Brain EEG Signal Processing For Controlling a Robotic Arm

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***Abstract*—Researchers recently proposed new scientific methods for restoring function to those with motor impairments. one of these methods is to provide the brain with a new non-muscular communication and control channel, a direct Brain-Machine Interface (BMI). This paper presents a Brain Machine Interface (BMI) system based on using the brain electroencephalography (EEG) signals associated with 3 arm movements (close, open arm and close hand) for controlling a robotic arm. Signals recorded from one subject using Emotive Epoc device. Four channels only were used, in our experiment, AF3, which located at the prefrontal cortex and F7, F3 , FC5 which located at the supplementary motor cortex of the brain. Three different techniques were used for features extraction which are: Wavelet Transform (WT), Fast Fourier Transform (FFT) and Principal Component Analysis (PCA). Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm was used for classifying the three considered tasks. Classification rates of 91.1%, 86.7% and 85.6% were achieved with the three used features extraction techniques respectively. Experimental results show that the proposed system achieved high classification rates than other systems in the same application.**

I. Introduction

Many different disorders can disrupt the neuromuscular channels through which the brain communicates with and controls its external environment.

Researchers recently proposed new scientific methods for restoring function to those with motor impairments, one of these methods is to provide the brain with a new non-muscular communication and control channel, a direct Brain-Machine Interface (BMI),for conveying messages and commands to the external world or devices.With this technology there is no longer people feel disabilities to control devices such as: robot arm, wheelchair and any other devices[1].

An important type of BMIs is the non-invasive systems utilizing (EEG) signal of the brain to measure the brain activity [2]. The non-invasive systems are the systems in which the data are recorded by sensors placed over the scalp to avoid the risks of surgery and the high cost during planting sensors under the scalp in the invasive technique.

This paper presented a new non-invasive system for controlling a robotic arm using Brain EEG signal processing. Four channels only were used (AF3, F7, F3 and FC5) to improve the system unobtrusiveness and still achieved a high recognition rates ranges from 77.8% - 91.1% for 3 classes of movement, which are: close, open arm and close hand. Data were recorded using the emotive Epoc headset [3] from a healthy, male, 26 years old subject. Wavelet Transform (WT), Fast Fourier Transform (FFT) and Principal Component Analysis (PCA) techniques were used for features extraction. Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm is used for classification in this research.

The reminder of this paper proceeds as follows. Section 2 presents the previous work for brain robot interface systems. Section 3 explains the system methodology and illustrates the used techniques for feature extraction and data classification. Section 4 explains the experimental results of the proposed methodology for classifying the three arm movements. Conclusion and future work are illustrated in section 5.

II. Related work

This research presented a non-invasive system utilizing the EEG brain signals for controlling a robotic Arm. Researches in this area are of potentially enormous value for patients with motor impairments and also the people who lose their arms.

John Donoghue and his team at Brown University developed a BrainGate Neural Interface system [4]. The BrainGate system is a neuromotor prosthetic device consisting of an array of one hundred silicon microelectrodes, each of which is 1mm long . The device, which has been implanted in a patient's (who suffered from spinal cord injury) motor cortex, detects electrical activity that is associated with the planning of movements, and transmits them to a series of computers.The signals are translated by the computers, which then produce an output that controls the movements of a multi-jointed robotic prosthetic prosthesis to grasp and move an object, just by thinking about the movements necessary to do so. But the main drawback of this system is that, it is an invasive system.

Rajesh Rao, at the University of Washington's Neural Systems Laboratory, has developed a brain-machine interface (BMI) which can be used to control the movements of a small humanoid robot. The device is non-invasive, it is based on (EEG), and consists of a cap fitted with 32 electrodes. The cap gathers electrical signals (event-related potentials) from the surface of the motor and premotor cortices and sends them to the robot. Currently, the device can only be used to convey

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basic instructions, such as which direction to move in, and to pick up an object, to the robot [5]. The great number of used electrodes makes this system obtrusive.

In literature [6] Honda Research Institute, Japan, has demonstrated a Brain-Machine Interface (BMI) that enables a user to control an ASIMO robot using nothing more than thought. Wearing a headset containing both (EEG) and near-infrared spectroscopy (NIRS) sensors, the user simply imagines moving either his right hand, left hand, tongue or feet - and ASIMO makes a corresponding movement. The system is still huge and slow, and the commands are quite crude and imprecise.

[7] Currently in progress in developing a research project on EEG-based BMI for controlling ASIMO robot. The system utilizing two complementary EEG components, the P300 event-related potential, a discrete selection mechanism triggered by rare, relevant stimuli in a sequence of background stimuli, and the imagination of movement, based on the principle that the sensorimotorcortex activity is identical whether a movement is actually performed or only imagined.

[8] Developed an EEG-based Brain Computer Interface (BCI) that consists in register the brain rhythmic activity through electrodes situated on the scalp, in order to differentiate one cognitive process from rest state, and use it to control one degree of freedom of the robot arm. Several cognitive process or ”tasks” were used to control the robot arm. One of the tasks consists in a ”motor imagery”: to think that is performing a movement with the right arm. This motor task has been selected because, as indicated in [9], to imagine a movement generates the same mental process and even physical that to make the movement, only that the movement is blocked. It has been tested other cognitive process, such as recite the ”Our Father” or ”Happy Birthday”.The system used four channels. The electrodes were disposed according to the 10/20 International System [3]. These are situated in the positions F4, FP2 (above the prefrontal cortex), Cz, C3 (above the motor cortex) and ground on Oz.Wavelet transform was used for feature extraction and MLP NN was used as a classifier. The input data to the classifier algorithm was the concatenation of the four channels spectrum.The selected parameters for the neural network are: 1 hidden layer, 30 neurons in that layer, a learning rate value of 0.03 and momentum of 0.2. The number of epochs has been limited to 1000. Different frequency bands have been tested into the frequency range between 0 to 32 Hz. For the cognitive process ”Motor Imagery (right arm)”, band between 16 and 31Hz offered good results (with less error 17%) and when a more specific band like between 24 and 31 Hz was selected results are improved(error = 16%). Also the total band (0-31) provided error rate of 20%.For the cognitive process ”Recite Our father” the results were worse, but not so bad. As previously, better results were obtained if a subband of the 0-32 Hz range is selected (error=26%).

Some other researches have been developed for another category of brain robot interface, to enhance post-stroke rehabilitation of arm or hand movement such as researches [10]-[14].The recent research in this approach is [15], a combined BCI-robotics system developed at the Max Planck Institute for Intelligent Systems, which used a BCI- based shared-control strategy to drive a Barret WAM 7-degree-of-freedom robot arm that guides a subject’s arm. They decoded only (one dimensional) movement intentions. Experimental validation of the system’s setup was carried out both with healthy subjects and stroke patients using a 35-electrode EEG-based BCI module.The signals are processed into 20 online features per electrode by discretizing the normalized average power spectral densities into 2 Hz frequency bins in the frequency range (2-42 Hz). The online decoding decided between three movement intentions of the patient, i.e., flexion, resting and extension, using the features described above. Two linear support vector machine (SVM) classifiers [16] were generated to classify the three movement intentions.

In [17] they used the frequency band [0- 32] Hz.Four channels were used in the experiment to detect 4 tasks,One of the tasks was imagery the right arm a movement and the other tasks were the reading of some words. WT was used for feature extraction and MLP neural network trained by the standard Back Propagation (BP) algorithm is used for classification. NN parameters were :1 hidden layer, 30 neurons in the hidden layer and number of epochs was 1000. The experiment achieved large error rate of 30%.

In [18] 16-electrodes were used for extracting the features. It detected three tasks that were: imagining the right, left arms movement and the rest state. LDA (linear discriminate analysis) is used for classifying two of the three tasks only and with law classification rate.

KATZ’s method was used in [19] for feature extraction to detect two tasks that are: imagining left and right hand movements. It achieved 77% classification accuracy using support vector machine (SVM) technique which considered a law rate in compare to other used techniques for classification in this application.

In [20] 62 channels were used to extract the features, which caused inconvenience to the subject during the recording process and increased the run time used for processing the data. Band pass filter between 1 to 100HZ was used to remove artifacts and unwanted signals. The results of EEG classification for left and right hand movements imaginary for three subjects A, B, and C was about 86.3%.

In this research the EEG dataset were acquired from a healthy subject, 26 year old, male during the moving of his right hand. The EEG dataset were extracted by four sensor (AF3,F7,F3, FC5) for three tasks (close, open arm and close hand) with non-invasive technique using the Emotive EPOC Neuroheadset. Band pass filter with frequency band between 0.5 HZ-45 HZ was used to filter the signals and remove the artifacts. Wavelet Transform (WT), Fast Fourier Transformation (FFT) and Principal Component Analysis (PCA) techniques were used for features extraction. Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm was used for classification, using the three different feature extraction techniques to compare.

WT technique achieved the max classification rate that reached to 91.1% in our experiment. Experimental results show that, the proposed system achieved high classification rates than other systems in the same application.

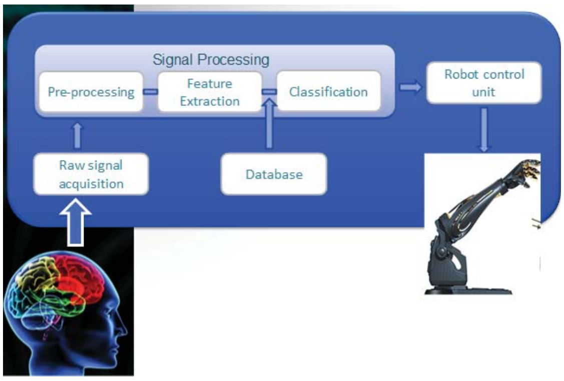

Fig. 1. Proposed System Methodology For Controlling a Robot Arm

III. Proposed System Design

The aim of this research is to classify three different tasks of arm movements (close arm, open arm and close hand). As illustrated in fig.1.

The system's methodology consists of five main steps. The first step was Signal acquisition, that has been done using Emotiv headset. The second step was signal preprocessing, to remove the noises and unwanted data. The third step was features extraction from the EEG signals. The fourth step was classification of the signals to three classes that corresponding to the three arm movements. The last step is to send a controlling command to the robot arm interface to simulate the desired movement.

A. Signal acquisition

Taking into account of reducing distraction to subjects, a reduced number of electrodes must be used in order to improve the system unobtrusiveness. So in this research four EEG channels only were used using the four sensors (AF3,F7,F3 and FC5) placed on the left part of the scalp. All dataset were taken from the Emotive EPOC Neuroheadset that enables to record the EEG signals from 14 channels, according to the international 10-20 System for electrodes placement as shown in fig.2.

An evaluation for the channels seclection has been done using Emotiv SDK (research edition) Test Bench.The Test Bench enables to trace the power of the signals for selected channels from the 14 channels of the Emotiv-Headset, and also trace the power of the 4 rhythm of the signal using Fast Fourier Transform (FFT) as shown in fig.3. According to the evaluation done, AF3,F7,F3 and FC5 channels were selected for data acquisition for their spatial properties, so it seemed to give high power signals at the recording conditions. Also the more power continuous rhythms were Alpha and Beta rhythms. Another reason for selecting this band is that, it produced best results in [8].

All data were acquired from a healthy subject, 26 year old male during moving his right hand .The headset samples all channels at 128 samples/second. Seven seconds epoch is used, then we have a total of 896 samples for each channel and a total of 3584 samples for the 4 channels used.The middle 5 seconds only were used, thus we reduced the number of samples to be 2560 samples. 220 iterations were recorded for each movement

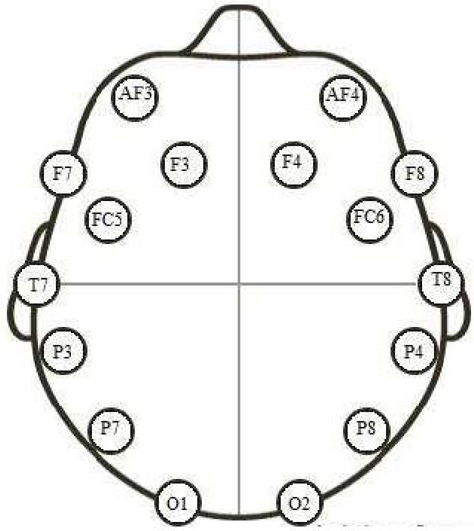

Fig. 2. Emotiv EPOC Headset Standard10-20 Electrodes Placement

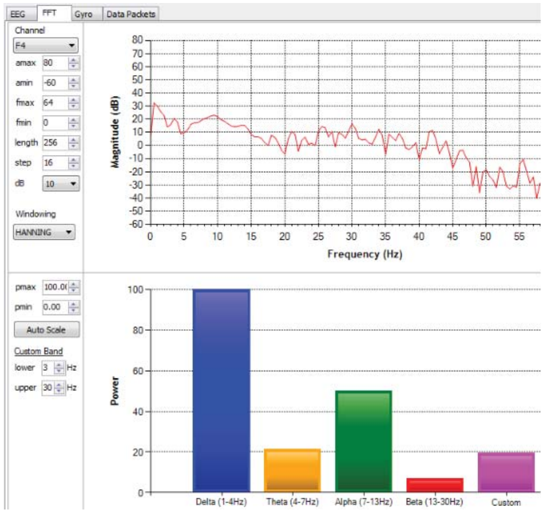

Fig. 3. The Test Bench using Fast Fourier Transform (FFT) for (f4) channel

intention (170 iterations were used for training, 20 iterations were used for validation and the remaining 30 were used for testing for each class).

B. Preprocessing

The EEG signals were filtered with band pass filter between 0.5 and 45Hz using a 5^{th} order Butterworth filter to remove the unwanted artifacts.

Using a Bandpass filter to reduce the frequency band used, reducing the numbers of channels (channel selection) and reducing the number of features, have a direct impact on reducing the execution time, and increasing the utilization of memory which enhance the system performance.

C. Feature extraction

Features extraction from the EEG signals were implemented using different techniques to compare. Since the EEG is a non-stationary signal many methods such as time domain, frequency domain, and time-frequency domain methods were used [21]. Wavelet transform (WT) was the most appropriate choice to use time-frequency domain methods as a vital for feature extraction [22]. The output of the Wavelet packet decomposition can be computed by the following equation:

$$wpt = wpdec(x, Level,' haar') \tag{1}$$

where $wpdec$ is a one-dimensional wavelet packet analysis function, $Level$ split the data vector x into Tree nodes for making the computation in each node. In our system the EEG data were decomposed into (Haar) mother wavelet with five-level wavelet packet decomposition (WPD).

The second feature extraction method used is the fast Fourier transformation (FFT), to extract the frequency components of the signal and then select the required components. FFT [23] computes the DFT where

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\Pi kn/N} \tag{2}$$

where k=0,1,...,N-1, x_n is the sampled values, N is the total number of samples in the vector.

The third and the last method used is the Principal Component Analysis (PCA) technique, that generally used to dimensionally reduce the original data to first n Eigen values [24], [25]. PCA performs an orthogonal linear transformation to a new coordinate system, such that the original signals were decomposed in uncorrelated components which were ordered according to decreasing variance.The PCA transformation matrix W

$$W = [w_1, w_2, ..., w_n] \tag{3}$$

can be obtained by performing a general eigenvalue decomposition of the covariance matrix $R = XX^t$ where X is the input signal(s) and $w_1, ..., w_n$ are n normalized orthogonal eigenvectors of XX^t corresponding to n different eigenvalues $\lambda_1, \lambda_2, ..., \lambda_n$ in descending order. The PCA transformation (Y) of X is then given by:

$$Y = W^t X \tag{4}$$

where the rows of Y are uncorrelated to each other.

D. Classification

Neural network has been used by many researchers to classify the EEG signal [26]. In this research, multi-layer Perceptron Neural Network trained by a standard back propagation algorithm was used for classification. The recorded data were randomly divided into training and testing sets. Every time the system was executed 220 trials were used for each task (170 trials were used for training,20 iterations were used for validation and the remaining 30 trials were used for testing). Extracted features are then defined as input neurons to the neural network algorithm.

The output layer should contain 3 neurons for the three classes that represent the three arm movement that we want to classify. The number of neurons in the input layer varied according to the length of the features vector. Since there are no certain rules for choosing the number of hidden layers, hidden neurons, many tests were done to select the optimal configuration for the neural network, with each features set used as will be explained in the experimental results.

IV. Experimental Results

During the experiment, subject is required to sit at rest with eyes close in a silent room, wearing the Emotiv Epoc headset and then continuously doing the required movement for 7 seconds. Data were recorded from the four channels AF3,F7,F3 and FC5 at sampling frequency of 128 Hz for the middle 5 seconds only.Three different features extraction methods were used as follows.

1) Fast Fourier Transform (FFT): The top ten Fast Fourier Transform amplitude values were taken. Thus we have 10 features for each channel and a total of 40 features for the 4 channels used.

2) Wavelet Transform (WT): Five levels Wavelet Packet Decomposition was applied on the EEG signals. Coefficients from nodes (5 2), (5 3), (5 4), (5 5), (5 6) and (5 7), which represents frequencies from 8 Hz to 32 Hz were extracted for further processing. The mean, μ(x), standard deviation, σ(x), and entropy, ε(x) were computed by the following equations respectively:

$$\mu = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{5}$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2} \tag{6}$$

$$\varepsilon = - \sum_{i=1}^{N} P(x_i) \log_2(x_i) \tag{7}$$

where N is the total number Coefficients in the vector, P is the probability of x_i

Values of each coefficient vector were calculated and used as features. Thus we have 6*3=18 features for each channel and a total of 72 features for each subject.

3) Principal Component Analysis (PCA): (PCA) technique was used to dimensionally reduce the original data to first n eigenvalues.So we have 4 eigenvectors corresponding to 4 eigenvalues in descending order for each channel and a total of 16 features for the 4 channels.

Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm was used for classification. The number of neurons in the input layer varied according to the length of the features vectors. preliminary tests were done to find the optimal configuration for the neural network in terms of: number of hidden layers (1 or 2), number of neurons in the hidden layer (10 or 15) and the maximum number of iterations (epochs) in the learning process (100, 500, 1000 or 5000).

For each features set, the configuration that produced optimal weights (which lead to maximum correct classification rate in the testing) for I/O mapping was used as shown in TableI.

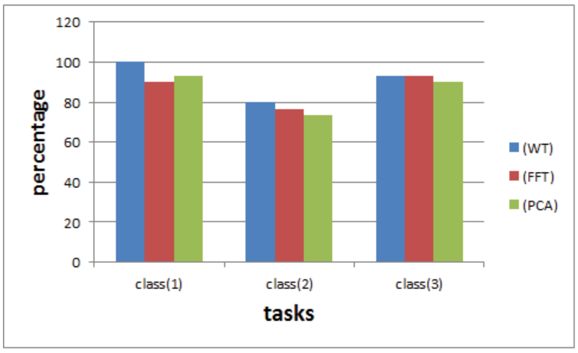

Fig. 4. Classification Rates for the Three Tasks using (WT),(FFT) and (PCA) Feature Extraction Techniques

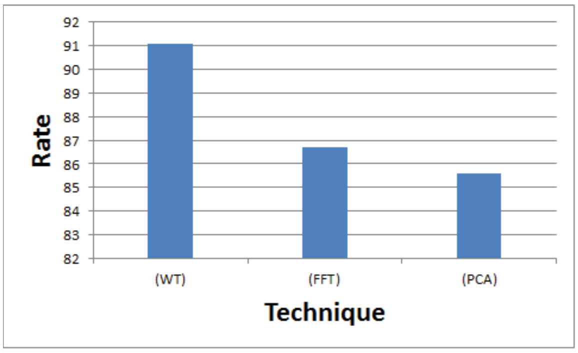

Fig. 5. Total Classification Rates using (WT),(FFT) and (PCA) Techniques

Table I
THE CLASSIFICATION ACCURACIES ACCORDING TO NN PARAMETERS AND FEATURE EXTRACTION METHOD

NN parameters \ Feature Extraction	(WT)	(FFT)	(PCA)
1-h layer 10 - neurons epochs-500	91.1	86.7	85.6
1-h layer 10 -neurons epochs-1000	89	82.6	81.2
1-h layer 15 - neurons epochs-1000	88.7	81.7	80.6
1-h layer 10 -neurons epochs-5000	85.9	80	77.8

The activation function used was the sigmoid function, the learning rate was 0.03 and the training stopped when either the maximum number of epochs reached the recorded value in Table I, or the mean square error reached to a small value such as 0.001. The correct classification rate (CC-rate) is calculated according to the following equation:

$$CCrate = C_t/T_n * 100\% \tag{8}$$

Where C_t is the total number of correct classifications and T_n is the total number of testing trials.

Data were analyzed using Matlab 2011. Classification rate for each movement intention using each features set is recorded in Table II. Graphical representation for the results is as shown in Fig.4. Total classification rates for the three used feature extraction methods as shown in fig.5.

Table II
AVERAGE CLASSIFICATION RATES FOR THE THREE TASKS (CLOSE ARM, OPEN ARM, CLOSE HAND) USING THE OPTIMUM NN CONFIGURATION

Tasks	Class 1	Class 2	Class 3	Total	Rate
(WT)	30/30	24/30	28/30	82/90	91.1%
(FFT)	27/30	23/30	28/30	78/90	86.7%
(PCA)	28/30	22/30	27/30	77/90	85.6%

30 trials were used for each task with each feature extraction method and a total of 90 trials for the three tasks.An important notice we must mention here is that, increasing the test samples logically enhances the percentage rate.

V. CONCLUSIONS AND FUTURE WORK

This paper presented a new non-invasive system for controlling a robotic arm using Brain EEG signal processing. In our model the EEG dataset was a real dataset. It was acquired from a healthy subject, 26 year old, male during moving his right hand using the Emotive Epoc headset device. The EEG signals were extracted by four sensor (AF3,F7,F3 and FC5) for three tasks (close, open arm and close hand). Wavelet Transform (WT), Fast Fourier Transform (FFT) and Principal Component Analysis (PCA) techniques were used for features extraction. Data were classified using the Back Propagation (BP) neural network of parameters: one hidden layer, 10 neurons, a learning rate of 0.03 with Maximum Epoch 500. Classification rates of 91.1%, 86.7% and 85.6% were achieved with the three used features extraction techniques respectively. Future work will be in trying to classify more actions and using other techniques for features extraction and classification to enhance the classifier performance.

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