Automated Wheelchair System using Brain Computer Interface

Anish Mitra[1], Arjun Shilotri[2], Meghana Rangarajan[3], Nivedita Jyothi[4], Sandesh RS[5]

[1]Department of Electronics and Instrumentation Engineering, R.V. College of Engineering, Bengaluru
[2]Department of Electronics and Instrumentation Engineering, R.V. College of Engineering, Bengaluru
[3]Department of Electronics and Instrumentation Engineering, R.V. College of Engineering, Bengaluru
[4]Department of Electronics and Instrumentation Engineering, R.V. College of Engineering, Bengaluru
[5]Assistant Professor, Department of Electronics and Instrumentation Engineering, R.V. College of Engineering, Bengaluru

---***---

Abstract - *In the last two years the electric vehicle market has boomed exponentially. The turn of the decade has produced some of the most advanced vehicles which remove dependence on fossil fuels and mainly derive their power from rechargeable batteries. These technologies enable faster speeds, higher efficiencies, and a more environmentally friendly transportation system. Coupling the battery with a means of accessing the planet's most available energy supply, solar radiation, including solar panels, has helped to expand the range of such electric cars. Such hybrid vehicles cannot actually mean everyday commuter vehicles or road cars. The range of electric cars is incredibly large, ranging from commercial vehicles for children to multi-purpose vehicles, to wheelchairs for the otherwise competent. In this review paper, we will be reviewing various technologies with respect to making an automated wheelchair that can not only make it user friendly, but also, we will be exploring various methods and techniques wherein we can make the wheelchair cost friendly as well.*

Key Words: **Automated wheelchair, Arduino, sensors, Brain Computer interface, BCI, Autonomous navigation system**

1. INTRODUCTION

For a developing nation such as India, where the economy is still growing, essential items have to be inexpensive to those in need. In today's busy world where people don't have enough time for anything, the independence of the elderly and physically disabled people is very necessary. For the older generations as well as the physically disabled, wheelchairs are extremely necessary and their demand has risen over the past few decades due to the efficacy of the treatment, which increases the quality of life. Nonetheless, wheelchairs are not accessible in India due to high import duties and high costs for most of those who need it. Simple wheelchairs are inadequate for some people, and therefore require electric wheelchairs, which appear to be much costlier. Automated wheelchairs that are interfaced with sensors and a unit for data processing are classified as smart wheelchairs. Assistive robotics significantly strengthens the lives of those mentally disabled. In recent years, robots have available a wide variety of assistive and guidance systems to make their lives less complex and motile. Such robots are extremely powerful and allow the consumer to move around easily. Especially for individuals with particular conditions and illnesses, there are multiple management mechanisms that are evolving and improving in recent times. Developed technologies are strongly effective in replacing the existing, outdated systems. This innovative approach is beneficial for people with disabilities who can't move their wheelchair by themselves. A wheelchair model acts as a robot model, which comprises an in-built microcontroller These wheelchairs are built so as to be able to maneuverer independently without additional assistance. Via this function patients can make their wheelchair movements simpler on their own.The thought of interfacing machines with minds has always been very intriguing. The recent advances in the fields of neuroscience and engineering are making this idea a reality. This might potentially allow us to augment human physical and mental capabilities. We can use the neural signals from the brain activity can be used affect their environment. The field of BCI (Brain computer interface) can enable patients suffering with quadriplegia and stroke patients to control prosthetic devices for walking or controlling their environment as it provides them means for hands free control of various electrical devices and have very significant applications in the operation of neuroprostheses.

Here we are addressing various technologies that can be used to build a cheap automatic wheelchair in order to make it affordable and available to the general population of the country. What we've found is that most wheelchairs have only manual mobility. Motorized wheelchairs are also available, but these are very expensive. It also evaluates the BCIs and its applications and limitations when it comes to developing an automated

2. THEORY AND CONCEPTS

Brain-computer interfaces (BCI) are computer-based systems that allow communication between the brain and various machines [2]. They acquire signals from the brain using electrodes that may be placed on the skull or intracranially, process the signal and convert them into commands that may control various devices. The BCI systems use and measure the signals generated by the CNS by placing electrodes on scalp or cortex region of the brain and not the output from the peripheral nervous system or the muscles. The most popular principle of a brain computer interface control is that the individual can learn to voluntarily change the neural activity in their brain which is then acquired by the electrodes placed. The user is trained to come up with brain signal and therefore the BCI system is trained to decode the signal and translate them into commands which relies on the user's intention and control the output device. There are different types of signals based on the source of the signal that can be used in BCI systems.

The most commonly used signals are the neuronal postsynaptic membrane polarity changes. The scalp EEG is extensively used in BCIs. This is extremely safe, easy and not expensive to acquire. The most important problem of scalp EEG is that the signal gets attenuated in the process of passing through the dural region, skull and scalp tissues. This might lead to the loss of a lot of important information.

2. 1 ELEMENTS OF A BCI

The BCI system consists of 4 main components [30]. These components are administered by a protocol that defines all the minute characteristics pertaining to the BCI system including details of the signal processing, timings of the operation, the nature of the device commands and the performance. The operating protocol enables the BCI system to be flexible and adapt itself according to the user's needs.

1. **Signal acquisition:** This involves measurement of the brain signals using either a scalp or an intracranial sensor. These signals are filtered and amplified so that they are apt for signal processing. These signals are converted into a digital form so that they can be transmitted to a computer.

2. **Feature extraction:** The digital signals obtained are analysed to extract relevant characteristics of the signal and converting them into form that can control prostheses. These features must have very high correlation with the user's intent.

3. **Translation algorithm:** An algorithm converts the extracted characteristics into instructions that can control various output devices. The algorithm must be dynamic so that it can adapt to changes in the signal characteristics and the subject's intent

4. **Output devices:** The output instructions from the algorithm control the output devices and perform functions like letter choice, robotic arm control, cursor control, etc. The device output provides feedback to the subject, which closes the loop.

The components of the BCI system are shown in the Figure1. The electrical signals from the brain activity are read by electrodes which can be placed on the scalp, on the cortex or within the brain which are amplified and converted into a digital form. Significant signal characteristics are translated into instructions that can control prostheses. Feedback from the device allows the user to adapt the brain signals in order to improve the performance of the BCI system.

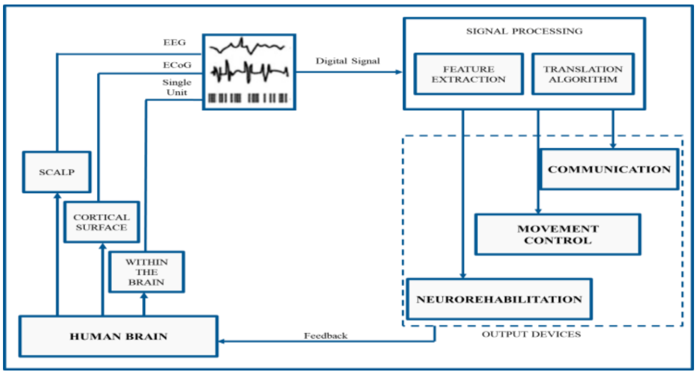

Figure 1: Elements of a brain computer

2.2 NON-INVASIVE BCI SYSTEMS

Non-invasive scalp EEG is the most dominant methodology used in the analysis of brain signals and its performance in the real time interactions of humans with their surroundings. There are other non-invasive brain activity monitoring methods which include Infrared spectroscopy (fNIR), Functional Magnetic resonance Imaging (fMRI), position emission tomography (PET) and magnetoencephalography (MEG). Among all these, EEG is the only one that uses sensors that are portable and can be used for reading signals the user is moving [25]. It is also superior to the other modalities in terms of resolution and the areal of the brain that can be monitored.

Even though EEG has so many applications in the field of medicine, it is used much more in the clinical field than in daily life applications as it is considered to be too prone to noise [24]. As the current EEG technology is not sophisticated the researchers are also not very confident about the signal acquires and the sources of the signal. The current EEG monitoring practice has a complex procedure which involves the preparation of the skin, application of gel electrode and attaching a lot of sensors. The users don't have enough knowledge to handle these sensors on a day to day basis. Therefore, sizeable efforts are necessary to bridge this gap.

A few commercial EEG systems have been developed [14]-[22] that are in used in investigations regarding the BCI systems and in gaming applications that use BCI technology.

To make this system more efficient, we need better signal acquisition hardware, we must be able to validate the BCI system and the end product must be reliable.

2.2.1 Signal generation

The brain activity evolves along with age and maturity of the human brain. This is also affected by the number of personal attributes very heavily. It would be very useful if we could monitor the brain activity on a day to day level to study our cognitive evolution. But due to the impractical procedure of the current EEG technology it is not possible to monitor our brain activity. But having sophisticated EEG systems will enable us to monitor large populations who have diverse personal traits and create a large database.

An EG is the signal obtained due to several simultaneous neural activities occurring in the brain. They are affected by the current mental state of the user and several external inputs and the signals which are an input or an output to the internal organs of the user [26]. Even having a person's eyes closed or open will completely result in a different EEG signature [27]. Therefore, understanding the current mental status of the user and considering contextual information plays a key role in the development of BCI systems using an EEG signal.

Surface EEG is not capable of capturing single neuron activity. This represents a summation of multiple neuron activity. The tissues present between the EEG signal and the source of the brain activity attenuates and smears the brain signal. This is mainly because of the difference in the conductive properties of the skin, skull, the cerebrospinal fluid (CSF), the dura and pia matter of the brain [28]. Understanding their properties is very essential when we are thinking of building a BCI system that lasts over a lifespan.

2.2.2 Signal Acquisition

The EEG design used in clinical applications is the use of electrodes are (Ag / AgCl) placed on the scalp using electrolytic gel[32]. The electrolytic gel closes the gap between the skull and the electrodes for the ionic current flow and it increases the adhesion of the electrodes to the scalp. This model is featured in Figure 2A.

But this setup is very complicated and involves a lengthy process of preparing the skin and application of the gel. The placement of the electrodes is also very critical, and the user might not have the knowledge to perform this process.

Therefore, the recent developments focus on the development of sensors that don't use conductive gel. These are called dry electrodes and they have pins that penetrate the hairy regions [22]. They contain electrodes which are Ag/AgCl or gold plated. These electrodes can be used until the conductive layer fades [33]. But the stabilization time needed for this type of electrode is larger. This system is more prone to noise and decreases the quality of the signal and is comparatively more fragile. This system is represented in Figure 2B.

2.2.3 Brain signal Analysis

The EEG signal undergoes several steps before its analysed and we discussed in an earlier section. During signal pre-processing the recorded signals are re-referenced, the signals undergo band-pass filtering and are resampled and epoched. The clean EEG segments are selected.

The extraction can be performed manually in the clinical environment but is impractical if we are extending its applications for a day to day use. For real time applications we need methods that can extract features from the EEG signal. This is considered as a part of the artefact handling process.

Artifact includes all the signals that are present in the EEG signal but Is not a part of the brain signal. There are different classes of artifact [24][29].

1. **Environmental Artifacts:** This includes interference from the power lines present in the environment or EMI produced by the body itself.

2. **EEG acquiring apparatus Artifacts:** This arises due to the interference of the circuitry present in the EEG systems.

3. **Artifacts arising from inappropriate use of the EEG system:** This is due to the improper usage of the EEG system leading to measurement error.

4. **Physiological Artifacts:** This is due to the distortions of the EEG because of the other electrical signals generated by the human body.

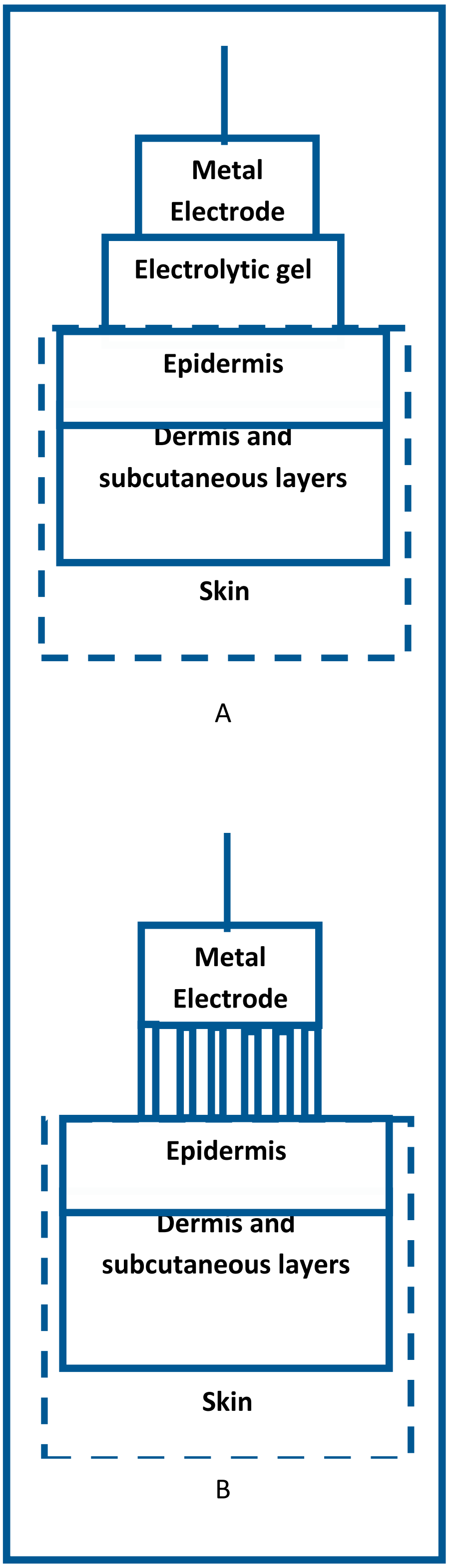

Figure 2:
Figure 2A: Electrodes using conductive gel
Figure 2B: Dry electrodes with pins

5. **Motion Artifacts:** This occurs due to the change in geometric measurement, coupling between the user's skin and the sensor and deformation of the user's tissue.

All these can be avoided using artifact reduction methods. This involves identifying the artifact components in the signal and isolating the original signal from the obtained signal. The features are then extracted from the clean EEG signal.

2.3 BCI SYSTEMS IN WHEELCHAIRS

Brain-computer interfaces (BCIs) based on electroencephalograms (EEG) have recently been encouraging the production and implementation of BCI technologies, as they are compact, simple, safe, and inexpensive. A major application of EEG-based BCI is the wheelchair control which has received considerable attention.

Given below are some examples of the studies that were conducted by various people on brain-controlled wheelchair :

Study 1- Tanaka et al developed a brain-controlled wheelchair, in which the patient can control the wheelchair movement by doing motor imaging. [3]

Study 2- In this study, a wheelchair has been proposed using BCI. The consumer guided the wheelchair 's left-turning, right-turning, and forward movements by imaging the left-hand clenching, gripping the right hand, and pushing on both feet, respectively. [4]

Study 3- In this study, a hybrid BCI incorporating Motor Image (MI) and P300 was used to control wheelchair speed and direction. In brief, the user conducted left -or right-hand Motor Image to create direction control signals and changed the wheelchair speed with foot imagery or by relying on a blinking button. [5]

Study 4- Diez et al built a BCI wheelchair based on visual-evoked steady-state (SSVEP) potentials, in which four control commands (go ahead, turn left / right, and stop) were available [6].

There are three obstacles with a brain-controlled wheelchair: [7]-[9]

The control of the wheelchair is multi objective including functions of start and stop, control of course and control of speed. The task of generating various control signals is difficult for an EEG-based BCI. Although we may receive several control commands using a P300 or SSVEP, it takes time to generate an effective control command

·The efficiency of a BCI is user dependent. For example, a lot of users are unable to conduct the Motor Image required to generate direction control signals.

·Controlling a wheelchair for a long period of time will create a substantial mental burden for the user, particularly for people with disabilities.

Such problems can be resolved using an automatic form of navigation. The autonomous navigation system, however, cannot perform any of the control functions. The autonomous navigation system for example cannot identify the user's desired destination. Therefore, a human machine interface (HMI) is required to communicate the wishes of the user to the navigation device. In seriously disabled individuals, such as patients with amyotrophic lateral sclerosis (ALS), there are obstacles to using a typical HMI, such as usage of a keyboard. Thus, BCI technology could be an alternate choice [10].

Shared management methods for wheelchairs were developed over the last few years. Such strategies leverage the power of the human and autonomous navigation system by allowing various elements of the system to be managed in circumstances involving teamwork [11].

Example of an study wherein both autonomous navigation systems as well as brain controlled wheelchair techniques are used:

Milla´n et al presented a mutual control BCI wheelchair system in which steering commands were obtained by constantly observing the brain data of the patient and data from a laser range finder (LRF); a background filter focused on environmental information was developed to filter incorrect BCI commands[12]. Milla'n et al. have suggested another form of joint wheelchair control . In particular, a dynamic system was designed for navigation that could generate naturally smooth trajectories by integrating the user's BCI commands, and vision sensor obstacle information. The BCI commands were received from motor imageries of the user for these two common control systems.

The key benefits of this method are –

1. No environmental information is needed a priori.
2. Trajectories are not set and calculated in real time.
3. Both systems will automatically avoid obstacles if necessary

The disadvantages of this method are –

1. To reach a destination, a large number of BCI commands were required that could exhaust the user.
2. The wheelchair could not be halted in free space by the user; rather, the wheelchair would only halt until it docked at a possible goal.

In this review paper, we will be reviewing the technique wherein they have created an adaptive wheelchair that integrates a BCI based on MI or P300 with an autonomous navigation system, in which users choose one of the candidate destinations using the BCI based on MI or P300s. The autonomous navigation system designs a route, and then drives the wheelchair to the destination, based on the direction decided and the wheelchair's current position. Throughout the navigation time, the user does not have to pay attention to the control; therefore, the user's workload is significantly eased. Since the candidate destinations and paths are created dynamically based on the current environment observed by two webcams, our program is sensitive to environmental changes (e.g. newly installed furniture). The user can also request a stop order via the BCI. Here, we will be giving more importance to the BCI techniques used. (W)

3. AUTONOMOUS NAVIGATION SYSTEM

The wheelchair system consists of the following sensors [1]:

·A Laser rangefinder which is placed on a steel prop

·Two encoders on the central wheels

·An ultrasonic sensor array which are fixed to the wheelchair

A 2-D vector map is manually made, gives the coordinate information for the wheelchair and obstacle localisations. Most of the distance measurement devices like the laser rangefinder and sonars can only detect limited distances[23]. This will pose a disadvantage when it comes to detecting obstacles of different heights. So, two webcams are places on the walls with opposite orientation. [31][32]

Once the system gets activated, the obstacle map is updated. Once the calibration is performed based on a homography technique and a homography matrix is obtained the object localization process is performed using threshold segmentation method and morphological operations.

An optimal path is selected from all the other options for the paths in order to minimize the time taken for navigation. After this is obtained the path is calculated and is employed as the feedback of a PID tracking algorithm which gives the reference angular speed. Once this speed is obtained the proportional-integral-derivative algorithm drives the wheelchair.

4. BRAIN COMPUTER INTERFACE

A BCI is employed during wheelchair motion to pick a destination and issue a stop command. The user can pick between two types of BCI systems [1]

MI-based BCI: This is usually for patients with visual impairment

P300-based BCI: this is for users with regular vision

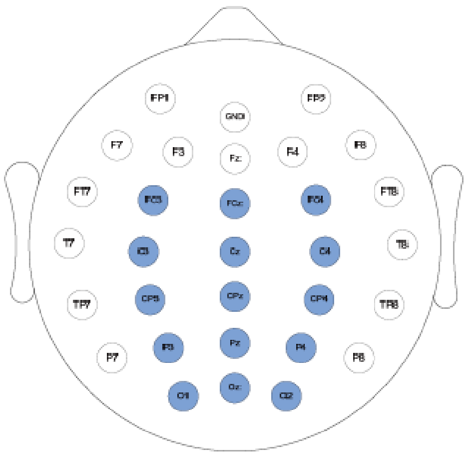

Figure 3:
EEG Cap with the 15 Electrodes

4.1 EEG Data Acquisition

An EEG cap is used to obtain the EEG signals from the brain by using fifteen electrodes. The placement of electrodes is shown in figure 3 [1]

These signals are amplified and converted into digital signals with a sampling frequency of 250Hz and is passed through a band pass filter.

4.2 Motor Imagery based BCI

Destination Selection: In the graphical user interface shown in the figure 4, there are two vertical bars on either side which are used for visual feedback. When n MI for left or right hand is detected by the BCI, the corresponding bar is filled with the colour red. The amount of this bar that has been filled is proportional to the output of the motor imagery detection. There are two horizontal bars which show the threshold of the detection.

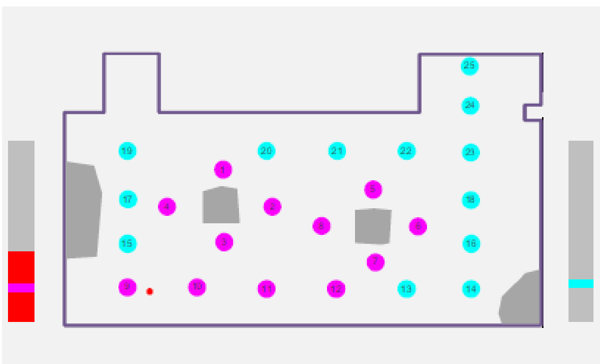

Figure 4:
GUI used in MI based BCI

Stop command: If the user gives a left-hand command for three seconds, then they can issue a stop instruction. Once this instruction is issued, the wheelchair stops, and the user interface shifts to its initial state. The user can pick another destination to start the wheelchair.

Motor Imagery Detection: to detect any MI, the system records the EEG signal for 1200 ms and that signal is spatially filtered. A feature vector is extracted and then is sent to a support vector machine. A predicted class is used to determine the left/ right hand MI.

4.3 BCI that uses P300

Destination Selection: This is carried out in two steps [1]. [i] the user thinks of the number corresponding to the location that they desire and in 20secs [ii] the P300 graphical user interface appears, as shown in figure 5. The numbers on the interface correspond to the destinations. The user determines the destination by focussing on the number on the interface. Once the destination is selected the user should focus on the o/s button to validate the destination selection. Once this is selected, the wheelchair automatically moves.

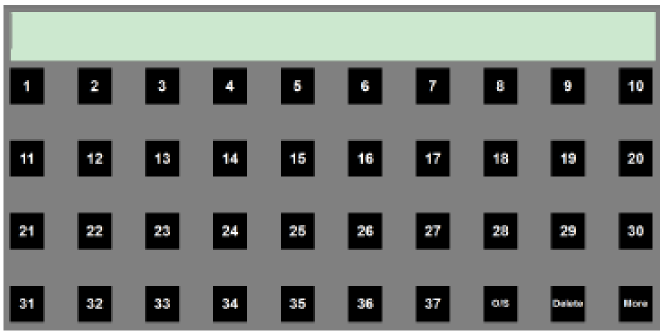

Figure 5:
GUI used in P300 based BCI

Stop command: The P300 detection is performed every 1.2 sec once the wheelchair is in motion. If O/S button is detected by the P300, the system issues a stop command to the wheelchair.

P300 Detection: The EEG signals are bandpass-filtered and sampled. EEG signals are recorded from each channel to obtain a vector. This corresponds to a button in the interface.

5. RESULTS

When subjects were taken to a room with a few pieces of furniture and were asked to move around[1]. The output is shown in figure. The metrics that were involved in the evaluation of the BCI systems were[34][35]:

Concentration Time: The amount of time the user spent in selecting the destination, including the incorrect ones

·Concentration time for each selection: The amount of time the user spends in selecting anything in a MI-based BCI.

·False destination selection: The wring selections of destinations in the BCI

·Response time: it is the time taken by the system to stop the wheelchair after the user sends a stop command

·Success Rate: It is the ratio of the number of stops that were successful to the total number of stops

·Error distance: The distance between the centre of the wheelchair and the stop area.

False activation rate: The number of times the wheelchair stopped when the user did not intend it to per minute.

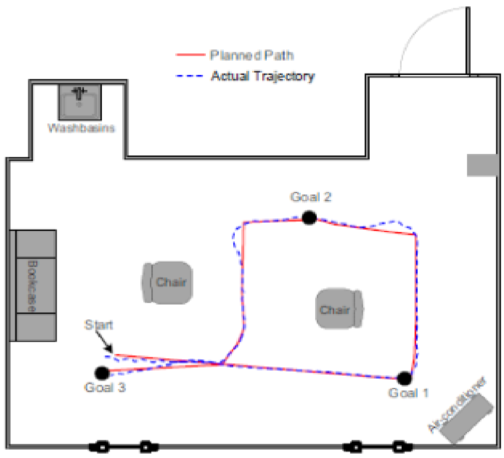

Figure 6A: Results obtained from MI based BCI systems

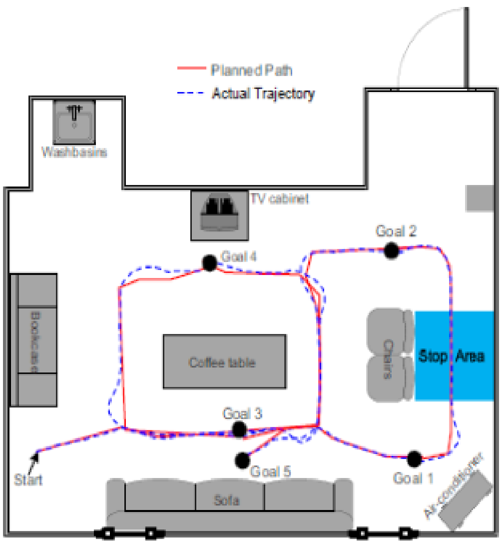

Figure 6B: Results obtained from P300 based BCI systems

6. CONCLUSIONS

In this paper, we present an intelligent wheelchair that combines a Motor Imagery- or P300-based BCI and an automated navigation system. Two experiments were conducted wherein one experiment was conducted based on Motor Imagery and the other experiment was conducted based on P300. The results that were obtained from conducting these two experiments showed the effectiveness of the system that was built. This wheelchair system proved to have various advantages:

1. The candidate destinations and paths are created automatically based on the actual current climate, which means that our system will adjust to environmental changes.

2. Once the user selects a destination with the BCI our wheelchair will automatically navigate to it. No additional mental commands need to be issued by the user. Thus, the user's workload is significantly eased.

3. The user can issue a stop command via the BCI during wheelchair motion.

The technology used to build this system mentioned in the paper provides the users with a direct communication interface and allows users to determine destinations without manual help. Therefore, solving the drawbacks that previously made devices had thrown at them. The system examined in this paper can be seen as an expansion of an already existing framework [13]. Why this method operates is that a destination was chosen by the user using a BCI. The wheelchair, which had been operated by the automated navigation system, navigated to the destination without any user commands. The candidate destinations and paths were predefined, however, which meant that a technician would need to redefine the candidate destinations and paths after a change to the atmosphere had occurred. This difficulty was resolved in our program by the collection of nominee destinations and route preparation prior to wheelchair service. Our method's only drawback is that our wheelchair only fits a room fitted with webcams

7. FUTURE SCOPE

The intensity to extend the system to allow the wheelchair to move in more complex indoor or outdoor environments without using webcams in the future study. Previous studies have shown that some people with disabilities can perform similarly when using either P300-or Motor Imagery-based BCI to healthy people. We also need to improve the system for severely disabled people in future, keeping their limitations in mind.

8. REFERENCES

1.Rui Zhang, Yuanqing Li, Yongyong Yan, Hao Zhang, Shaoyu Wu, Tianyou Yu, and Zhenghui Gu, Control of a Wheelchair in an Indoor Environment Based on a Brain-Computer Interface and Automated Navigation, DOI - 10.1109/TNSRE.2015.2439298, IEEE Transactions on Neural Systems and Rehabilitation Engineering

2.Jerry J. Shih, MD; Dean J. Krusienski, PhD; and Jonathan R. Wolpaw, Brain-Computer Interfaces in Medicine, 2012 Mayo Foundation for Medical Education and Research, doi:10.1016/j.mayocp.2011.12.008.

3.K. Tanaka, K. Matsunaga, and H. O. Wang, Electroencephalogram based control of an electric wheelchair," IEEE Trans. Robot., vol. 21, no. 4, pp. 762–766, Aug. 2005.

4.K. Choi and A. Cichocki, "Control of a wheelchair by motor imagery in real time," in Proc. 9th Int. Conf. Intell. Data Eng. Autom. Learning, 2008, vol. 5326, pp. 330–337.

5.J. Long, Y. Li, H. Wang, T. Yu, J. Pan, and F. Li, "A hybrid brain computer interface to control the direction and speed of a simulated or real wheelchair," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 20, no. 5, pp. 720–729, 2012.

6.P. F. Diez, S. M. Torres M¨uller, V. A. Mut, E. Laciar, E. Avila, T. F. Bastos-Filho, and M. Sarcinelli-Filho, "Commanding a robotic wheelchair with a high-frequency steady-state visual evoked potential based brain–computer interface," Med. Eng. Phys., vol. 35, no. 8, pp.

7.Q. Zeng, B. Rebsamen, E. Burdet, and C. L. Teo, "A collaborative wheelchair system," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 16, no. 2, pp. 161–170, 2008.

8.T. Taha, J. V. Mir´o, and G. Dissanayake, "Pomdp-based long-term user intention prediction for wheelchair navigation," in Proc. IEEE ICRA, Pasadena, LA, May 2008, pp. 3920–3925.

9.S. P. Parikh, V. Grassi Jr, V. Kumar, and J. Okamoto Jr, "Usability study of a control framework for an intelligent wheelchair," in Proc. IEEE ICRA, Barcelona, Spain, Apr. 2005, pp. 4745–4750.

10.L. Bi, X. Fan, and Y. Liu, "Eeg-based brain-controlled mobile robots: A survey," IEEE Trans. Human Mach. Syst., vol. 43, no. 2, pp. 161–176, 2013.

11.A. C. Lopes, G. Pires, and U. Nunes, "Assisted navigation for a brainactuated intelligent wheelchair," Robot. Auton. Syst., vol. 61, no. 3, pp. 245–258, Mar. 2013.

12.J. Mill´an, F. Gal´an, D. Vanhooydonck, E. Lew, J. Philips, and M. Nuttin, "Asynchronous non-invasive brain-actuated control of an intelligent wheelchair," in Proc. IEEE/EMBS 31st Annu. Int. Conf., Minneapolis, MN, Sept. 2009, pp. 3361–3364.

13.T. Carlson and J. d. R. Millan, "Brain-controlled wheelchairs: A robotic architecture," IEEE Robot. Autom. Mag., vol. 20, no. 1, pp. 65–73, Jun.

14.2013.NeuroSky. (2013, Dec.). [Online]. Available: http://www.neurosky.com

15. Emotiv. (2013, Dec.). [Online]. Available: http://emotiv.com

16. InteraXon. Dec. 2013, [Online]. Available: http://www.interaxon.ca

17. g.tec. (2013, Dec.). [Online]. Available: http://www.gtec.at

18. Qasar. (2013, Dec.). [Online]. Available: http://www.quasarusa.com

19. Mindo. (2013, Dec.). [Online]. Available: http://mindo.com.tw

20. Neuroelectrics. (2013, Dec.). [Online]. Available: http://www.neuroelectrics.com

21. Cognionics. (2013, Dec.). [Online]. Available: http://www.cognionics.com

22. S. Patki, B. Grundlehner, A. Verwegen, S. Mitra, J. Xu, A. Matsumoto, J. Penders, and R. F. Yazicioglu, "Wireless EEG system with real time impedance monitoring and active electrodes," in Proc. Biomed. Circuits Syst. Conf., 2012, pp.108–111.

23.Y. Li and S. T. Birchfield, "Image-based segmentation of indoor corridor floors for a mobile robot," in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., Taipei, Oct. 2010, pp. 837–843.

24.J. Pan and X. Jiao, "New application, development and aerospace prospect of fNIR," Engineering, vol. 5, no. 5B, pp. 47–52, 2013.

25.S. L. Bressler and V. Menon, "Large-scale brain networks in cognition: Emerging methods and principles," Trends Cognitive ci., vol. 14, no. 6, pp. 277–290, 2010.

26.R. J. Barry, A. R. Clarke, S. J. Johnstone, C. A. Magee, and J. A. Rushby, "EEG Differences between eyes-closed and eyes-open resting conditions," Int. J. Psychophysiology, vol. 118, no. 12, pp. 2765–2773, 2007.

27.P. Wen, "The impact of inhomogeneous tissue anisotropy on potential distribution within head model," Australasian Phys. Eng. Sci. Med., vol. 26, no. 3, pp. 115–118, 2003.

28.G. Geetha and S. N. Geethalakshmi, "Scrutinizing different techniques for artifact removal from EEG signals," Int. J. Eng. Sci. technol., vol. 3, no. 2, pp. 1167–1172, 2011.

29.Berger H. Uber das electrenkephalogramm des menchen.Arch Psychiatr Nervenkr. 1929;87:527-570.

30.Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, Vaughan TM. Brain-computer interfaces for communication and control. Clin Neurophysiol. 2002;113(6):767-791.

31.C. H. Lin, S. Y. Jiang, Y. J. Pu, and K. T. Song, “Robust ground plane detection for obstacle avoidance of mobile robots using a monocular camera,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., Taipei, Oct. 2010, pp. 3706–3711.

32.A. Criminisi, I. Reid, and A. Zisserman, “A plane measuring device,” Image Vis. Comput., vol. 17, no. 8, pp. 625–634, 1999

33..L.-D. Liao, I.-J.Wang, S.-F. Chen, C. Jyh-Yeong, and C.-T. Lin, “Design, fabrication and experimental validation of a novel dry-contact sensor for measuring electroencephalography signals without skin preparation,” Sensors, vol. 11, no. 6, pp. 5819–5834, May 30, 2011.

34.brain-actuated wheelchair based on a p300 neurophysiological protocol and automated navigation,” IEEE Trans. Robot., vol. 25, no. 3, pp. 614–627, 2009.

B. Rebsamen, C. Guan, H. Zhang, C. Wang, C. Teo, M. H. Ang, and E. Burdet, “A brain controlled wheelchair to navigate in familiar environments,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 18, no. 6, pp. 590–598, Dec. 2010