Portable EMG Data Acquisition Module for Upper Limb Prosthesis Application

Sidharth Pancholi and Amit M. Joshi, *Member, IEEE*

***Abstract*— Electromyography (EMG) signals are gaining popularity to develop the prosthetics. In this paper, an efficient multichannel EMG signal acquisition system has been proposed for upper limb prosthetic application. Various arm exercises have been performed to obtain EMG signals from five different arm muscles for the validation of developed hardware. The muscle's position has been selected by palpation method. Furthermore, the classification algorithms have been examined for seven different activities. Total 29 subjects have been chosen (25 intact and four Amputees) to acquire the EMG data by these activities. To classify the recorded EMG data set, nine time domain and seven frequency domain features have been extracted. A comparative analysis of different classifiers is presented for different muscle position of electrodes. The signal processing and classification algorithms have been processed in MATLAB 2016a. The accuracy of classification ranges for different classification algorithms from 57.69% to 99.92% for all subjects.**

***Index Terms*— Acquisition, classification, LDA, k-NN, prosthetic, sEMG, SVM, QDA.**

I. INTRODUCTION

ELECTROMYOGRAPHY (EMG) signals are becoming one of the vital biological parameters which have wide range of applications in biomedical engineering, prosthetic device development, human machine interaction (HMI) and rehabilitation devices [1]. The electromyogram (EMG) is a bio-potential signal which is acquired by electrodes through a muscle fiber skin to observe the muscle activity. It is also associated with neural signal, sent from spinal cord to muscles [2], [3]. The voltage range of EMG signal is 50 uV to 100 mV and the frequency is varied from 10 Hz to 500 Hz for surface Electromyography(sEMG) [4]. The sEMG signal is acquired by applying noninvasive electrodes.

Many people lost their limbs due to accidents; some people don't have their limbs by birth. These people cannot perform their daily routine work such as holding or moving an object, eating etc. One solution for these amputees is EMG based artificial limb or Prosthetic device [5]–[8]. EMG based prosthetic device uses EMG signal to control the action of artificial limb with the help of motor [9]. This device includes data acquisition module, machine learning algorithm for EMG pattern recognition and mechanical structure for controlling. Although many signal processing software and high level EMG signal acquisition systems are available in the market they are expensive (e.g. NeXus-10, BIONOMADX). There are systems developed, based on instrumentation amplifiers (INA2141 or INA128), are difficult in design and provide time delay in signal processing for multichannel acquisition [10]. A four channel EMG acquisition system was developed based on instrumentation amplifier (INA326) and operational amplifiers for initial signal smoothening. However each channel requires an individual INA326 and operational amplifiers (AD8603) for conditioning which makes the system cumbersome and complex. The system based on instrumentation amplifiers require multiplexer to combine the data from multiple channels into single channel for wireless transmission, which makes system expensive. Active electrode based system also proposed but each channel requires separate cable and interfaces this make system expensive. The power consumption of this kind of acquisition system is also very high [11]. System based on ADS1294 IC has utilized up to four channels EMG signal acquisition in the paper [12]. Since it has only 4 differential inputs, therefore it can acquire less muscle activities at a time. A small EEG/EMG recorder was developed in the paper [13]. It required separate ADC which has only 12 bit resolution, and fixed sampling rate. A FPGA based hybrid EMG signal acquisition system was also proposed for effective EMG measurement and separation processing. The main drawback of the system was delay time [14], [15]. In this paper, a multichannel system is being proposed for prosthetic device, which is wireless, cost effective and compact in design. The prototyping cost of this system is approx. INR 5000 (78 USD) which includes; analog front end, DSP processor, passive components, Electrodes or leads, PCB designing and wireless module.

The pattern recognition for EMG consists of two parts, features (attributes) extraction and classification (machine learning). In the feature extraction process, the dimensionality of the sEMG dataset is reduced to form a feature vector. This is helpful to retrieve the useful information and also useful to remove an unwanted data. The accuracy and classification time in pattern recognition depend upon these features [15]. The features are extracted through the segmentation of sEMG signal rather than extracting through individual sample in order to keep structural information.

There are evident gaps between devices and control approaches of prosthetic limb. The large data set is required for effective pattern classification and if the number of classes increases then huge amount of training data is needed to

Manuscript received November 30, 2017; accepted February 19, 2018. Date of publication February 27, 2018; date of current version March 22, 2018. The associate editor coordinating the review of this paper and approving it for publication was Prof. Octavian Postolache. *(Corresponding author: Sidharth Pancholi.)*

The authors are with the Department of Electronics and Communication Engineering, Malaviya National Institute of Technology, Jaipur 302017, India (e-mail: sid.2592@gmail.com; amjoshi.ece@mnit.ac.in).

Digital Object Identifier 10.1109/JSEN.2018.2809458

improve classification results. In this study, a visual feedback mechanism is used for the training of amputees to improve cognitive abilities of brain. The perception of the missing limb is still attached to the body, is called phantom limb. Almost 60% to 80% amputees feel this sensation of phantom limb.

Sometimes, this sensation is painful. Muscles activation signals usually present in the residual part of the arm for the amputated limb. Brain always looking for the signals from the amputated part, However visual feedback system is introduced for reducing the many chronic neurological disorders related to the phantom limb pain [16]–[19]. This visual feedback system can be utilized in improvement of pattern classification of the missing limb for prosthetic application [20]–[22].

Proposed device is validated for arm activity recognition, where 25 healthy subjects (15 Male and 10 Female) and 4 amputees have been considered for EMG data acquirement. In the subsequent stage, machine learning strategies have been used for recognition of different arm exercises. Five muscles have been chosen for acquiring EMG data and 16 features (time and frequency domain) have been calculated. Further, EMG data have been classified for different arm activities including all feature sets as well as an individual feature set of each channel.

In the proposed work, a bio-potential acquisition module and a java based GUI is developed to display the real time data. The hardware module is wireless, portable, power efficient and has eight channels. Section II presents the system architecture for the proposed system. Section III emphasis on proposed data acquisition model. Section IV describes overlapping windowing technique Section V covers feature extraction process, while section VI explains the EMG pattern classification. Results are discussed in Section VII and conclusion is derived in Section VIII.

II. System Architecture

The acquisition module of EMG signal comprises of different parts such as electrodes, differential Amplification, antialiasing filter, conversion of analog signal into digital signal and display system. Electrodes or leads act as a channel between muscle tissue skin and inputs of amplifier [17].

The hardware module is based on ADS1298 IC (Texas Instruments) and ARM cortex M4 series processor, shown in Fig. 1.

The ARM cortex M4 processor is widely used in DSP applications; it is cost effective and has low power consumption. GUI displays real time EMG signal and also provides the data in requisite format so that the signal of every channel can be analyzed. In the proposed system, the important parts of acquisition module (differential amplifier, filtering, and analog to digital converter) are in a single chip (ADS1298). For the overvoltage and surge protection each channel of the system has been featured with the protection circuit, which is shown in Fig.2. In this protection circuit schottky diodes and a second order passive low pass filter have been used. Schottky diodes have high switching speed and the low pass filter has cut-off frequency is 1 KHz.

There are several benefits of such types of bio-potential acquisition systems [18]:

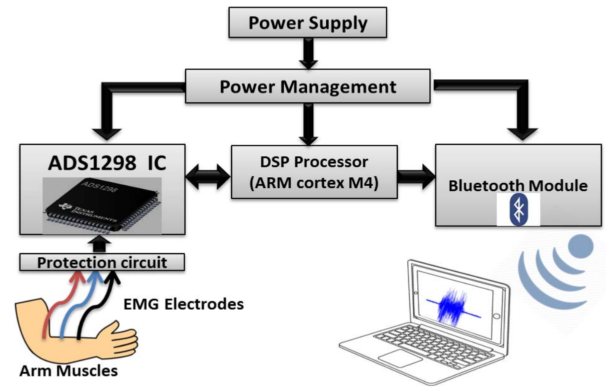

Fig. 1. Block diagram representation of proposed system.

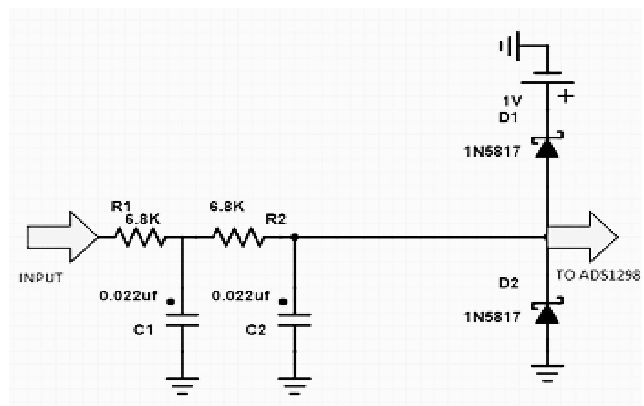

Fig. 2. Over voltage protection circuit.

a) The system has extremely low power consumption in order of 0.75mW/channel.
b) The selection of sampling frequency may be done as per necessity.
c) A safety feature is also provided for Lead off Detection.
d) Programmable gain provides the flexibility to select appropriate gain.
e) System is smaller in size that can be used as a wearable device in future.

For the wireless communication Bluetooth module has been used of 2.4 GHz frequency ISM Band. This module provides optimal balance between power demand and transmission in the short range communication and use Gaussian frequency shift keying modulation. The operating temperature of this module is $-20°C$ to $+74°C$. Further, a java based GUI is developed which shows real time data. The signals are acquired at 4000 samples/sec on Intel core i3 computer with 2.54 GHz and 3.80 RAM.

III. Proposed Data Acquisition Protocol

The impedance of skin should be less in order to acquire the meaningful information from the EMG signal. Therefore, the skin of subject should be cleaned before acquisition of EMG signal. Dead skin cells and hairs must be removed from the skin surface. For this, abrasive gel should be used to remove the dead skin [23], [24]. Also moisture content can weaken the signal, so there should not be any sweat drops

Fig. 3. Amputee 1: Wrist disarticulation.

TABLE I
MUSCLE POSITIONS FOR ACQUISITION OF EMG SIGNAL

S. No.	Age	Gender	Height	Weight	Reason for Amputation
1.	32	Male	172 cm	79 Kg	Accident
2.	44	Male	168 cm	88 Kg	Cancer
3.	52	Male	177 cm	77 Kg	Accident
4.	38	Male	171 cm	90 Kg	Accident

on the skin. Main procedure that has been carried out for acquisition of signal from surface is described below:

Total 25 healthy subjects (10 females and 15 males) and 4 Amputees have been enlisted for acquisition Remaining arm percentage is calculated as the ratio between the length of amputated arm and the length of contralateral forearm from the elbow. All the amputees are wrist disarticulated; Fig. 3 shows the picture of amputated hand of subject 1. Each amputee is requested to give information about their age, gender, height, weight and reason of amputation that is shown in Table I.

a) Subsequently, subjects were asked to sit at a desk on laboratory chair. Seven upper-limb activities (exercises) have been performed five to six times for normal subjects and four time for amputees: i. Hand open (HO), ii. Hand closed (HC), iii. Wrist extension (WE), iv. Wrist flexion (WF), v. Soft gripping (SG), vi. Medium gripping (MG), and vii. Hard gripping (HG), shown in Fig 4.
b) The training has been provided to overcome cognitive effort prior to acquisition.
c) A band pass filter of frequency range of 20 Hz to 500 Hz and an amplification gain 12x have been applied. Sampling frequency is fixed at 4000 Hz.
d) The EMG dataset of the right arm exercise has been prepared through five muscle positions, using bipolar Ag-AgCl (Silver – silver chloride) electrodes 2 mm diameter spaced 12 to 36 mm apart. Muscles positions of electrode placement are shown in Table II.

The Intact subjects were asked to perform each experiment, with their right hand in comfortable position. While amputees asked to execute movements as naturally as possible with both the limbs missing and intact, by looking in the mirror and normally without any mirror. Mirror was used to create reflection of the undamaged limb, it makes a perception in the subject mind that both arm is doing same exercise. This create visual feedback to the human brain, this is shown in Fig.5. Five muscles have been chosen for the study using palpation method [25].

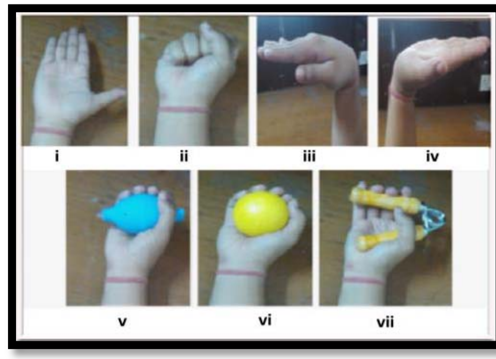

Fig. 4. Performed Activities. (i) Hand Open. (ii) Hand Close. (iii) Wrist Flexion. (iv) Wrist Extension. (v) Soft Gripping. (vi) Medium Gripping. (vii) Hard Gripping.

TABLE II
MUSCLE POSITIONS FOR ACQUISITION OF EMG SIGNAL

S.No.	Channels	Muscles Name
1.	Channel 1	Extensor Carpi Ulnaris Muscle
2.	Channel 2	Extensor Digitorum Communis muscle
3.	Channel 3	Extensor Carpi Radialis Longus muscle
4.	Channel 4	Flexor Farpi Radialis Muscle
5.	Channel 5	Biceps Brachii Muscle
6.	**Ref. Electrode**	**Elbow**

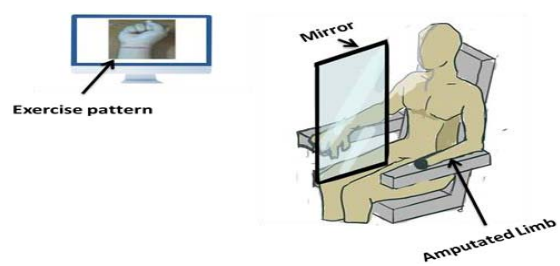

Fig. 5. Data acquisition setup for the amputees.

IV. EMG DATA SEGMENTATION

There is a need for data segmentation when data is processed for the feature extraction; in these segmentations data is considered as quasi- stationary. Two main parts should be considered properly in order to design appropriate data segmentation strategy; namely the window length (segmentation length) and the amount of overlapping between two consecutives segments. The segmentation window length has trade-off between classifier accuracy and classification response time. As the segmentation length increases the classification performance improves, on the other hand classification length must be small enough to satisfy the hard real time performance of the myoelectric control. Many experiments have been carried out by researchers with different segment length. In the literature, a delay of 150 $\sim$ 250 ms interval is considered for EMG activity segmentation [26]. In the presented work, window size has been taken of 250 ms (1000 samples) with window shift of 25 ms, shown in Fig. 6.

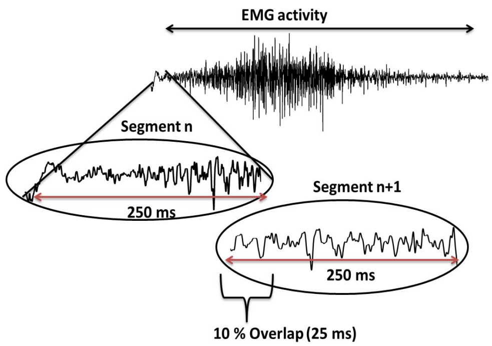

Fig. 6. Feature extraction process by applying overlapping window technique.

TABLE III
EXTRACTED FEATURES FOR THIS STUDY

S.No.	Time Domain Features (TDM)	S.No.	Frequency Domain Features (FDM)
1.	Integrated EMG (IEMG)	**1.**	Mean Frequency (MNF)
2.	Mean Absolute Value (MAV)	**2.**	Median Frequency (MDF)
3.	Modified mean absolute value type 1 (MMAV 1)	**3.**	Peak frequency Power (PKF)
4.	Modified mean absolute value type 2 (MMAV 2)	**4.**	Mean frequency Power (MFP)
5.	Wilson Amplitude (WAMP)	**5.**	Frequency Median (FMD)
6.	Root Mean Square (RMS)	**6.**	Frequency Mean (FMN)
7.	Waveform Length (WL)	**7.**	Modified Frequency Median (MFMD)
8.	Zero Crossing (ZC)		
9.	Simple Square Integral (SSI)		

V. FEATURE EXTRACTION

Various noise and artifacts are likely to be merged along with EMG signals at the time of acquisition, thus the required information remains mixed inside the raw EMG signal. The use of these types of signals directly into the classification process decreases the classifier's efficiency, so there is a need to extract useful information or features from raw EMG signal. The set of features has to be applied by naming or labeling for supervised machine learning. This is called feature vector preparation, which is applied into the classification process. A useful feature vector must contain the valuable information and remove the irrelevant information (noise) [27], [28]. Several EMG features have been proposed by the scientists to increase the accuracy of classification. In this paper two feature group, time and frequency domain, have been examined, shown in Table III [29], [30].

There are some unwanted elements in feature matrix, which are not required in the processing; these parameters or attributes can be removed by feature selection techniques. Dimensionality reduction of feature matrix is a method to reduce the dimension of an original feature vector, while maintaining the information of discrimination and eliminating the remaining useless data. This reduces the time of computation for data classification [31]–[34]. In the proposed work, the feature selection is carried out by manual channel selection method. In this work, total 5 channels data has been considered for the classification and subsequently the classification accuracy of each channel has been calculated.

VI. EMG PATTERN CLASSIFICATION

In the feature extraction process EMG signal represents as a Feature vector, which is fetched as an input to the classifier. As EMG signals is not directly applied to the classifier, due to the randomness of the EMG signal and also larger dimension. The Electromyogram classification process mainly depends on the quality of the extracted features. Feature extraction step in the classification, enhances the concentration of information of the signal [35], [36]. In the presented work, different classification techniques have been used to understand which classifier has better performance for the activity classification. Six different types of machine learning algorithms have been chosen for comparative analysis of classification: k-nearest neighbors (k-NN), linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), Support Vector Machine (SVM), Random Tree (RT) and Random Forest (RF). In the k-NN classification predication of the test data is evaluated by measuring distance from the training samples. In this work, to determine the class of the testing data Euclidean distance is calculate and $k = 10$ has been considered. Classification through LDA shows more robustness while not being trained iteratively compared to SVM, KNN, RT and RF. In the LDA classification technique discrimination function is used to determine the class and each class is considered an identical.

The classification algorithm of QDA can be realized as a more common version of LDA, which splits the classes by a quadratic plane instead of linear plane, as executed in LDA [24]–[27]. In the QDA covariance matrix is calculated for each class separately. Both LDA and QDA are interchangeable and perform well when the feature size is large. Random forest is a Decision tree based classifier which is composed of a number of decision tree classifier. Random forest classifier shows better result of classification, however it requires larger time than LDA and QDA [37]. SVM classification consists of a hyper surface in the space that is used for classification of the data set. The performance of classifier would be higher when the margin of hyper surface from nearest training points of all classes is greater. It is initially design to classify binary classes but many approaches introduced to determine multiclass problems also [38]. In this work, RBF (Radial Basis Function) has been used as SVM kernel. Random tree classifier is sort of decision tree classification technique, which takes less time than random forest. Classifier data set has been divided into training data set (50% of all data), testing data set (30% of all data) and validation data set (20% of all data). For the classification of amputee's data, training Data used which has obtained by visual feedback and testing data has taken normally (without visual feedback).

VII. RESULT AND DISCUSSION

There are different external and internal causes of low frequency noise that can reduce the quality of EMG signal

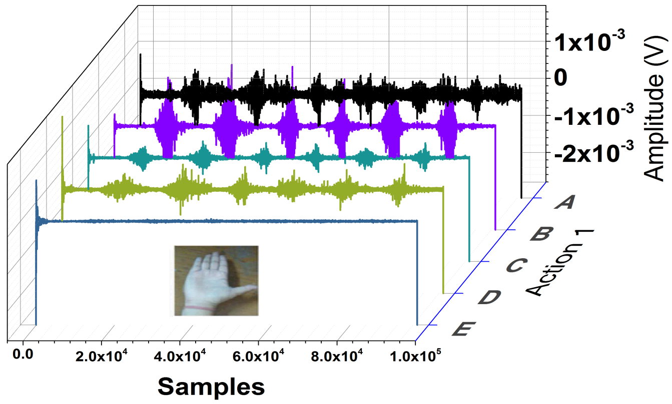

Fig. 7. All 5 channels wave form representation for Hand Open (HO) activity: A (channel 1), B (channel 2), C (channel 3), D (channel 4), and E (channel 5).

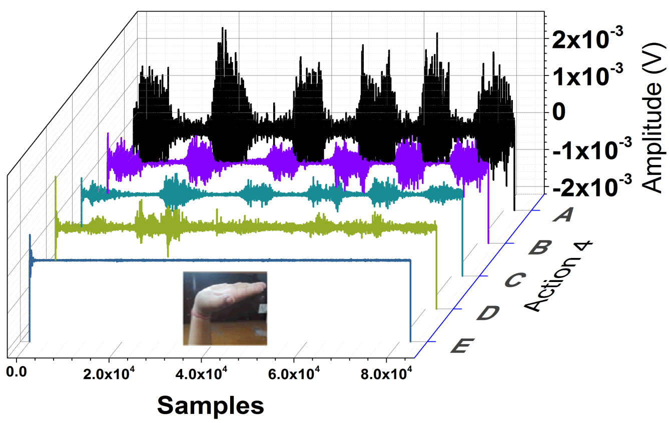

Fig. 8. All 5 channels wave form representation for Wrist Extension (WE) activity: A (channel 1), B (channel 2), C (channel 3), D (channel 4), and E (channel 5).

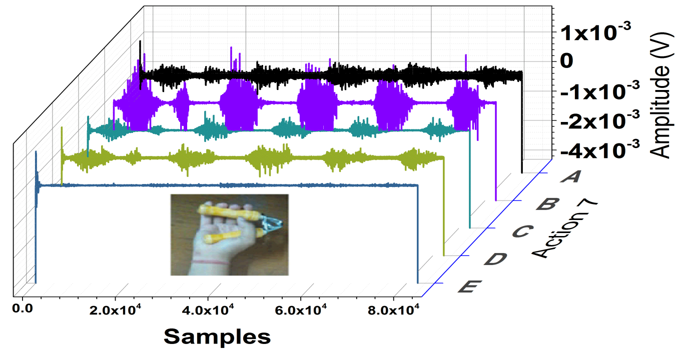

Fig. 9. All 5 channels wave form representation for Hard Gripping (HG) activity: A (channel 1), B (channel 2), C (channel 3), D (channel 4), and E (channel 5).

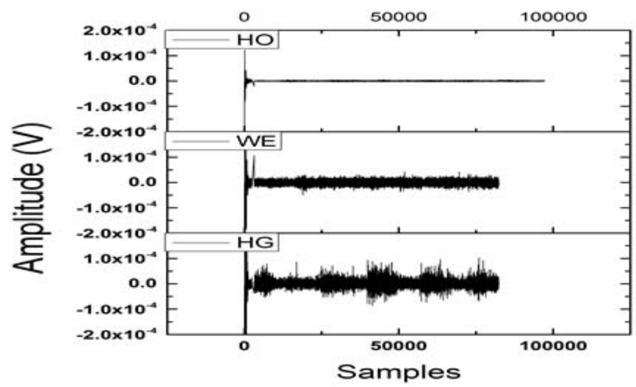

Fig. 10. Channel 5 (Biceps Brachii muscle) EMG signal for HO, WE and HG activities.

during acquisition. The two external sources of noise, EMG leads motion artifact and power line interference. These two noises can be almost removed with suitable circuit design. The two external noise sources generate in the electronics circuitry of the amplification system, the skin-electrode interface (electrochemical noise) and thermal noise artifact.

Combination of these two noises produce the baseline noise which is sensed whenever a sensor is appended to the skin. The movement artifact noise is generated at Electrode-skin interface. This is due to: (a) the muscle movement occurs below the skin [39], and (b) when a force impulse moves via muscle and skin underlying the sensor causing a movement at the electrode skin interface [40], [41]. The consequential time-varying voltage is formed across the two electrodes, which is the main concern of noise sources and needs attention. In our preliminary work, it has been analyzed that Butterworth band pass filter of 6th order has fast settling time and it exhibits less overshoot. So this filter is applied for the removing high frequency noise, base line error and motion artifacts of 20 Hz to 500 Hz range. Furthermore, three different activities waveform: activity HO, activity WE, activity HG, have been presented for all 5 channels for analysis purpose, Fig.7 to Fig. 9 respectively. EMG signal is continuously generated in channel 1 (Extensor Carpi Ulnar muscle) because this muscle is always stretched in rest condition for activity WE and activity HG. By Performing activity HG, EMG signal of larger amplitude has been produced in the channel 2 (Extensor Digitorum Communis muscle). The rest condition of activity WE and WF is same and produce continuous EMG signal in channel 4 (Flexor Farpi Radialis Muscle). However, the channel 1 produces larger amplitude for these two activities. EMG signal is generated on the channel 5 (Biceps Brachii muscle) by performing gripping activities, shown in Fig. 10. The Amplitude of EMG signal varies with respect to intensity of gripping. Harder the gripping, greater would be the amplitude of EMG signal. In the next step for classification, total 80 features (5 channels), are considered for all 29 subject data. Where, the Random Forest, k-NN and Random tree classifiers have shown better results.

The classification results through LDA and QDA are also satisfactory. Further classification accuracy has been calculated by each channel (16 features each channel). The channel 5 has better performance as compare to other channels, shown in Fig 11. The total arm activities have been divided into two categories. Activities HO, HC, WF, WE are included in first category, rest of three gripping activities (SG, MG, HG) are included in second category. Same procedure is followed on these two categories separately as explained above. The classification performance for both the category is shown in Fig. 12 and Fig. 13 respectively. The classification

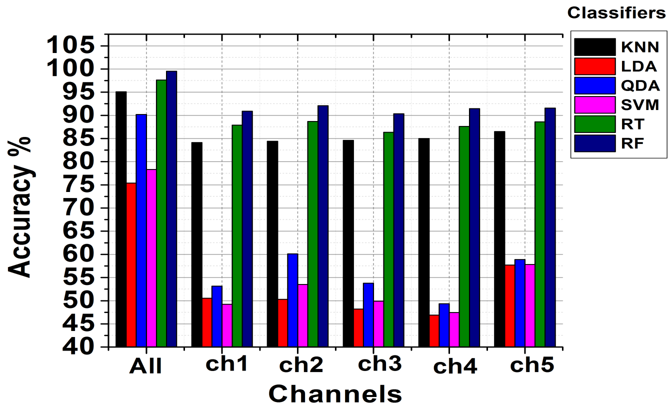

Fig. 11. Classification accuracy Comparison for different classification algorithm including all performed activities: All (All channels), ch 1 (channel 1), ch 2 (channel 2), ch 3 (channel 3), ch 4 (channel 4), and ch 5 (channel 5).

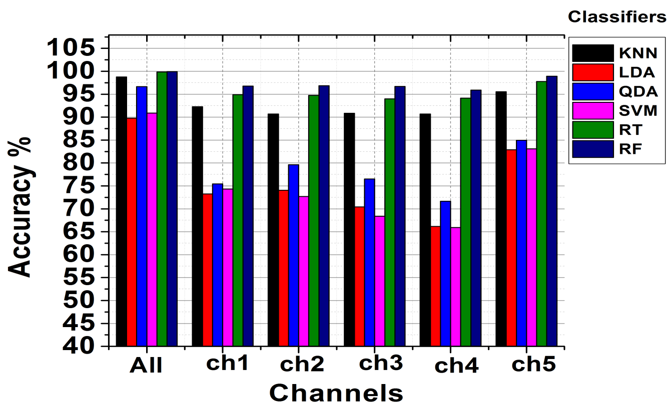

Fig. 12. Classification accuracy Comparison for different classification algorithm including HO, HC, WE and WF activities: All (All channels), ch 1 (channel 1), ch 2 (channel 2), ch 3 (channel 3), ch 4 (channel 4), and ch 5 (channel 5).

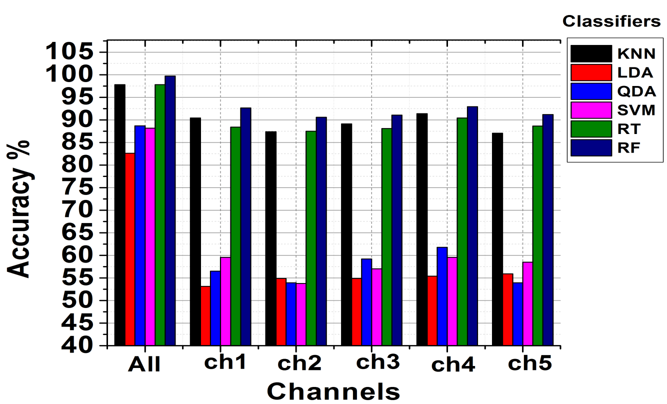

Fig. 13. Classification accuracy Comparison for different classification algorithm including SG, MG and HG activities: All (All channels), ch 1 (channel 1), ch 2 (channel 2), ch 3 (channel 3), ch 4 (channel 4), and ch 5 (channel 5).

accuracy is increased for each category. The contribution of channel 5 in classification accuracy is maximum for first category and contribution of channels 1 and 4 are maximum in second category. The classification accuracy of first category is better than second category. The activities performed in first category are quite different from each other's, but the

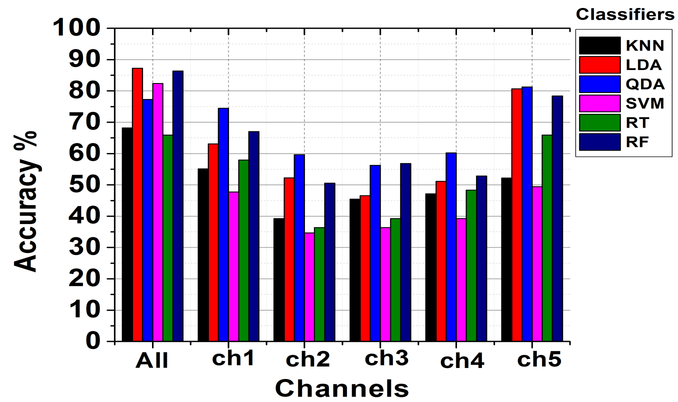

Fig. 14. Classification accuracy Comparison for different classification algorithm including all activities for prosthetic: All (All channels), ch 1 (channel 1), ch 2 (channel 2), ch 3 (channel 3), ch 4 (channel 4), and ch 5 (channel 5).

activities of second category resemble each other to some extent. By dividing the total activities into two categories, the classification accuracy of discriminant analysis (LDA, QDA) is improved. These classification algorithms (LDA, QDA) are less complex, simpler to implement and require less time in training process [36]–[38]. LDA classifiers increase its performance when the huge number of features is used [39]. LDA with 5 channels has shown better classification accuracy when activities are quite different. For all Activities classification, the accuracy ranges corresponds all channels 99.54% maximum for random forest and minimum 75.38% for LDA classifier. In case of individual channels, channel 2 and channel 5 shows better classification performance. Channel 2 and channel 5 both shows maximum performance in case of random forest classifier which is 92.07% and 91.56% respectively. However channel 5 has minimum of 57.68% for LDA classifier.

A. Category 1 EMG Pattern Classification

In this category the classification accuracy has been improved for all the classification algorithms. Some of HO activities misclassified and predicted as HC activity and vice-versa. In case of all channels all the algorithms shows better classification performance maximum (99.92%) achieved by random forest classifier and minimum (89.76%) by the LDA. classifiers. So for the myoelectric control these kinds of activity can be easily classified in the short time.

B. Category 2 EMG Pattern Classification

In this category, different gripping activity has been performed. Maximum classification accuracy is achieved by Random forest (99.70%) and minimum by LDA (82.63%). Although, less amplitude signal is generated on the channel 5 (Biceps Brachii muscle) in comparison of other channels, by performing all activities but it has shown better classification results.

C. EMG Pattern Classification for Amputees

The classification performance is evaluated separately for Amputee's data, highest accuracy has been achieved by LDA

TABLE IV
CONFUSION MATRIX FOR HEALTHY SUBJECTS WITH RANDOM FOREST CLASSIFIER

True / Pred.	HO	HC	WF	WE	SG	MG	HG
HO	1584	0	0	0	10	8	0
HC	4	3378	0	0	4	0	2
WF	0	0	2316	0	0	0	0
WE	0	2	0	1352	0	4	0
SG	8	0	0	0	1234	0	4
MG	2	2	0	0	8	1538	10
HG	12	2	0	0	10	10	1698

TABLE V
CONFUSION MATRIX FOR AMPUTEES WITH RANDOM FOREST CLASSIFIER

True / Pred.	HO	HC	WF	WE	SG	MG	HG
HO	86	4	0	0	10	8	0
HC	0	71	0	0	1	2	4
WF	0	0	73	0	0	1	0
WE	0	0	1	57	0	1	0
SG	2	0	0	0	47	18	2
MG	0	2	0	0	18	50	4
HG	1	3	2	0	3	4	60

classifier with all five muscles signals, and random forest classifier has better performance. Channels 5 (Biceps Brachii Muscle) has performed better for different EMG patterns. Lowest classification patterns detected by the SVM classifier. When training models are prepared with normal data then classification accuracy has been achieved at most 78% with random forest classifier and 73% by LDA. In the case of training model prepared with visual feedback setup and tested it with normal data, the classification accuracy significantly improved by 87% with LDA and by 85% with Random forest as shown in Fig. 14. In the both the cases, healthy subjects and the amputees the random forest classifier has performed satisfactory and consistent. Confusion matrix of the Random forest classifier for both the cases healthy and amputees' pattern classification have been shown in Table IV and Table V respectively. Even the feature matrix size is less but it consume more time than other classification algorithms.

TABLE VI
COMPARISON OF COST WITH OTHER AVAILABLE DEVICES

S.No.	Product	Channels	Price in commercial market
1.	PhysioLab [39]	1	$90 ($90x8) for 8 channels
2.	MyoWare Muscle Sensor [40]	1	$37.95 ($37.95x8) for 8 channels
3	NeXus-10-mkii [41] (Include software cost)	4	$2900
4.	**Proposed device**	**8**	**Prototyping cost ($78)**

VIII. CONCLUSION

The paper presents a wireless and compact EMG data acquisition module for prosthesis application. This system has advantage of online visualization of signal during EMG activity and also passes the data in required format (.xls, .txt and .csv etc.) for the offline processing.

The proposed system has capability to record several EMG based activities for analysis purpose. In this paper, five channels have been considered for EMG data acquisition.

In the classification process, the accuracy has been calculated for all five channels as well as each available channel. During feature extraction process, total 16 features have been selected for the feature matrix preparation. The k-NN and Random forest classifier have better performance in case of smaller feature vector size. However, LDA has excellent performance for larger feature vector size. The results show that the proposed system has potential to recognize the real time activity for the upper limb arm. Cost comparison has been shown in the Table VI.

REFERENCES

[1] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, "Techniques of EMG signal analysis: detection, processing, classification and applications," *Biol. Procedures Online*, vol. 8, no. 1, p. 11, 2006.
[2] R. Merletti and L. R. Lo Conteab, "Surface EMG signal processing during isometric contractions," *J. Electromyogr. Kinesiol.*, vol. 7, no. 4, pp. 241–250, 1997.
[3] D. Stashuk, "EMG signal decomposition: How can it be accomplished and used?" *J. Electromyogr. Kinesiol.*, vol. 11, no. 3, pp. 151–173, 2001.
[4] D. Farina and R. Merletti, "A novel approach for precise simulation of the EMG signal detected by surface electrodes," *IEEE Trans. Biomed. Eng.*, vol. 48, no. 6, pp. 637–646, Jun. 2001.
[5] P. C. Doerschuk, D. E. Gustafon, and A. S. Willsky, "Upper extremity limb function discrimination using emg signal analysis," *IEEE Trans. Biomed. Eng.*, vol. BEM-30, no. 1, pp. 18–29, Jan. 1983.
[6] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *J. Rehabil. Res. Develop.*, vol. 48, no. 6, pp. 643–659, 2011.
[7] C. A. Avizzano, E. Ruffaldi, and M. Bergamasco, "A novel wearable biometric capture system," in *Proc. 22nd Medit. Conf. Control Autom. (MED)*, Jun. 2014, pp. 351–355.
[8] J. Z. Liu *et al.*, "Accessory hardware for neuromuscular measurements during functional MRI experiments," *Magn. Reson. Mater. Phys., Biol. Med.*, vol. 13, no. 3, pp. 164–171, 2002.
[9] C. Castellini and P. van der Smagt, "Surface EMG in advanced hand prosthetics," *Biol. Cybern.*, vol. 100, no. 1, pp. 35–47, 2009.

[10] A. Pradhan *et al.*, "Acquisition and classification of EMG using a dual-channel EMG biopotential amplifier for controlling assistive devices," in *Proc. IEEE Annu. India Conf. (INDICON)*, Bengaluru, India, Dec. 2016, pp. 1–5.

[11] W. Guo, X. Sheng, H. Liu, and X. Zhu, "Development of a multi-channel compact-size wireless hybrid sEMG/NIRS sensor system for prosthetic manipulation," *IEEE Sensors J.*, vol. 16, no. 2, pp. 447–456, Jan. 2016.

[12] D. H. de Oliveira and A. Balbinot, "Portable electrocardiograph based on the integrated circuit ADS1294 using an Android application as interface," *Health Technol.*, vol. 5, no. 2, pp. 147–154, 2015.

[13] S. Di Pascoli, D. Puntin, A. Pinciaroli, E. Balaban, and M. Pompeiano, "Design and implementation of a wireless in-ovo EEG/EMG recorder," *IEEE Trans. Biomed. Circuits Syst.*, vol. 7, no. 6, pp. 832–840, Dec. 2013.

[14] Y.-H. Hsueh, C. Yin, and Y.-H. Chen, "Hardware system for real-time EMG signal acquisition and separation processing during electrical stimulation," *J. Med. Syst.*, vol. 39, p. 88, Sep. 2015.

[15] H. Huang, P. Zhou, G. Li, and T. A. Kuiken, "An analysis of EMG electrode configuration for targeted muscle reinnervation based neural machine interface," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 1, pp. 37–45, Feb. 2008.

[16] C.-W. Hsu and C.-J. Lin, "A comparison of methods for multiclass support vector machines," *IEEE Trans. Neural Netw.*, vol. 13, no. 2, pp. 415–425, Mar. 2002.

[17] S. M. Khoddami, N. N. Ansari, and S. Jalaie, "Review on laryngeal palpation methods in muscle tension dysphonia: Validity and reliability issues," *J. Voice*, vol. 29, no. 4, pp. 459–468, 2015.

[18] *ADS129x Low-Power, 8-Channel, 24-Bit Analog Front-End for Biopotential Measurements, Datasheet SBAS459K*, Texas Instrum., Dallas, TX, USA, Jan. 2010

[19] C. Cipriani *et al.*, "Online myoelectric control of a dexterous hand prosthesis by transradial amputees," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 3, pp. 260–270, Jun. 2011.

[20] J. J. A. Mendes, Jr., M. B. Pires, S. Okida, and S. L. Stevan, "Robotic Arm activation using surface electromyography with LABVIEW," *IEEE Latin Amer. Trans.*, vol. 14, no. 8, pp. 3597–3605, Aug. 2016.

[21] L. H. Smith, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "Determining the optimal window length for pattern recognition-based myoelectric control: Balancing the competing effects of classification error and controller delay," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 2, pp. 186–192, Apr. 2011.

[22] A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 40, no. 1, pp. 1–12, Jan. 2010.

[23] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Syst. Appl.*, vol. 39, pp. 7420–7431, Jun. 2012.

[24] W. Houjie, G. Jin'an, and F. Hao, "Portable biopotential signal acquisition system of ADS1298 anolog front-end," *Microcontrollers Embedded Syst.*, vol. 2, p. 012, Feb. 2012.

[25] M. A. Oskoei and H. Hu, "Myoelectric control systems—A survey," *Biomed. Signal Process. Control*, vol. 2, no. 4, pp. 275–294, 2007.

[26] D. Farina *et al.*, "The extraction of neural information from the surface EMG for the control of upper-limb prostheses: Emerging avenues and challenges," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 4, pp. 797–809, Jul. 2014.

[27] F. Haque, M. Nancel, and D. Vogel, "Myopoint: Pointing and clicking using forearm mounted electromyography and inertial motion sensors," in *Proc. ACM Conf. Human Factors Comput. Syst.*, 2015, pp. 3653–3656.

[28] S. Benatti *et al.*, "A versatile embedded platform for EMG acquisition and gesture recognition," *IEEE Trans. Biomed. Circuits Syst.*, vol. 9, no. 5, pp. 620–630, Oct. 2015.

[29] C. J. De Luca, L. D. Gilmore, M. Kuznetsov, and S. H. Roy, "Filtering the surface EMG signal: Movement artifact and baseline noise contamination," *J. Biomech.*, vol. 43, no. 8, pp. 1573–1579, 2010.

[30] E. Gokgoz and A. Subasi, "Effect of multiscale PCA de-noising on EMG signal classification for diagnosis of neuromuscular disorders," *J. Med. Syst.*, vol. 38, p. 31, Apr. 2014.

[31] J. Winslow, P. L. Jacobs, and D. Tepavac, "Fatigue compensation during FES using surface EMG," *J. Electromyogr. Kinesiol.*, vol. 13, no. 6, pp. 555–568, 2003.

[32] T. Keller, A. Curt, M. R. Popovic, A. Signer, and V. Dietz, "Grasping in high lesioned tetraplegic subjects using the EMG controlled neuroprosthesis," *Neurorehabilitation*, vol. 10, pp. 251–255, Jan. 1998.

[33] E. Langzam, E. Isakov, and J. Mizrahi, "Evaluation of methods for extraction of the volitional EMG in dynamic hybrid muscle activation," *J. Neuroeng. Rehabil.*, vol. 3, p. 27, Nov. 2006.

[34] E. Langzam, Y. Nemirovsky, E. Isakov, and J. Mizrahi, "Muscle enhancement using closed-loop electrical stimulation: Volitional versus induced torque," *J. Electromyogr. Kinesiol.*, vol. 17, no. 3, pp. 275–284, 2007.

[35] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–854, Jul. 2003.

[36] M. Zardoshti-Kermani, B. C. Wheeler, K. Badie, and R. M. Hashemi, "EMG feature evaluation for movement control of upper extremity prostheses," *IEEE Trans. Rehabil. Eng.*, vol. 3, no. 4, pp. 324–333, Dec. 1995.

[37] K. Soo, H. H. Choi, C. S. Moon, and C. W. Mun, "Comparison of k-nearest neighbor, quadratic discriminant and linear discriminant analysis in classification of electromyogram signals based on the wrist-motion directions," *Current Appl. Phys.*, vol. 11, no. 3, pp. 740–745, 2011.

[38] V. S. Ramachandran and E. L. Altschuler, "The use of visual feedback, in particular mirror visual feedback, in restoring brain function," *Brain*, vol. 132., no. 7, pp. 1693–1710, 2009.

[39] *PhysioLab Biosignal Module (Mini-Size Module With Isolation Power & Signal)-3 Types (PSL-iEMG: 1-Channel EMG Anaglog Amplifier Module)*. Accessed: Nov. 29, 2017. [Online]. Available: https://www.amazon.com/PhysioLab-Biosignal-Module-Mini-size-isolation/dp/B013OUBLI2?th=1

[40] *MyoWare Muscle Sensor*. Accessed: Nov. 28, 2017. [Online]. Available: https://www.sparkfun.com/products/13723

[41] *NeXus-10-mkii*. Accessed: Nov. 28, 2017. [Online]. Available: https://www.mindmedia.com/products/nexus-10-mkii

Sidharth Pancholi received the M.Tech. degree from Thapar University, Patiala, India, in 2016. He is currently pursuing the Ph.D. degree in biomedical engineering with the Malaviya National Institute of Technology, Jaipur, India. He has two years of industry experience. His current research interests include biomedical signal processing, prosthetic device development, and embedded systems.

Amit M. Joshi received the Ph.D. degree from the National Institute of Technology, Surat, India, in 2015. He is currently an Assistant Professor with the Department of Electronics and Communication, Malaviya National Institute of Technology, Jaipur. He has eight years of teaching experience and two years of industry experience. His current research interests include biomedical signal processing, VLSI DSP Systems, and embedded system design.