

EEG-Based Brain-Controlled Mobile Robot

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Abstract: This project discusses about a brain controlled robot based on Brain Computer Interfaces (BCI). BCIs are systems that can bypass conventional channels of communication (i.e., muscles and thoughts) to provide direct communication and control between the human brain and physical devices by translating different patterns of brain activity into commands in real time. With these commands a mobile robot can be controlled. The intention of the project work is to develop a robot that can assist the disabled people in their daily life to do some work independent of others. Here, we analyze the brain wave signals. Human brain consists of millions of interconnected neurons. The pattern of interaction between these neurons is represented as thoughts and emotional states. According to the human thoughts, this pattern will be changing which in turn produce different electrical waves. Muscle contraction also generates unique electrical signals. All these electrical waves will be sensed by the brain wave sensor and converts the data into packets and transmits through Bluetooth medium. The brain wave raw data is sent to the computer and it will extract and process the signal using MATLAB platform. Then the control commands will be transmitted to the robot module to process. With this entire system, we can move a robot based on the human thoughts and it can be turned by blink muscle contraction.

Key Words: Brain-computer interface (BCI), brain controlled mobile robot, EEG, human factors, performance evaluation, shared control.

I. Introduction

The main aim of this project is to control a device based on electrical signals of brain. Brain Computer Interface (BCI) is a communication system, which enables the user to control special computer applications by using only his or her thoughts. Almost all of the research work on BCI are based on electroencephalography (EEG) recorded from the scalp. EEG is measured and sampled as the user imagines different things (for example, moving an arm). Different preprocessing and feature extraction methods are applied to the EEG sample of certain length depending on the type of BCI. The task-specific EEG signals or patterns are then detected from the EEG samples. BCI research was first started in 1960's, but it was in 1990's when it got serious. So far, over 20 BCI research groups have taken various approaches to the subject. Some of the BCI research groups have built an online BCI, which can give feedback to the subject. Despite the recent technological developments numerous problems still exist in building efficient BCIs. The biggest challenges are related to accuracy, speed and usability. However, BCI could provide a new communication tool for people suffering from so called locked-in syndrome where they are completely paralyzed physically and unable to speak, but cognitively intact and alert.

II. Brain-Computer Interfaces (BCIS)

A brain-computer interface can be defined as a communication system that does not depend on the brains normal output pathways of peripheral nerves and muscles i.e., a BCI should be able to detect the user's wishes and commands while the user is silent and immobilized. The brain activity must be monitored for this using various techniques.

EEG recordings from these techniques give continuous and instantaneous recordings of the brain activity (time resolution about 1 ms), which is required for real-time BCI.

Once the EEG of a user has been recorded, the BCI must then detect the user's commands from the EEG. Two main approaches are followed in achieving this. In the first approach the subject concentrates on a few mental tasks (for example, imagining an arm movement). Concentrations on these mental tasks produce different EEG patterns. The BCI can then be trained to classify these patterns. In the second approach called the

operant conditioning approach the user has to learn to self-regulate his or her EEG response (for example change the rhythm amplitude). Unlike in the pattern recognition approach, the BCI itself is not trained but it looks for particular changes (such as higher amplitude of a certain frequency) in the EEG signal. This requires usually a long training period, because the entire training load is on the user. According to Allison [1] there are at least five components necessary for effective BCI system: 1) Knowing what to look for; 2) Knowing the relevant physiological signals; 3) Gathering the data from the user; 4) Extracting useful information from the raw signal; 5) Interface design. The BCI can classify two mental tasks and provides feedback in the form of cursor control. It has also “reject” option, if the probability of the classification does not exceed some predefined level. The purpose of this chapter is to explain the concept of the BCI. First, the other part of the interface, the human brain, is examined. Then, the basic principles of electroencephalography (EEG) are explained. BCIs are divided into two above mentioned approaches. Then, the EEG measurement and the components of BCI system are defined. Feedback, human training issues and BCI performance measurement are explained after that.

2.1 Electroencephalography (EEG)

This is a method used in measuring the electrical activity of the brain. Brain electrical activity is generated by billions of neurons (nerve cells). Each of these neurons is connected to thousands of other neurons. All the signals from other neurons sum up in the receiving neuron and when this sum exceeds a certain potential level, the neuron fires nerve impulse. EEG can measure the combined electrical activity of millions of neurons. An EEG is characterized by its amplitude and frequency. The amplitudes of the EEG signals typically vary between 10 and 100 V (10 and 50 V in adults). The electrical activity goes on continuously in every living human’s brain without rest. The brain remains active even when one is unconscious. Allison [1] lists four prerequisites, which must be met for the activity of any network of neurons to be visible in EEG signal: 1) The neurons must generate most of their electrical signals along a specific axis oriented perpendicular to the scalp; 2) The neuronal dendrites must be aligned in parallel so that their field potentials summate to create a signal which is detectable at a distance; 3) The neurons should fire in near synchrony; 4) The electrical activity produced by each neuron needs to have the same electrical sign. Various properties in EEG can be used as a basis for a BCI:

1. Rhythmic brain activity
2. Event-related potentials (ERPs)
3. Event-related desynchronization (ERD) and event-related synchronization (ERS).

Band Frequency [Hz]

Delta (Δ) < 3.5

Theta (Θ) 4-7.5

Alpha (Α) 8-13

Beta (Β) >13

Rhythmic brain activity:

EEG rhythms are associated with various physiological and mental processes. The alpha rhythm is the principal resting rhythm of the brain, and is common in wakeful, resting adults. Auditory and mental arithmetic tasks with the eyes closed lead to strong alpha waves, which are suppressed when the eyes are opened (by a visual stimulus).

The alpha wave is replaced by slower rhythms at various stages of sleep. Theta waves appear at the beginning stages of sleep. Delta waves appear at deep-sleep stages. High-frequency beta waves appear as background activity in tense and anxious subjects. The absence of the normal (expected) rhythm in a certain state of the subject could indicate abnormality. The presence of delta or theta (slow) waves in a wakeful adult would be considered to be abnormal. Focal brain injury and tumors lead to abnormal slow waves in the corresponding regions. Unilateral depression (left - right asymmetry) of a rhythm could indicate disturbances in cortical pathways. Spikes and sharp waves could indicate the presence of epileptogenic regions in the corresponding parts of the brain [2].

Event-related potentials (ERPs)

ERP is a common title for the potential changes in the EEG that occur in response to a particular “event” or a stimulus. These changes are so small that in order to reveal them, EEG samples have to be averaged over many repetitions. The “random” fluctuations of the EEG, which are not stimulus-locked, get removed as a result of this. The most commonly studied ERP is P300. Positive deflection in the EEG occurs about 300 ms after the stimulus onset. P300 is commonly recorded during an “odd-ball paradigm”. In it the subject has been told to respond to a rare stimulus, which occurs randomly and infrequently among the other, frequent stimuli. Evoked potentials (EPs) is a subset of the ERPs, that rise in response to a certain physical (visual, auditory, somatosensory etc.) stimulus. A typical evoked potential is the Visual evoked potential (VEP) that reflects the

output features of the entire visual pathway. The EEG over the visual cortex varies at the same frequency as the stimulating light.

Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS)

ERD and ERS can be defined as follows:

1. ERD is an amplitude attenuation of a certain EEG rhythm.
2. ERS is an amplitude enhancement of a certain EEG rhythm.

In order to measure an ERD or an ERS, the power of a certain frequency band (for example, 8-12 Hz) is calculated before and after certain “event” over a number of EEG trials. The event can be externally-paced (such as light stimulus) or internally paced (such as voluntary finger movement). The power (averaged over a number of trials) is then measured in percentage relative to the power of the reference interval. The reference interval is defined, for example, as 1 second interval between 4.5 and 3.5 seconds before the event (i.e. during the rest). The ERS is the power increase (in percents) and the ERD is the power decrease relative to the reference interval (which is defined as 100 %). To keep the power at the reference interval at the resting level, the interval between two consecutive events should be random and not shorter than a few seconds.

2.2 BCI approaches

An ideal BCI could detect the user’s wishes and commands directly. However, this is not possible with today’s technology. Therefore, BCI researches have used the knowledge they have had of the human brain and the EEG in order to design a BCI. There are basically two different approaches that have been used. The first one called a pattern recognition approach which is based on cognitive mental tasks. The second one is called an operant conditioning approach and is based on the self-regulation of the EEG response.

2.3 EEG Measurement

The recording of the EEG signals is performed by fixing an electrode on the subject scalp (Fig-2.) using the standardized electrode placement scheme.

The subject is asked to wear an Electrode Cap through which the signals are acquired. Several channels of the EEG are recorded simultaneously from various locations on the scalp for comparative analysis of activities in different regions of the brain. The International Federation of Societies for Electroencephalography and Clinical Neurophysiology has recommended the 10 — 20 system of electrode placement for clinical EEG recording, which is schematically illustrated in Fig- 1. The name 10 — 20 indicate the fact that the electrodes along the midline are placed at 10, 20, 20, 20 and 10% of the total nasion - inion distance; the other series of electrodes are also placed at similar fractional distances of the corresponding reference distances. The inter-electrode distances are equal along any antero-posterior or transverse line, and electrode positioning is symmetrical. EEG signals may be used to study the nervous system, monitoring of sleep stages, biofeedback and control, and diagnosis of diseases such as epilepsy [2].

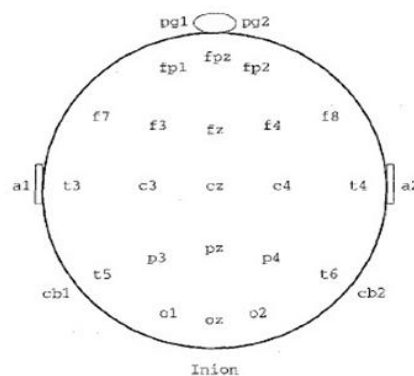


Fig- 1: The 10 — 20 system of electrode placement

Notes regarding channel labels: pg - naso-pharyngeal, a - auricular (ear lobes), fp - prefrontal , f - frontal, p – parietal, c - central, o - occipital, t – temporal, cb – cerebellar, z – midline, odd numbers on the left, even numbers on the right of the subject [2].

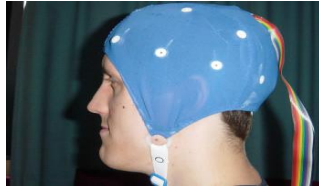


Fig- 2: A Subject wearing an electrode cap

Reference and bipolar recordings

The EEG recordings can be divided into two major categories: Reference recordings and scalp-to-scalp bipolar linkages. In the reference recording each electrode is referred to either distant reference electrode, one common electrode on each side of the head or to combined activity of two or more electrodes. The reference electrode(s) must be placed on the parts of the body where potential remains fairly constant. Usually reference electrodes are placed on the ear lobes or on the mastoid bones behind the ear. In addition to one single reference electrode two reference electrodes shorted together can be used. In bipolar recordings differential measurements are made between successive pairs of electrodes.

2.4 BCI Components

A typical BCI device consists of several components. These include electrode cap, EEG amplifiers, computer and subject's screen. A critical issue is how the user's commands, i.e., the changes in the EEG, are converted to actions on the feedback screen or the application. This process can be divided into five stages:

1) Measurement of EEG

This is done by using the electrodes. Many BCIs use a special electrode cap, in which the electrodes are already in the right places, typically according to the international 10-20 system [2] (see section 2.3.). It saves time because the electrodes do not have to be attached one by one. Typically, less than 10 electrodes are used in online BCIs with sampling rates of 100-400 Hz.

2) Preprocessing

This includes amplification, initial filtering of EEG signal and possible artifact removal. Also A/D conversion is made, i.e. the analog EEG signal is digitized.

3) Feature extraction

In this stage, certain features are extracted from the preprocessed and digitized EEG signal. In the simplest form a certain frequency range is selected and the amplitude relative to some reference level measured. Typically the features are certain frequency bands of a power spectrum. The power spectrum (which describes the frequency content of the EEG signal) can be calculated using, for example, Fast Fourier Transform (FFT), the transfer function of an autoregressive (AR) model or wavelet transform [5]. No matter what features are used, the goal is to form distinct set of features for each mental task. If the feature sets representing mental tasks overlap each other too much, it is very difficult to classify mental tasks, no matter how good a classifier is used. On the other hand, if the feature sets are distinct enough, any classifier can classify them.

4) Classification

A variety of classifiers have been used to translate these extracted features from EEG signals into an output command, from simple classifiers such as nearest neighbor, linear discriminant analysis (LDA), to nonlinear neural networks (NN), support vector machines (SVM), and statistical classifiers [3].

LDA is a widely used linear classifier. Compared with the other methods, the main advantages of LDA include the following: 1) It is simple to use and 2) it has low computational complexity. Thus, numerous brain-controlled mobile robots used LDA to develop the classifiers of BCI systems. Artificial neural network (ANN) is a widely used nonlinear modeling method for regression analysis and classification, which is based on biological neural networks. The main advantage of ANN as a classification method is its ability to approximate arbitrary nonlinear decision functions by minimizing the error in classifying training data. Unlike ANN, SVM does not need to set up many configurations and parameters [3]. Another advantage of SVM is that it has good generalization characteristics and is especially suitable for the cases, where a small amount of training data is gained. In addition, the two kinds of classifiers were widely applied into brain-controlled mobile robots [3].

Statistical classifiers classify one new instance into a particular class by selecting the highest one from the estimated posterior probabilities of all classes based on observed features of the new instance and prior knowledge. The main advantage of statistical classifiers is that it can represent the uncertainty of EEG signals. It has been applied into brain-controlled mobile robots [6], [7]. However, the robustness of all existing BCI

systems is not satisfactory due to the non stationary nature of noninvasive EEG signals. Considering that the natural change of brain signals over time and the change of brain activity patterns since the users develop new capabilities as subjects gain experience, *Mill'an* proposed that a possible research direction to improve the robustness is the online adaptation of the classifier during its use to drifts in the brain signals, and preliminary results have shown the feasibility and advantage of this method [8]. In addition, there are a few software tools that are widely used to process the EEG data such as EEGLAB [9] and BCI 2000 [10], which can help researchers develop brain-controlled mobile robots. More details of classifiers, applications, and issues regarding BCI systems can be seen in several reviews of BCI [1], [11], [12], [13], [14]–[18], [19].

5) Device control

The classifier's output is the input for the device control. The device control simply transforms the classification to a particular action. The action can be, e.g., an up or down movement of a cursor on the feedback screen or a selection of a letter in a writing application. However, if the classification was "nothing" or "reject", no action is performed, although the user may be informed about the rejection.

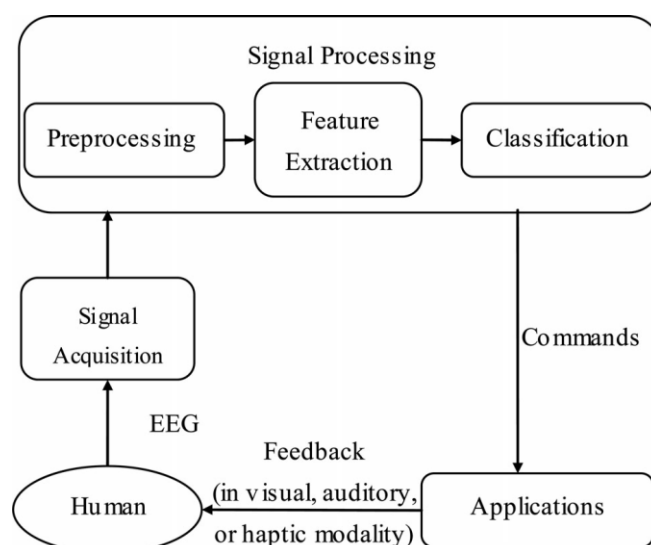


Fig- 3: Schematic of the main BCI components [3]

III. Actual System

Actual system can be mainly divided into 3 stages. In the first stage, a brain sensor with the help of EEG, acquires the raw data (signals) from the brain and transmits it in the form of packets via Bluetooth to the next stage the processing unit. The signals are processed here and then sent to the robotic module through serial data transmission using a ZIGBEE module. Based on the data and the commands received through the ZIGBEE module, the robot performs actions accordingly. MpLab software was used to program the PIC microcontroller used to communicate with the robot.

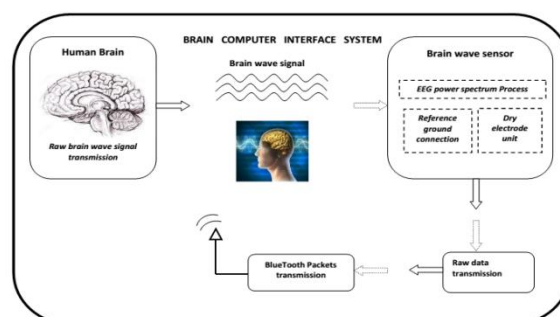


Fig- 4: Block Diagram-1

Fig-4 shows the first stage of the system (Data acquisition) and Fig- 5 shows the next two stages of the system i.e., Data processing and Robotic module.

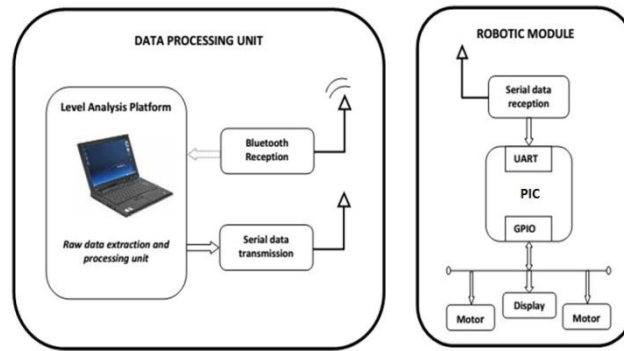


Fig- 5: Block Diagram-2

IV. Simulation And Results

Simulation showing the working of the robot was developed using KIEL and Proteus softwares. The on-off switch represents 5 eye blinks which activates the system. Once the system has been activated it works based on the input given. The FRONT, BACK switch is provided such that the motors (representing the wheelchair) move forward when it is high and backwards when it is low. The SIDE MOTION switch is provided to activate right and left motions. Once this switch is high, then based on the position of the RIGHT, LEFT switch, the side motions take place. Right side motion occurs when the switch is high and left side motion occurs when the switch is low. The variable resistance represents the ultrasonic sensor (for obstacle detection). When it is high, it indicates that an obstacle has been detected and the motors either stop or change their directions. The lcd displays the different actions performed by the motor based on the input commands received.

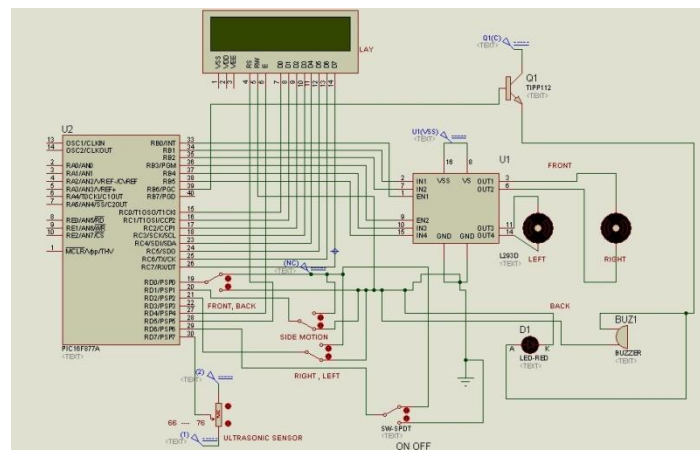


Fig- 6: Simulation Diagram

The following table shows the different comments the lcd displays based on the actions performed by the motor obtained depending on the input commands received in the simulation.

Table-1: Simulation Results

Switch Position	FRONT, BACK	SIDE MOTION	RIGHT, LEFT	VARIABLE RESISTANCE
HIGH	FRONT	Activated	RIGHT if high. LEFT if low	Obstacle Detected
LOW	BACK	Not Activated	Not Activated	No Obstacle Detection

V. Conclusions

Brain controlled mobile robots have been receiving a lot of attention due to its immense scope in the medical areas. The signals received from the brain can be used conveniently to control a robot and make it perform the actions we desire. These robots may also find applications in defense as well.

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