HUMAN MACHINE INTERFACE FOR CONTROLLING BIONIC HAND

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Table of Contents

CERTIFICATE

This is to certify that the work titled "**HUMAN MACHINE INTERFACE FOR CONTROLLING BIONIC HAND**" submitted by **VISHNU TEJA (07102289),Deepansh Arora(07102257),Deepak Sharma(07102198)** of Jaypee Institute of Information Technology, Noida has been carried out under my Supervision.

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I take this opportunity to express my heartfelt gratitude and appreciation to our mentor, Mr.Naveen Babu, whose guidance and constant support and encouragement has been vital to the successful completion of the first part of our major project.

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SUMMARY

In this report, the concept of human–machine interface intended for the task of bioprosthesis decision control by means of sequential recognition of the patient's intent based on the electromyography (EMG) signal acquired from his/her body has been presented. The EMG signal characteristics, the problem of processing the signals including acquisition and feature extraction and their classification are discussed.

LIST OF FIGURES

LIST OF SYMBOLS & ACRONYMS

EMG : Electromyography

RMS: Root Mean Squared

ULDA : Uncorrelated Linear Discriminant Analysis

ZC: Zero crossing

WL: Waveform length

RMS: Root Mean Square

VAR: Variance

MAV: Mean Absolute Value

IEMG: Integrated EMG

CHAPTER 1 - INTRODUCTION

1.1 INTRODUCTION

An EMG(Electromyography) based human-machine interface for a biomechanical prosthesis hand has numerous applications fields like bio-medical science; space robotics; entertainment robotics; etc. Its primary purpose is to reconstruct the complex movements of the human hand as closely as possible via natural EMG signals arising out of the muscles.

Electromyographic control uses the EMG electrical signal which is generated due to depolarization of the cell membrane of the muscle fibers during contraction. The two main nerves which supply signals to the upper arm muscle group are the median and the ulnar nerves. The upper arm muscle group is known as the flexor-pronator muscle, which we are targeting . EMG is a complex signal and is different for each person, making the design of the prosthesis more challenging. The amplitude of the EMG signals is of the level of a few micro-volts and has a frequency between 50-350 Hz. The signal has to be amplified and passed through a band pass filter and envelope detector before it can be used for processing. The various features of the signal are extracted and are classified according to the K-Nearest neighbor algorithm into various classes of hand movement. The percept sequences are mapped into actions which are realized by the actuator unit.

1.2 PROBLEM STATEMENT

To develop a portable and multipurpose bionic robotic hand complete with articulated fingers and thumb, which can be controlled via natural muscle response and capable of performing various hand gestures. To extract features from the EMG signal and classify them as belonging to various types of hand gestures.

CHAPTER 2 - LITERATURE SURVEY

2.1 A. Phinyomark, S. Hirunviriya, C. Limsakul, P. Phukpattaranont. "Evaluation of EMG Feature Extraction for Hand Movement Recognition Based on Euclidean Distance and Standard Deviation", IEEE 2010

-In EMG hand movement recognition, the first and the most important step is feature extraction. The optimal feature is important for the achievement in EMG analysis and control. In this paper, a statistical criterion method using the ratio between Euclidean distance and standard deviation, which can response the distance between two scatter groups and directly address the variation of feature in the same group as a selection tool to find the optimal EMG feature. Fifteen features that have been widely used to classify EMG signals were used. The optimal feature is conducted to demonstrate the validity of the proposed index. The features are classified into six classes of hand gestures : wrist flexion (wf), wrist extension (we), hand close (hc), hand open (ho), forearm pronation (fp), and forearm supination (fs).

A. Feature Extraction Stage ::

1) **Integrated EMG (IEMG):** IEMG is normally used as an onset detection index that is related to EMG signal sequence firing point. IEMG is the summation of the absolute values of EMG signal amplitude, which can be expressed as ::

$$\mathrm{IEMG} = \sum_{n=1}^{N} |x_n| \ .$$

2) **Mean Absolute Value (MAV):** MAV is similar to IEMG that normally used as an onset index to detect the muscle activity. MAV is the average of the absolute value of EMG signal amplitude. MAV is a popular feature used in EMG hand movement recognition application. It is defined as ::

$$\mathrm{MAV} = \frac{1}{N} \sum_{n=1}^{N} |x_n| \ .$$

3) **Modified Mean Absolute Value 1 (MAV1):** MAV1 is an extension of MAV. MAV1 uses weighting window function (wn) to improve the robustness of MAV. It is calculated by

$$\mathrm{MAV1} = \frac{1}{N}\sum_{n=1}^{N} w_n \left| x_n \right|,$$

$$w_n = \begin{cases} 1, & \text{if } 0.25N \le n \le 0.75N \\ 0.5, & \text{otherwise}. \end{cases}$$

4) **Variance (VAR):** VAR captures the power of EMG signal as a feature. Normally, variance is mean of square of deviation of that variable. However, mean value of EMG signal is close to zero. Therefore, variance of EMG signal can be defined as

$$\mathrm{VAR} = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2 .$$

5) **Root Mean Square (RMS):** RMS is related to constant force and non-fatiguing contraction. Generally, it similar to SD, which can be expressed as

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} .$$

6) **Waveform length (WL):** WL is the cumulative length of waveform over time segment. WL is similar to waveform amplitude, frequency and time. The WL can be formulated as

$$\mathrm{WL} = \sum_{n=1}^{N-1} \left| x_{n+1} - x_n \right| .$$

7) **Zero crossing (ZC):** ZC is the number of times that the amplitude values of EMG signal crosses zero in x-axis. In EMG feature, threshold condition is used to avoid from background noise. ZC provides an approximate estimation of frequency domain properties. The calculation is defined as

$$\mathrm{ZC} = \sum_{n=1}^{N-1} \left[\operatorname{sgn}(x_n \times x_{n+1}) \cap |x_n - x_{n+1}| \geq threshold \right];$$

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

8) **Willison amplitude (WAMP):** WAMP is the number of time resulting from the difference between EMG signal amplitude of two adjoining segments that exceeds a predefined threshold, which is used to reduce background noises like in the calculation of ZC and SSC. It is given by

$$\mathrm{WAMP} = \sum_{n=1}^{N-1} f\left(|x_n - x_{n+1}|\right);$$

$$f(x) = \begin{cases} 1, & \text{if } x \geq threshold \\ 0, & otherwise. \end{cases}$$

9) **Auto-regressive (AR) coefficients:** AR model described each sample of EMG signals as a linear combination of previous EMG samples (xn-i) plus a white noise error term (wn). In addition, p is the order of AR model. AR coefficients (αi) are used as features in EMG hand movement recognition. The definition of AR model is given by

$$x_n = -\sum_{i=1}^{p} a_i x_{n-i} + w_n \ ,$$

B. Classification of Features

1) Eucledian Distance ::

ED is the most common use of distance. It is calculated as the root of square differences between co-ordinates of a pair of objects. We used ED as a separation index. In addition, SD is the most robust and widely used measure of the variability. SD is used as a compactness index. The ED(p,q) is defined as

$$ED(p,q)=\sqrt{(p_{\text{ch1}}-q_{\text{ch1}})^2+(p_{\text{ch2}}-q_{\text{ch2}})^2},$$

2) **Standard deviation**

$$SD=\sigma=\sqrt{\frac{\sum_{w=1}^{N_W}(r_w-\mu)^2}{N_W}},$$

where r is the feature of the wth window of NW and μ is the feature mean of all windows.

The best performance of classification is obtained when the ED value is high and the SD value is low.

2.2 Han Pang Huang, Yi Hung Liu, Chun Shin Wong; "Automatic Emg Feature Evaluation For Controlling A Prosthetic Hand Using A Supervised Feature Mining Method : An Intelligent Approach"; IEEE Conference On Robotics And Automation, 2006.

Electromyograph (EMG) has the properties of large variations and nonstationarity .There are two issues in the classification of EMG signals. One is the feature selection, and the other is the classifier design. Subject to the first issue, the paper propose a supervised feature mining (SFM) method, which is an intelligent approach based on genetic algorithms (GAS), fuzzy measure, and domain knowledge on pattern recognition.

EMG Feature Candidates and Extractions :: Eight types of prehensile postures to be classified are : power grasp (PG). hook grasp (HG), wrist flexion (WF), lateral pinch (LP), flattened hand (FH), centralized grip (CEG), thwe-jaw chuck (TJC), and Cylindrical grasp (CYG)

Feature Extraction :: Mean Absolute Value (MAV), Variance (VAR), Waveform Length (WL), Norm, Number of Zero Crossings, Autoregressive model, Histogram EMG, Variance(VAR) are some of extracted features.

Supervised Features Mining (SFM) ::

→ **Compactness index ::** Suppose that there are I classes $(C_1,\dots,C_k,\dots,C_l)$ to be classified, and each class has p patterns. The feature space is an n-dimensional feature space $F=(F_1,\dots,F_n)$. The distance between a pattern $F_j \in C_k$, and its corresponding mean in class C, is defined as the normalized Euclidean distance:

$$d_k(F_j)=\left[\sum_{i=1}^{n}\left(\frac{|F_{ij}-m_{ki}|}{\alpha_{ki}}\right)^2\right]^{1/2}, \quad F \in C_k$$

where

$$\alpha_{ki}=N_1\cdot\max_i|F_{ij}-m_{ki}|, \quad F_i \in C_k$$

Note that mki denotes the mean of class C, along the ith feature axis, and α_{ki} is a normalization factor, in which N1 is a positive number so that the value of dk(Fj) would lie in the interval [0, 0.5], and p is the class size.

SFM found that the two features, forth-order auroregressive model (ARM) and histogram ofEMC signals (HEMG), are the better two Features for the EMG classification than others (for the eight kinds of prehensile postures). In the experiments, some classification results based on K-NN method verify the validity of feature ranking results obtained from SFM.

2.3 Chan ADC, Green GC, "Myoelectric control development toolbox", 30th Conference of the Canadian Medical & Biological Engineering Society, Toronto, Canada, M0100, 2007.

In this paper, a simplistic pattern recognition system which is based on a linear discriminant classifier is described. This system is used to compare feature reduction methods, which demonstrates superior performance of uncorrelated LDA (ULDA) to PCA feature reduction.

Feature Extraction

Features are computed from the MES using a sliding analysis window. The sliding window is with analysis windows of 256 ms in length, spaced 32 ms apart. A single feature vector is produced from each analysis window. Feature extraction methods that have been implemented include features for: root mean square, mean absolute value, integrated absolute value, autoregressive coefficients, zero crossings, and slope sign changes.

Feature Reduction

Feature reduction methods that have been implemented are PCA and ULDA. PCA is an unsupervised method (i.e. the method does not require class labels) of feature reduction. It is a statistical method that identifies the linear projection of features that correspond to the principal variations in the data. LDA is a supervised method (i.e. the method uses features with class labels), which maximizes the ratio of the between-class distance to the within-class distance. This method suffers from the problem of singularity in the scatter matrix that occurs in undersampled problems (i.e. when the feature vector dimension is much larger than the sample size). ULDA is an enhancement to LDA, which imposes the additional requirement that reduced features be statistically uncorrelated with one another; thus, minimizing redundancies. The singularity problem is resolved using the generalized singular value decomposition .

Classification

Classification is simply performed using an linear discriminant classifier. The advantage of this classifier is that it does not require iterative training, avoiding the potential for under- or over-training. In addition, a high dimensionality problem can be well linearized during feature reduction if done properly. This reduces the potential that non-linear classifiers, such as MLPs, will achieve high classification accuracies.

2.4 Evelyn Morin, Alex Andrews, Linda McLean;"Optimal Electrode Configurations for Finger Movement Classification using EMG"; 31st Annual International Conference of the IEEE EMBS,2009

This study investigates the effect of different electrode array sizes and arrangements on finger movement classification accuracy. This is done with two goals in mind: firstly, to determine those configurations—and more generally, array sizes—that yield the highest classification performance, and secondly, to determine whether an upper limit exists above which additional electrodes offer no advantage, and therefore contribute only to production cost and computational load. A configuration that yields a high classification accuracy while using few electrodes would have a very useful application in prosthetic control.

Eight electrodes (Delsys DE-2.1) were placed around each subject's forearm at approximately one third of the forearm length from the head of the radius; the first electrode was placed just superior to the ulna and distances between adjacent electrodes were approximately equal.

Several options for each of the six main system elements were used in the optimization process:

- **Classifier:** Linear discriminant analysis (LDA) classifier,
- **Multilayer perceptron (MLP**), and statistical classifier (Stat.), which classified a feature set using the z-value of each feature relative to the training set distribution;
- **DR method:** No DR, principal components analysis DR to 48 dimensions (PCA-48), and PCA DR to 64 dimensions (PCA-64);
- **Feature sets:** Root-mean-square (RMS), Hudgin's time domain features (TD), variation on auto- and cross correlation values (CV), spectral power magnitudes (SPMs), short-time Fourier transform (STFT), wavelet transform (WT), and higher order statistics (HOS);
- **Window divisions:** 1, 2, and 7;

- **Window length:** 160 ms, 224 ms, and 256 ms;
- Window skew: -105 ms, -125 ms, and -145 ms.

For each array size between one and seven electrodes, the optimal arrangement of electrodes was determined empirically for each subject. Classification accuracies were determined using the subject specific optimal electrode arrangements for each array size.

Optimal classification systems are subject-dependent, and therefore that it benefits classification accuracy to tailor classification systems to each subject. The results found in this study suggest that the best performing electrode arrangement for each array size may also be subject-dependent. For each array size, the best performing electrode locations were determined for each subject, with the resulting classification accuracies ; however, it may be the case that other optimal arrangements exist: those that yield accuracy values not significantly different from those with the highest mean. Determining these other arrangements would provide more data on the effect of electrode configuration on classification accuracy.

2.5 Dori Peleg, Eyal Braiman, Elad Yom-Tov, and Gideon F. Inbar, Fellow; "Classification of Finger Activation for Use in a Robotic Prosthesis Arm"; IEEE Transactions On Neural Systems And Rehabilitation Engineering, Vol. 10, No. 4, December 2008;

In this paper they propose using the electromyographic signals recorded by two pairs of electrodes placed over the arm for operating such prosthesis. Multiple features from these signals are extracted whence the most relevant features are selected by a genetic algorithm as inputs for a simple classifier. The objective of this study is to use these EMG signals to successfully identify when a finger is activated and which finger is activated. There is no one-to-one mapping of muscles to fingers. Operating a finger causes activation in a number of muscles, some of which are associated with other fingers.

In this paper, a combination of a K-nearest neighbor (KNN) classifier and a genetic algorithm (GA) for feature selection is used, resulting in an average error rate of approximately 2%.The EMG signals were amplified 2500 times and sampled (after antialiasing filter with a cutoff frequency of 250 [Hz]) together with the microswitch states, using a Bio Pac Student Lab PRO kit at a sampling frequency of 500 [Hz].

- **Finger activation identification**

  The objective in this stage is to find the intervals of finger activity (without regard to identity). This was achieved using envelope detection on the EMG signal recorded from both electrode pairs. The calculation of the envelope of the signal is a three-staged process. First, the signal is passed through a high-pass FIR filter with a cutoff frequency of 30 [Hz]. Then, the absolute value of the resulting signal is taken. Finally, the signal is passed through a low-pass FIR filter with a cutoff frequency of 2.5 [Hz].

- **Feature extraction**

  By trial and error it was found that the best interval from which to extract features was between 0.4 [s] and 1.6 [s] after the envelope crossed the threshold. The first is the amplitude

  of the discrete Fourier transform (DFT) of the EMG signal: The frequency region between 0 [Hz] and 250 [Hz] was divided into 20 equal sections of frequencies and each section was characterized by its mean and variance values.

- **Classification**

  A standard KNN classifier measures the distance between a test measurement and the labeled training examples and the label which appears most frequently in the K nearest examples is chosen as the label of the test measurement. The modified KNN classifier is different from the standard KNN classifier only when there are an equal number of appearances of two or more labels in the K nearest training examples.

- **Feature selection**

  In this paper, a genetic search algorithm was used for selecting the best subset of features for selection by the classifier. A genetic algorithm attempts to simulate a process similar to nature's evolutionary process. The algorithm works by encoding many possible solutions to the problem and iteratively improving them.

2.6 Xin Lui,Rui Zui; "PERFORMANCE OF VARIOUS EMG FEATURES IN IDENTIFYING ARM MOVEMENTS FOR CONTROL OF MULTIFUNCTIONAL PROSTHESES", Neural Engineering Research Center And Key Laboratory For Biomedical Informatics And Health Engineering, Shenzhen Institute Ofadvanced Technology, Chinese Academy Of Sciences 2School Of Control Science And Engineering, Shandong University

In this paper, we evaluated classification performance of electromyography (EMG) four time-domain features and autoregressive model features and their combination in identifying 11 classes of arm and hand movements in both able-bodied subjects and amputees. For the evaluation of performance of EMG pattern recognition in identifying various movements, the amputees should be used.
In this paper, we stress the classification performance of various combinations of the four TD features in identifying the intended movements. And then the effect of AR model order numbers on classification accuracy was evaluated for selection of an optimal AR order number. Finally, we combined AR model coefficients with the optimal AR order number with each of the four TD features and analyzed the classification performance of each combination. Besides the able-bodied subjects, the subjects with arm amputation also were involved in this study.

EMG pattern-recognition-based movement prediction is mainly composed of two cascaded parts: feature extraction and motion classification. Feature extraction is to extract parameters from EMG recordings, which can represent EMG characteristics. Motion classification is to predict the intended movement by decoding these features.

Two sets of characteristic features extracted from EMG recordings were used to represent the EMG data for classification of the intended movements.

- **The TD feature** set, first proposed by Hudgins et aI., composed of four time domain statistics of the EMG: mean absolute value (MAV),zero crossing (ZC), slope sign change (SSC), waveform length (WL).EMG signal can be modeled as a linear AR time series:

  x(n) =- Lakx(n-k)+u(n) (J)

  Where x(n) denotes the recorded signal at discrete time n,{ak, k=1,2,.. ....p} are AR model coefficients, p is the AR model order, and urn) is the residual white noise.

- **Linear discriminant analysis (LDA**) was used to build an EMG pattern classifier for classification of different movements.

Compared with able-bodied subjects, the classification accuracy achieved by amputee was about 20% low. This suggested that the classification performance in identifying different movements with able-bodied subjects might not apply in amputees. Averagely speaking, the classification accuracy achieved by all the subjects increased in accordance with the increment of AR model order. When the order number of the AR model was less than fifth, the classification accuracy had a rapid increasing process. When the order number was greater than fifth, the accuracy increase slowed down and reached a plateau. This suggests that a six-order AR model may be an optimal model for classification of movements.
Subjects performed four different exercises, two trials each,on a standard keyboard using their right hand. All exercises involved 20 instances of four different keypress motions: j with the second digit, k with the third digit, l with the fourth digit, and ; with the fifth digit. Each of the four exercises required the keystrokes to be typed in a unique fashion:

- Exercise 1: ordered keystrokes paced at 1 per second,
- Exercise 2: ordered keystrokes, freely paced,
- Exercise 3: non-ordered keystrokes paced at 1 per second,
- Exercise 4: non-ordered keystrokes, freely paced,

Where ordered keystrokes involved 20 repeated strokes of each key, in the order j, k, l, and then ;. Freely paced exercises allowed the subject to type at any comfortable pace under approximately three keystrokes per second. Exercises were guided by a computer program, written in MATLAB 7, which dictated the keystroke order, kept pace in paced exercises, and recorded the characters typed and corresponding time indices.Subjects were instructed to sit in a comfortable typing posture throughout each exercise.

For each array size between one and seven electrodes, the optimal arrangement of electrodes was determined empirically for each subject. The performance of a myoelectric signal classification system depends on many factors, one of which is the configuration of the electrode array. Two specific improvements are possible through the optimization of the electrode array: first, an increase in classification accuracy,and second, a reduction in production cost and computational time, if comparable performance can be attained using fewer electrodes. A classification accuracy of 92.7% was attained using seven electrodes

CHAPTER 3 - Analysis, Design and Modelling

3.1 Overall Description of the project

3.1.1 Product perspective – The software extracts various features from the raw EMG signal and reduces them(ULDA). Using these features classifies it by LDA(Linear Discriminant Analysis classifier algorithm) . The Classifier has to be trained using sample test signals .

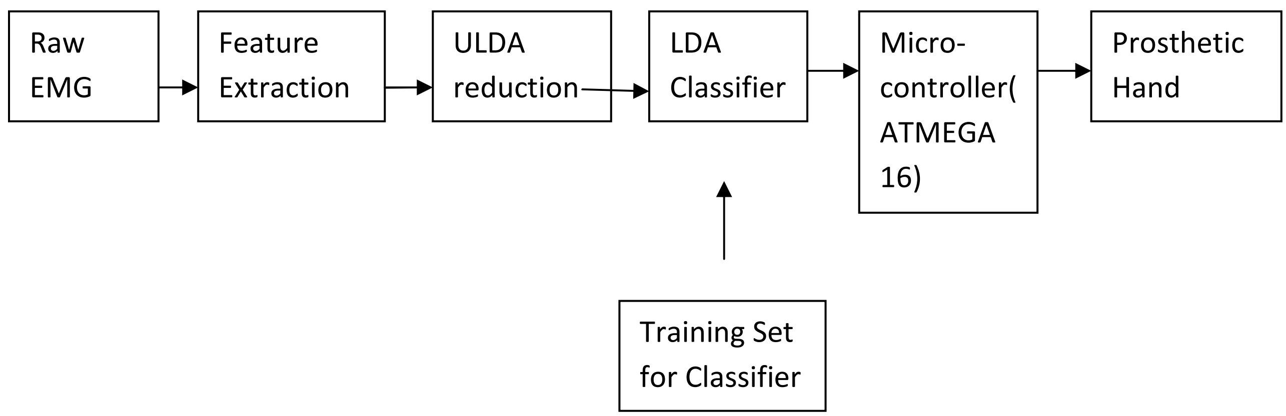


Fig:2 linear Modeling of System

3.1.1.1 System interfaces : The software accesses the database of signals through file handling operations. It reads the value of the signal at a particular instant of time and applies various signal processing operations on it. The output would be sent to a micro controller which would move the prosthetic limb.

3.1.1.2 User interface : The users EMG response would be used to determine his intent which would be identifier by the classifier and mapped to the corresponding hand gesture. The signal dataset includes sample EMG signal and the training data used to train the classifier.

3.1.1.3 Hardware interfaces : The subject/patients EMG signal response has been recorded using standard Ag/AgCl surface myo-electrodes. The raw signals them amplified using instrumentation amplifier(INA 129 by Texas Instruments). It is then passed through a band pass filter having a frequency in the range of 50-450 Hz. The signals are then recorded and stored in a database. The output of the software are then sent to a microcontroller and are mapped to the actual prostheric hand.

3.1.1.4 Software interfaces : The following main software interfaces have been used :

a) Simulink : It was used for the real-time acquisition of the EMG signals from the electrodes. Further it displays the signal in a graphical form and supports signal file handling and signal processing by means of providing a programming environment.

3.1.1.5 Operations

a) Data processing : It included applying various feature extraction methods to the signal. Features included Mean Absolute Value (MAV), Variance (VAR), Waveform Length (WL), Number of Zero Crossings, Root Mean Square (RMS), etc. The features were used as input to the ULDA classifier.

b) User actions : The user or more specifically the patient's EMG response for each hand gesture has unique features which have to be extracted and classified.

3.1.2 Product functions : The major functions of the product include :

a)Feature Extraction : Some of the features extracted are :

1) Integrated EMG (IEMG):

2) Mean Absolute Value (MAV):

3) Variance (VAR):

4)Root Mean Square (RMS):

5)Waveform length (WL):

6)Zero crossing (ZC):

7)Auto-regressive (AR) coefficients:

b) Feature Reduction : Feature reduction methods that have been implemented are ULDA(Uncorrelated Linear Discriminant Analysis). LDA is a supervised method (i.e. the method uses features with class labels), which maximizes the ratio of the between-class distance to the within-class distance. This method suffers from the problem of singularity in the scatter matrix that occurs in undersampled problems (i.e. when the feature vector dimension is much larger than the sample size). ULDA is an enhancement to LDA, which imposes the additional requirement that reduced features be statistically uncorrelated with one another; thus, minimizing redundancies.

c) Classification : Classification is simply performed using an linear discriminant classifier. The advantage of this classifier is that it does not require iterative training, avoiding the potential for under- or over-training. In addition, a high dimensionality problem can be well linearized during feature reduction if done properly. This reduces the potential that non-linear classifiers, such as MLPs, will achieve high classification accuracies.

3.1.3 User characteristics : The user of this system may include a patient who is having an amputation above the forearm. In this case the EMG electrodes are placed over the forearm and the data is recorded for all the hand gestures the user imagines he is doing. Note that the EMG is a complex signal; the signals for the hand may be in summation with signals intended for other muscle groups while recording at the forearm. The EMG response may vary from user to user, thus a system has to be configured for each user separately.

3.1.4 Constraints :

a) Hardware : The EMG electrodes have to be of high quality to counter noise while extracting the signal. Also, needle electrodes may capture the signal more accurately than the surface electrodes as they are directly inserted into the specific muscle and prevent crosstalk from other muscle groups due to their small surface area.

b) Reliability : The system may not be 100% correct all the time partly because there is a high probability of noise interfering with accurate predictions and the signal parameters may vary from user to user.
c) Cost : The system has to be kept low cost for it to be user widely. The major costs associated with this project are the costs of the electrodes, amplifiers, motors etc.
d) Processing capabilities of the system : The EMG signal may have to be sampled at a higher rate in order to get a higher accuracy. But this would also cause more load on the processing sub-system.
e) Noise : There is a high probability of noise, because the signal is of micro-volt range and even the smallest factors can cause a problem. Thus it is essential at the time of data capture, noise must be kept to a minimum.

3.1.5 Assumptions and dependencies : The success of the system depends on the quality and quantity of the dataset used. At present the project uses a training dataset, that has been acquired from eight different loctions on the forearm using Ag/AgCl Myo-tronics electrodes. Increasing the number of electrodes will also have an impact on the quality of the prediction but will increase the processing load. The type of electrodes used will also have an effect on the outcome.

The analysis window size is 256 ms (it is generally agreed that a delay that is less then 300 ms is acceptable for myoelectric control), which are spaced 128 ms apart for training data and 32 ms apart for testing data.

The Feature set is as mentioned above. Note that a different combination of this may give a different result.

3.1.6 Apportioning of requirements : Hardware implementation part will be done in next semester. Software simulation is shown with procured dataset.

3.2 Specific requirements

3.2.1 External interfaces :

a) Name : Training Dataset : MES were collected from seven sites on the forearm and one site on the bicep using Duo-trode Ag-AgCl electrodes (Myotronics). MES data were collected as the subject underwent seven distinct limb motions: hand open, hand close, supination, pronation, wrist flexion, wrist extension, and rest. Within each trial, the subject repeated each limb motion four times, holding each motion for a duration of three seconds each time. The order of these limb motions was randomized.

b) Description of purpose : This dataset is used to prepare the range of values which will define a particular class.

c) Source of input or destination of output : On the basis of this set, a feature training dataset will be generated.

d) Accuracy : Classification accuracy of around 92% .

e) Timing : Signals were sampled at 3 kHz using an analog-to-digital converter board. MES data were downsampled to 1 kHz prior to pattern classification.

f) Relationships to other inputs : Is used to compute the feature training set. The feature training set and the class training set are further used as inputs for the ULDA algorithm to perform feature reduction . The sample signal's features are extracted and are classified on the basis of the data generated by the ULDA algorithm using the Linear discriminant analysis.

g) Data formats : The training dataset file has a .daq extension.

3.2.2 Functions

a) Validity checks on the inputs : The signal should be amplified with a gain of 1000 and care should be taken to ensure noise is kept to a minimum. It should be sampled at around 1KHz.

b) Exact sequence of operations :

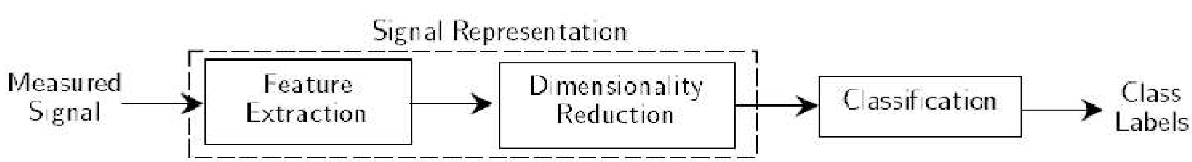


Fig:2 Sequence of Operation

The software has 3 main stages :

a)Feature Extraction : Feature extraction methods that have been implemented include features for: root mean square, mean absolute value, integrated absolute value, autoregressive coefficients, zero crossings, and slope sign changes. Analysis windows of 256 ms in length in increments of 128ms are used. A single feature vector is produced from each analysis window.

b)Feature reduction : Feature reduction methods that have been implemented are ULDA. ULDA chooses feature projections that optimize class separability. The resultant feature vector, after feature reduction, will have a dimensionality that is less than the number of classes.

c)Classification: Classification is simply performed using an linear discriminant classifier. The advantage of this classifier is that it does not require iterative training, avoiding the potential for under- or over-training. In addition, a high dimensionality problem can be well linearized during feature reduction if done properly.

d) Responses to abnormal situations

1)Overflow : The process of feature extraction may (and often does) result in feature vectors with high dimensionality. Feature reduction is employed to reduce the dimensionality, simplifying the task of the classifier and diminishing effect of the curse of dimensionality (i.e. the exponential increase in the feature space with the addition of each new feature)

2) Error handling and recovery : The errors that are present occur during transitional periods, which are expected as the system is in an undetermined state between contractions. Indeed, if we removed the analysis windows that are 256 ms before and after the transition, the classification error is 7.46%.

e) Effect of parameters :

1)Sliding window Size : The analysis window size is 256 ms (it is generally agreed that a delay that is less then 300 ms is acceptable for myoelectric control), which is spaced 128 ms apart for training data and 32 ms apart for testing data. Data that were 256 ms before or after a change in limb motion were removed from the training set to avoid transitional data.

2) Training Set size : A training set consisting of simultaneous data from 4-8 different locations on the arm is considered good for accuracy.

f) Relationship of outputs to inputs

1) Input/output sequences :

Feature extraction : Input- Training set/sample EMG signal;

Output : Features(including RMS, AR coefficients)are extracted(analysis window size is 256 ms , spaced 128 ms apart for training data and 32 ms apart for testing data.)

Feature reduction : Input : class_training; feature_training; training_index data sets

Output : Reduced dimensionality of dataset using ULDA

Classifier : Input : Training sequence; input EMG signal(with extracted features)

Output : Classfied data; Mapping to hand gesture

2) Formulas for input to output conversion :

a)Feature reduction :

1) Integrated EMG (IEMG):

$$\mathrm{IEMG} = \sum_{n=1}^{N} |x_n| \; .$$

2) Mean Absolute Value (MAV):

$$\mathrm{MAV} = \frac{1}{N}\sum_{n=1}^{N}\left|x_n\right| \ .$$

3) Variance (VAR):

$$\mathrm{VAR} = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2 \ .$$

4)Root Mean Square (RMS):

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \ .$$

5)Waveform length (WL):

$$\mathrm{WL} = \sum_{n=1}^{N-1}\left|x_{n+1} - x_n\right| .$$

6)Zero crossing (ZC):

$$\mathrm{ZC} = \sum_{n=1}^{N-1}\left[\operatorname{sgn}\left(x_n \times x_{n+1}\right) \cap \left|x_n - x_{n+1}\right| \geq threshold\right];$$

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

7)Auto-regressive (AR) coefficients:

$$x_n = -\sum_{i=1}^{p} a_i x_{n-i} + w_n \ ,$$

3.2.3 Performance Requirements

a)No. of Channels : The sytem has eight channels recording data from eight different locations on the arm. MES were collected from seven sites on the forearm and one site on the bicep. More the number of channels, higher the accuracy.

b)Signal properties : These signals were amplified , with a gain of 1000 and bandwidth of 1 Hz to 1 kHz . Signals were sampled at 3 kHz .

c)Feature Selection : We have currently used nine features. The features are assigned weights after studying their effect on the accuracy. The features,RMS and WL have been given highest weightage.

3.2.4 Logical database requirements

a)Extract_feature

1) training_data : (x X 8), x – Total samples of a particular channel
2) win_inc=128(Amount by which window is incremented)
3) win_size=256(Total size of the analysis window)

b)Get_class :

1)Training_data : (x X 8), x – Total samples of a particular channel

2)Training_Motion : 1-7(Represents different hand gestures)

3)Training_index : Starting index of data matrix for a particular motion

4)win_inc=128(Amount by which window is incremented)

5) win_size=256(Total size of the analysis window)

c)Remove_change_classes :

1)Feature_training : Extracted nine features of a window of data for training the classifier.

2)Class_training : The corresponding class value for the feature training set.

d)UncorrelatedLDAreduction :

1)Feature_training

2)Feature_testing : Extracted features of the testing dataset

e)Ldaclassify :

1)Feature_training

2)Feature_testing

3)Class_training

4)Class_testing

3.2.5 Design constraints :

1)Accuracy of EMG electrodes : The electrodes used are surface/non-Invasive electrodes. Needle/Invasive electrodes give more accurate readings than the surface electrodes.

2)Tradeoff between accuracy and response time : The processing time will increase as the size of the dataset increases(larger dataset for more accuracy). This can be a downplaying factor in systems with low processing power.

3)Implementation for seven types of hand gestures only.

3.2.6 Software system attributes

a) Reliability : The system's success depends on proper feature selection and the quality of the training dataset used. The system should use the training set which provides maximum accuracy and minimum error. Trial and error may be required in this.

b) Availability : Training data set with eight channels of EMG data is acquired from 8 different locations on the forearm and biceps. MES data should collected as the subject undergoes seven distinct limb motions: hand open, hand close, supination, pronation, wrist flexion, wrist extension, and rest.

c)Security : The process of feature extraction may (and often does) result in feature vectors with high dimensionality. *Feature reduction* is employed to reduce the dimensionality, simplifying the task of the classifier and diminishing effect of the *curse of dimensionality* (i.e. the exponential increase in the feature space with the addition of each new feature) . Ideally, feature reduction proceeds in a manner that reduces intra-class variations, while inter-class variations are maintained or enhanced. In addition to improving the *signal quality* and reducing the *noise*, feature reduction may also seek to reduce redundancies in the feature vector.

d) Maintenance : Maintain a database of training sets. The database should include datasets acquired in different sessions from all 8 locations and having all the seven classes of hand motions.

e) Portability : Yes. The code can be ported into other languages like java.

3.3 Design

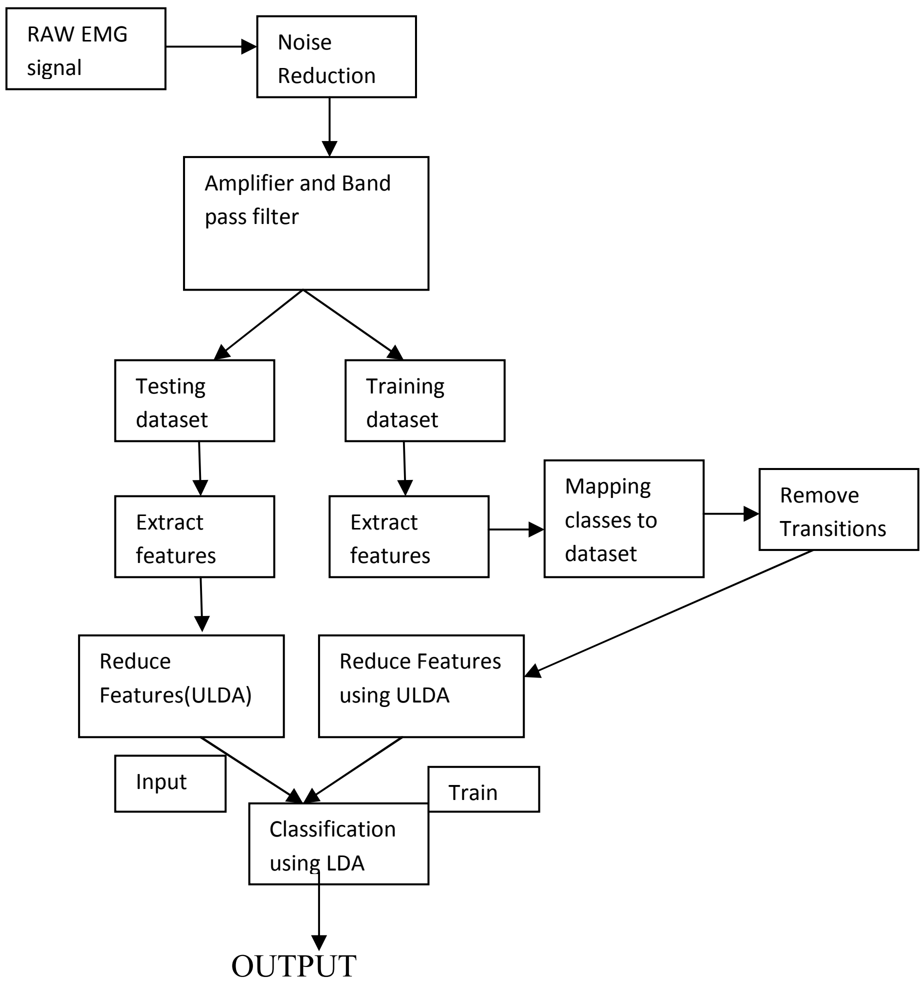


Fig:3 Complete Sequence Diagram

3.4 Use Case Diagrams

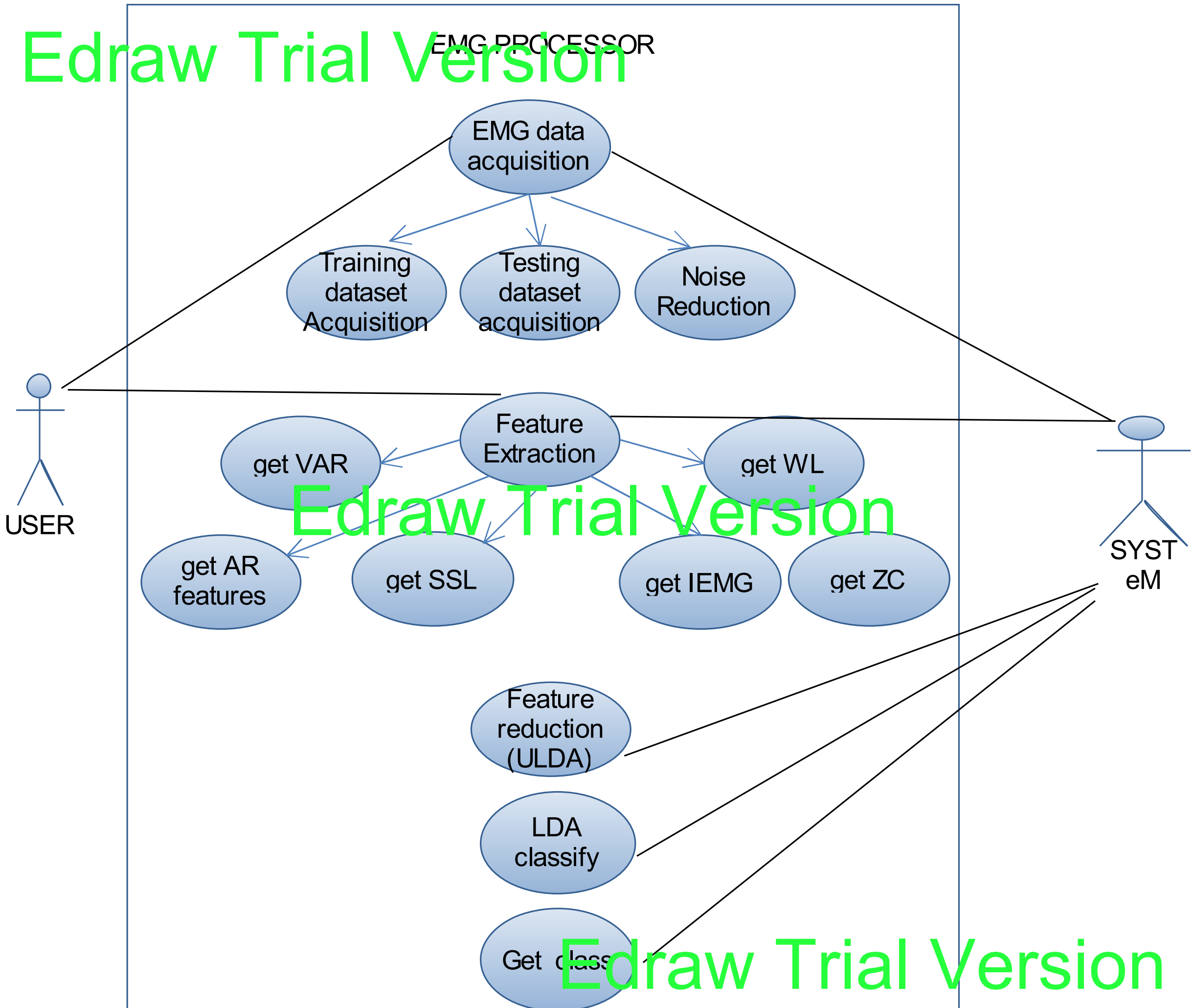


Fig:4 Use Case Diagram

3.5 Class Diagram

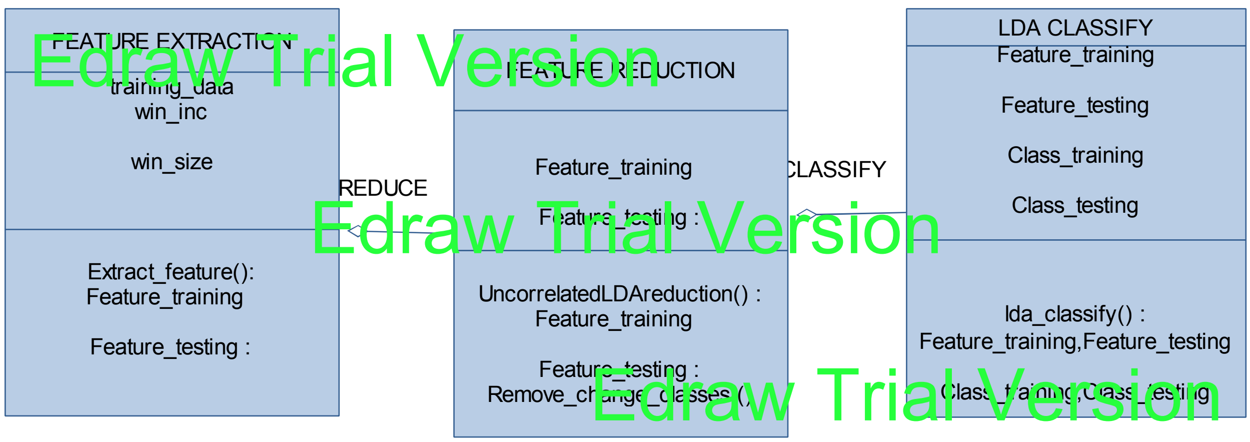


Fig:5 Class Diagram

3.6 Risk Analysis

Priority	Risk Description	Probable Cause	Impact on time line	Impact on performance
1)	Noise at source	a)External Noise b)Inherent Noise	Very High probability of misclassification	Quality of the dataset is affected
2)	High Dimensionality of feature of data	the exponential increase in the feature space with the addition of each new feature)	High	Can increase processing time exponentially
3)	Insufficient	The training	High	Accuracy

	training data	data may not be large enough for the classifier		compromised
4)	Error at transition point(change from one motion to the other)	Randomness at time of transition	Medium	Can cause mis-Classification
5)	No post-processing applied on the data	Spurious misclassification	Medium to low	Small error introduced

Table:1 Risk Analysis

3.7 Risk Mitigation Plan

Priority	Risk Description	Risk Mitigation
1	Noise at source	Use differential amplifier which cancels the common noise in the electrodes
2	The dimension of the data is larger than the datasize. It is also called the singularity problem.	Apply feature reduction technique ,ULDA to reduce the dimensionality of data. In addition to improving the *signal quality* and reducing the *noise*, feature reduction may also seek to reduce redundancies in the feature vector.
3	Insufficient training data	Have a sufficiently large number of data samples taken from 8 different locations on

		the forearm
4	Error at transition point(change from one motion to the other)	To mitigate this error some samples(eight) are removed from above and below the point of transition
5	No post-processing applied on the data	Apply efficient class post processing on the output.This uses the current classification result, along with the previous 8 classification results (with an analysis window spacing of 32 ms, this corresponds to the classification results within the last 256 ms) and makes a classification.This reduces spurious misclassifications.

Table: 2 Risk Mitigation Plan

CHAPTER 4 : IMPLEMENTATION, TESTING, AND RESULTS

4.1 Implementation

There are mainly six steps in which we are training the system using EMG training data file along with its motions.

1)Load_data : Load data of RAW EMG signal along with its corresponding motions . In emg signal recording there may be some errors due to some environmental noise, or circuit related or any other kind of error. So to remove some percentage of error we take mean of particular channel and subtract it from raw emg signal . So a constant error get removed from the data.

2) Extract Feature: We are calculating 9 features associated with EMG data. For this we are using 256 window size with 128 moving window increment .We are using 256 samples of data values for every feature value . We store each of these feature data values in an array.

3)Get class after calculating all nine features of emg data with window size of 256 ,i.e we have to assign the feature_training dataset to its corresponding class ,in accordance with motions files .Note that initially every set of 256 data samples have their own class.So after calculating features of 256 window set ,we assign to that feature a particular motion.

4) Remove_change_classes : At the point of transition, there may be some redundant feature values. So we may get error,assigning a different class as motion value. So we are removing eight features values before and after every point where motion changes .

5)Uncorrelated Linear Discriminent Reduction : High-dimensional data appear in many applications of data mining, machine learning, and bioinformatics. Feature reduction is commonly applied as a preprocessing step to overcome the curse of dimensionality. Uncorrelated Linear Discriminant Analysis (ULDA) was recently proposed for feature reduction. The extracted features via ULDA were shown to be statistically uncorrelated,which is desirable for many applicationsPrincipal Component Analysis (PCA) is another method which can be employed for feature reduction. But it has been shown that ULDA outperforms PCA. Its limitation is that some useful information may be lost in the PCA expansion.

6)Classification using linear discriminant analysis(LDA classify)

Discriminant analysis often produces models whose accuracy is very high. Discriminant analysis can be used only for classification (i.e., with a categorical target variable), not for regression. The target variable may have two or more categories.

- A transformation function is found that maximizes the ratio of between-class variance to within-class variance

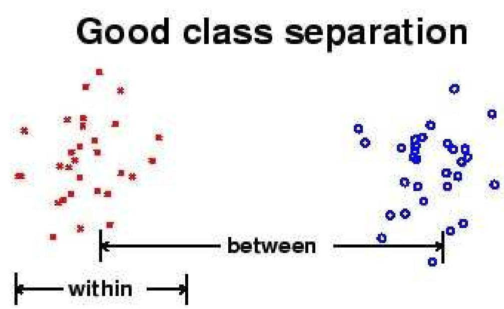


Fig:6 Class Separation

- The transformation seeks to rotate the axes so that when the categories are projected on the new axes, the differences between the groups are maximized. The following figure shows two rotates axes. Projection to the lower right axis achieves the maximum separation between the categories; projection to the lower left axis yields the worst separation.

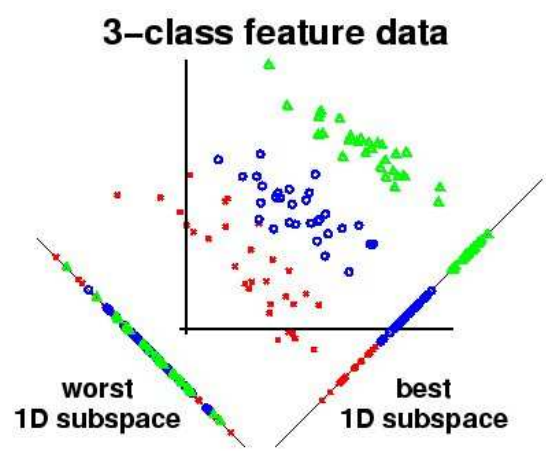


Fig:7 3-class Feature Data

4.2 Testing

4.2.1 Test plan identifier

a) Black Box testing

b) White Box Testing

4.2.2 Test items

- Extracting features
- Remove Transition Classes
- LDA Classificaion
- Efficient class classification

4.2.3 Features to be tested/Risk

Features to be tested	Risk
Presence of external noise in EMG data	High
Remove transition state	High
Associating class with features	High
ULDA Reduction	High
Efficient class classifier	Low

Table : 3 Features

4.2.4 Features not to be tested

- One feature value of a particular motion. A combination of features has to be used
- No. of channels : No. of channels is assumed to be eight

4.2.5 Strategy for test cases

For a particular subject we are experimenting with testing data from different sessions to determine which one is most accurate for a particular motion. We are assigning different weights to the 9 features in accordance with their relative contribution to accuracy.

There are 10 subjects. For every subject 4 sessions and 6 trials in each session. Every trial has one data file and motion files.

There are seven classes of motions :

1) Hand open,

2) Hand close,

3) Wrist flexion,

4) Wrist extension,

5) Supination,

6) Pronation, and

7) Rest.

4.2.6 Test Cases

TEST 1: Using all features with different weights

TEST 2: With same user, same session and same trial

TEST 3: With same user, same session and different trial

TEST 4: With same user, different session, and different trial

TEST 5: With different user, different session, different trial

4.3 RESULTS

The motion classification error from the testing data is 8.56%. To improve classification accuracy efficient class post-processing is used. The efficient class uses the current classification result and previous eight classification result. The class occurring the maximum no of times in the past eight result is chosen. We are getting a maximum accuracy of 97.34% in some data. The average accuracy is 95.45%.

CHAPTER 5: FINDINGS, CONCLUSIONS AND FURTHER WORK

5.1 Findings :

a)Giving weights to the features has increased the accuracy

b)We have observed that other similar work conducted in this area have implemented only a few features. We have implemented a set of 9 features which has resulted in a better accuracy than others.

5.2 Conclusions

A simplistic pattern recognition system for myoelectrically controlled upper arm prostheses is presented in the report. This system uses nine features, namely Mean Absolute Value (MAV), Variance (VAR), Waveform Length (WL), Number of Zero Crossings(ZC), Root Mean Square (RMS),Integral EMG(IEMG),Slope Sign Changes(SSC), Root Mean square(RMS), which are extracted from the signal.
Effective feature reduction is demonstrated using ULDA. In addition to improving the *signal quality* and reducing the *noise*, feature reduction may also seek to reduce redundancies in the feature vector.

With a linear discriminant classifier, an average classification accuracy of 95.45% was achieved over 10 subjects.

5.3 Further Work

As of now we have performed classification using offline data with high accuracy. In the future we aim to do classification for real time data acquired from the muscles of the user and

implement a mechanical hand controlled on the basis of it.

5.4Snapshots

For Class Hand Close :

1. AR Feature Graph

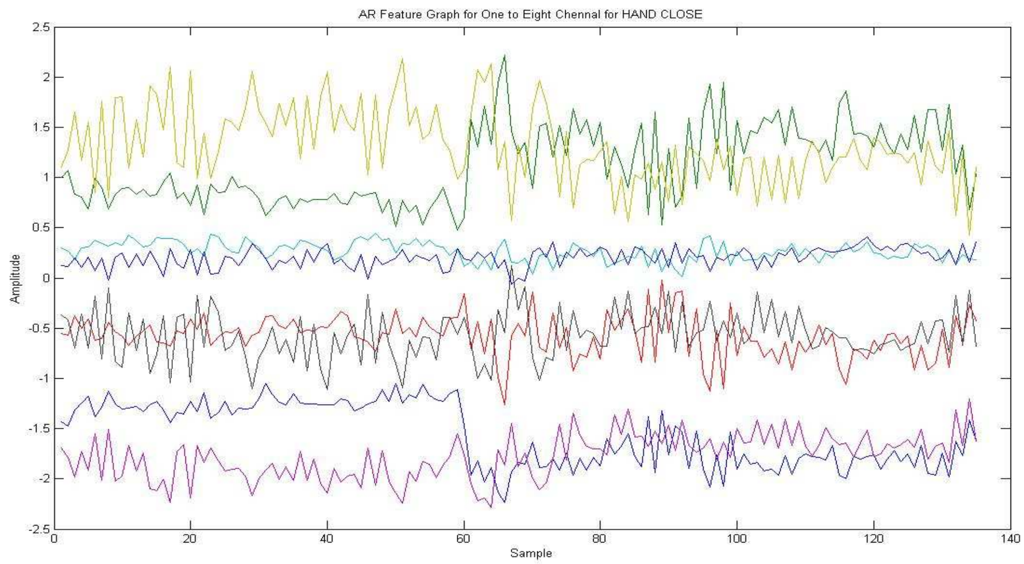


Fig: 8 AR Feature

2. IAV Feature Graph

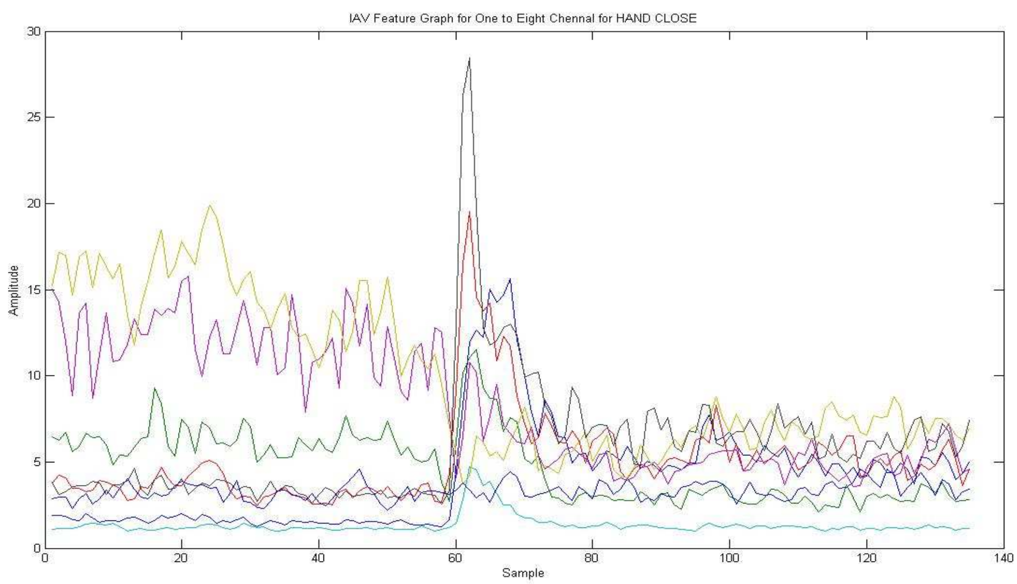


Fig: 9 IAV Feature

3. MAV(Mean AVG Value)

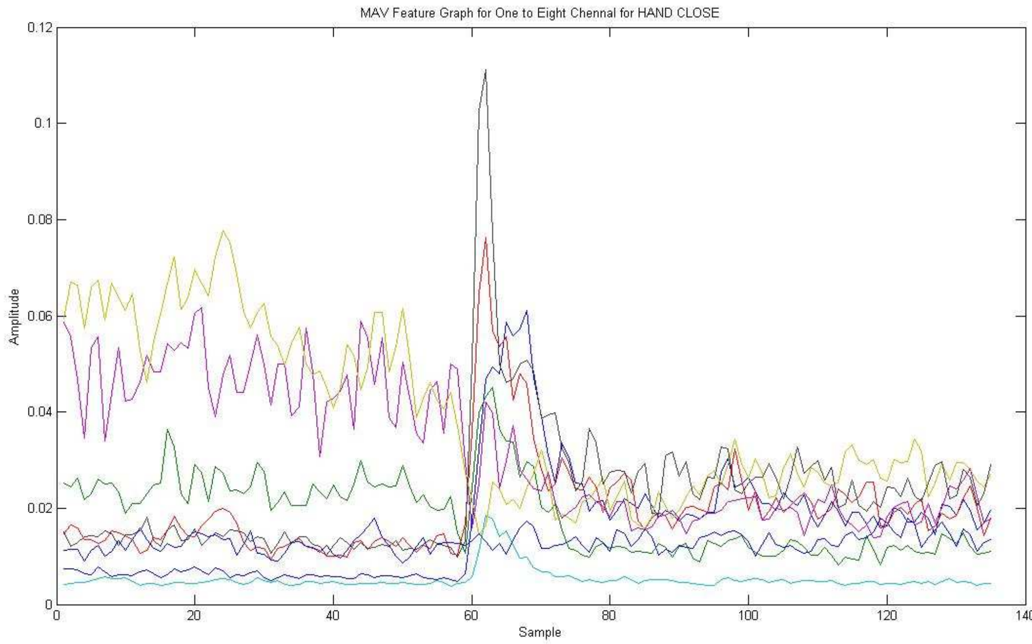
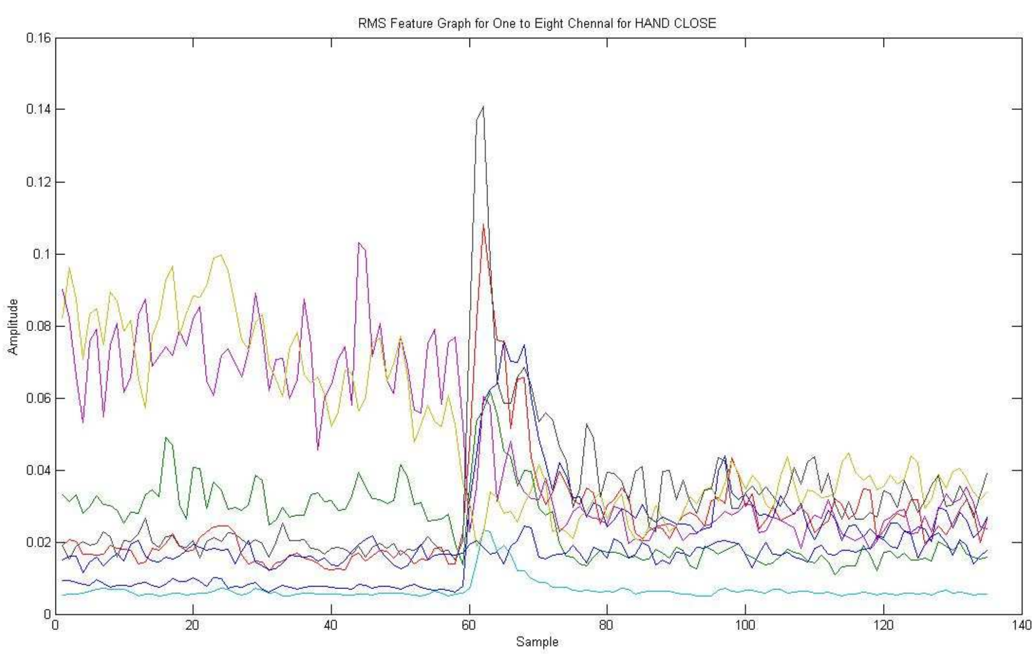


Fig: 10 MAV Feature

4. RMS(Root Mean Square Valuse)

Fig: 11 RMS Feature



5. SSC(Slop Sign Changes)

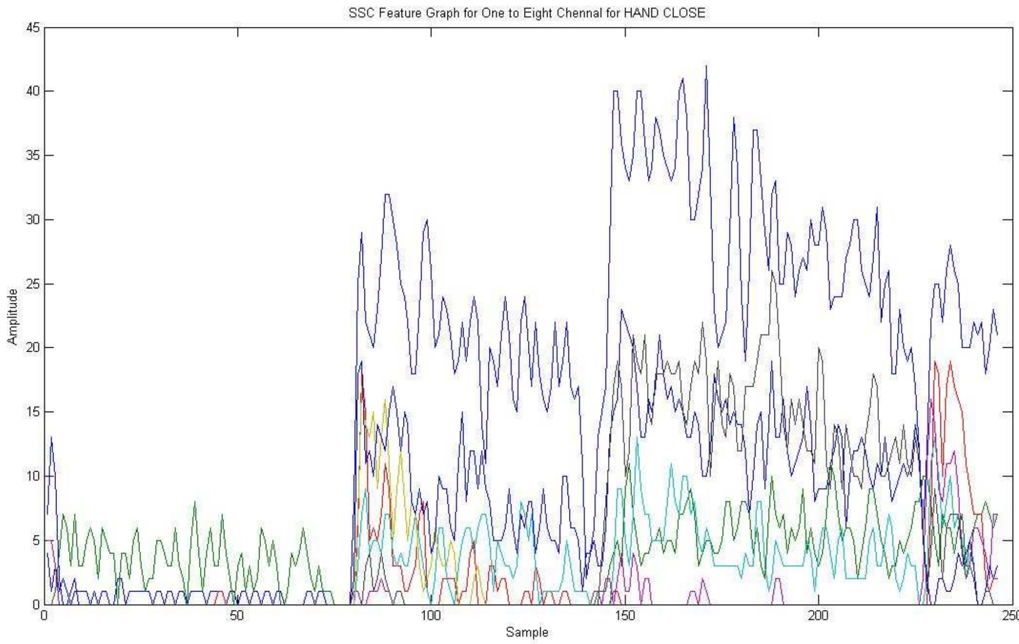


Fig: 11 SSC Feature

6. SSI(Simple Square Integral)

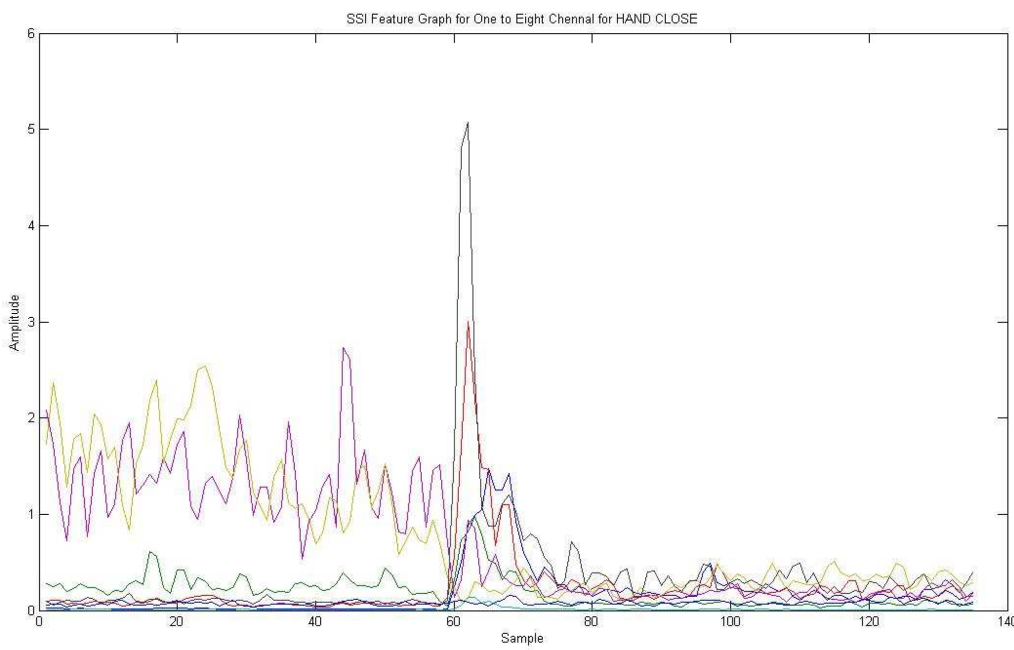


Fig: 12 SSI Feature

7. VAR(Variance)

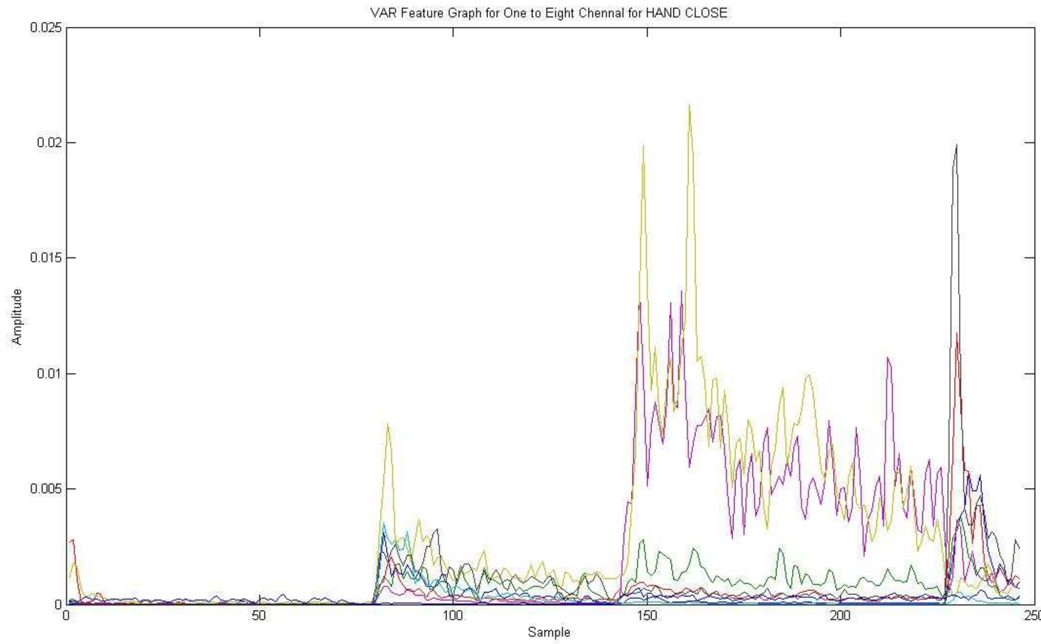


Fig: 14 VAR Feature

8. WL (Wave Form Length)

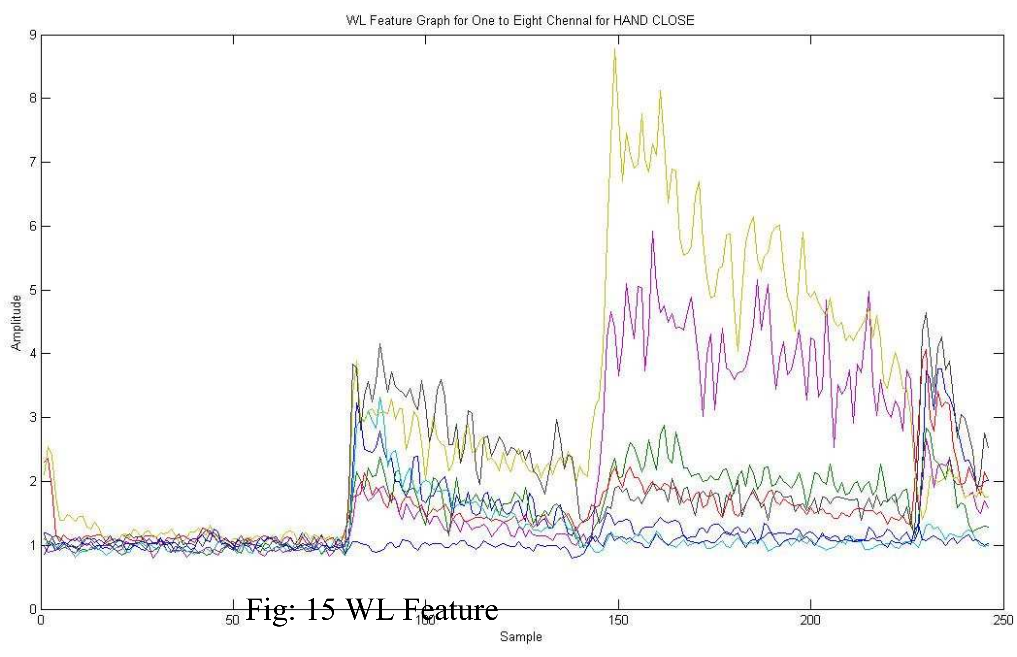


Fig: 15 WL Feature

9. ZC(Zero Crossing)

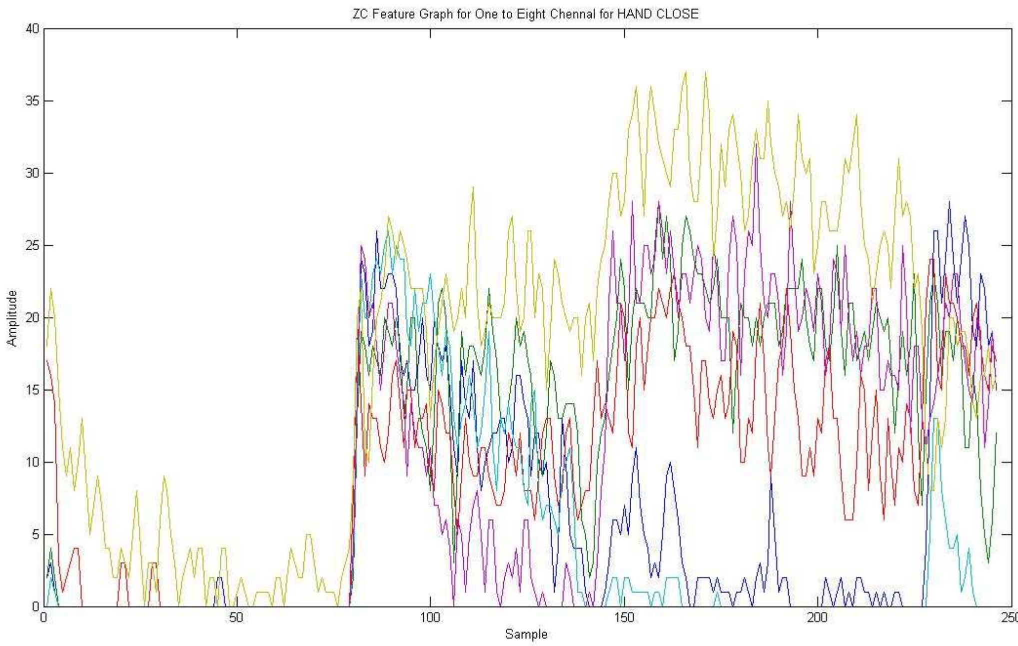


Fig: 16 ZC Feature

10)Successful classification and error

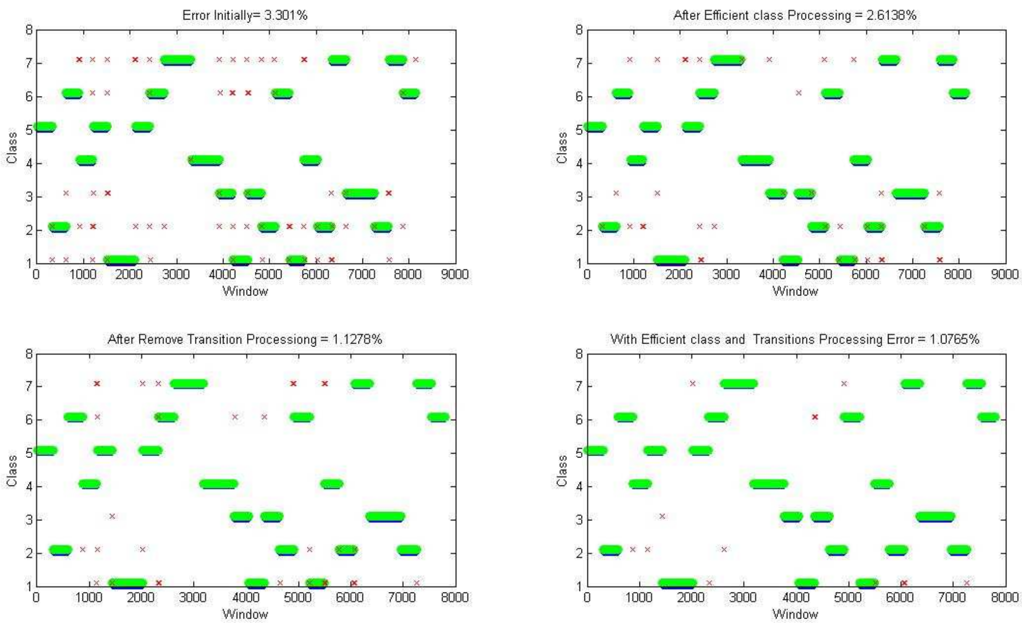


Fig: 17 Classification

11)Actual class vs output class vs no of samples

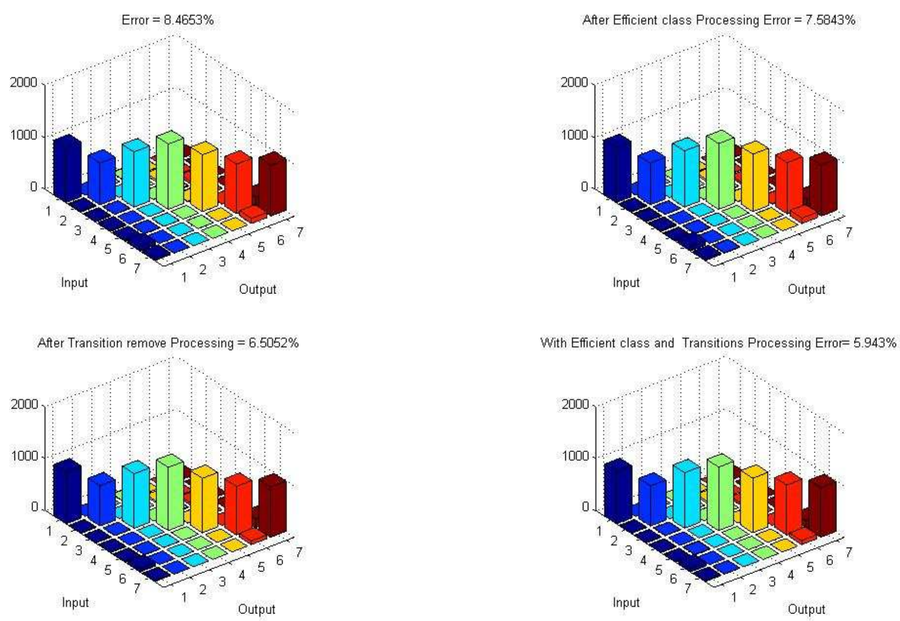


Fig: 18 Output Vs Actual Class Vs No. of Sample

12)RAW EMG Signal for channels :

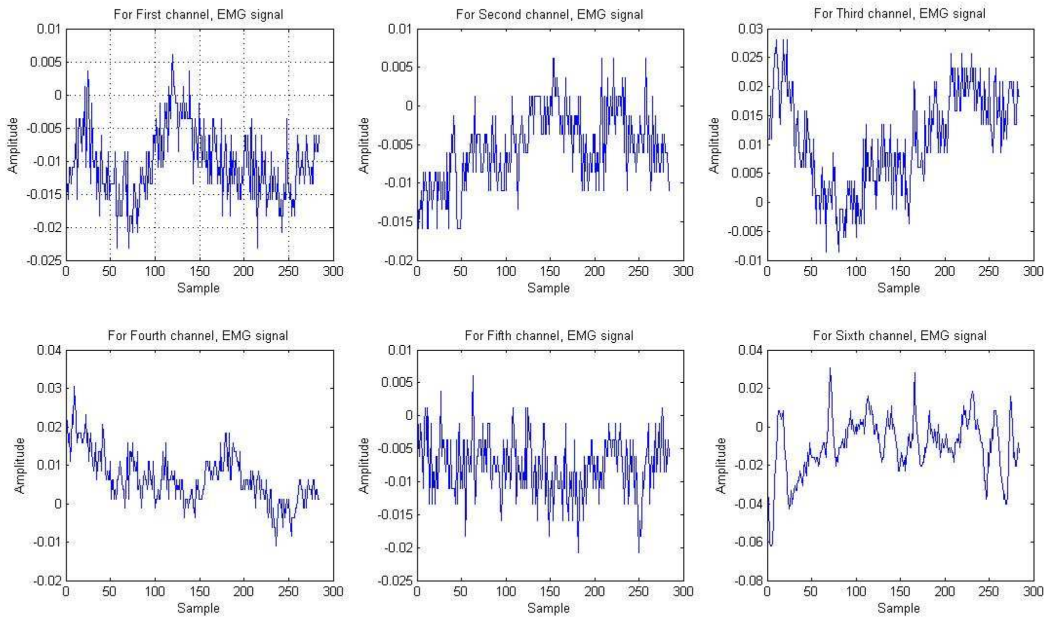


Fig: 19 RAW EMG Signal

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APPENDIX

A. ANNOTATED BIBLIOGRAPHY

Park SH, Lee SP , EMG Pattern Recognition Based on Artificial Intelligence Techniques- Seok-Pil Lee (B.S., M.S., and Ph.D. in electrical engineering from Yonsei University, Seoul, Korea), Sang-Hui Park (B.S., M.S., and Ph.D. degrees in electrical engineering from Yonsei University, Seoul) have presented a simple model of EMG pattern recognition through feature extraction, reduction and classification.

TOOLS DESCRIPTION

SimulinkCode Platform: Windows and Linux
Compiler : LCC
Other tools : EMG Lab, Code Blocks
EDRAW 4.6