EMG Feature Extraction and Classification Implementation on FPGA

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by

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Certificate

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This is to certify that the Dissertation Report on " **EMG Feature Extraction and Classification Implementation on FPGA**" by **Chandrakanta Meena** is bonafide work completed under my supervision, hence approved for submission in partial fulfillment for the Master of Technology in Vlsi Design, Malaviya National Institute of Technology, Jaipur during academic session 2018-2019 for the full time post graduation program of session 2017-2019. The work has been approved after plagiarism check as per institute rule.

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Abstract

This project comprises the design and implementation of an Electromyography(EMG) signal classification system that can distinguish between different gestures. Electromyography(EMG) is the detection of Electrical Signal that is generated from muscles when they contracts. It basically detects the movement of muscles.The purpose of this paper is to the introduced best method for feature extraction and classification to control the prosthetic arm.First,All the features implemented in MATLAB and then best extracted feature in terms of accuracy and low computational time is determined.The best feature feed as an input to the classifier.In this proposed work, we had taken four activities i.e. Hand Open(HO), Hand Close(HC), Wrist flexion(WF) and Wrist extension(WE).In Order to evaluate the System 12 channels of EMG is collected.For this we had taken 9-time domain(TD) features and 2 frequency domain(FD) features.This study estimated the performance of Time domain(TD) and Frequency domain (FD) features in discriminating EMG signal for four activities, Hand Open(HO),Hand Close(HC),Wrist flexion(WF) and Wrist extension(WE).The sampling rate for signal acquisition is 2000 samples per second.To examine the performance of the feature,Linear Discriminate Analysis(LDA) was introduced.LDA gives good results for given data and it is less complex compare to other classifiers.The present study showed that the TD features obtained the highest classification accuracy but more computation time.The results were supported by LDA classifier and TD features showed best classification accuracy in EMG signal classification.Processing time for hardware implementation is less compared to software implementation.

Declaration

I declare that,

1. The work contained in this dissertation is original and has been done by me under the guidance of my supervisor.

2. The work has not been submitted to any other Institute for any degree or diploma.

3. I have followed the guidelines provided by the Institute in preparing the dissertation.

4. I have conformed to the norms and guidelines given in the Ethical Code of Conduct of the Institute.

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Contents

List of Figures

List of Tables

Abbreviations

LDA	**L**inear **D**iscriminant **A**nalysis
HDL	**H**ardware **D**iscription **L**anguage
FPGA	**F**ield **P**rogrammable **G**ate **A**rray
TD	**T**ime **D**omain
FD	**F**requency **D**omain
SVM	**S**upport **V**ector **M**achine
MAV	**M**ean **A**bsolute **V**alue
MMDF	**M**odified **M**ean **F**requency
MLP	**M**ultilayer **P**erception
BRAM	**B**lock **R**andom **A**ccess **M**emory
ANN	**A**rtificial **N**ural **N**etwork
ZC	**Z**ero **C**rossing
IAV	**I**ntegrated **A**varage **V**alue
SSC	**S**lope **S**ign **C**hange
SSI	**S**imple **S**quare **I**ntegral
WL	**W**aveform **L**ength
RMS	**R**oot **M**ean **S**quare
IP	**I**ntellectual **P**roperty

Chapter 1

Introduction

1.1 Electromyography

Surface Electromyography(sEMG) is a noninvasive technique that records and detects electrical muscle activity in the form of electrical signals that is used to diagnose neuro-muscular conditions.The generated electrical signal from muscle activation is known as a myoelectric signal that can be detected by the electrodes attached to the skin surface.This electrical signal sends to the wireless device which is connected to the PC so that all the activities of EMG signal can be observed on PC.After acquiring EMG signal it is converted into digital signal after that features will be obtained from the digitized EMG data.Feature extraction is a technique to extract essential information from EMG signal and eliminates the undesired signal.An EMG converts these signals into numbers or graphs to help doctors to make a diagnosis.

1.2 Problem Statement

To create a suitable system for EMG Signal Classification, note that EMG signals are physiological signals and contain a lot of noise and variability.These elements create classification more difficult as the EMG signal for similar movement will never be the same.Many of the

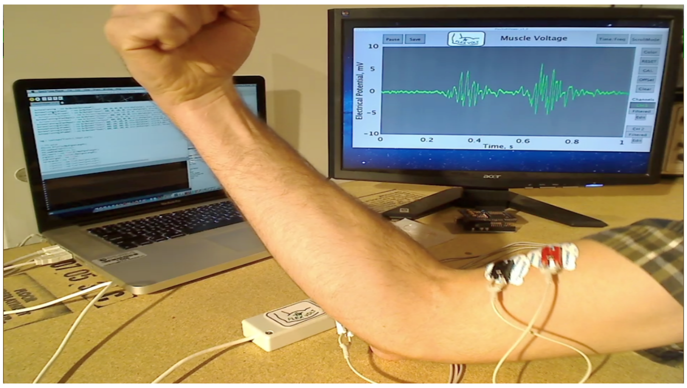


Figure 1.1: Acquiring EMG Signal

current methods used such feature extraction methods that are robust to noise. After several studies, In real word prosthetic control still lacks in Pattern Recognition[5].Electrode shift and doffing or variations in limb condition decreases accuracy. For increasing robustness number of channels is also increases, but by the increasing number of channels, the computation time also increases. For a less computation time, prosthetic control research has concentrated on using less number of sEMG channels.It has been recorded that as the number of input channel increases robustness is also increases in non-stationary conditions in EMG signal classification[9].In current prosthetic control, microprocessors are less suitable for high-density EMG data classification because of higher computation time.The main purpose of this work is to implement a controller for classifying high-density EMG signals.A prosthetic controller should be an embedded system.Inside the Prosthetic controller, it must be able to perform the computation independently. Feature extraction and classification units take more computational time compared to the software, so for that, we have used accelerated hardware design on FPGA in this project.

1.3 Objective

The objective of this project is to examine the performance of extracted features from the EMG signal. Performance in term of high accuracy of the classification and low computation time. This study distinguished the performance of the TD and FD features.TD features were simple and efficient in EMG pattern recognition[6] and they need less computation time because they do not require any transformation. On the other hand, FD features were used to determine the EMG power spectrum in frequency form so they require transformation so they need more computational time compared to time domain methods but in most of the cases their classification accuracy more compared to the time domain.To evaluate the feature performance, linear discriminant analysis (LDA) is used to classify the EMG pattern. Previous studies indicated the highest classification, illustrated the best feature performance in discriminating EMG signals.Removal of noise due to power-line harmonics or electrode shifts and filtering are the most common preprocessing steps. The robustness of a system can improved by increasing number of channels but by increasing the number of channels computation time is also increases. while processing EMG signal feature extraction units and classifier take more computation time for that we designed accelerated hardware in which all feature extraction units and classifier were designed on an embedded platform. There are so many advantages of the embedded prosthetic controller over software-only solutions. Embedded prosthesis controllers are small size and show moderate energy consumption.They hold a Large number of memory elements and logic blocks. In comparison with a microprocessor, FPGA runs on a much slower clock rate that results in less power consumption compared with a general purpose DSP. A Hardware description language (HDL) is used for programming FPGA, which decrease the complexity in designing a digital system. In this operation performed in parallel and FPGAs can be reprogrammed.In this paper we will compare both software and hardware results.

1.4 Literature Review

The concept of controlling artificial limbs by electromyographic control started since 1970s. At that time to control artificial limb, an amplitude level coding algorithm method is used. This method would typically require the subject to create the same amplitude in the EMG signal to obtain the wanted action of the prosthetic design.This was a simple method to a complex problem. The disadvantage of this type of control is that it takes considerable amount of time in training the subject to create an EMG signal of desire amplitude, and its results are not always reproducible. EMG Signal is random signals this indicates that an EMG signal is produced a unique signal when a subject tries to close or open their

Hand. Because of this researchers started to search for more precise statistical analysis for EMG signal classification.

In 1993, 5-TD Features were suggested by Hudgins et: mean absolute value slope,mean absolute value(MAV), zero crossing(ZC),Waveform Length(WL) and slope sign change(SSC). According to Tsai et al,for extracting EMG features,required time is around 10ms for 200ms samples gathered for both regular and amputee subjects. In TD ZC and SSC features constitute difficult Frequency information they do not require conversion from the TD to FD.In the detection of movement of the hand, Ahsan et al. extracted EMG alerts using VAR, MAV, SSC, ZC, RMS SD.Another TD feature discovered in the same year, Maximum amplitude(MAX) that is used along RMS and SD to perform EMG signal classification in hand-lifting.In which best performance is given by SD in comparison to RMS and MAX.Balbinot and Favieiro noted that features in TD, mainly RMS seems to be the most suitable parameter correlated to MAX, MAV, ZC, SSC and WL as it presents a quantitative model in electrode selection, so it delivers the best performance for identifying facial gestures.

In pattern recognition,only a few studies used FD as feature extraction method. Median power frequency(MNP) and Mean frequency(MNF) calculated from power spectrum are most commonly used features for EMG signal classification, particularly for muscle contractions. Phinyomark et al modified the traditional features in a fashion for finding robust features.By calculating median and mean from the EMG amplitude spectrum rather then power spectrum,They modified the median and mean frequency,which is defined by modified median frequency(MMDF) and modified mean frequency(MMNF).Many studies have examined the performance of FD and TD features.Phinyomark et al. compared TD and FD features by taking 27 TD and 11 FD feature performance to identify hand movements.Another work of Kendell et al. describes the selection of electrode-pair based on the 6 TD and 5 FD features of EMG signal. In this study,for electrode selection TD features are more consistent than FD features.In 2013,Another survey conducted by Phinyomark et al.,have examined that for long time TD features gives better than FD features in terms of classification.

In 2006, Oskoei et al. Obtained Combined feature by combining both FD and TD features.The result suggests that only by using TD features satisfying accuracy cannot achieves for identifying the motion patterns suggesting that for more satisfactory recognition multiple features should achieve. To overcome the weakness of TD features,which is suitable only for stationary signals,ensemble of TFD features is introduced which able to give high classification in nonstationary environment. Surprisingly,The major disadvantage of TFD features is high-dimensionality of feature vectors.To decrease the dimensionality of the EMG data while keeping its discrimination capability, dimensionality reduction technique is introduced.This technique increases classification accuracy.

The extracted features feed as an input to the classifier.Classifiers distinguish extraordinary classes of the extracted features.Then,the acquired classes are used for giving commands to the controller.There so many methods for classifying EMG data which includes,Bayesian classifier(BC), Artificial neural networks(ANN),fuzzy logic (FL),multilayer notion (MLP),support vector machines (SVM),linear discriminant evaluation (LDA) and K-nearest neighbor (KNN).The SVM is a kernel-based method and has emerged as a more attractive device for gadget gaining knowledge of jobs, which include regression and classification. SVM, which is a statistics classification method offered by Vapnik, is generated from the training process by the use of the training records.Following, type is accomplished at the trained model. the main problems faced in Organizing the SVM model is to determine the kernel function and its parameter values. This method resulted in 73% accuracy, while, 96.75% had been won by using hybridizing SVM and particle swarm optimization (PSO) in finding neuromuscular problems.

1.5 Methodology

The general block diagram of the whole procedure is shown in Figure 1.1.The EMG pattern recognition processing chain contains:Data Acquisition, Data Windowing, Feature Extraction and Classification.At first, all four subjects get prepared for EMG signal recording.It was done by conductive electrodes attach to the surface of the skin.In this work four pairs of surface electrodes are used and they positioned in bipolar configuration on the affective muscle involved in chosen gestures. The whole project is divided into two parts, software and hardware. Firstly, We have implemented EMG feature extraction and classification on MATLAB for different window length then after comparing the results of TD and FD in MATLAB best feature extraction method is implemented on FPGA. It takes the data from the MATLAB and feed as an input to the classifier and then finds the classification results.

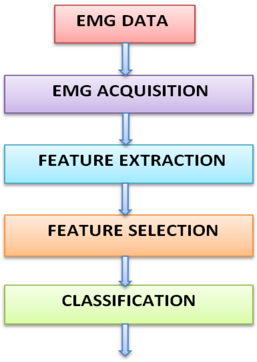


Figure 1.2: EMG Data Processing

1.6 Outline

The remainder of this work as follows, In Chapter 2, it gives information about background of EMG signal acquisition,characteristics of EMG Signal and Windowing technique and in Chapter 3 it discuss about Feature extraction methods both in TD and FD and in Chapter 4 it talks about classification methods.Chapter 5 gives the software and hardware implementation and experimental results and finally, it brings a conclusion and Future Scope in Chapter 6.

Chapter 2

Basic of Electromyography(EMG)

2.1 Physiology

Myoelectric signals are measurable signals which emerge during muscle activation that is generated due to a small electric current produced by the ion exchange across the muscle membranes. There are 2 types of EMG present first surface electromyography(sEMG) that is noninvasive technique and second is needle electromyography(NEMG) that is an invasive technique. sEMG reads muscles activity on the skin surface that encloses a muscle. Electrodes are attached to the skin and give a rough assessment of the muscle action.sEMG gives knowledge on the duration and onset time,and relative intensity of muscle movement.In NEMG a sharp needle is inserted into the skin in the muscle. NEMG is more accurate because of this, it is used in medical diagnostics for the evaluation of muscle disorder. Invasive needle electrodes collect signals better than surface electrodes and can reach to the muscle fibers. In sEMG the signal is made of all muscle fiber motion potentials happening in the muscles under the skin. Surface electrodes do not hurt the user, and for this reason, they are preferred and used in this project to get muscle activity in satisfying quality. 2 types of sEMG electrodes are present: wet electrodes and dry sEMG electrodes. sEMG electrodes are connected to the skin using the conductive gel as an intermediary layer to assure good conductivity between the skin and the electrode.

2.1.1 Sensing and Positioning

The EMG signal acquisition the process starts with the recording of the EMG signal from the skin surface with the help of the surface electrodes.To receives differential EMG signal It requires 3 electrodes: 2 electrodes which connected to the inputs to the differential amplifier and 1 electrode which is reference electrode attached to the ground.For the non-invasive assessment project of muscles the 2 electrodes should be separated at a distance of 20mm according to the guidance of the sEMG. Figure is illustrating the recommendations.

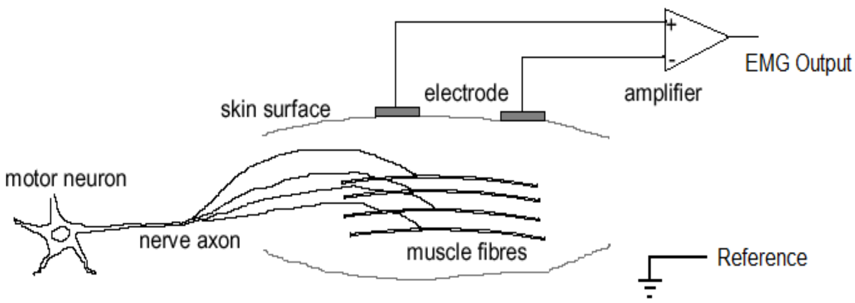


FIGURE 2.1: EMG acquisition from muscles[17]

2.1.2 Characteristics of EMG signal

sEMG signals have a frequency contains from 0 to 500 Hz, including dominant energy from 50 to 150 Hz but content may be useful at up to 2000 Hz. The amplitude of the EMG signal varies from 50 V up to 30mV.The characteristics of EMG signals and different EMG equipment features define the quality of an EMG signal detection. Besides electrodes characteristics and motor units, there are other agent that distort and add unwanted noise to the EMG signal. A dc offset due to half cell potentials in the tissues can be as high as 300 mV. Ambient 60 Hz noise from power supplies may result in power line noise threefold the magnitude of the SEMG signal. Signals generated from motor units of neighboring muscles may result in misleading information about the examined muscle. Inherent noise caused by electronic equipment can range from zero to thousands of Hz can also lead to misleading information. Noise due to motion artifacts due to electrode or cable movement varies from the frequency range of 1 to 5 Hz.

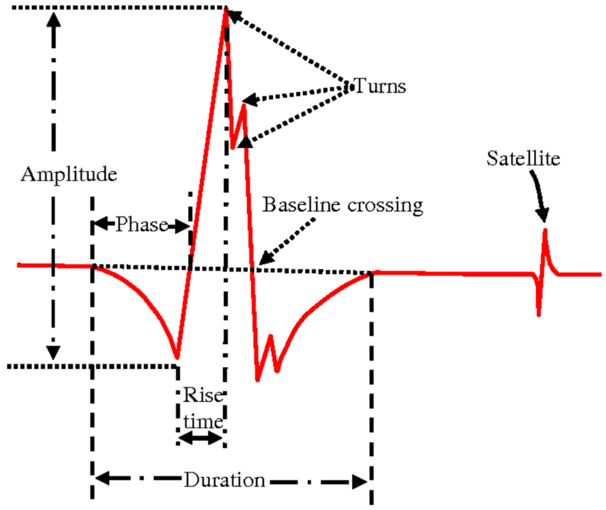


FIGURE 2.2: EMG signal Parameters

2.1.3 Noise affecting to the EMG Signal

EMG signal consists of two types of noises transducer noise and ambient noise

2.1.3.1 Ambient Noise

Electromagnetic devices causes ambient noise for example computers, power lines, force plates, etc.Ambient noise produced due to device which is plugged into AC outlet.This noise contains a wide range of frequency elements.But, the dominant frequency is corresponding to the frequency of the AC power supply i.e 50Hz or 60Hz.

2.1.3.2 Transducer Noise

Transducer noise is from the junction of the electrode and skin. Surface electrodes convert the muscles generated current into electronic current.This electronic current stored in either digital or analog form and handled by electronic circuits as a voltage. 2 types of noises result from this transduction noise.

- DC Voltage Potential: This is due to the impedance difference between the electrode sensor and skin and from reductive and oxidative chemical reactions in contact region between conductive gel and electrodes.
- AC Voltage Potential: It is produced by impedance fluctuations between the skin and conductive transducer.By using Ag-AgCl electrodes this impedance can be reduced because these electrodes consist of a silver metal surface that is plated with a thin layer of AgCl material.

The purpose of EMG measurement is to maximize the SNR.The Noise in the EMG signal is reduced by technological development. The most important development is to introduce a bipolar recording method.To suppresses signals that are common to input electrodes in Bipolar electrode organizations used differential amplifier.Basically, Differential amplifier creates difference in the potential at one electrode to the other electrode and then amplifies the difference.In contradiction, generated signals from muscles tissue which is near to the electrodes will not destroy and will be amplified results in increasing the signal to noise ratio(SNR).The electrode-skin contact is determined by the resistance of the underlying tissues and skin and to the capacitance of electrodes.This is known as electrode-skin impedance.

2.2 EMG Acquisition

Data Acquisition is the method of sampling alerts that measure real global bodily conditions and changing the resulting samples into digital numeric values that may be manipulated with the aid of a pc. In EMG Acquisition, the Raw sEMG signal was sent to the wireless device which is connected to the PC by the USB. Then we can observe the change of sEMG in the computer.

Typically, sEMG signal acquisition performed in 2 stages.The first stage contains electrode–amplifier stage that includes detection of signal and preamplification.This stage is attached nearer to the skin,this stage contains the electrodes for detection and the electronic amplification system that integrated within a single package. The second stage is

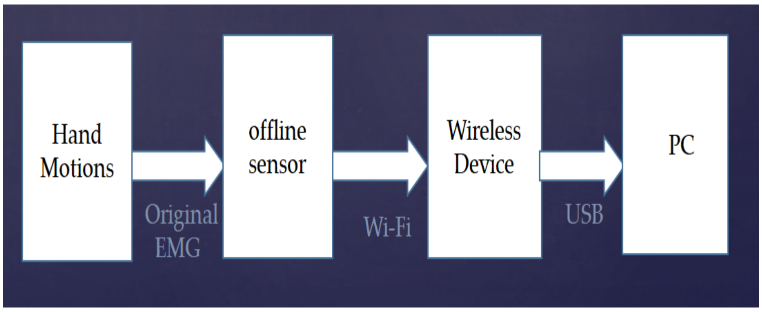


FIGURE 2.3: Offline experiment

signal conditioner stage that includes filters for noise removal and analog to digital converters. An electrode–amplifier stage first detects the EMG signal and then amplifies desired signal and removes the undesired noise. The input impedance of electrode–amplifier stage is high that limit current that is produced from the muscles.This stage reduces signal distortion and attenuation.Low output impedance drives the subsequent electronic level without change in output voltage.Raw EMG signal is mixed with noise.These noise frequencies can be high as well as low.Low pass filter removes high frequency noise and high pass filter removes low frequency noise.After removing noise the Analog signal is converted into digital signal by the analog to digital converter(ADC).The number of bits used by an ADC,is known as quantization.The resolution of the ADC is determined by the quantization bits.The more number of quantization bits will lead to less resolution of the ADC;the more it will help in control purposes.

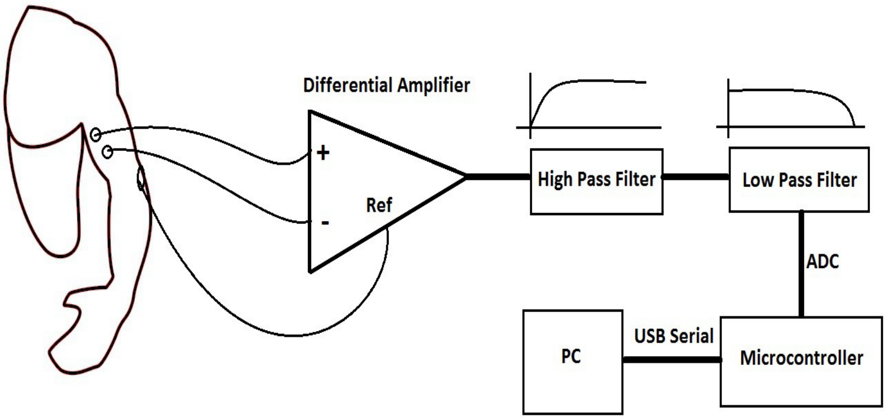


FIGURE 2.4: Block diagram indicating all steps for driving a robotic arm[14]

2.2.1 Window approach

The EMG signal's stochastic nature makes it important to extract identifying features from the analysis window T_a.All the features are calculated from analysis window.An overlapping window approach given by Englehart[7] to increase classifier decisions. Figure 2.5 illustrates about the approach. From T_a,all the features are obtained. Consequently,T_d

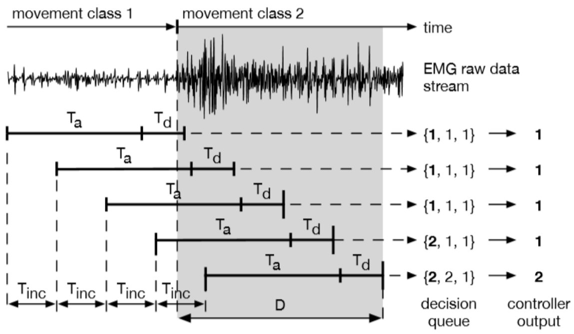


FIGURE 2.5: Window approach to EMG Signal classification

is the Processing time of the system to complete pattern identification. Last n classifier decisions is added to a decision queue to remove misclassification then, class which has maximum vote passed to the controller. To make classification decision more strong,A new $t_a$window is calculated after T_{inc} period. In this T_d should be smaller or equal to T_inc.

$$D = \frac{1}{2}.T_a + (\frac{n+1}{2}).T_{inc} + T_d \tag{2.1}$$

To minimize D, we have to minimize T_{inc}, T_a, T_d, and n. by minimizing T_a controller delay reduces but because of this classification accuracy reduces. The optimal value for T_a is come out between 150 ms and 250 ms, according to Smith et al.[7]. By minimizing n, it increases controller delay and larger value decreases more misclassifications.

Chapter 3

Feature Extraction Methods

Feature extraction is a technique to extract essential information from the EMG signal and eliminates undesired signal.EMG Feature extraction methods divided into 3 types.There are first Time Domain(TD),second Frequency Domain(FD) and third is Time-Frequency Domain(TFD).In present work ,only first 2 feature method considered,which are TD and FD because features in the last group,TFD cannot be directly used.In time-frequency feature methods we have to use dimensionality reduction techniques before sending to the classifier to reduce their high dimensions.Therefore,study of TD and FD feature extraction properties has recently become most useful technique in the EMG signal classification.

3.1 Time Domain Feature Extraction Methods

Time Domain(TD) Features are fast and easy implementable because they don't require any conversion. They can be calculated by raw EMG data. The major drawback of TD features is the nonstationary property of the EMG signal. TD values will be calculated by amplitude values that are much interfered by noise. The Time-Domain Features includes,

3.1.1 Integrated EMG

IEMG feature is represented as a summation of the EMG signal amplitude absolute values of the EMG signal amplitude, which can be represented as

$$IEMG = \sum_{i=1}^{N} |X_i| \tag{3.1}$$

where X_i denotes the EMG signal in a segment i and N represents length of EMG Signal

3.1.2 Mean Absolute Value

MAV is defined as the average of sEMG signal's total absolute values. It can be expressed as:

$$MAV = \frac{1}{N} \sum_{i=1}^{N} |X_i| \tag{3.2}$$

3.1.3 Modified Mean Absolute Value Type1

MAV1 is the advancement of basic MAV feature.For increasing robustness of MAV feature,weighted window function w_i is included in the MAV equation ,which is expressed as

$$MAV1 = \frac{1}{N} \sum_{i=1}^{N} W_i |X_i| \tag{3.3}$$

$$W_i = \begin{cases} 1 & if \quad 0.25N \leq i \leq 0.75N \\ 0.5 & otherwise \end{cases}$$

3.1.4 Root Mean Square

RMS is the amplitude modulated Gaussian Random Process of the muscles activation process.It can be expressed as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} X_i^2} \tag{3.4}$$

3.1.5 Waveform Length

It is the improvement of IEMG feature . It is defined as the cumulative length of waveform over the segment.It can be represented as

$$WL = \sum_{i=1}^{N-1} |X_{i+1} - X_i| \tag{3.5}$$

3.1.6 Variance

VAR is the average of the deviated square values of that variable.however mean value of the EMG signal is nearly 0. hence,variance of EMG signal is expressed as

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} X_i^2 \tag{3.6}$$

3.1.7 Simple Square Integral

It uses energy of EMG signal. It describes as the summation of square values of the EMG signal amplitude ,which is expressed as

$$SSI = \sum_{i=1}^{N} X_i^2 \tag{3.7}$$

3.1.8 Zero Crossing

ZC is represents frequency information of the EMG signal in TD.It couts the number of times that EMG amplitude crosses zero amplitude level.

$$ZC = \sum_{i=1}^{N-1} [sgn(x_i * x_{i+1}) \cap |x_i - x_{i+1}|] \tag{3.8}$$

$$sgn(x) = \begin{cases} 1 & if \quad x > threshold \\ 0 & otherwise \end{cases}$$

3.1.9 Slope Sign Change

This feature represents frequency information of the EMG signal in TD.It counts the number of times that slope of EMG signal sign changes.Threshold is included to eliminate background noise of the EMG signal.The mathematically expression of SSC is given below

$$SSC = \sum_{i=1}^{N-1} [sgn(x_i * x_{i+1}) \cap |x_i - x_{i+1}| \geq threshold]$$

$$sgn(x) = \begin{cases} 1, & if \quad x \geq threshold \\ 0, & otherwise \end{cases}$$

3.1.10 Auto Regressive Coefficient

AR model tries to model the signal by calculating previous samples of the signal.In this each sample represents the linear combination of previous samples.it is defined as

$$x[n] = -\sum_{i=1}^{p} a_i x[n-i] + e[n] \tag{3.10}$$

Here x[n] is the data which is the combination of n data points,p is degree of the AR model, a_i is the AR coefficient and e[n]is white gaussian noise which do not depend on previous samples.

3.2 Frequency Domain Feature Extraction Methods

Frequency domain features are calculated by transforming raw EMG signal in frequency domain and then by finding Power Spectral Density(PSD).A basic concept in the study of EMG signals is the notion of the frequency content of a signal, i.e, the contribution of each specific frequency in the signal.The information which can not easily getting from TD can easily seen by transforming signal into FD.Fourier Transform is the well known techniques for finding the frequency content of any signal for aperiodic signals and Fourier series for periodic signals.FD features require more computation time because they require transformation but FD features are more accurate than TD features.classification accuracy more compared to time domain features.

3.2.1 Mean Frequency

Mean frequency is calculated by finding the sum of product of the frequency and EMG power spectrum and then divided it by total sum of the spectrum intensity given as

$$MNF = \frac{\sum_{i=1}^{M} f_i P_i}{\sum_{i=1}^{M} P_i} \tag{3.11}$$

Here, f_i is frequency of spectrum, P_i is EMG power spectrum and M is the length of frequencies.

3.2.2 Median frequency

Median frequency is the frequency at which EMG spectrum is equally divide in 2 regions of equal amplitude.

$$\sum_{i=1}^{MDF} P_i = \sum_{i=MDF}^{M} P_i = \frac{1}{2} \sum_{i=1}^{M} P_i$$

3.2.3 Peak Frequency

At Peak frequency maximum power is obtained in EMG power spectrum.

$$PKF = max(P_i) \tag{3.13}$$

3.2.4 Mean Power

Mean Power denotes average power of the EMG power spectrum.It is given by

$$MNP = \frac{\sum_{i=1}^{M} P_i}{M}$$

Chapter 4

Classification

After extracting features from both TD and FD the EMG signals are ready for classification.In recent literature,many classification algorithms present.Support Vector Machines(SVM),Linear Discriminant Analysis(LDA), Artificial Neural Networks(ANN) and KNearest Neighbor Algorithm(KNN) are the most common classification algorithms. In current work LDA classifier is used because of its easy implementation and robustness.For given EMG data LDA gave high classification accuracy compared to other classifiers.LDA classifier was utilized to classify EMG pattern based on four classes.LDA is one of the robust classifier and it is good in reducing the dimensionality of features without separating the classes. Meanwhile, LDA Previous studies indicated LDA was simple and it showed high classification performance

4.1 SVM Classifier

The support vector machine(SVM) is a binary learning machine algorithm. The basic idea of this algorithm is to deal with complicated pattern recognition as in the case of non-linearity. It would be significant to notice here that for a linearly separable set of 2D points which belongs to one of two classes, more than one separating straight lines give the answer to the problem. In the case of multiple solutions, an intuitive pattern is usually determined to estimate lines. A line is not good if it passes nearer to the data points it means it will be affected by noise and because of this it will not generalize correctly. Hence, we have to find the line which is farthest from all the data points. Therefore, the process of the SVM algorithm is to determine the plane that gives the minimum distance from the training data set.An approach that is essential to the improvement of the vector learning calculation is the inner product kernel between the vector drawn from input data and support vector. The support vectors comprise a little subset of information separated by taking into account the samples itself. The learning algorithm to construct SVM is also referred to as a kernel method. However, SVM achieved increased computational complexity[15].

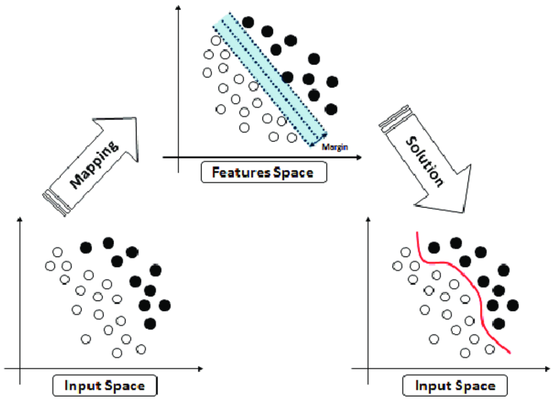


FIGURE 4.1: Two classes not linearly separable can be made separable using SVM

4.2 LDA Classifier

Linear Discriminant Analysis is the simplest classifier and most commonly used classifier in the research area. It is a process used in statics, machine learning, pattern recognition, and many more to separate classes by linearly combining all the feature vectors.LDA maximizes the component axes for class-separation, as shown in Fig.

Listed below are the general steps for performing a linear discriminant analysis

- First,Calculate the d-dimensional mean vectors for each class from the data set and mean for whole data set. Letμ_1 denotes class1 mean and μ_2 denotes the class2 mean,

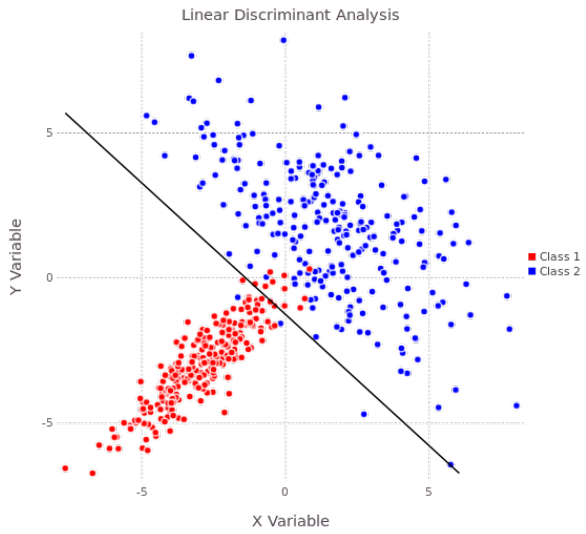


FIGURE 4.2: Scatter plot of two classes separated by LDA

and μ represents the mean of whole data set, which is taken by the addition of class1 and class2.

$$\mu = \mu 1 * p_1 + \mu 2 * p_2 \tag{4.1}$$

where p_1 and p_2 shows the two-class prior probabilities.

- Compute with in class scatter matrix(S_w) and between class scatter matrix(S_b).

$$cov_i = (x_i - \mu_i)(x_i - \mu_i)^T \tag{4.2}$$

$$S_w = 0.5 * cov_1 + 0.5 * cov_2 \tag{4.3}$$

here cov_1 is the covariance matrix of class1 and cov_2 is the covariance of class2.

$$S_b = \sum_i n_i * (\mu_i - \mu) * (\mu_i - \mu)^T \tag{4.4}$$

here n_i shows size of class i and $S_w$represents with in class scatter matrix and S_b shows between class scatter matrix.

- Calculate the eigenvalues and corresponding eigenvector for the scatter matrices.

$$W = S_w^{-1} S_b \tag{4.5}$$

calculate eigen values of W matrix and arrange them in ascending order and then calculate the eigen vector corresponding to biggest eign value.

- Transform the data sets by using LDA classifier to obtain the transformation matrices.

$$Y_i = (T_i)^T * X_i \tag{4.6}$$

where $(T_i)$is the Eigen vector which calculates from the W Matrix.

- Once the transformed data set obtained by LDA,Euclidean distance is used for the classification of data.

$$dis_n = (Y_i)^T * X - \mu_{tran} \tag{4.7}$$

where n is the class number,μ_{tran} is the complete mean of transformed data and X denotes the test data vector for which we want to find the class.From eq.4.7 n euclidean distance for n classes for each test data point are obtained.The minimum Euclidean distance shows that the test data belongs to minimum distance class.

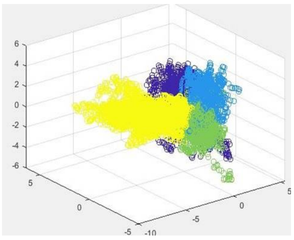
Chapter 5

Project Implementation

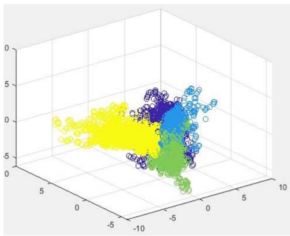
5.1 Software Implementation

We first implement all the features in MATLAB.In this, we evaluate the characteristics of EMG features in space by inspection of scatter plots and by observing criterion values.Here we have taken data from 12 channels.

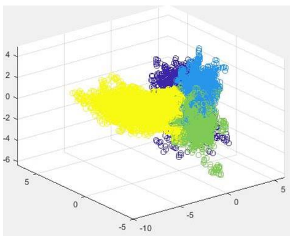
5.1.1 MATLAB Scatter Plots



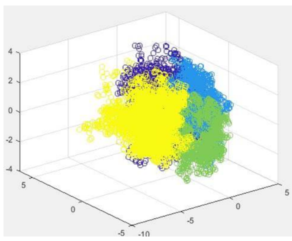
(a)



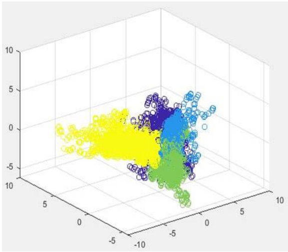
(b)



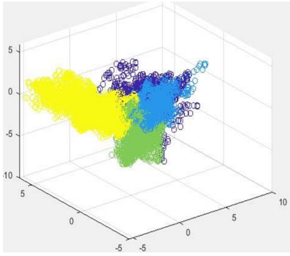
(c)



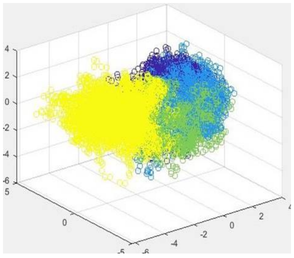
(d)



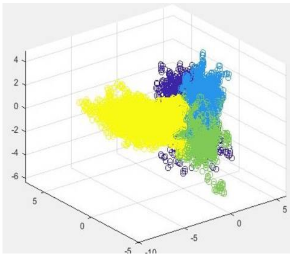
(e)



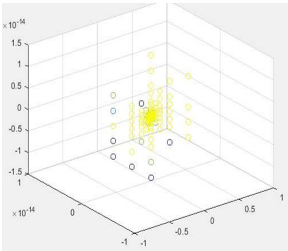
(f)



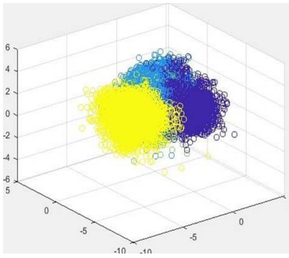
(g)



(h)



(i)



(j)

FIGURE 5.1: Scatter Plots of TD and FD features for 12 channels and 4 class: (a) RMS (b) VAR (c) MAV (d) SSC (e) SSI (f) WL (g) ZC (h) IAV (i) MNF and, (j) AR

The Scatter Plots of TD and FD features are shown in Fig.a-j,here different colours shows different classes.3-D scatter plots show the data in 3 dimensional space.EMG data was of 2644x13 dimension and it reduced to 2644x3 dimension by using LDA dimisional reduction method.

5.1.2 Davies–Bouldin (DB) criterion

This Criterion is used to estimate feature space quality.It needs the computation of distance between clusters.For this worst condition is determined for each cluster and finally the DB criterion values is obtained by averaging the worst case separation between clusters.In this work we have calculated Criterion Values and Processing time for different Window length.

Method	criterion value	Optimal K	processing time(sec)
RMS	12.4745	4	0.050423
ZC	4.5799	4	0.221086
IAV	7.2510	4	0.0477016
AR	26.3551	4	0.316268
MAV	7.2510	4	0.040275
VAR	10.8167	4	0.034084
SSC	10.5790	4	0.211699
SSI	10.8167	4	0.033842
WL	10.8041	4	0.034525
MNF	15.5305	4	0.093754
Dp Ratio	492.90	4	0.114138

Table 5.1: Window Length=200 Samples

Method	criterion value	Optimal K	processing time(sec)
RMS	27.1212	4	0.05990
ZC	4.5998	4	0.245929
IAV	9.7255	4	0.049601
AR	26.4538	4	0.319271
MAV	9.7255	4	0.044492
VAR	7.6257	4	0.0.063851
SSC	10.0760	4	0.266519
SSI	7.6257	4	0.038802
WL	9.0511	4	0.043555
MNF	18.7737	4	0.128494
Dp Ratio	48.7751	4	0.222866

Table 5.2: Window Length= 250 Samples

Method	criterion value	Optimal K	processing time(sec)
RMS	16.1020	4	0.077811
ZC	4.0139	4	0.254405
IAV	7.4109	4	0.050168
AR	289.5110	4	0.470805
MAV	7.4109	4	0.067836
VAR	8.2922	4	0.099533
SSC	7.9595	4	0.386417
SSI	8.2922	4	0.061172
WL	9.8205	4	0.052480
MNF	17.5982	4	0.187435
Dp Ratio	23.3571	4	0.328445

Table 5.3: Window Length=300 samples

here, Table 1 shows the criterion values , processing time and optimal k values for different TD and FD features for window length=250 samples and $T_inc = 140$ Samples and Table 2 for Window Length=200 samples and in Table 3 for Window Length=300 samples.For less criterion values it shows maximum separation between classes means classes are easily differentiable.Based on obtained classification accuracies in given Table,optimal features were examined.Best criterion values are obtained for Zero Crossing(ZC),Integrated EMG(IAV) and Variance(VAR).

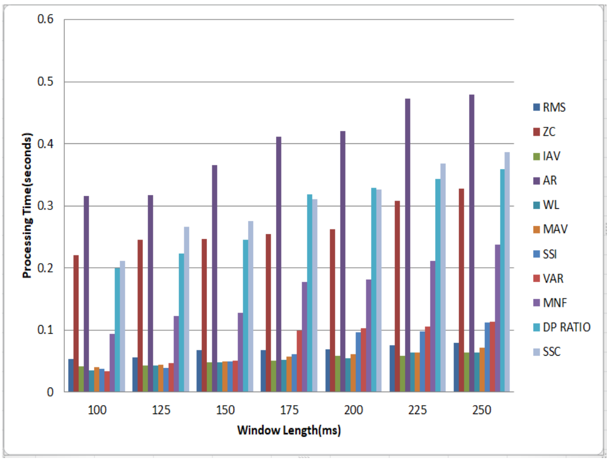


FIGURE 5.2: Variation of processing time with different window length

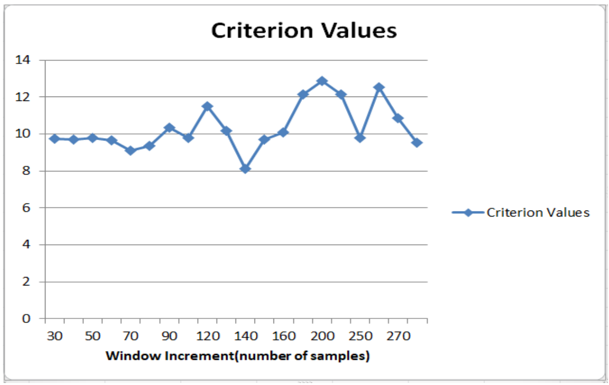


FIGURE 5.3: Variation of Criterion Values for different window increment

here,Fig 5.2 shows the variation of Processing time with respect to Window length.As the number of samples increases processing time is also increases.Processing time is maximum for AR,SSC and MNF features. Fig 5.3 shows the Variation of criterion values with T_{inc}.The Optimal Value of Criterion values comes at 140 samples.

5.2 Hardware Implementation

We have Implemented Time Domain Features on FPGA by creating IP and Implemented Linear Discriminant Analysis(LDA) algorithm for 4 classes and 2 channels in Vivado HLS.here all operations were performed in the 32 bit floating point format.FPGA stands for field-programmable gate array which is essentially an integrated circuit.The main reason for choosing FPGA is that it would decrease the requirement for extra clunky piece of equipment.Embedded prosthesis controllers has small size and show a moderate power consumption. They carry a Large number of memory elements and logic.A hardware description language(HDL) is used to program an FPGA,which reduces the complexity in designing a digital system.FPGA runs at a slower clock rate compared to microprocessors results in less power consumption compared to a general purpose DSP.On FPGA all operations performed in parallel whereas in microprocessor operations executes serially.FPGAs can be reprogrammed.In this project FPGA used to develop the EMG classification system was the zynq7000.For improvement,it was originally decided to apply a soft core processor to run the classification algorithm on the FPGA. This would enable the development in C and bypass the requirement to develop a complicated algorithm in Verilog.

5.2.1 Feature Extraction on FPGA

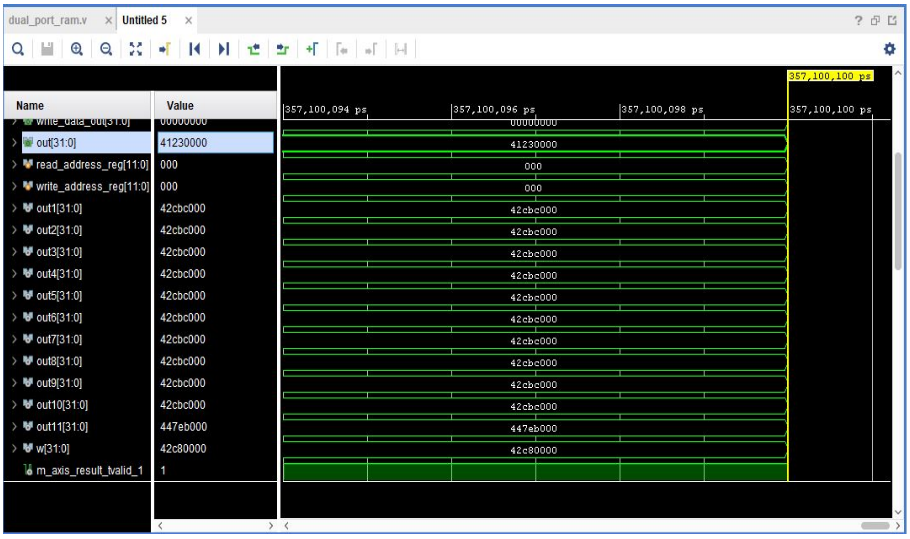


Figure 5.4: Simulation Waveform of FPGA Implementaion of Mean Average(MAV)

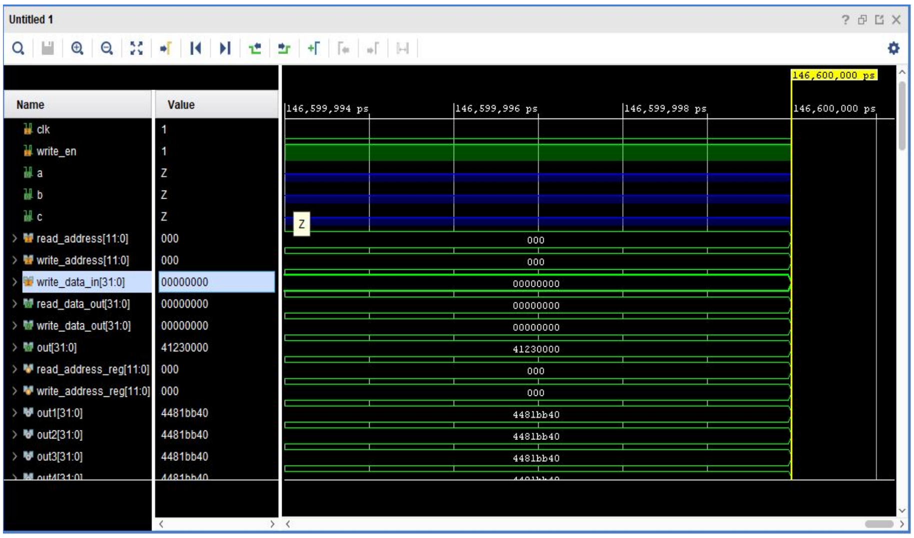


FIGURE 5.5: Simulation Waveform of FPGA Implementaion of Root Mean Square(RMS)

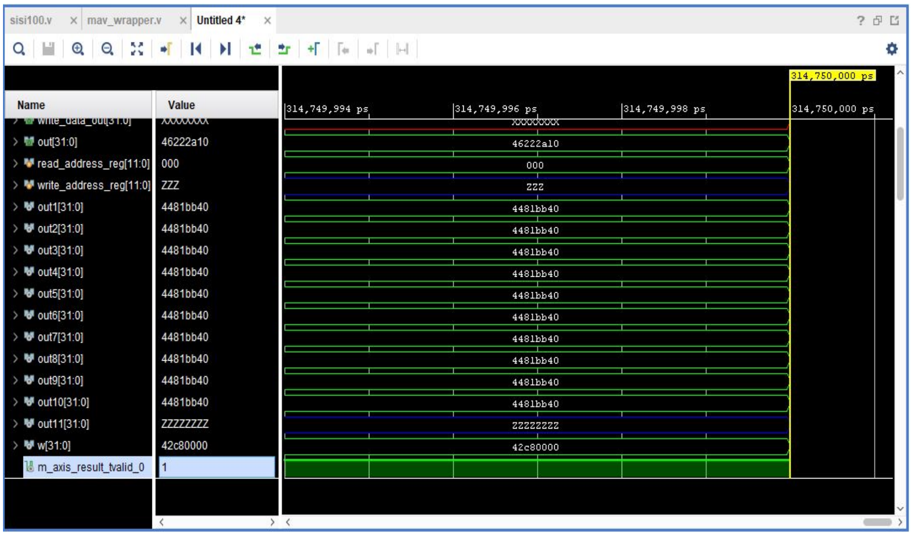


FIGURE 5.6: Simulation Waveform of FPGA Implementaion of simple square integral(SSI)

here,we have calculated MAV,RMS,VAR,SSI and WL for 100 samples in floating point by using floating point IP.In Fig 5-9, out denotes the final output of the complete block.All input data is stored in the designed block RAM that is connected to floating point modules. here, we have calculate the resource utilization and power analysis of simple square integral.

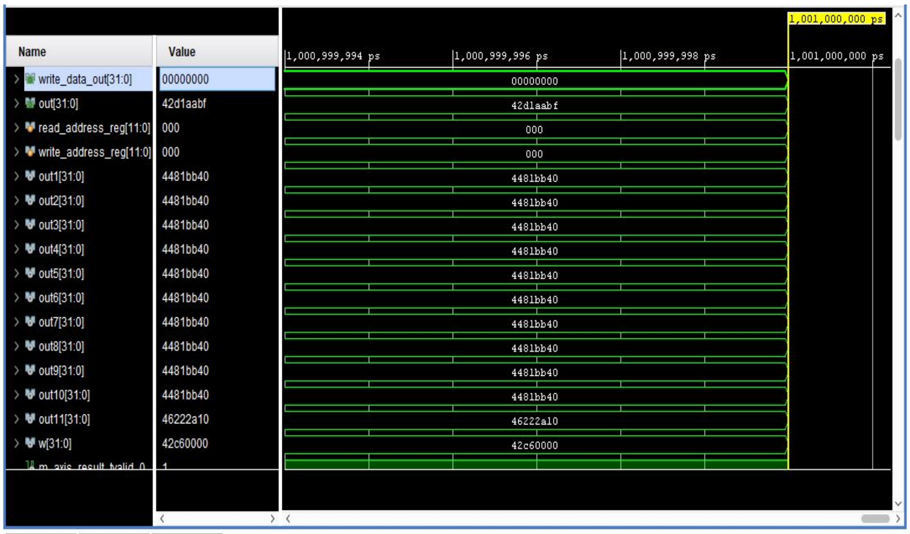


FIGURE 5.7: Simulation Waveform of FPGA Implementaion of Mean Variance(VAR)

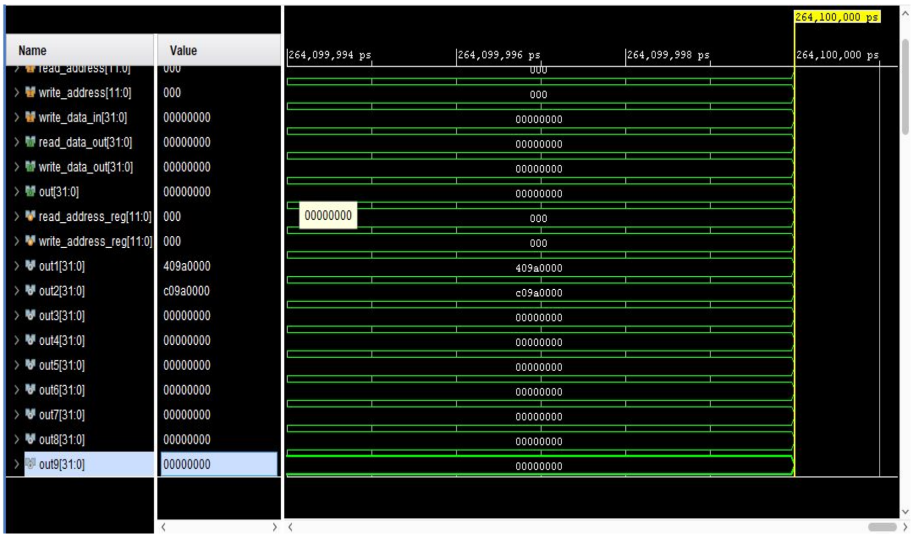


FIGURE 5.8: Simulation Waveform of FPGA Implementaion of Waveform Length(WL)

Resource	Utilization	Available	Utilization %
LUT	39462	63400	62.24
LUTRAM	2887	19000	15.19
FF	75350	126800	59.42
BRAM	4	135	2.96
DSP	398	240	165.83
IO	157	210	74.76

TABLE 5.4: FPGA Report for device utilization

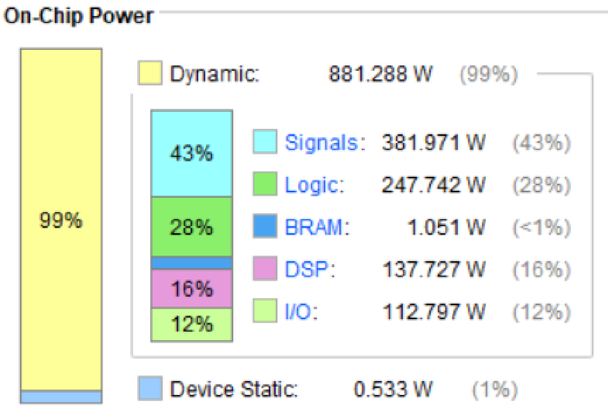


FIGURE 5.9: Synthesis report for power analysis

5.2.1.1 Comparison between Software and Hardware Results

In given Table 5.4 both software and hardware results were compared and found that processing time for hardware implementation is much less than the software implementation.Processing time for feature extraction for hardware implementation comes in micro seconds which is much less than software solution.These implementation is carried out on 64-bit Operating system on Windows 10 platform which has Intel Core i5-8250U CPU@1.6GHz and total installed memory is 8 GB.

Feature Extraction Method	Software Results(sec)	Hardware Results(sec)
RMS	0.06	$9\text{x}10^{-6}$
MAV	0.045	$4.2\text{x}10^{-6}$
SSI	0.039	$7.2\text{x}10^{-6}$
WL	0.043	$6.4\text{x}10^{-6}$
VAR	0.07	$10.6\text{x}10^{-6}$

TABLE 5.5: Comparison of Processing Time for both Software and Hardware

5.2.2 Classifier Algorithm Implementation on FPGA

For the classification of actions, we have used multiclass LDA as defined by[8]. The algorithm is implemented with a set of extracted feature vectors from training data for each class in the training phase and a covariance matrix and mean vectors are calculated then all covariance matrices are averaged, inverted and then Multiplied with the matrix containing all mean vectors, and we obtain the projection matrix W. In the classification stage feature vectors are projected to a k-dimensional space where k is the number of classes and finally calculate the distance for test vector from each class. minimum distance denotes that the test vector is from that class. The distance with the minimum value describes the predicted class. here, We have implemented the LDA algorithm in Vivado High-Level Synthesis(HLS) for 4 classes and 2 channels for 100 samples. In this we have taken 4 sets of extracted features of 100 X 2 dimension from these we have calculated Within class(S_w) and Between class(S_b)scatter matrices.after that we calculated projected set of data matrices and finally calculated the distance from each data set.here, we have taken the test vector from first class only and the distance will be minimum for first class.

$$S_b = \begin{bmatrix} 0.000057 & 0.000057 \\ 0.000057 & 0.000058 \end{bmatrix}$$

$$S_w = \begin{bmatrix} 0.007627 & 0.007735 \\ 0.007735 & 0.007943 \end{bmatrix}$$

here,Calculated distance is $dist_1$=0.000000,$dist_2$=-0.000034,$dist_3$=-0.000044,$dist_4$=-0.000041,from these distance for first class is minimum,it means test vector belongs to class first.

5.2.2.1 LDA Implementation for less data value

- In this we have taken two dimensional data set for four classes i.e set1,set2,set3,set4.

$$set1 = \begin{bmatrix} 2.1 & 2.24 \\ 2.2 & 2.13 \\ 2.3 & 2.41 \\ 2.4 & 2.51 \\ 2.5 & 3.16 \end{bmatrix} \qquad set2 = \begin{bmatrix} 4.1 & 4.24 \\ 4.2 & 4.13 \\ 4.3 & 4.41 \\ 4.4 & 4.51 \\ 4.5 & 5.16 \end{bmatrix}$$

$$set3 = \begin{bmatrix} 6.1 & 6.24 \\ 6.2 & 6.13 \\ 6.3 & 6.41 \\ 6.4 & 6.51 \\ 6.5 & 6.16 \end{bmatrix} \qquad set4 = \begin{bmatrix} 8.1 & 8.24 \\ 8.2 & 8.13 \\ 8.3 & 8.41 \\ 8.4 & 8.51 \\ 8.5 & 8.16 \end{bmatrix}$$

- First Compute the mean of each data set and the entire data set

$$uone = \begin{bmatrix} 2.3 & 2.49 \end{bmatrix}$$

$$utwo = \begin{bmatrix} 4.3 & 4.49 \end{bmatrix}$$

$$uthree = \begin{bmatrix} 6.3 & 6.29 \end{bmatrix}$$

$$ufour = \begin{bmatrix} 8.3 & 8.29 \end{bmatrix}$$

$$utotal = \begin{bmatrix} 5.3 & 5.39 \end{bmatrix}$$

- Compute within class and between class scatter matrix.In LDA, S_w and S_b are used to find criteria for class separability.All the co variance matrices are symmetric.

$$S_{b1} = \begin{bmatrix} 45 & 43.5 \\ 43.5 & 42.05 \end{bmatrix} \qquad S_{b2} = \begin{bmatrix} 5 & 4.5 \\ 4.5 & 4.05 \end{bmatrix}$$

$$S_{b3} = \begin{bmatrix} 4.99 & 4.49 \\ 4.49 & 4.049 \end{bmatrix} \qquad S_{b4} = \begin{bmatrix} 45 & 43.49 \\ 43.49 & 42.049 \end{bmatrix}$$

$$S_{btotal} = \begin{bmatrix} 100 & 96 \\ 96 & 92.199 \end{bmatrix}$$

$$S_{w1} = \begin{bmatrix} 0.10000 & 0.22200 \\ 0.222000 & 0.647800 \end{bmatrix} \qquad S_{w2} = \begin{bmatrix} 0.100000 & 0.22200 \\ 0.22200 & 0.647800 \end{bmatrix}$$

$$S_{w3} = \begin{bmatrix} 0.10000 & 0.022000 \\ 0.022000 & 0.107800 \end{bmatrix} \qquad S_{w4} = \begin{bmatrix} 0.10000 & 0.022000 \\ 0.022000 & 0.107800 \end{bmatrix}$$

$$S_{wtotal} = \begin{bmatrix} 0.400000 & 0.488000 \\ 0.488000 & 1.511200 \end{bmatrix}$$

- To find non-redundant group of features calculate eign vector corresponding to largest eigen value.

$$MaximumEignValue = 257.42$$

$$Eigenvector = \begin{bmatrix} 10.024647 \\ -1.000 \\ 18.811758 \end{bmatrix}$$

- Calculate Transformed Data Set

$$yone = \begin{bmatrix} 18.811758 \\ 19.924225 \\ 20.646687 \\ 21.549152 \\ 21.901617 \end{bmatrix} \qquad ytwo = \begin{bmatrix} 36.861053 \\ 37.973515 \\ 38.695984 \\ 39.598450 \\ 39.950909 \end{bmatrix}$$

$$ythree = \begin{bmatrix} 54.910347 \\ 56.022808 \\ 56.745277 \\ 57.647736 \\ 59.000202 \end{bmatrix} \qquad yfour = \begin{bmatrix} 72.959648 \\ 74.072105 \\ 74.794571 \\ 75.697029 \\ 77.049500 \end{bmatrix}$$

- Once the transformed data set are achieved,Euclidean distance is computed.Euclidean distance is used to classify data points.

Feature Extraction Methods	LDA Classifier Accuracy(%)	SVM Classifier Accuracy(%)
RMS	66.80	77.91
MAV	70.15	78.70
SSI	61	75.80
WL	78.84	88.36
VAR	63.89	76.85
ZC	68.52	73.02
IAV	67.33	79.76
SSC	71.58	79.23
MNF	38.62	39.15
AR	74.21	86
MAV,RMS,WL,VAR	88	90.89

Table 5.6: Comparison of accuracy achieved from LDA and SVM classifier

Table 5.6,represents the comparison of accuracy of LDA classifier and SVM classifier.In this process accuracy is calculated by using average of the results of iterative process,for this we have taken 10 iterations.Accuracy of SVM classifier is more than LDA classifier but LDA is also gives good result for selected features.In current literature LDA in combine with time domain features is best suited for pattern recognition.

5.2.3 HLS Design Flow

- First Create a C, C++ or SystemC representation of the design and a testbench that describes its desired behavior.
- Make the behavioral design functioning adequately and achieve the testbench.
- Compile the design by Vivado HLS to create RTL (VHDL or Verilog) then Synthesize the C algorithm into RTL implementation that creates comprehensive reports.Utilize the RTL to achieve VHDL or Verilog simulation of the design.
- Once the design has been fixed, install it into the Vivado Design Suite's physical-implementation process to program it into a device and run it on hardware or by exporting it into IP to turn the design into a reusable IP, then stitch the IP into a design by using IP Integrator.

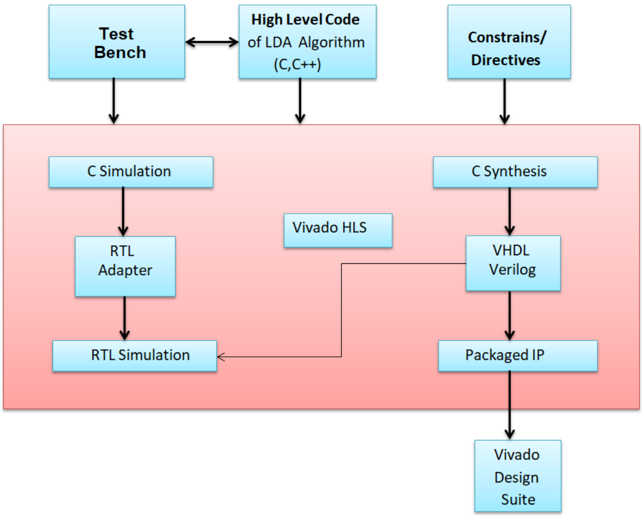


FIGURE 5.10: HLS Design Flow

5.2.3.1 Vivado HLS synthesis Report

Vivado synthesis report shows the hardware utilization for both LDA training and LDA testing.Hardware utilization report shows the number of LUTs,FF,BRAM and DSP uses of FPGA.

Name	BRAM_18K	DSP48E	FF	LUT
DSP	-	1	-	-
Expression	-	-	0	3492
FIFO	-	-	-	-
Instance	-	40	4832	9461
Memory	30	-	256	52
Multiplexer	-	-	-	4194
Register	-	-	4076	-
Total	30	41	9164	17199
Available	214	170	81200	40600
Utilization (%)	14	24	11	42

(a)

Name	BRAM_18K	DSP48E	FF	LUT
DSP	-	-	-	-
Expression	-	-	-	-
FIFO	-	-	-	-
Instance	-	-	-	-
Memory	-	-	-	-
Multiplexer	-	-	-	-
Register	-	-	-	-
Total	0	0	0	0
Available	214	170	81200	40600
Utilization (%)	0	0	0	0

(b)

FIGURE 5.11: Resource utilization report: (a) LDA Training (b) LDA Testing

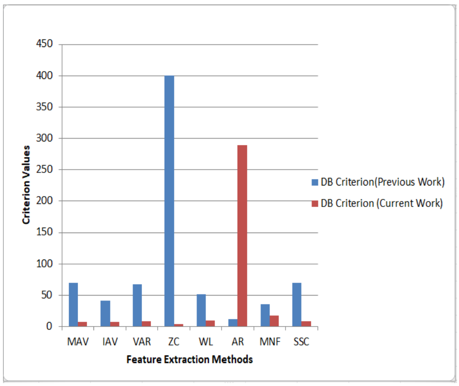
5.3 Comparison with previous Studies

Results are compared with the previous studies based on Classification Accuracy. This study shows that accuracy achieved by SVM classifier is more compared to other classifiers though Results of LDA classifier is also comparative good with TD features. The

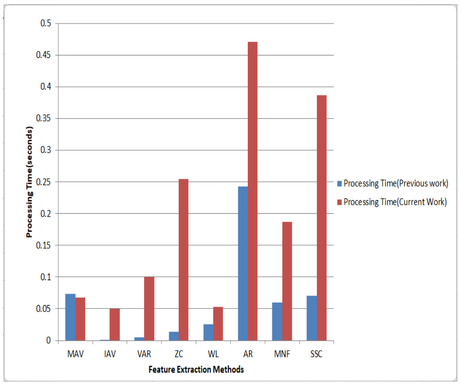
Author	Feature Extraction methods	Classifier	Accuracy(%)
Yi Zhang,Xuyang Zhu July,2017[11]	MAV,ZC,RMS,IEMG	SVM	66.96
Carl Peter Robinson[18] 2017	RMS,WL,ZC	kNN Classifier	90.15
M. Hamedi, Sh-H. Salleh[12] 2012	MAV	SVM	84.6
Angkoon Phinyomark[5] 2009	MAV,WL,ZC,SSC	-	95.67
Present Work	MAV,RMS,WL,VAR	LDA	88
Present Work	MAV,RMS,WL,VAR	SVM	90.89

TABLE 5.7: Comparison with previous results on the basis of Classification accuracy

accuracy achieved with LDA is 88%, which is acceptable. Processing time of LDA is much less because it implemented on Hardware. Results are compared with the study of Reza Boostan[15] on the basis of DB Criterion and processing Time.This study shows that obtained Criterion values for present work is much better than previous one.This is achieved by selecting proper Window length and Window increment.



(a)



(b)

FIGURE 5.12: Comparision with previous results on the basis of: (a) Criteron Values (b) Processing time

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

- This work introduce a design for HD EMG prosthetic embedded controller for hardware acceleration.The method was implemented on a Xilinx Zynq platform.In this work we have compared the Processing time of both Hardware and Software Implementation and conclude that computation time for hardware is much less than software solution.The accelerated hardware design obtained speed-ups over the software-only solution.
- Processing time taken by TD Features is less than FD features because they don't require any transformation.The major drawback of time domain features is the non-stationary characteristic of the EMG signal.
- In this work we have calculated Criterion values and Processing time for each feature extraction method and show the variation of criterion values and processing time for different window length and found that optimal window length is 125ms and optimal value of T_{inc} is 140 samples.The results show that MAV, WL, ZC gives the best Simulation Results from the scatter plots.They have least criterion value compared to other methods and MAV,WL,SSC and AR show good classification accuracy.By combining MAV,VAR,RMS and WL,classification accuracy for lda is 88% and for SVM classifier it come out 90.89%.It shows that SVM classifier gives better classification accuracy compared to LDA classifier but LDA is also gives good

result for selected features.In current literature LDA in combine with time domain features is best suited for pattern recognition.

- The system is able to utilize dynamic FPGA reconfiguration to adapt to noisy input data,trading off increased controller delay against improved movement recognition accuracy.

6.2 Future Work

- The scope of the project is mostly restricted to the implementation and development of a system that can able to classify EMG signals. There is no effort to update on modern analytical methods. The initial purpose of the project was to implement the EMG classification system entirely on an embedded platform; both training and classification must be implemented on an embedded platform. This would guarantee a practical solution where all the operation would require substantially less number of equipment and fewer methods.
- For increasing robustness number of channels should also increases for that high density myoelectric processing equipment should be used that can be capable to perform all the operations in parallel so that speed can be improve and should minimize the cost.For processing high density myoelectric signal accelerated hardware design should be implemented.All feature extraction and classification should be completely implement on embedded platform.

Bibliography

[1] Boschmann, Alexander et al. FPGA-based acceleration of high density myoelectric signal processing. 2015 International Conference on ReConFigurable Computing and FPGAs (ReConFig) (2015): 1-8.

[2] Altin, Cemil, Orhan Er. " Comparison of Different Time and Frequency Domain Feature Extraction Methods on Elbow Gestures EMG." European Journal of Interdisciplinary Studies [Online], 2.3 (2016): 35-44. Web. 24 Jun. 2019

[3] Too, Jingwei et al. Classification of EMG Signal Based on Time Domain and Frequency Domain Features. (2017).

[4] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, Feature reduction and selection for EMG signal classification, Expert Syst. Appl., vol. 39, no. 8, pp. 74207431, Jun. 2012.

[5] Angkoon Phinyomark, Chusak Limsakul, and Pornchai Phukpattaranont ,"A Novel Feature Extraction for Robust EMG Pattern Recognition ",DECEMBER 2009.

[6] X. Ren, L. Dai, Y. G. Soo, H. Asama and F. Duan, "Comparing the sEMG recognition effects between computer and DSP," 2016 35th Chinese Control Conference (CCC), Chengdu, 2016, pp. 4841-4846.

[7] Smith, Lauren H. et al. Determining the Optimal Window Length for Pattern Recognition-Based Myoelectric Control: Balancing the Competing Effects of Classification Error and Controller Delay. IEEE Transactions on Neural Systems and Rehabilitation Engineering 19 (2011): 186-192.

[8] Tharwat, Alaa Gaber, Tarek Ibrahim, Abdelhameed Hassanien, Aboul Ella. (2017). Linear discriminant analysis: A detailed tutorial. Ai Communications. 30. 169-190,. 10.3233/AIC-170729.

[9] Syed Kamran Haider, Malik Imran Daud , Aimin Jiang,"Evaluation of P300 based Lie Detection Algorithm",Electrical and Electronic Engineering 2017, 7(3): 69-76,july 2017. , Zubair Khan1

[10] Alaa Tharwat,Tarek Gaber,Abdelhameed Ibrahim,Aboul Ella Hassanien ,"Linear discriminant analysis: A detailed tutorial", May 2017.

[11] Zhang, Yi et al. Extracting time-frequency feature of single-channel vastus medialis EMG signals for knee exercise pattern recognition. PloS one (2017).

[12] Hamedi, Mahyar et al. Comparison of different time-domain feature extraction methods on facial gestures' EMGS. (2012).

[13] Bellingegni, Alberto Dellacasa et al. NLR, MLP, SVM, and LDA: a comparative analysis on EMG data from people with trans-radial amputation. Journal of NeuroEngineering and Rehabilitation (2017).

[14] Amna Khan, Zareena Kausar, Saad Malik,"Comparison of Linear Discriminant Analysis and Support Vector Machine Classifications for Electromyography Signals Acquired at Five Positions of Elbow Joint"International Journal of Mechanical and Materials Engineering Vol:11, No:7, 2017.

[15] Jamal, Muhammad. (2012). Signal Acquisition Using Surface EMG and Circuit Design Considerations for Robotic Prosthesis. 10.5772/52556.

[16] Reza Boostaniand Mohammad Hassan Moradi, Evaluation of the forearm EMG signal features for the control of a prosthetic hand,20 march2003.

[17] Jamal MZ, Signal acquisition using surface EMG and circuit design considerations for robotic prosthesis. INTECH Open Access Publisher, 2012

[18] Robinson, Carl Li, Baihua Meng, Qinggang Pain, Matthew. (2017). Pattern Classification of Hand Movements using Time Domain Features of Electromyography. 1-6. 10.1145/3077981.3078031.