JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

ANALYZING BRAIN WAVE ACTIVITY BRAIN COMPUTER INTERFACE

Dr. Sachin Pandey

Faculty of computer science, Govt. TRS College, Rewa, M.P

ABSTRACT

For scientists and academics, the pursuit of direct communication between a person and a machine has always been an appealing issue. Ancient mythology and contemporary science fiction stories are only two examples of how these concepts have gripped humankind's imagination. The Brain Computer Interface (BCI) technology is a potent tool for user and system communication. In human history, it has been occurring at a rate that is unparalleled. They enable muscle-free direct connection between the brain and the computer. Different machines can be driven by the signals produced by the brain. BCI has the potential to help increase human thinking concentration by enabling direct brain-to-physical device communication and control. The system uses a variety of EEG electrodes to detect a wide range of scalp signals, Opanci GUI, Open Vibe, and MATLAB to analyses and convert the information into actionable commands.

KEY WORDS Brain Computer Interfaces, Brain signal acquisition, BCI applications, Mind commands, Brain monitoring, BCI challenges

INTRODUCTION

For scientists and academics, the pursuit of direct connection between a person and a machine has always held appeal. The Brain-Computer Interface (BCI) system has successfully established a direct link between the human brain and the outside world. A brain-machine interface (BCI) that works with outside variables in real-time. In order to communicate with the computer and produce the desired result, the BCI system uses signals from the user's brain activity. It allows users to use brain activity to control external devices that are not managed by muscles or peripheral nerves. For researchers, BCI has always been an interesting field. It has recently developed into a delightful field of study and a potential way to demonstrate a direct link between the brain and technology. This idea has been used in numerous research and development projects, and it has also turned into one of the areas of science that is increasing the quickest. Many scientists experimented with and used different BCI kinds of human-computer interaction. But from a straightforward idea in the early days of digital technology, it has developed into incredibly sophisticated signal recognition, recording, and analysis methods. The first Electroencephalogram (EEG), which depicts the electrical activity of the brain as measured through the scalp of a human brain, was captured in 1929 by Hans Berger. EEG signals have been used clinically to detect brain illnesses since the author tested it on a youngster with a brain tumor.

People have long wished for the power to interface with technology solely by thinking or to develop tools that can look into another person's mind and thoughts. Ancient mythology and contemporary science fiction stories are two examples of how these concepts have gripped the imagination of humanity. However, it has only just begun to become possible for humans to communicate directly with the human brain thanks to developments in cognitive neuroscience and brain imaging technologies. This capability is made feasible by the use of sensors that can keep an eye on certain of the mental functions that correspond to physical brain functions. It's closer than you might believe to being able to operate a computer just with your head. It has already been clinically proven that brain-computer interfaces, which allow computers to read and interpret signals directly from the brain, can let quadriplegics, persons with "locked in syndrome," and stroke victims man oeuvre their own wheelchairs or even use a robotic arm to drink coffee. Direct brain implants have also assisted those who have lost their vision in regaining some of their vision.

The Brain Computer Interface (BCI) technology is a potent tool for user and system communication. In order to provide commands and finish the interaction, there are no additional hardware requirements or physical movements needed. BCIs were initially created by the research community with biomedical uses in mind, which resulted in the creation of assistive technology. They have made it easier for physically disabled or locked-in individuals to regain their capacity to move around and replace lost motor functioning. The scientific community has been inspired to investigate how BCI interacts with non-paralyzed persons through medical applications by the positive future forecast for BCI.

Information is now available in a dizzying amount, comes from several sources, and daily introduces new points of view and material. People encounter visionary concepts on a daily basis, some of which have the potential to revolutionize society. A number of developments and technologies, including genetic engineering, brain-computer interfaces, mind-controlled computing, the abolition of ageing and/or death, and others, are pointing to such a profound transition. There are constantly fresh discoveries, innovations, developments, and learning opportunities thanks to the speed and acceleration of technology. In human history, it has been occurring at a rate that is unparalleled. In general, it may be claimed that the globe is currently experiencing a technological revolution. The field of brain-computer interfaces is one such technology (BCI)

The BCI (brain-computer interface) is a method of using human intention to operate an object, such as a computer, wheelchair, or neuroprotein, without relying on the brain's typical output channels for controlling muscles and peripheral nerves. They enable muscle-free direct connection between the brain and the computer. BCI is the only means of communication for patients who have significant physical impairments, such as amyotrophic lateral sclerosis (ALS), paralysis, brain-stem stroke, cerebral palsy, spinal cord injury, or other neuro-muscular illnesses. Several functional imaging modalities, including EEG, MEG, fMRI, and others, are currently accessible for research. One of these non-invasive tools Because it promises to deliver high temporal resolution of the measured brain signals, electroencephalography (EEG) is distinct and often utilized. It is also reasonably convenient, economical, safe, and simple to use BCI for both healthy users and the impaired.

LITERATURE REVIEW

M. F. Mridha et.al (2021) The field of brain-computer interface (BCI) is a cutting-edge, multidisciplinary area of ongoing research that is based on hardware, biomedical sensors, signal processing, and neuroscience. In the past few decades, this field has seen a number of ground-breaking studies. There hasn't yet been a thorough evaluation that covers the entire BCI area. Therefore, this paper presents a thorough overview of the BCI sector. This study supports the importance of this field by examining several BCI applications. Then, a clear explanation of each BCI system component, including procedures, datasets, feature extraction approaches, evaluation measurement matrices, and classifiers, follows. A brief description of the technology or hardware, namely the sensors utilized in BCI, is also attached. The study then explores a number of unresolved BCI problems and presents them along with potential solutions.

Ji-Hoon Jeong et.al (2022) As a method of interfacing the brain with external equipment, the brain-computer interface (BCI) has been studied. Over the years, BCIs have been used for purposes other than communication and command. The objective of the 2020 international BCI competition was to deliver high-quality neuroscientific data for free access that could be used to assess the level of technical advancements in BCI at the time. We explore some more recent application directions for BCI even if there are still many obstacles to overcome: EEG(+ear-EEG) detection in an ambulatory setting, I few-shot EEG learning, (ii) micro-sleep detection, (iii) imagined speech decoding, (iv) cross-session categorization, and (v) EEG(+ear-EEG) detection. Researchers from a wide range of backgrounds and nations competed in the competition to address these issues, in addition to scientists from the BCI area. Each dataset was produced and divided into three pieces, which were then made available to the contestants as training and validation sets, then a test set. Through the 2020 competition, notable BCI advancements were found and some trends of interest to BCI researchers were revealed.

Gan Wang et.al (2022) The usage of brain-computer interfaces (BCIs) for control is growing. Such BCIs can be used as an interface for man-machine integration, for leisure activities like gaming or semi-autonomous driving, or to help people who lost their ability to move or control their limbs. The effectiveness of algorithms utilized for thought decoding has been constrained thus far. We demonstrate how one may considerably enhance the performance of BCIs in determining which motor activity was envisioned by a person by first extracting temporal and spectral properties from electroencephalography (EEG) signals and then using deep learning neural networks to classify those features. Our movement prediction approach uses a radial basis function neural network for classification and the Sequential Backward Selection technique to jointly select temporal and spectral information. When compared to cutting-edge benchmark algorithms, the technique exhibits an average performance improvement of 3.50%. Using two well-known public datasets, our approach achieves accuracy of 90.08% on the first dataset (against an average benchmark of 79.99%) and 88.74% (versus an average benchmark of 82.01%) on the second dataset. We propose that integrating characteristics from several modalities coupled with neural network classification algorithm is likely to boost the performance of BCIs across diverse activities given the substantial variability within- and between-subjects in EEG-based action decoding.

Junchen Liu et.al (2021) The non-invasive brain-computer interface (BCI) has been the subject of substantial research during the past ten years. Electrodes with advanced properties, such as high conductivity, long-term effectiveness, and biocompatibility, must be developed for electroencephalogram (EEG) collection in order to expand the practical applications of BCI technology. In this study, a semidry silver nanowire/PVA hydrogel/melamine sponge electrode was created for long-term EEG signal monitoring. The electrolyte solution can be continually delivered to the scalp-electrode contact while being utilized thanks to PVA hydrogel's ability to store water. The stratum corneum can be penetrated by the electrolyte solution, which lowers the impedance of the scalp electrode to 10–15 k. The flexible structure gives the electrode mechanical stability, improves wearer comfort, and narrows the distance between the scalp and the electrode to lower contact impedance. In light of this, a long-term BCI application based on measurements of motion-onset visual evoked potentials reveals that the new electrode's 3-hour BCI accuracy (77% to 100%) is roughly equivalent to that of conventional electrodes supported by conductive gel during the first hour. Additionally, the BCI approach has been substantially enhanced by the BCI system based on the new electrode, which can maintain low contact impedance on the scalp for 10 hours.

Nabil Ajali-Hernández et.al (2022) In all facets of society, pattern recognition is a topic that is becoming more and more significant. from the industry's process optimization to the medical field's disease identification and diagnosis. This chapter introduces brain-computer interactions. systems that can process and interpret brain signal patterns using machine learning and deep learning algorithms. A hybrid deep/machine learning ensemble system for recognizing brain patterns is suggested in this chapter. It has the ability to identify patterns and communicate decisions to BCI systems. A public database (Physio net) that contains information on both motor and mental tasks is used for this. This chapter's development includes a succinct assessment of the current state of the art, a presentation of the model together with some outcomes, and some encouraging conclusions.

RESEARCH METHODOLOGY

Signal Detection There are a few requirements that the EEG device must meet in order to implement the BCI for piloting a car. The device must, first and foremost, be useful and portable. As a result, we used dry gold cup electrodes to create an EEG headset that looks like a cap. We primarily need Alpha and Beta waves because they show that the brain is both active and at rest. But LPF, BPF, and Notch filters are used to reduce environmental interference, power line noises, EMG (muscle) and EKG (heart) signals in the data we receive. The 10/20 framework is a widely accepted method of representing the location of scalp electrodes. The link between the position of the electrodes and the cerebral cortex area beneath depends on the framework. The electroencephalogram is captured using these scalp electrodes (EEG).

a) Reasoning, planning, organizing, movement, emotion, and critical thought are all functions of the frontal lobe.

b) Movement, introduction, acknowledgment, and perception of inputs are all related to the parietal lobe.

c) Occipital lobe-related to visual processing.

d) The temporal lobe is involved in memory, sound-related observation and response.

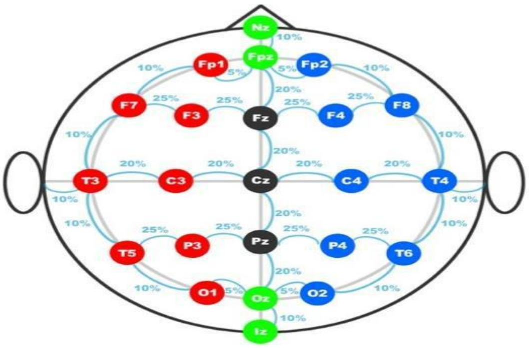

Figure 1: 10/20 Placement of Electrodes.

Preprocessing of Signals

EEG signals must first undergo signal preprocessing before being analyzed. With the goal of trimming EEG data so that noise and artefact components that entered the EEG system are decreased and the EEG signal is ready for analysis, this stage may comprise a number of processes. The following procedures are involved in preprocessing:

a) referencing recorded signals again.

b) signal band-pass filtering.

c) the signals being resampled.

d) Segmenting or peaching signals

e) deciding which EEG segments are clean.

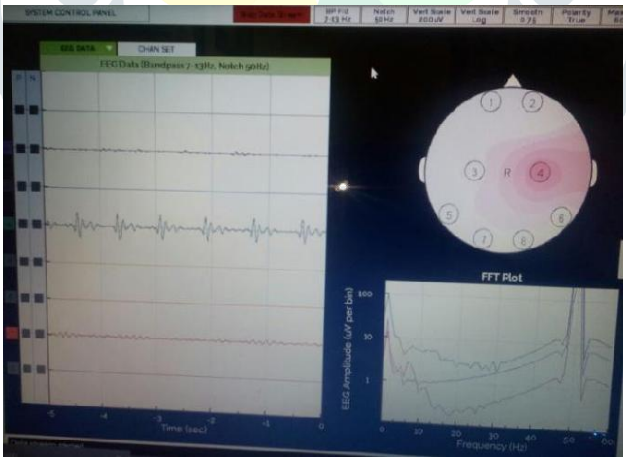

Figure 2: Analysis of Brain Waves at Open Bic GUI.

In electroencephalography, a phenomenon known as beta rebound is an event-related synchronization that occurs after a movement has ended in the beta-band at a frequency of about 16.5 Hz, though it can also occur at other frequencies. Beta rebound has been observed to occur at frequencies of 17 Hz for hand movement and 23 Hz for foot movement.

The study of cortical dynamics benefits from the application of spatial filters. This method spatially interjects EEG signals by modelling the head shape as a unit circle and using orthogonal bases on the circle. The filtering is then completed by computing the interjection work's analytical Laplacian. In order to highlight relevant signals in the middle frequency region, this filter can only high-pass EEG signals.

Low-frequency drifts are frequently observed in FMRI data, which are assumed to be caused by both physiological and physical (scanner-related) noise. These signal drifts invalidate event-related averaging and dramatically diminish the power of statistical data. Therefore, one of the most crucial preprocessing procedures is the elimination of low-frequency drifts. The temporal high-pass filter is used to eliminate the signal drifts because they are slowly increasing and falling. An operational amplifier with programmable gain (PGA) can have its gain adjusted by external digital or analogue signals.

Processing of Signals

We were able to obtain the required data depending on the BCI purpose after completing the fundamental signal processing using MATLAB and Open Vibe.

Signal data must be provided in meaningful chunks for the spectral analysis to function effectively, which is accomplished via time-based epochal Ing. The Bluetooth module, which is an international low power wireless standard, was then used to transfer the data to the vehicle's electrical system. Figure 3 depicts how the devices are connected to one another.

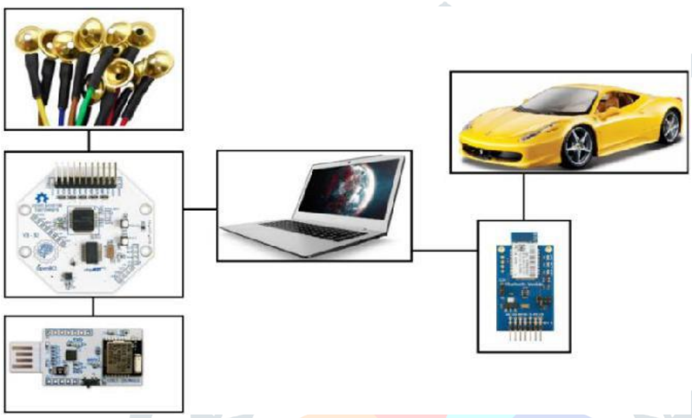

Figure 3: Device Interconnection of the System.

IT EQUIPMENT AND SOFTWARE

Since brain impulses range in frequency from 8 to 30 Hertz, we first designed a variety of EEG instrumentation circuits to reduce line disturbances and enhance the brain signals. We employed a variety of instrumentation amplifier ICs, including the AD620, LM358, INA128, CA3130, and ADS1299.

ADS 1299 is a suitable choice if small size and efficiency are factors, however this results in a complex and dense circuit board since it has 8 differential, high gain, low noise input channels that are compatible with active and passive electrodes. Along with the eight EEG channels, we also input accelerometer data, which cancels out offsets caused by muscle or body electrode movement. We can also use this data for other input purposes. Data is sent from processing units, such as PCs, laptops, and even smartphones, via RFD union. For a device that runs on DC power, Bluetooth Low Energy (BLE) offers excellent speed and simple communication with low energy consumption.

Later, we used an Open BCI 32-bit board to measure and record the electrical activity of the brain (EEG), as well as the electrical activity of the heart (EKG) and muscles (EMG). The Open BCI 32bit board uses the ADS1299 for biopotential measurements, the PIC microcontroller for on-board processing, and it also has the ability to write EEG data to an SD card or send it through Bluetooth to software running on a computer [31]. OPENBCI firmware and Chip Kit Bootloader, two open-source, user-friendly programming environments for certain microcontrollers, are programmed that support this situation. On the processing side, software includes MATLAB with EEGLAB and ERPLAB for analysis as well as Open Vibe, an open-source environment that aids in channeling data gathering and also develops EEG peach techniques that aid in simultaneously creating and separating events and stimuli. Software called Open Vibe is used to create, test, and use brain computer interfaces.

Figure 4: Raw EEG Waveforms at MATLAB (single channel).

Figure 5: Filtered EEG Waveforms at MATLAB.

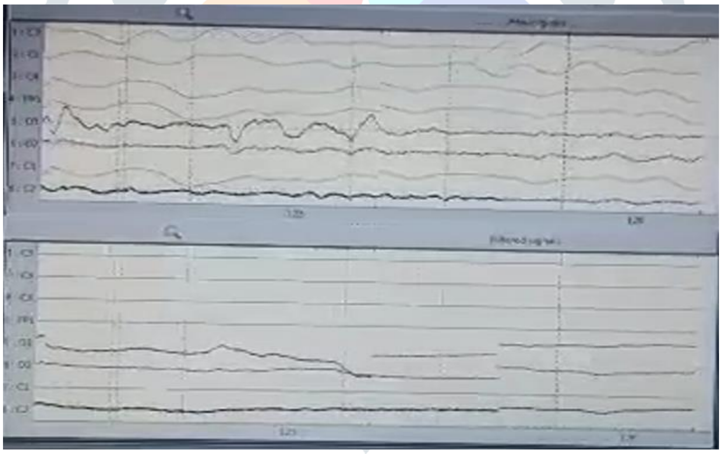

Figure 6: Raw and Filtered EEG data at Open Vibe (movement of hands).

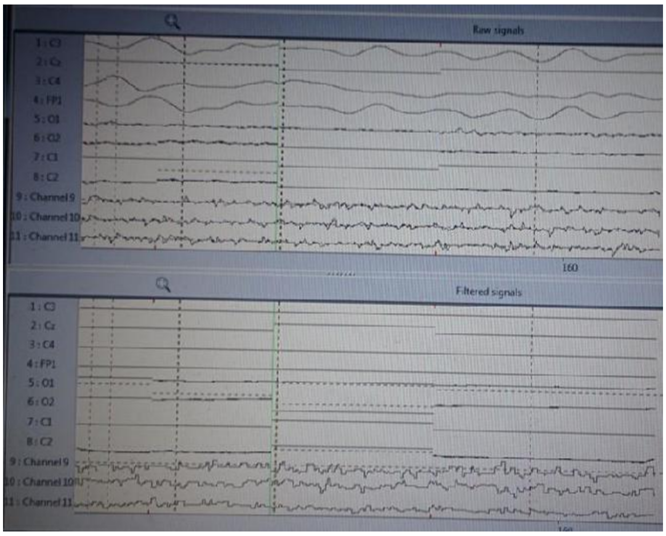

Figure 7: Raw and Filtered EEG data at Open Vibe (calm and resting state).

Hardware Implementation Challenges

Due to their high accuracy and precision, the sensors needed for hardware implementation are quite expensive. Due to interference from noise, even if the hardware is integrated, accurate brainwave measurement is not guaranteed. Therefore, 32-bit Open Bic board was used to perform the necessary task quickly and effectively.

The quantity of decisions, the accuracy of target recognition, and the average decision-making time all affect how quickly information is transferred via BCI.

B. Technical Difficulties There are problems with the electrophysiological features of the recorded brain signals, including non-stationarity, disturbance, small preparation sets, and the going with dimensionality problem.

CONCLUSION

EEG signals have been used clinically to detect brain illnesses since the author tested it on a youngster with a brain tumor. For many years, people have dreamt of being able to interface with technology solely through thinking or building tools that can look into people's minds. In conclusion, it can be argued that a technological wave is currently underway to alter the world due to the optimistic future forecast for BCI, which has pushed the scientific community to examine the involvement of BCI in the life of non-paralyzed individuals through medical applications. The field of brain-computer interfaces is one such technology (BCI) Several functional imaging techniques, including EEG, MEG, fMRI, and others, are currently available for research. This is mostly accomplished using an Open BCI board, which is a brain computer interface. Open Vibe, MATLAB, and the Open BCI GUI are used to handle and analyses the data. It has an analogue component that is used to amplify and filter the data that has been gathered. Later on, software is utilized to further analyses the data and determine the association between the signals in the brain's relaxed state and the information gathered during the questioning. To verify the system's dependability and to make changes, more testing on many elements is required. It can be improved by adding additional electrodes and channels to produce a better and more precise raw EEG that more accurately categorizes brain activity.

REFERENCES

1. M. F. Mridha et.al (2021) Brain-Computer Interface: Advancement and Challenges

2. Ji-Hoon Jeong et.al (2022) 2020 International brain–computer interface competition: A review

3. Gan Wang et.al (2022) Brain-Computer Interface using neural network and temporal-spectral features

4. Junchen Liu et.al (2021) Ten-Hour Stable Noninvasive Brain-Computer Interface Realized by Semidry Hydrogel-Based Electrodes

5. Nabil Ajali-Hernández et.al (2022) Analysis of Brain Computer Interface Using Deep and Machine Learning

6. D. J. McFarland and J. R. Wolpaw, "EEG-based brain-computer interfaces," *Current Opinion in Biomedical Engineering*, vol. 4, pp. 194–200, 2017.

7. J. Wang, Z. Feng, N. Lu, and J. Luo, "Toward optimal feature and time segment selection by divergence method for eeg signals classification," *Computers in Biology and Medicine*, vol. 97, pp. 161–170, 2018.

8. M. Miao, H. Zeng, A. Wang, C. Zhao, and F. Liu, "Discriminative spatial-frequency-temporal feature extraction and classification of motor imagery EEG: a sparse regression and Weighted Naïve Bayesian Classifier-based approach," *Journal of Neuroscience Methods*, vol. 278, pp. 13–24, 2017.

9. L. Wang, X. Liu, Z. Liang, Z. Yang, and X. Hu, "Analysis and classification of hybrid bci based on motor imagery and speech imagery," *Measurement*, vol. 147, Article ID 106842, 2019.

10. M. Z. Baig, N. Aslam, H. P. H. Shum, and L. Zhang, "Differential evolution algorithm as a tool for optimal feature subset selection in motor imagery eeg," *Expert Systems with Applications*, vol. 90, pp. 184–195, 2017.

11. B. Nakisa, M. N. Rastgoo, D. Tjondronegoro, and V. Chandran, "Evolutionary computation algorithms for feature selection of eeg-based emotion recognition using mobile sensors," *Expert Systems with Applications*, vol. 93, pp. 143–155, 2018.

12. R. Lahiri, P. Rakshit, and A. Konar, "Evolutionary perspective for optimal selection of eeg electrodes and features," *Biomedical Signal Processing and Control*, vol. 36, pp. 113–137, 2017.

13. J. Jin, H. Fang, I. Daly et al., "Optimization of model training based on iterative minimum covariance determinant in motor-imagery bci," *International Journal of Neural Systems*, vol. 31, no. 07, Article ID 2150030, 2021.

14. T. Wen and Z. Zhang, "Effective and extensible feature extraction method using genetic algorithm-based frequency-domain feature search for epileptic EEG multi-classification," 2017,

15. A.K. Maddirala and K. C. Veluvolu, "Eye-blink artifact removal from single channel eeg with k-means and ssa," *Scientific Reports*, vol. 11, no. 1, pp. 1–14, 2021.