomposition of Patient with Neuropathy Signal.

Figure 3.6 Displays the Wavelet Decomposition of a Neuropathy patient signal.

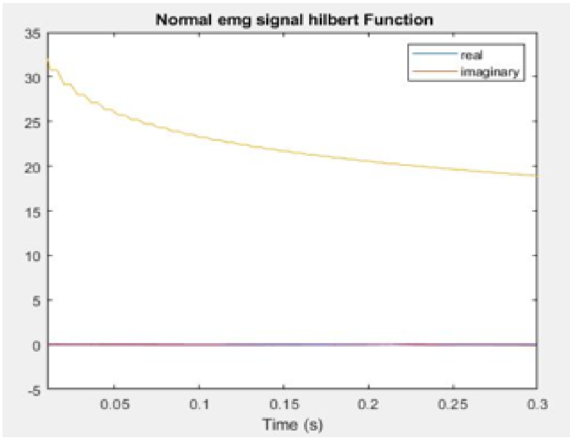

Figure 3.7 Normal EMG Signal Hilbert Function

A typical EMG signal's Hilbert function is depicted in Figure 3.7.

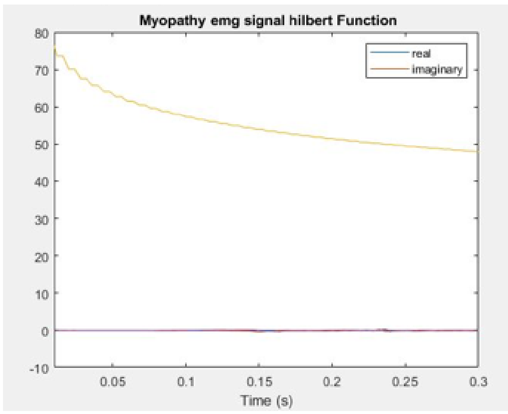

Figure 3.8 Myopathy EMG Signal Hilbert Function

Myopathy EMG Signal Hilbert Function is illustrated in Figure 3.6.

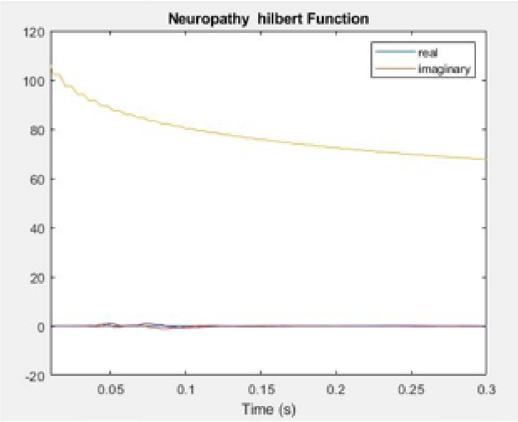

Figure 3.9 Neuropathy EMG Signal Hilbert Function

Figure 3.9 displays the Hilbert Function for the Neuropathy EMG Signal.

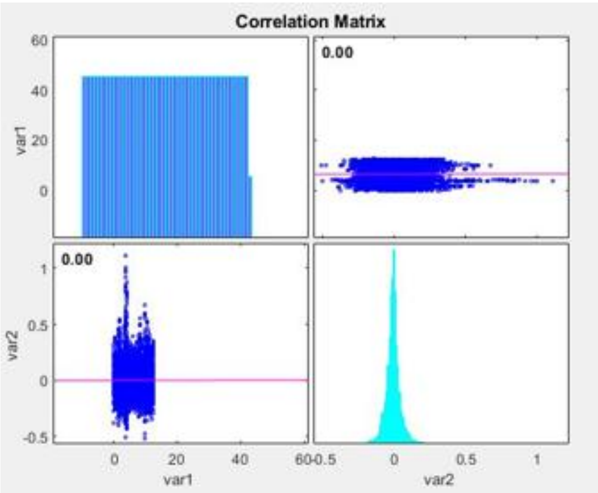

Figure 3.10 Correlation Matrix for Normal EMG Signal

In figure 3.10, the correlation matrix for a normal EMG signal is displayed.

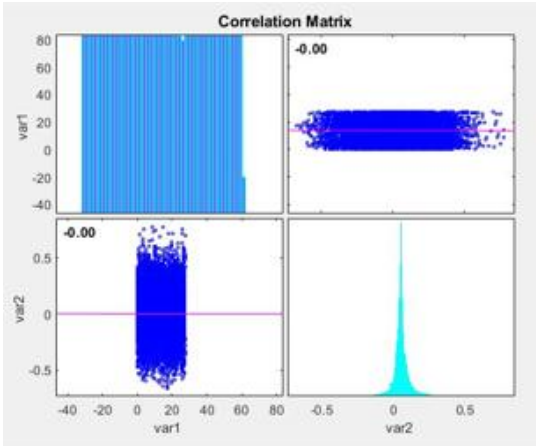

Figure 3.11 Correlation Matrix for Myopathy EMG Signal

The correlation matrix for the EMG signal associated with myopathy is shown in figure 3.11

Figure 3.12 Training Process

Figure 3.12 demonstrates the evaluation of the accuracy and losses for the training procedure.

4. CONCLUSION

The Wavelet Decomposition method for automated diagnosis of muscle diseases using EMG signals is proposed in this project. The detection and classification of neuromuscular diseases based on features extracted from EMG signals have been reported in the project. A cross-correlation-based feature extraction technique was examined for the discrimination of healthy, myopathy, and neuropathy EMG signals. Several time- and frequency-domain features were presented for the detection of abnormal EMG signals. Convolutional neural networks (CNN), a powerful classifier, is applied, and the projected outcomes are precise. Finally, the classification of myopathy, healthy, and neuropathy electromyograms was done using CNN classifiers, respectively.

5. REFERENCES

1. M. Al-Hammadi et al., "Deep Learning-Based Approach for Sign Language Gesture Recognition With Efficient Hand Gesture Representation," in IEEE Access, vol. 8, pp. 192527-192542, 2020.

2. P. B. Shull, S. Jiang, Y. Zhu and X. Zhu, "Hand Gesture Recognition and Finger Angle Estimation via Wrist-Worn Modified Barometric Pressure Sensing," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 4, pp. 724-732, 2019.

3. X. Chen, Y. Li, R. Hu, X. Zhang and X. Chen, "Hand Gesture Recognition based on Surface Electromyography using Convolutional Neural Network with Transfer Learning Method," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 4, pp. 1292-1304, 2021.

4. Z. Yang and X. Zheng, "Hand Gesture Recognition Based on Trajectories Features and Computation-Efficient Reused LSTM Network," in IEEE Sensors Journal, vol. 21, no. 15, pp. 16945-16960, 2021.

5. W. Song et al., "Design of a Flexible Wearable Smart sEMG Recorder Integrated Gradient Boosting Decision Tree Based Hand Gesture Recognition," in IEEE Transactions on Biomedical Circuits and Systems, vol. 13, no. 6, pp. 1563-1574, 2019.

6. X. Hu, H. Zeng, A. Song and D. Chen, "Robust Continuous Hand Motion Recognition Using Wearable Array Myoelectric Sensor," in IEEE Sensors Journal, vol. 21, no. 18, pp. 20596-20605, 2021.

7. A. A. Pramudita, Lukas and Edwar, "Contactless Hand Gesture Sensor Based on Array of CW Radar for Human to Machine Interface," in IEEE Sensors Journal, vol. 21, no. 13, pp. 15196-15208, 2021.

8. S. Pancholi and A. M. Joshi, "Electromyography-Based Hand Gesture Recognition System for Upper Limb Amputees," in IEEE Sensors Letters, vol. 3, no. 3, pp. 1-4, Art no. 5500304, 2019.

9. W. Zhang, J. Wang and F. Lan, "Dynamic hand gesture recognition based on short-term sampling neural networks," in IEEE/CAA Journal of Automatica Sinica, vol. 8, no. 1, pp. 110-120, 2021.

10. U. Côté-Allard et al., "Deep Learning for Electromyographic Hand Gesture Signal Classification Using Transfer Learning," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 4, pp. 760-771, 2019.