Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2018) 26: 707 – 720

doi:10.3906/elk-1606-296

Brain–computer interface: controlling a robotic arm using facial expressions

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Received: 20.06.2016 • **Accepted/Published Online:** 19.12.2017 • **Final Version:** 30.03.2018

Abstract: The aim of this paper is to develop a brain–computer interface (BCI) system that can control a robotic arm using EEG signals generated by facial expressions. The EEG signals are acquired using a neurosignal acquisition headset. The robotic arm consists of a 3-D printed prosthetic hand that is attached to a forearm and elbow made of craft wood. The arm is designed to make four moves. Each move is controlled by one facial expression. Hence, four different EEG signals are used in this work. The performance of the BCI robotic arm is evaluated by testing it on 10 subjects. Initially 14 electrodes were used to collect the EEG signals, and the accuracy of the system is around 95%. We have further analyzed the minimum requirement for the number of electrodes for the system to function properly. Seven (instead of 14) electrodes in the parietal, temporal, and frontal regions are sufficient for the system to function properly. The accuracy of the system with 7 electrodes is around 95%.

Key words: Brain–computer interface, electroenchephalograpy signal, facial expressions, robotic arm

1. Introduction

Electroencephalography (EEG) is a noninvasive method to record the electrical activity of the brain. EEG is widely used in the diagnosis of neurological disorders [1] and development of brain–computer interfaces (BCIs) [2–5]. BCIs translate the EEG signal into useful commands that can control output devices [6]. One of the many uses of BCIs is to enable disabled people to perform their daily activities without being dependent on other individuals. Different components of a BCI system are shown in Figure 1.

An EEG signal can be decomposed into four frequency components, namely beta, alpha, theta, and delta waves [7,8]. Beta waves have relatively low amplitude and their frequency ranges from 12.5 to 30 Hz. These waves appear when people are engaged in conversation. Alpha waves are slower than beta waves but have higher amplitude than beta waves. The frequency of alpha waves ranges from 7.5 to 12.5 Hz. These waves occur when people are listening to music, watching TV, or meditating. The frequency of theta waves ranges from 4 to 7.5 Hz. This state represents the presleep or semiawake state also known as the hypnoidal state. Delta waves have the highest amplitude and the slowest frequency, ranging from 0.5 to 3.5 Hz. This brainwave is associated with dreamless sleep. It is important for restoration of health and of the immune system. There are two more types of brainwaves, known as gamma and mu waves. The frequency of gamma waves range from 25 to 100 Hz. It represents an excited mental state and is advantageous for learning. Mu waves have the same frequency as alpha waves (7.5 to 12.5 Hz), but, unlike alpha waves, these are found at the sensori motor cortex. They represent the resting state of motor neurons. These waves play an important role in the function of the human brain.

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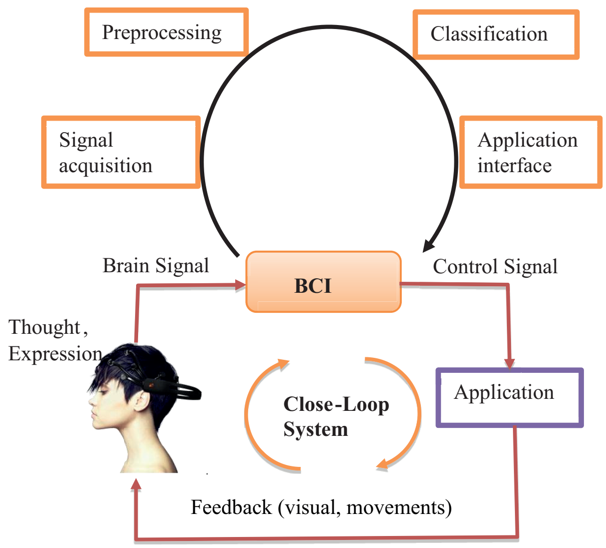

Figure 1. The different components of a BCI system.

One of the most interesting parts of BCI development is that these devices can be controlled by human thoughts. It may be very useful for people who lose the ability to use their muscles because of total or partial paralysis of their entire motor system due to stroke, traumatic brain injury, or cerebral palsy. These patients are fully conscious and alert, but are unable to use their muscles. Hence they can use the power of their brains along with the required interface and output devices to perform an action, e.g., wheel chair control or prosthetic arm control. In order to control a device using thoughts, some training is needed. For example, the subject may visualize closing his or her hand. The signals of this thought (hand-closing) will be collected; features will be extracted and then programmed into the BCI system. Later, when the subject thinks of closing his or her hand, the robotic hand will close automatically [5].

2. Overview

This section will give a brief overview of the hardware devices and software needed to design and develop a BCI-based system to control a prosthetic/robotic arm.

2.1. Data acquisition

The EEG signal is acquired from the brain using a wireless Emotiv EPOC headset [9,10] that receives EEG signals via electrodes placed on the human scalp (San Francisco, CA, USA). The Emotiv EPOC headset has 14 electrodes plus 2 reference electrodes that are located at positions AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, and O2 based on the international 10–20 system [11,12] of electrode placement. Here AF stands for anterior frontal, F stands for frontal, FC stands for fronto-central, P stands for parietal, and O stands for occipital. Two reference electrodes (CMS/DRL) are placed on P3/P4 as shown in Figure 2. The EEG data are acquired at a sampling rate of 128 Hz.

The Emotiv software development kit is provided by the Emotiv systems. This software package contains Emotiv Control Panel, EmoComposer, Emokey, and TestBench. The Emotiv Control Panel displays the mapping of the headset setup and the signal strength of each channel. It has three built-in suites: Expressiv Suite, Affectiv Suite, and Cognitiv Suite. The Expressiv Suite can detect facial expressions based on the user's

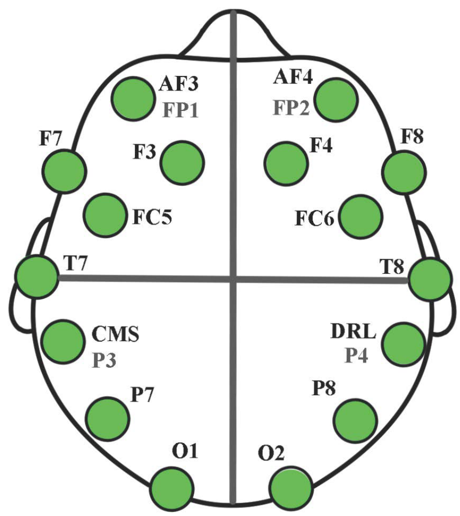

Figure 2. Emotiv EPOC sensor positions.

EEG signals. It uses an animated face to display the user's current expression. It can recognize 12 types of expressions and allows users to adjust the sensitivity of the signals. The interface of Expressiv Suite is shown in Figure 3. The Affectiv Suite reads the user's emotional state and the Cognitiv Suite reads conscious thoughts for movements and activity.

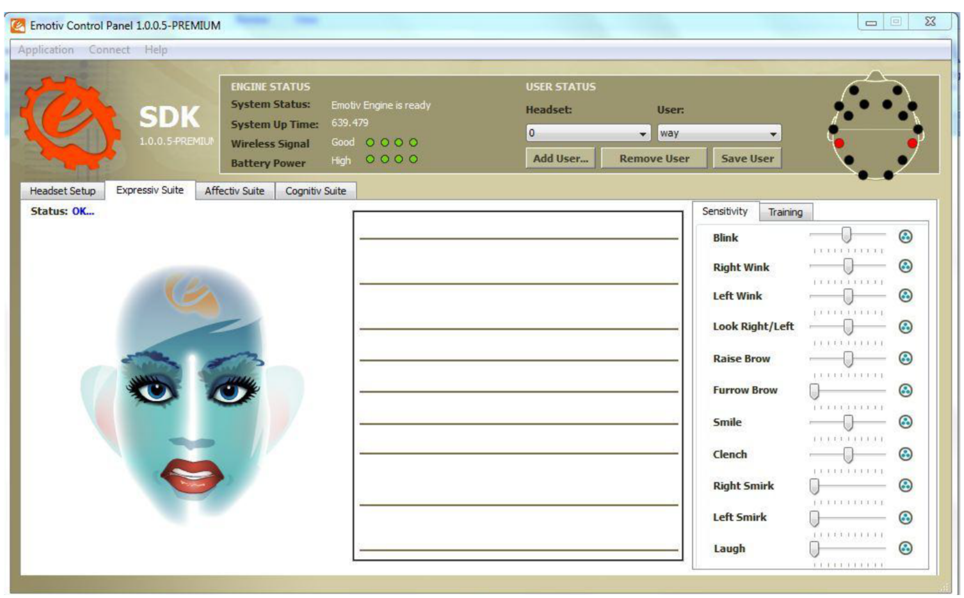

Figure 3. Interface of the Expressiv Suite.

2.1.1. EmoKey

The EmoKey is a program that allows the user to define keystrokes for sampled EEG signals. This program is connected to either Emotiv Control Panel or EmoComposer. An EPOC user can generate a keystroke(s) for a specific signal(s). Hence it is possible to use EmoKey to navigate and operate a device using these keystrokes.

After defining the keystroke, the user can save the key mapping for future use.

2.1.2. TestBench

The TestBench displays a graph of real-time raw EEG signals. The raw EEG signals can be recorded and saved for future playback by using the TestBench. This program also allows the user to observe the magnitude of fast Fourier transform and delta, theta, alpha, and beta bands.

2.2. Output devices

2.2.1. Arduino UNO

The Arduino UNO 2015a [13] is an electronic board with a built-in microcontroller that is based on the ATmega328. It is a tool for making devices that can be easily designed and programmed by the users, as shown in Figure 4.

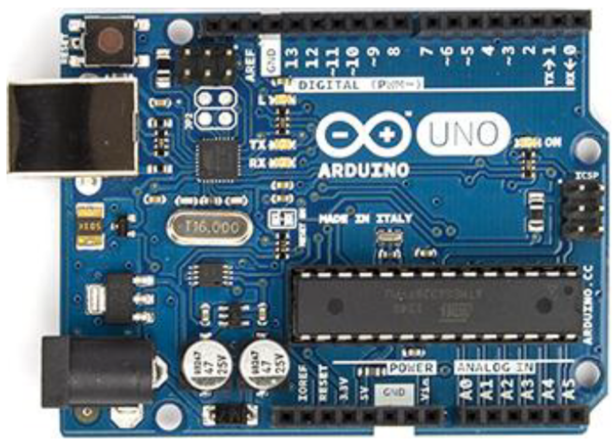

Figure 4. Arduino UNO.

2.2.2. InMoov Robot

Gaël Langevin is a French sculptor and model maker who had no real robotic engineering experience. He started a personal project to create a life-size humanoid robot called InMoov in January 2012 [14]. The InMoov robot shown in Figure 5 was designed with open source 3D software and can be printed using any 12 $\times$ 12 $\times$ 12 cm 3D printer. Those 3D part files (.stl) are open source and they are downloadable from Gaël's website (InMoov.blogspot.com). Gaël came up with the idea to incorporate servos and an Arduino to yield a programmable robotic hand. The hand can be controlled by using a keyboard and is able to move at many speeds. In 8 months, Gaël's project went from a simple hand to a torso, arms, and head. This robot has a moving capability just like a human being. The fingers are able to move, the hand is able to twist, and the elbow is able to flex and extend [15].

2.2.3. Robotic arm

In this paper, the hand part of the robotic arm is printed by a 3D printer based on the design of the InMoov robot. After printing and assembly, the forearm and elbow parts are built using craft wood. Five servo motors (TowerPro SG90, Taiwan) are attached to the forearm wooden board and bound to each finger of the printed

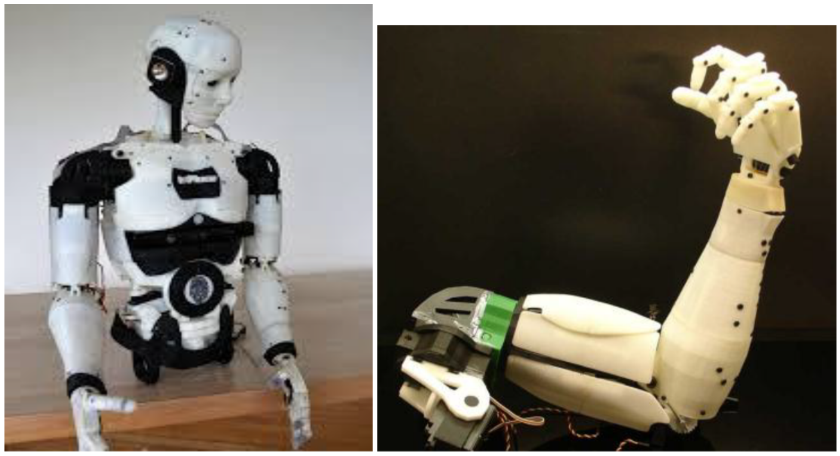

Figure 5. InMoov robot and the robotic arm.

hand part with fishing string. After that, the forearm and elbow are connected by a metal gear servo motor (RDS 3115). Lastly, the 6V battery holder and the Arduino board are attached to the elbow part. Figure 6 shows the design of the robotic arm.

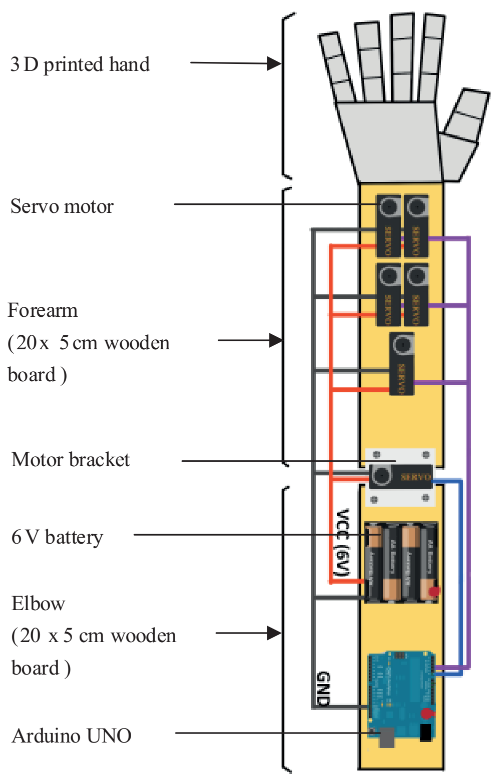

Figure 6. Design of the robotic arm.

3. Methodology

3.1. Design of the BCI system

The main objective of this research is to design a simple BCI-based robotic arm that is able to make four moves (flex and extend the elbow, make and release a fist) using EEG signals. To realize this project, a device that collects EEG signals as the input and converts the signals into mechanical output is necessary. The designed system consists of five steps, as shown in Figure 7. The first step is to acquire the brain signal for a specific thought/activity from a user by using the EPOC headset and Emotiv software. The robotic arm is designed to have four moves and so four different EEG signals generated using four different facial expressions are used in this work. The system is designed using the Expressiv suite provided by the Emotiv software. Since the EEG signals from different users may be different, it is necessary to create a profile for every subject/user.

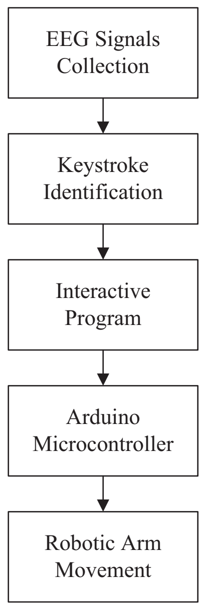

Figure 7. Block diagram of the BCI-controlled robotic arm.

3.2. Signal processing and EEG feature extraction

For this project, Expressiv Suite is chosen to control the robotic arm. In order to enable the robotic arm to perform four motions, four EEG signals are required using different facial expressions, as shown in Table 1. For every user, a profile is maintained so that the EEG signals are sampled and trained. To sample these signals, click on the “Training” button on the right-hand side of the software interface, select the expression to train, then click on “Start Training” and make the expression for 8 s. After that, click on the “Sensitivity” bar and adjust the sensitivity of the signals until the accuracy is better. Save and update the user profile after training and sensitivity adjustments.

The Emokey allows the user to define keystrokes for each EEG signal. These keystrokes will be sent as input to the Arduino microcontroller. The keystrokes are assigned for every expression and related movements, as shown in Table 1. In order to send commands from a personal computer to an Arduino microcontroller, an interface program is developed in MATLAB. The Arduino microcontroller will be programmed so that it can make the robotic arm move as described by the keystrokes from the computer. The flow chart of the complete system is shown in Figure 8.

Table 1. List of EEG signals and the corresponding robotic arm response.

Signal	Movement	Keystroke	Action
Left smirk	Make a fist	1	Finger motors turn 180°
Right smirk	Release fist	2	Finger motors turn 0°
Raise brow	Flexion of elbow	3	Elbow motor turn 150°
Look left/ right	Extension of elbow	4	Elbow motor turn 0°

3.3. Interface program

The keystroke information stores the EEG signature of the specific movements; this information is transferred to the robotic arm to perform a motion. This is done via an interface developed in MATLAB. An application with at least four buttons (for four types of arm response) is created and each button is assigned a specific hot-key. The hot-keys are defined by EmoKey. The flow of the interactive program to send the keystrokes from the computer to the Arduino microcontroller is shown in Figure 9. This interface sends input from the computer to the microcontroller of the robotic arm.

3.4. Arduino microcontroller

The robotic arm is driven by several servo motors that are controlled by the Arduino UNO R3 electronic board. The responses of the servo motors are listed in Table 1. This microcontroller is programmed so that it can read input from the computer and give output to all motors as shown in Figure 9.

3.5. Experimental procedure

3.5.1. Experiment 1: analysis of the performance of the system

The BCI system is tested on ten subjects to evaluate the sensitivity and accuracy of the system. Due to the malfunction of one of the electrodes (AF3) of the EPOC headset, all the subjects were tested with thirteen electrodes only. Thus, the term "full set of electrodes" refers to thirteen electrodes instead of fourteen. The flow of the experiment is as follows:

- Wear the Emotive EPOC headset.
- Create a user profile for each subject using the Emotiv control panel.
- Select Expressiv Suite from the control panel and train the subject. "Neutral" signal, followed by "Raise Brow," "Left Smirk," "Right Smirk," and "Look Left or Right." The subjects were advised to remain calm during the whole process.
- The subjects control the robotic arm and repeat each motion ten times.
- The data are recorded and analyzed.

3.5.2. Reduction of electrodes

The above experiment is performed using the full set of electrodes in the headset. The EEG data used to control the robotic arm are obtained from facial expressions. The control of the robotic arm involves the motor region of the brain and therefore we tried to decrease the number of electrodes used for the system based on the hypothesis that electrodes in the frontal and motor region will be more important [16].

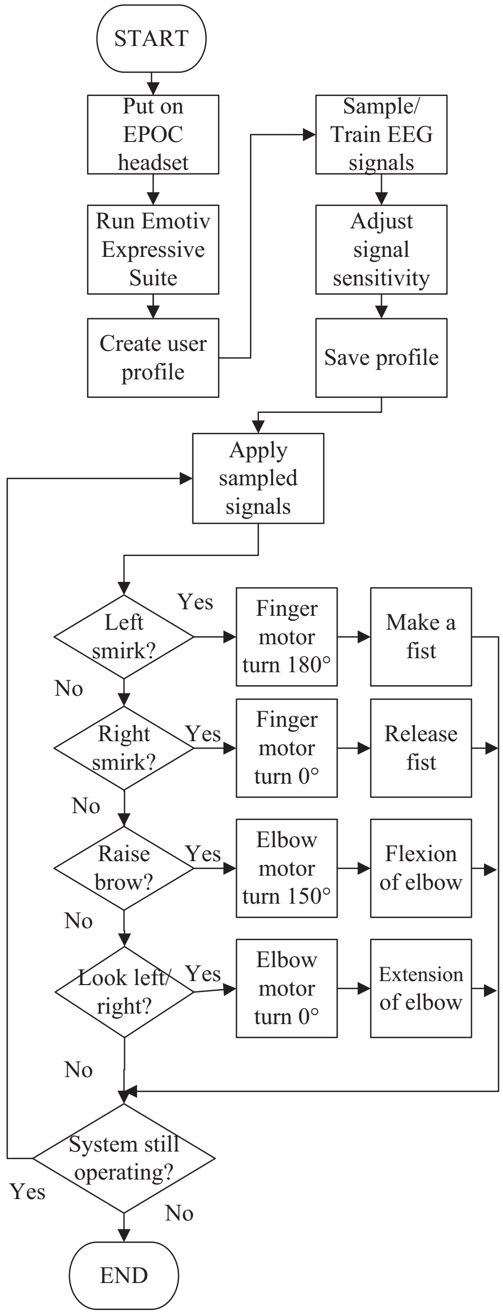

Figure 8. Flowchart of the BCI system.

We performed an analysis to find the minimum number of electrodes that are required by this BCI system without any degradation in the performance. The electrodes were removed one by one and the accuracy of the system was evaluated. With each electrode removed, the system was tested ten times for each move and the data were recorded to determine the accuracy. If the accuracy of the system is above 85%, we can assume that the electrode can be safely removed as it may not be essential for the proper functioning of the system. However, if the accuracy falls below 85%, then that electrode is considered important for the system. Later,

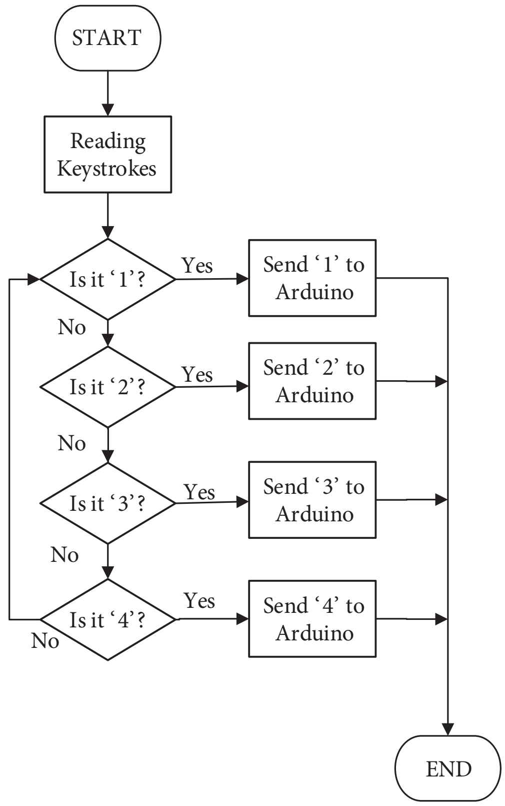

Figure 9. Flowchart of the interface program (signals are sent from the computer to the Arduino microcontroller).

the removed electrode was put back and another electrode was removed for testing purposes. This step was repeated until all electrodes had been tested.

3.5.3. Experiment 2: performance of the system with reduced electrodes

In order to test the accuracy of the system, the same test as in experiment 1 was performed in the same subjects with the reduced number of electrodes.

4. Results and discussion

The BCI-based robotic arm is tested on ten subjects. Each subject is tested ten times for each action; as there are four actions, the total number of trials for each subject is forty. In order to determine the accuracy of the system, first we need to define some metrics to measure the performance of the system [5]. These metrics are true positive (TP), false negative (FN), true negative (TN), and false positive (FP). The definitions of these performance metrics are given in Table 2.

The term "correct input" means the correct expression that is required to make the robotic arm to perform the desired move. To find out the value of TP or FN of an action, we need to refer to the result when the subject is doing a correct expression ten times. On the other hand, to find out the value of TN and FP of an action, we refer to the results generated by the other three actions, which result from the rest of the thirty trials. After the outcomes are defined, we can determine the sensitivity, specificity, and accuracy of the system. The sensitivity is also known as TP rate; it refers to the measure of positives that are correctly defined.

Table 2. Definition of performance metrics.

Outcome	Definition
True positive	Correct input, correct output
False negative	Correct input, incorrect output
True negative	Incorrect input, incorrect output
False positive	Incorrect input, correct output

The specificity, also known as TN rate, refers to the measure of the proportion of negatives that are correctly defined. Lastly, the accuracy defines the overall performance of the BCI system. The formulae of sensitivity, specificity, and accuracy are given in Eqs. (1) to (3).

$$\text{Sensitivity } = \frac{TP}{TP + FN} \tag{1}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{2}$$

$$\text{Accuracy } = \frac{TP + TN}{TP + FN + TN + FP} \tag{3}$$

Table 3 shows the performance of Subject 1. Table 4 and Figure 10 show a graph of the performance of all subjects. The minimum accuracy achieved is 0.85 for Elbow Extension by subject 10. There are some possible factors that may affect the accuracy, for example the emotion of the subject. Some subjects feel nervous when they cannot move the arm correctly and some subjects feel irritated because each experiment takes more than 30 min. However, when we look at the average accuracy in Figure 11, we can observe that all average accuracies are above 0.92 and the average overall accuracy of ten subjects is 0.95. Hence, we may conclude that the performance of the BCI-based robotic arm is good.

Table 3. Performance of subject 1.

Actions -Subject 1	TP	FN	TN	FP	Sensitivity	Specificity	Accuracy
Elbow flexion	9/10	1/10	30/30	0/30	0.9	1.000	0.950
Elbow extension	8/10	2/10	30/30	0/30	0.8	1.000	0.900
Close hand/make fist	9/10	1/10	29/30	1/30	0.9	0.967	0.900
Open hand/release fist	10/10	0/10	27/30	3/30	1.0	0.900	0.950

4.1. Determining the minimum number of electrodes required

In the previous experiment, ten subjects were tested to control the robotic arm. After the experimental results were found satisfactory, we proceeded to determine the minimum number of electrodes that are required for the system to work efficiently. One electrode is removed at a time from the EPOC and the performance of the system is observed. This step is repeated until all electrodes are tested. The results of the electrode removal are shown in Figure 12. When the accuracy of the BCI system falls below 85% by the removal of an electrode, that electrode is labeled an important electrode. However, if the accuracy of the system remains above 85%, even

Table 4. Performance of all subjects with full set of electrodes.

Number	Elbow flexion	Elbow extension	Make fist	Release fist	Average
1	0.950	0.900	0.900	0.950	0.925
2	1.000	0.867	0.983	1.000	0.963
3	1.000	1.000	0.950	1.000	0.988
4	0.950	0.933	0.933	0.883	0.925
5	0.950	0.883	1.000	0.900	0.933
6	0.983	0.983	1.000	0.950	0.979
7	0.950	0.900	0.983	1.000	0.958
8	1.000	0.883	0.950	0.933	0.942
9	0.933	0.867	0.933	1.000	0.933
10	0.950	0.850	0.983	0.950	0.933
Average	0.97	0.91	0.96	0.96	0.95

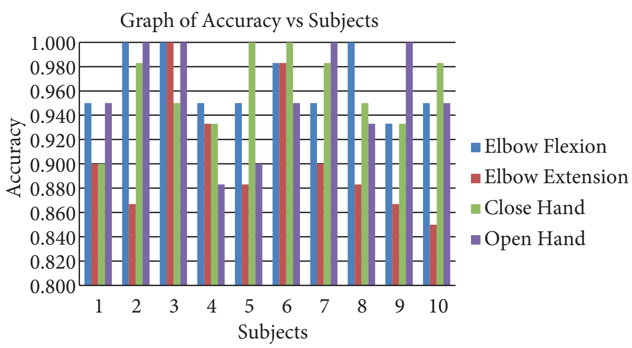

Figure 10. Graph of accuracy versus subjects for different moves with the full set of electrodes.

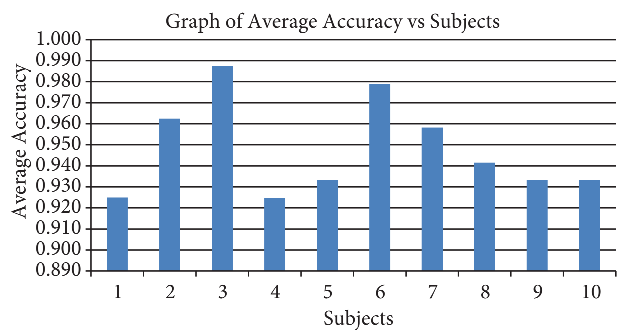

Figure 11. Graph of average accuracy versus subject for full set of electrodes.

after the removal of an electrode, then that electrode is not considered important and can be safely removed from the system. Hence, six electrodes are considered safe to remove; these are F3, FC5, F4, FC6, O2, and O1. The remaining 8 electrodes are considered important for the proper functioning of the system; these are P7, P8, T7, T8, F7, F8, AF4, and AF3, located in the parietal, frontal, and temporal regions. Figure 13 gives a visualization of the status of the electrodes.

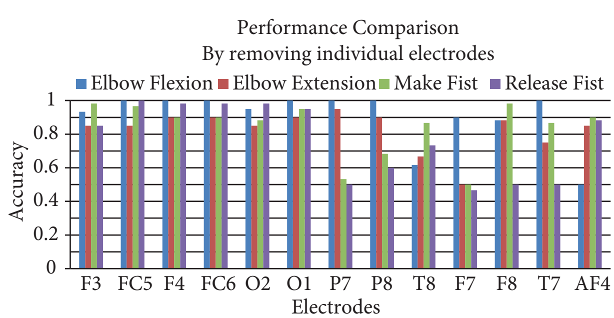

Figure 12. Comparison of performance by removing individual electrodes.

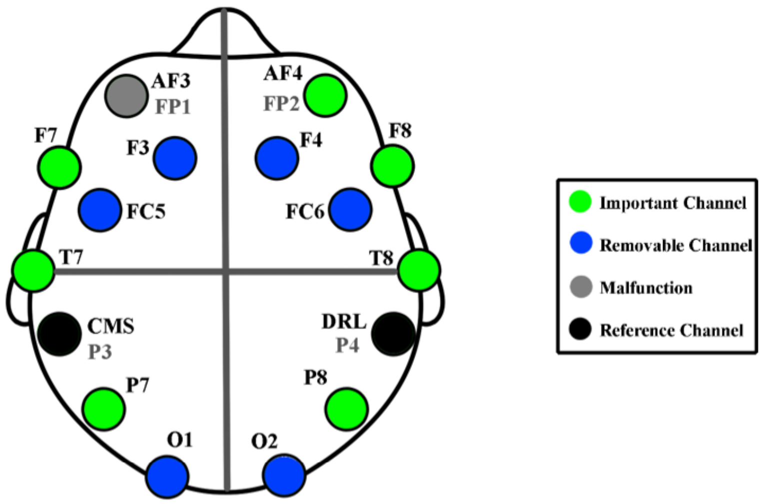

Figure 13. Visualization of the status of electrodes for BCI-controlled robotic arm.

4.2. Result of Experiment 2 (with seven electrodes)

Finally, the performance of the BCI system is tested with 7 electrodes on the same subjects following the same experimental procedure. The accuracy of the system is given in Table 5 and Figure 14. We can observe that the lowest accuracy achieved is 83.3%. The average accuracies are above 90%, while overall average accuracy is 95%, as shown in Figure 15. Figure 16 compares the results of Experiment 1 and Experiment 2; the average difference is only 0.316% and so the performance of the system using seven electrodes is considered satisfactory.

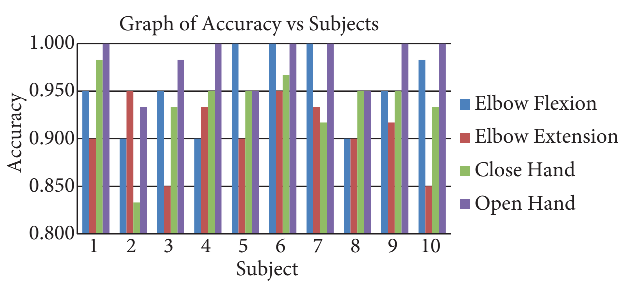

Figure 14. Graph of accuracy versus subject with reduced set of electrodes.

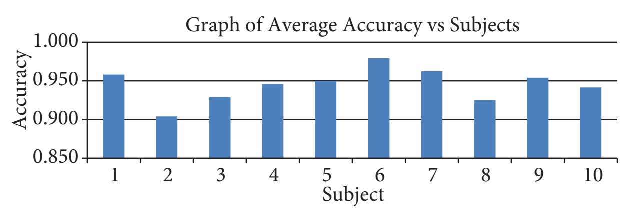

Figure 15. Graph of average accuracy versus subject for reduced set of electrodes.

In this experiment, instead of using facial expressions to control the BCI system, we have used the power of the human mind to control the robot [17]. Hence, the robotic arm is controlled using the thought process. The Cognitiv Suite of the Emotiv control panel can be used to acquire the user's conscious thoughts and intents to control the robot. The cognitive suite provides a graphical user interface for training. In this project, we have used Push and Pull cognitive states for training the cognitive activity to make and release a fist. This method was tested on two subjects with two moves only, but could not achieve very good results. The average accuracy achieved was around 50%. One of the reasons for the poor performance was that the subjects chosen found it difficult to use the thought process. Hence we may conclude that some subjects may need longer time to train themselves.

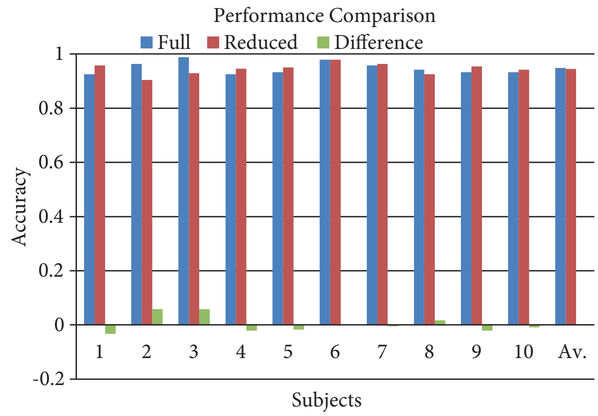

Figure 16. Comparison of performance with full and reduced set of electrodes.

Table 5. Performance of subjects with reduced set of electrodes.

Subject Number	Accuracy				
	Elbow flexion	Elbow extension	Make fist	Release fist	Average
1	0.950	0.900	0.983	1.000	0.958
2	0.900	0.950	0.833	0.933	0.904
3	0.950	0.850	0.933	0.983	0.929
4	0.900	0.933	0.950	1.000	0.946
5	1.000	0.900	0.950	0.950	0.950
6	1.000	0.950	0.967	1.000	0.979
7	1.000	0.933	0.917	1.000	0.963
8	0.900	0.900	0.950	0.950	0.925
9	0.950	0.917	0.950	1.000	0.954
10	0.983	0.850	0.933	1.000	0.942
Average	0.95	0.91	0.94	0.98	0.95

5. Conclusion and recommendations

In this paper, a BCI-based robotic arm that can be controlled by EEG signals generated from facial expressions is designed and developed successfully. An Emotiv EPOC headset was used to collect the EEG signals generated by facial expressions using the built-in Expressiv suite for feature extraction. The proposed robotic arm is able to make four moves (make and release a fist, extend and flex the elbow) using EEG signals resulting from left smirk, right smirk, raise brow, and look left or right. The EEG signals were trained using Expressiv Suite, which is provided by Emotiv software.

The robotic arm consists of three parts: hand, forearm, and elbow. The hand part has many joints. It was printed using a 3D printer and based on the hand design from the InMoov project. In order to reduce the cost of this project, the forearm and elbow part were built using wooden board. Six servo motors were attached on the forearm part to make the robotic arm move, while the power supply and Arduino board were attached to the elbow part.

The complete system was tested on ten subjects to determine its performance. The overall accuracy of the system is around 95%. We further investigated the minimum number of electrodes required by this system to have the same level of performance. It was concluded that the system performs equally well with only seven electrodes. The simplified system was tested on the same subjects and the overall accuracy of the system is around 95%. The robotic arm created in this project is controlled by facial expressions, which may not be a very ideal method. The ideal way to control the artificial limbs is using thought or imagination without making any physical movement. To enhance this system into an ideal system, deeper research on cognitive neuroscience is necessary.

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