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ANALYSIS OF FEATURE TRAINING SET FOR IMPROVING CLASSIFICATION ACCURACY

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Abstract – *Electromyogram (EMG) signals give electrical manifestation of contraction of recorded muscle. EMG signals acquired from different muscle sites can be used to classify different hand movements based on the features extracted from the signals. The six time-domain features and autoregressive coefficient of 3rd order is used to form feature vector. The PCA-feature projection method is used to reduce the dimensionality of feature vector. The feature correlation of features RMS and AR of order 1 for forming class-cluster of for forming class cluster is highest compared to other feature combinations. The feature vector, obtained by applying PCA to seven feature set, shows maximum inter-class separability and uses 3 principle components of features for identification of 6 upper-limb movements.*

Key Words: EMG signal, feature extraction, Time-domain features, feature correlation, linear discriminant analysis

1. INTRODUCTION

The Electromyogram signals recorded from muscle give rich information of intent of motion. Because of its non-invasive nature, the signals obtained on further processing has various applications in field of rehabilitation engineering for controlling prosthetic arm. The EMG signals are noisy and non-stationary so for obtaining useful information, various time and frequency features are extracted from it.

Myoelectric control feasibility has been demonstrated by many researchers for various features and classification methods.[1-4] EMG signals are utilized successfully in decoding intended upper-limb movements. The EMG signals obtained from healthy subjects are considered an emulation of trans radial amputee's control signals extending from various muscles for various movements. In myoelectric control, the main challenge is recognizing user's intention of movement. Pattern recognition of EMG signal is used for classifying the acquired EMG signals into predefined movement sets. The pattern recognition of EMG signal was first developed in 1970s. [5, 6] In 1993, Hudgins developed real time and accurate pattern recognition method for myoelectric control.

The pattern-recognition of EMG signals consists of windowing, feature extraction, feature reduction and classification. The segmentation of EMG signals is done to maintain its stationary nature. The analysis window length should be less than 300 ms. [2] The overlapping window is preferred over disjoint as it offers lesser processing time.[3] The time-domain features are highly preferred because of its computational speed. Mean Absolute Value (MAV), Integrated Absolute Value (IAV), Root Mean Square (RMS) , Slope Sign Change (SSC), Zero Crossing (ZC), Wave-length (WL) are extracted from the signal and feature vector of m*n dimension is formed(m=windows, n=no of features).This feature vector, if fed to classifier, requires high computational time hence it undergoes dimensionality reduction. The dimensionality reduction reduces with-in class distances while maximizing inter-class separability.

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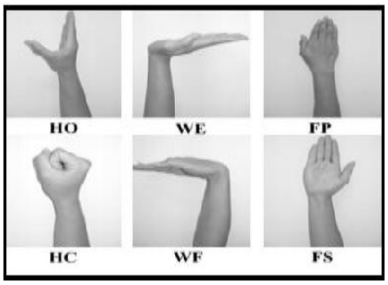
2. METHODOLOGY

2.1 Data Acquisition

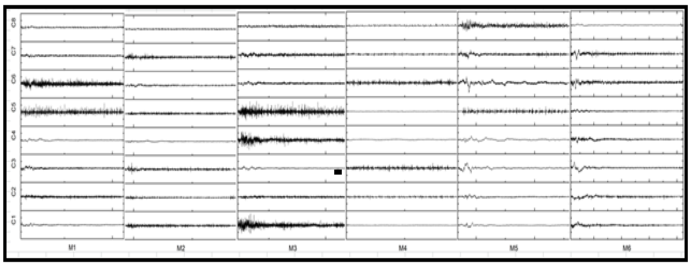
EMG signals are recorded from the muscles enlisted in the table and data utilised is same used in [7]. EMG signals are recorded from eight electrodes placed on upper-limb muscles using Ag/Ag-Cl electrode and ground electrode placed on wrist. Seven basic upper-limb movements : wrist extension (WE), hand open (HO), supination (S), wrist flexion (WF), hand close (HC), pronation (P) and rest (R) were recorded, amplified with 1000 gain sampled at 3kHz with BW of 1Hz to-1KHz and is down-sampled from 3KHz to 1KHz. The Fig. 1 shows the six movements of the forearm.

	Muscle	Principle Movement
Channel 1	Flexor digitorum	Wrist Flexion
Channel 2	Flexor ulnaris	Wrist Flexion
Channel 3	Brachioradialis,	Forearm Pronation
Channel 4	Pronator teres	Forearm Pronation
Channel 5	Flexor carpi radialis,	Forearm Pronation
Channel 6	Extensor digitorum	Wrist Flexion
Channel 7	Extensor carpi ulnaris	Wrist Flexion
Channel 8	Biceps brachii	Forearm Suppination

(a)



(b)

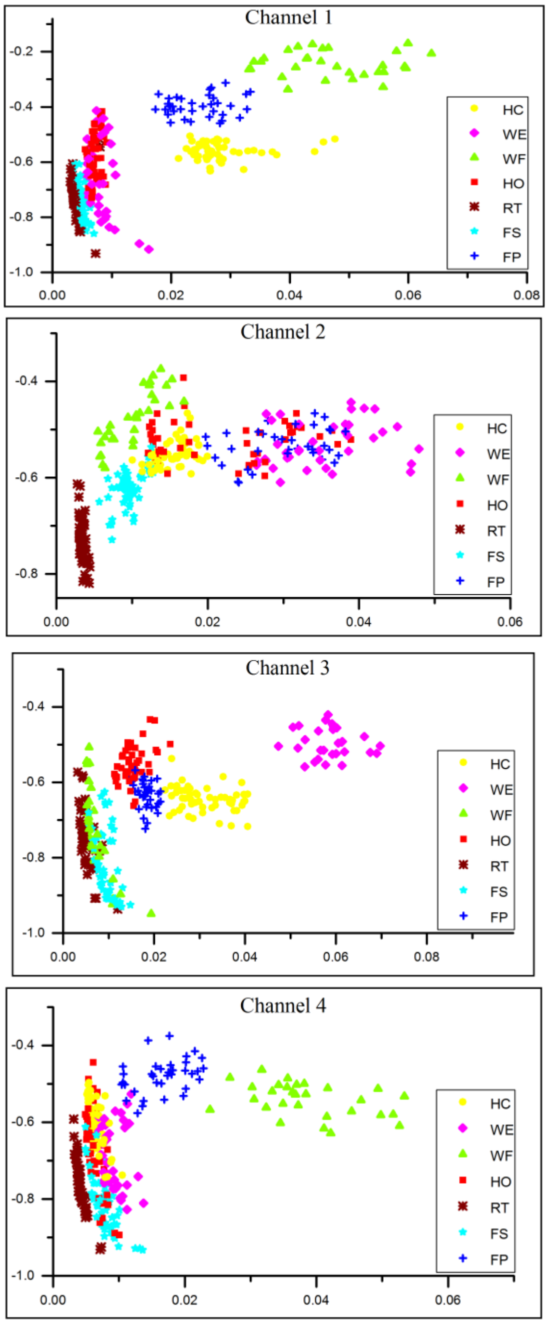


(c)

Fig -1: (a) Muscle recording sites on upper limb (b) Six movements of upper arm (c) Six movements' signals obtained from 8 channels

2.2 Feature Extraction

The EMG signal is stochastic hence instantaneous sample has little information about the muscular activity. For this reason, features are extracted from EMG signal very cautiously. Success of classification method depends on extraction and selection of features. Features are computed from EMG signal using overlapping sliding window. The characteristics of EMG signals are captured by the feature set. Computational complexity and accuracy trade-off should be considered while choosing feature sets. The length of analysis window is 256ms with an increment of 128ms for training data and 32 for testing data. The transitional data 256ms before and after arm movement was removed from feature training set. The time-domain features- Mean Absolute Value (MAV), Integrated Absolute Value (IAV), Root Mean Square (RMS), Slope Sign Change (SSC), Zero Crossing (ZC), Wave-length (WL)[1]and autoregressive model are extracted from the signal. The feature correlation of different combinations of features was obtained. The feature correlation between RMS and AR model of order 1 were able to separate different classes of movements as shown in figure 2.



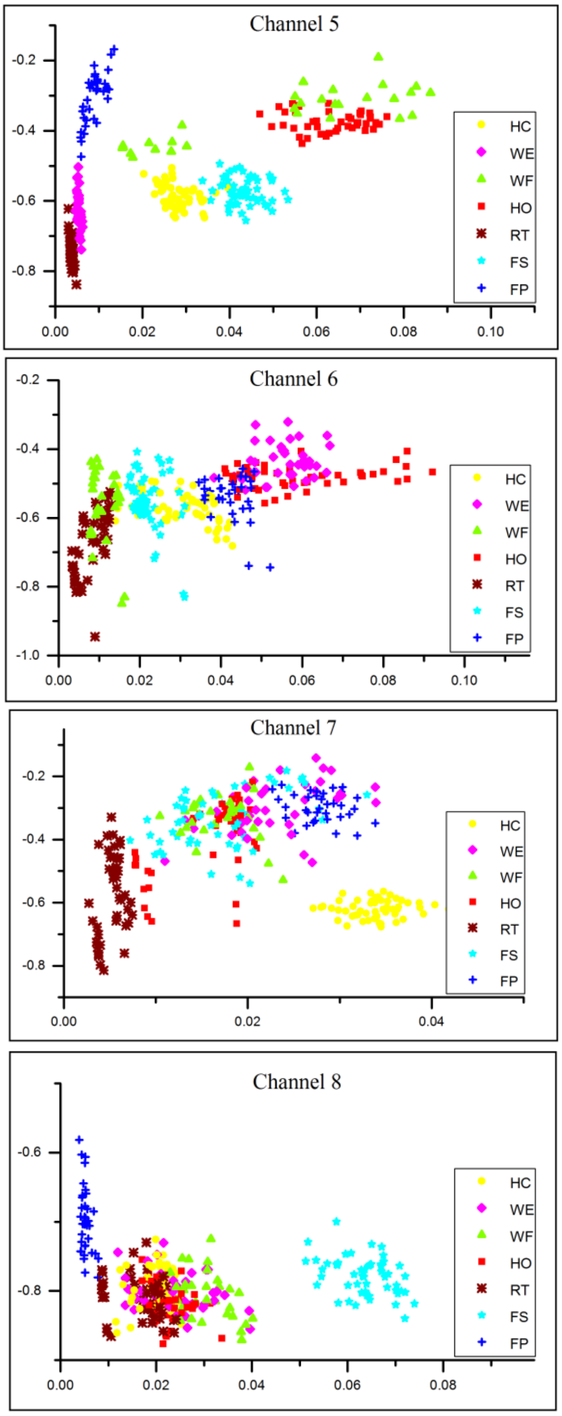


Fig -2: Feature correlation of RMS-AR1 from all 8 channels

The order of autoregressive model is determined by sampling rate and highest frequency of bandwidth. The sampling rate is 1 ms and highest frequency is 1KHz so AR model order N=1/fh*ts hence order 1 is chosen for autoregressive model.

Different muscles play principle role in different movements, for example-biceps brachii plays principle role in elbow flexion movement hence it will show major muscle contraction activity during the elbow flexion. The table enlists the movements identified from various channels from the clusters formed from RMS-AR1 correlation. The movements identified from different channels shown in table are same as principle movements of the muscles listed in table 1.

Channels	Movements					
	HO	HC	WF	WE	FS	FP
1		✓	✓			✓
2			✓		✓	
3	✓	✓		✓		✓
4			✓			✓
5	✓	✓		✓	✓	✓
6						
7		✓				
8					✓	✓

Table -1: Movements identification with RMS-AR1

2.3 Linear Discriminant Analysis

Linear Discriminant Analysis is a dimensionality reduction method based on linear transformation approach. It maximizes both the data variance as well as inter-class separation of data set. Feature vector set is reduced by retaining dataset characteristics that most contribute to its variance. The figure 3 shows block diagram representation of LDA feature dimensionality reduction method based on finding co-variance of the dataset and Eigen values are projected on the feature vector to form new reduced feature vector.

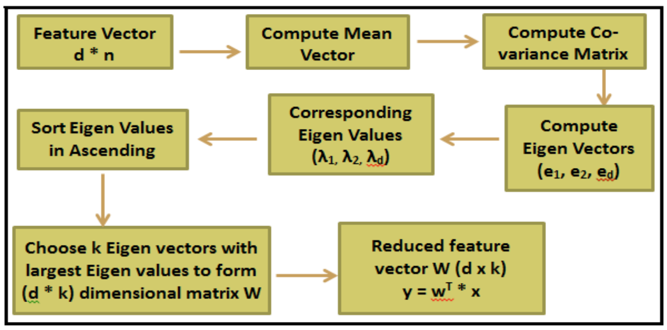


Fig -3: LDA feature dimensionality reduction flow.

The dimension of feature vector will be 'm x n' where m is the number of analysis windows and n is the number of features.The features are extracted from each analysis window from all 8 channels hence total 'm x n x l' feature vector will be obtained where l is the number of channels used for recording.The figure 4 shows the dimensionality reduction of feature vector using LDA where k is number of eigen values taken after arranging the eigen vector in ascending order.

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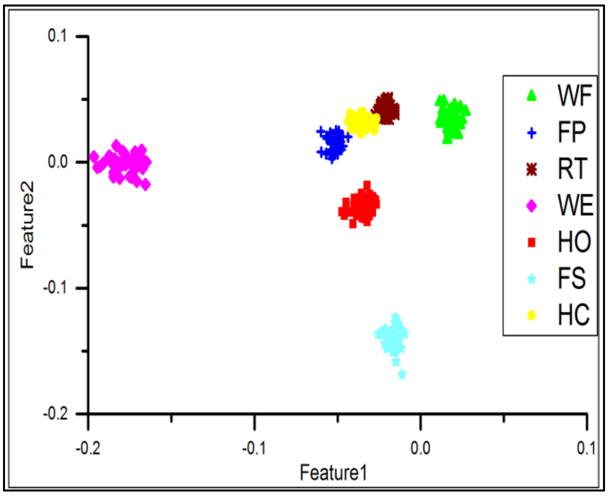
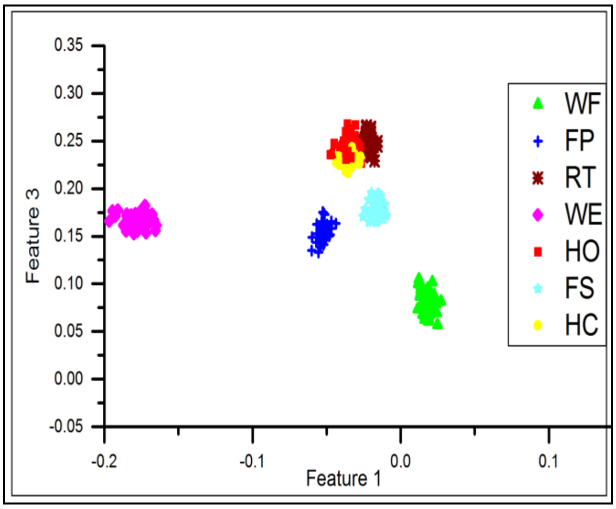
The feature vector obtained is evaluated by using feature correlation approach that correlates two feature components against each other in order to form clusters belonging to different classes of movements.

3. RESULT AND CONCLUSION



(a)



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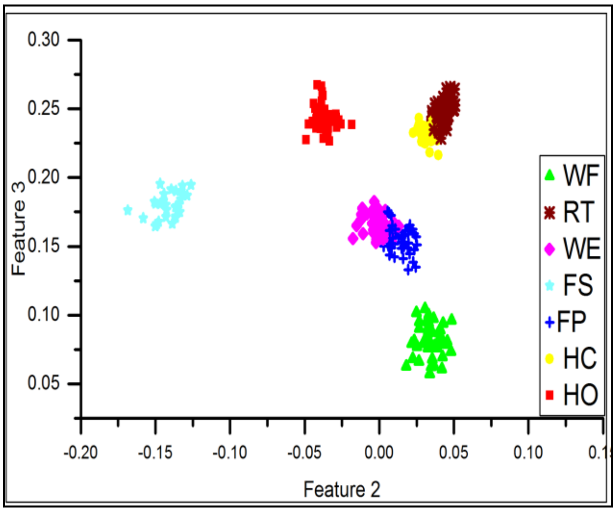
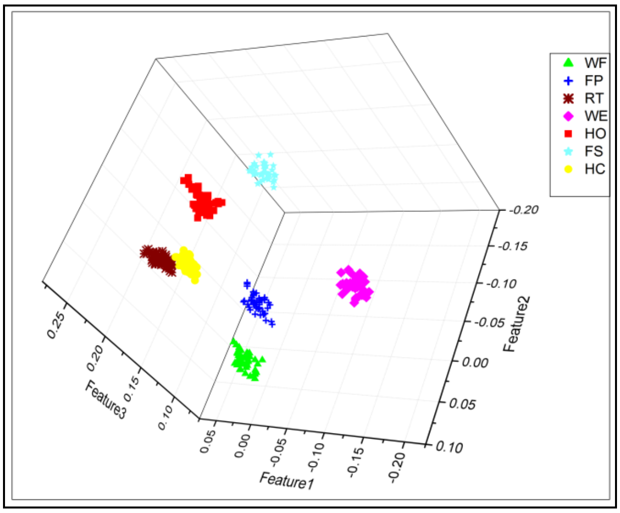


(c)



(d)

Fig -4: (a),(b),(c) 2D scatter plot, (d) 3D scatter plot of features

As shown in figure 4, on correlating feature1 and feature 2 forms a cluster of features belonging to same class of movement. Using only two features of newly formed feature vector, all six movements are identified efficiently. Such feature training set when fed to classifier gives better classification compared to original feature vector.

LDA	Movements					
	HO	HC	WF	WE	FS	FP
F1-F2	✓	✓	✓	✓	✓	✓
F2-F3				✓		✓
F1-F3	✓		✓		✓	

Table -2: Movements identified by feature correlation

The results shown in figure 6 suggest that combination of all six time domain features and autoregressive of order 1, after applying linear discriminant analysis and post- processing proves to be good feature training set.

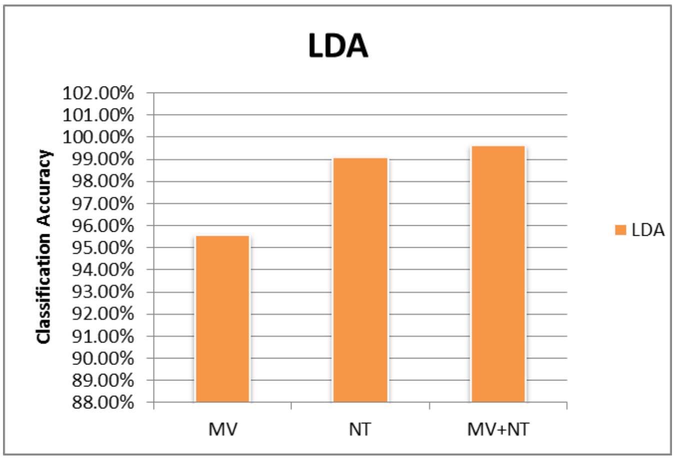


Fig -5: Classification accuracy after applying Majority Voting (MV), no-transition (NT), both MV and NT

The transition data between the movements set the system to undetermined state hence to increase the classification accuracy and decrease the computation time, these transition data are removed.

Another post-processing done to improve the classification accuracy is majority voting. It uses current and previous 8 classification results contained in 256 ms with a window increment of 32 ms and makes decision based on the frequency of class occurrence. The graph shown in figure 7, proves all seven features with LDA dimension reduction to be efficient training set for movement classification.

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