ANALYSIS OF ELECTROENCEPHALOGRAPHIC SIGNAL ACQUISITION USING EPOC EMOTIV FOR USE IN ROBOTIC ARM MOVEMENT

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Abstract - In recent years, new research has brought the field of electroencephalograph (EEG)-based brain–computer interfacing (BCI) out of its early stages into a phase of relative maturity through many demonstrated prototypes to assist the periphery compromised patients. It is a worth- while technology for disabled people enabling them to reinstate a damaged motor nerve or any neural pathway. This study introduces the development of Brain computer interface by means of a non-invasive wireless electroencephalograph (Emotiv EPOC system) and its application to control a prototype robotic arm. After the pre-processing and spectral analysis of raw EEG signals, an averaged peak value for selected channels were obtained as a feature vector for each movement. Two algorithms namely, linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) were used to differentiate the raw EEG data into their associative movements. Performance of a classification algorithms were assessed, which revealed that the accuracy was 71.77 (±0.76) % and 86.57(±0.79) % of LDA and QDA respectively. Feature vector resulted in superior performance of 86.57 (±0.79) % with QDA. The averaged peak value of PSD for selected seven channels were then used to move a robotic arm successfully in the two directions i.e. "Up (elbow flexion)" and "Down (elbow extension)".

Index Terms - Electroencephalogram (EEG), brain-controlled interface (BCI), Power spectrum density (PSD).

I. INTRODUCTION

A Brain-Computer Interface (BCI) is a bridge that concentrate on developing new augmentative communication and control technology that does not depend on the brain's normal output pathways of peripheral nerves and muscles [1]. EEG based BCI systems can be invasive or noninvasive, latter one with the great prominence for the researchers as it provides ease to acquire EEG by-passing the surgical procedure [2].

At present, the main motivation to BCI research and development is to provide rehabilitation for severe neuro muscular disabilities such as amyotrophic lateral sclerosis (ALS), strokes, and severe cerebral palsy. This is a great assistance for periphery compromised or amputated people in their daily routine [3]. People with a severe motor incapacity now have the possibility of performing a range of actions which were impossible without BCIs. One of the most important component of BCI is the acquisition of good quality EEG signals and feature extraction using different algorithms [4].
Application of EEG based BCI involves the spectral component analysis for the detection of any neuropathy [5]. Using online filtering, feature extraction and classification requires extensive training and it is computationally intensive if number of channels is large. Due to this fact, complex classifiers are only suitable for off-line processing [6]. Among feature extraction, power spectral density (PSD) and for classifiers, linear classifier was found to be speedy as compared to most of the other classifiers for BCI applications [7], [8], [9]. This paper presents an EEG based BCI system for controlling a robotic arm with a simpler and cost-effective approach. The EEG signals were processed using a simple filtering, feature extraction by power spectral density. Epoch Emotiv system (Emotiv Inc. San Franciso, CA, USA) is a wireless, portable and low- cost system used to acquire EEG signals non-invasively. Features of movement were identified and distinguished from one another by using linear classifiers. The feature extracted then can easily be interfaced with the hardware of robotic arm via commonly used micro-controller, an Arduino Board. It is hypothesized that using this approach, the EEG signal acquisition, processing and interfacing could be performed easily and more efficiently. It would also provide opportunity for research groups and students to carry out research studies with least expanses.

This paper is organized as follows: section 2 describes the methodology; starting from EEG data acquisition, signal processing which includes sub section of feature extraction, classification, architecture of a robotic arm and interfacing. Section 3 provides some important results, while section 4 concludes the paper.

II. METHODS

This section describes the approach used in the implementation of an EEG based BCI. Figure 1 shows the work flow of the study. EEG data were acquired using a wireless and cost effective Emotiv EPOC system. Algorithms were designed and implemented off-line to process the signals using Matlab (Math Works, Inc. MA, USA).

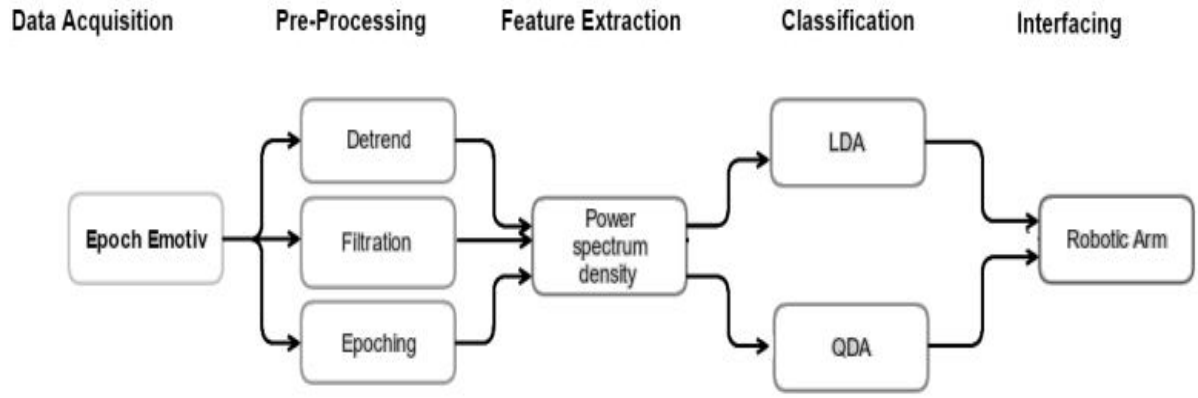

Figure 1. Block diagram of work flow of a purposed EEG based BCI system, starting from the acquisition of EEG signals from Emotiv then pre-processing the signals to free them from noise, extracting PSD as a feature vector and passing the identified features from classifiers. The last application based interfacing step in which extracted features were translated into control signals to move a prototype robotic arm.

A. Data Acquisition

Based on the advancing research and latest developments in neuro engineering, Emotiv EPOC ® presents a revolutionary robust personal interface for human computer interaction [10]. It is a high resolution, multi-channel, wireless neuro headset. Easy to wear with full range of motion and use with any operating window. Channel names based on the international 10-20 electrode location system are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, with Common Mode Sense/Driven Right Leg (CMS/DRL) references in the P3/P4 locations.

Data Acquisition parameters were: Sampling Frequency= 128 Hz, Resolution 14 Bits (1LSB = 0.51µV), Bandwidth = 0.2 to 43 Hz (5th order Sinc Filter, 50 Hz Notch).

B. Subjects

This study was approved by the ethical committee of the Department of Bio-Medical Engineering, Riphah International University (Pakistan). EEG signals were acquired from eight volunteers among which five were male and four were females. A consent form was signed prior to the study. Volunteers were briefed about the data acquisition procedure. Before acquiring data, the comfort of volunteers was assured. For good quality EEG signals volunteers were trained first to follow the protocol and then data were recorded. Electrodes were hydrated to reduce impedance and then fixed to the headset. Headset was checked to be fully connected by indicating green color at test bench display. If not, then more saline was used to have complete connection of electrode with skin. Then EEG signals were recorded for every individual by following a protocol.

C. Experimental setup

Sequence of the protocol for "up" and "down" movement can be seen from the Table I. "up" and "down" movement was based on elbow flexion and extension. Volunteers were visually given a cue to move their dominant right arm in upward (flexion) direction towards their shoulder at moderate pace. By doing so the event-related potential (ERP) get captured at the motor cortex region of the brain. Electrodes placed directly on that region records the stereotyped electrophysiological response to a command. Markers were inserted at every cue to have exact instant of movement initiation. Pace and duration of movement were synchronized by designing a protocol video which volunteers followed. Volunteers moved their arm from rest position to flexion in 8 seconds that is it took them 8 seconds to fully fold their arm. The arm was then held in the same position for 2 seconds. Upon 3rd cue; the arm was extended downwards at moderate pace back to the rest position in an 8 seconds duration.

The arm was left again at rest for 2 seconds in this position. The same sequence was repeated. Considering the muscle fatigue phenomena, data acquisition procedure was divided into three sessions each consisting of thirty movements that is trial of ninety movements per flexion, extension, up and down.

Table I- Sequence of protocol for the "UP" and "Down" Movement

Cue	Movement	Degrees	Duration
1	up (flexed)	5	8 sec
2	fully flexed	5	2 sec
3	down (extension)	90	8 sec
4	fully extended	90	2 sec
Repeat from cue 1st again			

D. Pre-processing

Event Related Potential which are an electrophysiological response due to specific motor movement, is 'hidden' within continuous EEG signal stream [11]. Preprocessing of raw EEG is mandatory to have noise and other artifacts free data.

Conventionally filtration is achieved by using Butterworth band pass filters [12] to remove noise and extract the required EEG signals. Butter worth filter was applied. High-frequency noise was mitigated by using sixth order low-pass filter with a cut-off frequency of approximately 30 Hz [13]. High pass filters with a cut-off frequency of 0.5 Hz were used to remove the disturbing very low frequency noise of less than 0.5 Hz [14]. As the movement based potentials of right arm is more prominent at left hemisphere of the brain therefore only seven channels namely AF3, F7, F3, FC5, T7, P7 and O1 were considered for further processing.

E. Feature Extraction

The raw EEG signal of movement execution was time domain signal where the signal features were submerged into the noise and the signal energy distribution was scattered [9]. Based on previous studies, features extracted in frequency domain are one of the best to recognize the mental tasks based on EEG signals [15]. As known, the PSD $S_x(f)$ is the Fourier transform of the auto-correlation function as follows:

$$S_x(f) = \int_{-T}^{T} R_x(\tau) e^{-j2\pi ft} dt \qquad (1)$$

Where,

$$R_x(\tau) = E\{x(t)x^*(t+\tau)\} \qquad (2)$$

Power spectral densities were calculated for all the useful mentioned channels and for all movements. The average of these trials were calculated using pwelch function from Matlab with a Hanning window and a single peak value was obtained as a feature vector for each class.

F. Classification

Classification of the feature vectors has to be performed to determine the discriminant function that differentiates the classes [24]. Discriminant classifiers were developed to differentiate features, namely, Linear Discriminant Analysis (LDA)and Quadratic Discriminant Analysis (QDA) After extracting features in a form of PSDs, it was fed to classifier to get discriminant into respective movement templates. 75% of the data (68 classes of each movement) were used as training set and 25% (22 classes of each movement) as testing data.

G. Architecture of Robotic arm

The mechanical structure was a small scale realization model for human arm. QCAD (manufacturer and its address) is a computer aided design software that was used for preparing the 3D design. The custom made prototype robotic arm had 4 Servos. Power wire of all servos were attached to the 5V pin of the Arduino. Servo shield was used to make these connections indirectly to Arduino board. Signal wire of servo for the shoulder, two for the elbow and one for a gripper was attached to the digital pin 9, 10, 11, and 12 respectively of the Arduino board. Prototype robotic arm mechanical design had one servo placed underneath the base to provide "left" and "right" movements as it rotates on the servo horn, it mimics the shoulder of a human arm. Two servos were placed at the elbow because it needed more torque to lift "up" and "down". It was used to perform the actions of up and down movement. Last servo was attached to the gripper which performs grabbing/ gripping actions. Rotating the servos to 0 degree would have brought them to down position and rotating them to 180 degrees would brought the elbow to up position. Pulse width modulated signal from Arduino was sent to the servos when the specific key command from GUI was received, Thus resulting in the rotation of the servo and hence the robotic arm. Both the movements that was "up", and "down" were executed by the robotic arm when the command by the GUI was sent. The PSD average for every movement was fetched and sent to the servos to move in accordance to the key pressed on GUI.

H. Interfacing Control signals to the Robotic arm

Major venture was to translate the extracted EEG features into control signals that would interface with the prototype robot and make it to move. Arduino was used as a connecting medium between extracted control signals of the brain with the actuator that is a prototype robot. It has a buffer that stores data received through the port and prevent the loss of information. Arduino development board was interfaced to Matlab using the ArduinoIO library. This library contains pre-defined functions used to control the arduino pins. The system was able to compare and identify the average peak value (PSD) for all the seven channels and sent it to the robotic arm through GUI. The feature extracted from EEG were fed to a robotic arm. It was programmed to move in accordance with the acquired information A graphical user interface was designed to stimulate the real scenario that send the signals to the robotic arm related to the respective extracted movement from the raw EEG signals. For a serial communication between arduino and Matlab, the robotic arm was connected to Arduino through the serial port of the PC using COM port. When Arduino receives the code for keys pressed on the GUI the appropriate PSD average for each action was compared to the database and then the servos attached to Arduino were brought to an action accordingly.

III. RESULTS

For EEG based BCI application, good quality EEG signals were acquired. EEG signal processing plays a vital role in extracting the qualitative features which would be used for communication and command to an assistive device. To accurately classify the features

according to the related movement a problem of large feature's number is encountered. Along with the PSDs, Time Frequency analysis was also done in order to affirm that the features extracted were actually the Event Related Movement Potentials. Time-frequency representation that is spectrograms of the average of all trials are shown in Figure 4. EEG signal can represented as oscillations in a time-frequency analysis but

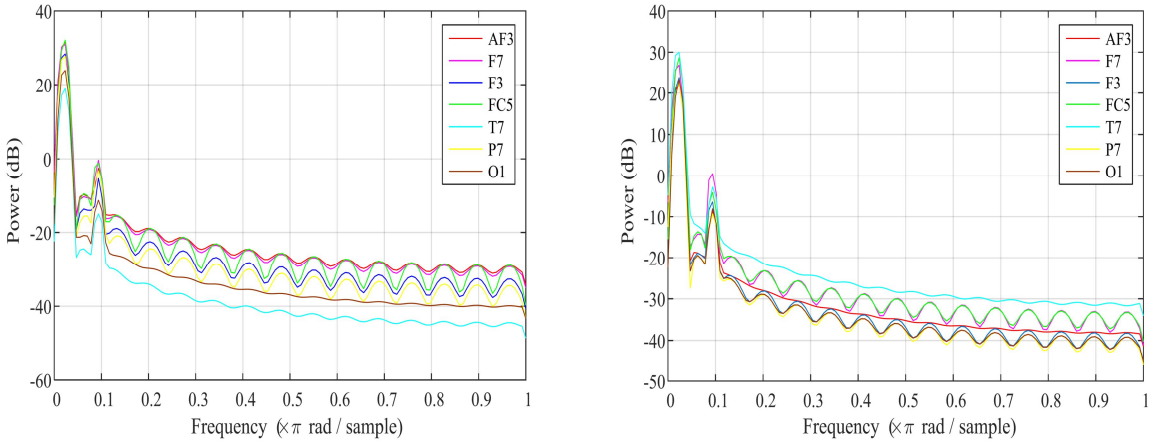

Figure 3. Power spectral densities for "Up" movement" and "Down movement" of 8 seconds. Different colors depict the selected seven electrodes.

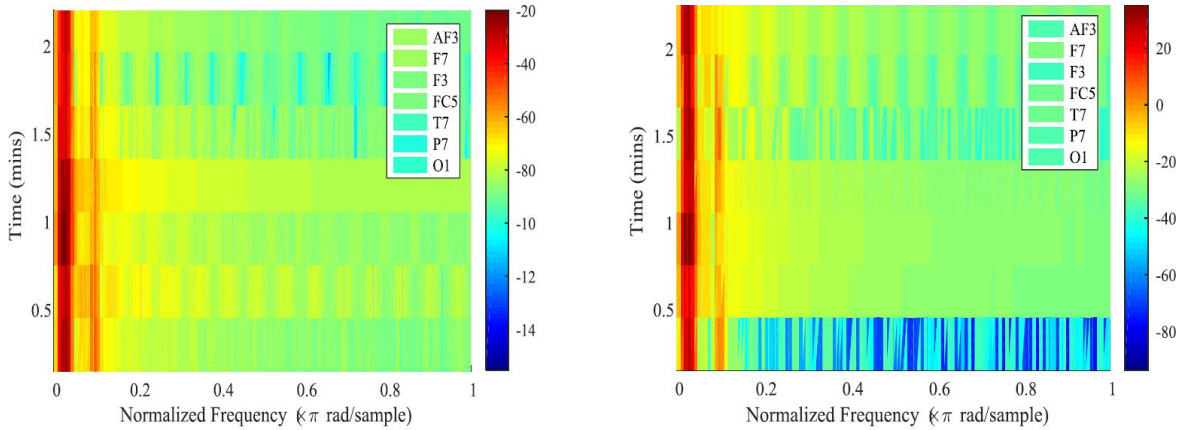

Figure 4. Normalized frequency verses time analysis (Spectrogram). Up movement", and "Down movement. Spectrogram for each movement, shows that the PSD of the signal has frequency bands where peaks are found, the average of the power for each class and each frequency component as time run for the ninety trials are different for different movements. For ease of visibility 2.2 seconds are displayed in spectrogram instead of 8 seconds.

It is due to the signal's statistical characteristics change with respect to time which makes EEG non stationary, thus features must be computed in a time-varying manner. Therefore, channel selection and spectral analysis have been used in this study. After filtration, feature selection method was performed using Power Spectral Density (PSD). It does not imply that the signal is oscillatory. Time-frequency analysis of the EEG can give additional valuable information to the traditional visual interpretation, by providing an image of the spectral EEG contents varying with time. The PSD is calculated by Fourier transforming the estimated autocorrelation sequence which is found usually by Welch's method producing modified periodograms. The PSD of the signal has frequency bands where peaks are found, this peaks correspond to frequency <10 Hz, that has been already documented in both motor and premotor cortices for movement [16], [17]. PSD peaks can be seen in figure 4. Normalized Power spectrum that corresponds to the fact that movement related potentials are present. For every movement one can see the PSDs are totally different and can easily be distinguished by the classifier.

Table II-Accuracies of QDA classifier for all subjects and selected channels.

Subject	AF3	F7	F3	FC5	T7	P7	O1
1	85	85	86	87	85	86	83
2	86	86	86	86	87	87	85
3	86	84	85	86	86	86	86
4	86	86	85	85	87	87	86
5	88	85	85	86	86	86	85
6	86	87	86	86	87	86	86
7	85	85	85	86	85	85	85
8	86	85	86	87	86	87	85

Mean	86	85.37	85.5	86.12	86.12	86.25	85.12
S.D (±)	0.93	0.92	0.53	0.64	0.83	0.71	0.99

For classification, all the PSDs of seven channels were used. For each subject there was seven channels among which each channel had 90 PSD's as a feature vector per movement so it makes total of 2520 feature vector per subject. Table II and III shows the performance of the two classification algorithms.

Table III - Accuracies of LDA classifier for all eight subjects.

Subject	AF3	F7	F3	FC5	T7	P7	O1
1	75	75	74	70	75	73	74
2	72	74	77	76	75	70	70
3	72	73	74	74	71	70	74
4	75	74	76	75	76	73	72
5	71	74	73	71	70	71	69
6	75	70	71	75	71	76	79
7	76	71	75	71	75	72	74
8	75	71	70	72	76	78	74
Mean	72.25	71.75	71.625	71.75	72	71.75	71.25
S.D (±)	0.89	0.89	0.74	0.89	0.76	0.71	0.46

As seen in figure 5 Feature vector resulted in superior performance of 86.57 (±0.79) % with QDA. For every subject QDA had higher accuracies than LDA in all the seven selected channels as it does not consider the covariance of classes. LDA uses hyper plane as a discriminate while QDA is more complex than LDA. The averaged peak value of PSD for selected seven channels were then used to move a robotic arm successfully in the both directions i.e. "Up (elbow flexion)" and "Down (elbow extension)".

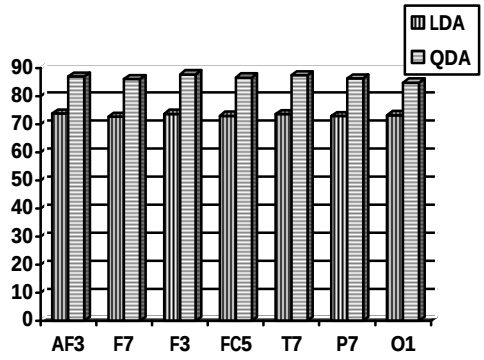

Figure 5. Comparison of Classifier's performance per all seven channels. QDA has superior performance in every channel across the average of channels.

IV. CONCLUSIONS

This study presents an EEG based BCI system for controlling a robotic arm with a simpler low computational complexity and cost-effective approach. Good quality EEG signals were acquired using wireless headset, Epoch Emotiv. Although, EEG data acquisition using Emotiv hardware system has already been explored for BCI research such as study conducted by Shashibala et al. [18] where Emotiv EPOC was preferred due to its higher number of sensors among all portable low-cost BCI headsets available in the market. EPOC headset is relatively simple to use and offers mobility due to its wireless technology. The Emotiv EPOC has been explored for variety of applications, owing to its accessibility for researchers. Another study reported by Lievesley et al. [19] found it useful for disabled patient for controlling computers. Poor et al. [20], also analyzed Emotiv EPOC to be an effective method for controlling computers. The use of the Emotiv EPOC has also been explored in the area of controlling robotic systems through non-invasive BCI [8]. Stytsenko et al. [21] tested the reliability and validity of the acquired EEG data compared to a conventional EEG system, in which they concluded that real time EEG data acquired from Emotiv is comparable to the one acquired by using conventional EEG devices. Many studies evaluated the detection accuracy of Epoch Emotiv [22]. The system was evaluated on its ability to accurately detect and classify the designed tasks and had an acceptable level of accuracy, yielding a platform for noninvasive BCI system.

Performance of a classification algorithms were assessed, which revealed that the accuracy was 71.77 (±0.76) % and 86.57(±0.79) % of LDA and QDA respectively. The results of this study suggest that the feature vector for specific movement was 86% accurate according to QDA and using the above interface one can easily move a robotic arm via an EEG signals of specific movement.

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