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FEATURE EXTRACTION FOR EMG BASED PROSTHESES CONTROL

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Abstract
The control of prosthetic limb would be more effective if it is based on Surface Electromyogram (SEMG) signals from remnant muscles. The analysis of SEMG signals depend on a number of factors, such as amplitude as well as time- and frequency-domain properties. Time series analysis using Auto Regressive (AR) model and Mean frequency which is tolerant to white Gaussian noise are used as feature extraction techniques. EMG Histogram is used as another feature vector that was seen to give more distinct classification. The work was done with SEMG dataset obtained from the NINAPRO DATABASE, a resource for bio robotics community. Eight classes of hand movements hand open, hand close, Wrist extension, Wrist flexion, Pointing index, Ulnar deviation, Thumbs up, Thumb opposite to little finger are taken into consideration and feature vectors are extracted. The feature vectors can be given to an artificial neural network for further classification in controlling the prosthetic arm which is not dealt in this paper.

Keywords:
Electromyogram (EMG), Auto-Regressive (AR) Model, EMG Histogram

1. INTRODUCTION

Prosthesis is a field of biomechatronics, the science of fusing mechanics with human muscle, skeleton and nervous system to assist or enhance motor control lost by trauma, disease or defect. One of the main requirements of prosthetic arm is that it should be as near as possible to a natural arm. The artificial arm can either be mechanical, electrical or myoelectric.

Myoelectric control is based on the myoelectric signal, or electromyogram (EMG), which is a measure of neuromuscular activity detected directly from within the muscle or from the skin surface. Myoelectric signals have an advantage that they can be detected on the skin surface without any injury to the patient. A myoelectric control system maps a set of features drawn from the myoelectric signal to a particular function, such as flexion of a prosthetic wrist. This type of control system has been frequently used in the field of powered prostheses, as it provides a user with the potential for naturally-evoked movement control [1], [6]. A successful myoelectric control system is one in which three key issues are sufficiently addressed: accuracy, intuitive control, and acceptable response time, the probability of rejection of a prosthesis by the user is strongly influenced by these factors.

The myoelectric signal represents the temporal and spatial summation of motor unit action potentials within the pickup region of the recording electrode. The muscle fibres of a motor unit are innervated by a single motor nerve and contract together upon receiving an electrical stimulus, called an action potential, which is sent from the motor cortex of the brain to the muscle fibres via the motor nerve. The summation of the action potentials in the single fibres of the motor unit is called the Motor unit action potential (MUAP).

Many factors contribute to the difficulty in extracting sufficient information from the EMG for prosthetic control such as electrode placement, electrode type, skin preparation and subcutaneous fat between the electrode and the muscle. These problems can be overcome by extracting data from multiple EMG sites and by using efficient feature extraction techniques. Autoregressive model tolerant to electrode placement noise [2], [3] and mean frequency which is tolerant to white Gaussian noise [1] are used.

The paper is organised as follows, the section 2 deals with system architecture for prosthetic arm and data acquisition. Feature extraction concepts in section 3, the simulation results are given in section 4 followed by conclusion in section 5.

2. SYSTEM ARCHITECTURE AND DATA ACQUISITION

The EMG signals are acquired after proper skin preparations and are amplified before being filtered and sampled. The pre-processed signals are then used to extract features and subsequently the extracted features are given to a classifier as shown in Fig.1.

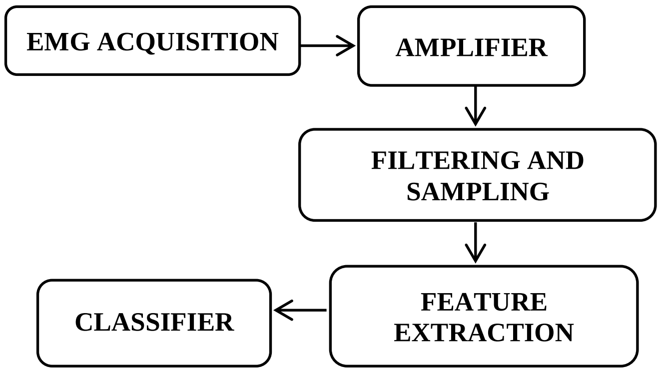


Fig.1. System architecture of prosthetic arm

2.1 DATA ACQUISITION

NINAPRO database consists of kinematic and SEMG data from the upper limbs of 27 intact subjects while performing 52 finger, hand and wrist movements. The database is publicly available to download in standard ASCII format [5]. Surface EMG was collected from a subject's forearm skin while performing a number of movements of interest, or producing force patterns of interest. While intact subjects were examined by recording SEMG from the same arm, in the case of amputees recording of SEMG was from a stump while eliciting movements of interest either by imitation or bilateral coordinated motion. Surface EMG activity was gathered using ten active double-differential OttoBock MyoBock 13E200 surface EMG electrodes which had an amplification factor of 14000 [5].

The 52 movements were divided into four main classes as given in Table.1.

Table.1. Upper limb movements in the NINAPRO database

CLASSES	MOVEMENTS
Basic finger movements	Flexions and Extensions
Isometric and isotonic movements	Hand postures
Wrist movements	Abduction , pronation and supination
Functional movements	Grasping movements

The data in the NINAPRO database was acquired by the following procedure: The subject sits comfortably on an adjustable chair, in front of a table with a large screen. The SEMG electrodes, data glove and inclinometer are worn on the right hand. The subjects are presented with short movies appearing on the screen and are asked to simply replicate the movements depicted in the movies as accurately as possible. After the training phase, a sequential series of ten repetitions of each class of movements is presented to the subject while data are recorded. Each movie lasts five seconds and three seconds of rest are allowed in-between movements. In order to avoid muscle fatigue and its influence on the SEMG signal, 5 minutes of rest are allowed between the training sequence and the first exercise and between each exercise and the following one. In total, the experiment lasts about 100 minutes.

2.2 FILTERING AND SAMPLING

The EMG signals for various classes of hand movements have to be filtered to extract the region of EMG activity. In the spectrum of EMG signals most of information is contained in frequencies up to 500 HZ. Second order Butterworth band pass filter with cut off frequencies 20 Hz and 500 Hz is used. Butterworth filter exhibits a maximally flat response without any ripples in the pass band region. With amplitude distinction being very critical in EMG analysis, low distortion Butterworth filter is preferred. Sampling is done in accordance with the nyquist criterion the signal is then sampled at 2 KHZ.

3. FEATURE EXTRACTION

EMG signals can be used to control prosthetic limbs. In a real time system considering the memory constrains the original signal dimensions have to be minimized by mathematically modeling it [6]. Feature extraction techniques are one among the signal modeling techniques that represent an EMG signal with lesser vector space in a way that it would still be distinguishable.

3.1 AUTOREGRESSIVE MODELLING

Different movements correspond to various modes of muscle contraction and hence, the time signature of raw EMG signal varies. Hence, time series analysis would serve the purpose of feature extraction. Time series is a chronological sequence of observations of a particular variable, in this case, the amplitude of the raw EMG signal. The time series is based on the modeling of a signal to predict future values as a linear combination on its past values and the current value. A model that depends only on the previous outputs of the system is called an autoregressive model (AR). A model that depends only on the inputs to the system is called a moving average model (MA). And finally, a model based on the inputs and on the outputs is considered an autoregressive-moving-average model (ARMA).

The advantages of modeling the signal using autoregressive mode are

- Variations in the positioning of the electrodes on the surface of the muscle do not severely affect the AR coefficients.
- The amount of information to be presented to the classifier is greatly reduced so additional dimensionality reduction techniques are not required. Therefore, the total processing time is also reduced.

3.1.1 Model Order:

Any time series signal can be approximated by an AR model of finite order M. The order of an autoregressive model represents the amount of information necessary to predict an estimate of the signal. The lowest frequency that can be represented by a model is given by 1/ (MT), where M is the model order and T is sampling period. For a lowest frequency of 500Hz and sampling period of 0.5 ms, the model order required would be 4 implying that the.EMG signal would be represented by four AR coefficients.

3.1.2 Least Mean Squares Approach:

AR model is specified by linear prediction formulas that attempt to predict an output y[n] of a system based on the previous outputs (y[n-1], y[n-2], ...) and on the inputs (x[n],x[n-1], x[n-2], ...). Deriving the linear prediction model involves determining the coefficients $a_1, a_2\ldots, a_M$.

The below Eq.(1) defines the AR model,

$$y_k = \sum_{(i=1)}^{M} (a_i x_{k-i} + \omega_k) \tag{1}$$

where,

y_k is the estimated signal in a discrete time k.

a_i is the AR-coefficient.

ω_k is the error of the calculation process.

M is the order of the model.

A common strategy to calculate the AR-coefficients is to use the least mean square (LMS) algorithm. It provides an iterative and fast method to figure out the parameters of the AR-model adaptively. Algorithm to compute AR coefficients,

- Initialize the filter coefficients with zeros.
- Calculate the predicted value of the input signal $\hat{y}(n)$

$$\hat{y}(n) = -\sum_{m=0}^{M} (a_m) y(n-m) \tag{2}$$

- Estimate the prediction error $e(n)$ using the Eq.(3) and Eq.(4)

$$e(n) = y(n) - \hat{y}(n) \tag{3}$$

$$e(n) = y(n) + a_1(n)y(n-1) + \ldots + a_M(n)y(n-m) \tag{4}$$

- Update the AR-coefficients using the constant of convergence μ.

$$a_m(n+1) = a_m(n)2*\mu*e(n)y(n-m) \quad (5)$$

3.2 EMG HISTOGRAM AS A FEATURE VECTOR

EMG histogram is an extension of zero crossing method which compares a single threshold to the EMG signal. Since EMG signal deviates highly from its base line when the muscle is in high contraction levels, it would be informative to measure the frequency with which EMG signal reaches multiple amplitude levels.

The voltage range is subdivided symmetrically about the baseline and they are grouped into bins. The frequency of occurrence of each bin range is computed. This is visually represented as a bar graph. Increasing the number of bins would increase classification accuracy. Trial and error methods showed that fixing nine bins would provide sufficient distinction between different classes of movements.

3.3 MEAN FREQUENCY

White Gaussian noise (WGN) is one of the major interfering random signals in electromyogram acquisition. Since white Gaussian noise has a spectral component that is spread out in the entire frequency domain, removal of it through typical filtering would mean loss of useful information.

Noise reduction algorithms need to be implemented in the pre-processing stage to eliminate white Gaussian noise. Mean frequency of an EMG signal is a global parameter that distinctly differentiates one movement from another even in the presence of white Gaussian noise,

The mean frequency is computed as follows,

- Initialize two variables say sum and *a* to *be* zero.
- The amplitude spectrum of the EMG signal is computed using FFT algorithm.
- The variables *sum* and *a* are updated in a loop running till the length of the amplitude spectrum using the Eq.(6) and Eq.(7)

$$sum = sum + |(Y(k)) \times (f(k))| \quad (6)$$

$$a = a + |Y(k)| \quad (7)$$

$$\text{Mean frequency} = (sum/a) \quad (8)$$

where,

$Y(k)$ is the amplitude spectrum at k^{th} instant

$f(k)$ is the corresponding frequency at k^{th} instant

4. IMPLEMENTATION RESULTS

The EMG signals are analysed using the MATLAB version 7.8.0.347 (R2009a). The EMG database for different class of hand movements are taken from the NINAPRO database and .MAT files are created from them. The created files are loaded into the MATLAB workspace. The database contains information from fifteen electrodes of which the first five channels represent signals corresponding to transition of muscle from rest to motion and the last five correspond to transition from motion to rest. Of the remaining five channels electrode data corresponding to seventh channel was chosen and the data from corresponding column is extracted.

As mentioned earlier the EMG signals are band pass filtered from 20 to 500 HZ and subsequently sampled at 2 KHz nyquist frequency. The pre-processed EMG signals for hand open and wrist extension movements are shown in Fig.2 and Fig.3.

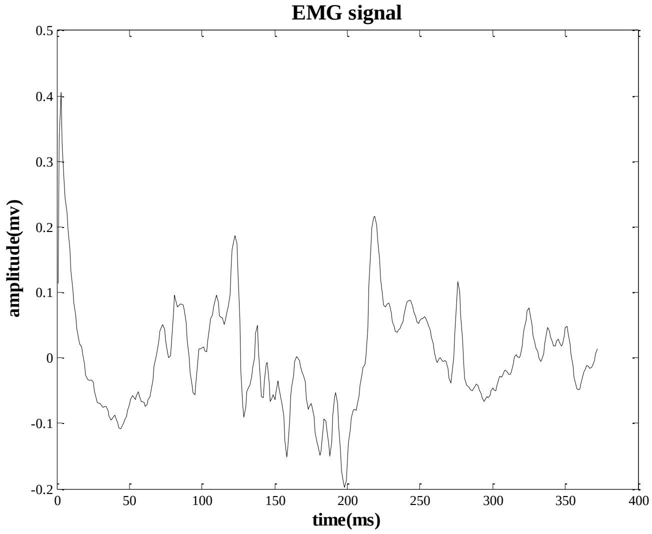


Fig.2. EMG Signal for hand open

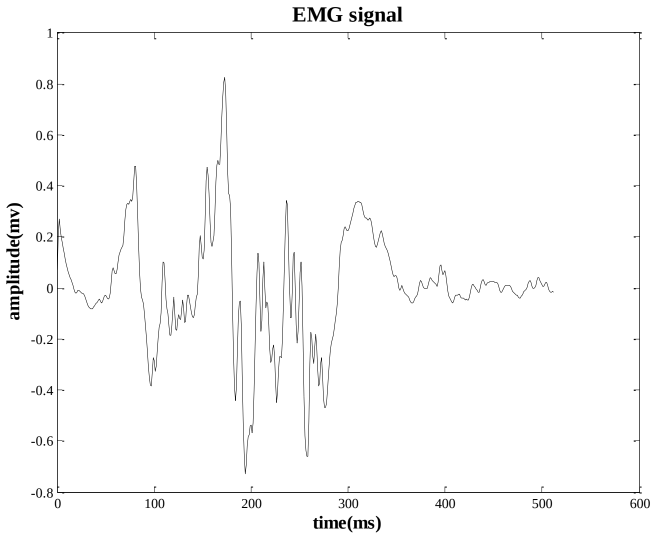


Fig.3. EMG Signal for wrist extension

4.1 SIMULATION RESULTS AND DISCUSSION

The original signal spaces is modelled in such a way that, different classes of hand movements are represented with minimum feature vectors and are still distinctly distinguishable. Three different feature vectors are extracted from the pre-processed EMG signals.

4.1.1 Autoregressive Coefficients:

Auto regressive coefficients of order four are extracted for all the eight classes of hand movements and the results are presented in the Table.2. Different hand movements can be identified based on those values of four auto regressive coefficients.

Table.2. Autoregressive Coefficients

MOVEMENTS	AR COEFFICIENTS			
Hand close	-2.4364	2.6442	-1.6197	0.4573
Hand open	-2.2168	2.1844	-1.3331	0.4078
Wrist flexion	-2.1940	1.9738	-1.0069	0.2598
Wrist extension	-2.5332	2.8102	-1.7290	0.4770
Thumbs up	-2.3941	2.5991	-1.6104	0.4604
Thumbs oppose	-2.5056	2.7063	-1.6072	0.4391
Pointing index	-2.1124	2.0157	-1.1514	0.3181
Ulnar deviation	-2.6588	3.0647	-1.9109	0.5229

4.1.2 Mean Frequency:

The mean frequency corresponding to eight classes of hand movements are extracted from the pre-processed EMG signals and the results are presented in Table.3. From the tabulated results it is seen that the hand, wrist and thumb movements mean frequency are distributed at equal intervals whereas pointing index and Ulnar deviation lies in the maximum and minimum frequencies.

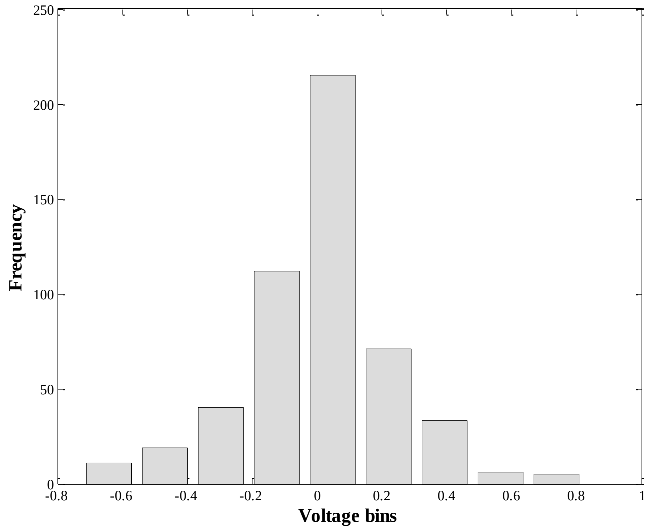
From the values obtained as mean frequency is used to find the corresponding hand movements.

Table.3. Mean Frequency for Eight Classes of Hand Movements

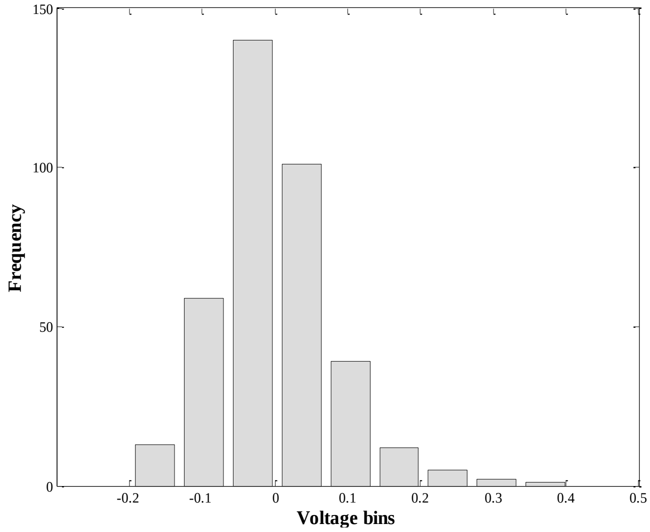
MOVEMENTS	MEAN FREQUENCY
Hand close	74.2074
Hand open	73.9951
Wrist flexion	65.3644
Wrist extension	63.3118
Thumbs up	77.6220
Thumbs opposite	65.0770
Pointing index	86.7386
Ulnar deviation	59.7719

4.1.3 EMG Histogram:

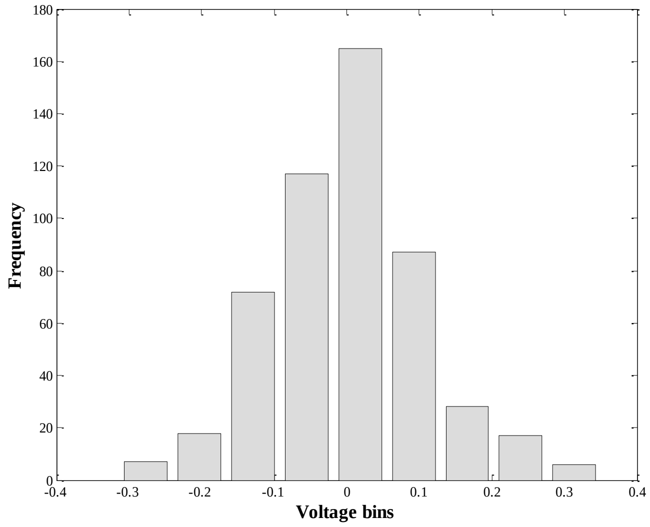
The pre-processed EMG signals are divided into nine symmetric voltage bins(X axis) and the frequency of occurrence of different amplitude values (Y axis) are calculated and plotted as a bar graph. The results for eight classes of hand movements are shown in plot1and plot2. In this work EMG histogram has the highest clarity among the available feature extraction techniques. Different hand movements can be easily found by observing the EMG histogram plots.



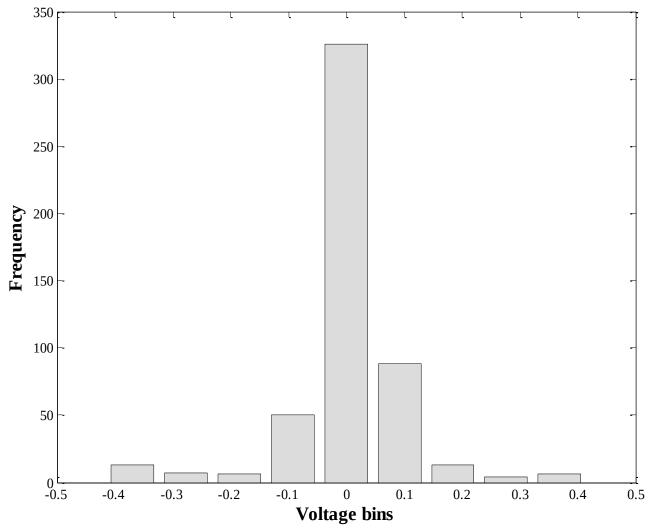
4(a). Wrist Extension



4(b). Hand Open

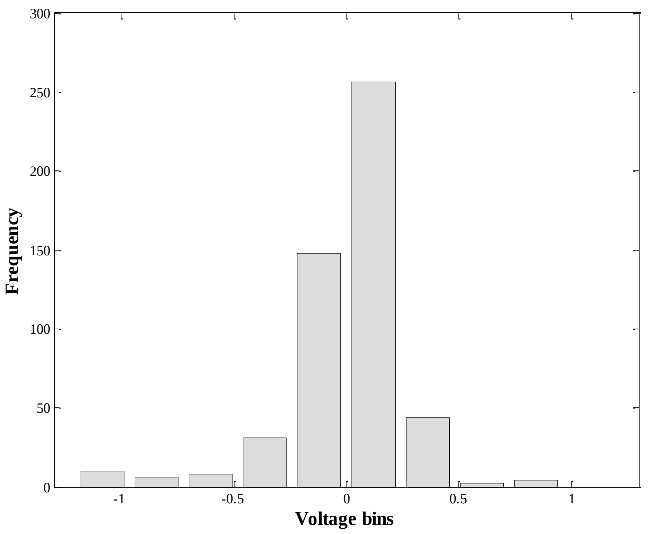


4(c). Hand Close

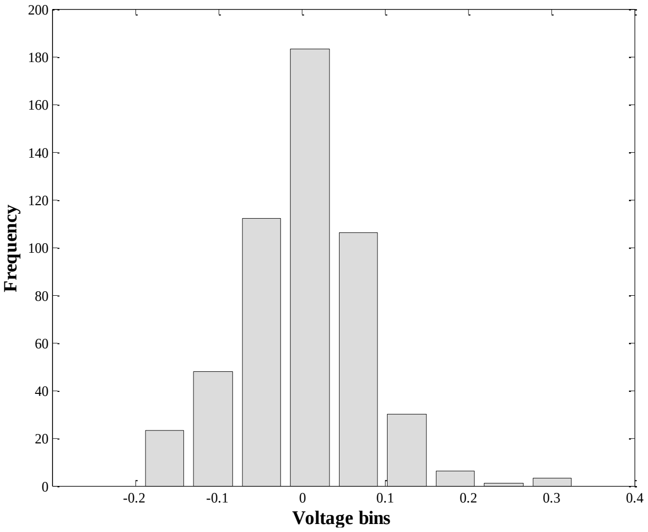


4(d). Wrist Flexion

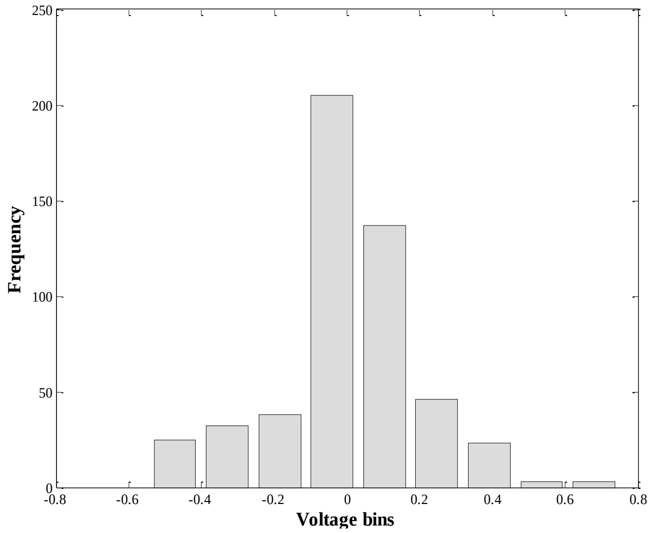
Fig.4. EMG Histogram plot1



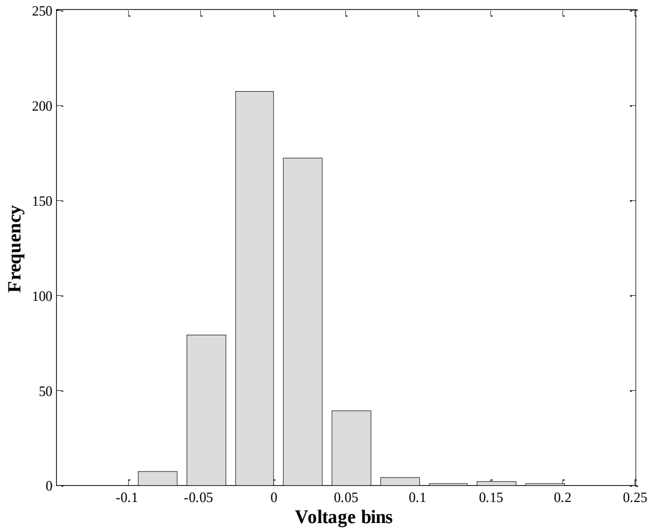
5(a). Ulnar Deviation



5(b). Thumbs Up



5(c). Thumbs Opposite



5(d). Pointing Index

Fig.5. EMG Histogram plot2

5. CONCLUSION

The work presented here considers eight classes of hand movements including hand open, hand close, Wrist extension, Wrist flexion, Pointing index, Ulnar deviation, Thumbs up, Thumb opposite to little finger and three feature extraction techniques, auto regressive modeling, mean frequency and EMG histogram were used. From the results it was seen that EMG histogram provided much better distinction between different classes of movements. So it is suggested that apart from four auto regressive coefficients, the feature vectors obtained from EMG histogram and mean frequency be combined and given as input to neural network. Multilayer perceptron (MLP) that uses gradient descent backpropogation algorithm for training could be used as a classifier because unlike support vector machine which is a binary classifier, the adaptability of multilayer perceptron is high when the numbers of classes are increased.

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REFERENCES

[1] Angkoon Phinyomark, Chusak Limsakul and Pornchai Phukpattaranont, "A Novel EMG Feature Extraction for Tolerance of Interference", *Journal of 13th Annual Symposium on Computational Science and Engineering,* pp. 407- 413, 2009.

[2] P.C. Doerschuk, D.E. Gustafson and A.S. Willsky, "Upper Extremity Limb Function Discrimination Using EMG Signal Analysis", *IEEE Transactions on Biomedical Engineering*, Vol. 30, No. 1 pp. 18-29, 1983.

[3] Edgard Lamounier and Alcimar Soares, "Virtual Prosthesis Control Based on Neural Networks for EMG Pattern Classification", *Journal of Intelligent Information System*, 2003.

[4] G. Hefftner, W. Zucchini and G.G. Jaros, "The Electromyogram (EMG) as a Control Signal for Functional Neuromuscular Stimulation - Part 1: Autoregressive Modeling as a Means of EMG Signature Discrimination", *IEEE Transactions on Biomedical Engineering*, Vol. 35, No. 4, pp. 230-237, 1988.

[5] Manfredo Atzori, et. al., "Building the Ninapro Database: A Resource for the Bio robotics Community", *IEEE International Conference on Biomedical Robotics and Biomechatronics*, pp. 1258-1265, 2012.

[6] Monson H. Hayes, "*Statistical Digital Signal Processing*," Pearson, Fourth Edition, 2007.

[7] P. Parker, K. Englehart and B. Hudgins, "Myoelectric Signal Processing for Control of Powered Limb Prostheses", *Journal of Electromyography and Kinesiology,* Vol. 16, No. 6, pp. 541-548, 2006.

[8] G.N. Saridis and T.P. Gootee, "EMG Pattern Analysis and Classification for a Prosthetic Arm", *IEEE Transactions on Biomedical Engineering*, Vol. 29, No. 6, pp. 403-412, 1982.