



A REVIEW ON BRAIN COMPUTER INTERFACE

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ABSTRACT

A brain-computer interface (BCI) establishes a link between the human brain and the external devices. BCIs measure the brain activity for fetching the user's intent and subsequently provide the control signals to the supporting hardware. This technology has varied uses ranging from assistive devices for disabled individuals to advanced simulator control. The main use of BCI is as an assistive technology for individuals suffering from loss of motor control caused by spinal cord injury, amyotrophic lateral sclerosis or any other possible incidence. BCIs take advantage of the brain's electrochemical signals. There are billions of neurons in human brain with trillions of interconnections known as synapses. These devices also make use of neuroplasticity which is the brain's ability to change physically and functionally over time. Author has discussed the basics of BCI in this paper and has presented details regarding brain waves, control centers of various organs in brain, invasive and non-invasive sensors. This paper also presents a summary of the research work going on in this area.

Keywords: Brain computer interface, neuron, sensormotor rhythms, control center, electroencephalography.

1. Introduction

Brain-computer interface (BCI) is an interface established between a brain and a device that receives signals from the brain to command some external activity with the help of a computer or any other electro-mechanical device. It translates neuronal information into command signals which are capable of controlling external software or hardware. This interface facilitates a direct communication pathway between the brain and the target object. BCI intercepts signals from neurons and uses proper combination of hardware and software to translate the signals into commands, thereby enabling a disabled person to perform desired tasks or control a mechanized wheelchair or prosthetic limb through thoughts alone. At present brain-interface devices need deliberate conscious thoughts; but efforts are going on to develop future applications such as prosthetic control which would be able to work effortlessly. Development of electrodes or sensors for fetching the brain signals is one of the biggest challenges in developing BCI technology. It is also expected to make surgical methods for implanting these electrodes minimally invasive. Traditionally the brain accepts an implanted mechanical device in BCI and controls the device by producing desired signals. Current research in this area is focused on the development of non-invasive BCI. Brain is practically "disconnected" from its target (such as a limb or the facial musculature) in spinal cord injury, brainstem stroke, and a host of neuromuscular disorders, thereby preventing mobility and movements. BCIs are often used as assisted living devices for persons with sensory or motor impairments (Wolpaw et al, 2002; Daly et al, 2008). This is particularly a helpful aid for individuals who suffer from severe motor disabilities. Researchers have been working with BCIs based on electroencephalography (EEG) with the goal of helping persons with motor impairments such as spinal-cord injury (SCI), amyotrophic lateral sclerosis or stroke survivors (Daly et al, 2008).

BCIs, in general involve four components:

- (1) Sensors or electrodes for measuring brain activity
- (2) Automated software for converting brain activity into commands
- (3) Interface to control an output device in real-time
- (4) An operating environment to control the interaction between these components and the user

A BCI device basically consists of sensors (often in the form of ‘electrodes’) that receive brain signals, an amplifier to boost the weak signals, and a proper hardware that translates these signals into commands to control devices or computer programs. The constituent components of BCIs can be made portable and/or wearable. BCI controlled devices can offer assistive technology for people with disabilities, internet devices for healthy people and computer games or toys. Figure 1 presents a self explanatory schematic diagram of basic BCI system.

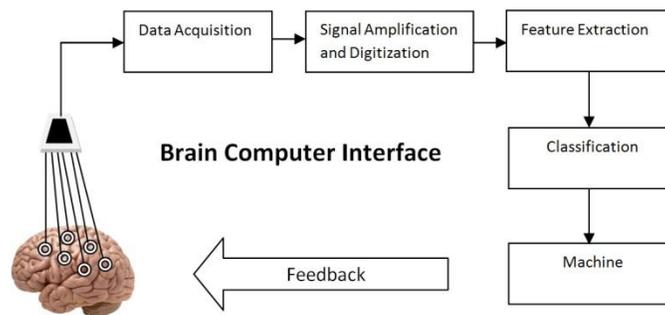


Figure 1: Functional block diagram of Brain computer Interface

2. Components of BCI

2.1 Brain signals

A BCI records and interprets or decodes brain activity to generate useful command signals. Neurons (brain cells) transmit electrical signals to communicate with each other. It is possible to intercept these signals or ‘brain activity’ with advanced electrical sensors. These brain signals play vital role in day-to-day life of all living creatures. Movements of healthy creatures are possible because the brain sends signals via the central nervous system to the muscles of the body. Precise communication between the brain and muscles make all kinds of actions of body possible. This communication between the brain and body muscles disrupts or breaks due to medical conditions such as stroke or neuromuscular diseases and subsequently leads to paralysis or cerebral palsy. In many such cases the brain is still able to generate the activity signals for intended movements and a BCI can use the brain signals to control assistive devices.

BCIs are designed to read the signals produced from the brain at different locations in the human head, translate these signals into commands that can control the hardware/computer.

Brainwaves which are detected using sensors placed on the scalp are divided into bandwidths to describe their functions, but are best thought of as a continuous spectrum of consciousness. Human brainwaves change according to our actions and feelings. We can feel tired, retarded, lethargic, or dreamy when lower frequency brainwaves are dominant. On the other hand, the higher frequencies are dominant when we feel energetic, or hyper-alert.

Table 1: Various brain waves and their functions

Type of Brain wave	Frequency Region	Function
Infra-low (Slow Cortical Potentials)	(<.5HZ)	Higher brain functions Brain timing and network function
Delta Waves Deep Sleep Wave, slow, loud brainwaves (generated in deepest meditation and dreamless sleep)	(.5 to 3 HZ)	Suspend external awareness, source of empathy. Healing and regeneration
Theta Waves	(3 to 8 HZ)	Learning, memory, and intuition
Alpha Waves Deep Relaxation Wave	(8 to 12 HZ)	Overall mental coordination, calmness, alertness, mind/body integration and learning
Beta Waves	(12 to 38 HZ)	Fast activity, present when we are alert, attentive, engaged in problem solving, judgment, decision making
Gamma Waves	(38 to 42 HZ)	Pass information rapidly and quietly, expanded consciousness and spiritual emergence, insight and peak focus Generated when the brain is learning new information, sharply concentrating, or storing memories.

2.2 Brain function

Every part of body has a tiny part in the brain through which it performs its activities. In general each part of the body has its own ‘control center’ in the brain that is responsible for its movements. It is possible to detect the activities of various active centers with the help of various techniques. This helps BCIs to detect the movement of body parts from the brain activity. A special quality of the brain is that these control centers are also active when we simply think about making a movement without actually moving.

Table 2: Control centers in brain

Brain Part	Action
Motor Cortex	Movements
Sensory Cortex	Pain, Sensations
Parietal Lobe	Language Comprehension
Temporal Lobe	Hearing, Intellectual and Emotional functions
Occipital Lobe	Primary Visual Area
Wernicke’s Area	Speech Comprehension
Frontal Lobe	Judgment, Foresight, voluntary movement, Smell
Broca’s Area	Speech
Brainstem	Swallowing, breathing, Heartbeat, Wakefulness center and involuntary functions
Cerebellum	Coordination

Persons who suffer from locked-in syndrome (LIS) still have fully functioning control centers in their brains. They are able to activate distinct areas in their brain by the ways of thinking about a particular movement, or attempting to make movements even if they are not able to move the part of the body which is controlled by that particular area of their brain. Various brain functions, in addition to movements of body parts, can be detected. Brain areas are involved in different aspects of numerical calculations, understanding language and speaking. When these areas are active a BCI can detect if a person is doing calculations in their head, or is talking. In brief we can say that there are many distinct areas in the brain that a person can intentionally turn on and/or off by performing different physical tasks. BCI can be used as a realistic and promising

assistive technology for persons suffering from paralysis by detecting, interpreting and utilizing mental tasks performed by them.

2.3 What can a BCI do with the brain signals?

Brain signals can be obtained by placing the electrodes exactly on brain areas can be controlled by the person. After detecting a signal it can be converted to a command to operate a device or software. A pre-programmed computer can use this information to perform specific tasks. This way a BCI can be used to make a computer mouse ‘click’ every time the person counts backwards in his/her head and select from a menu in a computer program. Such controls are already commonly used by people suffering from paralysis with special ‘buttons’ that can be activated by whatever type of movement they are still able to make, such as lifting their eyebrows or with a little movement of their fingers. Thus, a BCI device can also be used as a ‘button’ to control many types of devices designed for button press control.

Usage of sensorimotor rhythms (SMRs) is also being utilized in one particular type of BCIs. SMRs are electrical oscillations (i.e., mu [8–12 Hz] and beta [18–30 Hz]) in electroencephalographic (EEG) activity recorded over sensorimotor cortices. Amplitudes of these signals change with movements, imagined movements, or preparation for movements. Needy persons can learn through a training protocol to alter the SMR amplitude. They can use this control to move a computer cursor or operate another device (Pfurtscheller et al, 2012; Perdakis et al, 2014; Leeb et al, 2015).

It is important to distinguish that there are various neurological as well as engineering challenges between building BCIs for the peripheral nervous system (PNS) and central nervous system (CNS). In particular, miniaturization of processing units, isolation of targeted structures, replacement of failed probes, and delivery of nonmaterial, etc. are the major aspects to be looked upon. Understanding the information transfer and processing of the nervous system are amongst the most urgent challenges faced by the biomedical community, with a plethora of academic and clinical applications. It includes better understanding of aging, neurodegenerative diseases and interfaces for prosthetics and implants. For example, recent advances in chronic neural recording devices have facilitated the willful control of robotic prosthetic limbs for the treatment of

paralysis and improved seizure prevention with chronic telemetry in refractory epilepsy (Cook et al, 2013; Morrell, 2011). There are many different kinds of potential BCIs that will each serve independent functions. However, all systems must tackle three fundamental problems: accurate recording of information from relevant neural systems, decoding such information, and stimulating and manipulating neuronal dynamics in appropriate as well as meaningful ways. Further, BCIs must present real-time feedback to the user. It is essential for the BCI system to act as per user's intent so that the user can recognize whether he/she successfully conveyed the desired command or not.

3. Present Status

In a research paper authors (Winda et al, 2017) have proposed system adopted Linear Predictive Coding (LPC) coefficients as the feature of the person's mind and Support Vector Machines to develop the brain signal recognition system. In their work, brain signal was processed and provided as input to the recognition system. Right-Left sign lamp based on the brain signal recognition system could potentially replace the button or switch of the specific device in order to make the lamp work. The system then would decide whether the signal is 'Right' or 'Left'. The decision of the Right-Left side of brain signal recognition would be sent to a processing board in order to activate the automotive relay, which would be used to activate the sign lamp. In another research (Jalal Karam et al, 2016) a Radial Basis Functions (RBF) Artificial Neural Network (ANN) was constructed and a BCI was implemented using NeuroSkyS EEG biosensor for the recognition of brain signals. The analysis was presented through the consideration of a noisy environment to simulate a BCI in real world applications. The data were transmitted via Bluetooth for MATLAB documentation and recognition rates in the highest 70 percent were recorded.

An EEG Based Emotion Recognition System has been proposed in a study (Lahane et al, 2014). They have presented a model for making a system which is able to detect human emotion through brain signals. In another study (Hiwaki et al, 2018) authors have presented a study on noninvasive measurement of dynamic brain signals using light penetrating the brain. They verified that diffused near-infrared light penetrating through the upper jaw and into the skull,

which they termed as opt encephalography (OEG), led to the detection of dynamic brain signals that varied concurrently with the electrophysiological neural activity.

Superconducting Quantum Interference Devices (SQUIDs) are widely used to detect the extremely weak magnetic field of brain. In order to measure brain activity in normal environment, a group of researchers (Wang et al, 2017) have constructed and proposed a measurement system based on highly sensitive Magneto-Impedance (MI) sensor. They have reported the study of measuring Auditory Evoked Field (AEF) brain waves. The system was improved in this study, and the sensor signals could be processed in real-time to monitor brain activity. In this study, they measured the alpha rhythm and the P300 brain activity in the frontal, the parietal and both the temporal regions using a real-time measuring and processing system based on highly sensitive MI sensor.

4. Measurement of brain signals

It is essential to measure the brain signals in order to make proper devices for their interpretation. Various techniques are available for measuring these signals. These techniques offer certain advantages as well as disadvantages. Fundamentally there are three types of BCI systems; invasive; partially invasive, and non-invasive.

Noninvasive and invasive methods both benefit from improved recording techniques. Invasive methods being used at present do not adequately deal with the expectation for long-term stability of their results. The brain's complex reaction to an implant is still inadequately understood and might hamper long term performance. Skills of the person placing noninvasive EEG electrodes play vital role in their performance. These electrodes need periodic maintenance to ensure sufficiently good contact with the skin. Improvement in methods for extracting key features from EEG signals and fetching device control signals from them would also help in improving the BCI performance.

Conventional techniques for noninvasive measurement of brain signals such as functional magnetic resonance imaging (fMRI), near-infrared spectroscopy (NIRS), magneto encephalography (MEG), and electroencephalography (EEG), suffer from critical limitations in spatial or temporal resolution. A commonly used technique, electroencephalograph (EEG) uses

electrical sensors (electrodes) that are placed on the scalp. These electrodes can also be placed under the scalp directly on or in the brain tissue. This requires a surgical procedure to place such electrodes. This method provides better signals as compared to signals recorded from the scalp. It is possible to place the electrodes on the brain without causing any damages. This has accelerated use of implantable BCIs for paralyzed people. Near-infrared spectroscopy (NIRS) can be used to measure brain activity by exposing the skull through near-infrared light. As such NIRS does not require any surgery.

A variety of sensors for monitoring brain activity exists, and could in principle provide the basis for a BCI. These include electroencephalography (EEG), electrocorticography (ECoG), magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging (i.e., functional Near InfraRed (fNIR)) (Kübler et al, 2005).

EEG is a least invasive alternative which is recorded from the scalp. These BCIs support much higher performance than previously assumed, including two- and three dimensional cursor movements. Extensive user training is required for the acquisition of such high levels of control. Furthermore, EEG has low spatial resolution, which will eventually limit the amount of information that can be extracted, and it is also susceptible to artifacts from other sources (McFarland et al, 2008).

The second alternative uses ECoG, which is recorded from the cortical surface (Wilson et al, 2006). It has higher spatial resolution compared to EEG (i.e., tenths of millimeters vs. centimeters), broader bandwidth (i.e., 0–500 Hz vs. 0–50 Hz), higher signal strength (i.e., 50–100 μ V vs. 10–20 μ V), and far less vulnerability to artifacts such as EMG (Ball et al, 2009) or ambient noise. While this method is invasive, the use of these electrodes that do not penetrate the cortex may combine excellent signal fidelity with good long-term stability.

The third and most invasive alternative uses microelectrodes to measure local activity (i.e., action or field potentials) from multiple neurons within the brain (Taylor et al, 2002). Cortex provides signals having higher fidelity and can support BCI systems that require lesser training than EEG-based systems. However, clinical implementations of intracortical BCIs are currently impeded mainly by the difficulties in maintaining stable long-term recordings, by the

substantial technical requirements of single-neuron recordings, and by the need for continued intensive expert oversight. For these reasons, practically all BCI demonstrations in humans to date have been achieved with, and the examples in this book are using or meant for, EEG or ECoG recordings.

A study reported in 2012 (Chi et al, 2012) compares wet electrodes to dry and through hair, noncontact electrodes within a steady state visual evoked potential (SSVEP) BCI paradigm. They have also presented the construction of a dry contact electrode, featuring fingered contact posts and active buffering circuitry. In addition to this they have also introduced the development of a new, noncontact, capacitive electrode that utilizes a custom integrated, high-impedance analog front-end.

Brain-computer interface (BCI) technology is utilized in paired associative stimulation (PAS) to evaluate movement imagery in real-time. Pas uses this information to control feedback presented to the patient. Another group (Sabathie et al, 2016) introduced this approach and the RecoveriX system, a hardware and software platform for PAS. They have also presented initial results from two stroke patients who used RecoveriX, followed by future directions.

Stroke is a major cause of acquired disability which results in distal upper extremity functional motor impairment. Ongoing research to evaluate the effectiveness of BCI-based stroke rehabilitation for hand therapy is currently in progress. A review of the progression and future implications of brain-computer interface therapies for restoration of distal upper extremity motor function after stroke has been proposed (Remsik et al, 2016). Further, researchers (Almajidi et al, 2014) have presented the design and characterization of novel, differential functional NIRS sensors, intended to record hemodynamic changes of the human motor cortex in the hand-area during motor imagery tasks. They have reported on the spatial characterization of a portable, multi-channel NIRS system with one module consisting of two central light emitting diodes (LED) (770 nm and 850 nm) alongwith four symmetric pairs of photodiodes (PD). These diodes resemble a plus symbol. The other sensor module includes four similar and differential light paths crossing in the center of a star. Apart from the literature presenting technological developments of BCI there are some papers where the ethical challenges of BCI have been discussed (Burwell et al, 2017). The intent of medically ailing users regarding control of their

life saving equipments may be questionable at times (Glannon, 2014). The impulsive responses of BCI users may cause irreparable losses to them.

4. Conclusions

Brain-computer interfaces provide a new communication-and-control option for individuals for whom conventional methods are ineffective. Brain-Computer Interface (BCI) is a fast-growing emergent technology in which researchers aim to build a direct channel between the human brain and the computer. A BCI derives its outputs from brain activity which is directly consciously controlled by the user, independently from external events, for controlling an application. It is a collaboration in which a brain accepts and controls a mechanical device as a natural part of its representation of the body. The BCI can lead to many applications especially for disabled persons. A brain-computer interface (BCI) systems permit encephalic activity to solely control computers or external devices. Accordingly, people suffering from neuromuscular diseases can highly benefit from these technologies, since a computer could allow them to perform multiple tasks. Further development of applications is also needed, particularly applications of BCI technology to rehabilitation. The design of rehabilitation applications hinges on the nature of BCI control and how it might be used to induce and guide beneficial plasticity in the brain. As the rise in the BCI, the user would be haunting with the privacy issue; it means that attackers would be able to hack targets brain. Undoubtedly there is great potential in BCI devices but there are certain possible ethical implications as well. The benefits of BCIs can introduce moral and societal challenges. It is, therefore, important to consider the impact of this technology on legal and moral responsibilities of both user as well as producer.

References

Almajidy R. A., Kirch R. D., Christ O. & Hofmann U. G. (2014). Estimating the spatial resolution of fNIRS sensors for BCI purposes. *Proc. SPIE 8945, Design and Performance Validation of Phantoms Used in Conjunction with Optical Measurement of Tissue VI*, 894504. doi: 10.1117/12.2037351; <https://doi.org/10.1117/12.2037351>.

- Ball T., Kern M., Mutschler I., Aertsen A. & Schulze-Bonhage, A. (2009). Signal quality of simultaneously recorded invasive and non-invasive EEG. *NeuroImage*, 46(3), 708–716. DOI:10.1016/j.neuroimage.2009.02.028.
- Chi Y. M., Wang Y. T., Wang Y., Maier C., Jung T. P. & Cauwenberghs G. (2012). Dry and Noncontact EEG Sensors for Mobile Brain–Computer Interfaces. *EE Transactions on Neural Systems and Rehabilitation Engineering*, 20(2). DOI: 10.1109/TNSRE.2011.2174652.
- Cook M. J., O'Brien T. J., Berkovic S. F., Murphy M., Morokoff A., Fabinyi G., D'Souza W., Yerra R., Archer J., Litewka L., Hosking S., Lightfoot P., Ruedebusch V., Sheffield W. D., Snyder D., Leyde K., Himes D. (2013). Prediction of seizure likelihood with a long-term, implanted seizure advisory system in patients with drug-resistant epilepsy: a first-in-man study. *Lancet Neurol.*, 12(6), 563–71.
- Daly J. J. & Wolpaw J. R. (2008). Brain–computer interfaces in neurological rehabilitation. *Lancet Neurol.* 7, 1032–1043.
- Glannon W. (2014). Ethical issues with brain-computer interfaces. *Front Syst Neurosci.*, 8, 136. DOI: 10.3389/fnsys.2014.00136.
- Hiwaki O. & Miyaguchi H. (2018). Noninvasive measurement of dynamic brain signals using light penetrating the brain. *PLoS One*, e0192095. Published online 2018 Jan 31. DOI: 10.1371/journal.pone.0192095, 13(1).
- Karam J., Majeed S. A., Christofer N. Y. & Mirskhulava L. (2016). Neural Network for Recognition of Brain Wave Signals. *Int. J. of Enhanced Research in Science, Technology & Engineering*. 5(10), 36-42.
- Kübler, A., Nijboer F., Mellinger J., Vaughan T. M., Pawelzik H., Schalk G., McFarland D. J., Birbaumer N. & Wolpaw J. R. (2005). Patients with ALS can use sensorimotor rhythms to operate a brain–computer interface. *Neurol.* 64(10), 1775–1777. DOI:10.1212/01.WNL.0000158616.43002.6D.

- Lahane P., Lokannavar S., Gangurde A., Bhosale P. & Chidre P. (2014). EEG Based Emotion Recognition System. *Int. J. of Computer Science and Information Technologies*, 5(6), 7656-7658.
- Leeb R., Tonin L., Rohm M., Desideri L., Carlson T. & Millan J. d. R. (2015). Towards independence: a BCI telepresence robot for people with severe motor disabilities. *Proc IEEE*; 103, 969–982.
- McFarland D. J., Krusienski D. J., Sarnacki W. A. & Wolpaw J. R. (2008). Emulation of computer mouse control with a noninvasive brain–computer interface. *J. Neural Eng.*, 5(2), 101–110. DOI:10.1088/1741-2560/5/2/001.
- Morrell M. J. (2011). RNS System in Epilepsy Study Group: Responsive cortical stimulation for the treatment of medically intractable partial epilepsy. *Neurology*, 77(13), 1295–304.
- Pfurtscheller G. & McFarland D. J. (2012). BCIs that use sensorimotor rhythms. In Wolpaw JR Wolpaw EW Brain–Computer Interfaces: Principles and Practice. New York, NY: Oxford University Press, 227–240.
- Perdikis S., Leeb R., Williamson J., Ramsay A., Tavella M., Desideri L., Hoogerwerf E. J., Al-Khodairy A., Murray-Smith R. & Millán J. D. (2014). Clinical evaluation of BrainTree, a motor imagery hybrid BCI speller. *J Neural Eng.*, 11: 036003. pmid:24737114.
- Remsik A., Young B., Vermilyea R., Kiekoefer L., Abrams J., Elmore S. E., Schultz P., Nair V., Edwards D., Williams J. & Prabhakaran V. (2016). A review of the progression and future implications of brain-computer interface therapies for restoration of distal upper extremity motor function after stroke. *Expert Rev Med Devices*. 13(5), 445–454. DOI: 10.1080/17434440.2016.1174572.
- Sabathiel N., Irimia D. C., Allison B. Z., Guger C. & Edlinger G. (2016). Paired Associative Stimulation with Brain-Computer Interfaces: A New Paradigm for Stroke Rehabilitation. In: *Schmorrow D., Fidopiastis C. (eds) Foundations of Augmented Cognition:*

- Sasha Burwell S., Sample M. & Racine E. (2017). Ethical aspects of brain computer interfaces: a scoping review. *BMC Medical Ethics* 18:60. DOI: 10.1186/s12910-017-0220-y.
- Taylor D. M., Tillery S. I. & Schwartz A. B. (2002). Direct cortical control of 3D neuroprosthetic devices. *Science*, 296, 1829–1832.
- Wang K., Cai C., Yamamoto M. & Uchiyama T. (2017). Real-time brain activity measurement and signal processing system using highly sensitive MI sensor. *AIP Advances*, 7(5), 056635. <https://doi.org/10.1063/1.4974528>.
- Wilson J., Felton E., Garell P., Schalk G. & Williams J. (2006). ECoG factors underlying multimodal control of a brain–computer interface. *IEEE Trans. Neural Syst. Rehabil. Eng.*, 14, 246–250.
- Winda A., Sofyan, Sthevany & Vincent R. S. (2017). Intelligent automatic right-left sign lamp based on brain signal recognition system. *IOP Conf. Series: Earth and Environmental Science*, 109, 012019.
- Wolpaw J. R., Birbaumer N., McFarland D. J., Pfurtscheller G. & Vaughan T. M. (2002). Brain–computer interfaces for communication and control. *Clin. Neurophysiol.* 113, 767–791.