Brain-Computer Interface:

An Emerging Application

Rukmini Bose
Professor Gerald Moulds
University of California Santa Cruz
15 December 2020

This IEEE-style report will introduce the topic of brain-computer interface technology, how it works, and its practical applications. The intended audience for this report is anybody who is familiar with human cognition, neuroscience, or engineering and is interested in how these fields may work together to build assistive neuro-tool technologies for people with severe disabilities.

***Abstract*—The field of brain-computer interfaces has grown exponentially in the last couple of decades and continues to grow with new discoveries everyday. Brain-computer interfaces can be thought of as a system that gathers data on the activity in the central nervous system, or CNS, and translates it into artificial output that replaces, restores and improves the natural CNS output. This can ultimately change its interactions between the CNS and its external or internal conditions [1]. This paper is intended for anybody who is interested in how computer technology can be implemented with neuroscience to create neurorehabilitation tools. The paper will give a brief introduction to brain-computer interfaces, how they work, some examples of real-life applications, and finally discuss the ethics of this new technology.**

***Index Terms*—brain, IEEE, technology, software, hardware, neurorehabilitation**

I. INTRODUCTION

A brain-computer interface, or a BCI, is a hardware and software communications system that allows for signals received from the brain to be translated into actions for a computer software [1]. It allows for people to interact with their surroundings without the use of their peripheral nerves and muscles. A BCI works in three main steps; it collects brain signals, interprets them, and outputs commands to a connected machine, depending on the nature of the brain signal received [2]. The BCI's ability to create a non-muscular path to demonstrate a person's intentions to an external software can be advantageous in many ways, especially in the medical field. With extensive research, BCIs are becoming popular among assistive centers to improve the quality of life and reduce the cost of intensive care for patients with severe motor disabilities.

Artificial intelligence and machine learning skills are used in order to build brain-computer interfaces that can recognize a specific set of brain signals using five main stages– signal acquisition, signal enhancement, feature extraction, classification, and the control interface [3].

Brain-computer interface technology was not a hotspot for research and development until recently. Originally, the complex idea of a technology being able to translate brain signals into a vastly different computer software was thought of as too daunting and seemed impossible to others. However, recent research within the last two decades has led to new discoveries and developments to the BCI field that brings hope to many. Researchers specializing in vastly different fields such as neuroscience, psychology, engineering, computer science, and rehabilitation have come together to work on brain-computer interfaces with high hopes and many successes of implementing BCIs to assist patients with severe motor disabilities [3]. The P300 Brain Painting, motor-based imagery training, and smart wheelchairs are just a few examples.

II. HOW IT WORKS

A. Brain Activity

The human nervous system consists of two main parts: the central nervous system and the peripheral nervous system. The brain is the main organ of the central nervous system, consisting of over 100 billion neurons, or individual nerve cells that are connected to each other by dendrites and axons [5]. Everytime a human moves, thinks, or feels, these neurons are producing small electric signals that are passed from neuron to neuron at speeds as fast as 250 mph [7]. These signals are generated by differences in electric potential carried by ions on the membrane of every neuron. Where an electric current is leaving a neuron, there is a positive polarity, and where a current is entering, there is negative polarity [5]. These currents, also known as primary currents, are most commonly located and embedded in the brain tissue and are strong enough to reach the skull and scalp. The voltage differences are what are considered the electric brain signals. In addition, the myelin sheath of a neuron is a protective covering that surrounds a neuron that tries to insulate the travelling signals, yet some of the electric signal is bound to escape. These escaping signals of voltage differences are what are detected by a BCI and can be interpreted to direct an external device.

B. Five Stages to a Successful BCI

While there are many different types of brain-computer interfaces, each version of the technology uses the same steps to successfully implement a BCI. Artificial intelligence and machine learning concepts are used in order to build brain-computer interfaces that can recognize a specific set of brain signals in five main stages– signal acquisition, signal enhancement, feature extraction, classification, and the control interface [3]. The signal acquisition and preprocessing stages are in charge of capturing and filtering the initial brain signals. They do this in several different processes such as noise reduction and artifact processing.

The feature extraction stage searches and identifies any noticeable information on changes in the recorded brain signals. As the incoming brain signals can be very complex, it is nearly impossible to find any meaningful information without the help of different processing algorithms to search for content [8]. Some of these algorithms include time-frequency representations, Hjorth parameters, and slow cortical potential calculations (SCPs). Once these changes have been identified, the signals are mapped out, analyzed, and grouped together according to their distinct features.

In the classification stage, machine learning techniques are used to recognize and choose the signals with the desired features for this particular task, proceeding finally to the control interface stage where these chosen signals are translated into meaningful commands for an external device, such as a wheelchair or a computer [3].

Many challenges may arise during these steps of acquiring, analyzing, and translating the brain signals, which are often critical to the entire process of a BCI. For example, the extraction of distinct features among the brain signals is very risky; the raw data of the useful signals is often mixed with other electric signals, making it difficult to differentiate between the two [3]. Furthermore, electric signals are not always stationary and can become distorted when technologies such as an electroencephalogram (EEG) are used to acquire the signals.

III. TYPES OF BCI

The ideal brain-computer interface is "bi-directional", having the ability to both record from and to stimulate the nervous system [5]. This means that the pathway of a signal can also work in the opposite direction, where scientists can assess what type of signal is sent to the brain by neurons when a person is doing a certain task– whether that be seeing, thinking, or moving. Analyzing the signal allows for scientists to produce those exact signals into a patient's brain who may be lacking the ability to do one of these tasks, allowing them to successfully perform a task with the help of a BCI. For example, researchers have been able to interpret the type of signal that is sent to the brain via the optic nerve when a person sees colors. With this information, they can rig a BCI camera that sends those exact signals to a blind patient's brain, allowing them to essentially "see" colors without eyes [5].

Depending on the type of work scientists may want to do, they choose from two main types of brain-computer interface technology– the non-invasive and invasive BCIs. The easiest and least expensive method is using a non-invasive BCI, in which electrical sensors are placed on the exterior of the scalp to measure the electrical potentials produced by the brain. This can be developed with the help of an electroencephalography (EEG), magnetoencephalography (MEG) or magnetic resonance tomography (MRT). However, the EEG-based BCI using electrodes is the most common and preferred type of non-invasive BCI, as they are easily processed and decoded by computer software.

Now, there are two main types of electrodes used by a BCI: the wet and dry electrodes. Wet electrodes use a saline solution of gel, increasing conductivity because the electrical distance is minimized. Most wet electrodes are made of stainless steel, gold, or silver and are covered with a silver chloride coating. Dry electrodes are more convenient and much easier to use, but they can lose higher frequencies of incoming brain signals. For this reason, because many electrodes as possible are required to capture as much of the signal as possible, they are arranged in a wearable cap that is easy to take on and off [8].

While non-invasive methods are the most widely-used type of BCI due to its efficiency, the resolution of the electric signals are slightly distorted and challenging to read, since the skull acts as a wall that makes it harder for these signals to pass through.

To get a higher-resolution signal, scientists may use an invasive brain-computer interface, where the micro-electrodes are placed directly into the brain cortex to measure the activity of a single neuron. To use an invasive BCI, a patient must undergo an extensive and expensive neurosurgical process.

Fig. 1. Gold-coated EEG wet electrodes [8]

However, the quality of the spatial resolution is much higher than that of an EEG, since the signal does not have to travel as far to reach the scalp [8]. This gives researchers a more precise feedback and direct reception of the electric signals, allowing them to understand which area of the brain the signal is coming from. It is also important to note that the use of an invasive BCI comes with many risks. During neurosurgery, the patient's body may reject the foreign object being implanted. In addition, BCIs that are left in the brain long-term tend to cause some formation of scar tissue in the brain's gray matter, ultimately blocking the electric signals [7].

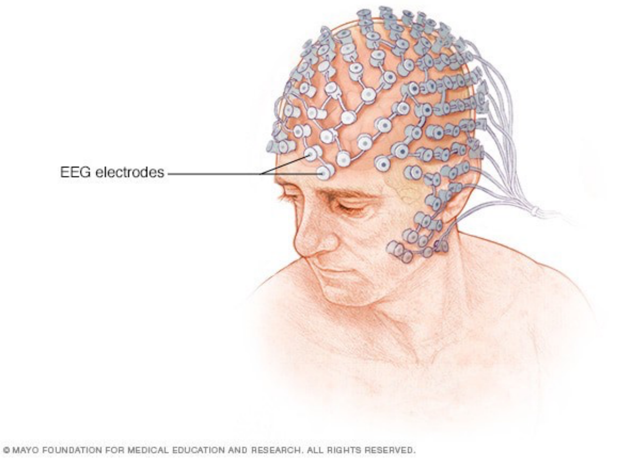

Fig. 2. Non-invasive BCI cap made up of many dry electrodes [9]

IV. BCI APPLICATIONS

Brain-computer interfaces have been contributed into various fields of research, including the medical, educational, and entertainment fields. At the moment, as the BCI technology is most prevalent in clinical applications, users include individuals who are severely diabled by neuromuscular disorders or serious injuries. However, there is high hope for BCIs to be further implemented for entertainment purposes for the general public in the future as well.

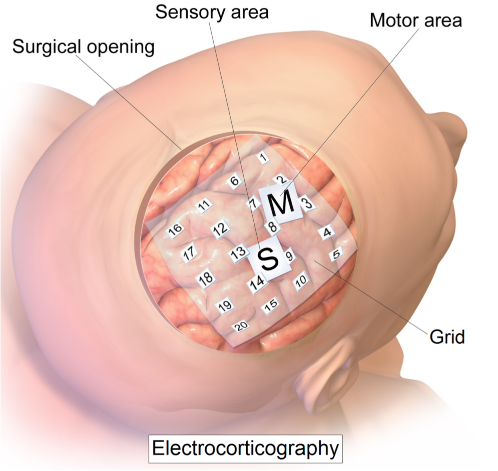

Fig. 3. To insert an invasive BCI, a patient's skull must be opened and the microchip must be planted into the brain's gray matter itself. Location of the microchip depends on the what the BCI application's intentions are [7].

A. *Medical Applications*

Brain-computer interfaces are mostly popular among the healthcare field in the form of various applications that can take advantage of incoming brain signals. They can be used for methods of prevention, detection, diagnosis, rehabilitation, and restoration [4].

1) Prevention: With the help of BCIs, different consciousness level determination systems have been developed. This allows for researchers to investigate the various attentiveness influences that smoking and alcohol can have on brain waves. Gathering information on this allows for scientists to understand which brain waves and brain areas are mostly inhibited under severe alcoholism, and ultimately can help reduce the risk of deaths from being under the influence [4].

In addition, traffic accidents are considered to be the main cause for death or injury; therefore, analyzing their causes for later prevention has been a rising concern for many researchers [4]. Various reasons for traffic accidents such as motion sickness can be studied with the help of brain-computer interfaces. Motion sickness is a result of sensory overload and sending conflicting sensory information between the body, inner ear, eye, and brain. This results in a person's inability to maintain self-control and having a diminished monitoring and alertness system, ultimately leading to traffic accidents. With the help of auditory-evoked BCI systems, the human auditory signals can be measured to report one's motion sickness level in real time and ultimately use this information to help reduce the risk of motion-sickness-related traffic accidents.

2) Detection and Diagnosis: The mental state monitoring function of brain-computer interface systems has helped researchers in also detecting various health issues. Some examples of these are abnormal brain structures such as a brain tumor, seizure disorders such as epilepsy, sleep disorders such as narcolepsy, and brain swelling such as encephalitis [4]. EEG-based brain tumor detection systems have been on the rise, as they are a cheap alternative to MRI and CT-SCAN detection systems. Similarly, BCI systems have been developed to recognize EEG abnormalities of a patient with epilepsy and ways to control its effects.

Lastly, BCI systems have been able to successfully diagnose dyslexia at a very early age by measuring brain activity behavior [4]. Dyslexia is a learning disability that makes it difficult for people of all ages to read and write. By diagnosing it at an early age, it helps those affected to get the extra help they need to gain their basic reading and writing skills as soon as they can.

3) Rehabilitation and Restoration: Brain-computer interfaces are currently very popular among assistive and rehabilitation centers to help people recover from serious mobility injuries or neuromuscular disorders. People who benefit most from BCIs are those suffering from the most severe motor disabilities, including people with amyotrophic lateral sclerosis (ALS), spinal cord injury, stroke, and other neuromuscular diseases or injuries. Injuries located closer to the brain generally lead to higher grades of paralysis and more loss of function. In some cases, paralysis may be so severe that a person is unable to move almost no part of their body. This is known as Locked-in Syndrome, or LiS. With this condition, it is generally not possible to speak and communication is only possible through subtle facial movements such as eye blinks [8].

Brain-computer interfaces that can restore communication ability of people with such severe paralysis are currently being developed. With extensive research, there are high hopes for such patients to be able to communicate with an extensive vocabulary, send messages through the internet, and do simple tasks such as turning on and off appliances without the help of others. In addition, the brain structures associated with many of these injuries or disorders can be reorganized and restored through neuroplasticity, or the ability for the brain to rehabilitate itself by reforming new neural connections [8].

4) Motor Imagery-Based Rehabilitation: Using brain-computer interfaces for neurorehabilitation involves the recording and decoding of local brain signals generated by the patient, as they try to perform a motor or mental imagery task. Mental imagery tasks can be either kinaesthetic, where a patient can "feel" the movement in your mind, or visual, where a patient can "see" the movement from one's imagination or a 3rd-party stimulus. The main objective is to promote the recruitment of selected brain areas involved and to facilitate neural plasticity, or the ability to rewire synaptic connections in the brain. The recorded signal can be used in several ways. One way to objectify and strengthen motor imagery-based training by providing the patient with feedback on the imagined motor task. A BCI can use this to infer a user's intent and assist them in their motor commands.

Several studies indicate different proposals of an effective training method for motor-based imagery training that utilizes feedback for left and right hand imagery using a brain-computer interface[15]. Experiments were carried out to gauge a better understanding on the most optimal training method. These experiments included the comparison of a subject practicing motor imagery of left and right hand movement without any visual feedback and another experiment in which the subject is trained with the support of visual feedback [17]. Many of these experiments were conducted in a loud environment to simulate a distracting environment. One particular experiment showed groundbreaking results–a significantly greater performance from patients who were provided visual feedback, even in a distracting environment.

These experiments used healthy subjects in their prime ages between 19 and 22. The subjects were randomly divided into two groups. The first group experimented with motor-imagery training with visual feedback training before attempting the motor-imagery training without the feedback. The second group experimented with motor-imagery training without visual feedback before training with visual feedback.

During each motor-imagery based training, each subject sat on a chair facing the computer screen. A distracting environment was simulated through their headphones, which were worn during the entirety of every training session. Every subject was required to stay still and gaze at a computer monitor and follow the instructions displayed on the screen.

During the non-visual motor-imagery training session, each subject completed two 20-second trials with a 5-minute break between each. During each trial, when an image of a cross was shown on the screen, the subject was told to relax. When an arrow pointing to the right appeared, the subject was expected to imagine moving their right hand and similarly for the left side. It is important to note that no other visual feedback was added to each trial apart from the cross and arrow images.

The visual motor-imagery training session consisted of 20 trials. Similarly, when a cross appeared on the monitor, the subject was asked to relax [17]. However, after that a blue ball would appear in the middle of the top of the screen and a green bar was shown on one of the sides of the screen. The ball would be animated to fall down and the subjects were instructed to use their left or right hand motor imagery to catch and move the ball to the side that the green bar was on. The EEG signals were recorded when the ball moved toward the green ball. After the visual motor training, a simple trial of non-visual feedback was conducted to record the EEG data after the visual feedback training. EEG signals were recorded from the sensorimotor cortex and later analyzed. Comparing the EEG results of each of the subjects, there was substantial evidence that visual motor-based imagery training had a greater impact on the subject's ability to imagine to do motor tasks [17].

These results show that with the use of BCIs, there is much hope for patients with neuromuscular disorders to be able to communicate or move again. Promoting the recruitment of selected brain areas involved and to facilitate neuroplasticity, there is much hope that brain-computer interfaces can be successful in reversing the effects of neural damage to the brain and allowing patients who were once paralyzed to move and communicate once again.

They may also be used to create BCI-based wheelchairs and prosthetics. Recently, a robot was operated using brain waves that were collected by EEG and fNIRS [16]. These are just a few ways that BCIs can be implemented in the real world. BCI technology is still fairly new but there is a lot of potential for it in the future.

B. *P300 Brain Painting*

Among different electric signals that a brain produces is the P300 event-related potential, which can be used to build several types of brain-computer interfaces for both assistive and therapeutic purposes. The P300 event-related potential, or ERP, is an electrophysiological response to an internal or external stimulus that is evoked during a sensory, motor, or cognitive task [10]. It is the largest and most noticeable ERP component that is generated when a subject is met with a decision-making task. Being such a strong signal, it can be easily recorded using an non-invasive EEG cap. Using this to their advantage, researchers have been able to create BCIs that measure the P300 wave for different applications, including the P300 brain painting therapy, smart wheelchairs, gaming, lie detection, and stroke rehabilitation.

As paralysis can hinder many patients' abilities to communicate, they had no means of a creative outlet until recent inventions of the P300-Brain Painting–a recent application that allows for users to paint pictures using the activity of their brain only. Simply put, the brain painting software will use the P300 waves as a control signal for the painting application using a non-invasive connection to link the brain and computer together.

To enable the brain to control what a patient may see on a computer screen, the user will wear an EEG cap that is composed of numerous dry electrodes, which is connected to an amplifier [11]. The electrodes are positioned mainly on the frontal-central parietal lobe and occipital midline of the brain–

the two main structures that are responsible for decision-making. Some additional electrodes cover the parieto-occipital area, which relate to visual tasks. Then, the user will see the painting items flashing in columns and rows; this is also known as the “P300-Matrix” [12]. The user will focus his or her attention on a single element of the matrix for a couple of seconds, the brain signals that are elicited during this decision-making process will generate a corresponding output of what painting tool will be selected on the matrix to use to draw on a digital canvas.

The effects of the P300 Brain Painting have been massive among neurorehabilitation and assistive centers. This new way of expressing one’s creativity and communication has helped many patients deal with mental health issues such as depression or anxiety that may have developed in correlation to their disability. It allows for patients to feel like they are a member of society again and can improve their overall quality of life [12].

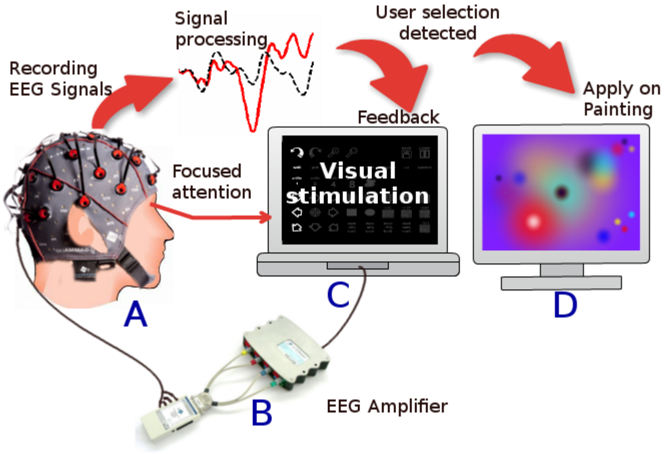

Fig. 4. Simplified setup of Brain Painting. A: the end-user with the EEG cap. B: EEG amplifier. C: stimulation monitor. D: canvas monitor [12]

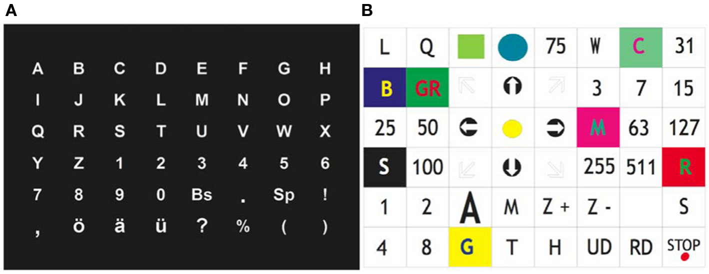

Fig. 5. Example of P300 Matrix. (A) is an example of a P300 Speller in which patients can write words by choosing figures from the matrix. (B) is an example of tools that compose a P300 Brain Painting Matrix [11].

C. Smart Wheelchairs

Another application of a brain-computer interface to assist disabled individuals is the idea of a smart wheelchair. A typical smart wheelchair would be composed of an omnidirectional wheelchair, a lightweight robotic arm, a target recognition module and an autocontrol module. It will use the “you only look once” (YOLO) algorithm that can recognize and locate a specified target destination in real time, using the wheelchair and robotic arm to complete the operation successfully [13]. Previous assistive wheelchairs would use an alternative controller, such a joystick, that could directly control a wheelchair. However, this would require even the slightest bit of motor ability and control from a patient to operate. Because of that, a smart wheelchair that can be controlled solely based on one’s brain activity would be much more advantageous to users who are severely paralyzed and have little to no motor ability.

The basic function for a wheelchair is to simply transport a user from place A to place B. It is important for a wheelchair system to be as intuitive and easy to use as possible– especially for patients with a disability [13]. To do so, many smart wheelchairs are implemented based on virtual reality technology; specific locations or destinations in a user’s environment will be constructed and displayed in an N x M polar grid. The user will be able to select a destination through a P300-based BCI, in a similar fashion to the way users may use a P300 Brain Painting BCI that was mentioned earlier. The target recognition module will recognize, locate, and confirm the selected target in an online environment. Then, the auto navigation module will steer the wheelchair to its selected destination. Oftentimes, the pathway to reach the destination will be straightforward. However other times, the system may deal with a more dynamic environment that requires the help of the robotic arm as an additional actuator to do so. For example, a user may choose to travel to a different room, yet there is a closed door that is in the way. Therefore, the BCI system must recognize the distance the destination is, any obstructions that are in the way, and determine if the obstructions can be dealt with in order for the user to travel successfully. The wheelchair is responsible for travelling up to the closed door, where now the robotic arm will have to open the door for the user and wheelchair to pass through.

The logistics and architecture of how a smart wheelchair brain-computer interface is able to successfully complete such complex tasks involve four main parts– the hardware and software structure, target detection and localization, the target solution, and the wheelchair and robotic arm control [13].

The hardware structure is a flexible wheelchair that is constructed with an omnidirectional chassis, allowing for the wheelchair to travel in any direction and to rotate with zero radius. This makes the wheelchair well-accommodated to navigate even in complicated environments like tight spaces or a cluttered room. In addition to the main structure of the wheelchair is the robotic arm that can provide extra navigation for more complicated tasks, such as opening a door or picking up a water bottle [13]. A kinetic camera is also placed on the back support of the wheelchair to capture the depth streams for areas in the front of the wheelchair and to constantly upload this data onto the cloud, allowing for real-time navigation. Low cost lidars are placed on the front right and back left corners of the wheelchair that are constantly measuring the distance of every object within the wheelchair's range.

The software structure of the smart wheelchair is composed of modules that communicate with each other to ensure efficiency and effectiveness. To do so, a robot operating system (ROS) is employed for the main software structure. ROS obtains the data from the hardware structure including the devices and sensors and inputs them in complex algorithms that will later allow for robot control.

In order for the patient to operate the wheelchair in versatile environments, a target detection and localization algorithm is used to recognize targets in real time. Specifically, the deep-learning-based method, or the "you only look once" (YOLO) algorithm is in charge of detecting targets at fast speeds [13]. After a target is detected, the bounding box for the target must be confirmed. This means that has to be confirmation that the wheelchair is able to place itself at its target within a certain limit of distance. To do so, 3D points are extracted from a bounding box that is 60% of the target's original size. The orientation of the target is calculated as well, as this can greatly affect the quality of a human interaction with the target. For example, if the selected target was a person, the wheelchair must be able to travel to the target person and place itself in front of the person, not in the back, as human interaction is face-to-face.

After all of the data of recognizing the location of a target is confirmed, the most optimal solution must be determined; a lot of the time, a user may want to interact with the target after reaching its destination. To do so, the BCI system must be able to "predict" what the user may want to do at his or her destination by using different algorithms and comparing data on behaviors from the past. For example, if a user were to select a person sitting on a chair, the BCI will assume that the user's goal is to have a conversation with a person who is sitting. Therefore, the wheelchair needs to realize to stop at a distance that is comfortable for human communication– about 80cm. If a user were to select a bottle that is placed on a table, the optimal solution would be to reach the target, pick up the bottle, and bring it to the user's mouth. To do the latter steps, the robotic arm must be pre-calibrated to wrap its fingers around the bottle, to locate the user's mouth, and to tilt the bottle at a steady rate for the user to drink.

Finally, the wheelchair and robotic arm will do as the previous steps have instructed it to do. Each hardware aspect of the BCI system contains its own ROS package that carries important data to carry out the processes easily. For example, the ROS package for the robotic arm will contain important information to move in a human manner and to keep the user's real-time location in mind at all times. All of these steps combined allows for a user to travel on a wheelchair without using any motor skills.

V. THE ETHICS DEBATE

With new and emerging technologies that are successfully able to do the impossible, there is always the debate of ethics and ethical concerns that must be addressed by the neuroscience community. These problems raise different concerns of topics such as managing patient expectations, personal identity, informed consent, and biological risks [9].

Because brain-computer interfaces have created high hopes to help patients with severe neuromuscular disorders live a normal life again, doctors may run into ethical problems surrounding a patient and his or her family's expectations of the technology. There are a list of different factors that could affect the ability of a BCI's success in helping a patient or not– cognitive capacity or the severity of a patient's disability are only a couple. The possibility of the BCI technology failing could create false hope and ultimately significant distress to patients, making it hard to determine if the positive outcomes are worth the risks. Furthermore, as discussed earlier, there are always the risks of a patient's body having bad reactions to the invasive BCI. Since the BCI field has only recently begun growing, there is also very little to no information on any risks an implanted BCI chip could have on a patient's brain in the long term. Non-medical safety issues are also important to keep in mind. Many areas for intense training and cognitive concentration for neurorehabilitation would require a patient to attend regular and challenging training sessions that can impose mental, emotional, and physical stress to a patient [14]. With these factors in mind, it is important to assess if the benefits will ultimately be worth the risk.

A patient's privacy is also an ethical problem to consider. Since BCIs are often viewed as a technology that is "able to read minds", which is very plausible in the near future, this can raise ethical questions of a patient's personal identity and privacy [9]. For example, how will a patient's data be transmitted and stored? Will there be ways for a patient to keep full ownership of his own data to avoid hackers or other people accessing his or her thoughts?

Legal implications also raise concern when debating on the ethics of brain-computer interfaces. Many BCIs are used to assist paralyzed patients to help them regain movement in their limbs by using prosthetics. Many researchers question who would be responsible in case an accident were to occur with such methods. It would be difficult to distinguish a malfunction in the BCI from a voluntary action.

Lastly, the possibility of BCIs to increase one's mental or physical ability would create an impact on society or even society's definition of "humanity" [14]. Many ask if patients using invasive BCIs in their daily life would be considered as equal to other humans. For example, would athletes with such prosthetic limbs be able to compete with others in a regular race? Similar questions may arise with one's increased mental ability with BCIs [9]. In addition, there are increasing concerns as to how a BCI may change a patient's idea of social identity, personality, and authenticity [14]. Could a patient who has spent their entire life unable to communicate and essentially being socially isolated, is able to live his or her life normally, run into issues of feeling a loss of personal identity and have a hard time transitioning back into society? These are all questions that are currently being debated and open to consideration when implementing new types of brain-computer interfaces.

VI. CONCLUSION

Brain-computer interfaces are a new type of technology that are of increasing interest to researchers, being an interactive technology that allows people to communicate and interact with the external world without using their muscles. It works in three main steps to do so; it collects brain signals, interprets them, and outputs commands to a connected machine depending on the nature of the brain signal received. With groundbreaking research and development on BCIs, this technology has been able to be applied in numerous fields– from the entertainment industry to medical and clinical applications. This report mainly talks about the clinical applications of a BCI and how they can be used to help patients with severe neuromuscular disorders feel like a functioning member of society and promote neuroplasticity in rehabilitation centers.

With major companies and business owners such as Facebook and Elon Musk investing in the BCI market, it is estimated to reach over \$2.67 billion by the year 20206. It is safe to say that this technology is on the rise and is gaining popularity quickly. Practical applications of brain-computer interfaces are starting to make its way into other industries as well, including the video game industry. It will be interesting to see how brain-computer interfaces can be implemented in a way for the general public to use as well.

REFERENCES

[1] J. J. Daly and J. E. Huggins, "Brain-computer interface: current and emerging rehabilitation applications," Arch. Phys. Med. Rehabil., vol. 96, no. 3 Suppl, pp. S1-7, 2015.

[2] D. Valeriani, C. Cinel, and R. Poli, "BrainComputer interfaces for human augmentation," Brain Sci., vol. 9, no. 2, p. 22, 2019.

[3] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain computer interfaces, a review," Sensors (Basel), vol. 12, no. 2, pp. 1211–1279, 2012.

[4] S. N. Abdulkader, A. Atia, and M.-S. M. Mostafa, “Brain computer interfacing: Applications and challenges,” Egypt. Inform. J., vol. 16, no. 2, pp. 213–230, 2015.

[5] A. Gonfalonieri, “A beginner’s guide to brain-computer interface and convolutional neural networks,” Towards Data Science, 25-Nov-2018. [Online]. Available: https://towardsdatascience.com/a-beginners-guide-to-brain-computer-interface-and-convolutional-neural-networks-9f35bd4af948. [Accessed: 15-Dec-2020].

[6] E. W. Sellers, D. B. Ryan, and C. K. Hauser, “Noninvasive brain-computer interface enables communication after brainstem stroke,” Sci. Transl. Med., vol. 6, no. 257, p. 257re7, 2014.

[7] E. Grabianowski, “How brain-computer interfaces work,” Howstuffworks.com, 02-Nov-2007. [Online]. Available: https://computer.howstuffworks.com/brain-computer-interface.htm. [Accessed: 15-Dec-2020].

[8] “Intro to Brain Computer Interface,” Neurotechedu.com. [Online]. Available: http://learn.neurotechedu.com/introtobci/. [Accessed: 15-Dec-2020].

[9] Q. Chatur, “An intro into BCI’s,” Medium, 11-Dec-2019. [Online]. Available: https://medium.com/@qais8317/an-intro-into-bcis-c5ff52570be9. [Accessed: 15-Dec-2020].

[10] R. Fazel-Rezai, B. Z. Allison, C. Guger, E. W. Sellers, S. C. Kleih, and A. Kübler, “P300 brain computer interface: current challenges and emerging trends,” Front. Neuroeng., vol. 5, p. 14, 2012.

[11] “Brain painting,” Uni-wuerzburg.de, 09-Aug-2018. [Online]. Available: https://www.psychologie.uni-wuerzburg.de/int/projekte/brain-painting/. [Accessed: 15-Dec-2020].

[12] University of Wurzburg-Institute of Psychology I, “Brain painting - research and art galleries - home,” Brainpainting.net. [Online]. Available: http://www.brainpainting.net/130-howitworks.php. [Accessed: 15-Dec-2020].

[13] J. Tang, Y. Liu, D. Hu, and Z. Zhou, “Towards BCI-actuated smart wheelchair system,” Biomed. Eng. Online, vol. 17, no. 1, p. 111, 2018.

[14] S. Burwell, M. Sample, and E. Racine, “Ethical aspects of brain computer interfaces: a scoping review,” BMC Med. Ethics, vol. 18, no. 1, p. 60, 2017.

[15] J. Han, S. Ji, C. Shi, S. Yu and J. Shin, ”Recent progress of non-invasive optical modality to brain computer interface: A review study,” The 3rd International Winter Conference on Brain-Computer Interface, Sabuk, 2015, pp. 1-2, doi: 10.1109/IWW-BCI.2015.7073037.

[16] RaviKumar K.M. and M. Siddappa, ”Electronically linked Brain to Brain communication in humans using non-invasive technologies,” 2015 International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT), Mandya, 2015, pp. 235-239, doi: 10.1109/ERECT.2015.7499019.

[17] S. Jo and J. W. Choi, ”Effective motor imagery training with visual feedback for non-invasive brain computer interface,” 2018 6th International Conference on Brain-Computer Interface (BCI), GangWon, 2018, pp. 1-4, doi: 10.1109/IWW-BCI.2018.8311524.