EEE G613: Advanced Digital Signal Processing Implementation of sEMG Based Indentification of Hand Motion using Wavelet Neural Networks

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***Abstract*—Surface Electromyography (sEMG) signals have applications in clinical and rehabilitation applications. The current challege is to reduce the data acquisition time, use minimum number of electrodes and obtain maximum classification accuracy. The paper uses a novel technique to use a wavelet neural network for classification. Additionally, an attempt has been made to use an adaptive noise filtering technique to further clean the signal.The sEMG signal is decomposed by discrete wavelet transform (DWT) and absolute maximum wavelet coefficients are selected from each level. The neural network is trained using back propagation with gradient descent algorithm. Furthermore, the performance of the wavelet neural network is compared with a normal neural network of similar architecture.**

***Index Terms*—sEMG signal, Wavelet Transform(WT), Discrete Wavelet Transform (DWT), Denoising, Artificial Neural Network (ANN), Wavelet Neutral Network(WNN)**

I. Introduction

Surface Electromyogram (sEMG), measured at the surface of the skin, provides valuable information about the neuro-muscular activity and is used for clinical diagnosis and control of assistive devices [1] [2]. Its application in control prosthetic hands has also presented a great challenge, due to the complexity of the sEMG signals, such as the desire for minimum length of signal used, reduction in number of electrodes and need for increased accuracy. This paper intends to investigate the sEMG-based identification of hand motion commands for the myoelectric prosthetic hand. The myoelectric prosthetic hand would be controlled by the sEMG signals of the amputee's residual muscles. An important requirement in this area is to accurately classify different EMG patterns for controlling a prosthetic device. For this reason, effective feature extraction is a crucial step to improve the accuracy of pattern classification [3]. However, the myoelectric control systems of these hand motions are controlled by the switch using ON–OFF commands in single muscle groups, and only limited hand motion commands can be classified. This is important, if we increased the number of hand motions then we get more dexterity of prosthetic hand to improve the Quality Of Life (QOL) of the amputees.

Previous researchers have focused on developing and optimizing the sEMG pattern recognition system to classifies many hand motion commands as possible. Ooinish [4] analyzed one channel of sEMG signals to obtain the power-assisted command. Alkan [5] utilized two channels of sEMG signals and classified four hand motion commands. Khezri [6] and Englehart [7] four channels got six hand motions using four channels. Xing [8] used four sEMG sensors and classified seven hand movements. Phinyomark [9] utilized five sEMG sensors and detected six hand movements. Rafiee [10] acquired twenty two sEMG sensors and classified sixteen hand movements. These studies focused on designing an effective sEMG pattern recognition system to classify more complex hand motion commands with higher accuracy, but did not pay close attention to limiting the number of sEMG sensors. Increasing the number of sEMG sensors increases the complexity of classification algorithms and deteriorates the real-time performance of the sEMG pattern recognition system. So,our goal in this paper is to obtain maximum accuracy using minimum number of sensors.

This paper utilises a DWT based feature extraction technique, where the absolute maximum coefficient from each level is taken as the input to the neural network. Wavelet analysis, has proven to be useful for various time-series analysis, such as compression and denoising. Wavelet analysis is able to handle the non-linearities in a signal. Additionally, DWT help in the reduction of feature size which is essential for faster training and noise reduction.

Taking just a single coefficient in a level only captures a small range of frequency components. It is possible that signal information is captured in other coefficients also. The authors have extended the scope of [11] by first denoising the signal using adaptive filtering techniques discussed in [12] followed by the feature extraction. The motivation of such a step was to allow more coefficients to be used for the features without worry of noise.

II. Literature Review

When searching for a paper for implementation, journals from reputed publishers like IEEE Xplore and Elsevier were used. The key words used were *biomedical*, *wavelet*, *denoising*, *classification*. Special care was taken to select a paper which was published from 2015.

III. Methodology

A. Dataset Details

Data has been acquired from [13]. The data was collected at a sampling rate of 500 Hz and was passed to a Butterworth Band Pass filter with cutoff at 15 Hz and 500 Hz respectively. Furthermore, the notch filter at 50 Hz was used to remove the effect of power line interference. Subjects were asked to perform 6 hand motions repetitively and their sEMG signals were recorded from two electrodes placed on the Flexor Capri Ulnaris and Extensor Capri Radialis, with the reference electrode placed in the middle. [13] consists of data taken from a healthy subject in three consecutive days taken for 5 seconds. Each of the six actions are repeated 100 times.

In the original paper, signals were acquired from subjects. These acquisitions would be contaminated with environmental noise. Since the dataset used, already has clean signals, additive white gaussian noise was introduced to the signal such that the signal SNR was 25 dB.

B. Feature Extraction

After adding the noise, features have to be extracted from the signal. Wavelet transforms provide both time and frequency analysis. Since these signals are being used for prosthetic purposes, the time of data acquisition for classification has to be lesser than 300 ms. The signal is broken into windows of 200 ms. The Discrete Wavelet Transforms are computationally efficient for continuous wavelet transforms and also are ideal for the analysis of non-stationary signals like EMG. Using Mallat algorithm as seen in Figure 1, the signal is decomposed into three levels and the coefficients are obtained. The mother wavelet selected was the *coif5* wavelet. The maximum absolute value of approximate coefficients of

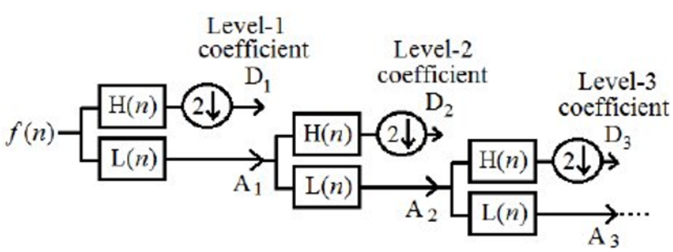

Fig. 1. Block Diagram of Mallat algorithm

the last level and the maximum absolute value of detail coefficients of every level is taken as the feature to be passed into the neural network.

The dataset for a given day consists of 6 actions, each action is repeated 100 times. 5 seconds of data correspond to 25 segments. Hence the size of the dataset is 15000. The data is broken into a 50-50 train-test split.

Before passing the data into the neural network, the data has to be normalized. Special care is taken to normalize the data using the scale from the training data only.

The data is normalized using Equation 1.

$$x_{norm} = (x*_{max} - x*_{min}) \times \frac{x - min(x)}{max(x) - min(x)} + x*_{min} \quad (1)$$

C. Neural Network Architecture

The wavelet neural network consisted of one hidden layer with a wavelet activation layer as seen in Figure 2. Since there are two sensors, the size of the feature is 8, hence the number of input neurons will be 8. 17 hidden neurons were considered. Finally, there are 6 output neurons as there are 6 possible

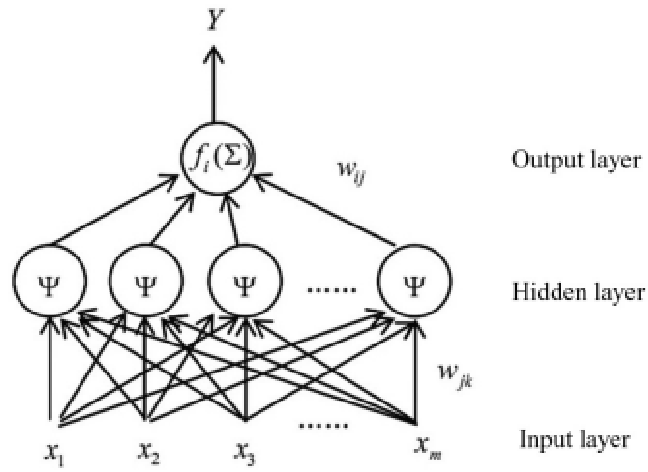

Fig. 2. Structure of Wavelet Neural Network

classes. The targets are in one-hot encoding. The output layer has a linear activation function.

Similarly, in the normal artificial neuron network, the structure is kept identical to that of the wavelet neuron network with the difference being in the activation of the hidden layer. In the normal neural network, a sigmoidal activation function is used.

In the normal neural network, the output of the j^{th} node of the hidden layer is given by Equation 2

$$\Phi(net_j) = \Phi(\frac{1}{1 + e^{-net_j}}) \quad (2)$$

In the wavelet neural network, the output of the j^{th} node of the hidden layer is related to the mother wavelet activation function as in Equation 3.

$$\Psi_{a_j,b_j}(net_j) = \Psi(\frac{net_j - b_j}{a_j}) \quad (3)$$

Where a_j represents the scaling factor of the wavelet and b_j represents the translation factor of the wavelet. The initial value of a_j is randomly initialized between 0 and 5. Whereas b_j is randomly initialized between -10 and 10. Weights of the neuron are randomly initialized between 0 and 0.1.

The wavelet function used was the Gaussian wavelet whose equation is given by Equation 4.

$$\Psi_1(z) = -ze^{-0.5z^2} \quad (4)$$

The error is computed using Equation 5, where the desired output or target of the i^{th} output node is d_i and the output of the neural network is y_i.

$$E = \frac{1}{2} \sum_{i=i}^{N} (d_i - y_i)^2 \quad (5)$$

The neural networks are trained using back-propagation using gradient descent. It is important to note that the translation and scaling factor of the wavelet neural network are trainable. Hence unlike normal neural networks where the activation function in a given layer are identical, the activation function of the hidden layer of the wavelet neural network will be fine tuned to the training data. This intuitively suggests that the network should have stronger classification abilities.

The trainable parameters are updated using Equation 6 where η_1 and η_2 are learning rates equal to 0.03 and 0.01 respectively.

$$\begin{aligned} w_{jk} &= w_{jk} - \eta_1 \frac{\partial E}{\partial w_{jk}} \\ w_{ij} &= w_{ij} - \eta_1 \frac{\partial E}{\partial w_{ij}} \\ a_j &= a_j - \eta_2 \frac{\partial E}{\partial a_j} \\ b_j &= b_j - \eta_2 \frac{\partial E}{\partial b_j} \end{aligned} \tag{6}$$

D. Novel Idea: The Adaptive Noise Filter

Adaptive noise cancellation is an alternative technique of estimating signals corrupted by additive noise or interference. The design of fixed filters requires a priori knowledge of both the signal and the noise, i.e. if we know the signal and noise beforehand, we can design a filter that passes frequencies contained in the signal and rejects the frequency band occupied by the noise. Adaptive filters, on the other hand, have the ability to adjust their impulse response to filter out the correlated signal in the input. They require little or no a priori knowledge of the signal and noise characteristics.

As sEMG signals are non-stationary in nature, this adaptive filtering method is best suitable to denoise the sEMG signals. During recording the sEMG signals, there occurs some noise and the received sEMG signal is distorted and it is difficult to classify the signals. The block diagram of an Adaptive Noise Canceller is shown in Figure 3.

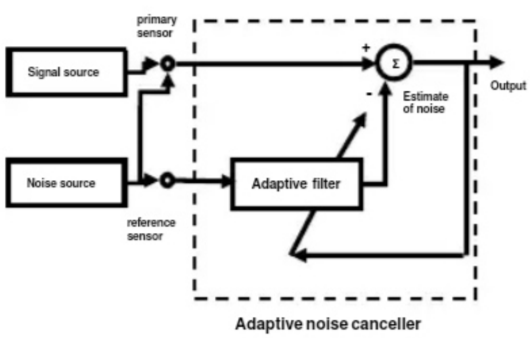

Fig. 3. Adaptive Noise Canceller

The primary sensor receives the distorted signal $x(n)$ which has a original sEMG signal $s(n)$ and an additive noise signal $v(n)$ as seen in Equation 7.

$$x(n) = s(n) + v(n) \tag{7}$$

The reference sensor receives the noise $w(n)$ and it is uncorrelated with signal $s(n)$ yet correlated with noise v(n). Here the filter coefficients are adjustable to the noise error. The output of the filter i.e. $y(n)$ take off from distorted signal $x(n)$ and yields an error signal $e(n)$.

$$e(n) = x(n) - y(n) \tag{8}$$

Therefore the error signal will become,

$$e(n) = s(n) + v(n) - y(n) \tag{9}$$

Then the error signal will update to new filter coefficients of the adaptive filter. From the above equation, it is clearly shown that the noise component $v(n){-}y(n)$ is getting reduced. Therefore, it will gives a minimum distorted sEMG signal and it is also useful for classification.In this experimental setup, we have used Recursive Least Square (RLS) algorithm of adaptive filtering as it is better than existing adaptive filtering techniques.

IV. Results

Classification results of the original paper, our implementation and results with the adaptive filtering is presented in Tables I, III and II, respectively.

Additionally, loss function was plotted in Figure 4. The accuracy for each epoch was plotted in Figure 5 and Figure 6.

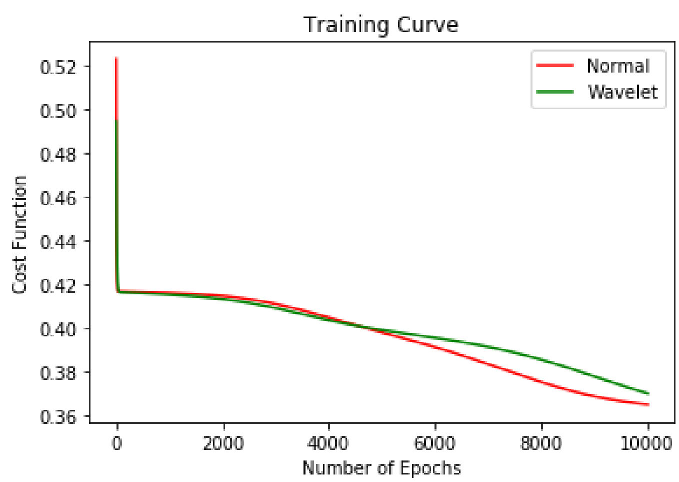

Fig. 4. Loss Curve

TABLE I
ACCURACIES OBTAINED BY PAPER

Classifier	WNN	ANN
Average Accuracy	94.67	93.22
Standard Deviation	1.8736	3.3244

TABLE II
ACCURACIES OBTAINED FOR NORMAL NEURAL NETWORK

S.No	Replication		Innovative Idea	
	Train	Test	Train	Test
1	31.22	31.54	31.22	31.56
2	38.30	38.36	38.32	38.86
3	41.38	42.09	41.40	42.86
Average	36.97	37.33	36.98	37.76

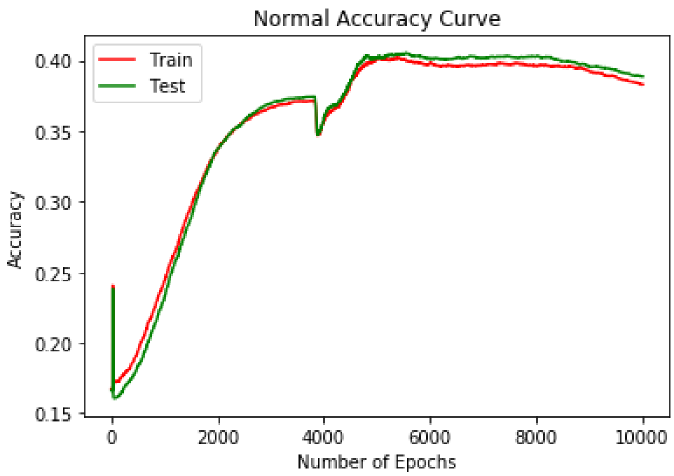

Fig. 5. Accuracy Curve of Normal Neural Network

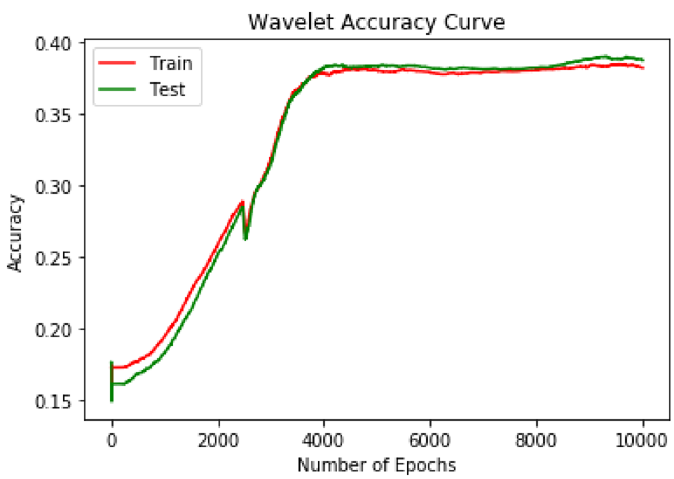

Fig. 6. Accuracy Curve of Wavelet Neural Network

V. Discussion

During the paper implementation, the results obtained are much different from the ones in the original paper. The possible reasoning for such a deviation can be attributed to:

- The dataset used is different from the paper
- The artificial noise introduced is not exactly like environmental noise which could have attributed to the poorer performance.
- The paper does not mention the initialization technique used for the weights and the learning rate ratios. Authors have attempted to experiment to find the optimum hyper-parameters.

Additionally, an attempt has been made to use a soft-max activation layer at the output and change the optimization loss function to cross entropy loss.

With the denoising technique as discussed in Section III-D, slight improvement in the accuracy is seen. It is seen that the wavelet neural network, trains faster than the normal neural network.

TABLE III
Accuracies Obtained for Wavelet Neural Network

S.No	Replication		Innovative Idea	
	Train	Test	Train	Test
1	30.45	31.24	30.46	31.44
2	37.96	37.85	38.21	38.73
3	40.98	41.74	41.33	42.29
Average	36.46	36.94	36.67	37.48

VI. Conclusion

The authors have attempted to replicate the paper [11]. Since the dataset used is not available publicly, data from [13] was used. After feature extraction, the data was passed into a normal neural network and wavelet neural network. Additionally, an adaptive denoising technique was used in attempts to improve the training accuracy. Denoising has improved the classification accuracy slightly increasing the wavelet neural network accuracy from 36.94% to 37.48%.

Appendix

The code for the neural network and feature extraction as well as the extracted data are available at https://github.com/saksham36/WaveletNeuralNetwork

Acknowledgment

The authors would like to thank Dr. Ananthakrishna Chintanpalli for this opportunity to explore this paper. His invaluable guidance has helped the authors throughout the project duration.

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