Feature Extraction and Pattern Recognition of EMG-based Signal for Hand Movements

Mosarrat Jahan[1], Munish Manas[1], Bharat Bhushan Sharma[1], Babu Bikash Gogoi[2]
[1]Electrical Engineering Department
Jamia Millia Islamia (A Central University)
New Delhi, India
[2]Department of Energy
Tezpur University (A Central University)
Assam, India
mosarrat.jahan@gmail.com, msd.gkg85@gmail.com, mbbs.sharma@gmail.com, bbksh431@gmail.com

***Abstract*— EMG pattern recognition has been developed to interpret the performance of different functional movements. It can be used to develop the movement control techniques of assistive devices for people who are physically disabled. Suitable features in time domain are extracted from three different hand movements. The EMG signal was recorded from Cubitus (Elbow) bending, Carpus (Wrist) twist, Brachium (Arm) twist and Palm contraction of forty eight healthy subjects (male and female) by two pairs of Ag-AgCl surface electrodes on the right and left antebrachium. The performance of the classifier indicates EMG-based recognition accuracy for similar movement of right vs. left is found to be more than 95% and for different movement of around 90%. Also, the classification accuracy for average data set is achieved around 93-97% when compared for left and right hand.**

***Keywords*— electromyograph; prosthesis; signal classification; pattern recognition.**

I. INTRODUCTION

In EMG-based pattern recognition, EMG signal is preprocessed the spectral frequency component of the signal and extracted some features before performing classification. EMG signal is a set of electrical signal.

Nearly, 15 million people in the world suffer from ceribral vascular accidents annually, out of which 5 million people were permanently disabled due to such accidents[1]. The most common disability caused by a ceribral vascular accident is any kind of physical limitation such as weakness or hemiparesis, which badly affects the quality of life. In most of the cases, movements of the Carpus (Wrist) , Brachium (Arm) , and Antebrachium are affected. It is necessary to improve the restoration of these upper limb functions, due to their importance in daily activities [2], [3]. A number of mechatronic devices (e.g., the MIT-Manus robot [4], [5] and the MIME robot [6], [7]) are designed for robot-aided stroke rehabilitation for the purpose of improving these upper limbs functionality [3], [4].

Some of the rich motor control information is stored in the EMG signals emerging from the movements connected with arms and forearms, from which the user's intentional movement can be detected. One of such important case is of the analysis of electromyogram (EMG) signals recorded from the surface of amputed residual muscles of the victim that can be used as prosthesis control signals for designing mechatronic devices [8]. Myoelectric control has also been reported in robot-aided therapy for the subjects of cerebral vascular accident. These Myoelectric control are based on the "ON–OFF" control strategy. The robotic systems developed by this myoelectric control operates with a predefined trajectory or action by triggering the system by EMG signals [9].A very complex spatial coordination of different muscles makes the functional tasks related with upper limbs, a possibility. Thus, the task of realizing the control of these multiple degree of freedom movements is done by mapping certain parameters between a muscle and a degree of freedom. The development of myoelectric control systems through EMG signals pattern recognition techniques has become a\ important area of research [8]. The assumption for this development principle is that the features extracted from the recorded EMG signals emerging from a limb give a reflection of a pattern formed by multiple muscle activity [10]. In this study the feature extraction from the EMG signals emerging from different hands movements has been done and thereafter, three features classified for each movement. Pattern recognition technique has been developed for identifying the limb movement under consideration.

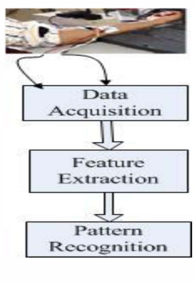

Fig. 1. Block diagram of different stages of EMG Recognition.

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II. EXPERIMENTS AND DATA ACQUISITION

In this section, we represent experimental procedure for recording EMG signals. Data acquisition and experimental set up for EMG recording is indicated in Fig. 3. The EMG signal was recorded from Cubitus (Elbow) bending, Carpus (Wrist) twist, Brachium (Arm) twist and Palm contraction of forty eight healthy subjects (male and female) by two pairs of Ag-AgCl surface electrodes on the right and left antebrachium. Each electrode was separated from the other by 2 cm. A band-pass filter of 10-500 Hz bandwidth and an amplifier with 60 dB gain was used. The biomedical testing instrument chosen for this specific experimentation was BIOPAC MP 30 system and a recording connected laptop for the display and analysis of the recorded EMG signals. The complete experimental setup is shown in Fig. 1. Following the ethical practices protocol for biomedical experimentations, extreme care was taken while performing this Non-Invasive EMG testing in which a written consent from all the subjects was taken and proper arrangement for the earthing and insulation was made. The sample rate for the recording of these EMG signals was set at 500 samples per second. In order to restrict the frequency of the recorded EMG signals between 50 to 500 Hz we have set a high pass filter in BIOPAC MP 30 system human machine interface software with the threshold frequency as 1 KHz. The acquisition length of the each experiment was set to be of 30 second and frequency of the signal displayed was set at 30 Hz. Raw EMG signal for three movement types are as shown in Fig. 2.

III. FEATURE EXTRACTION AND CLASSIFICATION

Feature Extraction

A set of features was extracted to characterize the EMG data for classification of the intended movements. Root Mean Square value, Zero-crossing count, Normalized energy are the popular features used in EMG for movement control application. These are the three features for each movement being analyzed in this study which means that the length of the feature vector is nine. The above mentioned three features are defined as follows. Let $x_i(t)$ be the time varying signal at channel i and $C_i(k)$ be the absolute value of the signal at channel *i*.

A. Mean Absolute Value (Mav)

It is the average rectified value (ARV) which can be derived from the moving average of full-wave rectified EMG. In particularity, it is calculated by taking the average of the absolute value of EMG signal. It represents the simple way to estimate contractile force of muscle. It is calculated as

$$MAV = \frac{1}{M}\sum_{m-1}^{M} |Y_m| \quad (1)$$

Where M is the length of the signal and Y_m represents the EMG signal in a segment.

B. Root Mean Square (RMS)

It is represented as amplitude modulated Gaussian random process whose RMS is related to the constant force and non-fatiguing contraction. Its value has been used to quantify the electric signal because it reflects the physiological activity in the motor unit during contraction. It can be expressed as

$$RMS = \sqrt{\frac{1}{M}\sum_{m-1}^{M} Y_m^2} \quad (2)$$

C. Variance of EMG (VAR)

The variance is the mean value of the square of the deviation of that variable of EMG signal. Generally it uses power of EMG signal. The value of EMG variance can zero. It can be expressed as

$$VAR = \frac{1}{M}\sum_{m-1}^{M} Y_m^2 \quad (3)$$

D. Standard Deviation (SD)

It is used to find out the threshold level of muscle contraction activity. It is the amplitude of the EMG signal. It can be expressed as

$$SD = \sqrt{\frac{1}{M-1}\sum_{m-1}^{M} (Y_m - \bar{Y})^2} \quad (4)$$

Where Y_m is the mean value of EMG signal.

E. Mean Frequency (MNF)

The mean frequency is that frequency where the product of the frequency value and the amplitude of the spectrum is equal to the average of all such products throughout the complete spectrum. It can be used as a feature for assessment of muscle fatigue in surface EMG signals. It can be calculated as

$$MNF = \sum_{m-1}^{M} \omega_m p_m / \sum_{m-1}^{M} p_m \quad (5)$$

Where ω_m is frequency of spectrum.

F. Zero Crossing (ZC)

Zero crossings is a feature that tracks the number of times the waveform crosses zero, switching from a positive signal to a negative one, and vice versa. It is the number of times the amplitude values crosses the zero y-axis. It provides the approximate estimation of frequency domain properties. It can be expressed as

$$ZC = \sum_{m-1}^{M} [\![sgn(Y_m \times Y_{m+1}) \cap |Y_m - Y_{m-1}| \geq threshold]\!] \quad (6)$$

G. Slope Sign Change (SSC)

It is similar to ZC and another method to represent the frequency information of EMG signal. The number of changes between positive and negative slope among three consecutive segments are performed with the threshold function for avoiding the interference EMG signal. It can be expressed as

$$SSC = \sum_{m=2}^{M-1} [\![f[(Y_m - Y_{m+1}) \times Y_m - Y_{m-1}]]\!] \qquad (7)$$

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

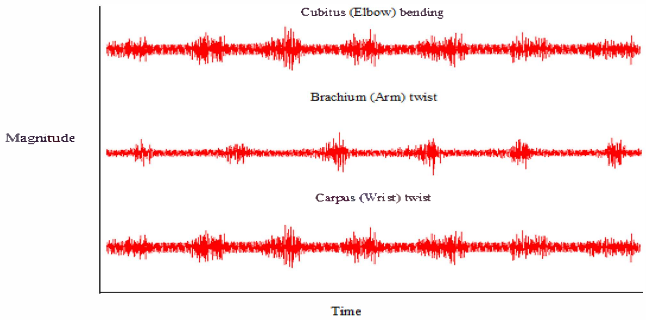
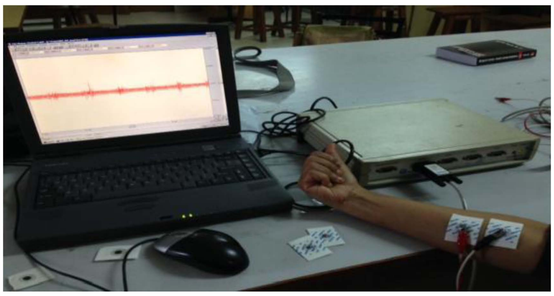


Fig. 2. EMG signal amplitude for three different movements.

(a) Male subject



(b) Female subject

Fig. 3. Data acqusition experimental setup

IV. Results and Discussions

Classification of signal into a given number of classes using various features can be achieved by various statistical methods. We tested the result on four subjects' datasets, there are 4 sets of data for each subject: four sets of data are for Right hand and four sets of data are for Left hand for four different kinds of movements Cubitus (Elbow) bending, Carpus (Wrist) twist, Brachium (Arm) twist and palm contraction. The sampling rate is 500 samples / sec.

Basically the EMG data set used in this work has a dimension of [channel, trial, sample], [1×3×500]. Fig. 2 shows the EMG signals for three types of movement for 500 samples. All features have been implemented in MATLAB (R 2013a) and different stages of EMG pattern recognition are shown in Fig. 1. We are taking three features of the right and left hand per trial individually and then taking the average feature value of both the hands, hence, the data obtained after feature extraction is applied to the input of the classifier and results were tested. This procedure is repeated for all the four possible combinations and results are tested for all. Using this heuristic, we were able to test each group of data independently and then compare result obtain from average feature values. Performance of the classifier, i.e., accuracy is obtained by confusion matrix. Accuracy is calculated for all four groups of combination of data for various movement of right and versus left hand.

Feature vector of movements for both Right and Left hand is indicated by a matrix form as given in equation (8).

$$\begin{bmatrix} \mathrm{RMS1} & \mathrm{RMS2} & \mathrm{RMS3} \\ \mathrm{ZC1} & \mathrm{ZC2} & \mathrm{ZC3} \\ \mathrm{VAR1} & \mathrm{VAR2} & \mathrm{VAR3} \end{bmatrix} \qquad (8)$$

The performance of the classifier indicates EMG-based recognition accuracy for similar movement of right hand and left hand is found to be more than 95% and for different movement of around 90%.

Table 1: Various average feature values extracted for wrist twisting activity

Sl. no	RMS	MEAN	SD	VAR	MNF	ZC	SSC
1	0.287	0.151	0.279	0.01	7.097	257	278
2	0.247	0.097	0.048	0.045	4.371	128	128
3	0.259	0.127	0.063	0.063	6.628	159	172
4	0.258	0.096	0.067	0.067	5.369	203	210
5	0.175	0.067	0.034	0.034	3.825	253	287
6	0.228	078	0.041	0.041	4.425	234	237
7	0.3	0.89	0.044	0.044	5.00	122	172

Table 2: Various average feature values extracted for elbow bending activity

Sl. no	RMS	MEAN	SD	VAR	MNF	ZC	SSC
1	0.08	0.1048	0.227	0.073	4.27	197	271
2	0.189	0.0972	0.197	0.03	4.42	143	148
3	0.219	0.1393	0.237	0.049	2.87	125	137
4	0.182	0.0626	0.183	0.033	3.78	235	242
5	0.181	0.0601	0.180	0.03	3.93	182	194
6	0.2	0.0218	0.207	0.04	4.94	171	174
7	0.195	0.0664	0.195	0.038	4.75	128	129

Table 3: Various average features values extracted for arm twisting activity

Sl. no	RMS	MEAN	SD	VAR	MNF	ZC	SSC
1	0.232	0.127	0.233	0.054	8.00	164	162
2	0.196	0.082	0.196	0.038	4.33	117	118
3	0.283	0.175	0.283	0.075	6.62	134	137
4	0.272	0.108	0.272	0.047	5.37	217	220
5	0.287	0.089	0.247	0.028	3.82	275	227
6	0.247	0.229	0.248	0.069	4.42	273	226
7	0.184	0.058	0.184	0.034	5.00	198	202

Table 4: Various average feature values extracted for palm contraction activity

Sl. no	RMS	MEAN	SD	VAR	MNF	ZC	SSC
1	0.273	0.185	0.237	0.092	7.00	284	273
2	0.214	0.098	0.043	0.074	4.72	123	125
3	0.257	0.127	0.073	0.063	6.74	159	187
4	0.259	0.096	0.067	0.039	5.37	203	274
5	0.185	0.061	0.038	0.034	3.85	253	297
6	0.203	0.078	0.047	0.041	4.32	234	246
7	0.27	0.08	0.074	0.084	5.03	172	192

V. CONCLUSION

This study explores the comprehensive effort to explore the pattern recognition of movement using EMG signal. The result indicates that the recognition performance is quite robust. The reliable classification accuracy is achieved around 90-95 % for the same movement and 80-90% for different movements. The classification accuracy for average data set is achieved around 93-97% when compared for left and right hand. From the result we conclude that the features used for pattern recognition is successful in providing the discrimination between left and right hand movements. The classified EMG signals can be used to develop the human computer interface which would aid the disabled people to interact with computer devices.

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