Control of an upper-limb exoskeleton arm based on electromyographic pattern classifier for rehabilitation

Pradeepsurya Rajendran, Pasupathy S Alagirisamy*, Prithiviraj Maniram, Karthik Rajaram

***Abstract*— Rehabilitation of people afflicted with elbow joint ailments is quite challenging. Studies reveal that rehabilitation through robotic devices exhibit promising results, in particular exoskeleton robots. In this work, 1 degree of freedom active upper limb exoskeleton robot with artificial intelligence aided myoelectric control system has been developed for elbow joint rehabilitation. The raw surface electromyogram (sEMG) signals from seventeen different subjects for five different elbow joint angles were acquired using Myo armband. Time domain statistical features such as waveform length, root mean square, variance and number of zero crossings were extracted and the most advantageous feature was investigated for Artificial Neural Network (ANN) – a back propagation neural network with Levenberg-Marquardt training algorithm and Support Vector Machine (SVM) – with Gaussian kernel. The results show that waveform length consumes the least amount of computation time. With waveform length as input feature, ANN and SVM exhibited an average overall classification accuracy of 91.33% and 91.03% respectively. Moreover, ANN was 25% faster than SVM in classification.**

***Index Terms*— Artificial neural network, electromyography, exoskeleton, rehabilitation robotics, support vector machine.**

I. INTRODUCTION

PATIENTS with paralyzed upper limb due to stroke, sports injuries, trauma and occupational injuries often receive arm therapy. The goal of arm rehabilitation therapy is to regain motor functions, which are essential to do activities of daily living (ADL).

Conventional manually assisted therapies are labor intensive, time consuming and also expensive [1] and it has been evidently proved that robot assisted therapies can enhance the training to reorder motor functions [2]. Also, it can reduce therapists' physical effort and help them to concentrate on therapy performance. Hence, exoskeleton robot – a machine that augments rehabilitation process by assisting sensory motor function (e.g., Arm, hand, leg and ankle) - has been developed to meet with labor-intensive, repetitive trainings [3]. An exoskeleton robot consists of an outer frame work worn by a human. This machine could be a passive device or an active device such as a powered system of motors or hydraulics [3]. The structure of an exoskeleton robot consists of joints and links which are corresponding to the human body, mostly anthropomorphic in nature and are worn by users close to their body [3]. For this work, we developed an upper-limb exoskeleton robot (called as REXAR – Robotic EXoskeleton for Arm Rehabilitation) to carry out the rehabilitation of an elbow joint.

Many factors such as biomechanics of the upper-limb, safety measures, types of acquisitions, power sources, material and weight of the system need to be considered when designing exoskeleton robot [4]. In addition, controlling upper-limb exoskeletons according to human motion intention is a challenging task in robot assistive technology. Since electromyogram (EMG) is a measure of motion intention, EMG signal is more effective in the intuitive control of assistive robots [5].

The measurement and recording of the muscle response or electrical activity in response to nerve's stimulation of the muscle by using metal electrodes is known as EMG. The procedure can be implemented in two ways: 1) *Noninvasive* wherein small sensors known as surface electrodes are placed on the skin surface to assess the ability of the motor neurons in sending electrical signals, this signal is referred as surface electromyogram (sEMG) and 2) *Invasive* method uses needle electrodes, which are directly inserted into muscle tissue to evaluate muscle activity [6]. The amplitude of EMG signal for both these methods is stochastic in nature and depending on the muscle under observation, the amplitude ranges from μV to mV [4]. Although the first method is preferred due to the favorable fact that it is less cumbersome, it is still susceptible to noise. Prominently, the electrical noise, which affect sEMG signal, can be categorized into following types, 1) Inherent noise in electronics equipment, 2) Ambient noise, usually the source being electromagnetic radiation, 3) Motion artefact, there are two main sources for motion artefact: (i) electrode interface and (ii) electrode cable. Motion artefact can be reduced by proper design of the electronic circuitry and set-up, 4) Inherent instability of

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signal - the amplitude of EMG is random in nature and is affected by the firing rate of the motor units, which is in the range of 0 to 20 Hz [7]. Proper design of electronic circuitry ensures limiting the noise from affecting the acquired EMG signal. In this work, all these discussed noises are eliminated by Myo armband – a commercial sEMG acquisition device with 8 medical grade electrodes, which in itself has the circuitry that amplifies the signal and filters the noise and hence the acquisition of signal of interest becomes facile.

Electromyography signals from the body's intact musculature can be used to identify motion commands for the control of an externally powered exoskeletons [3] [8]. Based on the signal processing methods, EMG based control system - myoelectric control system, is divided into two groups as pattern recognition based and nonpattern recognition based [9]. In [10] [11], pattern recognition techniques have been preferred to extract useful information from sEMG because it increases the variety of control functions and also improves robustness. Hence, in this work, pattern recognition techniques have been used. Pattern recognition based EMG processing consist of four major stages: 1) EMG data acquisition, 2) data segmentation, 3) feature extraction, and 4) classification. The accuracy of pattern recognition based control methods can be improved by selecting appropriate feature extraction methods and applying suitable classification algorithms [9] [12].

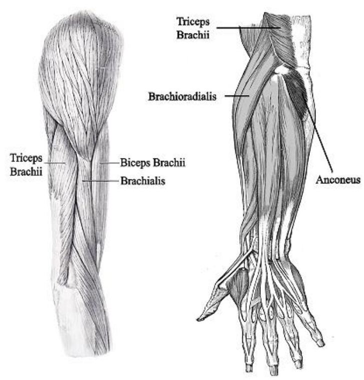


Fig. 1. Elbow flexion, extension muscles

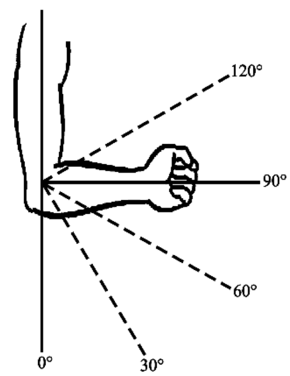


Fig. 2. REXAR's movable range

A. Exoskeleton design considerations

The active muscles for elbow flexion motion are: biceps brachii, brachioradialis, brachialis and for elbow extension motion are: anconeus and triceps brachii [8]. In [13, 14, Fig. 1], the muscles that are responsible for elbow flexion and extension movements are shown. The combinations of EMG signals from upper-limb muscles can be used as input data to control upper-limb exoskeleton robots [8]. Biceps brachii, brachialis and triceps brachii are principally responsible for elbow flexion and extension. Whereas, brachioradialis – the extension of triceps brachii muscle, and anconeus are smaller muscle group present in the forearm and will be neglected generally [8]. However, in this work, sEMG signal from these two muscles were used to control the exoskeleton arm because, the Myo arm band is effective in sensing sEMG signal from forearm muscles and its detail has been discussed in section II. To our knowledge, Myo arm band was not yet utilized for exoskeleton robot control in elbow joint rehabilitation application.

The anatomical range of motions for the elbow joint and the movable range of the proposed 1 degree of freedom (DOF) REXAR are shown in Table I. Considering the safety of the user and also to provide effective rehabilitation therapy, 0 – 120° is chosen as the REXAR's movable range of motion and it is depicted in Fig. 2.

TABLE I
RANGE OF MOTION

Types of motion	Anatomical range [15]			REXAR's range
	Source 1	*Source 2*	*Source 3*	
Elbow flexion	140°	140°	145°	120°
Elbow extension	0°	0°	5°-15°	0°

While designing the exoskeleton device, the natural formation of the bones have to be dealt in detail to provide safe and comfortable upper-limb motion. The interactions between the user and the exoskeleton arm are two types: 1) physical human robot interaction (pHRI) and 2) cognitive human robot interaction (cHRI) [4]. The pHRI mainly deals with the physical interaction between the human arm and the exoskeleton device. Whereas the cHRI takes intelligence into account for the control of the robot [4]. pHRI has a more substantial role than cHRI, in order to provide safer and comfortable motion. Therefore, different aspects under pHRI such as weight, dexterity, actuation, DOF, power transmission and compliance have to be considered [4].

Compliant exoskeleton devices have been developed specifically for elbow joint rehabilitation with the development of human machine interaction. Certain devices such as the ULERD [16] were designed with adjustable link length between the elbow and the wrist and also the angle between the forearm and the wrist can be varied. Since the ULERD was light in weight, it was used as a portable machine. Another rehabilitation mentioned in [17] is the NEUROExos, in which the exoskeleton was designed with double – shelled structure so as to improve the rigidity, maximize the pHRI and minimize the pressure on the skin. The design perks of REXAR have been discussed in the section II.

B. Control system

The control systems for exoskeleton robot are categorized based on the types of basic components used for execution and the functions they serve. The different types of control systems in exoskeleton are mechanical, electrical, electro-mechanical, myoelectric, hydraulics, pneumatics and artificial intelligence-aided control system [5]. Since the myoelectric control system relies on neural information from muscle contraction, it is more effective in controlling exoskeleton as per human motion intention and hence this system provides better intuitive control than other kind of control systems [5].

In myoelectric control system, sEMG signal is typically used for controlling the exoskeleton robots and it requires substantial analysis of the signal to extract useful information. A myoelectric control system is designated by considering three important aspects of controllability [18] : (i) the accuracy of movement selection - it is vital that the user's intent must be realized correctly and therefore accuracy must be as high as possible, (ii) the intuitiveness of actuating control - a control system should be capable of learning the muscle activation patterns chosen as the most natural by the user to actuate motion, and (iii) the response time of the control system - the response time of a control system should not introduce a delay which is recognizable by the user.

Artificial intelligence combined with myoelectric control system is the state of the art technique, in which correlations between neuromuscular activities are identified using machine learning algorithms like artificial neural network (ANN) [10] [11]. Using a pattern recognition technique to discriminate multiple degrees of freedom movements has shown a great promise in the research but the major challenge in this type is the requirement of large database and numerous trails to train the controller before application [5]. Precise positioning of the electrodes has been proven unnecessary by applying pattern recognition techniques [19]. However, it has been found that the number of electrodes used affects the overall accuracy of movement recognition [20]. In this work, artificial intelligence aided myoelectric control system has been employed to control the exoskeleton robot.

C. Feature extraction and pattern recognition

The success of pattern recognition system fundamentally relies on the choice of selecting best and substantial features suitable for the application [9]. Time domain processing is more popular than frequency domain and time-frequency methods such as short-time Fourier transform, the wavelet transform, and the wavelet packet transform because it has good discrimination power and less computationally exhaustive [7]. Hence, in this work, the features were extracted from the time-domain signal.

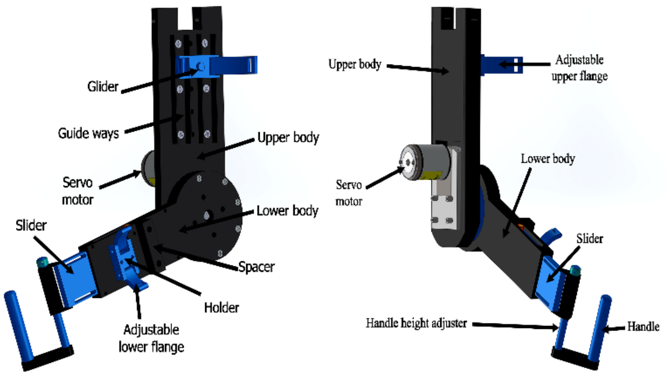
Among various types of pattern recognition techniques available to differentiate the functionality using the extracted features, it has been found that ANN can represent the relationship between sEMG signals and elbow joint angles very well [10] [11]. The performance comparison for two types of neural network architectures - Levenberg-Marquardt algorithm [LM] and Scaled Conjugate Gradient algorithm [SCG] based on statistical time and time-frequency based features shows that, LM outperforms SCG in classifying the EMG signals with correct and average classification rate of 88.4% [21]. Support vector machine (SVM) has also been used for the classification of sEMG signal [12] [22] and it exhibits discrimination power as good as ANN.

The objectives of this work are (i) development of an upper limb exoskeleton with 1 DoF active joint for elbow joint rehabilitation (ii) acquisition of sEMG signal from brachioradialis and anconeus regions for five different elbow joint angles from different subjects (iii) performance evaluation of four different statistical time domain features in terms of computation time and its accuracy with the classifiers (iv) comparison of ANN and SVM performances, for all the features taken independently as input, on the basis of average overall classification accuracy, (i.e., average of training accuracy, validation accuracy and testing accuracy) and time taken for classification. The novelties of this work are (i) usage of cost effective commercial device, Myo armband, for sEMG acquisition (ii) sEMG signal acquisition from brachioradialis and anconeus muscle group, unlike many work in which biceps brachii, brachialis and triceps brachii are the regions of interest (iii) performance evaluation of features in terms of computation time and algorithms in terms of classification time along with average overall classification accuracy.

II. MATERIALS AND METHODS

A. REXAR design

To demonstrate our concept, an exoskeleton arm (REXAR) was designed using DS SolidWorks and was also fabricated, the proposed design has been shown in the Fig. 3. The exoskeleton was made out of Aluminium 6061. Having it designed purely for elbow joint rehabilitation, the exoskeleton here has one degree of freedom (elbow flexion/extension) which is active. It was designed to be suitable for users with different arm lengths. The weight of the REXAR is approximately 3kg. A support link mechanism was designed not only to provide support for the user but also to counteract the weight of the entire exoskeleton arm. Since Mild Steel (MS) has minimum bending moment as compared to aluminium, it is used for fabricating the support structure. At the trailing end of support link, the proposed exoskeleton arm was attached like shown in Fig. 4. The support consists of 3 MS links attached serially, its length is adjustable and at its end, the exoskeleton arm is held in place. Typically, the actuation of upper limb exoskeleton devices is controlled by electric motors due to economy and controllability [23]. Hence, in REXAR, a DC servo motor with a torque of 380 kg-cm was used for the actuation of exoskeleton arm. The control commands for the motor were given through Arduino Uno by interfacing it with Matlab. The CAD model of the exoskeleton arm was analyzed statically using SolidWorks and the results are depicted in Fig. 5 and Table II. The results suggested that the design was safe and it was within the yield stress limit of the material. The arm can withstand a maximum load of 10 Kg.



(a) (b)

Fig. 3. REXAR design (a) View 1 (b) View 2

TABLE II
STATIC ANALYSIS OVERVIEW

Material	Aluminium 6061
Force applied	20N
Yield strength	5.5 *10^7
Maximum stress induced	3.943 *10^4 N/m^2
Max. Static Displacement	1.27 *10^-4 mm

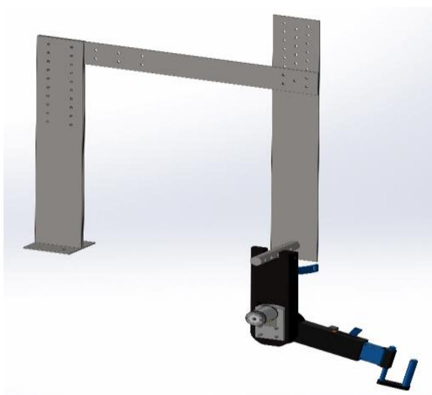
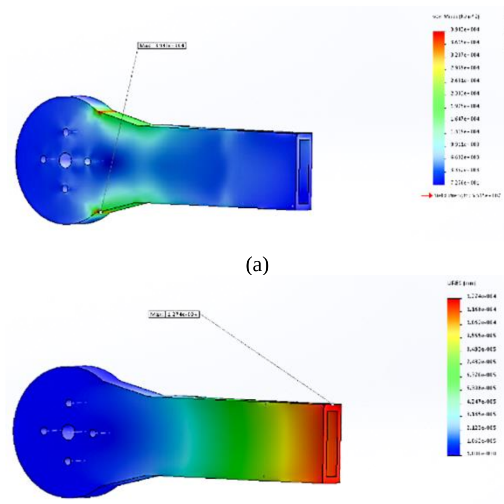


Fig. 4. Exoskeleton arm with support



(a)

(b)

Fig. 5. (a) Static analysis of the lower arm (b) Displacement of the lower arm

B. EMG sensor

The Myo armband, which is cheap and commercial, is a hand gesture recognition device developed by Thalmic Labs. It contains eight medical grade stainless steel surface EMG electrodes. Like other surface EMG electrodes, the signals acquired by the sensor represent the electric potential of the muscles due to muscle activation. The device has a proprietary processing modules, which filter the electric noises and provide EMG data at a sampling rate of 200Hz. The potential range of the Myo armband is between -128 and 128 in units of activation - integer values that represent amplified potentials [24]. These data can be transmitted to peripherals through its inbuilt Bluetooth module and this device also incorporates a nine axis inertial measurement unit (IMU) containing three axis gyroscope, three axis accelerometer and a three axis magnetometer. In this work, only raw sEMG signal from the sensor, for elbow flexion and extension, is utilized. This armband is not only flexible to fit the widest part of the forearm - the upper forearm but also suits better even for smaller arms. Unlike other sEMG sensors, the setup procedures for Myo armband is simple, it does not require the user to shave the skin surface over which the armband will be worn. The arm band and its electrodes numbering is shown in Fig. 6.

Fig. 6. Myo – Gesture control arm band

C. Experimental setup

In this work, seventeen people, with no limb defects, volunteered for the sEMG recording process and the procedures were carried out with an informed consent and the rules of the declaration of Helsinki of 1975 were followed sternly. All are men with an average age of 24, an average weight of approximately 76.6 Kg, and an average forearm circumference of 25.68 cm. Before proceeding the process, all subjects were requested not to participate in any upper-limb related activities that would lead to fatigue. Before placing EMG sensor on the forearm of the subject, it was ensured that the surface of the skin was sweat free and dust free so that the reception of sEMG signal would be better. The Myo arm band was worn by the subjects like shown in Fig. 7.

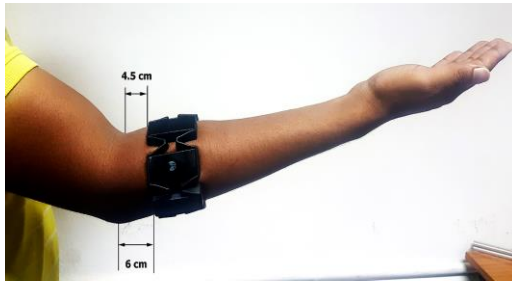


Fig. 7. Myo armband position

In a comfortably seated position**,** the subjects were asked to put on exoskeleton arm on the right hand. To avoid motion artefacts in sEMG measurement, it was ensured that there was no contact between the Myo armband and the exoskeleton arm. The sEMG measurements, for five different elbow joint angles, were conducted from 0^o to 120^o with an interval of 30^o, it is shown in Fig. 8. The raw sEMG data, in isometric contraction of the muscles, for each prescribed angle were recorded from all the eight electrodes. At each angle, 5 trials were carried out with each trial lasting for 60 seconds and half a minute of break in between trials. The raw sEMG data from Myo band were acquired, at a sample rate of 200, in Matlab using Myo sdk matlab mex wrapper. Thus, for all subjects, the raw sEMG data for all the mentioned angles were collected and saved for the feature extraction process. The accuracy and the response time of the control system are influenced by the length of the windowed signal. A longer window length will have a large amount of data and subsequently will result in greater classification accuracy but the trade-off in increasing the window length is the processing time required for feature extraction and classification. Thus, windowed portion of the signal must be smaller for faster response time of the control system and also it must contain sufficient amount of data about the motion intention of the user for greater classification accuracy. Therefore, having considered both these requirements, the raw sEMG signal was windowed for every 512 ms that corresponds to the window length of 102 data values and successively the features were calculated.

(a) (b) (c) (d) (e)

Fig. 8. Experimental setup (a) 0° (b) 30° (c) 60° (d) 90° (e) 120°

D. Feature extraction

Since the classification accuracy of the classifier largely depends upon the features extracted, proper selection of features is crucial. Time domain statistical features like variance, root mean square (RMS), waveform length (WL) and number of zero crossing (NZC) were extracted from the windowed portion of the raw sEMG signal and this process was implemented in Matlab environment without any pre-processing of the raw sEMG data from the Myo armband.

1) Waveform length

Waveform length is the cumulative length of the waveform over the segment. WL indicates a measure of waveform amplitude, frequency and duration [18]. It is given by

$$\mathrm{WL_k} = \frac{1}{N}\sum_{i=2}^{N} |X_i - X_{i-1}| \tag{1}$$

Where,
N is the length of k^{th} window
X_i is the i^{th} value of k^{th} window

2) Variance

Variance uses the power of sEMG signal as a feature. It is the measure of power of fluctuation of the signal from its mean value and it is calculated as

$$\mathrm{Variance_k} = \frac{1}{N}\sum_{i=1}^{N} |X_i - \overline{X}|^2 \tag{2}$$

Where, $\overline{X}$ is a mean value of k^{th} window

3) Root Mean Square

RMS is the measure of average power of the signal over a period of time and it is determined by

$$\mathrm{RMS_k} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} X_i^2} \tag{3}$$

4) Number of zero crossing

This is the measure of number of times the signal crosses zero, which is a simple frequency measure. The threshold (α) should be included in the zero crossing to reduce the effect of noise [18]. Given two consecutive samples X_i and X_{i+1}, the count of zero crossing is incremented only if

$$\{X_i > 0 \text{ and } X_{i+1} < 0\} \text{ or } \{X_i < 0 \text{ and } X_{i+1} > 0\} \text{ and } |X_i - X_{i-1}| \geq \alpha$$

E. Classification

The final step in the implementation of the system is the classification of input data into different classes based on key features. Two supervised learning algorithms such as artificial neural network and support vector machine had been trained and tested separately for four different features and the performance of the algorithms were compared in terms of average overall classification accuracy and classification time.

1) Artificial neural network

The features calculated from raw sEMG samples, from eight electrodes, were taken as input to neural network separately. The training, validation and testing processes were carried out using neural network pattern recognition toolbox in Matlab. The ANN architecture has three layers: input layer, tan-sigmoid hidden layer and linear output layer. Each layer (except the input layer) has a weight matrix W, a bias vector b and an output vector a (activation unit). The weight matrices, which are connected to inputs are called input weights (IW) and weight matrices coming from the hidden layer outputs are called layer weights (LW). Here, the network has 8 inputs, 10 tan-sigmoid neurons in the hidden layer and 5 linear neurons in the output layer. The ANN architecture has been shown in the Fig. 9. Depending on the application, neural network can be optimized by analyzing its performance through selecting different number of neurons in hidden layer [21]. If numbers of neurons are more in hidden layer, then the network requires more memory, the training becomes complicated and takes more time. However, if the numbers of neurons are too small, the network cannot adjust the weight properly and may result in over fitting, thereby making the network not generalized well when presented with different inputs [21]. Hence, for this work, after testing the network with different number of hidden neurons and hidden layers, single hidden layer with 10 hidden neurons has been chosen, because of its good average overall classification accuracy and lesser classification time. It has been ensured that the network is generalized well, in order to avoid over-fitting. The input feature vectors are normalized in the range of [-1, +1] for efficient and faster training of neural network. The training of network has been performed with Levenberg-Marquardt (trainlm) algorithm by separating the input data into 70% for training, 15% for validation and 15% for testing. Two early stopping criteria have been set for the improvement of the network

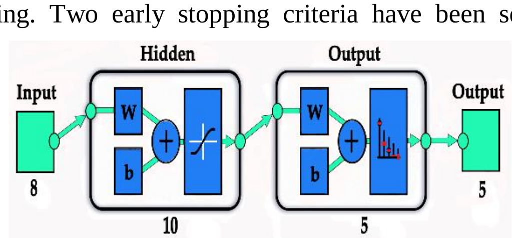


Fig. 9. ANN Architecture

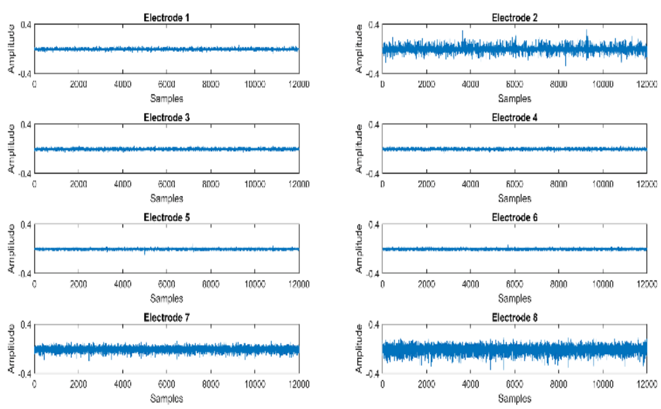
generalization. Training of the network will stop if validation checks reach 6 or if 1000 epochs are reached. For each subject's data, the network was trained using a total of 20,302 (samples) X 8 (elements), which are the total samples for five different elbow angles. Each sample represents the calculated feature from 512ms length of raw sEMG data.

2) Support vector machine

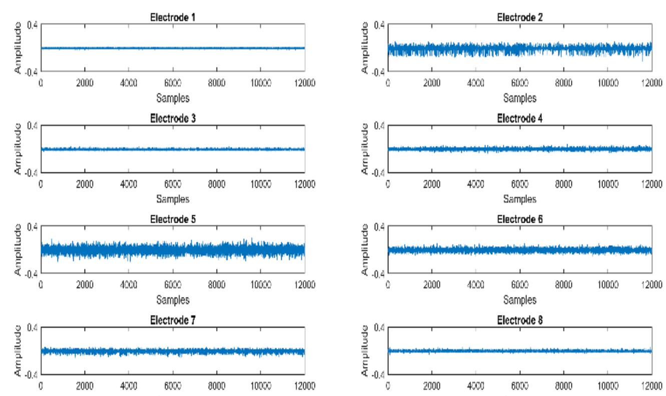
SVM is a popular tool in machine learning tasks involving classification and regression. It constructs a hyperplane or a set of hyperplanes in a high dimension feature space of training data which are mapped using a nonlinear kernel function [22]. Since it maximizes the margin around hyperplane, it is often referred as large margin classifier and typically, larger the margin around hyperplane, lower the generalization error of the classifier. In this work, the training and the testing processes of SVM were carried out using classification learner app in Matlab. For this, the cross validation method has been used with cross validation folds set to 15, the folds represent the partitioning of data. The app trains a model for each fold using all the data outside the fold, in this case, it is 85% of the data. Then, the app tests a model performance using the data inside the fold and calculates average test error over all folds. This method gives a good estimate of the predictive accuracy of the final model trained with all the data. Different kernels like linear, quadratic, cubic, and Gaussian with different kernel scales such as $\sqrt{p}$,$\sqrt{p}/4$ and $\sqrt{p}$ *4 (p denotes the number of predictors) were tested and evaluated, from which the Gaussian kernel with a kernel scale of $\sqrt{p}/4$ showed better accuracy in classification and hence it has been chosen for the classification process. The classification of five different classes, each corresponding to different elbow joint angle, has been performed with a multiclass method of one vs one (OVO). The performance of the algorithm was evaluated based on its average overall classification accuracy and classification time. The main motive of adopting SVM classifier in this work is to compare its classifying accuracy and classification time with that of the ANN classifier, in order to identify more suitable algorithm for real time control of exoskeleton robot in elbow joint rehabilitation application.

III. RESULTS AND DISCUSSION

The raw sEMG data for five elbow joint angles from one of the subjects have been shown in Fig. 10. In Fig. 10., X-axis represents the number of samples and a total of 12000 samples, which is equivalent to raw data for 60 second, are shown. Y-axis represents the amplitude of the signal and it is unitless. It is apparent from Fig. 10 that the signal from different electrodes show varying amplitudes at different angles.Though it is not definite and exhibits randomity at all angles, it can be distinguished by extracting appropriate features and classifying with machine learning algorithms.The features extracted for all angles have been shown in Fig. 11.



(a)



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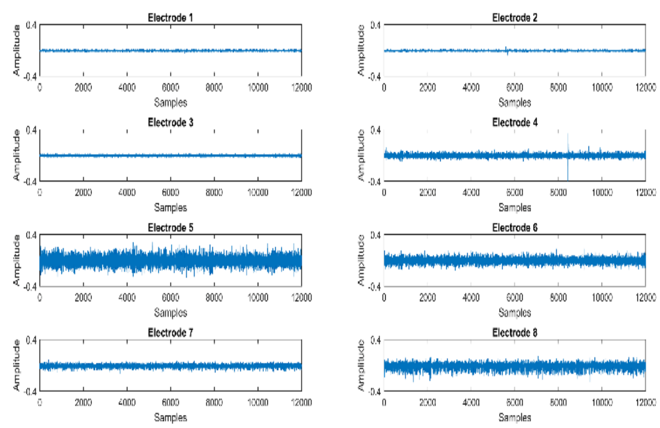

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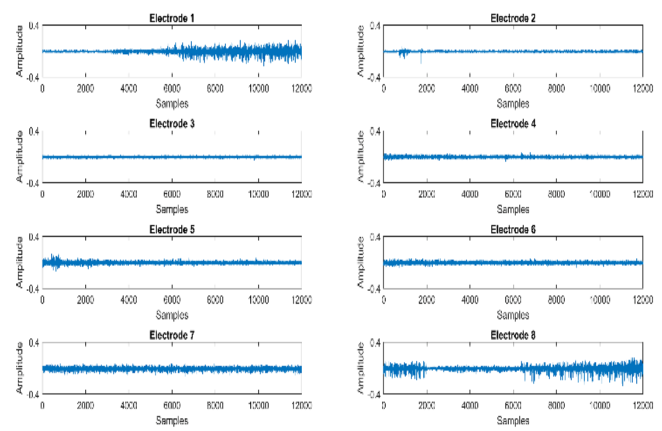

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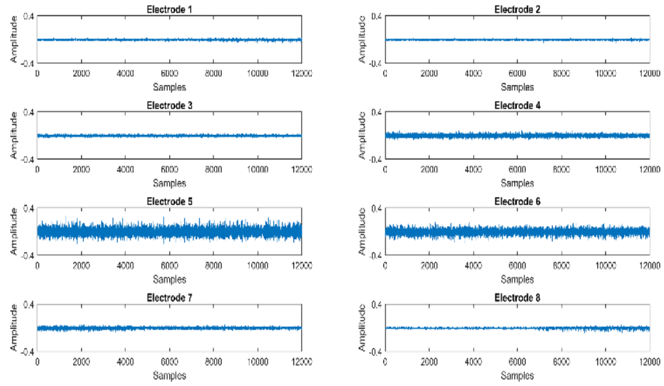
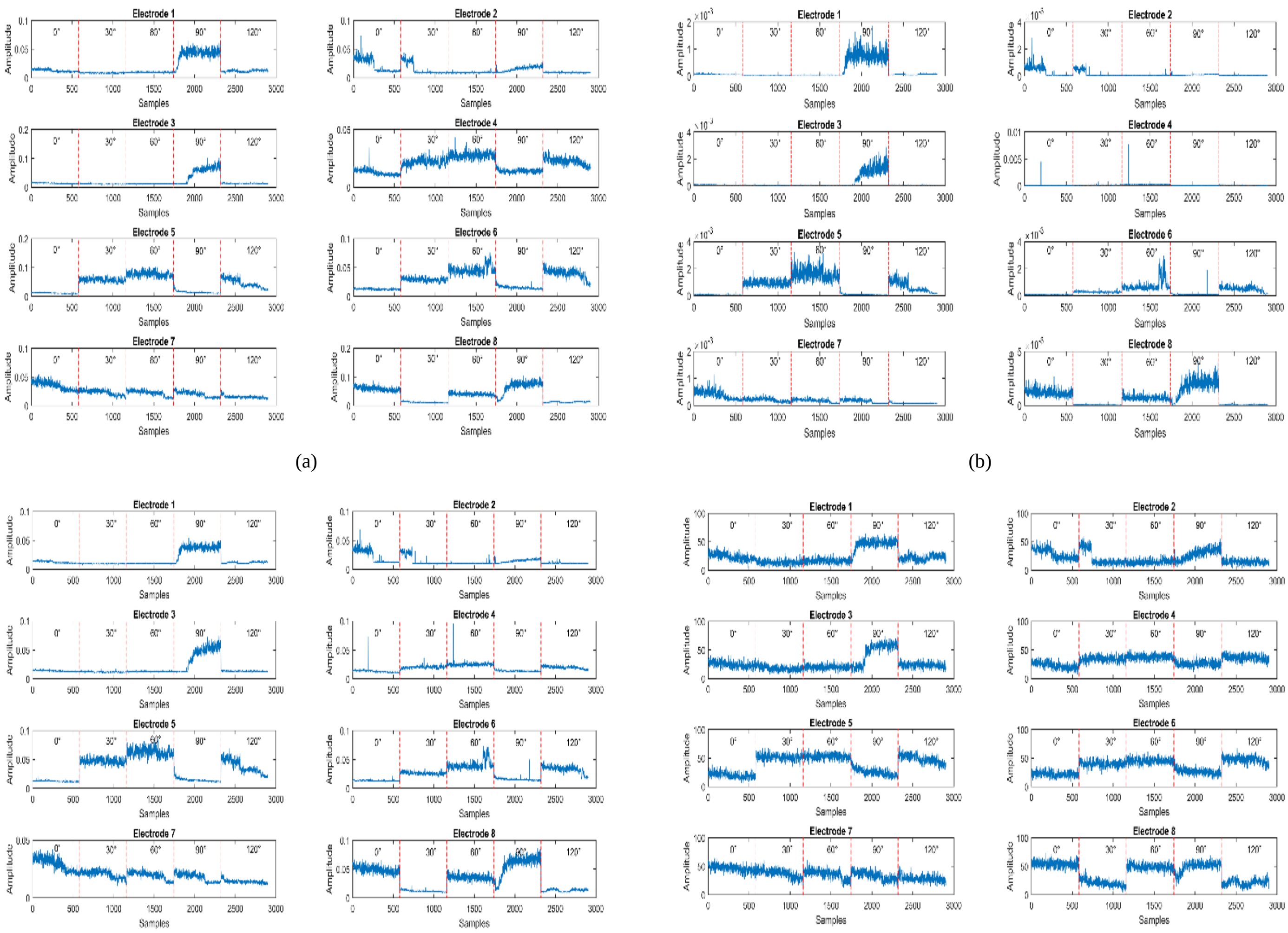


(e)

Fig. 10. Raw sEMG data from one of the subjects for different elbow joint angles (a) 0° (b) 30° (c) 60° (d) 90° (e) 120°



(a) (b)

(c) (d)

Fig. 11. Extracted features for all elbow joint angles from one of the subjects (a) Waveform length (b) Variance (c) RMS (d) NZC

In Fig. 11, each point in the graph represents the value of feature calculated from 512 ms windowed raw sEMG data. The amplitude, which is unitless, for different feature shows discrepancy for diferent angles but the fluctuation in amplitude of the samples for waveform length and RMS were almostsimilar. The most advantageous feature can be identified based on computation time and its average overall accuracy with classifier. In real time application, computation time is very crucial and even a small delay is unacceptable. The computation time of all these features were calculated using timeit() function, which is equivalent to a wall – clock time, in Matlab and the results are shown in Fig. 12. The time calculation was performed on 64 bit Matlab in windows

PC that has a following specifications: Intel ® Core^{TM} i7-3632QM CPU @ 2.20 GHz, x64 based processor, 8 GB RAM. From Fig. 12, it can be perceived that waveform length has the lowest computation time and RMS has the highest computation time.

TABLE III
ANN AND SVM ACCURACIES FOR DIFFERENT INPUT FEATURES

Subjects	Waveform length		Variance		Root Mean Square		Number of zero crossing	
	ANN	SVM	ANN	SVM	ANN	SVM	ANN	SVM
1	85.3	84.0	80.2	79.7	83.7	83.5	71.5	71.3
2	94.9	96.5	89.7	96.0	97.2	97.6	94.8	92.6
3	77.2	76.8	77.3	74.5	81.6	81.0	60.8	58.6
4	89.9	89.1	88.7	88.4	90.4	90.8	77.9	73.7
5	91.5	92.0	86.1	87.3	90.9	91.5	81.9	79.8
6	99.6	99.5	99.2	98.9	99.8	99.4	96.7	96.1
7	85.5	84.5	81.8	80.3	87.5	85.6	75.3	74.4
8	92.6	93.2	91.3	89.8	93.9	94.4	79.8	77.9
9	99.8	99.7	99.2	99.3	99.8	99.8	97.0	96.4
10	95.6	96.0	90.6	91.2	92.2	95.4	90.1	88.9
11	86.4	85.8	82.7	84.6	86.6	89.4	66.3	65.4
12	93.1	93.7	85.9	89.6	93.4	94.7	76.9	76.6
13	84.1	81.7	80.4	79.4	84.4	83.0	76.6	74.4
14	99.6	99.6	99.4	98.8	99.7	99.7	88.5	87.2
15	95.9	96	91.2	91.7	95.1	96.0	84.8	83.2
16	85.2	81.2	77.3	77.5	83.1	84.1	70.6	70.3
17	96.5	98.3	94.5	94.7	96.3	97.6	91.7	90.6
Average	*91.33*	*91.03*	*87.97*	*88.33*	*91.5*	*91.97*	*81.24*	*79.84*
Standard deviation	*6.51*	*7.39*	*7.40*	*7.93*	*6.13*	*6.44*	*10.79*	*10.89*

For each subjects' data, ANN (Levenberg-Marquardt [trainlm] algorithm) and SVM models (Gaussian kernel) were trained and tested with four features taken as input separately. The overall classification accuracy for all subjects have been presented in the Table III. It can obesrved that both ANN and SVM show highest average overall classification accuracy and least standard deviation with RMS as input feature and next to this, waveform length shows good result. Only these two features have an average overall classification accuracy over 91% and the difference in accuracy of these features, for both ANN and SVM, is less than 1%. The dispersion of accuracies of all subjects for both ANN and SVM, for all features, have been shown in Fig. 13.

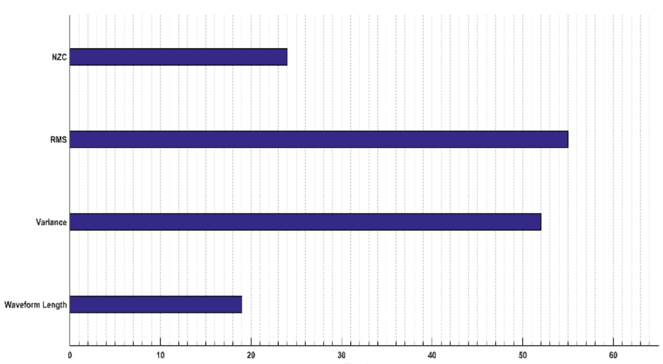


Fig. 12. Computation time of features

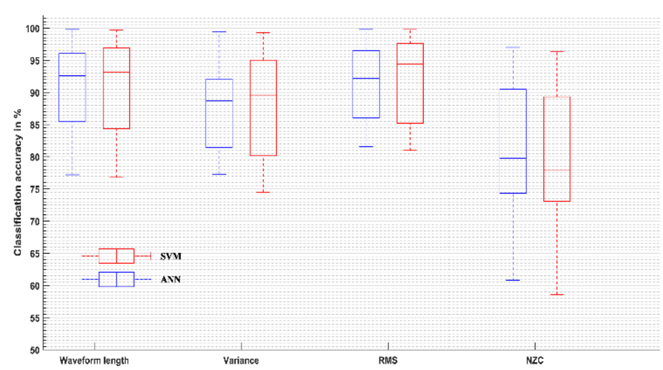


Fig.13. Spread of accuracies of ANN and SVM for all features

From Fig. 13., it can be observed that With RMS as input feature, ANN exhibits an accuracy of at least 92% for 50% of the subject, whereas SVM shows an accuracy of at least 94% for 50% of the subject. With waveform length as input feature, both ANN and SVM shows an accuracy of at least 92.5% for 50% of the subject. The accuracy has its greatest dispersion with NZC as input feature and also it exhibited least average overall classification accuracy and hence it is not efficient for this application. Though dispersion of accuracies of classifier, with variance as input feature, is similar to the dispersion of accuracies with waveform length being input feature, variance is not efficient for this application because the median of its dispersion is lower than the waveform length, also it consumes more computation time and resulted in lower accuracy. Besides, RMS consumes 189% more time than waveform length. Therefore, waveform length is a more advantageous feature for the classifier. In the case of classifier, classification time is an important aspect with regard to application, also it is the deciding parameter on choosing suitable algorithm, since the difference between avergae overall accuracies of ANN and SVM is very small. For that reason, the classification time for both ANN and SVM was calculated using timeit() function in Matlab and its result has been shown in Table IV. This result is same for all features.

TABLE IV
CLASSIFICATION TIME OF ALGORITHMS

Algorithm	Classification time in ms
ANN	9
SVM	12

ANN is 25% faster than SVM in classification because of its simpler architecture, as it has only one hidden layer with 10 hidden neurons. Adding more number of hidden layers and neurons (Deep Neural Network) would increase the overall classification accuracy but at an expense of higher classification time and costlier hardwares for processing. Therefore, two layer ANN with 10 hidden neurons will be an optimal model for this application.

IV. CONCLUSION

In this paper, a novel methodology was proposed to control 1 DOF, which is active, exoskeleton robot that has been designed and fabricated for elbow joint rehabilitation. The presented method was implemented using a low-cost commercial gesture control device – myo armband, which was used to acquire raw sEMG, from brachioradialis and anconeus, for five different elbow joint angles from 17 different individuals. Four different time domain statistical features were extracted from these raw data and two supervised learning algorithms, ANN and SVM, were trained and tested with these features separately, for classifying the data. The experiment results showed that high level of classification accuracy (~91%), in addition to least amount of time consumption for feature extraction and classification can be achieved using ANN trained on a waveform length feature. The limitation of REXAR is that it is not portable. The future work can be directed in the development of provisions for wrist and finger rehabilitation in the exoskeleton robot, additionally making the arm portable.

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