Linear and non-linear classification of EMG signals for probable applications in designing control system for assistive aids.

A Thesis submitted in partial fulfillment of the Requirements for the degree of

Master of Technology

In

Biomedical Engineering

By

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Under guidance of

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June 2015

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ODISHA, INDIA – 769008

CERTIFICATE

This is to certify that the thesis entitled "**Linear and non-linear classification of EMG signals for probable applications in designing control system for assistive aids.**" Submitted by ***Mr. Uvanesh K*** bearing roll no. ***213BM1005*** in partial fulfillment of requirement for the award of Master of Technology in "***Biomedical Engineering***" during session 2013-15 at National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any other Degree/Diploma.

Date: - 30 May, 2015

Place: - Rourkela

Dr. Kunal Pal
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Date: - 30 May, 2015

Place: - Rourkela

Uvanesh K.

ABSTRACT

EMG signal was acquired by placing electrodes on the surface of forearm muscle. The acquisition is made possible using a bio-potential amplifier (Gain ≈ 2500 with a cut off frequency of 1500Hz). The acquired EMG signal was processed further, so that the EMG signal can be classified into their corresponding category.[1] By using the raw EMG signal, the envelope of the signal were detected, then original EMG signal were extracted, later the extracted EMG signal was Wavelet processed. For preforming the classification, the features were extracted. By using the extracted features, Offline and Online classifications were performed. The results showed an accuracy of >95% (overall). For improving the performance of the classification, Boolean change state logic and Hall Effect sensor were used to design the control system.

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1 Introduction and Objectives

1.1 Introduction

In recent years, there has been a tremendous increase in the use of computerized machine with the human body for the betterment of human, who are physically impaired. To improve the quality of life of these physically impaired persons, many researches are going on in the area of robotics and rehabilitative engineering.[2] The techniques which acquire various biosignals for the performance of any mechanism (single/multi) or for replacing the corresponding human response directly can be called as Human-Machine Interface (HMI) or Human-Computer Interface (HCI). This is the key technology which constitutes human in the loop system.

1.1.1 Biosignals

Biosignal (often referred as bioelectrical signal) is a collection of electrical current produced by sum of electrical activity across any specific region of the organ/body. This acquired signal is normally a function of time with its amplitude, frequency and phase. This biosignals can acquire at the surface of skin by placing Silver/Silver-Chloride (Ag/AgCl) electrode. Some commonly used biosignals which are interfaced with HMI/HCI system are Electrocardiogram (ECG), Electrooculogram (EOG), Electroencephalogram (EEG), and Electromyogram (EMG), etc. These signals are acquired, then translated into machine level language (machine command) for the controlling the machine, such mechanism is very much required for improving the quality of life of the physically impaired persons.[2, 3]

1.1.2 Electrocardiogram (ECG):

The ECG signal is produced due to electrical activity of the heart (figure 1). This ECG signal can be acquired by placing electrodes on the patient’s body. These electrodes sense even a tiny change in electrical potential over the skin due to depolarization of the heart muscle during each heartbeat. The signal range of ECG signal is 0.01-300Hz. The instrument used to record the electrical activity of heart over a period of time is called as Electrocardiography.[4]

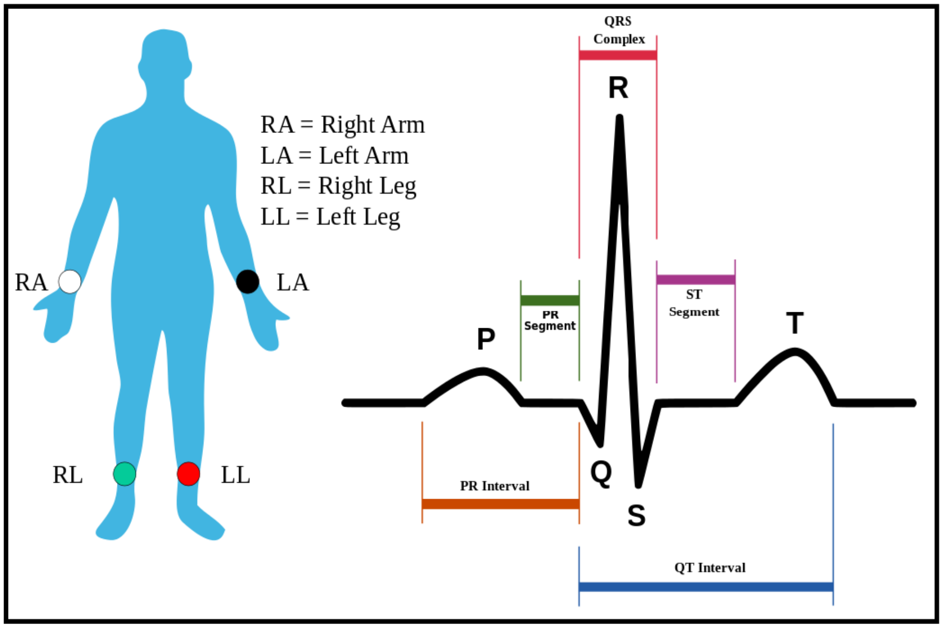

Figure 1: ECG electrode placement and its corresponding signal output (http://en.wikipedia.org/wiki/Electrocardiography#/media/File:SinusRhythmLabels.svg)

1.1.3 Electrooculogram (EOG)

The EOG signal is produced due to the change in electrical activity across corneo-retinal muscle i.e. it is the measure of potential difference exists between cornea (front side) and retina of the eye (back side) which is due to movement of eye (figure 2). The potential difference generate in these region is of 0.4 – 3.5mV. The EOG signal can be acquired by placing electrodes either above and/or below of the eye (vertically and/or horizontally) with forehead as ground. The EOG signal frequency is in the range of 0.1 – 10 Hz.[5]

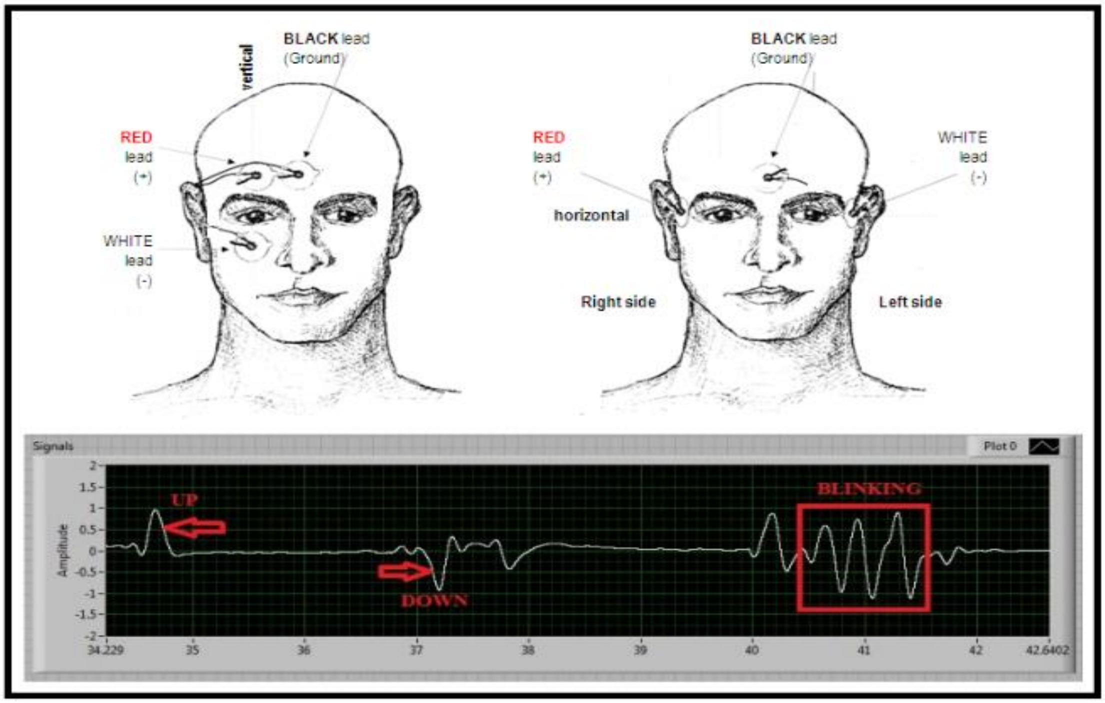

Figure 2: EOG electrode placement and its corresponding signal output (http://ttktamop.elte.hu/onlinetananyagok/physiology_practical/ch09s06.html)

1.1.4 Electroencephalogram (EEG)

The EEG signal is produced due to ionic current transfer between neurons present in the brain (figure 3). These EEG signal can be measured by placing electrodes over scalp. The signal range of EEG signals is 0.1 – 100Hz.[6] The EEG signal can be further classified into various wave patterns depending upon their diagnostic purpose which are shown in table 1:

Table 1: EEG signal wave pattern and its range:

Wave pattern of EEG signal	**Range (Hz)**
Delta waves	0.3 – 4
Theta waves	4 – 7
Alpha waves	8 – 15
Beta waves	16 – 31
Gamma waves	32 – 100

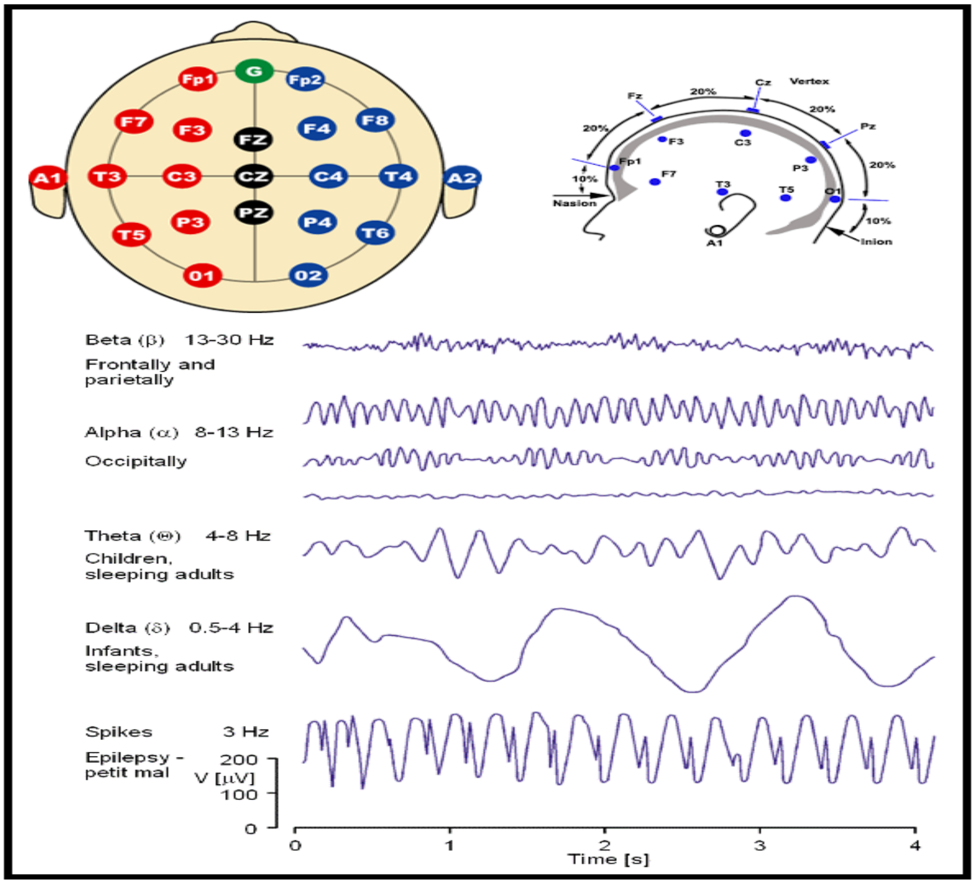

Figure 3: EEG electrode placement and its corresponding signal output (http://www.bem.fi/book/13/13.html)

1.1.5 Electromyogram (EMG)

The EMG signal is produced due to electrical activity of the skeletal muscle cells (neuromuscular activity or simply muscle movement (contraction and relaxation)). The EMG signal generated due to neuromuscular activity depends on both physiological and also anatomical properties of the muscle. This EMG signals are nothing but a collection of electrical activity from different motor units at a time. The instrument used to record the electrical activity of the skeletal muscle is called as Electromyography.[3, 7] The frequency range of the EMG signal is 5 - 3000Hz (figure 4).

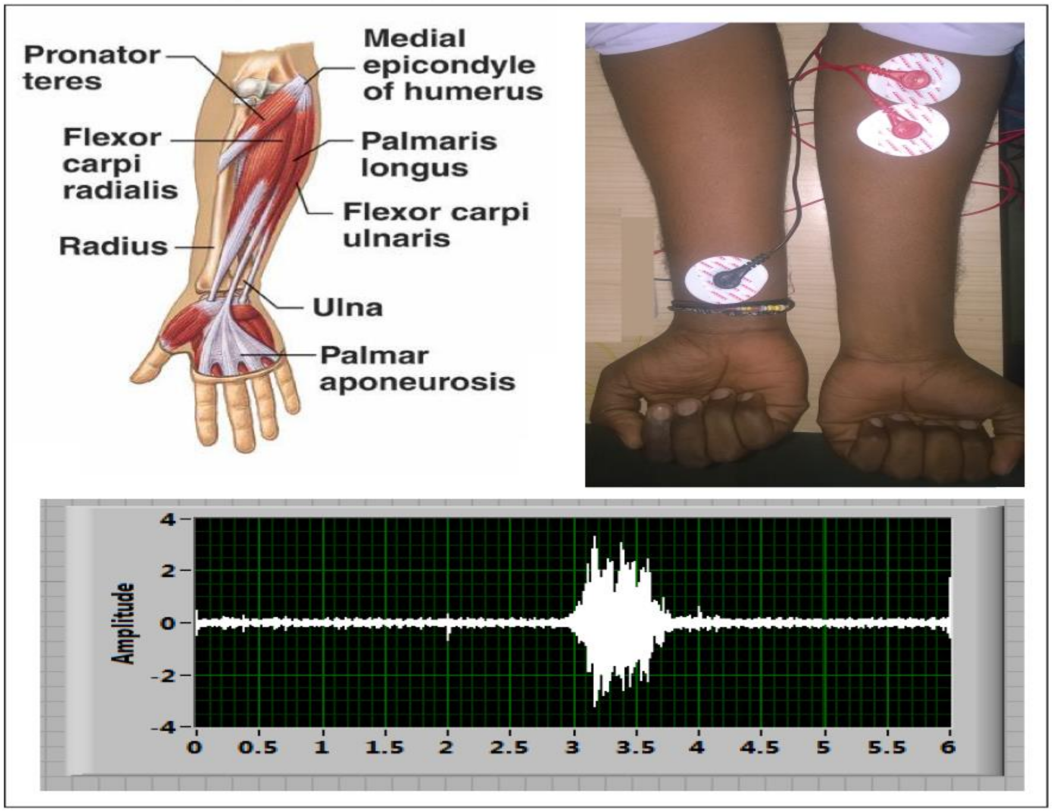

Figure 4: EMG electrode placement and its corresponding signal output (http://imgkid.com/palmaris-longus.shtml)

1.1.6 Human-Computer Interface/Human-Machine Interface (HCI/HMI) system

HCI/HMI system deals with the study of how a biological system interacts with the computer/machine so that an effective way of communication can be established for performing single or multiple tasks which in-turn used for replacement of a particular action/work of a physically impaired person or for diagnosis purpose or for some other purpose depending upon their use.[8-11] The block diagram of HMI/HCI system is shown in figure 5.

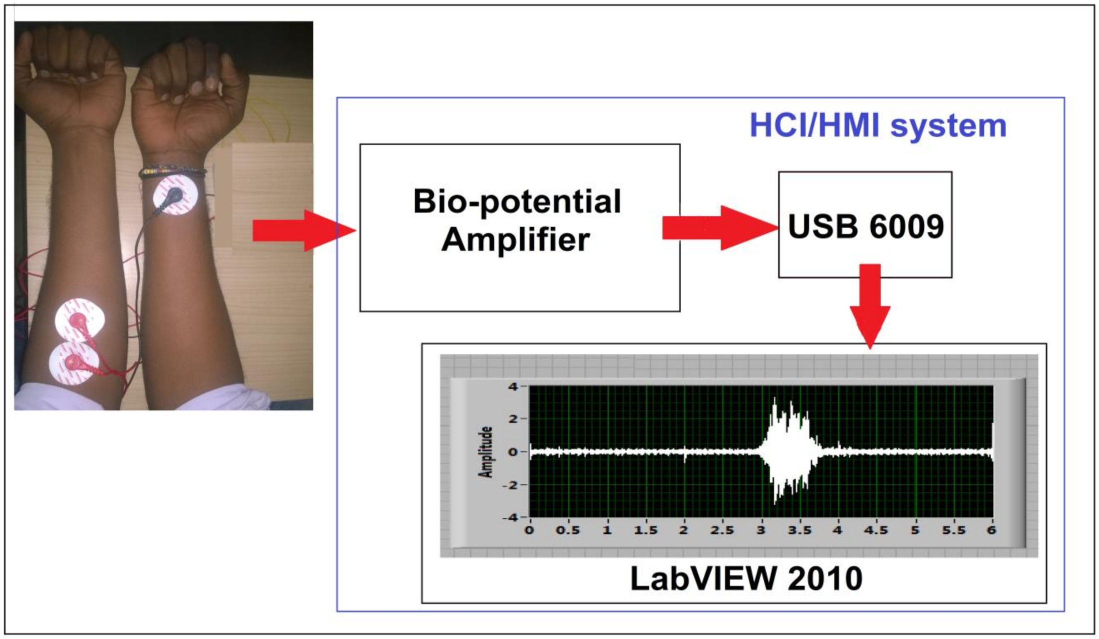

Figure 5: Block diagram of HCI/HMI system

1.2 Objectives

Taking inspiration from the literature, the following objectives were made. The signals from the different finger movement were recorded, processed, analysed and their classification has been done. The classification was made possible by designing a control system based on Boolean gate logic. Further for improving the efficiency of the designed control system, Hall Effect sensor with Boolean change logic is incorporated into the system. Later this system is tested by moving a wheelchair/robotic system.

- To design an EMG signal acquisition system.
- To develop a classification program for effective classification of EMG signals.
- To design a control system using the classified signals.
- To improve the efficient of the control system using Hall Effect sensor by incorporating Boolean change state logic.

2 Literature review

2.1 Biosignal based HMI/HCI system

Several attempts have been made to use various biosignals for building/constructing/designing an efficient Human-Computer Interface/Human-Machine Interface (HCI/HMI) system. These systems use hardware components additionally to perform/replace a desired work/task/function of the human body. For example, to control the movement of gesture, various sensors and motors with a control system is used to control the movement of the gesture depending on the generation of the specific signal for a specific movement. Some commonly used biosignals with HMI/HCI system are EOG signal[11], EEG signal[10] and EMG signal approach[8]. Biosignal based HMI/HCI system is required for the persons with physically impaired.[12]

2.1.1 EOG signal based HMI/HCI system

The eye movement probably the most commonly used for the development of rehabilitative aid like wheelchair. The eye is the main primary sub-systems of the human because the use of eye position directly relates us to the visual information of the positioning of the eye. So, by using the eye position, it is easy to design a control system for assisting a device and this system provides us non-invasive way of determining the position of the eye.[5] EOG can be electrically recorded by measuring the direction of the eye movement or position. This method provides us non-invasive nature of recording, easy to use/build the control system and low cost. Some of the limitations which make the system not to be used in real-life environment are problem related with head and eye movement interface, crosstalk and signal drift. To increase the stability of the system, the user has to be allowed to do free training.[13]

2.2.2 EEG signal based HMI/HCI system

Without relying on the normal neuromuscular pathways, the HMI/HCI will allow a human brain to take control over a computer/machine directly. This type of system will help the paralyzed patients with severe neuromuscular disorders to control an assistive device. The EEG records the change in cerebral electrical activity, which is originates from the post-synaptic region of the brain, aggregates/collects/assembles at the cortex of the brain and transfers/passes it through the skull to the scalp.[6] The EEG based system is used to acquire the EEG signal, extract the feature from the raw EEG signal and classify/convert, this signal into device control commands by using specific signal processing technique. The EEG signal based HMI/HCI device doesn’t depend upon peripheral nerves and muscles for the communication purpose. This system utilise the signal in the range of 8 - 12Hz (alpha waveform) and 18 - 25Hz (beta waveform) rhythms via motor imagery which results in de-synchronization of the produced rhythms over the cortex of the brain (sensorimotor cortex). Thus, the user can directly control the HMI/HCI system by modulating/switching the magnitude of these generated rhythms. The EEG based HMI/HCI system used non-invasive type with less technically demand and low cost devices but in the other hand, it also brings as a challenge in designing or used of proper signal processing and pattern recognition technique because the useful information/signal may hidden in the below the strong noise region, since it had poor SNR and very low frequency range.[6]

2.2.3 EMG signal based HMI/HCI system

Among the biosignals, the EMG signal are considered to be alternate input source to the HMI/HCI based systems because the EMG signal frequency range (0.1 - 3000Hz) is very high compared to that of ECG (0.01 – 300Hz), EOG (0.1 – 10Hz)and EEG (0.3 – 100Hz) signal. And EMG signal can be acquire on the surface of the skin using an electrode system. The main limitation of EMG based system is high possibility of signal contamination.[2, 14]

As compared to optical system, EOG can be effectively used for mouse pointer control but due to their complex learning and calibration process limits the use of this EOG based system. Whereas, the EEG signal has the amplitude range of 5 - 300μV (very less/small) because of which incorporation of higher gain bio-potential amplifier is required for pre-processing of the acquired signal is needed. Hence any movement like head, neck muscle movement will create larger signal commination. Hence the use of EMG signal is more convenient than other signals because non-invasive method with good SNR.

EMG signal are produced due to electrical current generated in muscle (during contraction and relaxation of the neuromuscular activity in the muscle). Moreover, surface EMG signals can be to measure isometric muscular changes which can’t be translated into movement. This makes it suitable for the use has motionless-gestures and to control the interfaces (without periodic calibration and without considering the external environment). [15]

In past few decades, the EMG based control systems have been employed in many rehabilitative and HMI/HCI based systems. Most commonly used EMG based system is hand gesture control for controlling peripheral/external device. The hand-gestures are recorded by measuring surface EMG signal (SEMG). The sensor which is used for measures the electrical activities of the muscular system can be employed for recording hand gestures movement.[1] Once the muscular activity is recorded, then the signal has to be classified into different categories or has different movement such as by measuring the flexion-extension (like finger& wrist) and supination by sensing the activity of the upper arm extremities; a control system can be designed.

2.2 Quantification of EMG signals by using Signal processing techniques

Raw EMG signal contain a lot of good information in the noisy form. To convert this information into the valuable form, we need to quantify it. For quantification purpose, different signal processing methods can be used on the acquired EMG signal for obtaining the desired EMG signal, later used for post-processing purpose. Various signal processing techniques like Wavelet analysis, time-frequency approach, Autoregressive method, Artificial Intelligence, Higher-order statistics, etc.

2.2.1 Wavelet analysis or Wavelet transforms (WT)

It is a powerful tool for local analysis of a non-stationary signal and also the fast transient signals. Wavelet analysis can be incorporated by implementing discrete time-filter banks. Theoretically, Wavelet analysis is chosen to match exactly the same shape of the signal, which yields best possible outcomes of the signal in the time axis.[16] In 1997, laterza and Olmo used multiresolution wavelet analysis for decomposing signal with multicomponent.[17] But in 1999, Pattichis *et al* discovered that analysis of signal at the different/various resolution levels using the WT is possible. The processing of the signal at different resolution levels is said to be multiresolution analysis. Here it makes use of the relationship present in between time-frequency plane and wavelet coefficients.[17] In 2003, Kumar *et al* said that according to wavelet function, the signal can be decomposed into various multiresolution components.[18] This function makes use of both dilation and translation in 2-dimensional cross-correlation time-domain for detecting the short time component within non-stationary signal. This Short Fourier Transform (SFT) can be used for finding out the spectral variation within the given time-domain. So the Wavelet analysis with various decomposing levels can be chosen for better contrast in EMG signal analysis and these methods can be used for finding muscle fatigue (i.e. muscle failure) by using the levels sym4 and/or 5, with the decomposition may be at level 8 and/or 9.

Phinyomark *et al* (2011), used wavelet analysis for extracting the features from an EMG signal. They have investigated the EMG signal features by selecting multilevel decomposition of EMG signal with different sub-bands (Multiresolution components). WT method is divided into Discrete Wavelet-Transform (DWT) and Continuous Wavelet-Transform (CWT). For using the WT in real-time engineering applications, the DWT was selected further for analysis. The DWT method will subsequently divide the signal into multiresolution sub-bands of coefficients. Here by using WT, the usefulness of multiresolution analysis can be investigated with respect to the different scale and local variation and the elimination of undesired frequency component also possible.

2.2.2 Time-frequency approach

This method investigates signal as the function of time. Some of the time-frequency approach methods used is Cohan-Class Transformation, Wigner-Ville Distribution and Choi-Williams Distributions. During contraction, the spectral components present in the muscle compressed towards the lower frequency range. Under dynamic contraction, this assumption doesn't hold because the signal changes over the time continuously. Based on the assumption, the signal can be classified as slow non-stationary signal and fast non-stationary signal. The slow non-stationary signal is due to the accumulation of the metabolites that causes the manifestation of the electrical potential at the muscle fatigue region. The fast non-stationary signal is due to variation in muscle force causes the modification in frequency components present in that signal.

2.2.3 Autoregressive (AR) time series method

AR method is used for studying EMG signal. The electrode is used to pick up, EMG signals from the activated muscles with minimal crosstalk. This technique is used to estimate the delayed intramuscular EMG and their spectral properties of the signal. This method is referred to as “tissue filter”; this method relates directly with the delay in intramuscular EMG signal with surface EMG signal by transforming time series parameters of intramuscular EMG signal to the acquired EMG signal for identification.[19]

2.3 Automated Neural Network (ANN)

ANN has an advantage to assist user not only in critical design stage, it also include state-of-the-art Neural network architectures and training algorithms by using error functions that allow us to interpretation of the corresponding results. By using the statistica software, we can able to generate C/C++ code, which in-turn helps us in deploying the fully trained network for further use.

2.3.1 Multilayer Perceptron’s (MLP)

It is a feed-forward ANN model that relates a set of input data with their corresponding output (class/type/category). It has multiple layers of nodes, which directly connects each layer to the next layer. The each node present in MLP can be related as neurons with a non-linear activation function. So, this neuron is said to be as processing element. The MLP is based on supervised learning technique for training the network through backpropagation method.

2.3.2 Radial Basis Function networks (RBF)

The RBF network uses RBF as the activation functions i.e. the inputs and the processing element/parameter is a linear combination of RBF, which gives us the output of the RBF network.

2.3.3 Training a Neural Network

The ANN includes fast and second-order training algorithms like Conjugate Gradient descent (first order algorithms) and BSFGs (it's a memory-less BFGS which uses less amount of memory). This is an iterative training process which tracks both training error and testing error independently. So, when testing is completed, we can able to check the performance against training and testing to validate the samples or results.[15]

2 Materials and Methods

2.1 Volunteer Selection

For acquiring the EMG signal, the electrodes are placed over the Flexor carpi radialis, Palmaris longus and Flexor carpi ulnaris muscles, over the forearm of the volunteer. The volunteer was selected based on BMI (Body Mass Index) criteria; if the BMI is good then the volunteer is perfect for any study. So, depending upon the BMI, a healthy volunteer (age 24) was chosen for the study. The volunteer was first trained to generate nearly similar kind of EMG signal before acquiring the EMG signal.

2.2 EMG signal acquisition

A biosignal amplifier circuit was designed and developed by our group previously. The same biosignal amplifier circuit with same modification was used for acquiring the signal.[2, 20] The developed biosignal amplifier has a gain of about 2500 times, integrator circuit (12.45Hz), LPF (with cut-off frequency f_c of 1591Hz) and leg drive circuit (for efficient ground and isolation purpose). The schematic representation of EMG bio-potential amplifier, its 3D view in Ultiboard software (Ver. 11.0, National Instruments, USA) and its pictograph is shown in figure 6.

Figure 6: (a) the schematic representation of the EMG bio-potential amplifier; (b) its 3D view (Ultiboard software) and its pictograph.

The acquired signal is then passed through a USB 6008 data acquisition system which is regarded as “sEMG-DAQ” system. The acquired signal via DAQ reaches the LabVIEW 2010 software (National Instruments, USA). Here post-processing is taken place and the signal is record as the data in the computer.[20] A overview about the process is shown in figure 7.

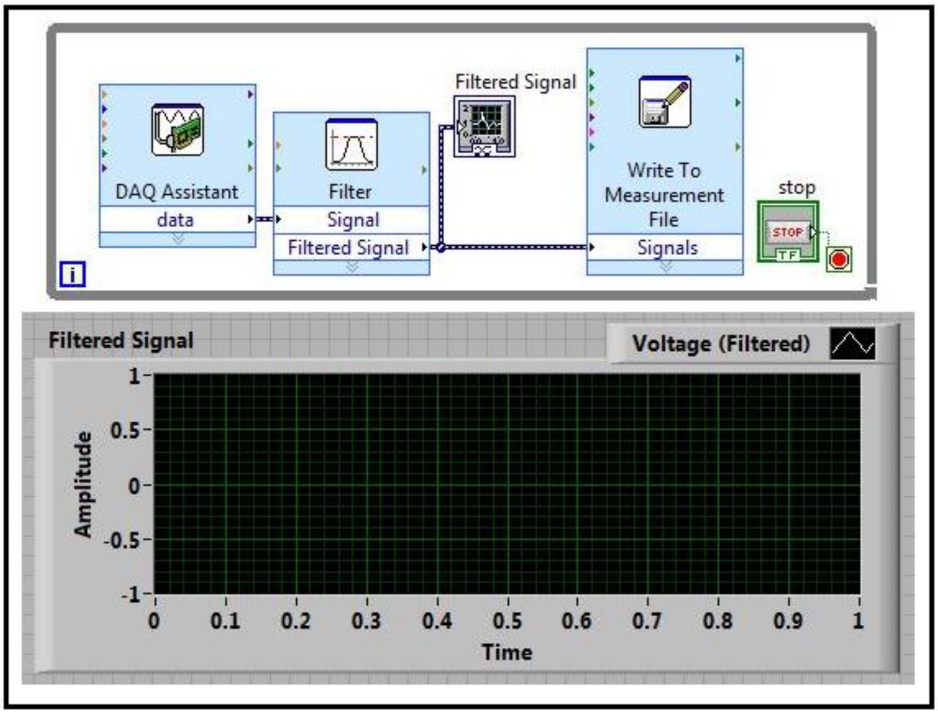

Figure 7: Block diagram and front panel view of the acquisition program designed in LabVIEW 2010

2.3 Post-processing (Signal processing and feature extraction)

The acquired EMG signal was further processed using LabVIEW 2010 software. For extracting the features from the recorded EMG signal, the statistical functions are used.[21] The statistical function includes Arithmetic Mean (AM), Median, Mode, Standard deviation (SD), Variance, Summation, Kurutosis, Skewness, Entropy, Log entropy, Energy and signal Length are used as features and the calculated features were save the data in a text file.[22, 23] The extracted features were analyzed using ANOVA (for determining significantly different features). The representative feature extraction LabVIEW program was shown in figure 8.

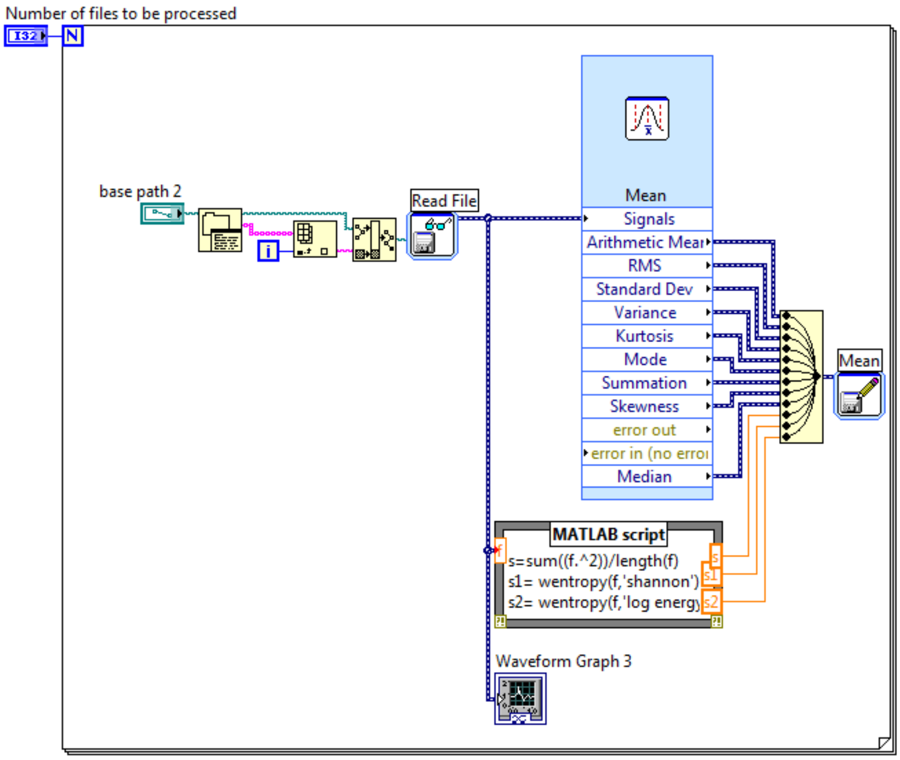

Figure 8: LabVIEW program for calculating features of the acquired EMG signal

2.3.1 Offline Classification

The offline classification of the acquired signal was done using Statistica sotware (Ver. 12.5, Statsoft Inc, USA). The importance predictor was calculated using CARD, Boosted Tree and Random Forest classification method. By using these results, the classification of EMG signal has been done using ANN and the results have been reported.[16]

2.3.2 Online classification

Using the LabVIEW 2010 program, a control system has been designed by using basic Boolean gate logic expression. The using of Boolean gate logic is similar with conditional if statement. If the statement is true then only the result will be true otherwise the result will be in false state only. Further for improving the efficiency of the developed control system, we used Hall Effect sensor (AH34) has an additional input to the Boolean state change logic. If anyone terminal given to Boolean state change logic is true, then the output will be true because its output depend not only on the present but also on the previous results too. This can help us in triggering the robotic wheelchair prototype (in-house developed module) to move to a particular distance (time of flight management).[23, 24]

2.4 Hall Effect Sensor

A Hall Effect sensor is a type of transducer that varies its output voltage, when a magnetic field is created by brings a magnet in contract to the sensor. This makes the sensor to use as switching devices, speed detection, positioning and also in current sensing applications.[24]

2.4.1 Principle of working of Hall Effect sensor

When a beam of charged particles held in the magnetic field, across the forces of action, deflected in a straight path, then the flow of electron in that conductor is called as "beam of charged carriers". During the applied magnetic field, the direction of electron in conductor flows perpendicular to that of force of action, which makes the one plane of the conductor to get more negatively charged and other plane to get more positively charged. The voltage different between these two planes is called as "Hall Voltage"

When the magnetic and electric filed applied, the charged particles becomes balanced, then the separation of charged particle will not take place. If the current is unchanged, then the Hall voltage is the measure of net magnetic flux density across the conductor, this is because the output voltage linearly depend on magnetic flux density; if there is a sharp decrease in the output voltage at each magnetic field i.e. during applied magnetic field, this is due to threshold. The schematic representation of principle of working of Hall Effect sensor and its connection diagram is shown in figure 9.

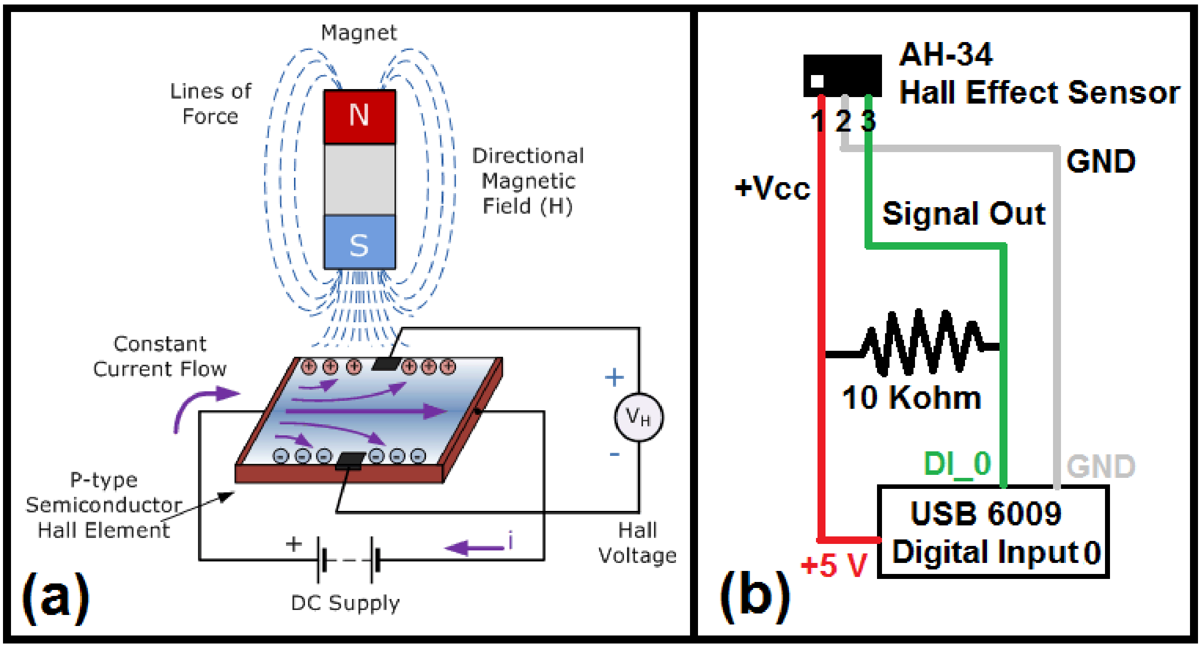

Figure 9: (a) Schematic representation of working of principle of Hall Effect sensor; and (b) its connection diagram.

4 Results and Discussions (Offline Classification of EMG signal)

4. Offline classification of Surface EMG signal

4.1 Overview

The surface EMG signal is acquired using the in-house developed Bio-potential amplifier circuit. The surface EMG signal is acquired by placing silver/silverchloride electrode (the EMG electrode was procured from BPL healthcare pvt ltd, IN) on the forearm muscle (Flexor carpi radialis, Palmaris longus and Flexor carpi ulnaris muscles).[25] The acquired surface EMG signal is processed in LabVIEW 2010 software and saved as "text file" format for future use. The acquired surface EMG signal is then passed through a LabVIEW program written for extracting the statistical features like Arithmetic Mean (AM), Median, Mode, Standard deviation (SD), Root Mean Square (RMS), Variance, Summation, Kurtosis, Skewness, Entropy, Log entropy, Energy and signal Length. The extraction of features from the acquired surface EMG signal is of 3 types.

1. Signal-1

   The signal due to smoothening (figure 10) the unipolar EMG signal after rectification using rectangular window of 2000 moving average window size.

2. Signal-2

   The signal is acquired directly, the extraction of original surface EMG signal from the raw surface EMG signal (figure 11). The extraction of surface EMG signal is possible by finding the difference in the signal after applying thresholding of (>0.5V in amplitude).

3. Signal-3

   Here the signal 2 is made is pass through the Discrete Wavelet Transform. By using the Multiresolution wavelet analysis, the signal is decomposed. By selecting the appropriate decomposition WT, the signal is reconstructed and the statistical features of these signal is found by using decomposition dB07 with level 9 (figure 11).

Signal 2 and 3 uses original bipolar signal for analysis purpose.

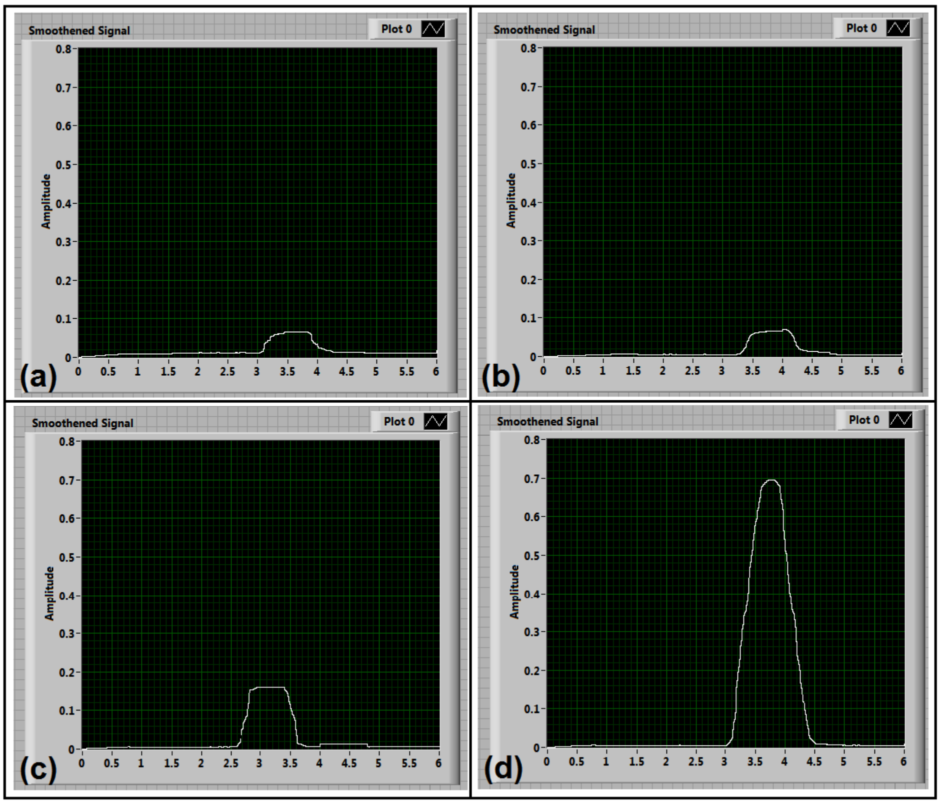

Figure 10: The signal after applying Smoothening over the unipolar EMG signal (a) left; (b) Right; (c) Forward; and (d) Backward movement signal.

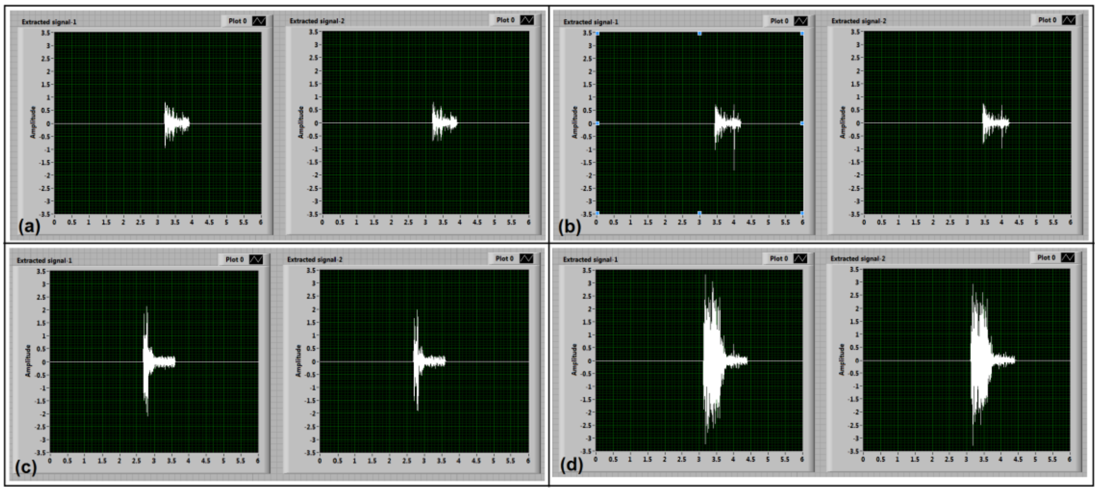

Figure 11: The EMG signal extracted by subtracted after applying thresholding over the raw EMG signal, and Signal after Wavelet Transformed (a) left; (b) Right; (c) Forward; and (d) Backward movement signal.

4.2 Results and discussions

The surface EMG signals are acquired using LabVIEW program. The acquired surface EMG signals is then stored as text file format. Using read the file option, the stored file is read. Using the statistical palette (right click → goto Express option → goto Signal analysis option → select Statistical palette), the features like Arithmetic Mean (AM), Root Mean Square (RMS), Median, Mode, Standard deviation (SD), Variance, Summation, Kurutosis and Skewness were calculated by selecting the options present in that palette. For finding the Entropy, Log entropy and Energy, the Mathscript is used. [26]

To find Length of surface EMG signal, first we need to convert the bipolar signal into unipolar signal. Then on the unipolar signal, using triangular window of 2000 FWHM moving average window function is applied, this results in creation of envelope i.e. only the peak value of the each signal will get highlighted. By applying a dynamic thresholding of about 0.5, now the output will either has high ("1") if it is greater than 0.5 or else Low ("0") if it is lesser than 0.5. Now multiply the output with the original signal, the resultant will be the extracted signal (signal-2), if a DWT is used and the signal is reconstructed, then the resultant signal will be Wavelet transform extracted EMG signal (signal-3). After dynamic thresholding, convert the Dynamic datatype into 1-D array of scalar (Right click → goto Express option → goto Signal Manipulation option → select Convert DDT palette). Using Search 1-D array option by keeping the condition lower value has "0" and higher value has "1", search for the value and use reverse search 1-D array palette, to detect the 1-D array of scalar values. By subtracting the normal 1-D array with scalar and reversed 1-D array with scalar, we will get the length of the signal. By using the option Extract portion of the signal option, the original surface EMG signal is extracted and displayed. The entire signal processing technique is explained through a flowchart given in figure 12 with corresponding stepwise results.[26]

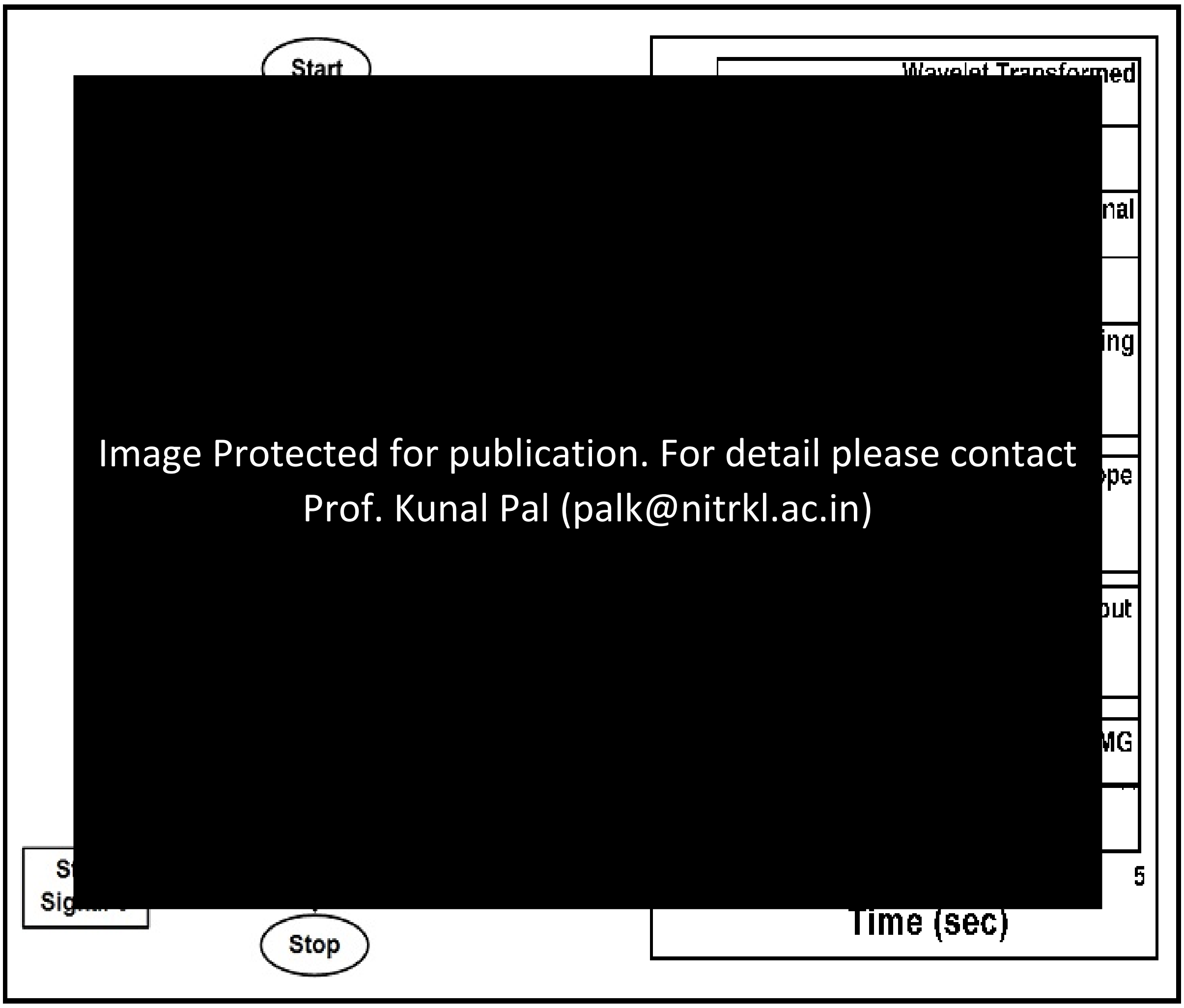

Figure 12. The flowchart of signal processing mechanism for extracting signal from the raw surface EMG is shown with stepwise result.

A signal is taken into account and using signal processing program designed in LabVIEW 2010 were analyzed and the resultant output is save in a text file format. The block diagram and front panel view of the signal processing technique is shown in the figure 13.

Here, the conversion bipolar signal into unipolar signal is done by simply squaring of the signal which is nothing but rectification process. I used, this digital method instead of using passive/active electronic circuit because I don’t want to increase computation burden on the hardware.

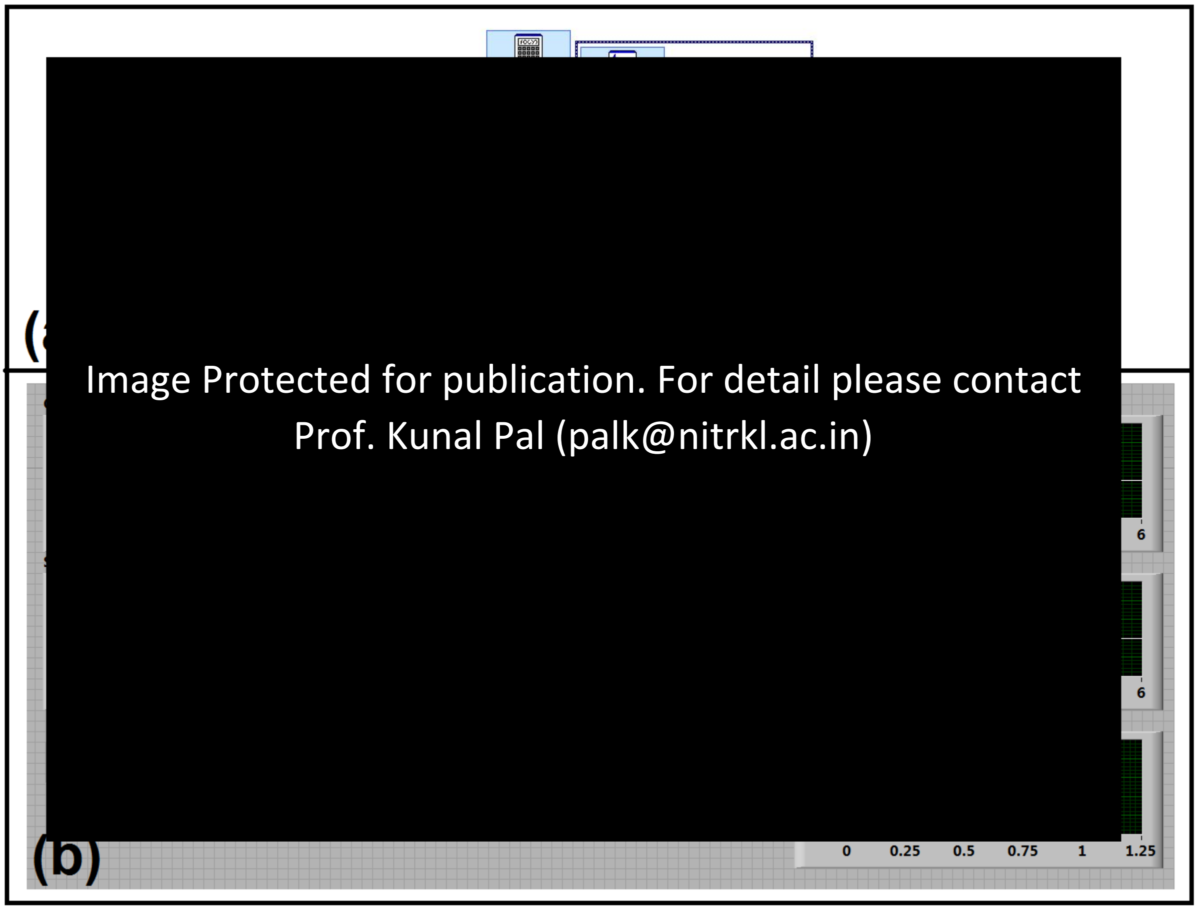

Figure 13: (a) Block diagram; and (b) front panel view of the signal processing technique for extracting Signal (Signal1-3).

The Statistical features which are used for calculating the features of the envelope of the EMG Signal, Extracted EMG Signal and Wavelet transformed EMG Signal are shown in the table 2. The corresponding LabVIEW program which is designed to extract the feature is shown in the figure 14.

Table 2. The Features obtained from Statistical palette and by using Matlabscript palette is tabulated.

[redacted]

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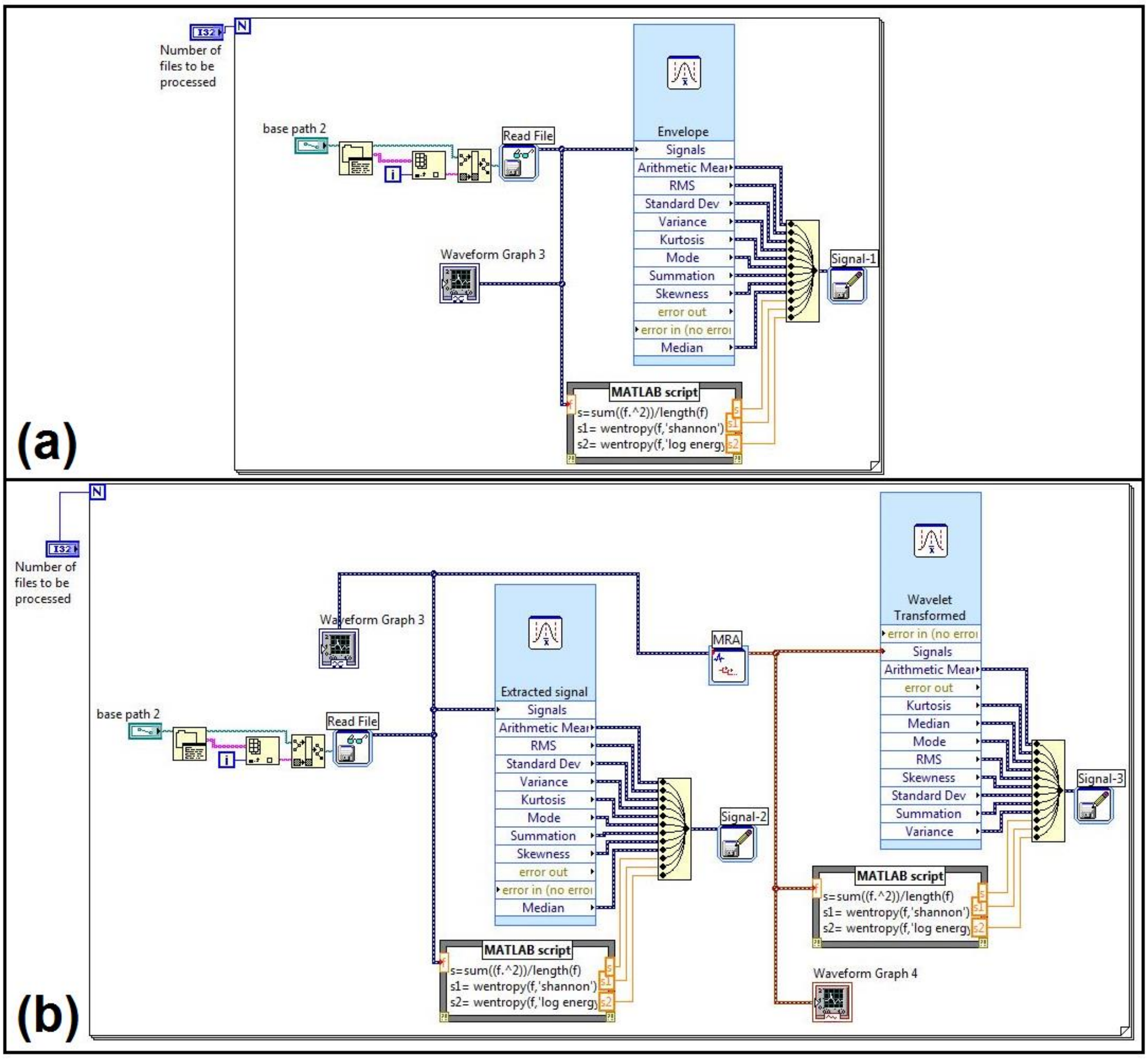

Figure 14: the LabVIEW program designed for calculated features of signals (1-3) using Statistical Palette and also by using Matlabscript palette (a) for envelope signal; (b) for extracted signal and Wavelet Transformed extracted signal.

The ANONA results shows that all the values are significantly importance (<0.05). The table 3 shows the average and standard deviation values of the acquired surface EMG signal after smoothening function (signal-1). The table 7 shows the average and standard deviation values of the Extracted surface EMG signal (signal-2). The table 11 shows the average and standard deviation values of the Wavelet Transform Extracted surface EMG signal (signal-3).

For finding the predictor importance of the envelope created EMG signal (signal-1), Extracted EMG signal (signal-2) and Wavelet transformed extracted EMG signal (signal-3), the CART, Boosted tree and Random forest classifiers are used. The CART is a classifier trees which are designed for dependent variables that takes finite/particular/fixed number of unordered values/dataset for finding the important predictors. Generally CART can be defined as categorical dependent variable. Whereas, the Boosted tree classifier is used to compute a sequence of simple trees, where each tree belong to prediction residual value/dataset of the preceding trees. Random Forest classifier is generally a collection of simple tree predictors, where each tree is capable of representing a response if it is presented with a dataset of predictor values.

4.2.1 Classification of Signal-1 (Envelope signal/Smoothened signal)

The CART classifier is used to find the predictor importance of the envelope/smoothened signal, the resultant shows that the Arithmetic Mean, Summation, Entropy, Log entropy and energy of the signal have higher importance. Similarly, by using Boosted tree classifier, it has been found that Standard Deviation (SD), Variance and Summation have the higher importance. Similarly, for Random Forest classifier, Entropy has the higher importance.[26, 27] Table 3: the average and standard deviation values of the acquired surface EMG signal after smoothening function.

Classifiers	[redacted]	Mean ± SD [redacted]				[redacted]	[redacted]
[redacted]	Table Protected for publication. For detail please contact Prof. Kunal Pal (palk@nitrkl.ac.in)						
Random Forest	**Entropy**	0.002±0.0005	0.0008±0.0002	0.001±0.0002	0.0005±0.0003	--	1.000

The results obtained from linear and nonlinear type of classifier were used for classification in Automated Neural Network (ANN). In ANN classifier analysis, the MLP and RBF algorithm were used. The result suggested that the MLP algorithm shows better performance than the RBF algorithm. The best classification efficiency of 100% was obtained by using MLP algorithm, whereas 95 % was obtained by using RBF algorithm. The features which are used as the input for classification were AM, Summation, ED, Entropy, Log E, SD, Variance & Signal length (both MLP & RBF). The confusion matrix for the MLP and RBF ANN classification has been tabulated in Table 4, 5The detail of the MLP and RBF ANN algorithm is shown in the table 6.

Table 4 CONFUSION MATRIX OF MLP NETWORK (Signal-1)

[redacted]

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Table 5 CONFUSION MATRIX OF RBF NETWORK (Signal-1)

[redacted]

Table Protected for publication. For detail please contact Prof. Kunal Pal (palk@nitrkl.ac.in)

Table 6 Summary of active networks (Signal-1)

[redacted]

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4.2.2 Classification of Signal-2 (Extracted signal)

The CART classifier is used to find the predictor importance of the Extracted signal, the resultant shows that the RMS, SD, Variance and Signal length of the signal have higher importance. Similarly, by using Boosted tree classifier, it has been found that RMS, SD and Variance have the higher importance. Similarly, for Random Forest classifier, only RMS has the higher importance.

Table 7: average and standard deviation values of the Extracted surface EMG signal

Classifiers		Mean ± SD					Predictor
[redacted]							

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The results obtained from linear and nonlinear type of classifier were used for classification in Automated Neural Network (ANN). In ANN classifier analysis, the MLP and RBF algorithm were used. The result suggested that the MLP algorithm shows better performance than the RBF algorithm. The best classification efficiency of 90% was obtained by using MLP algorithm, whereas 85 % was obtained by using RBF algorithm. The features which are used as the input for classification were, SD, RMS & Signal length (both MLP & RBF). The confusion matrix for the MLP and RBF ANN classification has been tabulated in Table 8, 9. The detail of the MLP and RBF ANN algorithm is shown in the table 10.

Table 8 CONFUSION MATRIX OF MLP NETWORK (Signal-2)

[redacted]

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Table 9 CONFUSION MATRIX OF RBF NETWORK (Signal-2)

[redacted]

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Table 10 Summary of active networks (Signal-2)

[redacted]

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4.2.3 Classification of Signal-3 (Wavelet processed/Transformed Extracted signal)

The CART classifier is used to find the predictor importance of the WT Extracted signal; the resultant shows that the RMS, SD, Variance and Signal Length of the WT extracted signal have higher importance. Similarly, by using Boosted tree classifier, it has been found that Standard Deviation (SD), Variance and RMS have the higher importance. Similarly, for Random Forest classifier, only RMS has the higher importance.

Table 11: average and standard deviation values of the Wavelet Transform Extracted surface EMG signal

[redacted]

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Using WT, the extracted EMG signal is reconstructed. Here, I used dB07 decomposition with a level of 09.[18] The sub-bands used to reconstruct the extracted EMG signal are D3+D4+D5. Figure 15 shows the stepwise reconstruction of the extracted EMG signal as compared with original extracted EMG signal.

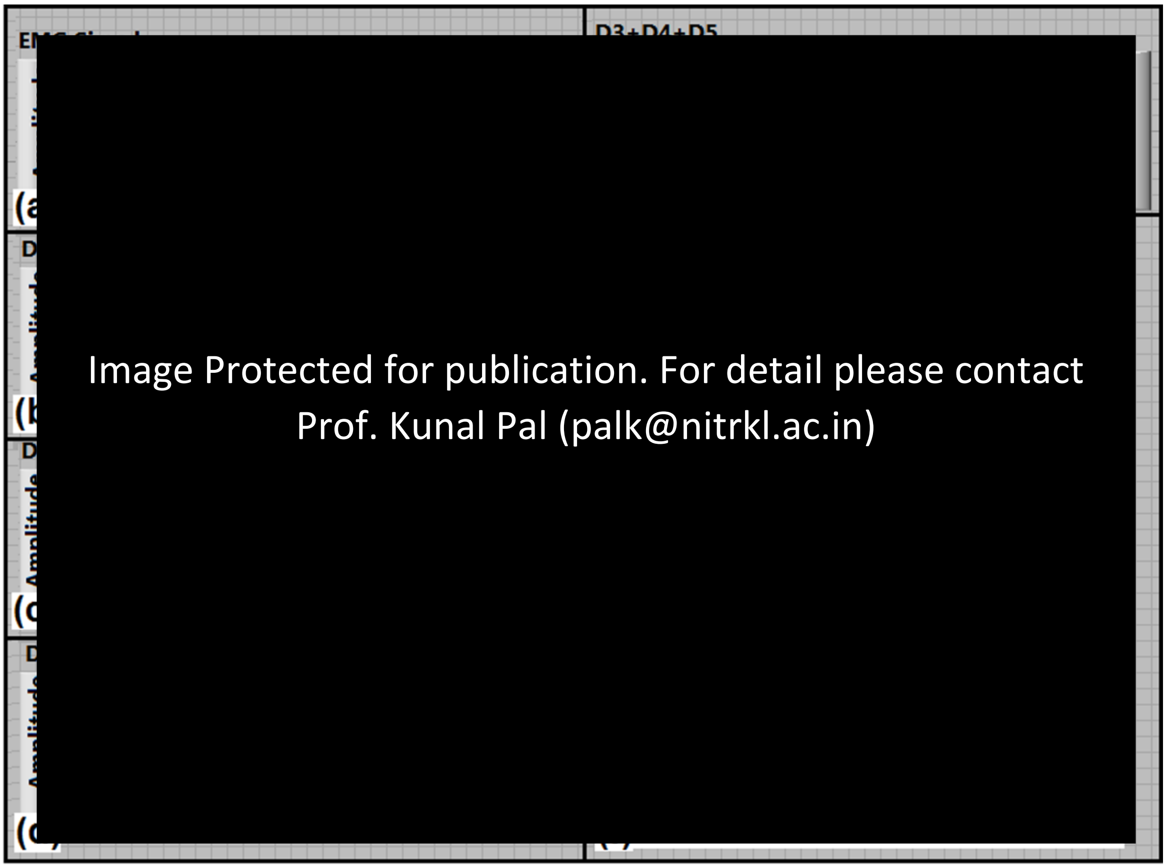

Figure 15: Wavelet Transformed Extracted EMG signal reconstruction (a) original EMG signal; (b) Sub-band D3; (c) Sub-band D4; (d) Sub-band D5; (e) Sub-band D3+D4+D5; and (f) WT extracted EMG signal (reconstruction)

The results obtained from linear and nonlinear type of classifier were used for classification in Automated Neural Network (ANN). In ANN classifier analysis, the MLP and RBF algorithm were used. The result suggested that the MLP algorithm shows better performance than the RBF algorithm. The best classification efficiency of 90% was obtained by using MLP algorithm, whereas 85 % was obtained by using RBF algorithm. The features which are used as the input for classification were AM, Summation, ED, Entropy, Log E, SD, Variance & Signal length (both MLP & RBF). The confusion matrix for the MLP and RBF ANN classification has been tabulated in Table 12, 13. The detail of the MLP and RBF ANN algorithm is shown in the table 14.

Table 12 CONFUSION MATRIX OF MLP NETWORK (Signal-3)

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[redacted]

Table 13 CONFUSION MATRIX OF RBF NETWORK (Signal-3)

Result Protected for publication. For detail please contact Prof. Kunal Pal (palk@nitrkl.ac.in)

[redacted]

Table 14 Summary of active networks (Signal-3)

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[redacted]

5 Results and Discussions (Online Classification of EMG signal)

5 Online classification of Surface EMG signal

5.1 Overview

The assistive devices help the person with different type of physical disability to perform their day today activities like Travelling from a place to another place, etc. Electromyogram (EMG) signals were produced due to depolarization of cell membrane of muscle fibers during contraction in the form electrical potential. Online classification of surface EMG signal allows us to control an electrically powered robotic wheelchair without using hand and/or any other means expect Surface EMG signal as an input to the device.[28]

The surface EMG signal is acquired by placing electrode over the skin of the forearm muscle. The surface EMG signal is acquired and pre-processed it using in-house developed bio-potential amplifier circuit because normally the strength of the biosignal will be very less, so it has to increase to a certain level so that we can use the biosignal for driving any assistive devices. The pre-processed EMG signal is analyzed in LabVIEW 2010. USB-6009 (NI-DAQ) was used as an interface between pre-processing unit and post-processing unit (LabVIEW software). With the help of previous offline classification results, using the importance predictors, a LabVIEW program was designed to classify the EMG signal into their corresponding category. For improving the efficiency of classification and to reduce the computation burden of using Artificial Neural Network (ANN), Boolean Gate Logic were used and the result are showing >95% of accuracy in classification. Further, Hall Effect Sensor is incorporated into the system to increase the efficiency and using Hall Effect Sensor, the time of travel (time of flight) i.e. the time to which the robotic wheelchair should move to a distance can be desired. The Hall Effect Sensor's output was given has one of the input to Boolean State change logic and another input is from the output of classification. The finger movement with corresponding category is tabulated. Table 15 shows the Finger used for the Wheelchair movement.[26, 28]

[redacted]

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5.2 Results and discussions

The surface EMG signal was acquired from the forearm muscle. The acquired surface EMG signal is pre-processed using Bio-potential Amplifier, to increase the surface EMG signal strength.[2] Using USB-6009, the pre-processed surface EMG signal is analysed in LabVIEW 2010. The analysis include feature extraction, creating envelope of the surface EMG signal, extracting raw surface EMG signal and last, Wavelet transform analysis of extracted EMG signal.[18] The program written in LabVIEW 2010 is shown in figure 16.

The summation was the feature which is used for designing the control system for detecting envelope signal category with the corresponding condition were tabulated in table 16.

[redacted]

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The RMS was the feature which is used for designing the control system for detecting extracted EMG signal category with the corresponding condition were tabulated in table 17.

[redacted]

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The RMS was the feature which are used for designing the control system for detecting Wavelet processed extracted EMG signal category with the corresponding condition were tabulated in table 18.

Movement	Condition
[redacted]	

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Using this above conditions, the control system was designed to classify the Signal (Envelope signal (signal-1), Extracted EMG signal (sigbal-2) and Wavelet Transformed extracted EMG signal (signal-3)). Using the palette called comparison, the incorporation of these conditions was made possible. Right click → Express → Arithmetic & Comparison option → select Comparison palette. The comparison palette is used as In-range comparison mode. The result of this In-range comparison mode will be of two states either High ("1") or Low ("0"). High, if the given condition is satisfied else the result will be Low.[28]

Figure 16 The Program written in LabVIEW 2010 for the classification of EMG signal (a) Block diagram View; (b) Representative front panel View (Left movement); (c) Right movement; (d) Start/Forward movement; and (e) Backward movement

For classify the signal (Signal-1-3), with the In-range comparison mode, a conditional if statement was constructed using Boolean gate logic.

Syntax:

If

{

(Summation > 500 && <640) && (RMS >0.071 && <0.095) && (RMS>0.07 && <0.09)

Then, the result should be “Left”;

else if

(Summation > 430 && <499) && (RMS >0.05 && <0.07) && (RMS>0.05 && <0.069)

Then, the result should be “Right”;

else if

(Summation > 700 && <950) && (RMS >0.11 && <0.15) && (RMS>0.1 && <0.14)

Then, the result should be “Forward”;

else if

(Summation > 1400 && <3600) && (RMS >0.2 && <0.28) && (RMS>0.18 && <0.26)

Then, the result should be “Backward”;

else

No action;

end

This was implement using the serial of In-range comparison option and also by using Ex-OR gate with AND gate. The Program designed for classifying Envelope signal is shown in figure 17.

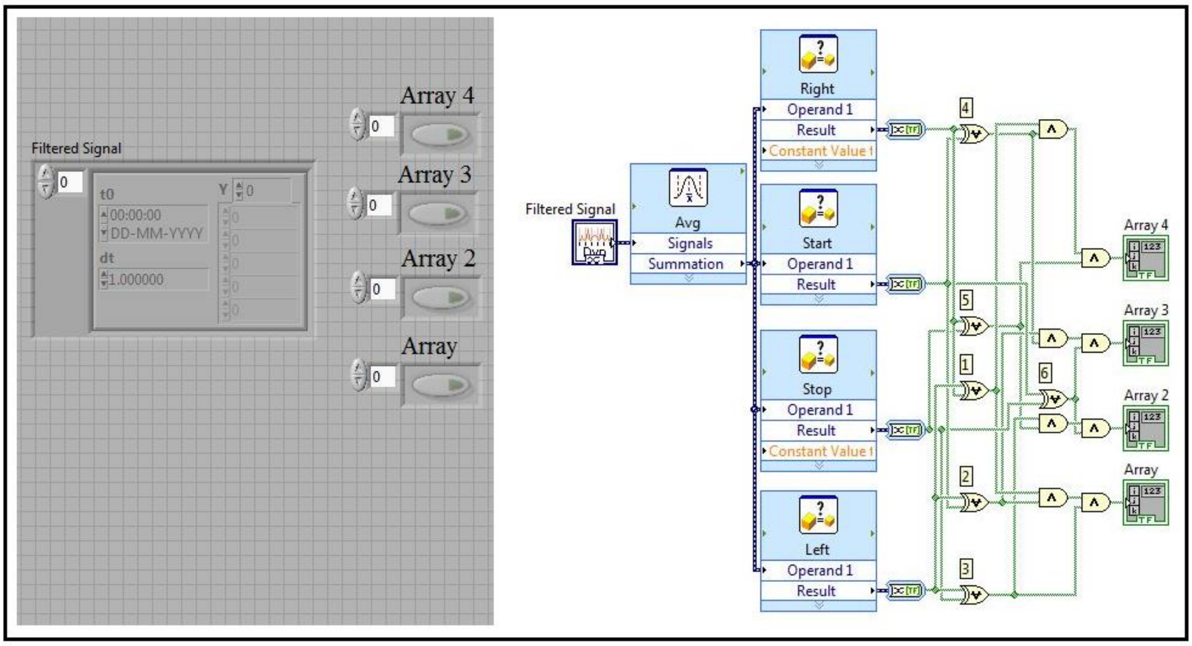

Figure 17 shows the Conditional If statement using EX-OR with AND Gate operation for classifying Envelope of the signal.

This was implement using the serial of In-range comparison option and also by using Ex-OR gate with AND gate. The Program designed for classifying Extracted EMG signal is shown in figure 18.

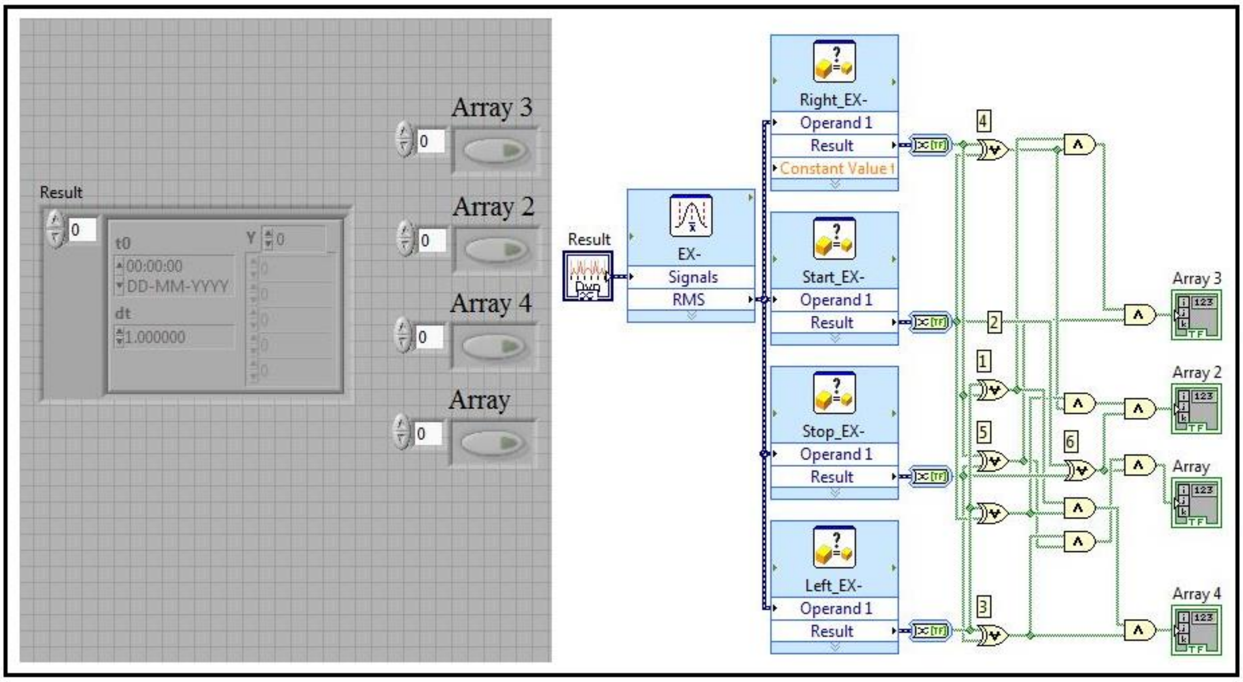

Figure 18 shows the Conditional If statement using EX-OR with AND Gate operation for classifying the extracted EMG signal.

This was implement using the serial of In-range comparison option and also by using Ex-OR gate with AND gate. The Program designed for classifying Wavelet Transformed extracted EMG signal is shown in figure 19.

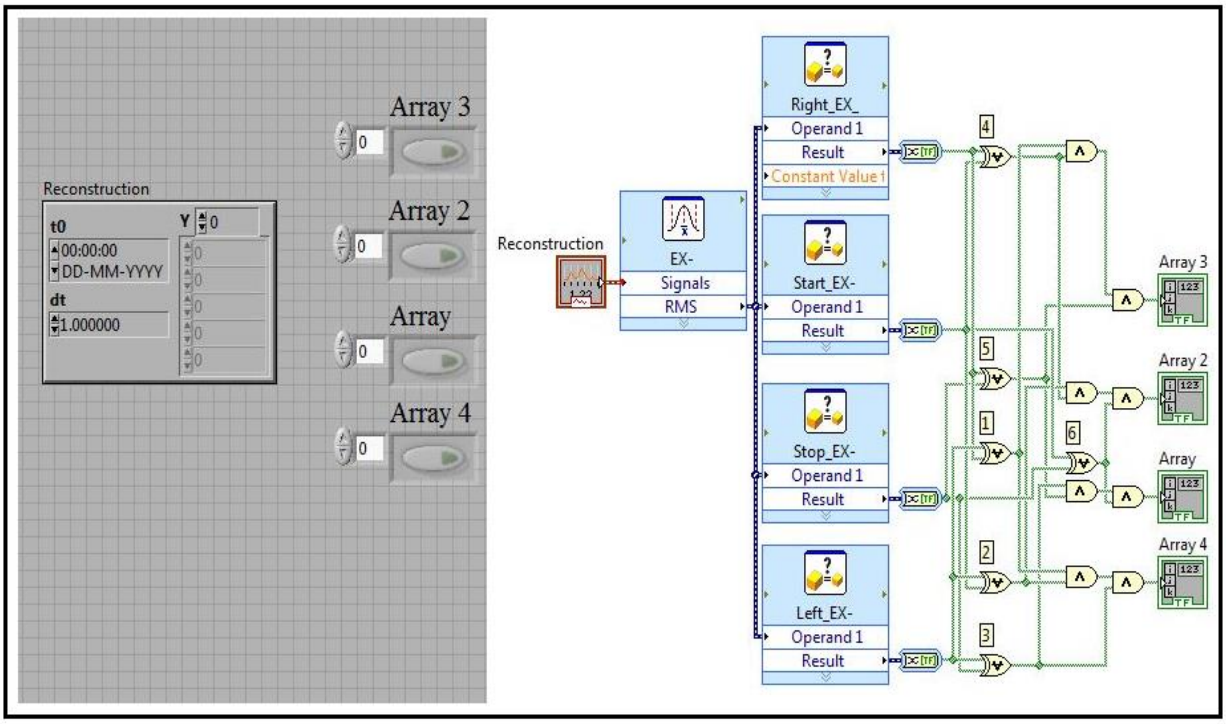

Figure 19 shows the Conditional If statement using EX-OR with AND Gate operation for classifying the Wavelet processed extracted EMG signal.

The result from these above stage where further compared used conditional if statement using AND gate. The program designed for further comparison is shown in figure 20.

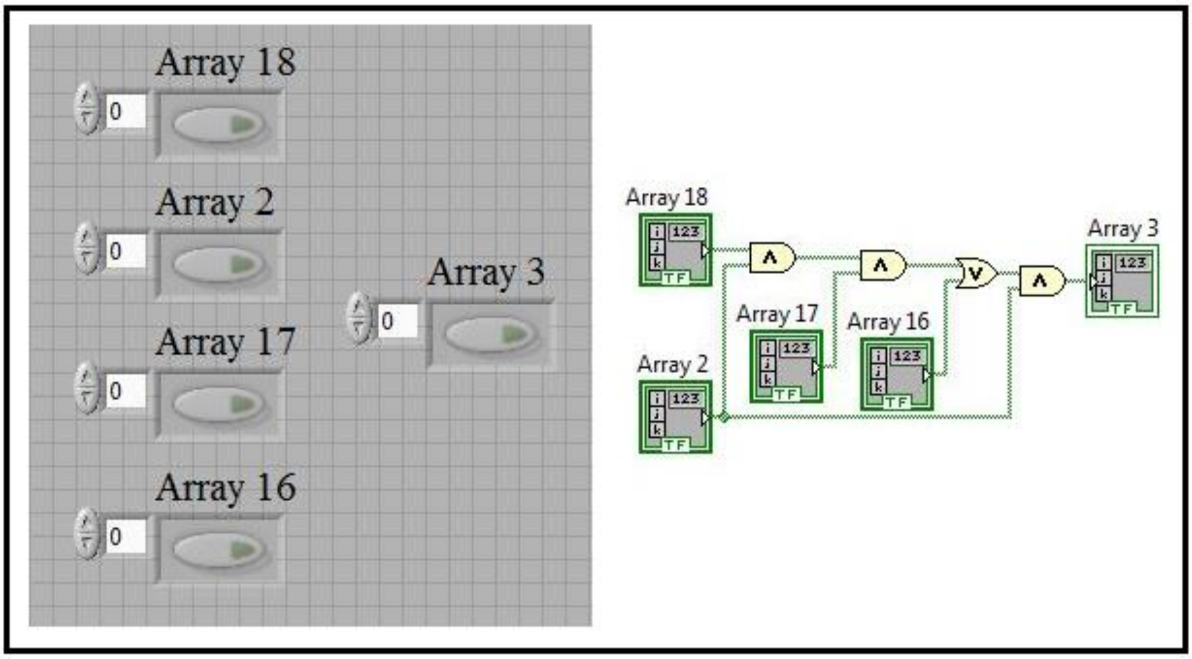

Figure 20 shows the Conditional If statement using AND Gate.

Table 19 Truth table of EX-OR Gate Logic

A	B	Result
0	0	0
0	1	1
1	0	1
1	1	0

Table 20 Truth Table of AND Gate Logic

A	B	Result
0	0	0
0	1	0
1	0	0
1	1	1

The EX-OR gate will be true only when any one of the input is High state (“1”) else the result will be Low state (“0”) which is shown in table 19.

The AND gate will be true only when both of the inputs is High state (“1”) else the result will be Low state (“0”) which is shown in table 20.

5.3 Implementation of Boolean State Change Logic

The Boolean State change logic depend on the previous output for the giving the present output. I.e. it will check what the previous output is before changing the current state. The program which is written in LabVIEW 2010 is shown in the figure 21.

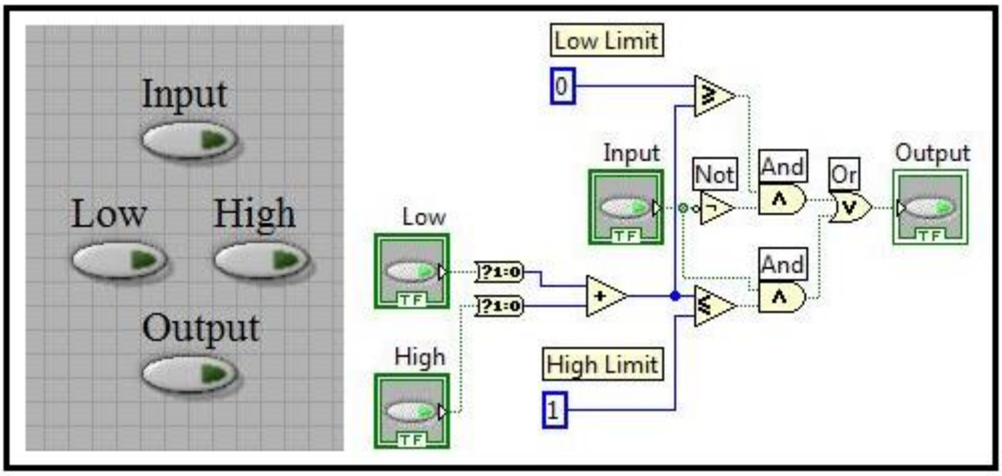

Figure 21 shows the Boolean State change logic (Front panel and Block diagram view of LabVIEW 2010)

Table 21 shows Truth table of Boolean State Change Logic.

[redacted]

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The complete flowchart of the control system designed is shown in the figure 22.

Figure 22 shows the complete flowchart of the control system designed (a) control system designed using EX-OR gate for one signal classification; and (b)the improved version of classification by incoroparating Hall Effect sensor and Boolean change state logic.

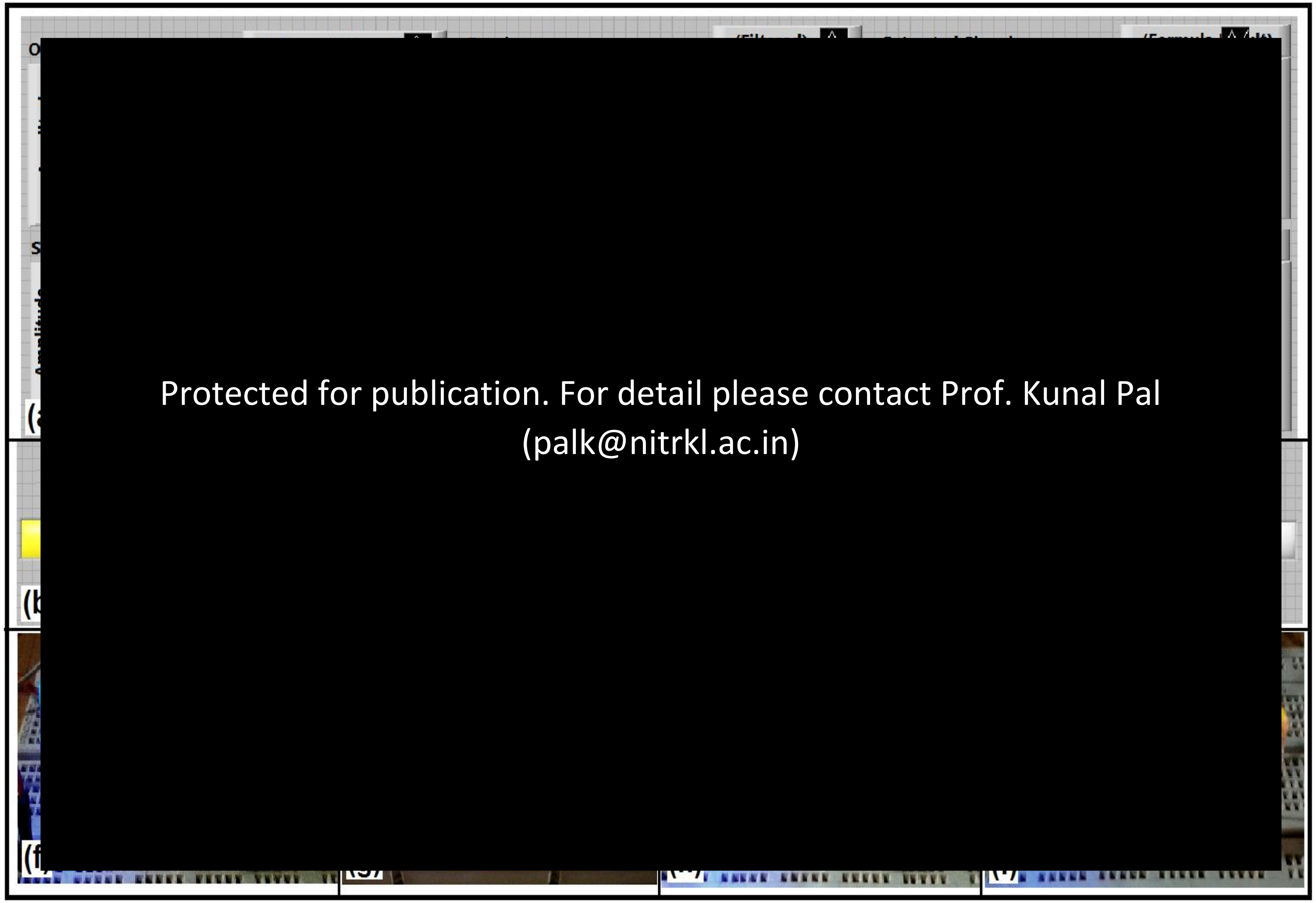

Figure 23 shows the Classification result of (a-e) Left, Right, Forward and Backward movements with (f-i) corresponding LED Panel indication.

Figure 24 shows (a) overall setup view with corresponding robotic Wheelchair movement; (b-e) Left, Right, Forward and Backward.

The movement of the robotic wheelchair was controlled using the finger movement. The rotation of the robotic wheelchair in the direction left hand side and right hand side can be possible by keeping one motor in on state and other motor in off state (i.e. neural). But for the forward and backward direction of motion of the robotic wheelchair uses both motor to run either in clockwise or anticlockwise depending upon the user input/program. The speed of the motor is kept constant nearly 100 rpm. The rpm is kept low because the robotic wheelchair travel distance depends upon the time of Hall Effect sensor and EMG signal available. The motor configuration during the different flexion of fingers has been tabulated in Table 22.

Table 22 Finger movements and their direction of the motion of the Wheelchair

[redacted]

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(+) Clockwise rotation, (-) Anticlockwise rotation and (0) Neutral

[redacted]

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Figure 25 shows the schematic representation of setup.

6 Conclusion and future scope

6.1 Conclusion

The current study discussed about the offline classification of EMG signal, which is acquired by placing electrodes on the surface of the forearm by flexing, the fingers in different ways.[26] The EMG signal is acquired, after pre-processing, the analysis were done to extract features from the acquired EMG signal. The envelope creation method/smoothening of the unipolar EMG signal show better results than the extracted and wavelet processed extracted signal. Classification efficiency of 95 – 100% was resultant by using MLP, whereas using RBF, the classification efficiency was resultant in 85 - 95%.[17] Using the importance predictors result found in offline classification, a control system was designed for online classification of EMG signal. The control system was designed using basic Boolean gate logic so there won't be any computational burden to the system. Using this control system designed, the motor-disabled persons can able to control the movement of the rehabilitation aids like robotic hand, Wheelchair, etc.[6, 22, 28] Furthermore, for increasing the efficiency of the designed control system, an additional feature was added to make the system more accurate in the sense of time of travel. This is made possible by incorporating Hall Effect sensor with Boolean change state logic. The output of the Boolean change state logic depend upon the previous output so if EMG signal input is getting turn off in the presence of Hall Effect sensor at on state, the Boolean change state provide a High state "1" output, which will keep the wheelchair in moving condition/travelling with respect to time.

6.2 Future scope

Using this type of control system in controlling wheelchair, will help the disabled person not to get more strain in activating/driving any robotic assist device/wheelchair. Because once a biosignal is lost after triggering an action is efficient to carry forward any action corresponds to that particular work.

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