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Bio-medical (EMG) Signal Feature Extraction Using Wavelet Transform for Design of Prosthetic Leg

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Abstract— In this paper, the surface Electromyographic signals are extracted using surface electrode. The two pairs of single-channel surface electrodes are utilized to measure the EMG signal obtained from forearm muscles. Then the Haar Transform of the Wavelet family was used to analyze the EMG signal. Later features in terms of root mean square, logarithm of root mean square, as well as standard deviation were used to extract the EMG signal. Among the various feature extracted from EMG signal states that root means square feature extraction method gives better performance as compared to the other features. In the near future, this method can be used to control a mechanical arm as well as robotic arm in field of real-time processing.

***Index Terms*— Electromyography signal, EMG, feature extraction, Wavelet Transform.**

I. Introduction

The Electromyography (EMG) is the study of muscular electrical signals. EMG is sometimes referred to a myoelectric activity. Many muscular undergo some abnormalities such as muscular dystrophy, inflammation of muscle, peripheral nerve damages which may result into an abnormal electromyogram. EMG signals can be recorded basically by two types of electrodes which are an invasive electrode also-called wire electrodes or needle electrodes and the second type is a non-invasive electrode also-called surface electrode. The Wire or needle electrode records the potentials of individual muscle fiber which is an ideal choice to evaluate the various muscle activities [1].

Electromyography (EMG) is a collective electrical signal acquired from muscles and includes valuable information about muscular contraction. The muscle activity is controlled by the nervous system which forms complicated properties for EMG because it is related to the anatomical and physiological characteristics of the muscles [2].

The features extracted from acquired raw EMG contribute to the different muscular contraction classification. The features extraction method used is based on the Wavelet Transform approach. A surface electrodes array is used for data acquisition system to acquire EMG raw data. The data acquisition system which we are using to extract EMG provides us to extract some features such as Root Mean Square (RMS), Logarithm of Root Mean Square (log RMS), MFCC, and Standard Deviation methods to extract the features [2].

The features which are extracted from the acquired EMG are serving for muscular contraction. As shown in Fig. 1 these signals are in two different forms and are conducted via two different types of nerves. The signals which are moving from the limbs towards the spinal cord are conducted via sensory nerves, and the signals which are moving from the spinal cord towards the limbs are conducted via motor nerves. And this is an unchangeable process hence the waves are termed as F-waves and H-reflexes. EMG signals are recorded in form of NCV i.e. nerve conduction velocity. Thus this NCV measures the ability of the motor nerve as well as the sensor nerve to conduct the electrical impulses [4]. Our features are based on the Wavelet Transforms approach. A two single-channel surface electrodes array is used as a data acquisition system to acquire EMG data by the best level of Wavelet family.

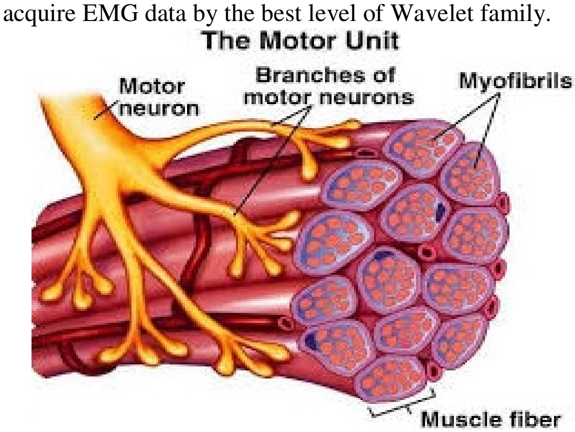

Fig. (1) Cross-sectional view of muscles

II. Wavelet Analysis Of EMG Data

The signal that consist of the EMG data has to be initially pre processed using three stages of pre processing which are EMG data acquisition, data segmentation and EMG feature extraction [2]. Two pairs of single-channel surface electrodes are used to measure and record the EMG signal on leg muscles. Then different levels of Daubechies Wavelet family are used to analyze the EMG signal. Finally these features are in terms of root mean square, logarithm of root mean square, and standard deviation are extracted from the EMG signal. The main frame GUI format is as shown in Fig. 2.

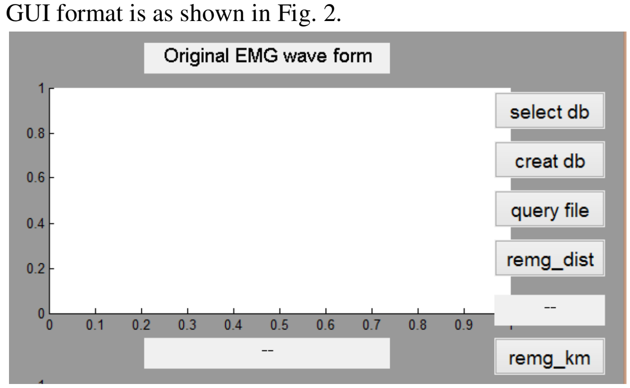

Fig. 2 GUI Main Frame screen using MATLAB

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A. Multi-channel EMG data Acquisition

EMG measurement is defined by the instrument called electromyogram. The acquisition system generally consists of an instrumentation amplifier, a notch filter, an offset adjustment, an isolator, a main amplification circuit, and the cathode ray tube (CRT) display. An instrument amplifier is a high common mode rejection ratio (CMRR) differential amplifier which works to acquire a weak signals or low amplitude signal included in the high-frequency noise signal. The notch filter gets rid of the 50Hz noise while keeping the EMG signal data intact [5]. The offset adjustment maintains the baseline level during the subject’s motion. The function of isolator is to separate front-end section from the rear-end section to protect the EMG signal from possible electrical shock to the patient. The main amplification circuit conditions the EMG prior to be display on the CRT display. The complexity of the electronic circuit becomes realized with the necessity to monitor the multi-channel of EMG. Such complicate designs, are made generally possible by the creation of entirely reconfigurable and programmable components. In this research, we acquire two EMG signal from the surface electrodes placed at the legs muscles [8]. An EMG control system based on pattern recognition includes three significant stages, respectively data acquisition, data segmentation and feature extraction [7].

B. Data Segmentation

The EMG signal obtained from the acquisition system is further de-noised using wavelet Transformation method. As the wavelet transform can localize both time and frequency components. Whereas the Fourier transform gives only the frequency components hence the wavelet transform is more preferable over Fourier Transform. More over the wavelet transform gives very high frequency resolution even at high frequency ranges, so the noise components in the desired signal are isolated farther. The discrete wavelet transform with four levels of decomposition is proposed the Daubechies mother wavelet transform family is selected and is made applicable as shown in Fig. 3.

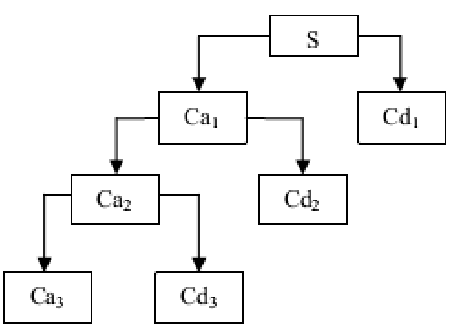

Fig. 3 Multi-resolution decomposition tree of EMG signal at third stage.

The window size of Daubechies Family mother Wavelet Transform can be modified by using the frequency analysis. Consequently, the signal analysis can be performed at the high frequency signals resulting into the same consequences as of the analysis at the low frequency. Combination of different wavelet windowing technique is used to describe the signal characteristics. Each wavelet is based on the same function called “mother wavelet”. These wavelets are the subset of mother wavelet operated with scaling and translation as shown in equation (1).

$S = Ca_3 + Cd_1 + Cd_2 + Cd_3$ ..... (1)

From the equation, the scaling and translation are represented as ‘a’ and ‘b’, respectively one for approximation and second for standard deviation from those of real values. The scaling is a process of compression or dilation of mother wavelet window resulting into the variation in its resultant frequency. The scaled wavelet is then normalized so as to maintain its energy level to be equal to meet the energy level of mother wavelet window. Therefore, if the φ (t) is the function of mother wavelet, a general term of wavelet with the position of ‘a’ and ‘b’ can be written as following by equation (2).

$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}\varphi\left[\frac{t-b}{a}\right] = \varphi(scale, position, t)$ .... (2)

C. Feature Extraction

i. RMS and logRMS

The root mean square (RMS) value of each channel was calculated to create a 2-D feature vector. It has been argued that the response time of the control system should not introduce a perceivable delay [9]. In the same set of data if the signal functions in a continuous f (t), which is set in the T1 ≤t ≤T_2can measure RMS of continuous functions from the equation (3)

$X_{RMS} = \sqrt{\frac{1}{T2-T1}\int_{T1}^{T2}[F(t)]DT_1^2}$ .... (3)

Similarly, the log-transformed feature space, demonstrates a more uniform scattering of points compared to the untransformed RMS features of an able-bodied participant [12]. That shown by equation (4)

$X_{RMS} = \log x_{RMS}$ .... (4)

ii. Standard Deviation

The standard deviation of EMG signal can calculate by the sample of signal that shown by equation (6)

$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$ .... (6)

III. Wavelet Transform

In the present work, Haar wavelet has been used as the mother wavelet. MATLAB software package version 7 is used to extract the DWT coefficients. For achieving good time-frequency localization, the preprocessed EMG signal is decomposed by using the DWT up to the fourth level. The smoothing feature of Haar wavelet made EMG more suitable to EMG changes and the feature set is composed of level 1,2,3, 4 coefficients cd1, cd2, cd3, and ca4. Most of the energy of the EMG signal lies between 0.5 Hz and 40 Hz. This energy of the wavelet coefficients is concentrated in the lower sub-bands ca4, cd4, and cd3. The level 1, 2 coefficients cd1 and cd2 are the most detail information of the signal and they are discarded. Since the frequency band covered by these levels contains much noise. It is less necessary for representing the approximate shape of EMG and the frequencies covered by these levels were higher than frequency content of the EMG. Coefficients cd3 and cd4 represent the highest frequency components and ca4 represent the lowest one. For the Haar wavelets, cd4 having length of 250 coefficients are generated. The obtained feature vectors form Haar wavelets decomposition is used as an input to the NN classifier. The process of wavelet decomposition is done for the 50 EMG signals for both normal as well as abnormal muscles with myopathy[7].

IV. EMG Data Distinguishing

After extraction of the various features from the EMG data then the various Features such as RMS, log RMS, MFCC, standard deviation are put to threshold so as to be distinguished between normal EMG and abnormal EMG. The entire database used to train the system to be self sufficient so as to recognize any unknown source EMG and differentiate if it lies between the normal EMG values or abnormal EMG values of pre-processed EMG Signal. The entire flow of Execution of the EMG signal feature extraction as well as signal classification is as shown in Fig. 4

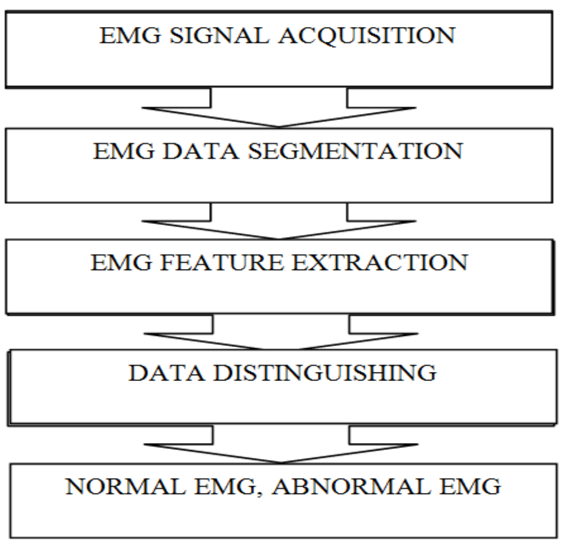

Fig.4. Flow of Execution the program

V. Results And Discussions

From the entire methods that we studied during the process we analyzed that the Haar Transform among the Daubechies Wavelet Transform Family, provides simpler way to distinguish between the normal as well as the abnormal EMG signals. This Haar Transform analyses the features in a very correct manner so as to be more precise in terms of the features being extracted from the EMG signals.

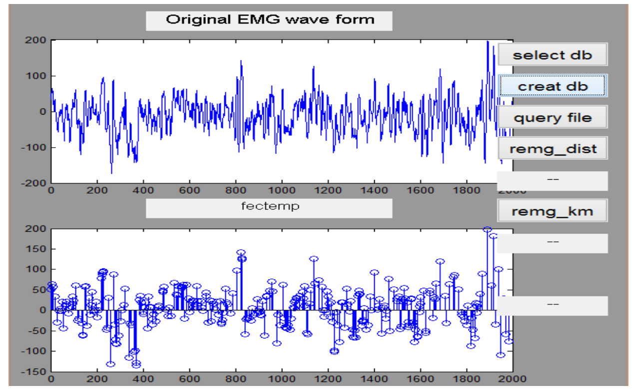

Fig.5. (a) Raw EMG signal. (b) Feature Extracted from EMG signal using Wavelet Transform.

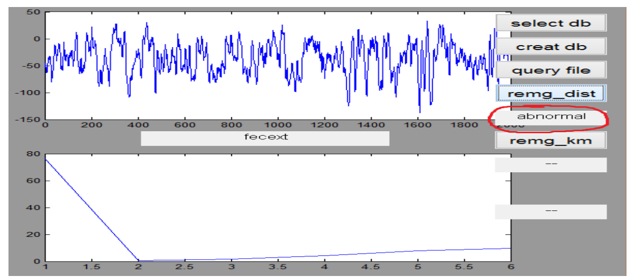

Fig.6. Distinguishing the signal to be an Abnormal Signal.

Conclusion

The RMS feature extraction method shows the best result compared to the other methods. Standard deviation feature is similar to the root mean square feature, and logarithm of root mean square feature can be expanding scale. The mfcc feature thus plays a main role in differentiating between a normal and an abnormal EMG. The feature set has been carefully chosen to have enough information for good accuracy. Thus this method serves useful to indentify normal healthy EMG signals so as to control Prosthetic leg and give more efficiency in the field of robotics in future. The technique mentioned in this paper is a good for the detection of myopathy as compared to the conventional instrumental ones. Hence, it is faster, efficient and robust as it is resistant to environmental hazards.

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