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Unobtrusiveness System for Controlling a Developed Microcontroller-based Robot Arm using Brain EEG Signal Processing

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Abstract

This paper presented a new unobtrusiveness non-invasive technique for controlling, hardware developed microcontroller-based, robot Arm using Brain EEG signal processing. The system can help the paralyzed arm patients, who have severe disabilities, to control robots that can help them in daily living activities. Also the robot can be used to simulate the desired human arm's movements in situation where there are difficult or dangerous conditions that human's arm cannot act under it in many real systems applications. Fast Fourier Transform FFT is used for feature extraction. Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm is used as a classifier to classify 4 different arm movements intention which are: Shoulder up, Shoulder down elbow up and elbow down. The proposed technique produced high classification rates of 80%, 90%, 80% and 80% for the 4 different movements respectively. Two channels only are used, in our experiment, F4 which located at the prefrontal cortex and FC5 which located at the supplementary motor cortex of the brain. This improves the unobtrusiveness of our system that still achieved good recognition rates in compare to other related works as shown in the experimental results. Another main contribution in this paper is the hardware development of a 8051 microcontroller based robotic arm that has six degrees of freedom for movements.

Keywords*: EEG Signal processing, Brain Computer Interface, Brain Robot Interface, Bio_signal Processing, classification of Brain signals, microcontroller-based Robtic arm*

1. Introduction

Many different disorders can disrupt the neuromuscular channels through which the brain communicates with and controls its external environment. Amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, and numerous other diseases impair the neural pathways that control muscles or impair the muscles themselves.

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.

Variety of methods for monitoring brain activity might serve as a BMI. These include, besides electroencephalography (EEG) and more invasive electrophysiological methods, magneto encephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging. However, MEG, PET, fMRI, and optical imaging are still technically demanding and expensive. Furthermore, PET, fMRI, and optical imaging, which depend on blood flow, have long time constants and thus are less amenable to rapid communication. At present, only EEG and related methods, which have relatively short time constants, can function in most environments, and require relatively simple and inexpensive equipment offer the possibility of a new non-muscular communication and control channel, a practical BMI.

An important type of BMIs are non-invasive systems utilizing electroencephalography (EEG) to measure the brain activity, which provides a high temporal resolution of the measurement and easy as well as locally unrestricted application, enabling portable devices that can operate in real time.

The EEG is the electrical signal generated by the brain and recorded in the scalp of the subject. These signals are spontaneous because there are always currents in the scalp of living subjects. In other words, the brain is never at rest [1]. EEG signal has five major wave patterns, which are Delta rhythm, Theta rhythm, Alpha rhythm, Beta rhythm and Gamma rhythm. Delta (0.5–4 Hz): These waves are primarily associated with deep sleep and may be present in the waking state. Theta (4–8 Hz): These waves have been associated with access to unconscious material, creative inspiration and deep meditation. It seems to be related to the level of arousal. Alpha (8–12 Hz): these waves have been thought to indicate both a relaxed awareness without any attention or concentration. It is brought out by closing the eyes and by relaxation. Beta (12-30) Hz: It is most evident in the frontal region and associated with active busy or anxious thinking and active concentration. Gamma range (30-45): the amplitudes of these rhythms are very low and their occurrence is rare [2].

This paper presented a new unobtrusiveness non-invasive system for controlling a developed, microcontroller based, robot Arm using Brain EEG signal processing. two channels only are used to improve the system unobtrusiveness and still achieved a high recognition rates ranges from 80%-90%for 4 classes of movements intentions, which are: Shoulder up, Shoulder down, Elbow up and Elbow down, that. Fast Fourier transform is used to extract features from the EEG signal. Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm is used for classification in this research. Other main contribution of this research is the microcontroller-based hardware development of the used robot Arm.

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 and the hardware architecture of the developed Robot Arm. Section 4 explains the experimental results of the proposed methodology for classifying the 4 arm movements. Section 5 explains the software used for system implementation. Conclusion and future work are illustred in section 6.

2. Related Work

This research presented a developed microcontroller-based robot Arm that can be controlled using a brain EEG signal processing. 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 [3]. The BrainGate system is a neuromotor prosthetic device consisting of an array of one hundred silicon microelectrodes, each of which is 1mm long and thinner than a human hair. The electrodes are arranged less than half a millimeter apart on the array, which is attached to a 13cm-long ribbon cable connecting it to a computer. 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 electroencephalography (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 basic instructions, such as which direction to move in, and to pick up an object, to the robot. This is because it detects the brain's electrical activity only indirectly from the electrodes on the scalp, and not from within the brain itself [4]. The great number of used electrodes makes this system obtrusive.

In literature [5] 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 electroencephalography (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.

[6] 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.

[7] 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. The robot arm used in the experiments was a FANUC LR Mate 200iB. This robot has six degrees of freedom. 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 [12], 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". These tasks are more complex cognitive process related with the language and memory. The system used four channels. An evaluation for the optimum position of the electrodes has been done with a fMRI-study. The electrodes were disposed according to the 10/20 International System [2]. These are situated in the positions F4, FP2 (above the prefrontal cortex), Cz, C3 (above the motor cortex) and ground on Oz. *w*avelet transform is used for feature extraction and MLP neural network trained by a standard back propagation algorithm 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. The error percentage of cross validation is the output of the neural network. Different frequency bands have been tested into the frequency range between 0 to 32 Hz to check which of them provide better results. 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 [8-13]. The recent research in this approach is [14], 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. To achieve high classification accuracy with EEG, they decoded only (one dimensional) movement intentions. Experimental validation of the system’s setup was carried out both with healthy subjects and stroke patients. A key step in the setup is the online decoding of the movement intention of the system using an 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 [15] were generated on-the-fly after a training section to classify the three movement intentions.

3. Proposed system architecture

As illustrated in Fig.1. The system’s methodology consists of five main steps which are: Signal collections (acquisition), signal preprocessing to remove the noises, features extraction from the EEG signals, classification of the signals to four classes that corresponding to the four movement intentions we want to recognize and then the last step is to send a controlling command to the robot arm interface to simulate the desired movement.

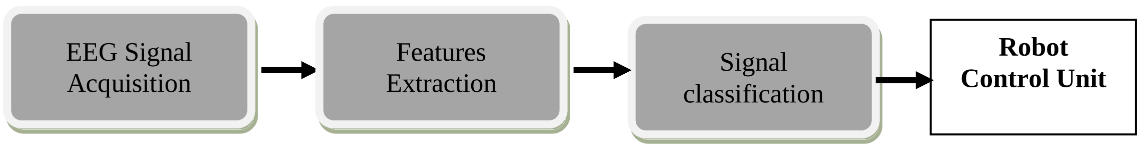
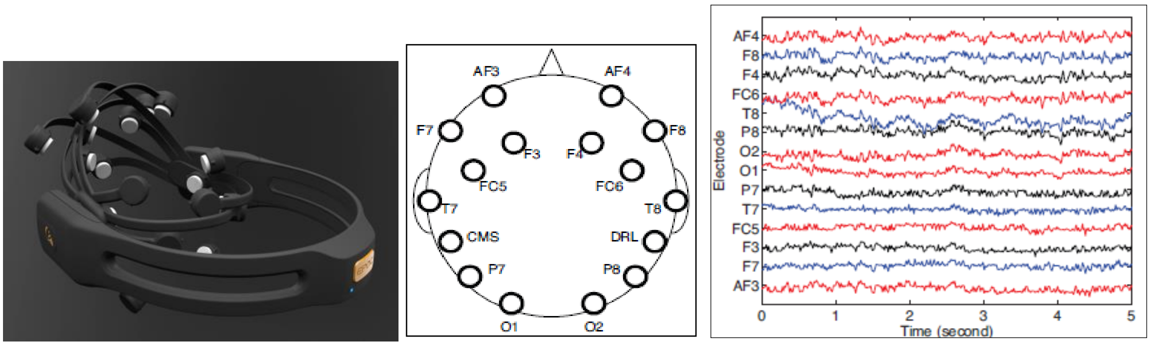


Figure 1. System Methodology

3.1 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 two channels only are used F4 (above the prefrontal cortex) and FC5 (above the supplementary motor cortex) to collect the brain data. We used the Emotiv EPOC headset [16] which has 14 electrodes and 2 reference electrodes (see Figures 2). The electrodes are placed according to the standard 10–20 international system [2] and are labeled as such [17]. The headset transmits encrypted data wirelessly to a Windows-based machine; the wireless chip is proprietary and operates in the same frequency range as 802.11 (2.4 Ghz). An evaluation for the optimum channels to be used 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 figure 3&4. According to the evaluation done, F4 and FC5 channels are 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 [7].

The headset samples all channels at 128 samples/second, each of which is a 4-byte floating-point number corresponding to the voltage of a single electrode. Seven seconds epoch is used, then we have a total of 896 samples for each channel. Data were collected from a healthy subject with 25 iterations for each movement intention (15 iterations are used for training and the remaining 10 are used for testing). The four movements intentions classified in this research are: shoulder up, shoulder down, elbow up and elbow down (for the Right arm). Subject was required to sit at rest in a silent room with eyes closed, and remain calm and relaxed, throughout the whole recording procedure.



(a) (b) (c)

Figure 2: a) Emotiv Epoc Headset. b) Headset Electrodes positions. c) raw data at rest state

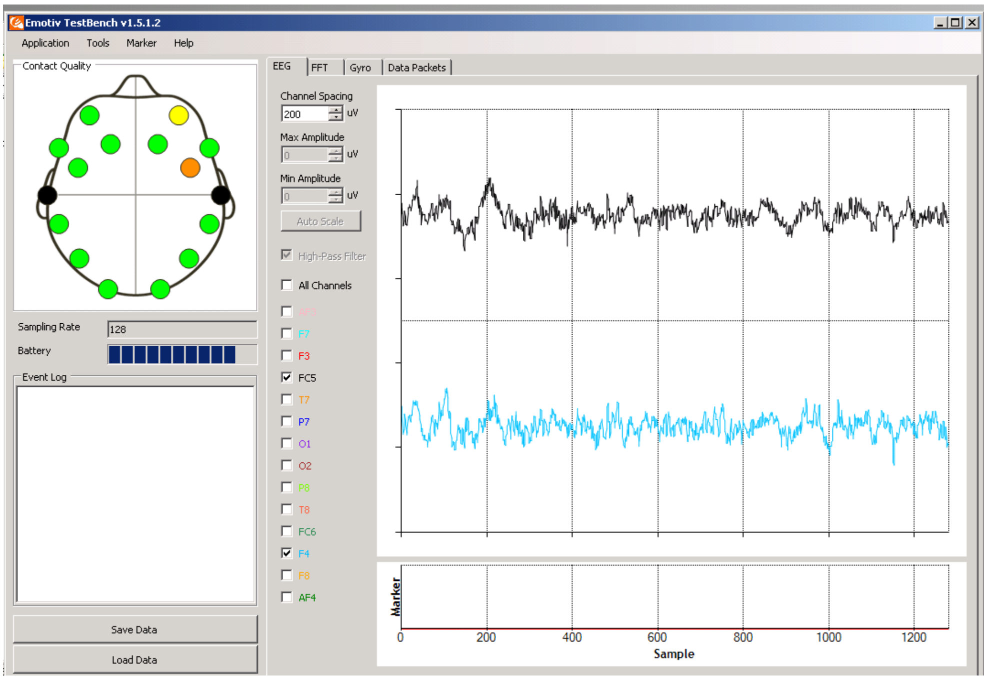


Figure 3. Channels Analysis using Emotiv SDK Test Bench

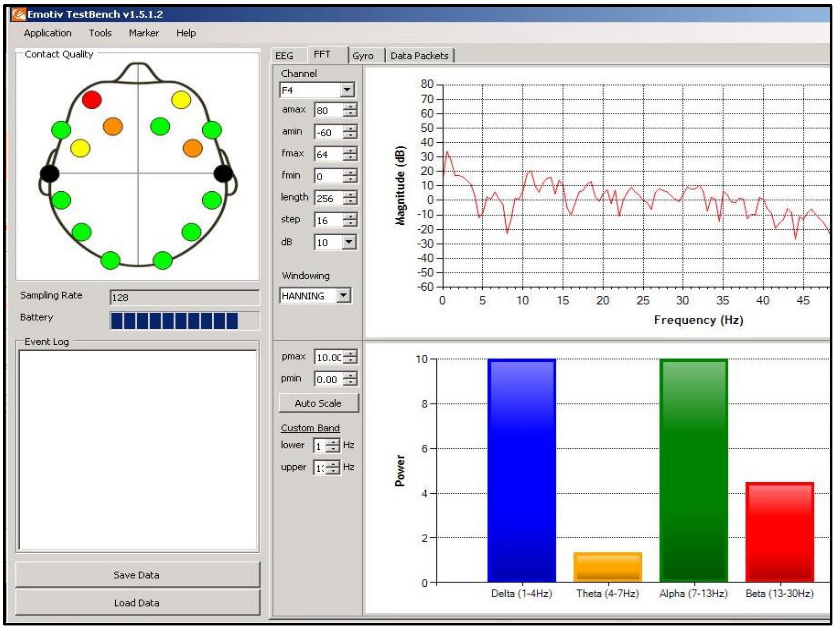


Figure 4. Frequency Bands Analysis for channel F4 using Emotiv SDK Test Bench

3.2 Signal preprocessing

EEG signal has five major wave patterns, which are Delta rhythm, Theta rhythm, Alpha rhythm, Beta rhythm and Gamma rhythm. Approximate ranges for these rhythms are as follows, as mentioned before in the introduction, Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12-30 Hz) and Gamma range (30-45 Hz) [1].

So in order to remove artifacts and obtaining better frequency characteristics, raw EEG signals must be filtered. The Emotiv SDK filtered the signal, using a band pass filter (Built in digital 5th order Sinc filter with bandwidth 0.2 - 45Hz) and digital notch filters at 50Hz and 60Hz, to remove other signals noises and the noise produced by alternating current at 50Hz generated by the recording console.

3.3 Features Extraction

Many research works are based on using Fourier transform for features extraction. The well-known discrete Fourier transform (DFT), with expression:

$$X(k) = \sum_{j=1}^{N} x(j) w_N^{(j-1)(k-1)}, \tag{1}$$

Where $w_N = e^{(-2\pi i)/N}$ is the N^{th} root of unity, is used herein to compute the DFT of each epoch. In our case, N is equal to 896 (128 Hz x 7 seconds).

The development of computationally efficient algorithms for the DFT is made possible if we adopt a divide-and-conquer approach. This approach is based on decomposition of an N-point DFT into successively smaller DFTs. This basic approach leads to a family of computationally efficient algorithms known collectively as Fast Fourier Transform FFT algorithms. The Radix-2 decimation in time (DIT) FFT algorithm rearranges the DFT of the function x(n) into two parts: a sum over the even-numbered indices and a sum over the odd-numbered indices as follows [18].

$$\begin{aligned} X(k) &= \sum_{m=0}^{(N/2)-1} f_1(m) W_{N/2}^{km} + W_N^k \sum_{m=0}^{(N/2)-1} f_2(m) W_{N/2}^{km} \\ &= F_1(k) + W_N^k F_2(k) \qquad k = 0, 1, \ldots, N-1 \end{aligned} \tag{2}$$

Where:
F1(k) and F2(k) are the N/2 point DFTs of the sequence f1(m) and f2(m) respectively. Where f1(m) & f2(m) obtained by decimating x(n) to even and odd numbered indices.

This result, expressing the DFT of length N recursively in terms of two DFTs of size N/2, is the core of the radix-2 DIT fast Fourier transform. The algorithm gains its speed by re-using the results of intermediate computations to compute multiple DFT outputs.

Features are extracted by selecting the frequency band of interest. Two different frequency bands are used for features extraction in this research. Each band produced different classification rate for each class of movement of the robot arm. These two bands are as follows.

1. For the first test, we select to use the frequency band from 8 to 30 Hz which represented the alpha, and beta EEG bands. As we found in the evaluation test using the Emotiv-SDK Test Bench, these bands had the highest power during our experiment. Also these bands produced the best results in [7].
2. For the second test, we used the top 10 frequencies that have maximum DFT amplitude values (maximum power spectrum).

3.4 Classification

Neural network has been used by many researchers to classify the EEG signal [19]. In this research, multi-layer Perceptron Neural Network trained by a standard back propagation algorithm is used for classification. The data collected are randomly divided into training and testing sets. Every time the system is executed; 60% of the data is used for training and the remaining 40% for testing. Extracted features are then defined as input neurons to the neural network algorithm.

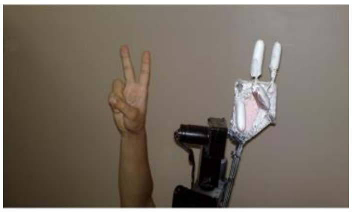
The output layer should contain 4 neurons for the four classes that represent the four arm movement that we want to classify. The number of neurons in the input layer varied according to the length of the features vector. The classifier performs a series of feed forward & back propagation processes with each pattern of the training set until the stopping criteria is met. During classification a feed forward operation is done on the input pattern & the desired class is given at the output layer. The maximum response of the output neurons is the index of the desired class. 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 feature set used as will be explained in the experimental results.

3.5 Hardware Developing of the Robot Arm

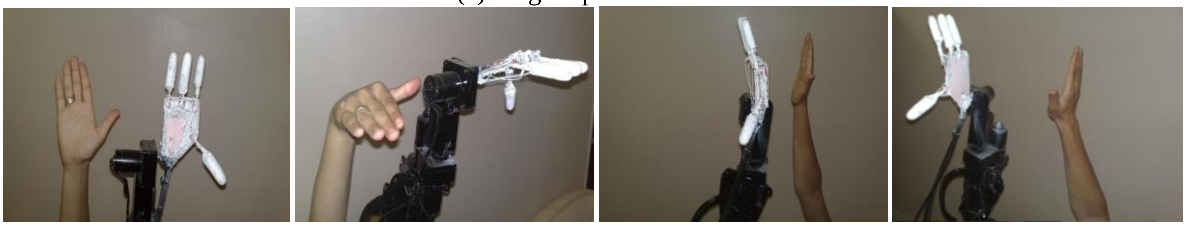
Another main contribution in this research is the hardware developing of the used robot arm. We suggested developing a simple low price Robot arm to simulate the recognized movement intention from the brain EEG signals. A 8051 microcontroller-based robotic arm is developed as shown in figure 5. The developed robot can be controlled to simulate a set of Six degrees of movements for the arm which are: finger close and open, hand up and down, hand right and left, Elbow up and Down, Shoulder up and down and moving the whole robot in one of the four directions (left, right, forward and backward) as shown in figure 6.

Figure 5. The Hardware Developed Robot Arm

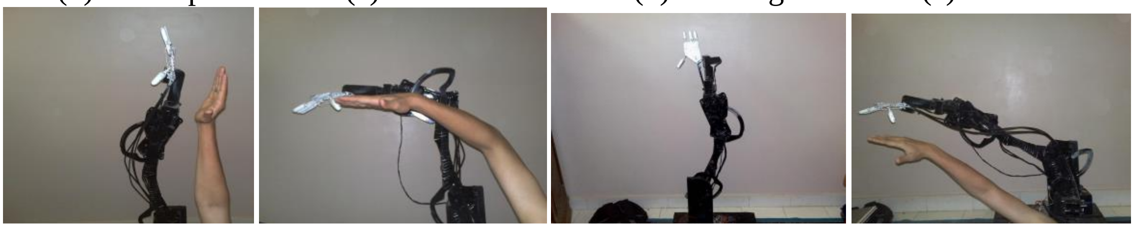
Usually the robot as the one developed in [20] is driven using stepper motors. But since the stepper motor is very expensive and we aim to develop a low cost robot arm, we used DC motors instead to drive our robot by controlling the motors to get the movement in the required direction. Ten DC motors are used to control the robot-arm to get the desired movement. To control any of the robot's motor we must send a controlling character code from the personal computer through the serial port (RS232 port) connection. The block diagram of the hardware components for the robot's motors interface (control unit) to the computer is as shown in figure 7. The main hardware components are illustrated as follows.



(a) Finger open and close



(b) hand up (c) hand down (d) hand right (e) hand left



(f) Elbow up (g) Elbow down (h) Shoulder up (i) Shoulder down

Figure 6. Robot Arm movements

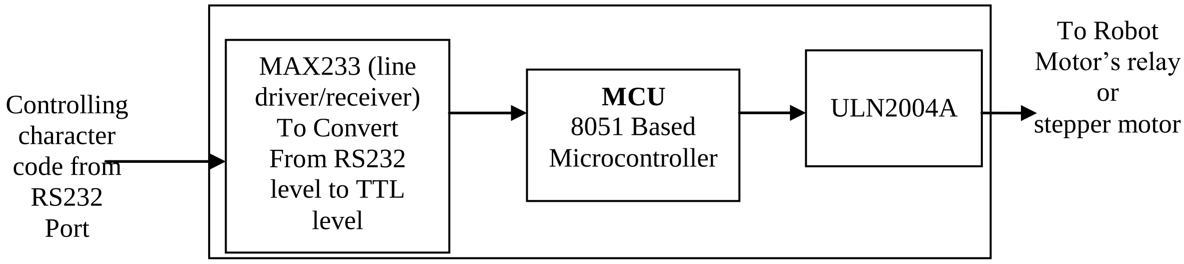


Figure 7. Block diagram of the main hardware components of the control unit of the Robot arm

Microcontroller

A microcontroller unit (MCU) is an entire computer manufactured on a single chip. Microcontrollers are usually dedicated devices embedded within an application e.g. as engine controllers in automobiles and as exposure and focus controllers in cameras. In order to serve these applications, they have a high concentration of on-chip facilities such as: *serial ports, parallel input/output ports, timers, counters, interrupt control, analog-to-digital converters, random access memory, read only memory, etc.*

We used the Atmel 8051 Microcontroller "AT89S52" Chip for our developed robot. It is a low-power, high-performance CMOS 8-bit microcontroller with 8KB of In-System Programmable (ISP) Flash Memory. Its pin configuration is as shown in figure 8 [21].

The AT89S52 provides the following standard features: 8K bytes of Flash, 256 bytes of RAM, 32 I/O lines, Watchdog timer, two data pointers, three 16-bit timer/counters, a six-vector two-level interrupt architecture, a full duplex serial port, on-chip oscillator, and clock circuitry. Detailed specifications can be found in [21].

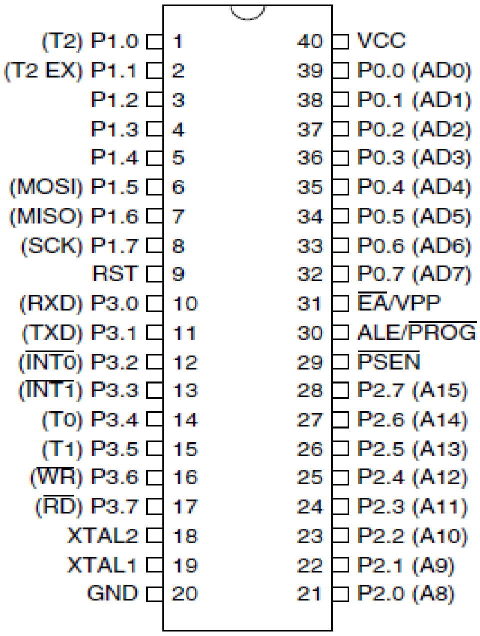


Figure 8. 40-lead PDIP pin configuration for AT89s52 microcontroller Chip [21]

MAX233 line drivers/receivers

A +5V-Powered, Multichannel RS232 line Drivers/Receivers (MAX233 chip from Maxim) is used to convert from RS232 voltage level to TTL voltage level. Pin configuration and typical operating circuit for MAX233 is as shown in figure 9 [22].

DC Motor

To rotate the rotor of the used DC motor we want a big electric current to pass through its coils. For the used motors in the developed arm robot we want 12 Volt and 4 Ampere, so we use relays to get this required high current.

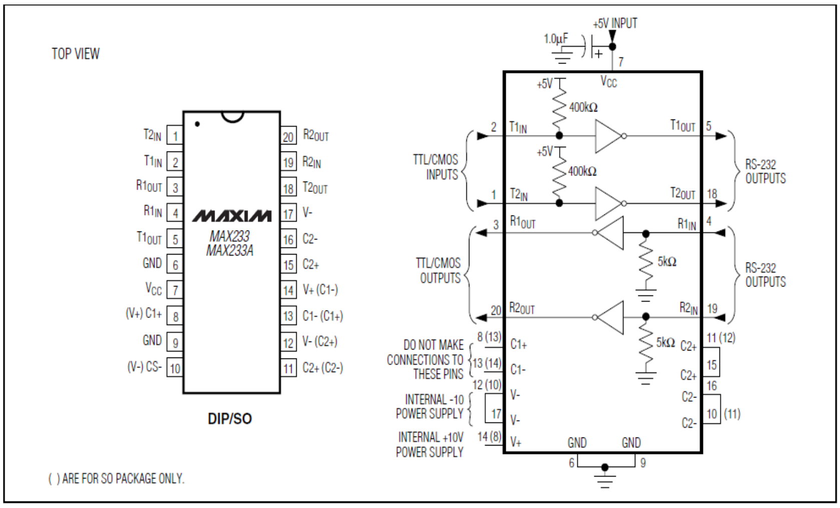


Figure 9. MAX233/MAX233A Pin Configuration and Typical Operating Circuit [22].

Relay

A relay is an electrically operated switch that uses an electromagnet to operate a switching mechanism mechanically. The used relay needs about 12 Volt and 100 mille Ampere of current to open the switch and pass a high current 12 volt and 4 Ampere to drive the rotor of the DC motor. Since the used 8051 microcontroller can operate 3 Volt and 10 mille Ampere only that can't open the relay, so we need external transistors which can operate 100 mille Ampere to the relay. So we suggested using ULN2004A chip.

ULN2004A

ULN2004A is a high voltage, high current Darlington array containing seven open collector Darlington pairs with common emitters. Each channel rated at 500mA and can withstand peak currents of 600mA. Suppression diodes are included for inductive load driving and the inputs are pinned opposite the outputs to simplify board layout as shown in figure 10 [23].

Hardware wiring of the main components of the robot arm control unit is as shown in figure 11.

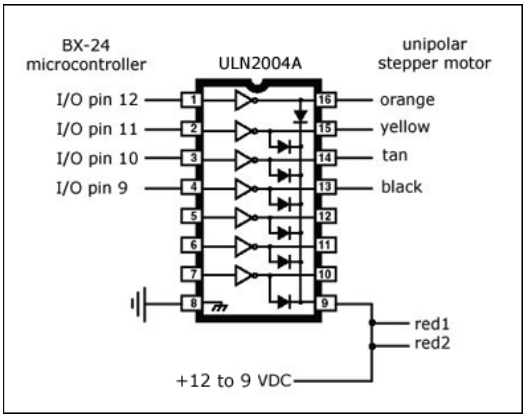


Figure 10. ULN2004A Pin Configuration [23].

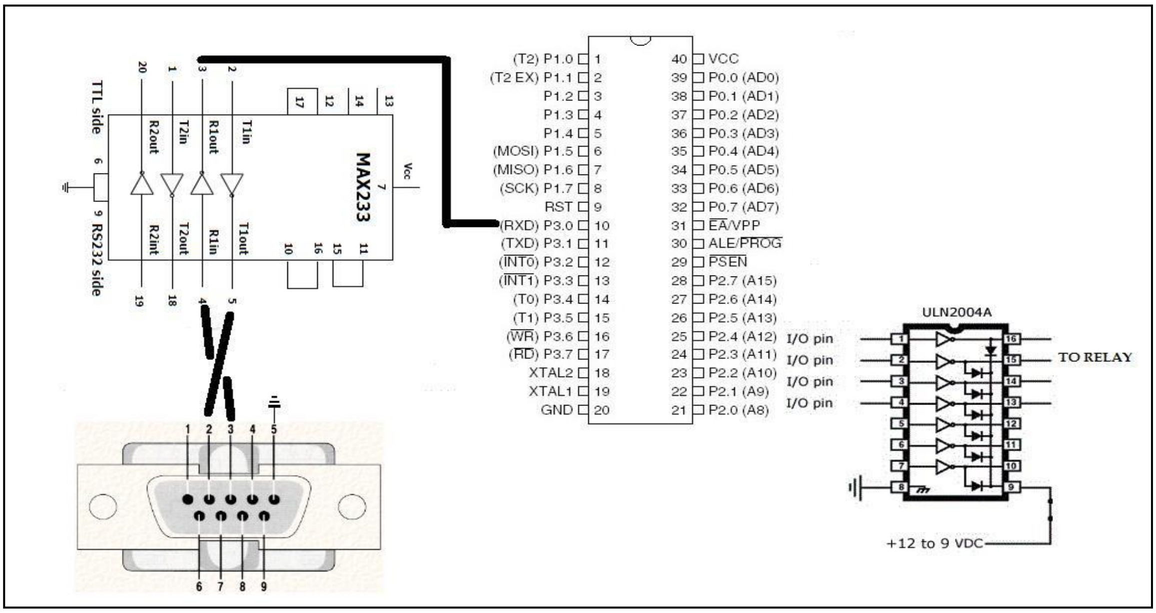


Figure 11. Hardware Wiring of the Robot-Arm Control Unit

3.6 Controlling the robot's motors

Microcontroller takes commands serially through RS232 serial port. If we want to rotate any motor so we need to send a special character to the microcontroller which decodes this character command and then executes the on-board program that we built to output the required signal and send it to the ULN to open the relay that belongs to this motor. We have 10 motors in our developed robot arm, each motor has three states: Forward, Backward and Stop. Computer send serially a block of 10 characters array of states of motors to the microcontroller such as for example: [stop, stop, stop, backward, forward, stop, forward, forward, backward, stop], the microcontroller then store it in its buffers and then check all motors' states and move the motors. C programming is used to develop the program for the 8051 micro-controller platform [24] that takes robot's motor signal (array of states) as input from RS232 port and controls the robot operation programmatically by sending the required control signals to the robot's motors (show figure 12).

4. Experimental Results for the EEG signal recognition

During the experiment, subject is required to sit at rest with eyes closed in a silent room, wearing the Emotiv Epoc headset and then continuously imagine the required movement for 7 seconds. Data are collected from the two channels F4 and FC5 at sampling frequency of 128 Hz. Two different features sets are used as follows.

1. Discrete Fourier Transform (DFT) amplitude values for the frequency band from 8-30Hz (Alpha and Beta Bands). Thus we have 23 features for each channel and a total of 46 features for the 2 channels used.

2. Discrete Fourier Transform (DFT) amplitude values for the Top ten frequencies that have maximum amplitude. Thus we have 10 features for each channel and then a total of 20 features for each subject.

Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm is used for classification. The number of neurons in the input layer varied according to the length of the features vectors, which are 46 and 20 for the two features sets used. Many 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 (100 or 1000) and the maximum number of iterations (epochs) in the learning process (100 or 1000). For each features set, the configuration that produced optimal weights (which lead to maximum correct classification rate in the testing) for I/O mapping is used as shown in table I. Thus we can conclude that, the classifier (neural network) configuration may play an important role in producing the best classification rate. The activation function used was the sigmoid function and the training stopped when either the maximum number of epochs (iterations) 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) for each movement is calculated according to the following equation:

$$CC\_rate = Ct/Tn * 100\% \qquad (2)$$

Where Ct is the total number of correct classifications and Tn is the total number of testing samples (10 samples for each movement). An important notice we must mention here is that, increasing the test samples logically enhances the percentage rate.

Classification rate for each movement intention using each features set is recorded in Table II. Graphical representation for the results is as shown in Figure 13. As shown in table II features set 1 produced better results than set 2. Error rates ranges from 10% - 20% are achieved. These results surpassed the results found in [7] with more movements recognized in this research.

TABLE I. Optimal Neural Network configuration for each features set

Features set	No. Input neurons	No . Iterations	No. hidden layers	No. neurons in hidden layer
1- DFT [8-30]	46	1000	1	1000
2- DFT top 10	20	1000	1	100

TABLE II. Classification Rate for each Arm movement for each features set

Movement		Shoulder up	Shoulder down	Elbow up	Elbow down
Features set 1	**Correct no**	8/10	9/10	8/10	8/10
	Rate	80%	90%	80%	80%
Features set 2	**Correct no**	7/10	8/10	8/10	7/10
	Rate	70%	80%	80%	70%

```
#include <reg51.h>
sbit sholder_d=P1^0;
sbit l_b=P1^1;
sbit l_f=P1^2;
sbit r_f=P1^3;
sbit r_b=P1^4;
sbit hand_r=P1^5;
sbit hand_l=P1^6;
sbit f_2_o=P2^0;
sbit f_2_c=P2^1;
sbit f_3_o=P2^2;
sbit f_3_c=P2^4;
sbit f_4_o=P2^6;
sbit f_4_c=P3^2;
sbit elbow_d=P2^3;
sbit elbow_u=P2^5;
sbit f_1_o=P3^3;
sbit f_1_c=P3^4;
sbit hand_d=P3^5;
sbit sholder_u=P3^6;
sbit hand_u=P3^7;
unsigned char finger1=0;          //b open // c close //a stop
unsigned char finger2 = 0;        //b open // c close //a stop
unsigned char finger3 = 0;        //b open // c close //a stop
unsigned char finger4 = 0;        //b open // c close //a stop
unsigned char hand_u_d = 0;       //b up // c down //a stop
unsigned char hand_r_l = 0;       //b right // c left //a stop
unsigned char elbow_u_d = 0;      //b up // c down //a stop
unsigned char sholder_u_d = 0;    //b up // c down //a stop
unsigned char motor_r = 0;   // b forward // c backward //a stop
unsigned char motor_l = 0;   / /b forward // c backward //a stop
unsigned char counter=0;
unsigned char x;
unsigned char go=0;

void OnSerialISR() interrupt 4
{ counter++;
if(counter>10)
{ counter=1; }
if (RI == 1)
{ x = SBUF; //store the received byte
RI = 0;
////////////////////// code check //////////////////////////////
if(counter==1)
{ finger1=x; } else if(counter==2) { finger2=x; } else
if(counter==3) { finger3=x; } else if(counter==4) { finger4=x; }
else if(counter==5)  { hand_u_d=x; } else if(counter==6)
{ hand_r_l=x; } else if(counter==7) { elbow_u_d=x; } else
if(counter==8) { sholder_u_d=x; } else if(counter==9)
{motor_r=x; } else if(counter==10) { go=1; motor_l=x; P0=20;
}
} }
//////////////////////////// Main //////////////////////////
void main(void)
{ P0=0;
P1=0;
P2=0;
f_4_c=0;
f_1_o=0;
f_1_c=0;
hand_d=0;
sholder_u=0;
hand_u=0;
TMOD=0x20; //use Timer 1, mode 2
TH1=0xFD; //9600 baud rate
SCON=0x50;
IE=0x90;
TR1=1; //start timer
while (1)
{
if(go==1)
{ go=0;
/// activating the states of the motors
if(finger1=='a') { f_1_o=0; f_1_c=0; } else
if(finger1=='b') { f_1_o=1; } else
if(finger1=='c') { f_1_c=1; }

if(finger2=='a') { f_2_o=0; f_2_c=0; } else
if(finger2=='b') { f_2_o=1; } else
if(finger2=='c') { f_2_c=1; }

if(finger3=='a') { f_3_o=0; f_3_c=0; } else
if(finger3=='b') { f_3_o=1; } else
if(finger3=='c') { f_3_c=1; }

if(finger4=='a') { f_4_o=0; f_4_c=0; } else
if(finger4=='b') { f_4_o=1; } else
 if(finger4=='c') { f_4_c=1; }

if(hand_u_d=='a')
{ hand_d=0; hand_u=0; } else
if(hand_u_d=='b') { hand_u=1; } else
if(hand_u_d=='c') { hand_d=1; }

if(hand_r_l=='a') { hand_r=0; hand_l=0; } else
if(hand_r_l=='b') { hand_r=1; } else if(hand_r_l=='c') {
hand_l=1;}

if(elbow_u_d=='a')
{ elbow_d=0; elbow_u=0; } else
 if(elbow_u_d=='b') { elbow_u=1; } else
if(elbow_u_d=='c') { elbow_d=1; }

if(sholder_u_d=='a') { sholder_d=0; sholder_u=0; } else
if(sholder_u_d=='b') { sholder_u=1; } else
if(sholder_u_d=='c') { sholder_d=1; }

if(motor_r=='a') { r_b=0; r_f=0; } else
if(motor_r=='b') { r_f=1; } else
 if(motor_r=='c') { r_b=1; }

if(motor_l=='a') { l_b=0; l_f=0; } else
if(motor_l=='b') { l_f=1; } else
if(motor_l=='c') { l_b=1; }
} } }
/////////////////////////// END Main ////////////////////////
```

Figure 12. The developed C program for programming the Microcontroller

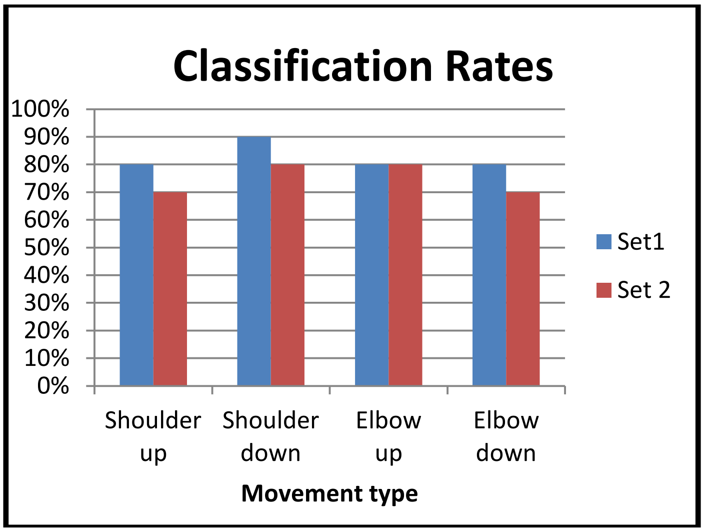


Figure 13. Classification Rate for each movement type with each features set

Once the decision of the current state is obtained, this information is translated to a pertinent robot command to produce the required movement.

5. System Implementation

Matlab 10 and Neurosolution package is used to implement the signal classification module. Proteus 7 Professional, software tool, is used to simulate the robot hardware design to trace it before wiring. The developed microcontroller C program that used to control the robot's motors is shown in figure 12. Keil uVision 4 software is used to debug and convert the developed C program to Hexa file format to be burned on the Microcontroller ROM chip. Visual C# is used to implement the interface program for controlling the robot through the PC after signal recognition.

6. Conclusion and Future Work

This paper presented a new unobtrusiveness non-invasive technique for controlling a developed microcontroller-based robot Arm using Brain EEG signal processing. The system can help the paralyzed arm patients, who have severe disabilities, to control robots that can help them in daily living activities. Fast Fourier Transform FFT is used for feature extraction using two different features sets. Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm is used as a classifier to classify 4 different arm movements' intentions which are: Shoulder up, Shoulder down elbow up and elbow down. The proposed technique produced high classification rates of 80%, 90%, 80% and 80% for the 4 different arm movements respectively. Taking into account of reducing distraction to subjects, two channels only are used, in our experiment, which located at the prefrontal cortex and the supplementary motor cortex of the brain. This improves the unobtrusiveness of our system that still achieved good recognition rates in compare to other related works as shown in the experimental results. Another main contribution in this paper is the hardware development of the used robot Arm. A simple hardware microcontroller-based robot arm is developed. It has six degrees of movement for fingers, hand, elbow and shoulder. Recognizing the other robotic arm's movements using the brain signals will be the main goal for our future work. Also enhancing the developed robot interface to reduce the time delay and enhance the response will be considered in our future work.

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