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Correlation Analysis of Electromyogram Signals

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ABSTRACT

An inability to adapt myoelectric interfaces to a user's unique style of hand motion. The system also adapts the motion style of an opposite limb. These are the important factors inhibiting the practical application of myoelectric interfaces. This is mainly attributed to the individual differences in the exhibited electromyogram (EMG) signals generated by the muscles of different limbs. In this project myoelectric interface easily adapts the signal from the users and maintains good movement recognition performance. At the initial stage the myoelectric signal is extracted from the user by using the data acquisition system. A new set of features describing the movements of user's is extracted and the user's features are classifed using SVM classification. The given signal is then compared with the database signal with the accuracy of 90.910 % across all the EMG signals.

KEYWORDS: *Electromyogram (EMG), Discrete Wavelet Transform (DWT), Support Vector Machine (SVM).*

I. INTRODUCTION

Now a days electromyoghrapy signals are broadly used for a various applications especially in the field of myoelectric controls and prosthesis. The electrical manifestation of the muscle contractions is called EMG, which is sent from the spinal cord to control the muscles which contain the various information about the neural signals [3]. The power of the EMG signals are somewhat related to the intensity of the motor neural which is used to drive muscle of the limb's [4].This property has been used in various application of bio-medical and practical applications, which includes myoelectric controlled prosthesis, where the surface EMG is recorded from the muscle of the limb's and after processing they are used for the activating certain prosthetic functions of the prosthesis like the close or open operation of the hands. A myoelectric controller usually consists of three main steps:1) Transformation 2) Feature Extraction and 3) Classification and then the results are compared with the normal subject's data.

In [5] may 2014, Al-Timemy in his proposed work he studied about the use of the multichannel sEMG signals to distinguish between the individual and the combined finger movements for the dexterous prosthetic control. Offline processing was used to evaluate the classification procedure which recorded the sEMG signals from the ten intact-limbed and six below-elbow amputee persons. It has been observed from the results that the high accuracies have been obtained from orthogonal fuzzy neighborhood discriminate analysis for feature reduction and for the classification Linear Discriminate Analysis (LDA) is used. However, the main limitations here are the participants are able to demonstrate in real time using a virtual environment. Another limitation is that this proposed system can only examine the figure movements irrespective of the hand movements. Also increase into the number of movements might increase the confusion between the movements.

In [6] December 2011, Englehart. K. & Hudgins. B, to extract suitable features from a myoelectric signals they use a combination of the principal component analysis and a wavelet packet to classify the six classes of hand motions. To control the myoelectric signals of four classes of hand motion they developed a wavelet-based system with a high accuracy more than 85%, low response time and a user interface control system.

In 2013 [7], Ganesh R. Naik, S. Easter Selvan and Hung T. Nguyen signals for the neuromuscular disorder, prosthesis and other real time applications they had done analysis of the EMG. In this the measured signals are the combinations of the electric potentials that get added from the surrounding muscles. Independent Component Analysis (ICA) is used is used for this EMG signal processing. However, the limitations are the ICA is unable to compute with the single channel EMG measurement which is used for the extraction. ICA algorithm separates the empirical mode decomposition algorithm which is used for the single-channel EMG signal to a set of noise-canceled intrinsic mode functions then this is further used for the classification purpose.

In 2015 [10] Pu Liu, Meera Dasog, Clancy and Edward A. the EMG pattern recognition was developed to study the different functional movements and how they actually perform, their performance was latter on interpreted. Different features of hand movements like elbow movement, wrist and arm movement was extracted in the time domain with the help of pair of Ag/Agcl surface electrodes on both the right and left hands. The accuracy of the proposed was more than 95% for the same hand movements and 93%-97% for the different hand movements.

In 2014[8] S.A. Fattah and A.B.M.S.U Doulah for the neuromuscular diseases which are obtained from the EMG signals they used two schemes. And also this proposed system is based on Discrete Wavelet Transform (DWT) for feature extraction. A few high energy DWT coefficients with the maximum value were extracted from the EMG signals in the first scheme. And later on in the second scheme, motor unit action potentials (MUAPs) were extracted by decomposition method. Based on the statically properties of the DWT coefficients the feature extraction was performed. In the next stage i.e. for the classification the K-nearest neighborhood (KNN) was used.

II. Methodology

The proposed system is used for the analysis of the EMG signals which are obtained from the muscles of the different limbs. In bio-medical to extract the useful information from the EMG signals, feature extraction is the most significant method used and also used on a large scale. Hidden information can be obtained with the help of feature extraction without containing any noise. There is a possibility that many noise signals may get add to the EMG signals as the amplitude of these signals is very low.

The EMG sensors are used for acquire the EMG signals from the muscles of the subject. Here we have used only two electrodes to get the EMG signals from the subject's muscles, for this surface EMG is used. The first step before insertion of the needle electrode is skin preparation. This typically involves simply cleaning the skin with an alcohol pad. Skin above the muscles under investigation was scrubbed with an alcohol wipe. In one study, a small bead of electrode gel was also massaged into the skin. Three EMG electrodes were placed transversely across each of the biceps and triceps muscles, midway between the elbow and the midpoint of the upper arm, centered on the muscle midline. Each electrode-amplifier had a pair of 4-mm (or 8-mm) diameter, stainless steel, hemispherical contacts separated by 10 mm(edge-to-edge),oriented along the muscle's long axis. The distance between adjacent electrode-amplifiers was approximately 1.75cm.

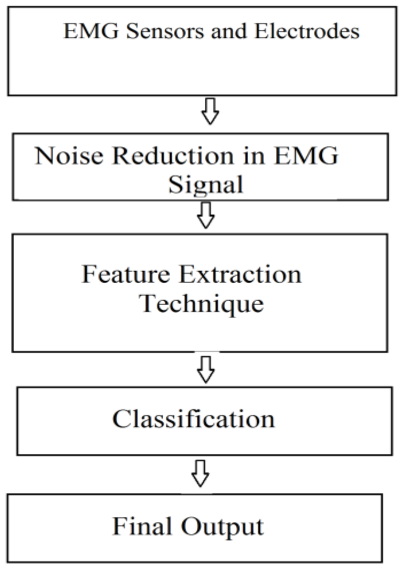

Figure1.-Flow Chart of the System

Further, this EMG signal is then converted into digital form with the help of the LPC2148. Then, the pre-processing of the EMG signals is done. Here, in this system the Discrete Wavelet Transform (DWT) technique is used for the feature extraction. As DWT gives a good frequency resolution at a high frequency and a time resolution at a low frequency which is most importantly required in a bio-medical field. To approximate the behavior of the continuous wavelet transform filter banks are used. The signal is composed of the high pass and a low pass filter.

The coefficients of these signals are obtained with the help of which we are able to obtain various signals. In our system we had use low pass signal for further processing. As the coefficients of the low pass signals are large, accurate and available with good stability, good range of features are obtained from this low pass signals. Further for pre-processing of the signals the Haar wavelet is used. Haar wavelet is a sequence of rescaled "square-shaped" functions is the basics of the wavelet. Amongst all the types of wavelet the Haar is the simplest type of wavelet. However, the limitation of the Haar wavelet is that it is not continuous in nature and hence cannot be used for differentiation. Hence is it very useful to use Haar wavelet for the analysis of signals with sudden transitions. Hence, we had used Haar Wavelet.

Features which are obtained in this system are:-

1) Mean- It is the average value of all the EMG signlas in the database.

2) Minimum level- Minimum amplitude (Min) is defined as the minimum amplitude of the signal. For different signals the minimum level of the signal is calculated.

3) Maximum level- Maximum amplitude (MAX) is defined as the peak amplitude of a signal. It is often used in areas where the measure of a signal that is not sinusoidal, it is the signal that swings above and below a zero value.

4) Varience- The variance is the mean value of the square of the deviation of that variable of EMG signal. Generally it uses power of EMG signal.

5) Standard Deviation- It is used to find out the threshold level of muscle contraction activity. It is the amplitude of the EMG signal. Standard deviation (SD) measures the spread of data from the mean. In signal processing, SD represents noise and other interference. It is used in comparison to the mean. This leads to the term: signal-to-noise ratio (SNR), which is equal to the mean divided by the standard deviation. Better data means a higher value for the SNR.

After this the next stage is the classification , so for the classification the Support Vector Machine (SVM) is used.For the classification and regression analysis the SVM is used.SVM are the supervized learing models which are associated learning algorithms. In addition to the linear analysis SVM can also perform the non-linear analysis.Also SVM gives a very good accuracy. After the completion of all this process the test EMG signal is compared with the data base signal if it matches the test signal then the given signal is normaol otherwise the signal is abnormal.

III. Results

Acquisition of the EMG signals is done with the help of EMG sensors from different subjects. Further, this signal is converted into digital form with the help of ARM 7.This signal is stored into excel sheet and then applied as an input to the MATLAB and then the pre-processing of this EMG signal is done the images of the input signal and the pre-processing signal is below. Further by applying the DWT the high pass signal and the low pass signal is obtained. Out of which the low pass signal is taken for the feature extraction and then the classification is done. For this test EMG signal 1, the test signal and the database signal matches hence, the result final result is normal. Whereas the for the test signal EMG signal 2, test signal and database signal does not matches hence we get the result as abnormal.

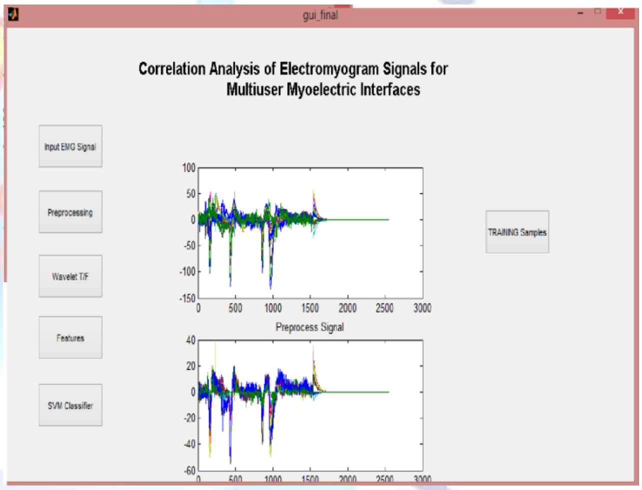

Figure 2. - Test signal 1 and the preprocessed signal.

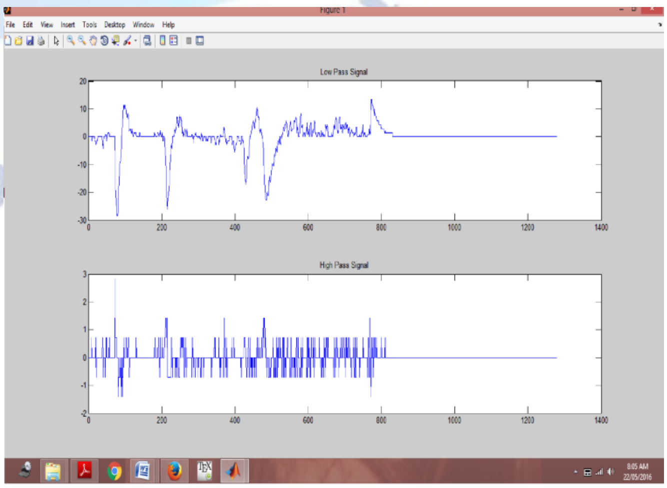

Figure 3- High pass signal and Low pass signal -test signal 1.

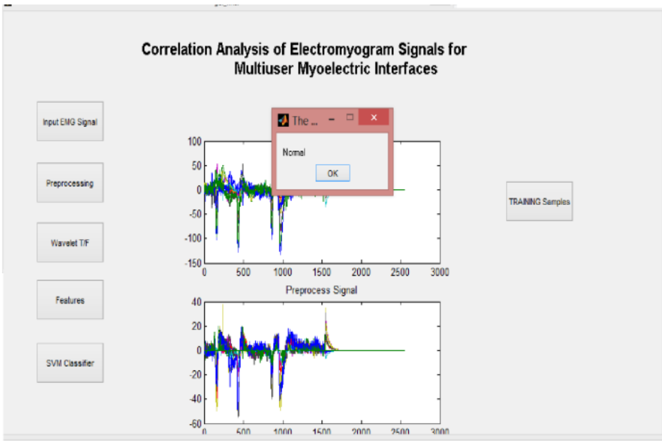

Figure 4 - Final output of the signal.

Now the test EMG signal 2 is applied. Fig.5 shows the input signal and the pre-processing signal. Fig.6 shows the high pass signal and the low pass signal of the test EMG signal 2.And the final output of the signal is shown in the fig.7.

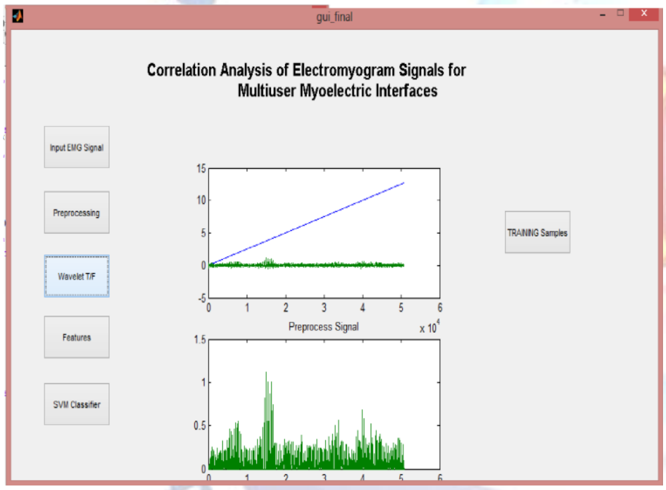

Figure 5. - Test signal 2 and the preprocessed signal.

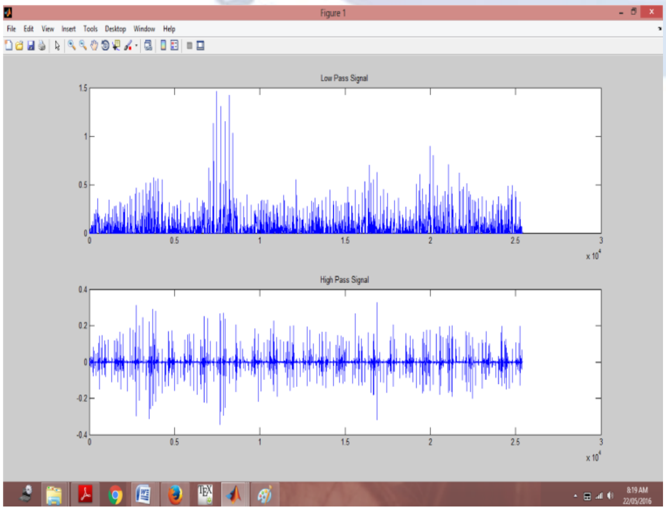

Figure 6. - High pass signal and Low pass signal -test signal 2

Figure 7 shows the final output of the test signal 2, which is an abnormal. So, we can say that the test 2 signal is not an EMG signal as it does not matches the database signal hence the results for it is abnormal.

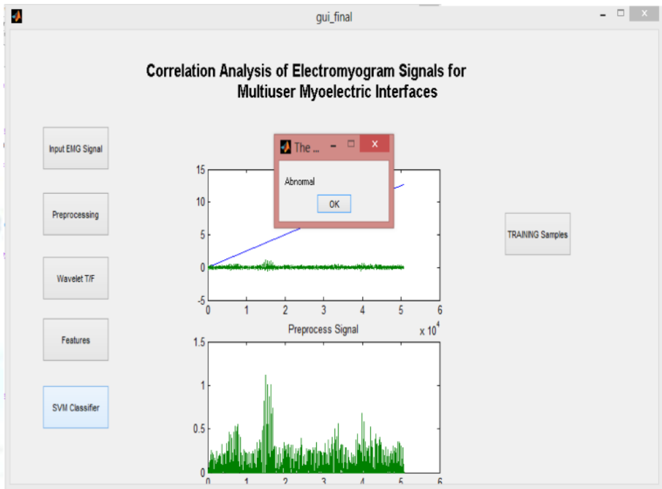

Figure 7. - Final output of the signal

Three parameters are considered for the evaluation of the signals. The performance parameters of the system are as follows:-

a) Accuracy- The degree to which the result of a measurement, calculation, or specification conforms to the correct value or a standard. Here, in this case it measures that how accurate our system is and after calculating the accuracy of 90.910 % is obtained.

b) Sensitivity- Sensitivity (also called the true positive rate, or the recall in some fields) measures the proportion of positives that are correctly identified as such (e.g., the percentage of sick people who are correctly identified as having the condition).Sensitivity refers to the test's ability to correctly detect patients who do have the condition. Consider the example of a medical test used to identify a disease. The sensitivity of the test is the proportion of people who test positive for the disease among those who have the disease. Mathematically, this can be expressed as:

$$\text{Sensitivity} = \frac{number\ \ of\ true\ positives}{number\ \ of\ true\ positives\ +number\ \ of\ false\ negatives}$$

Sensitivity = probability of positive test

c) Specificity- Specificity (also called the true negative rate) measures the proportion of negatives that are correctly identified as such (e.g., the percentage of healthy people who are correctly identified as not having the condition).Specificity relates to the test's ability to correctly detect patients without a condition. Consider the example of a medical test for diagnosing a disease. Specificity of a test is the proportion of healthy patients known not to have the disease, who will test negative for it. Mathematically, this can also be written as:

$$\text{Specificity} = \frac{\textit{number of true negatives}}{\textit{number of true negatives} + \textit{number of false positives}}$$

Specificity = probability of negative tests

SVM classification is then compared with the Probabilistic Neural Network (PNN). PNN is often used in classification problems. When an input is present, the first layer computes the distance from the input vector to the training input vectors. This produces a vector where its elements indicate how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its net output as a vector of probabilities. Finally, a compete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes. The comparison of both the classification is represented in the graphical form.

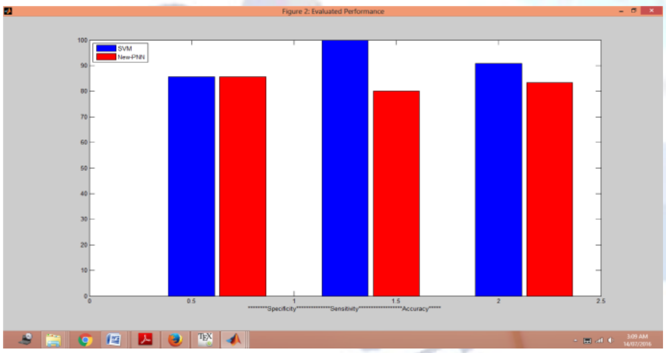

Figure 8- Comparison with PNN

IV. Conclusion

In this system, an approach for developing multiuser myoelectric interfaces using a DWT has been proposed. Firstly, in this system with the help of the EMG sensors EMG signals are adapted from the subjects. Then, pre-processing of the signals is done. The possibility of training the classifier on EMG features has performed. And this is then compared with the database signal with the accuracy of 90.910% across all the EMG signals is obtained. This method was able to overcome the limitations of the previous methods. And with the help of SVM classifier the classification is done. From this proposed system we were able to find out the applied signal is EMG as it matches the database signal. If the given signal does not match then the signal is abnormal.

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