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SVM-based Real-Time Classification of Prosthetic Fingers using Myo Armband-acquired Electromyography Data

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***Abstract*—In this work we applied real-time classification of prosthetic fingers movements using surface electromyography (sEMG) data. We employed support vector machine (SVM) for classification of fingers movements. SVM has some benefits over other classification techniques e.g. 1) it avoids overfitting, 2) handles nonlinear data efficiently and 3) it is stable. SVM is employed on Raspberry pi which is a low-cost, credit-card sized computer with high processing power. Moreover, it supports Python which makes it easy to build projects and it has multiple interfaces available. In this paper, our aim is to perform classification of prosthetic hand relative to human fingers. To assess the performance of our framework we tested it on ten healthy subjects. Our framework was able to achieve mean classification accuracy of 78%.**

***Index Terms*—EMG, finger movement, SVM.**

I. Introduction

Electromyogram (EMG) is a diagnostic measurement technique that measures electrical current during the movement or relaxation or contraction of muscles. EMG signal is acquired in two ways: invasive or non-invasive. In an non-invasive method, the EMG signal is obtained from the surface of the skin [1] and hence it is called surface EMG (sEMG). Whereas in invasive methods, the signal is obtained from the muscles inside the body. Such EMG signals are called intramuscular Electromyogram (iEMG). sEMG is the technique that acquires complex signals from a group of muscles for individual action, and requires classification techniques for motor movements. For prosthesis, several techniques have been used such as Wigner-Ville distribution [2], SVM [3], Naïve Bayes Classifier [4], Higher-Order Statistics [5], Artificial Neural Network [6], etc. The Support Vector Machine (SVM) is a method for locating a hyperplane in an N-dimensional space that classifies data points explicitly. [3]. The Nave Bayes classifier is another machine learning model that classifies signals based on probability. The classifier's core is built on the Bayes theorem [4]. In this paper, SVM has been employed on real-time sEMG signals.

Rehman M. suggested sEMG prothesis design for amputated human upper limb [7]. He suggested a low-cost limb prosthetic with a simple design for individual fingers. He employed the MyoWare sensor to acquire the sEMG signals, Arduino Nano to process and control the servomotors. Khushaba et al proposed that the upper limb amputation can be restored using myoelectric control [8]. Surface EMG Signals for classification of finger motions were applied by Sezgin et al [9]. They used bi-coherency analyses for flexor and extender muscles with surface electrodes. By use of an extreme learning machine (ELM), the sEMG signals were categorised based on phase matching in the electromyography signals (EMGs). The BIOPAC system MP150 from a group of 42 people, 22 males and 20 females, gathered EMG data. In [10], Kavya, S., et al proposed utilising surface EMG signals to control the hand as well as forearm movements of an orthotic arm. A total of four surface electrodes were used to collect EMG data. Two of the electrodes were surface electrodes, one was the reference electrode, and the other was the ground electrode. The inherent noise was removed using an 8th order Butterworth band-pass filter. SVM was used to classify the signals. In [11], Seo, Minsang et al. applied phantom–hand movements to collect the EMG data. They calculated the power of the signal by the root mean square (RMS) of these signals and processing it through a bandpass filter. This resulted in the removal of noise. They project the EMG activation vector into the predetermined motion and achieved the desired motion. The normalization technique was applied to find the correct direction vector of EMG activation.

Amirabdollahian et al. investigated the application of a support vector machine when analyzing hand grip movements with the help of wireless myoelectric wristband [12]. Mendez, I. et al. proposed the Myo Armband the segmentation of hand motion [13]. They used the Myo Armband (MYB) sensor to capture EMG data, which was then processed in MATLAB to compare the CONV and MYB, resulting in a decreased steady-state portion of the acquired signals. After that, the data was fed into a linear discriminant analysis (LDA) classifier. Bian F. et al. used sEMG data to create an SVM-based categorization of simultaneous hand motions [14]. Two digital filters processed the signals: the one was a filter bandpass and the other was a trap filter. The signals' short time average energy (STAE) and mean square error (MSE) were used as a criterion for determining whether sEMG segments were helpful. They performed different kernels such as SVM with S-kernel, SVM with RBF-kernel, linear kernel, and polynomial kernel, but subsequently applied linear kernel. The Naïve Bayes had as good accuracy rate as SVM but Naïve Bayes consumed relatively more time.

In, [12]–[15], Myo Armband (MYB) represented as a good candidate for our design. Myo Armband has 8 surface electrodes and has haptic feedback. Bluetooth connectivity is also available, hence, it is useful as a wireless wearable device. The proposed framework employed Myo Armband to acquire sEMG data. SVM was employed as it is efficient as compared to classification methods such as LDA [14], Naïve Bayes classifier [4], [14] , random forest [14], bi-coherence method [9]. In myoelectric control, mostly LDA has been used for real time application due to it simple structure and linearity property and hence with minimal delay time. But several studies have shown that LDA with simple structures have shown comparatively poor performance as compare to complexity of the non-linear SVM classifier which has shown state of the art performance for different finger movements [16], [17]. Delay should not be more than 300 ms for myoelectric control [18] and here we have shown that instead of linear classifiers, nonlinear SVM could also be implemented with acceptable delay time.

Raspberry Pi is used for the execution of SVM algorithm and control of the prosthetic hand. This paper also provides a description of the prototype hardware.

Section II discusses EMG signal collection, preprocessing, feature extraction, and classification. Sections III and IV present the results and discussion, respectively, while Section V concludes the study and suggests future improvements.

II. Methodology

The effect of motor loss of hand and finger have significant implications for the individual's quality of life, especially his or her ability to fully participate in a variety of work settings. A myoelectric control device for multiple finger motions has potential industrial applications, such as advanced human-computer interfaces.

This section explains SVM as a classification method for EMG-based finger movements. The process begins with the collecting of EMG signals and then proceeds to signal preprocessing, feature extraction, and classification. The method's block diagram is presented in Figure 1. The 3D printed robotic hand attached with the servo motors has been fabricated and used for finger movements through Raspberry Pi computer.

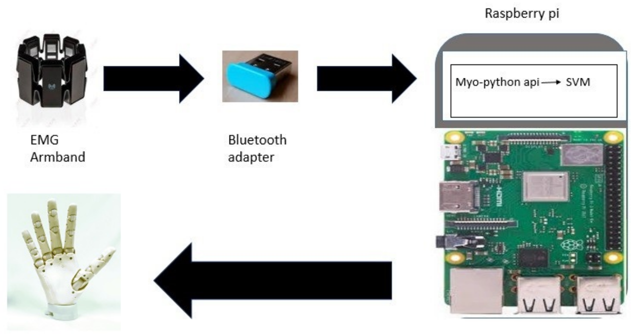

Fig. 1. Block Diagram

A. EMG Signal Acquisition and Pre-processing

EMG raw signals have been acquired using the Myo Armband sensor by utilizing eight channels placed on the skin of the forearm. The EMG signals are collected wirelessly via Bluetooth. Myo armband provides an amplified signal in the range of 0-3V that is directly fed to the microcontroller's analog-to-digital converter (ADC) (having a sampling frequency of 500Hz) and a programmable interface at around 25Hz to send EMG information from its sensors. sEMG signals of ten healthy subjects were acquired for each finger movement of hand. Movements include ring finger movement, thumb figure movement, middle figure movement, index figure movement, and pinkie finger. To eliminate the power-line noises, the input signals were preprocessed using a 50 Hz notch filter, and a fourth-order Butterworth bandpass filter with a cutoff of 20Hz to 500Hz to decrease the effect of undesired finger movements.

B. Feature Extraction and Classification

Features have been extracted after acquiring and preprocessing the raw sEMG signals, which is then fed to the Raspberry pi. The raw EMG signal comprises a long series of inputs that differs in randomness, resulting in complexity. To address the issue of curse dimensionality, the feature extraction process is used to condense only the most important EMG sections that display each class. Because vector components of a signal have no value on their own but only as a whole, determining the vector representation of the signal after filtering and digitizing it is critical. This study employs a total of four time domain feature extraction approaches, including a time-domain feature set containing waveform length (WL), root mean square (RMS), mean absolute value (MAV), and slope sign changes (SSCs). Whereas, RMS and MAV are alike and other ones are discriminatory. Each feature set is briefly described below through equations from equation 1 to equation 4.

1) Waveform length (WL)

$$\sum_{i=1}^{N-1} |x_{i+1} - x_i| \tag{1}$$

2) Root Mean Square (RMS)

$$\sqrt{\frac{1}{N}\sum_{I=1}^{N} x_i^2} \tag{2}$$

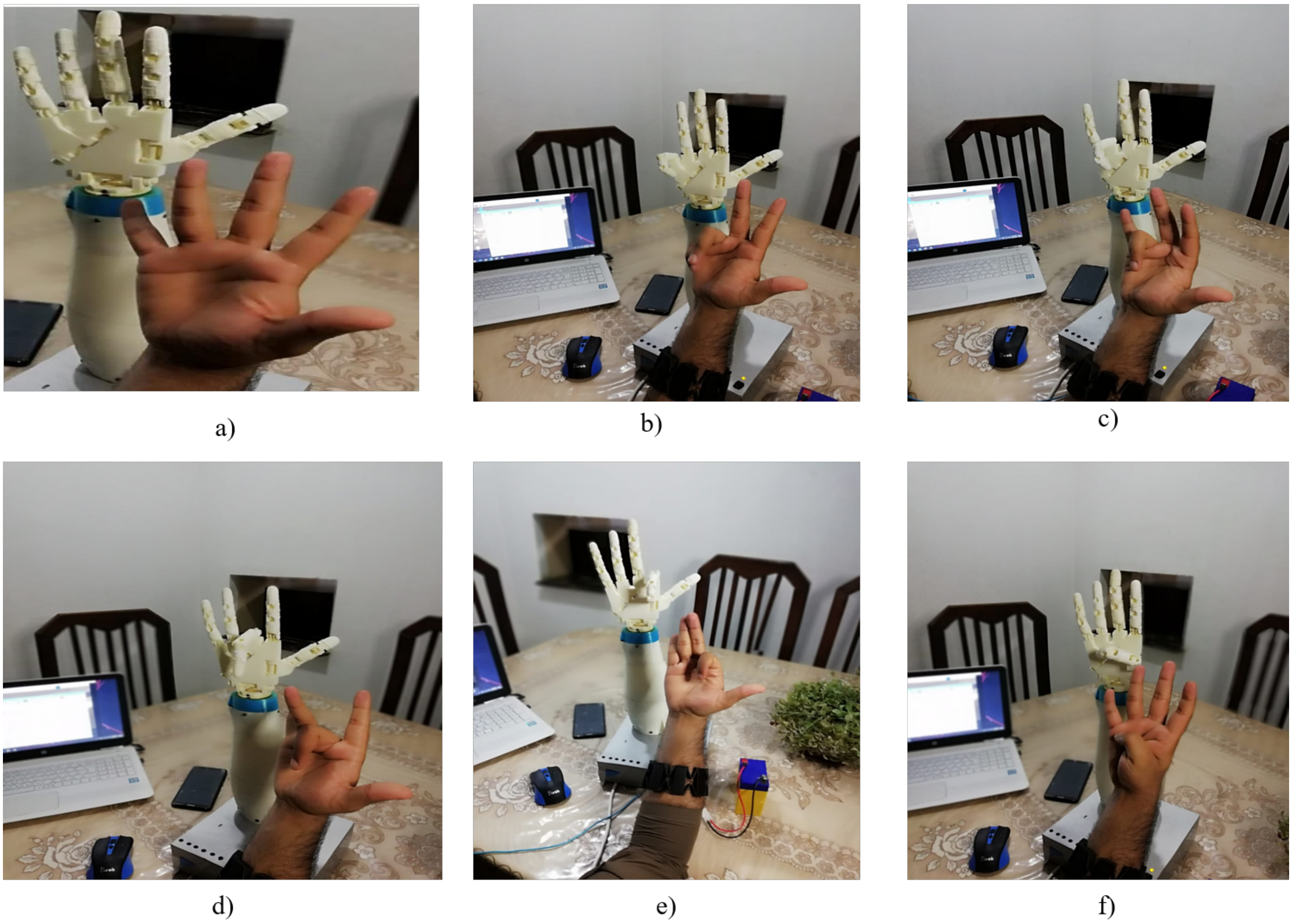

Fig. 2. Prosthetic hand mimicking different human finger movements: a) Fingers at rest, b) Pinkie finger c) Ring finger d) Middle finger e) Index finger f) Thumb

3) Mean Absolute Value (MAV)

$$\frac{1}{N}\sum_{I=1}^{N}|x_i| \tag{3}$$

4) Slope Sign Changes (SSCs)

$$\sum_{I=2}^{N-1}[f[(X_i - X_{i-1}) * (X_i + X_{i+1})]] \tag{4}$$

$$f(x) = \begin{cases} 1, & \text{if} \geq \text{threshold} \\ 0, & \text{otherwise} \end{cases}$$

SVM is being used to classify the motions of prosthetic fingers after the features are extracted and the model is trained. The Support Vector Machine (SVM) is a machine learning model that uses a classification algorithm to classify data into two or more categories. A support vector machine is an algorithm that allows to classify data by constructing a hyperplane. Because of its simplicity and robustness, the SVM algorithm is a well-established technique for learning how to identify new data from a set of classified events. It has been widely implemented in machine learning problems and sEMG processing. The tuning parameters of the SVM models are linear kernel, regularization parameter C which is equal to 1 and polynomial degree of value 3.

III. RESULTS

Multiple data collecting approaches were investigated in order to obtain strong EMG signals with a better signal-to-noise ratio (SNR) and significant event information. Usually, EMG signals are not noiseless because of various reasons such as disconnection of electrodes, artifacts, incapability of instruments to acquire data, fatigued muscles, etc.

In this work, the Myo band was employed to acquire EMG signals because of its capability to acquire signals accurately with faster results. Moreover, it is user-friendly and convenient to carry. Signals with rich motor control information and better SNR play an important role for better classification and consequently better control of the prosthesis. Performance of classification algorithms degrades if signals are noisy and have less information of motor control.

In this work, our goal was to classify finger movements in real-time using the Myo band. Bluetooth adapter was connected to Myo band to connect it to Raspberry-pi. We employed a support vector machine (SVM) algorithm in Raspberry-pi to classify two movements (open and close) of each of all five fingers. SVM was employed because it has better accuracy, computational complexity, and execution time as compared to the artificial neural network. Prosthesis (robotic hand) was connected to Raspberry-pi which controls

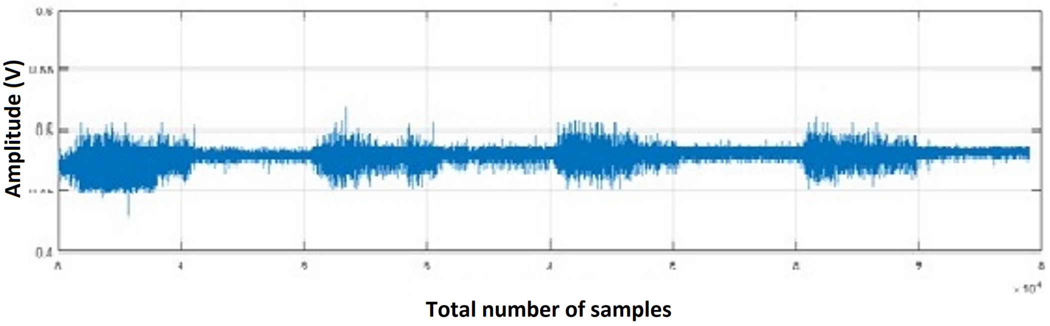

Fig. 3. EMG signals acquired from Myo band

TABLE I
TABLE OF THE ACCURACY OF TESTED PEOPLE

No. of subjects	Number of Tests	Number of Positive Tests				
		Thumb	Index	Middle	Ring	Pinkie
Subject 1	10	9	9	8	9	8
Subject 2	10	9	8	7	8	7
Subject 3	10	9	8	8	7	6
Subject 4	10	8	9	7	8	7
Subject 5	10	10	8	8	7	7
Subject 6	10	8	10	7	8	6
Subject 7	10	7	8	9	7	7
Subject 8	10	8	9	6	8	7
Subject 9	10	8	7	7	7	8
Subject 10	10	8	8	8	8	7
True Positive Rate		**84%**	**84%**	**75%**	**77%**	**70%**

the movements of fingers based on the input signal (having information of motor control) and its classification by SVM.

Figure 2 shows robotic hand mimics different positions of human fingers. Figure 2(a) shows robotic hand mimics the position of the human hand at rest. Figure 2(b) to 2(f) shows robotic hand mimicking closing positions of fingers pinkie, ring, middle, index, and thumb respectively.

Table I shows the performance of prosthesis to mimic the movement of different human fingers. Ten healthy subjects participated in the experiments to assess the performance of prosthetic hands. The target movements were fingers open (five times) and fingers close (five times) for each of all fingers of a hand. Therefore, the total number of movements for one robotic finger and entire hand to mimic was ten and fifty respectively. The acquisition for each movement was lasting for 40 sec. For ten subjects the total number of movements was 500. It can be seen in the table I that the mean true positive rate (TPR) for the thumb, index, middle, ring and pinkie finger was 84%, 84%, 75%, 77%, and 70% respectively. 84% TPR means that out of 10 movements of a finger, 8 times the prosthetic hand attempted correctly to classify the movement.

Figure 3 shows EMG signals acquired from the Myo band. It can be seen that there exists a visible difference between amplitude of epochs with movement and without movement (at rest).

IV. DISCUSSION

Ten healthy patients took part in experiments to assess the performance of prosthetic hands. SVM was employed in the real-time environment using Raspberry-pi. Results demonstrate the applicability of our proposed framework where the lowest mean TPR was 70% i.e. of pinkie finger and the highest TPR was 84% i.e. of Thumb. The possible reason for the low TPR of the pinkie finger could be the structure of the hand of different subjects which made it difficult to move the pinkie finger without moving the index finger. The interference of the muscles of the pinkie and index finger with each other could affect signals and consequently classification accuracy. As compared to [19] study on neuro-fuzzy classifier for 5 finger motions based on EMG signal analysis, the thumb finger has the lowest accuracy of 20% and the ring and little fingers have 100% accuracy. The average accuracy of classification is 72 percent. Missed classifications occur in the index and middle fingers, with the thumb finger accounting for the majority of missed classifications.

V. CONCLUSION

In this paper we aimed to perform real-time classification of prosthetic fingers movements such as they mimic the fingers movements of human hand. Our framework is based on SVM, a method widely used for classification of multiple classes. Myo arm band was used to acquire EMG data of ten healthy subjects. The acquired data is sent to raspberry pi through Bluetooth adapter which performs classification of fingers movements based on SVM algorithm. Results on test data suggest that real-time classification via SVM is a viable alternative to control movement of prosthetic fingers.

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