

Power Spectrum Analysis of sEMG Signals

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Abstract— Electromyography (EMG) involves evaluating and recording electrical / neural activity of muscle tissue, utilizing small electrodes attached to the skin or inserted into the muscle. EMG signals can be used to control the robotic device or prosthetic limb by wearing it or wirelessly. This paper summarizes the research done to utilize myoelectric commands interface that would permits multiple joints of a trans-radial prosthesis. The features have been computed for a 5 subjects on various kinds of grasps. The algorithm presents a fusion approach that not only extracts the features from the current analysis windows but, also fuses that with those extracted from previous windows for robust activity recognition. The algorithm has been evaluated on similar features from the test data to predict grasp patterns with higher accuracy levels.

Keywords— Electromyography, sEMG, Signal acquisition, feature extraction, hand grasp.

I. INTRODUCTION

EMG signals have proven to be effective command sources for control of prosthetic limbs, both clinically as well as in several research. Most commercially available prosthetic systems use a relatively simple scheme, whereby the amplitude of EMG signals recorded from two antagonistic sites beneath the socket are used to actuate one of the motors embedded in the prosthesis. The velocity of the prosthesis is proportional to the difference between the two EMG signals. The same two signals are used to operate each joint sequentially, using a quick twitch (i.e. co-contraction) of both signals to switch modes. Electrically-powered prostheses use small electrical motors, rather than motion of other body parts, to power terminal device (hand or hook), wrist, and elbow movements. Such systems are frequently controlled by recording electrical signals - known as "myoelectric signals" (MES) or "electromyographic" (EMG) signals - generated by the contractions of residual muscles using electrodes placed on the surface of the skin over the muscles, but can also be controlled by body movements via linear potentiometers, buttons, force sensitive resistors, or switches. A natural and intuitive approach for creating interfaces, is to look at the muscle activity of the user. This activity can be recorded by surface electromyography (sEMG) sensors, a non-invasive technique widely adopted both in clinical settings and research. The sEMG signals are non-stationary and represents the sum of subcutaneous motor action potentials generated through muscular contraction.

In the previous research, either the number of EMG channels are greater than or equal to the number of finger movements recognized, or only a small number of movements are considered. Having a large number of electrodes requires a large surface area on the forearm, which may be not suitable for amputee persons. Thus, it is desirable to reduce the number of channels in order to increase the usability of sEMG systems. In addition, this will reduce the cost and complexity of the required hardware, as well as reducing the processing time needed by the myoelectric controller to reach a decision. At the same time, the capability to discriminate a large number of finger movements must be preserved. An assumption guiding the work presented here is that this may be achievable through utilizing more advanced signal processing methods, extracting more information from each channel, and by carefully selecting the position of the electrodes.

II. LITERATURE REVIEW

The measured EMG signal includes various types of information such as muscle movement and muscle fatigue, and thus requires preprocessing depending on the purpose of use. It contains information about muscle movement in the low frequency band below 500Hz. To use this information, a band-pass filter or a low-pass filter is needed and to remove external power noise, a notch filter at 50Hz is used. Fig 2.4 shows the EMG signal waveform, in which (a) shows the measured EMG signals and (b) shows the EMG signals after preprocessing.

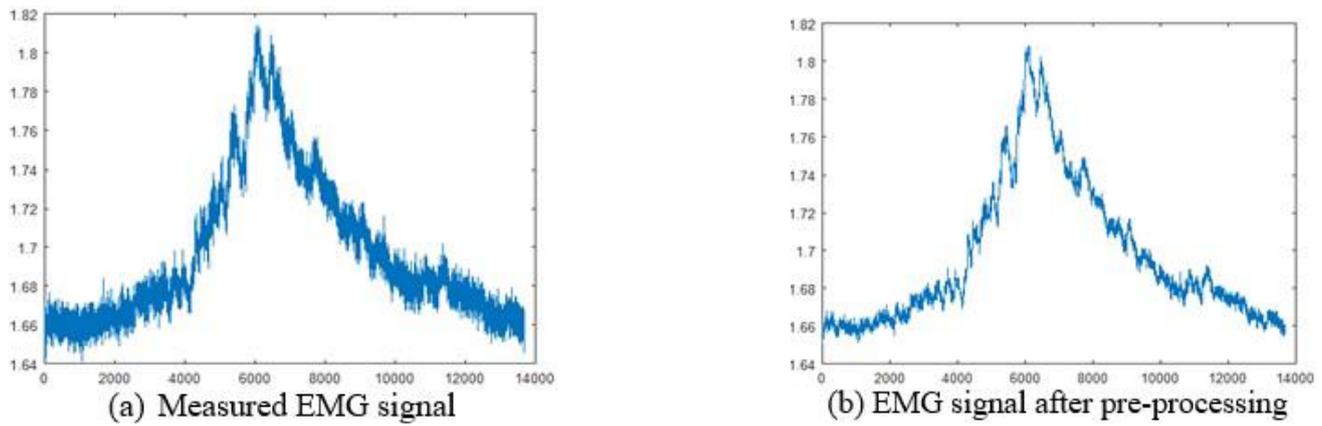


Figure 1: a) Measured EMG signal b) EMG after pre-processing

A number of different computational approaches have been taken to map EMG signals to the desired movements in a natural manner. Discrete movement types are often identified using pattern recognition approaches such as linear discriminant analysis (Saridis and Gootee 1982), fuzzy logic (Ajiboye and Weir 2005), and artificial neural networks (Kelly, Parker, and Scott 1990). Compared to traditional approaches, these methods allow a user to seamlessly (i.e. without the need for a separate mode switch) operate the joints of a prosthesis in a sequential manner. By taking advantage of distinct patterns of activity related to the intuitive movements of the missing limb, these approaches reduce the cognitive burden associated with traditional control methods. All the recent studies have shown the ability of amputees to use these pattern recognition-based myoelectric controllers to accurately position a virtual prosthesis (Simon et al. 2011a; Simon et al. 2011b). Still, when contrasted with natural arm and hand function, the seamless sequential control methods may be frustratingly slow for some users.

However, inertial sensors suffer from drift problem and the design of sensor placement need to be customized case by case based on kinematic principles. The Magnetic sensors form another type of track sensors with small sizes, high sampling rates, but large jitters and high latencies. Noort et al. (2016) developed a measurement system using the combination of inertial and magnetic sensors in order to track finger movements. Ma et al. (2011) designed a wireless magnetic hand motion tracking systems using small magnets placed on the finger tips. Both of inertial sensors and magnetic sensors need to be placed on human hands, which add external loads to human hand and will restrict hand movements.

The literature on sEMG-based gesture recognition primarily focuses on feature engineering, with the goal of characterizing sEMG signals in a discriminative way [11], [12], [13]. Recently, researchers have proposed deep learning approaches shifting the paradigm from feature engineering to feature learning. Regardless of the method used, the end-goal remains the improvement of the classifier’s robustness. One of the main factors for accurate predictions, especially when working with deep learning algorithms, is the amount of training data available. Hand gesture recognition creates a peculiar context where a single user cannot realistically be expected to generate tens of thousands of examples in a single sitting. Large amounts of data can however be obtained by aggregating the recordings of multiple participants, thus fostering the conditions necessary to learn a general mapping of users’ sEMG signal. This mapping might then facilitate the hand gestures’ discrimination task with new subjects. Consequently, deep learning offers a particularly attractive context from which to develop a Transfer Learning (TL) algorithm to leverage inter-user data by pre-training a model on multiple subjects before training it on a new participant. The below table shows the features of various related researches.

Table 1: Summary of literature review

Title	Feature Extraction	Authors	Motions
Recognize Finger Motions Using Wavelet Transform	Wavelet Transform	Jiang <i>et al.</i> , (2006)	Flexion-extension of thumb, index, middle fingers separately
Identify Low Level Muscle Activities Using Fractal Dimension Features	Independent Component Analysis (ICA)	Naik <i>et al.</i> , (2009)	Four finger group movements
Decode Individuated Finger Movements Using sEMG	TD features	Tenore <i>et al.</i> , (2009)	Flexion-extension for individual fingers and finger group movements
Decode Individuated	TD features	Kanitz <i>et al.</i> , (2011)	Individual finger

Finger Movements Using Genetic Algorithm			movements
Analysis of Intrinsic and Extrinsic Hand Muscle EMG for Improved Pattern Recognition Control	TD features	Adewuyi <i>et al.</i> , (2016)	Online study on wrist movements
Orthogonal Fuzzy Neighborhood Discriminant Analysis for Myoelectric Hand Control	A combination of TD and AR features	Khushaba <i>et al.</i> , (2010)	Forearm and wrist movements

III.METHODOLOGY

The methodology used in this research work incorporates information about the surface Electromyogram (sEMG) signal power spectrum characteristics derived from each analysis window while correlating that with the descriptors of previous windows for robust activity recognition. The proposed idea can be summarized in the following three steps:

- 1) Extract power spectrum moments from the current analysis window and its nonlinearly scaled version in time-domain through Fourier transform relations
- 2) Compute the orientation between the two sets of moments, and
- 3) Apply data fusion on the resulting orientation features for the current and previous time windows and use the result as the final feature set.

sEMG data from upastras database has been used which contains 3 female and 2 male persons sEMG data performing six classes of movements with different force levels is used to validate the proposed features.

The system is inspired by Rami Khusabha method of feature fusion, adopting a fusion approach that not only extracts the features from the current analysis windows but, also fuses that with those extracted from previous windows for robust activity recognition. In such a case, the local variability in the sEMG features is also correlated to the semi global variability as deduced by the time resolution of the previous windows. The research uses a database of hand movements taken from UCI Machine Learning Repository [20].

Instrumentation:

The data were collected at a sampling rate of 500 Hz, using as a programming kernel the National Instruments(NI) Labview. The signals were band-pass filtered using a Butterworth Band Pass filter with low and high cutoff at 15Hz and 500Hz respectively and a notch filter at 50Hz to eliminate line interference artifacts.

The hardware that was used was an NI analog/digital conversion card NI USB- 009, mounted on a PC. The signal was taken from two Differential EMG Sensors and the signals were transmitted to a 2-channel EMG system by Delsys Bagnoliã,, Handheld EMG Systems[20].

Protocol:

The experiments consisted of freely and repeatedly grasping of different items, which were essential to conduct the hand movements. The speed and force were intentionally left to the subjects will. There were two forearm surface EMG electrodes Flexor Capri Ulnaris and Extensor Capri Radialis, Longus and Brevis) held in place by elastic bands and the reference electrode in the middle, in order to gather information about the muscle activation.

The subjects were asked to perform repeatedly the following six movements, which can be considered as daily hand grasps:

- a) Spherical: for holding spherical tools
- b) Tip: for holding small tools
- c) Palmar: for grasping with palm facing the object
- d) Lateral: for holding thin, flat objects
- e) Cylindrical: for holding cylindrical tools
- f) Hook: for supporting a heavy load

Two different databases are included:

- 1) 5 healthy subjects (two males and three females) of the same age approximately (20 to 22-year-old) conducted the six grasps for 30 times each. The measured time is 6 sec. There is a mat file available for every subject.
- 2) 1 healthy subject (male, 22-year-old) conducted the six grasps for 100 times each for 3 consecutive days. The measured time is 5 sec. There is a mat file available for every day.

For each subject, there will be a mat file with 12 matrixes, in which matrix there are 30 (trials) rows and 3000 (points of the signal) columns for database 1, which has been taken in this research work.

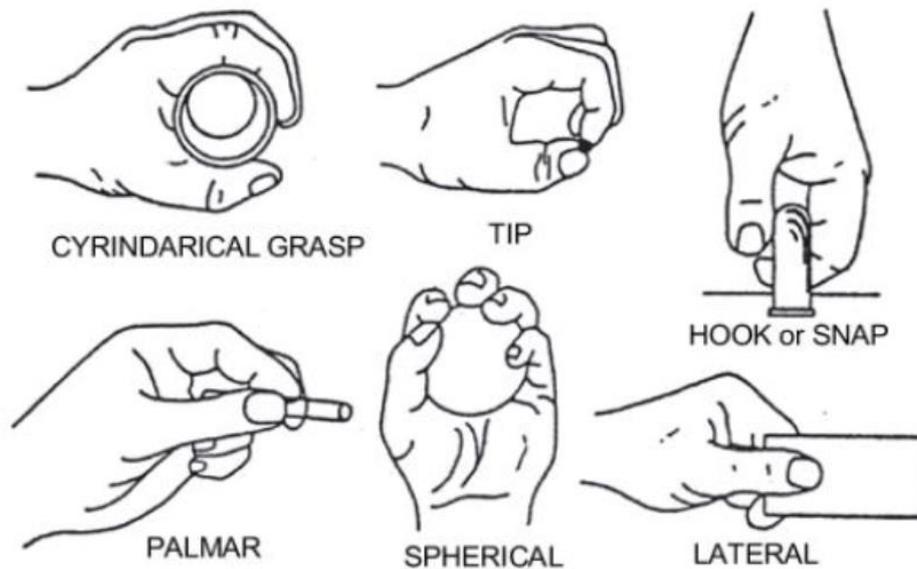


Figure 2: An illustrative diagram for the database

Each row of these tables has the whole signal per trial. The signal value is measured in Voltage. The figure 2 gives an illustration of the various movements of the hands for different grasps.

IV. PROPOSED WORK

The dataset contains two channels for each grasp for each subject. The baseline wandering, if any thus present is removed by subtracting the values of the channel 2 from that of the data values of channel 1. The root mean square zero order is then evaluated. The dataset consists of a sampled version of the EMG signal denoted as $x[j]$, with $j=1,2,\dots,N$, of length N and a sampling frequency f_s . The EMG trace within a certain epoch can be expressed as a function of frequency $X[k]$ by means of Discrete Fourier transform (DFT). The main derivations of the proposed method are based on Parseval's theorem which states that the sum of the square of the function is equal to the sum of the square of its transform. Root squared zero order moment: indicates the total power in the frequency-domain, or simply the strength of muscle contraction, which is given as:

$$\bar{m}_0 = \sqrt{\sum_{j=0}^{N-1} x[j]^2} \tag{1}$$

The higher order moments are then calculated by using the higher order derivatives. For this work Root squared fourth and eighth order moments have been evaluated. according to Hjorth the second moment can be considered as a power, but then of a modified spectrum $k^2P[k]$, corresponding to a frequency function $kX[k]$. The time equivalent of a k multiplied frequency function is the first derivative of the time function [21]. Thus

$$\bar{m}_2 = \sqrt{\sum_{k=0}^{N-1} k^2 P[k]} = \sqrt{\frac{1}{N} \sum_{k=0}^{N-1} (kX[k])^2} = \sqrt{\frac{1}{N} \sum_{j=0}^{N-1} (\Delta x[j])^2} \tag{2}$$

A repetition of this procedure gives the fourth order moment:

$$\bar{m}_4 = \sqrt{\sum_{k=0}^{N-1} k^4 P[k]} = \sqrt{\frac{1}{N} \sum_{j=0}^{N-1} (\Delta^2 x[j])^2} \tag{3}$$

The first two extracted features from the moment variables can be evaluated. The first feature is the log of the zeroth root mean square moment.

$$f1 = \log(m_0) \tag{4}$$

and the feature 2 as the log difference of the zeroth moment and the fourth order moment given as:

$$f2 = \log(m_0 - m_4) \tag{5}$$

The next feature evaluated is wavelength Ratio which can be defined as the waveform length feature as the summation of the absolute value of the derivative of the signals, the WL feature as the ratio of the waveform length of the first derivative to that of the waveform length of the second derivative.

$$f3 = \log \left(\frac{\sum_{j=0}^{N-1} |\Delta^2 x|}{\sum_{j=0}^{N-1} |\Delta^4 x|} \right) \tag{6}$$

The waveform length feature was shown to be very relevant for EMG classification tasks. However, the wavelength ratio feature further extends the work in the literature to form a feature that is invariant to amplitude scaling.

Feature matching:

The next step is to combine the three features into one feature matrix and calculate the feature matrix for each type of grasp, thus we get a feature template of each grasp.

$$Featf = [f1; f2; f3] \tag{7}$$

The matching and corresponding decision is made by finding the Euclidean distance matrix between the current EMG features and the stored template features for each .

Given an mx-by-n data matrix X, which is treated as mx (1-by-n) row vectors x1, x2,, xmx, and my-by-n data matrix Y, which is treated as my (1-by-n) row vectors y1, y2, ..., ymy, the euclidean distances between the vector xs and yt are defined as follows:

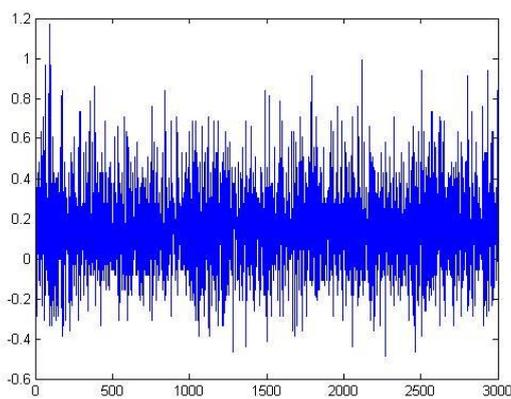
Euclidean distance:

$$D_{st}^2 = (x_s - y_t) (x_s - y_t)' \tag{8}$$

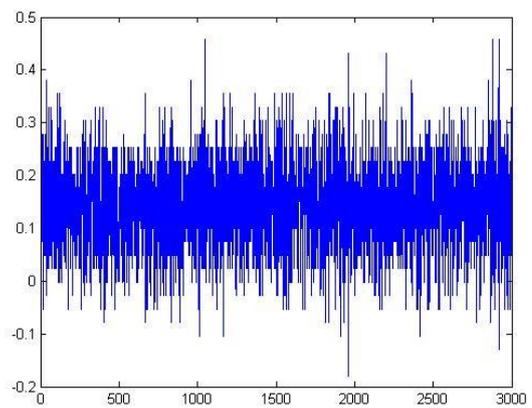
For testing the features are calculated for the testing row and Euclidean distance is evaluated. This minimum distance is evaluated and the corresponding template is identified, thus giving our desired result of matching.

V. RESULTS & DISCUSSIONS

Each channel consists of voltage values and MATLAB data file consists of a matrix of 30x3000 for each grasp for each person. This data represents readings taken at 30 different times during a day from each user and each row consists of 3000 voltage readings. A plot of the values is as shown in figure 3 below:



a) Channel 1 Signal



b) Channel 2 Signal

Figure 3: Female 1 lateral grasp dataset plot

The mean feature values are then calculated for each grasp position which is simply the mean of the 30 values for each feature.

$$Feature_mean = \text{sum(Features)} / \text{No. of instances} \tag{9}$$

The mean feature table is as represented below for each different grasp position.

Table 2: Mean Feature values for different Classes of Grasp

GRASP	Feature 1 Log(m0)	Feature 2 Log(m2-m4)	Feature 3 WZL
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Cylinder	2.6792	0.9509	0.4378
Hook	2.6998	0.9632	0.4261
Tip	2.5540	0.8272	0.4674
Palm	2.5573	0.8134	0.4289
Sphere	2.7146	0.9828	0.4299
Lateral	2.5207	0.7883	0.4582

Tests have been carried out on each row of the female 1 dataset and the matching is evaluated by calculating the minimum Euclidean distance of the features evaluated of the current testing dataset with that of the mean feature values of the dataset for 6 different classes of grasp. The below table 3 shows the accuracy results on each type of grasp for different persons is shown in table 3 to table 7 dataset.

As can be seen from the below table, for certain experiments, the accuracy is 100%, i.e. the algorithm was able to recognize the correct grasp type in all the 30 test instances, which is quite remarkable as compared to the erstwhile methods used in several previous researches. Even using advanced algorithms like fuzzy logic and machine learning, such high rate of recognition has not been achieved.

Table 3: Accuracy results for female 1 data testing

GRASP	Instances	True	False	Accuracy
Cylinder	30	24	6	80%
Hook	30	18	12	60%
Tip	30	20	10	66.67%
Palm	30	21	9	70%
Sphere	30	25	3	83%
Lateral	30	20	10	66.67%

Table 4: Accuracy results for female 2 data testing

GRASP	Instances	True	False	Accuracy
Cylinder	30	26	4	86.67%
Hook	30	23	7	76.67%
Tip	30	24	6	80%
Palm	30	27	3	90%
Sphere	30	29	1	96.67%
Lateral	30	28	2	93.33%

Table 5: Accuracy results for female 3 data testing

GRASP	Instances	True	False	Accuracy
Cylinder	30	30	0	100%
Hook	30	30	0	100%
Tip	30	22	8	73.33%
Palm	30	23	7	76.67%
Sphere	30	30	0	100%
Lateral	30	20	10	66.67%

Table 6: Accuracy results for male 1 data testing

GRASP	Instances	True	False	Accuracy
Cylinder	30	30	0	100%
Hook	30	29	1	96.67%
Tip	30	28	2	93.33%
Palm	30	25	5	83%
Sphere	30	29	1	96.67%
Lateral	30	26	4	86.67%

Table 7: Accuracy results for male 2 data testing

GRASP	Instances	True	False	Accuracy
Cylinder	30	24	6	80%
Hook	30	15	15	50%
Tip	30	28	2	93.33%
Palm	30	21	9	70%
Sphere	30	30	0	100%
Lateral	30	19	11	63.33%

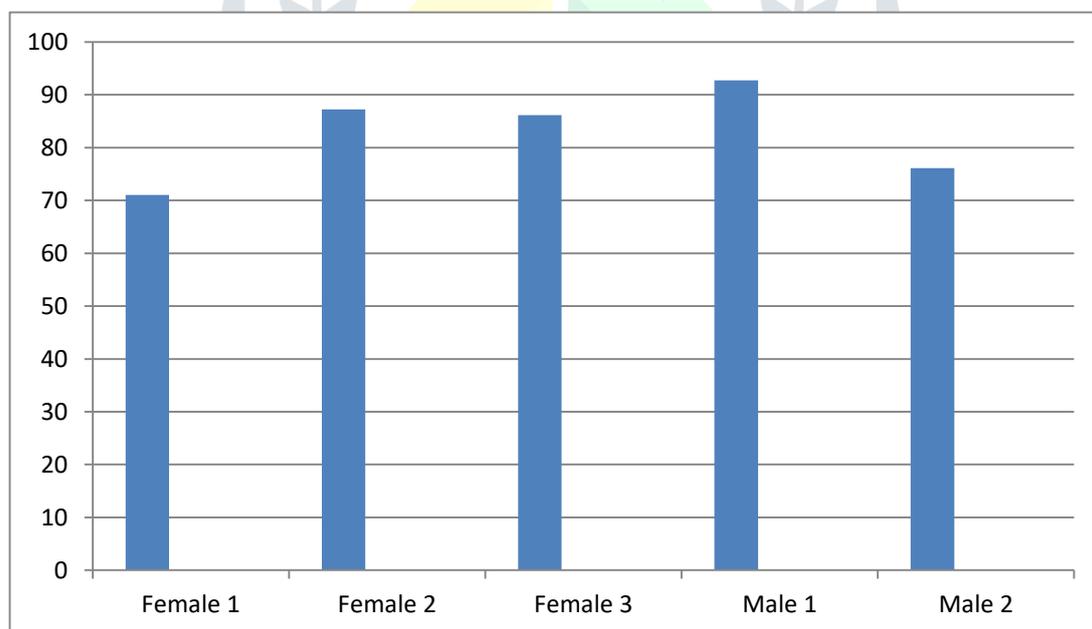


Figure 4.5: Average recognition percentage for each person

The above graph is figure 4, shows a comparison of recognition rates of each person on all grasp positions. The best result is obtained by male 1 with aggregate correct recognition across all classes of grasps to be as high as 92.72%. The lowest score in such comparison is obtained by the female 1 dataset with average recognition percentage across all grasp classes to be 71.05%. The combined average of the male and female dataset is made, to find out any gender specific patterns in terms of recognition. If it has anything to predict, the average positive recognition rate for the combined three female dataset is 81.46% while that of the two male dataset is 84.415.

A comparison of individual features i.e. feature 1, feature 2 and feature 3 was also carried out with that of the combined fusion of all three features in terms of percentage accuracy for all kinds of grasps for female 2 dataset. Table 4.7 shows the corresponding result. As can be seen from the table, it is quite inconclusive to be dependent on any one feature to exactly detect the correct value. The accuracy goes down to as low as .33% for lateral grasp in case of feature 3, while it also reaches a high of 96.67% for lateral grasp but on feature 2. Thus, it is evident from this comparison that the fusion of the three features gives much better results.

Table 8: A comparison with individual features

GRASP	Feature 1	Feature 2	Feature 3	Combined
Cylinder	56.67%	76.67%	10%	86.67%
Hook	56.67%	36.67%	70%	76.67%
Tip	63.33%	60%	26.67%	80%
Palm	83.33 %	70%	46.67%	90%
Sphere	86.67%	53.33%	53.33%	96.67%
Lateral	80%	96.67%	0.33%	93.33%

VI. CONCLUSION

The research focusses on analysis of sEMG and their power spectrum characteristics. The signals for EMG signals archived at UCI Machine Learning Repository was taken to develop and test a novel algorithm using time domain descriptor features, obtained from signal processing methods on the sEMG signals taken from a total of 5 persons including 3 female and 2 males. These dataset were taken during whole day at 30 different instances where the candidates were made to make 6 different movements of hand for cylinder grasp, hook grasp, palmary grasp, tip grasp, sphere grasp and lateral grasp. The signal obtained consists of voltage levels obtained from two channels. These signals were processed and feature like zeroth order moment, second order moment and fourth order moment were evaluated. The final feature matrix was a fusion of logarithm of root mean square, logarithm of difference of second and fourth order moment and wavelength ratio. These features are evaluated for each candidate at each instant and a feature bank is thus devised.

Extensive tests were then performed on each dataset by finding on similar features from the test data to predict grasp patterns with higher accuracy levels. In certain cases the highest correct recognition was found to be as high as 100% which is remarkable. The minimum correct recognition percentage was recorded at 50% as well. The overall positive recognition rate for different grasp tests was found to be approximately 82.6%, which is quite high as compared to similar experiments carried out in previous researches.

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