EEG Controlled Smart Wheelchair for Disabled People

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***Abstract* - Millions of people around the world suffer from mobility impairments. 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.**

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. Advancements in robotics, senor technology and artificial intelligence promises enormous scope for developing an advanced wheelchair. Brain computer interface (BCI) are systems that communicate between human brain and physical devices by translating different patterns of the brain activity into commands in real time.

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. 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.

Keywords—Brain-Computer-Interface(BCI),Electroencephalography (EEG), Artificial Neural Network (ANN.)

I. INTRODUCTION

A. Overview

Now a day's robot becomes an essential thing in industrial as well as in human life. These robots can provide a support to disable people in their day today life. A brain controlled wheelchair is one of the steps toward prime utilization of robot in human life. A healthy person can operate wheelchair with the help of joystick, keyboard etc. But with a person who does not have control on their muscle are unable to use these. For this reason some special technique has been proposed like eye tracking and many others. But it has some limitations. To overcome such challenges Brain Computer Interface (BCI) system has been developed which bypass all conventional methods of communication and directly interface brain of human being with communication devices. In proposed system brain send command directly to physical devices. Basically there are two types of Brain Computer Interface techniques, invasive and noninvasive technique. In invasive technique the brain signals are recorded by an implanting electrode directly into cortex of brain. In noninvasive technique electrode placed on scalp of brain.

Electroencephalography (EEG) is an example of noninvasive technique of detecting brain activity. EEG is a technique of recording a electrical activity along the scalp produced by firing of neurons within the brain. EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time as recorded from multiple electrodes placed on the scalp. EEG is generating due to neuron. Potential generated by neurons travels down, result into neurotransmitter. This neurotransmitter activates receptor in dendrite. By combination of receptor and neurotransmitter electric signal is generate which can measure at scalp. This voltage is ranges from 1uV to 100uV. This generating voltage is called EEG signal. This may vary according to brain activities of human being.

The EEG signals which are generate classified into different types according to their frequency range. Delta, Theta, Alpha, Mu and Beta wave are the types of EEG waves. Occurrence of these waves depends upon different activities performed by brain. For this proposed system Mu rhythm is use. These Mu waves find in frontal position of brain.

B. Objectives

The main objective of this project are as follows,

- To acquire and process the EEG signal from non-invasive BCI (Neurosky Mindwave) device using Matlab Software.
- To classify the EEG signal into four basic movements based on various visible and non visible user- input representations.
- Our project aims to build a smart wheelchair controlled by brainwaves and to analyze the EEG signal in term of attention and meditation level by using their peak and average value.

II. LITRATURE SURVEY

A literature review is a text of scholarly paper, which inclues current knowledge including substantive findings, as well as theoretical and methodological contributions to particular topic.

[1] X. Gao, D.Xu, M.Cheng and S.Gao et.al,are proposed the development of brain-computer interface (BCI) technology, researchers are now attempting to put current BCI techniques into practical application. This paper presents an environmental controller using a BCI technique based on steady-state visual evoked potential. The system is composed of a stimulator, a digital signal processor, and a trainable infrared remote-controller. The attractive features of this system include non-invasive signal recording, little training requirement, and a high information transfer rate. Our test results have shown that this system can distinguish at least 48 targets and provide a transfer rate up to 68 b/min. The system has been applied to the control of an electric apparatus.

[2] J. Jin, P. Horki, C. Brunner, X.Wang, C. Neuper, and G. Pfurtscheller et.al, are proposed a P300 spelling system is one of the most popular EEG-based spelling systems. This system is normally presented as a matrix and allows its users to select one of many options by focused attention. It is possible to use large matrices as a large menu (computer keyboard, etc.), but then more time is required for each selection, because all rows and columns of the matrix must flash once per trial to locate the target character in the row/column (RC) speller method. In this paper, a new flash pattern design based on mathematical combinations is suggested. This new method decreases the number of flashes required in each trial. A typical example of a 6x6 matrix is considered. Only 9 flashes per trial for the 6x6 matrix are required in this new method, which is 3 flashes less than the RC speller method (12 flashes per trial). In this paper, practical bit rate was used. Results from offline analysis have shown that the 9-flash pattern yielded significantly higher practical bit rate than the 12-flash pattern (RC pattern).

[3] B.ZAllison, E.W.Sellers, C.Brunner, P.Horki, X.Wang, and C.Neuper et.al, are proposed P300 brain-computer interface (BCI) systems typically use a row/column (RC) approach. This article presents a P300 BCI based on a 12 x 7 matrix and new paradigmatic approaches to flashing characters designed to decrease the number of flashes needed to identify a target character. Using an RC presentation, a 12 x 7 matrix requires 19 flashes to present all items twice (12 columns and seven rows) per trial. A 12 x 7 matrix contains 84 elements (characters). To identify a target character in 12 x 7 matrix using the RC pattern, 19 flashes (sub-trials) are necessary. In each flash, the selected characters (one column or one row in the RC pattern) are flashing. We present four new paradigms and compare the performance to the RC paradigm. These paradigms present quasi-random groups of characters using 9, 12, 14 and 16 flashes per trial to identify a target character. The 12-, 14- and 16-flash patterns were optimized so that the same character never flashed twice in succession. We assessed the practical bit rate and classification accuracy of the 9-, 12-, 14-, 16- and RC (19-flash) pattern conditions in an online experiment and with offline simulations.

[4] M.Cheng, S.Gao, and D. Xu et.al, are proposed “Design and implementation of a brain-computer interface with high transfer rates,” a brain-computer interface (BCI) that can help users to input phone numbers. The system is based on the steady-state visual evoked potential (SSVEP). Twelve buttons illuminated at different rates were displayed on a computer monitor. The buttons constituted a virtual telephone keypad, representing the ten digits 0–9, BACKSPACE, and ENTER. Users could input phone number by gazing at these buttons. The frequency-coded SSVEP was used to judge which button the user desired. Eight of the thirteen subjects succeeded in ringing the mobile phone using the system. The average transfer rate over all subjects was 27.15 bits/min. The attractive features of the system are non-invasive signal recording, little training required for use, and high information transfer rate. Approaches to improve the performance of the system are discussed.

[5] A. Lenhardt, M. Kaper and H.J Ritter proposed “An adaptive P300-based online brain-computer interface,” The P300 component of an event related potential is widely used in conjunction with brain-computer interfaces (BCIs) to translate the subject’s intent by mere thoughts into commands to control artificial devices. A well-known application is the spelling of words while selection of the letters is carried out by focusing attention to the target letter. In this paper, we present a P300-based online BCI which reaches very competitive performance in terms of information transfer rates. In addition, we propose an online method that optimizes information transfer rates and/or accuracies. This is achieved by an algorithm which dynamically limits the number of subtrial presentations, according to the subject's current online performance in real-time. We present results of two studies based on 19 different healthy subjects in total who participated in our experiments (seven subjects in the first and 12 subjects in the second one). In the first, study peak information transfer rates up to 92 bits/min with an accuracy of 100% were achieved by one subject with a mean of 32 bits/min at about 80% accuracy. The second experiment employed a dynamic classifier which enables the user to optimize bitrates and/or accuracies by limiting the number of subtrial presentations according to the current online performance of the subject. At the fastest setting, mean information transfer rates could be improved to 50.61 bits/min (i.e., 13.13 symbols/min). The most accurate results with 87.5% accuracy showed a transfer rate of 29.35 bits/min.

[6] H. Zhang, C. Guan, and C. Wang et.al, are proposed “Asynchronous P300-based brain computer interfaces: A computational approach with statistical models”. Asynchronous control is an important issue for brain-computer interfaces (BCIs) working in real-life settings, where the machine should determine from brain signals not only the desired command but also when the user wants to input it. In this paper, we propose a novel computational approach for robust asynchronous control using electroencephalogram (EEG) and a P300-based oddball paradigm. In this approach, we first address the mathematical modelling of target P300, non target P300, and non control signals, by using Gaussian distribution models in a support vector margin space. Furthermore, we derive a method to compute the likelihood of control state in a time window of EEG. Finally, we devise a recursive algorithm to detect control states in ongoing EEG for online application. We conducted experiments with four subjects to study both the asynchronous BCI's receiver operating characteristics and its performance in actual online tests. The results show that the BCI is able to achieve an averaged information transfer rate

of approximately 20 b/min at a low false positive rate (one event per minute).

[7] B. D. Seno, M. Matteucci, and L. T. Mainardi et.al, are proposed "The utility metric: A novel method to assess the overall performance of discrete brain-computer interfaces". A relevant issue in a brain-computer interface (BCI) is the capability to efficiently convert user intentions into correct actions, and how to properly measure this efficiency. Usually, the evaluation of a BCI system is approached through the quantification of the classifier performance, which is often measured by means of the information transfer rate (ITR). A shortcoming of this approach is that the control interface design is neglected, and hence a poor description of the overall performance is obtained for real systems. To overcome this limitation, we propose a novel metric based on the computation of BCI Utility. The new metric can accurately predict the overall performance of a BCI system, as it takes into account both the classifier and the control interface characteristics. It is therefore suitable for design purposes, where we have to select the best options among different components and different parameters setup. In the paper, we compute Utility in two scenarios, a P300 speller and a P300 speller with an error correction system (ECS), for different values of accuracy of the classifier and recall of the ECS.

[8] S. Fuchs, S. K. Andersen, T. Gruber, and M. M¨uller et.al, are proposed "Attentional bias of competitive interactions in neuronal networks of early visual processing in the human brain," Multiple objects in a visual scene compete for neuronal representation. We investigated competitive neuronal dynamics in cortical networks of early visual processing in the human brain. Coloured picture streams flickered at 7.42 Hz, evoking the steady-state visual evoked potential (SSVEP), an electrophysiological response of neuronal populations in early visual areas synchronised by the external pacemaker. While these picture streams were at a fixed location in the upper left and right quadrant, respectively, additional competing picture streams flickering at a different frequency were continuously changing the distance to the stationary streams by slow motion. Analysis of the 7.42 Hz SSVEP amplitude revealed significant amplitude decreases when the competing stimulus was closer than about 4.5 degrees of visual angle. Sources of the SSVEP suppression effect were found in early visual areas of the ventral and dorsal processing streams. Attending the stationary stimulus resulted in no difference in 7.42 Hz SSVEP amplitude regardless of spatial separation to the competing stimulus. Contrary to the predictions of the model, we found co-amplification of the competing stimulus at close spatial proximity accompanied by an increase of an inter modulation frequency, suggesting integrated neuronal processing of target and competing stimuli when both streams are close together.

[9] C. L. Gonsalvez and J. Polich et.al, are proposed "P300 amplitude is determined by target to-target interval", P300 event-related brain potential (ERP) measures are affected by target stimulus probability, the number of nontargets preceding the target in the stimulus sequence structure, and inter stimulus interval (ISI). Each of these factors contributes to the target-to-target interval (TTI), which also has been found to affect P300. The present study employed a variant of the oddball paradigm and manipulated the number of preceding non target stimuli (0, 1, 2, 3) and ISI (1, 2, 4 s) in order to systematically assess TTI effects on P300 values from auditory and visual stimuli. Number of preceding non targets generally produced stronger effects than ISI in a manner suggesting that TTI determined P300 measures: Amplitude increased as TTI increased for both auditory and visual stimulus conditions, whereas latency tended to decrease with increased TTI. The finding that TTI is a critical determinant of P300 responsivity is discussed within a resource allocation theoretical framework.

[10] D. J. Krusienski, E. W. Sellers, F. Cabestaing, S. Bayoudh, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw et.al, are proposed "A comparison of classification techniques for the P300 speller," This study assesses the relative performance characteristics of five established classification techniques on data collected using the P300 Speller paradigm, originally described by Farwell and Donchin (1988 Electroenceph. Clin. Neurophysiol. 70 510). Four linear methods: Pearson's correlation method (PCM), Fisher's linear discriminant (FLD), stepwise linear discriminant analysis (SWLDA) and a linear support vector machine (LSVM); and one nonlinear method: Gaussian kernel support vector machine (GSVM), are compared for classifying offline data from eight users. The relative performance of the classifiers is evaluated, along with the practical concerns regarding the implementation of the respective methods. The results indicate that while all methods attained not acceptable performance levels, SWLDA and FLD provide the best overall performance and implementation characteristics for practical classification of P300 Speller data.

[11] J. R. Wolpaw, N. Birbaumer, W. J. Heetderrks, D. J. McFarland, P. H. Peckham, G. Schalk, E.Donchin, L.A.Quatrano, C.J.Robinson, and T. M.Vaughan et.al, are proposed "Brain-computer interface technology: A review of the first international meeting," Over the past decade, many laboratories have begun to explore brain-computer interface (BCI) technology as a radically new communication option for those with neuromuscular impairments that prevent them from using conventional augmentative communication methods. BCI's provide these users with communication channels that do not depend on peripheral nerves and muscles. This article summarizes the first international meeting devoted to BCI research and development. Current BCI's use electroencephalographic (EEG) activity recorded at the scalp or single-unit activity recorded from within cortex to control cursor movement, select letters or icons, or operate a neuroprosthesis. The central element in each BCI is a translation algorithm that converts electrophysiological input from the user into output that controls external devices. BCI operation depends on effective interaction between two adaptive controllers, the user who encodes his or her commands in the electrophysiological input provided to the BCI, and the BCI which recognizes the commands contained in the input and expresses them in device control. Current BCI's have maximum information transfer rates of 5-25 b/min. Achievement of greater speed and accuracy depends on improvements in signal processing, translation algorithms, and user training. These improvements depend on increased interdisciplinary cooperation between neuroscientists, engineers, computer programmers, psychologists, and rehabilitation specialists, and on adoption and widespread application of objective methods for evaluating alternative

methods. The practical use of BCI technology depends on the development of appropriate applications, identification of appropriate user groups, and careful attention to the needs and desires of individual users. BCI research and development will also benefit from greater emphasis on peer-reviewed publications, and from adoption of standard venues for presentations and discussion.

[12] K. S. Ahmed, Department of Bio-electronics, Faculty of Engineering, MTI, Modern University for Technology and Information, Katamia, Egypt which comprised of a model based to detect the four movements (turn right – turn left – forward -stop) of wheelchair based on the eye blinks (right wink, left wink, single/double blinks). The WT coefficients were used as the best fitting input vector for classifier. Radial Basis Function network was used to classify the signals. The weighted energy difference between electrodes pairs F7 and F8 were used as features. Signals were recursively decomposed into high and low passed sub-bands, and the resolution of the spectrum was determined by the chosen decomposition level. The sub-band energy from the last 8 decomposition level was used to construct features from EEG signals. The sensitivity and specificity were calculated for 20 cases and there were 80% and 75% respectively.

[13] Jzau-Sheng Lin, Kuo-Chi Chen and Win-Ching Yang developed wheelchair using EEG waves and eye blinking pattern which was very much similar to Mr. Ahmed's Methods, differing only in the hardware used for EEG acquisition and the control commands.

[14] Robin Shaw, Everett Crisman, Anne loomis and ZofiaLaszewski developed Eye wink control which consisted of a non biosignal approach which basically consisted of a wearable eye-frame which had two infra-red eye wink detectors in front of both the eye sockets .

[15] DjokoPurwanto, Ronny Mardiyanto and Kohei Arai used a digital camera setup in front of the user to capture the eye information and to interpret the gaze direction, thereby controlling the movement of the wheel chair .

[16] A Ferreira, R L Silva, W C Celeste, TF BastosFilhoand M SarcinelliFilho developed several endeavours which made in the direction of developing a system driven by both, the EEG and the EMG signals. which added an interactive PDA along with the entire wheelchair assembly where several movement options were continuously flashed in front of the subject and for selection of a particular option, the subject had to close his/her e To avoid artefacts from EMG (and also EOG), they had used the band- pass filter with a pass band of0.53–30 Hz in the EEG detection. However, it was very difficult to perfectly reject the artefacts from EMG (and also EOG) even with the utility of the band pass filter .

[17] R. Barea, L. Boquete, M. Mazo and E. Lopez developed the control of wheelchair using biosignals which discusses the Wheelchair Guidance Strategies Using the EOG waves. This paper describes an eye-control method, based on electrooculography (EOG), for Guiding and controlling a wheelchair; the control is actually effected by eye movements within the socket.

[18] Dandan Huang, KaiQian Ding-Yu Fei WenchuanJia Xuedong Chen, and OuBaihad developed a 2-D virtual wheelchair based on the multi-class discrimination of spatiotemporally distinguishable phenomenon of event-related desynchronization synchronization (ERD/ERS) in electroencephalogram signals associated with motor execution/imagery of right/left hand movement.

III. METHODOLOGY

In brain machine interface user has to monitor his own brain waves in real time to control the given application. Hence for extraction of EEG signal from the brain, Mindwave device released by NeuroSky company is used. The Mindwave reports the wearer's mental state in the form of NeuroSky's proprietary Attention and Meditation eSense™ algorithms, along with raw wave and information about the brainwave frequency bands. The MindWave Mobile safely measures and outputs the EEG power spectrums (alpha waves, beta waves, etc), NeuroSky eSense meters (attention and meditation) and eye blinks. It uses the TGAM1 module and can perform automatic wireless pairing with iOS, Android, PC, or Mac device. The device consists of a headset, an ear clip, and a sensor arm. The headset's reference and ground electrodes are on the ear clip and the EEG electrode is on the sensor arm, resting on the forehead above the eye (FP1 position).

ThinkGear is the technology inside every NeuroSky product or partner product that enables a device to interface with the wearers' brainwaves. It measures the analog electrical signals, commonly referred to as brainwaves, and processes them into digital signals. Both the raw brainwaves and the eSense Meters (Attention and Meditation) are calculated on the ThinkGear chip.

NeuroSky's dry sensor technology is capable of detecting several different kinds of biosignals depending on where the sensor electrode is placed, including EEG, EOG, EMG, and ECG. On the forehead, EEG signals from the brain can be detected. Then electrical signal within the device that corresponds to the wave patterns detected is created.

So after processing the EEG signal in the software whatever the information signal is obtained is to be interfaced with controller. The BCI processes the inputs from the EEG headset which has to be interfaced with Arduino Microcontroller.

For interfacing of microcontroller and laptop USB to serial converter is used. The CP2102 is highly integrated USB to UART bridge controller providing a simple solution which includes a USB 2.0 full speed function controller, USB transreceiver, oscillator, EEPROM and asynchronous serial data bus (UART) with full modem control signals.

The Arduino Receives the Signals from BCI which has been programmed into it. An Arduino based wheel chair is built using a Servo Motor. A servomotor is a rotary actuator that allows for precise control of angular position, velocity and acceleration. It consists of a suitable motor coupled to a sensor for position feedback. It also requires a relatively sophisticated controller, often a dedicated module designed specifically for use with servomotors. The Arduino Microcontroller is programmed using Arduino and MATLAB Programming language to send the BCI output to perform forward backward and rotational movements in the wheelchair.

A. Circuit Diagram.

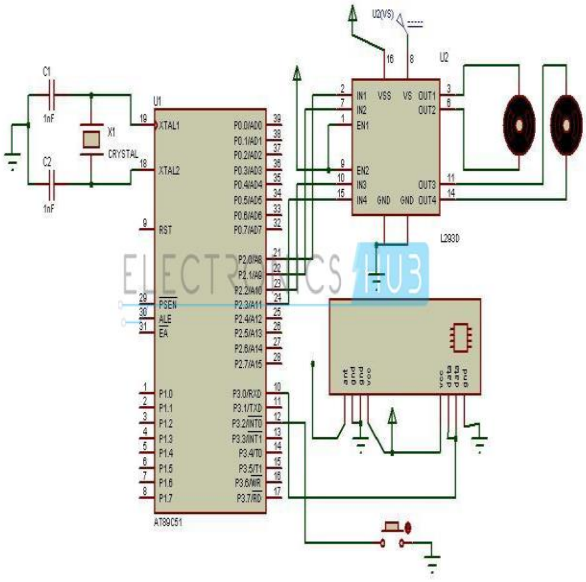

Fig. 1. Circuit Diagram

IV. IMPLEMENTATION

A. Data Acquisition:

EEG signals acquisition is mainly done by placing Mindwave head set on the scalp, the product of NeuroSky Technology that can be used for data acquisition.

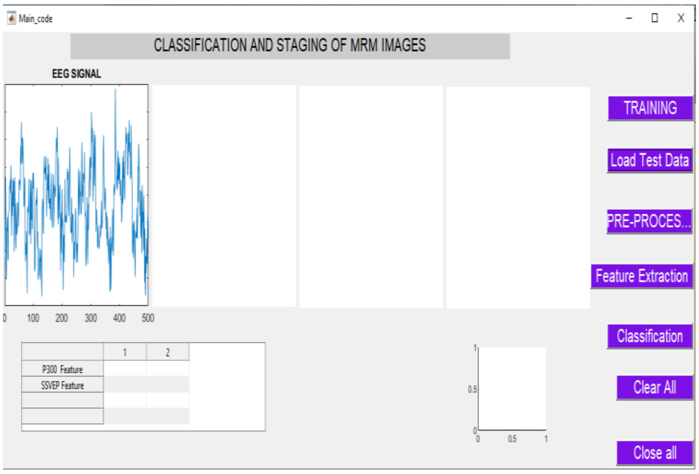

Fig. 2. Data Acquisition of the Signal

B. Preprocessing:

Using EEGLAB toolbox, we segmented the continuous EEG data into epoched datasets, each of which lasted from 0.5 s before to 1.1 s after the stimulus onset. Then, the ocular artifacts in each set were removed by the software.

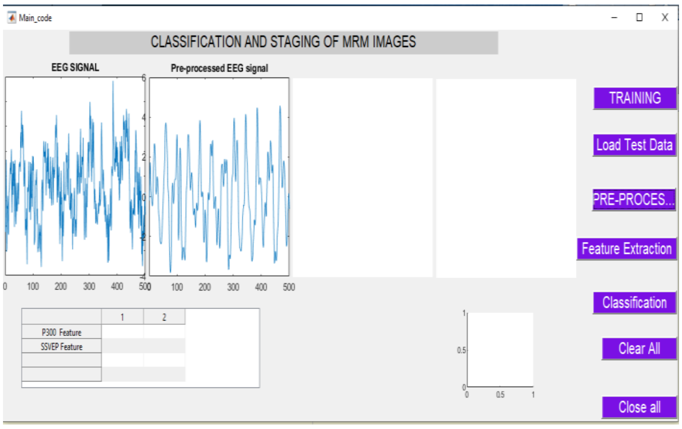

Fig. 3. Preprocessing of the Signal

C. Feature extraction and Classifications:

Feature extraction in BCI application is the process of extracting feature that can be used to distinguish the EEG signal into different classes. The features extracted from the EEG signals are used for classification and determining control action There is a certain amount of discrepancy in classifying the waves, since the signals are continuously being captured by the many electrodes present on the scalp.

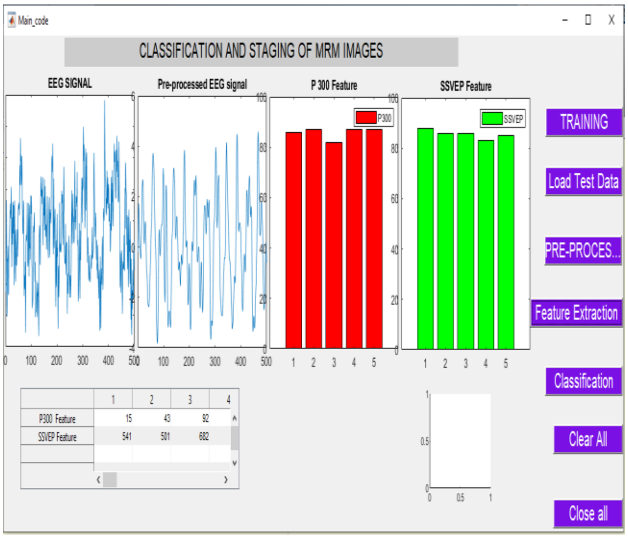

Fig. 4. Classification of the Signal

TABLE I. WHEEL CHAR MOVEMNTS.

M1	M2	Function
Low	High	Turn Right
High	Low	Turn Left
Low	Low	Stop Moving
High	High	Move Forward

The following types:
Delta: has a frequency of 3 Hz or below.
Theta: has a frequency of 3.5 to 7.5 Hz and is classified as "slow" activity.

Alpha: has a frequency between 7.5 and 13 Hz. Is usually best seen in the posterior regions of the head on each side,
Beta: beta activity is "fast" activity. It has a frequency of 14 and greater Hz. It is usually seen on both sides in symmetrical distribution and is most evident frontally.

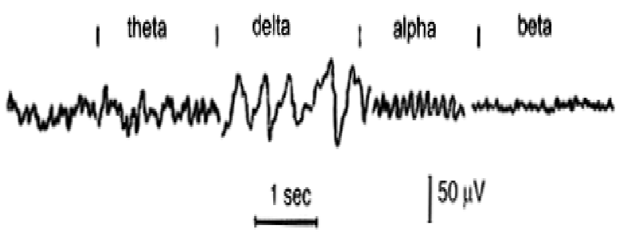

Fig. 5. variables used in the classification of EEG activity.

V. HARDWARE SOFTWARE REQUIREMENTS

A. Hardware Specifications

The hardware requirement of the project is as follows:

- Arduino Uno
- L293D
- 12V DC Motor
- DB9 Cable
- 7805 Regulator IC
- Neurosky Headset
- A C Adapter
- Robot case
- Robotic Wheels
- General Purpose Board
- Male to Male Jumper Wires
- Voltage Regulator

B. Software Specifications

The software requirement of the project is as follows.

- Operating system : Windows 10
- Coding Language : C
- Tool : MATLAB Version R2018b.

C. Software Tool

MATLAB version R2018b is the software tool used for the implementation of the proposed system.

- MATLAB Version R2018b:

  MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming environment. MATLAB is a modern programming language environment: it has sophisticated data structures, contains built-in editing and debugging tools, and supports object-oriented programming.

VI. RESULTS AND DISCUSSIONS

The neural activity in brain is recorded using non-invasive techniques (Mindwave sensor). Here we use a single electrode so it will be easy to use. It will provide better alternatives for individuals to interact with their environment in an efficient way. This project will help the physically challenged to lead an independent life with the help of their brain signals.

Various analyses were made on different subjects to analyze the states of the brain.

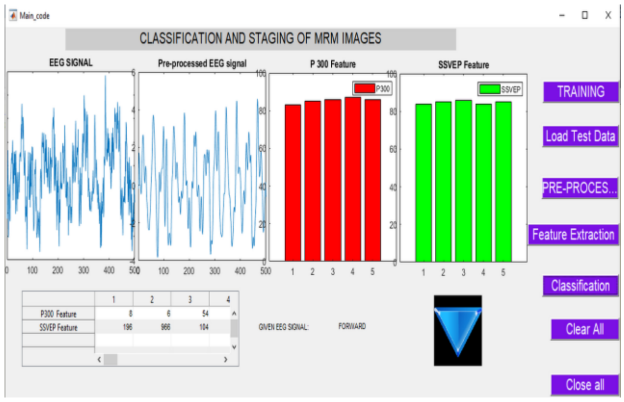

Fig. 6. EEG Signal Classification When Thinking Forward.

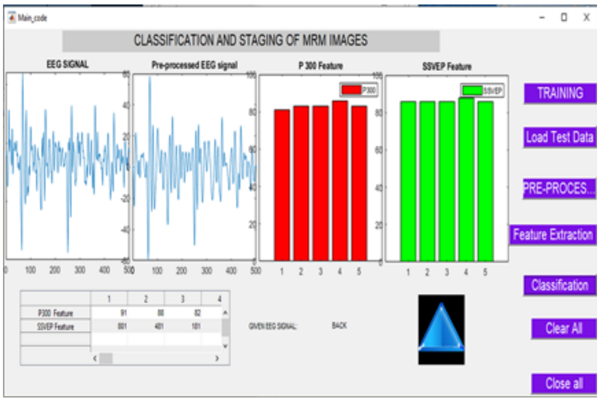

Fig. 7. EEG Signal Classification When Thinking Back

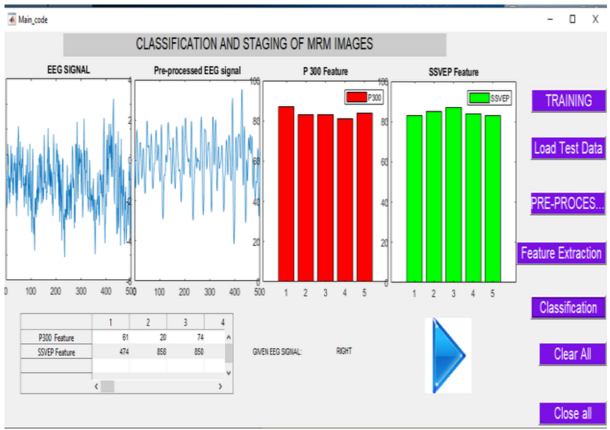

Fig. 8. EEG Signal Classification When Thinking right

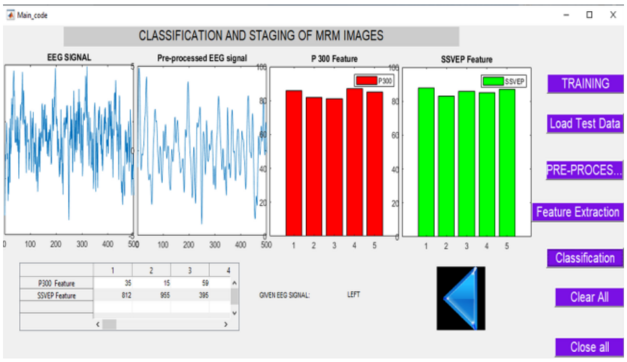

Fig. 9. EEG Signal Classification When Thinking Left

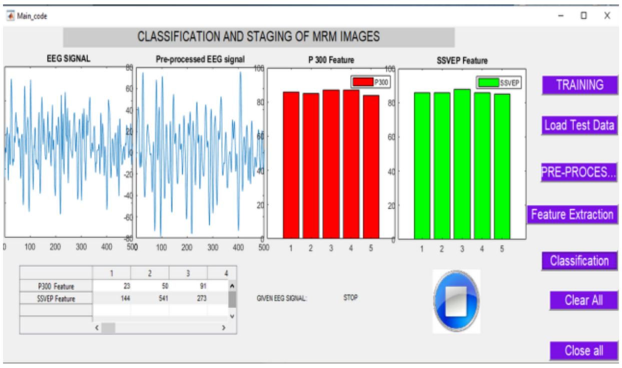

Fig. 10. EEG Signal Classification When Thinking Stop.

VII. APPLICATIONS ADVANTAGES AND DISADVANTAGES

A. *Application*

- It is mainly designed to help the physically disabled people who can't move their body.
- Bio-signals is the important factor that gives instructions to the EEG controlled headset.
- The disabled user can move independently without the help of anyone's help.
- The headset is light weight and easy to use by the user.

B. *Advantages*

- Minimal effort to mobilize: Minimal effort is needed to control the wheelchair because we use EEG controlled headset to move the chair.
- Independence: With an EEG controlled smart wheelchair, the users don't have to be depended on someone else to push the wheelchair.
- It mainly helps to those who are unable to move their hands or legs due to paralysis or any other physical disability.
- The EEG signal headset are light in weight and the signals generated are not harmful.
- The user can move the eyes to move in what direction they want to move.

C. *Disadvantages*

- Maintenance and repair: The cost of maintaining and repairing an EEG controlled wheelchair is higher than the manual wheel chair.
- Initial expense: smart wheelchairs are typically more expensive than the manual wheelchair.
- Size: EEG controlled smart wheelchairs are larger than manual wheelchair.
- Weight: EEG controlled smart wheelchairs are much heavier than manual wheelchair.
- Use of headset band: The use of EEG controlled headset is a must to receive the bio-signals from the human body.

VIII. CONCLUSION

Utilization of EEG signals are a significant research area which help physically challenged people. Brain controlled wheelchair is slow but reliable method for physically challenged person. The proposed system uses an KNN to overcome the previous challenges and to achieve higher accuracy. Stability of system depends upon user thoughts so users have to take more training of system. Brain-Computer Interface (BCI) is a method of communication based on voluntary neural activity generated by the brain and independent of its normal output pathways of peripheral nerves and muscles.

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