# EEG Based wheel chair using Neurons

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**Abstract**— The design of brain-computer interface for the wheelchair for physically disabled people is presented. The plan of the proposed framework depends on accepting, handling, and order of the electroencephalographic (EEG) signals and afterward playing out the control of the wheelchair. The quantity of exploratory estimations of mind movement has been finished utilizing human control orders of the wheelchair. In light of the psychological movement of the client and the control orders of the wheelchair, the plan of characterization framework dependent on recurrent neural network (RNN) is thought of. The plan of RNN based calculation is utilized for cerebrum impelled control. The preparation information is utilized to plan the framework and afterward test information is applied to gauge the presentation of the control framework. The control of the wheelchair is performed under genuine conditions utilizing course and speed control orders of the wheelchair. The methodology utilized in the paper permits lessening the likelihood of misclassification and improving the control exactness of the wheelchair.

**Keywords**— Brain-computer interface (BCI), Electroencephalography (EEG), Robotic Wheelchair

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## Introduction

**Mi**llions of people around the world suffer from mobility impairments [1]. People having mobility impairments need new devices with sophisticated technologies to help them for comfortable mobility. Wheelchair users having mobility impairments experience a high level of movement and functional limitation. Many patients are unable to control the powered wheelchair using conventional interface and also they are deemed incapable of driving safely [1]. Brain controlled wheelchair is being developed to provide mobility to the individuals who find it impossible to use a powered wheelchair due to motor, sensory, perceptual, or cognitive impairments [1]. Advancements in robotics, sensor technology and artificial intelligence promises enormous scope for developing an advanced wheelchair. Brain computer interfaces (BCI) are systems that communicate between human brain and physical devices by translating different patterns of the brain activity into commands in real time [2]. The electrical activity of the brain is monitored in real time using an array of electrodes, which are placed on the scalp in a process known as electroencephalography (EEG) [1]. Traditional EEG sensors are expensive and their use is limited only to hospitals and laboratories. The electrodes of EEG sensors require conductive gel on skin in order to facilitate reading signals [2]. The advantage of using a portable EEG brainwave headset is that it uses a dry active sensor technology to read brain electric activity. Traditional gel based EEGs can take up to 30 minutes to start acquiring data while the Neurosky headsets are ready to go in seconds. For this reason, headset based on Neurosky technology is cost- effective and easy to handle. The on board Think Gear IC processes raw signals, filters the noise and digitizes the signal [2-5]. The control system design for the wheelchair using various methods of BCI as well as speech and gesture recognition are discussed [2- 8], but the actual implementations are not shown. The multipurpose manual wheelchair is designed to serve various purposes of the patient as well as elderly people [9]. A wheelchair is designed which is controlled through Electro-oculography. The movement of the wheelchair direction is restricted to particular direction based on horizontal and vertical movements of the eye. But practically, eye will also have some oblique movements for which the wheelchair is not satisfactorily responding for the movement in particular direction [10]. The proposed work deals with engineering an interface between the human brain and an electric wheelchair using a portable EEG brainwave headset and firmware signal processing and filtering. The project

eliminates the drawbacks of conventional EEG by using a dry sensor technology to pick up EEG signals instead of using a conductive gel and reducing the time it takes to setup. This project aims at creating a cost efficient solution, later intended to be distributed as an add-on conversion unit for a normal wheelchair.
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## BCI

The first step toward a BCI is recording the activity of the living brain. This can be done invasively by surgically implanting electrodes in the brain, or non-invasively. In this section we will review various brain imaging technologies.

### Invasive Methods

Biologists can measure the potential at different parts of a single neuron in a culture. Recording neuron activity in a living brain is possible using surgically implanted micro-electrodes arrays, although it is no longer a single neuron recording but the activity of groups of neurons

### Electromagnetic Based Methods

The currents generated by an individual neuron are too tiny to be recorded noninvasively, however excitatory neurons in the cortex all have their axon parallel one to another and grouped in redundant populations called macro-columns [2] which act as macroscopic sources of electromagnetic waves that can be recorded non-invasively. Magnetoencephalography (MEG) Magnetoencephalography (MEG) [13–15] is an imaging technique used to measure the magnetic fields produced by electrical activity in the brain. Because of the low strength of these signals and the high level of interference in the atmosphere, MEG has traditionally been performed inside rooms designed to shield against all electrical signals and magnetic field fluctuations.

### Electroencephalography-(EEG)

Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain [26, 27]. The recording is obtained by placing electrodes on the scalp with a conductive gel or paste. The number of electrodes depends on the application, from a few to 128, and they can be mounted on a cap for convenience of use, The electric signal recorded is of the order of few microvolt, hence must be amplified and filtered before acquisition by a computer. The electronic hardware used to amplify, filter and digitize the EEG signal is of the size and weight of a book; it is easily transportable and relatively affordable. Spatial resolution is on the order of centimeters while the time of response to a stimulus is on the order of 100s of milliseconds.

### EEG-based BCIs

A Brain Computer Interface (BCI) is any system which can derive meaningful information directly from the user's brain activity in real time [8]. The most important applications of the technology are mainly meant for the paralyzed people who are suffering from severe neuromuscular disorders. Most BCIs use information obtained from the user's encephalogram (EEG), though BCIs based on other brain imaging methods are possible. This section briefly describes several EEG-based BCIs.

### BCI System Architecture

Figure 1 depicts BCI based control of the wheelchair. BCI system consists of an Emotiv headset connected to a computer. Emotive sensors supply information to the computer. The computer runs the signal processing and classification algorithms and is connected to a microcontroller that controls the movement of the wheelchair. The wheelchair can move in four directions. The speed of the wheelchair is taken as constant and the wheelchair can be switched on and off in the case of necessity. Taking into account the abovementioned functionality, the BCI system uses the following commands: move forward, move

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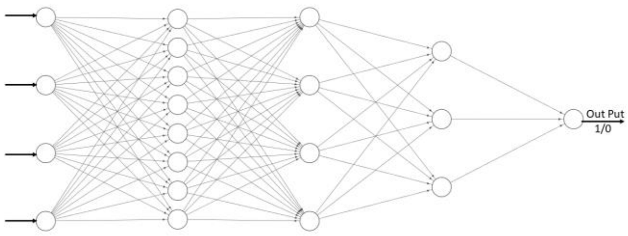
backward, turn left, turn right, and turn on and turn off the switch.

## Methodology




$$W=\frac{W1, W2, ...., Wn}{\sum\int W}$$

Figure 1.1

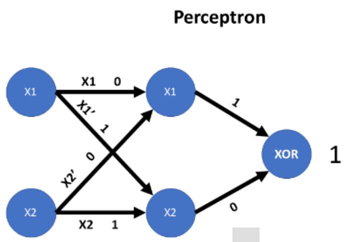



Figure 1.2

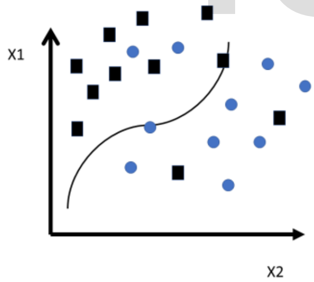



Figure 1.3

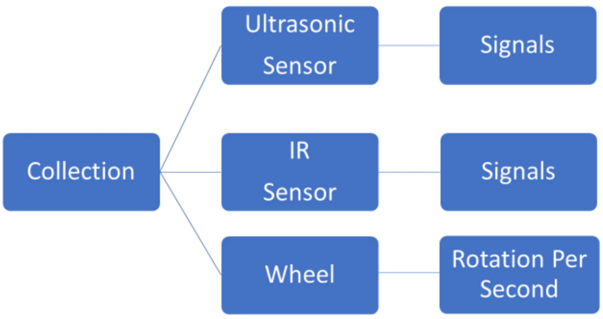



Figure 1.4

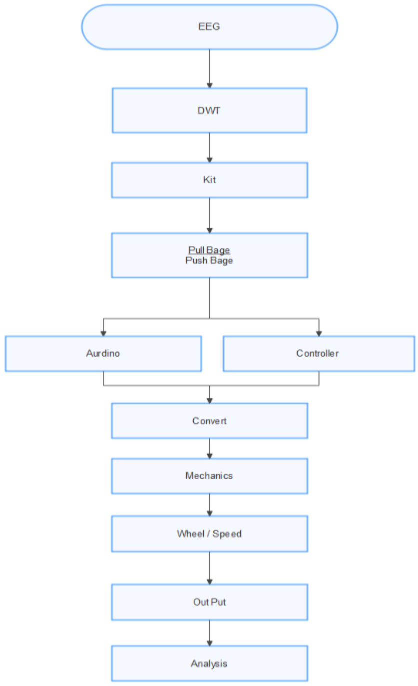



Figure 1.5

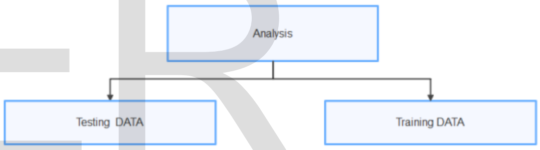



Figure 1.6

After frequency representation, all channels in the window are combined into a single unit so as to apply classification on all channels at once. The filtering operation is applied in order to select important features of the brain signals. These features are used for classification purpose.

Besides the above-described approach, we can use also another approach for signal processing. In the second approach, the acquired brain signal after windowing, normalisation, and combining operations is used for classification purpose:

In the paper, we use frequency representation of signals for classification. These signals are processed and classified. The output of classification system is used to control the wheelchair. Even though during training system reports 100% success rate in real-world conditions, it does misclassify, a state machine is used to further increase safety and reduce misclassification. As an example, the system will not transition from forward motion to backward motion without stopping in neutral. The output of the state machine drives the microcontroller which controls the motors on the wheelchair. The number of classes is equal to the number of control actions.

## Parameter Updates

In the recurrent IF-THEN rules the antecedent part represents the input space by dividing the space into a set of fuzzy regions and the consequent part describes the system behaviour in those regions. In the design of FNN model, the basic problem is the determination of the unknown parameters of antecedent and consequent parts. Recently, a set of different approaches has been applied for designing fuzzy IF-THEN rules. These are clustering, gradient algorithms the least-squares method (LSM) and genetic algorithms.
The basic parameters of the antecedent part are the centres and widths of the membership functions. Learning of RNN starts with the update of parameters of antecedent part of IF-THEN rules, that is, the parameters of the second layer of RNN For this purpose, FCM is applied in order to partition input space and construct antecedent part of recurrent IF-THEN rules. In the result of partitioning the cluster centres are determined. These centres correspond to the centres of the membership functions used in the input layer of RNN. Using the distances between the cluster centres, the widths of the membership functions are determined.

## Experiments and Results

The BCI system is simulated and used in real life applications. The EEG signals are measured with signal acquisition unit, the Emotiv EPOC headset. In the experiments, we have utilised 14 channels for measuring EEG signals. The measured EEG signals have different rhythms within the frequency band. The experiments show that measuring brain signals is difficult so we have tested our system using brain muscle signals.

## Conclusion and Future Scope

The mind wave headset records the electric activity of the brain and the wheelchair moves according to the mind attention or meditation level. This project deals with engineering an interface between the human brain and an electric wheelchair using a portable EEG brainwave headset and firmware signal processing and filtering. This project aims at creating a cost efficient solution, later intended to be distributed as an add-on conversion unit for a normal wheelchair.

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