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Citation: [AIP Conference Proceedings](#) **1559**, 37 (2013); doi: 10.1063/1.4824994

View online: <http://dx.doi.org/10.1063/1.4824994>

View Table of Contents: <http://scitation.aip.org/content/aip/proceeding/aipcp/1559?ver=pdfcov>

Published by the [AIP Publishing](#)

Brain Computer Interface for Operating a Robot

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Abstract. A Brain-Computer Interface (BCI) is a hardware/software based system that translates the Electroencephalogram (EEG) signals produced by the brain activity to control computers and other external devices. In this paper, we will present a non-invasive BCI system that reads the EEG signals from a trained brain activity using a neuro-signal acquisition headset and translates it into computer readable form; to control the motion of a robot. The robot performs the actions that are instructed to it in real time. We have used the cognitive states like Push, Pull to control the motion of the robot. The sensitivity and specificity of the system is above 90 percent. Subjective results show a mixed trend of the difficulty level of the training activities. The quantitative EEG data analysis complements the subjective results. This technology may become very useful for the rehabilitation of disabled and elderly people.

Keywords: Brain computer interface, EEG, robot.

INTRODUCTION

BCI is a field of biomedical signal processing, where signals are acquired and processed to operate devices. BCI gives alternative ways of communication between a user's brain and the environment, thus enabling people to control objects by their thoughts without any physical contact [1]. Since BCI does not need any physical movement, it might be the only communication system for disabled people who might not be able to speak or use other physical interface devices. Simple activities like, writing your email by simply thinking or able to maneuver your wheel chair without any help may be very useful to many people. For ordinary users BCI based games are gaining popularity, while other groups are using BCI for remote access, spying, and smart homes, etc. [2]-[5].

Electroencephalography (EEG) signals are created by the activity of neurons in the brain. The pattern of the EEG signals, correspond to the thoughts, emotions and behavior of an individual [6]-[8]. Human brain can produce five major brain waves, classified by their frequency ranges, known as Brain Rhythms. These major waves range from low frequency (0.5 Hz) to high frequency (100 Hz). These are known as delta (δ) (0 – 4 Hz), theta (θ) (4 – 8 Hz), alpha (α) (8 – 13 Hz), beta (β) (13 – 30 Hz), and gamma (γ) (30 – 100 Hz) waves [7].

Electrodes are placed over the scalp to acquire brain signals according to the international 10-20 system as shown in Figure 1 (a). The most common method of EEG signal recording from the brain is bipolar recording. Bipolar recording measures the potential difference between adjacent scalp electrodes. In advanced research or neural laboratories, often 64 to 131 recording electrodes are used to get more detailed data. However, an addition of electrodes may have less useful data unless that is supplemented by computer algorithms to manage the raw EEG data [9]. In some applications such as BCI, often a minimal number of electrodes (usually 14 recording electrodes as in Emotive EPOCH (Fig. 1(b)) are used and placed at movement related area in which the signals are strong using the conventional electrode positioning system.

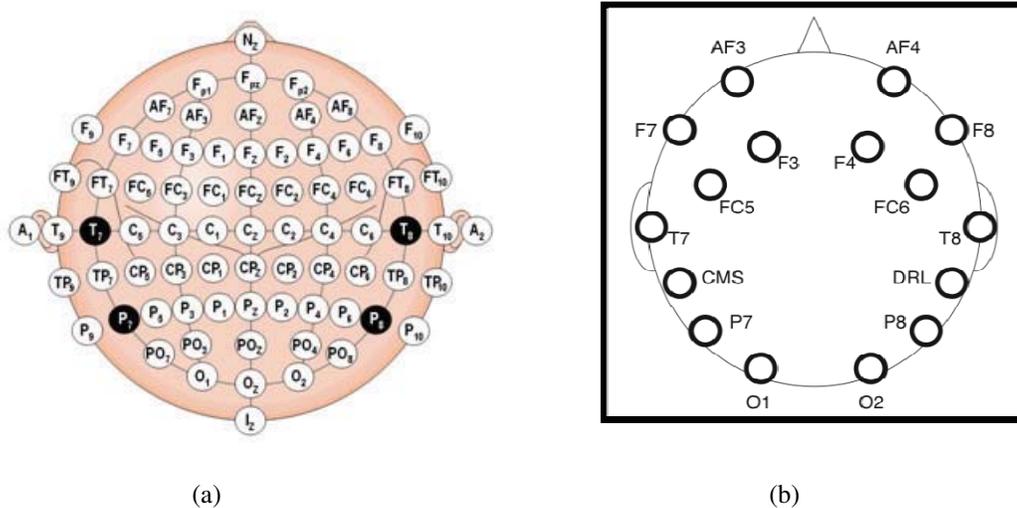


FIGURE 1. (a)The international 10-20 system or conventional electrode positioning, (b) Emotive EPOCH electrode positioning

In Fig. 1 (a) that shows the international 10-20 system, each site has a letter to identify the lobe and a number to identify the hemisphere location. The letters F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively. However note that there exists no central lobe; the "C" letter is used only for identification purposes. A "z" (zero) refers to an electrode placed on the midline. Even numbers (2, 4, 6, 8) refer to electrode positions on the right hemisphere, whereas odd numbers (1, 3, 5, 7) refer to those on the left hemisphere. The letter codes A, Pg and Fp, identify the earlobes, nasopharyngeal and frontal polar sites respectively. Figure 1 (b) shows the Emotiv headset that is equipped with 14 saline sensors: AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2 and two additional sensors CMS/DRL that serve as reference channels.

In this paper, we focus on the EEG signals produced by the brain electrical activity to control a robot. We are using a non-invasive device known as Emotiv EPOCH headset [10] to capture EEG signals that are used to control the movements of a Mindstorm NXT robot. The EEG signals are transmitted via bluetooth to the interface computer. These signals are read by the software and are analyzed and interpreted for further action. Based on the interpretation, a message is sent to the NXT robot via bluetooth to perform the specified action.

The rest of the paper is arranged as follows. In the next section we will provide an overview of the brain computer interface system. After that we will discuss the methodology adopted for training and testing. Later experimental results will be discussed followed by conclusion and references.

SYSTEM OVERVIEW

Figure 2 shows the block diagram of the proposed BCI system. It has three main modules: 1) Non-invasive EEG acquisition system, 2) An output device that needs to be controlled i.e. a NXT Robot, 3) Computer Interface.

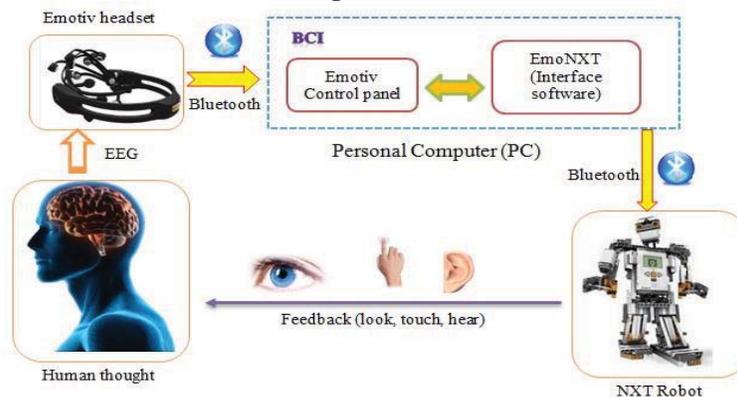


FIGURE 2. Block diagram of the proposed BCI System

NON-INVASIVE EEG ACQUISITION SYSTEM

The Emotiv EPOC is a neuro signal acquisition (EEG) and processing wireless headset that consists of 14 wet electrodes. It can detect/capture EEG signals [10] from the human brain. It is connected wirelessly through a USB dongle and provides 12 hours of continuous service via a lithium battery. Emotiv EPOC's sensor layout is planned carefully to gain optimum benefits for human machine interaction. Sensors are mostly located in the frontal cortex, so it is useful to detect upper face gestures and determine alpha waves while concentrating on the task. EPOC uses three built-in suites to determine the input signals. The user's facial expressions are analyzed by the Expressiv suite, the user's emotional state is interpreted by the Affectiv suite while the Cognitiv suite analyzes user's intent to control a movement.

Emotiv Software Development kit (SDK) comes with library and applications that allows the users to interpret the raw EEG signals and write a program to interface it with external devices without using the built in suites [10]. In this work, Cognitiv suite is used to evaluate the user's brainwave activity, when the user intends to perform a distinct physical action or many actions on a virtual (training) and a real object (testing/application).

Output device (NXT Robot)

The Mindstorms NXT robot is a programmable robotic kit from Lego that enables the design and construction of a robot, and sends the command to the NXT Intelligent

Brick via bluetooth connection. This NXT robot will receive a series of instructions from human brain via an interface PC to perform an operation. Furthermore, it comes with motors and sensors for robot's movement, and to detect any obstruction [11].

Computer Interface

The interface between the Emotiv EPOC and Mindstorms NXT Robot is developed by writing a program in C++. We call this interface EmoNXT. This program receives instructions from Emotiv API (application program interface) whenever the user thinks of a cognitive action (that has already been trained). The instruction received is processed and the output command is sent to the NXT robot via the bluetooth serial connection. The robot then follows the commanded action. A unique user profile for each user is required to map the user's brain-patterns. Figure 3 shows the block diagram of the interface between the EMOTIV and NXT robot.

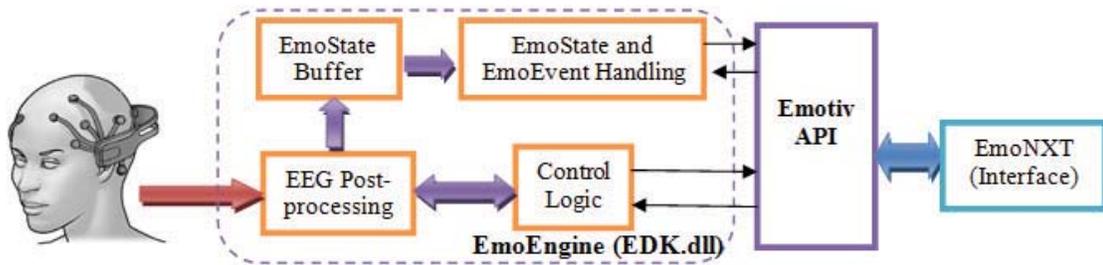


FIGURE 2. Block diagram of interface between EMOTIV and NXT robot

METHODOLOGY

The main goal of this research is to design, develop and implement a BCI system to control the NXT robot using EEG signals. The project utilizes an Emotiv EPOC headset, associated SDK and NXT development software to control a NXT Robot using EEG signals. To interface the Emotiv headset and the NXT Robot, first, Emotiv EPOC headset will acquire the EEG signals and transmit these signals via bluetooth to the computer, which will then be read by the Emotiv SDK. The software interface will interpret the results and pass it to EmoNXT interface. The EmoNXT will instruct the robot to perform an action.

The system function starts when the user thinks of a certain action (such as PUSH an object), then the Emotiv EPOC headset will receive the corresponding EEG signals and send it through the Emotiv EmoEngine to interpret and compare the data. This EmoEngine receives pre-processed EEG data and performs feature extraction and classification. The Emotiv detection system compares the trained EEG data with the current data from EmoEngine and translates it into EmoState. EmoNXT (interface software) receives input from EmoState and determines which action to perform. On the basis of which, a series of output commands/instructions are sent to NXT bricks via bluetooth COM port. This brick converts the input instruction from bluetooth and

controls the motor and sensors of the robot to perform the specific instructions such as move forward. This interface is illustrated in Fig. 3.

Hence the whole process may be divided into two steps; the training session and the testing/applying session. The training session needs visualization of the activity. The EEG signals are recorded during each session. Each user is required to have his own unique user profile.

Training Session

Before any control process is initialized, the action needs to be trained by visualizing it. In the Cognitiv suite, an animation with a 3D cube is displayed on the control panel (GUI-graphical user interface). We have trained four actions, that is, pull, push, left and right that correspond to move forward, move backwards, turn left and turn right respectively.

When the training session is complete, we can apply the trained action. When the system receives the signal from our visualization, it will compare the current signal with the recorded signal in order to perform any action on the cube. When the signal is matched with the visualization, the animated cube will be pushed, pulled, move left or move right according to our thoughts. After the virtual cube is well controlled, we can interface the recorded signal with the NXT Robot using EmoNXT.

After the training section is complete, the user is ready to apply the cognitiv event. The user needs to relax and visualize the action that he wants to perform, for example Push. The EmoNXT platform upon receiving the signal will display “Cognitiv State: Push Event”, and “Robot movement: move forward”. This indicates the user is applying push event and as a result the robot will move forward by a single step. Other cognitive events will result in respective robot movements.

EmoNXT (Emotiv Headset and Robot Interface)

EmoNXT is an interactive tool that provides interface between the NXT robot and Emotiv headset. It is written in C++ language. It sends command to the NXT robot corresponding to the cognitive action intended. The details can be found in [12].

The cognitive training is not very easy to control. It requires high relaxation and concentration level to control the movement of the animated cube. Therefore, a system that is trained by a different subject may not provide the expected performance when it is tested by another subject. For this purpose we have analysed the difficulty level of the virtual cognitive training and testing sessions using EEGlab, by calculating the average electrode power for each subject for cognitive training. We have also tried to correlate the EEG analysis with the subjective result of the difficulty level of the cognitive session obtained by asking the subjects to fill a questionnaire at the end of training/testing session.

The whole process may be divided into two steps; the training session and the testing session, that can be on a virtual object and an actual object i.e. robot in our case. The training session needs visualization of the activity. After the system is well trained it will operate according to our visualization or imagination. The sequence of steps is as follows:

- Training the Cognitiv Suite: Each user has to make his user profile for EEG acquisition. The Cognitiv Suite is used to acquire the user brain signals to control the robot. It provides a Graphical User Interface (GUI) for training a virtual 3D cube. Table 1 lists down the actions trained and tested.
- Actual motion control: After training, the robot is connected and actual testing is done on the robot to see the effect of cognitive training in real time, by thinking the same actions like pull, push etc. without the presence of the 3-D cube.

In order to assess the system we will find the sensitivity and specificity of the brain computer interface that was able to control the movements of the robot. The robot was able to carry out four instructions i.e. move forward, move backward, rotate right and left successfully. Table 1 shows movement of the NXT robot based on the cognitive action by the user. Table 2 shows the error definitions. The sensitivity and specificity of the system is calculated using Eq. (1) and Eq. (2). By correct cognitive action, we mean that we are trying to apply an action consciously, say Pull, so it is applied and the cube is pulled (seen coming forward on the screen). By incorrect cognitive action, we mean that we are trying to apply the pull command, but our brain is unable to pull, so instead of pull action, some other action is performed. Similarly incorrect cube action means that although it was supposed to move forward but it moves sideways.

TABLE 1. List of cognitive actions and robot motion (clockwise CW, counterclockwise CCW)

Cognitive action	NXT Robot movement	Motor movement
Push	Move forward	Motor B = CW, Motor C = CW
Pull	Move backward	Motor B = CCW, Motor C = CCW
Left	Turn left 5°	Motor B = CW, Motor C = CCW
Right	Turn right 5°	Motor B = CCW, Motor C = CW

TABLE 2. Error definitions for cognitive actions

True Positive	Correct cognitive action, Correct cube action
False Positive	Incorrect cognitive action, Correct cube action
True Negative	Incorrect cognitive action, Incorrect cube action
False negative	Correct cognitive action, Incorrect cube action

Calculation of sensitivity and specificity are shown below;

$$Sensitivity = \frac{\text{Number of True Positive}}{\text{Number of True Positive} + \text{Number of False Negative}} \quad (1)$$

$$Specificity = \frac{\text{Number of True Negative}}{\text{Number of True Negative} + \text{Number of False Positive}} \quad (2)$$

EXPERIMENTAL RESULTS

To test any cognitive action, one must train the EmoEngine to recognize the brain electrical activity for a specific user. Here we have tested the training on five different visualizations and examined which imagination will bring the highest power and accuracy. Table 3 and Fig. 3 show different visualizations for push action. Table 4 shows

results for PUSH action using 5 different visualizations. Table 5 shows results for robot motion caused by different cognitive actions tested by 3 subjects.

TABLE 3. Description of different visualizations of applying PUSH action

Imagination	Description
Pushing cube	animation cube in Emotiv SDK cognitiv action
Letter "P"	big 'P' letter in black font
Walk forward	walking forward with surrounding walls moving backward
Star	a 3D star in mono color
Red color	whole image in pure red color

FIGURE 3. Different visualizations for PUSH action



TABLE 4. Results for applying PUSH cognitive action by one subject (17 times)

Imagination	True +ve	False +ve	True -ve	False -ve	Sensitivity	Specificity
Pushing cube	9	1	4	3	0.75	0.8
Letter "P"	5	2	7	3	0.63	0.78
Walk forward	2	1	9	5	0.29	0.9
Star	0	0	10	7	0	1
Red color	5	6	3	3	0.63	0.33

TABLE 5. Results for robot movement based on cognitive action for 3 subjects (45 times)

Cognitive Action	True +ve	False +ve	True -ve	False -ve	Sensitivity	Specificity
Forward	45	0	45	0	1	1
Backward	42	3	43	2	0.95	0.93
Left	44	1	43	2	0.96	0.98
Right	44	1	45	0	1	0.98

It can be seen from Table 4 that visualizing the pushing cube for PUSH gives better results since the cube animation is displayed on the control panel. Table 5 shows the results of 4 cognitive actions. The sensitivity and specificity is above 90%, which means that the robot movements were efficiently controlled.

EEG Analysis and Difficulty Level Test for Different Cognitive actions for virtual visualization

The EEG study is conducted with 16 subjects (14 males, 2 females; mean age 22.39 ± 1.02 years). Four types of activities have been tested, that are Push, Pull, Left and Right. The subjects were asked to train two activities (Push and Pull) for 3 minutes, then rest for 2 minutes and then test each trained activity for 5 minutes. Then repeat the same procedure for Left and Right movement. EEG recordings were made while testing the different activities using Emotiv EPOCH headset on virtual 3D cube and

this data is analyzed using EEGLab [13] where power level of each electrode for each subject and activity level is calculated.

The significance level of the observations is calculated using one tail paired students t-test [14]. At the end of the session, subjects filled in a questionnaire that included information about their CGPA (cumulative grade point average), weekly physical activity and difficulty level of training testing sessions. The results show that during the training period, the PUSH cognitive action has moderate difficulty, while the rest of the actions are somewhat more difficult to train. During testing, left action is easy to apply, while the rest show moderate difficulty [15].

We have also classified the data into four different groups: 1) low CGPA, 2) high CGPA, 3) active life style, 4) in active life style, 5) low CGPA and active life style, 6) low CGPA and inactive life style, 7) high CGPA and active life style, 8) high CGPA and inactive life style. The distribution of the number of subjects in each group is shown in Table 6. Table 7 shows the normalized difficulty level experienced by different groups. The difficulty level is categorized into 3 groups; easy, moderate and difficult. The values in Table 7 represent the number of subjects experiencing the respective level of difficulty divided by the total number of subjects in that group.

TABLE 6. Distribution of subjects in different groups (total 16 subjects)

Type of Group	No of subjects
Low CGPA	8
High CGPA	8
Active lifestyle	8
Inactive lifestyle	8
Low CGPA+ active life style	5
Low CGPA+ inactive life style	3
High CGPA+ active life style	3
High CGPA+ inactive life style	5

TABLE 7. Normalized difficulty level data for different groups

Type of group	Difficult	Moderate	Easy
All subjects	0.22	0.42	0.36
Low CGPA	0.20	0.28	0.52
High CGPA	0.23	0.56	0.20
Active lifestyle	0.16	0.42	0.42
Inactive lifestyle	0.28	0.42	0.30
Low CGPA+ active life style	0.10	0.35	0.55
Low CGPA+ inactive life style	0.38	0.17	0.46
High CGPA+ active life style	0.25	0.54	0.21
High CGPA+ inactive life style	0.23	0.58	0.20

From the subjective results of those with low CGPA, it can be seen that they handled all the situations (push, pull, left, right) easily with very little effort. In general, they did not find it difficult. Their EEG result is not significant in general. This may be due to the fact that half of the participants find it difficult/moderate while

other half find it easy. Hence, the averaging cancels out the effects and the results are not significant in general.

Whereas those with high CGPA, it can be seen that they need moderate effort to do all the tasks. From the EEG results, it can be seen that at FC5, P8 and T8, delta, theta, and alpha are high for PUSH condition. As for the LEFT and RIGHT condition, theta and alpha are generally high for FC5, P7 and P8.

On the other hand for active subjects, it can be seen that they handled all the situations with moderate ease and little effort whereas their inactive counterparts found it slightly difficult to handle the trainings. From the EEG results, it can be seen that the first group shows decrease in various frequency levels. While the second group shows increase in various frequency levels for PULL and RIGHT condition.

From the subjective results of those with low CGPA and active lifestyle, it can be seen that they handled all the situations (push, pull, left, right) easily or with moderate effort. In general, they did not find it difficult. From the EEG results, it can be seen that at T7 and P7, theta, alpha and beta is high for rest conditions for PULL condition. Similar is result for RIGHT condition. As for the LEFT condition, delta is generally high. All this point to the fact that the subjects are not finding it difficult and they can do the task relatively easily.

On the other hand, the subjective result is equally divided for the low CGPA and inactive lifestyle participants. Their EEG result is not significant in general. This may be due to the fact that half of the participants find it difficult while other half find it easy. Hence, the averaging cancels out the effects and the results are not significant in general. Note that there are only 3 subjects in this group. So the analysis may not be significant.

For those with high CGPA and active lifestyle, subjective results show that the majority can do the tasks with moderate effort. The rest of the subjects are equally divided between easy and difficult. For those with high CGPA and inactive lifestyle, majority can do tasks with moderate effort and the rest of the subjects are equally divided between easy and difficult. The EEG results of both groups are almost opposite of each other. The first group shows decrease in various frequency levels while the second group shows increase in various frequency levels. This means that the second group requires more effort to complete the tasks as compared to the first group.

CONCLUSION AND DISCUSSION

This paper presents a non-invasive and cheap, real time brain computer interface system. In this system, the brain EEG signals are acquired by a 14 sensor headset, which are then fed to the robot via a computer interface. Four actions have been tested that are Push, Pull, Left and Right on the basis of which the robot performed the tasks such as move forward or backwards, rotate left or rotate right. It has been observed that the system developed was able to control the movements of the robot in real time with sensitivity and specificity of above 90%.

The system has been trained for 16 subjects. The results of initial evaluation and feedback from the subjects indicate that training a single task at a time is simple, but if the number of the tasks is increased then more effort is required. However, it can be

concluded that in future we can develop applications that will use the power of the human brain to perform actions in real and virtual environments. In future development, we plan to combine both affective action and cognitive actions to allow robot to perform more challenging tasks such as picking up an object.

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