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BCI Systems and Comparison of Various Signal Acquisition Techniques

¹ Sikandar Qammar, ² Urwah Imran

^{1,2} Department of Biomedical Engineering, School of Mechanical and Manufacturing Engineering, National University of Sciences and Technology, Islamabad, Pakistan

Corresponding Author: **Sikandar Qammar**

Abstract

Brain-Computer Interface (BCI) is an advanced, interdisciplinary and active research area based on neuroscience, signal processing, biomedical sensors, hardware, and more. It is a type of communication system that allows humans to communicate with their surroundings using control signals generated by brain wave activity without the involvement of peripheral nerves or muscles. Over the past decades, several pioneering research studies have been conducted on the suitability of different signal acquisition techniques for BCI. However, a comprehensive

review that fully covers this area has not yet been conducted. Therefore, this study provides a comprehensive overview including a comparison of different techniques for capturing the signal of BCI and briefly describes the advantages and disadvantages of each technique. This paper also presents optimum locations which can be used for acquiring EEG signals from the brain for using the EEG technique being the simplest, safest and most economic option.

Keywords: Brain Computer Interface (BCI), Signal Processing, EEG, Central Nervous System (CNS)

Introduction

BCI has always been an attractive area for researchers. More recently, it has become an interesting area of scientific investigation and a potential means of demonstrating a direct link between the brain and technology. It is also one of the fastest growing areas of research. Many scientists have tried and applied various methods of communication between humans and computers using BCI in various forms. However, from a simple concept in the early days of digital technology, today it has evolved into highly complex signal detection, recording and analysis techniques. In 1929, Hans Berger^[1] recorded for the first time an electroencephalogram (EEG)^[2] showing the electrical activity of the brain measured through the scalp of the human brain. The author tried it on a boy with a brain tumour. Since then, EEG signals have been used clinically to identify brain disorders. The concept of combining the brain and technology has always been of interest to the scientists, and recent advances in neurology and technology have made it a reality, paving the way for repairing and possibly enhancing human physical and mental capabilities. The sector flourishing the most based on BCI is considered the medical application sector. Cochlear implants^[3] for the deaf and deep brain stimulation for Parkinson's illness are examples of medical uses becoming more prevalent. In addition to these medical applications, security, lie detection, alertness monitoring, telepresence, gaming, education, art, and human enhancement are just a few uses for brain-computer interfaces (BCIs), also known as brain-machine interfaces or BMIs^[4].

This paper entails the applications of BCI while primarily focusing on its biomedical applications. Various uses of BCI are further explained briefly. Recognising signal acquisition as the most important step in BCI, different techniques are evaluated in light of their respective pros and cons which are further evaluated to classify the techniques in terms of the temporal resolutions, noise, cost effectiveness and safety limitations. The comparison provided by the end of the paper can be used as a basic reference for selection of techniques for a particular application in future.

Discussion

Applications of BCI

A BCI can be used for a variety of purposes, and the application dictates the design of the BCI. Robotics and advanced mechatronics have played a significant role in the development of assistive technologies to help people overcome a large range of disabilities. BCI's immediate purpose is to offer control and power to persons with extreme disabilities or people with partial or complete body paralysis. Various neurological neuromuscular disorders, such as amyotrophic lateral sclerosis, brain stem stroke, or spinal cord injury can be the cause of these disabilities. Such an interface would increase their quality of life and

would minimize the expense of intensive care at the same time. According to Nijholt^[5], BCI-based applications offer two eases of use. You can specify whether one can monitor or observe the other. Most command applications focus on manipulating brain impulses using electrodes to control external devices. Observational applications, on the other hand, focus on recognizing the subject's mental and emotional state in order to act appropriately in response to the environment. Some applications of BCI^[6] based on usability are described below:

Biomedical Applications

The majority of BCI integration and research has focused on medical applications, and many BCIs aim to replace or restore CNS function lost due to disease or accident. Other BCIs are narrower. In diagnostic applications, BCIs are also used for biological and emotional purposes, in CNS disease and post-traumatic therapy, and in motor rehabilitation. Biomedical technologies and applications can minimize the longevity of disease and empower people with reduced mobility to care, protect and support rehabilitation. The need to develop precise techniques that can process abnormal brain responses that can occur due to diseases such as stroke is a key challenge in developing such platforms.^[7] The following subsections go through each of these applications in further detail.

Substitute to CNS

This replacement means that CNS function lost due to diseases such as stroke or traumatic paralysis or spinal cord injury can be repaired or replaced. In addition, individuals with such diseases suffer from altered brain function and developing such technology can be difficult. Myoelectrics, known as motor action potentials, which capture electrical impulses in muscles, are currently used in several robotic prostheses. Bousseta, R. *et al.*^[8] provided a cognitive task that allowed movement in four directions, left, right, up and down in an experimental technique that used mental imagery to control the movement of a prosthetic robotic arm.

Assessment and Diagnosis

Using BCI in a clinical setting also aids in evaluation and diagnosis. Perales^[9] proposed a BCI to assess attention during play in adolescents with cerebral palsy. Another study^[10] explored using BCI to capture EEG characteristics as a tool for diagnosing schizophrenia. There are various diagnostic methods such as detection of brain tumors^[11], detection of breast cancer^[12], Parkinson's disease^[13] etc. Diagnosis of multiple diseases in the child is possible, including epilepsy, neurodegenerative diseases, movement disorders, inattentiveness, or various types of ADHD^[14]. Evaluation and diagnostic techniques are critical to patient health. How they work needs to be fine-tuned to ensure they are secure, acceptable, and accurate to industry standards.

Therapy and Rehabilitation

BCI is now being used in therapeutic applications in addition to neurological applications and prosthetics. Among many applications, motor rehabilitation after stroke has shown promising results with BCIs^[15, 16, 17]. Stroke causes long-term disability in the human body and prevents movement or vigorous activity of any kind due to impaired blood flow. BCIs can support the patients and treat

neurological disorders such as Parkinson's disease (PD), cluster headaches, and tinnitus. Deep brain stimulation (DBS) is an established treatment for Parkinson's disease because it provides electrical stimulation to specific areas of the brain that cause symptoms^[18]. Some stimulation BCI devices are used to treat migraine attacks and cluster headaches. Likewise, a CNS disorder known as tinnitus is also being developed to provide treatments by identifying the brain patterns altered by this disease^[19]. Finally, treatment of auditory hallucinations (AVHs), best known as schizophrenia, is an option alongside diagnosis.

Affective Computing

A user's emotions and state of mind are observed in affective computing BCI, and the environment can be manipulated to enhance or modify that emotion. Ehrlich, S. *et al.*^[22] created a closed-loop system in which music is generated and played based on the listener's emotional state. The connection between human emotional states and sensations can be studied using devices associated with the BCI system. Patients with neurological disorders can also benefit from affective computing to communicate their feelings to others^[23].

Structure of BCI System

The BCI system works in a closed loop system. A certain amount of feedback is returned for each user action. For example, movements of an imaginary hand can lead to commands to move a robotic arm. This simple arm movement requires a lot of process. In this regard, BCI is characterized as a tool that measures brain or central nervous system activity and transforms these signals into artificial output. As an artificial intelligence system BCI can identify a certain set of patterns in brain signals and can control the actuator after four consecutive phases. These phases include:

1. Signal acquisition
2. Pre-processing & Feature Extraction
3. Classification
4. Control interface

The stage of signal acquisition collects the signals from the brain and can also minimize noise and process artifacts. The pre-processing stage prepares the signals for further processing in a suitable manner. The feature extraction stage recognizes discriminative information in the recorded brain signals. The stage of classification classifies the signals considering the vectors of the function. The choice of a good classifier is necessary to achieve efficient pattern recognition in order to decipher the intentions of the user. Finally, the control interface step converts the classified signals into practical commands, for an actuator like a wheelchair, walker, or a computer. This structure of BCI is illustrated in figure 1.

Signal Acquisition Techniques

The human brain generates electrical signals known as EEG signals. These signals can be acquired through invasive and non-invasive techniques. While choosing between the invasive and non-invasive methods of signal acquisition, the resolution needed for proper translation and the feasibility of obtaining the signals are considered. The basic architecture of the BCI system was explained in the preceding section. It prompts us to investigate the classification of BCI system. Based upon various techniques, BCI system is classified as

follows.

Dependability

BCI can be categorized as dependent or non-dependent. Dependent BCI requires a specific type of motor control by the operator or healthy subject like eye (gaze) control. An independent BCI, on the other hand, does not allow individuals to exercise any form of motor control. This type of BCI is suitable for stroke or severely disabled patients.

Invasiveness

BCIs are also classified into three types according to their invasiveness: invasive, partially invasive, and non-invasive. Invasive BCIs are the most accurate because they are implanted directly into the cerebral cortex and allow researchers to monitor the activity of each neuron. There are two types of invasive BCIs: single-unit BCI, which detects signals from one brain cell location, and multi-unit BCI, which detects signals from multiple regions. Semi-invasive BCI uses an electrocorticogram (ECoG), a type of signalling platform in which electrodes can be placed at accessible edges of the brain to capture electrical impulses emanating from the cerebral cortex. This procedure is less invasive, but still requires a surgical opening in the brain. Non-invasive BCI uses external sensing rather than brain implants. Electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS) are all used for brain analysis. EEG is most commonly used due to the low cost and portability of the equipment.

Autonomy

BCI works synchronously or asynchronously and allows for time-sensitive or time-independent interactions between users and systems. A system is said to be synchronous BCI if the interactions are performed within a specified time in response to cues provided by the system. Asynchronous BCI allows subjects to engage with the system by creating mental tasks at specific points in time. A synchronous BCI is not as user-friendly as an asynchronous BCI. However, designing it is much easier than developing an asynchronous BCI. This classification is illustrated in figure 2.

Invasive Technique

In this technique, sensors are placed inside the human brain through surgery preferably in the motor cortex. The motor cortex is the area of the brain in which voluntary movements are organized, regulated, and carried out. Invasive BCIs seem to be the most accurate even though they are implanted directly into the cortex as allows to track every neuron's action. Invasive BCI has two separate units. The first one detects signals from a single location of brain whereas the second unit detects the signals from a different location [24]. This is a relatively expensive technique and while it involves complex technical details, it can be life threatening for the user.

Non-Invasive Technique

Non-invasive technologies and interfaces have been employed in a considerably more comprehensive range of applications. Non-invasive applications and technologies are becoming increasingly popular in recent years since they do not require any brain surgery. The non-invasive technique

involves the placement of electrodes through a headset on the human skull. Based on the application, 1 to 256 electrodes can be placed on the headset. Before the placement of electrodes, the surface of the skull is prepared by applying a gel or paste. This is done to reduce the contact impedance between the two surfaces. The non-invasive techniques are preferred over invasive techniques as they are fast, cheap, and involve lower health risks. The non-invasive techniques include Electroencephalography (EEG), Positron Emission Tomography (PET), Magnetoencephalography (MEG), functional Near IR Spectroscopy (fNIRS), and functional Magnetic Resonance Imaging (fMRI).

Electroencephalography (EEG)

EEG monitors electrical activity in the scalp produced by neurons in the brain. Multiple electrodes implanted directly into the scalp, primarily the cortex, are often used to rapidly record these electrical activities. Due to its excellent temporal resolution, ease of use, safety and affordability, EEG is the most widely used technique for capturing brain activity. Active and passive electrodes are two types of electrodes that can be used. Active electrodes typically have a built-in amplifier, whereas passive electrodes require an external amplifier to amplify the detected signal. The main purpose of implementing a built-in or external amplifier is to reduce the effects of background noise and other interfering signals caused by cable movement. One problem with EEG is the need to use gels or saline to reduce the resistance of skin electrode contacts. Additionally, the signal quality is poor and varies with background noise. The International 10-20 system of electrodes placement [25] is commonly used to implant electrodes on the scalp surface for recording purposes. Electrical activity across different frequency bands is commonly used to describe EEG.

Positron Emission Tomography (PET)

PET (positron emission tomography) is an advanced imaging tool for examining brain activity in real time. This allows non-invasive measurements of cerebral blood flow, metabolism, and receptor binding in the brain. PET has so far been used only for research due to its relatively high cost and the complexity of the associated infrastructure such as cyclotrons, PET scanners and radiochemistry laboratories. PET has been widely used in clinical neurology in recent years due to advances in technology and the prevalence of PET scanners to improve our understanding of disease etiology, aid in diagnosis, and monitor disease progression and response to therapy [26]. PET drugs such as radiolabelled choline, fluciclovine (18F-FACBC), and compounds targeting the prostate-specific membrane antigen are currently being investigated to improve diagnostic performance in non-invasive localization of prostate cancer [27].

Manetoencephalography (MEG)

The magnetic field produced by the flow of current in the brain is measured with MEG (Magnetoencephalography). Magnetic fields have better spatial resolution than EEG because they move through the skull much more easily than electric fields. Functional neuroimaging techniques are used to measure and assess the brain's magnetic fields. MEG is of increasing importance, especially for patients with epilepsy and brain tumours. It helps identify brain regions with average function in people with epilepsy, tumours, or other

mass lesions. Because MEG works with magnetic waves rather than radio waves, it can add additional information to EEG. MEG can also acquire signals with high temporal and spatial resolution. Therefore, to detect brain activity that produces small magnetic fields, the scanner must be brought close to the surface of the brain.

Functional Near Infrared Spectroscopy (fNIRS)

The infrared radiation is projected into the brain using fNIRS equipment to monitor improvements in specific wavelengths as the light is reflected. fNIRS often detects changes in regional blood volume and oxygenation. When a particular area of the brain works, it requires additional oxygen, which is given to the neurons via capillary red blood cells—the increased blood flow in the brain areas that would be most active at a given time. As a result, images with a high spatial resolution (1 cm) but lower temporal resolution (>2–5 s) could be obtained, comparable with standard functional magnetic resonance imaging.

Functional Magnetic Resonance Imaging (fMRI)

Non-invasive functional magnetic resonance imaging (fMRI) is used to assess changes in blood oxygen levels during brain activity. FMRI has excellent spatial resolution, making it ideal for identifying active regions of the brain [28]. The temporal resolution of fMRI is relatively low, ranging from 1 to 2 seconds [29]. Also, the resolution is low when it comes to head movements, which can lead to artifacts. It is a radiation-free, non-invasive and safe technique that is easy to use and has excellent spatial and temporal resolution.

Haemoglobin in the brain's capillaries carries oxygen to neurons. Blood flow increases due to the increased need for oxygen. When haemoglobin is oxygenated, its magnetic properties change. An MRI machine has a cylindrical tube with powerful electromagnets and can determine which areas of the brain are activated based on these differences. There is also a special application or software called diffusion MRI that takes advantage of the diffusion of water molecules to generate images from data or results. Diffusion-weighted and diffusion tensor imaging (DWI/DTI) facilitate this study of brain microarchitecture. Diffusion-weighted magnetic resonance imaging (DWI or DW-MRI) reproduces image changes in response to deviations in the diffusivity of water particles in the brain. Diffusion maps the stochastic thermal mobility of particles. Diffusion in the brain is defined by several factors, including the representation of the particles under study, temperature, and the microenvironmental structure in which diffusion occurs [30]. Diffusion tensor imaging (DTI) examines the three-dimensional shape of diffusion, also called the diffusion tensor. This is a powerful MRI modality that produces knowledge about the directionality of water motion within voxels. It exhibits non-invasive microscopic tissue features that surpass the capabilities of other imaging modalities [31].

Non-Invasive Techniques Comparison

A comparison of various non-invasive techniques for signal acquisition is drawn below:

Table 1: Comparison of Non-Invasive BCI Techniques.

Non-invasive BCI Techniques	Advantages	Disadvantages
EEG	<ul style="list-style-type: none"> ▪ High temporal resolution ▪ Low cost ▪ No safety limitations 	<ul style="list-style-type: none"> ▪ High noise ▪ Average spatial resolution
fNIRS	<ul style="list-style-type: none"> ▪ Good temporal resolution ▪ Fast 	<ul style="list-style-type: none"> ▪ Limited temporal resolution ▪ Expensive ▪ Complex design
MEG	<ul style="list-style-type: none"> ▪ Much deeper imaging 	<ul style="list-style-type: none"> ▪ Complex design ▪ Bulky Expensive
fMRI	<ul style="list-style-type: none"> ▪ High spatial resolution 	<ul style="list-style-type: none"> ▪ Low temporal resolution ▪ Expensive
PET	<ul style="list-style-type: none"> ▪ High spatial resolution 	<ul style="list-style-type: none"> ▪ High cost ▪ Low temporal resolution ▪ Safety limitations

Brain Locations for Obtaining EEG Signals

EEG is the most commonly used approach for BCI signal acquisition due to its high temporal resolution, low cost, and ability to record changes in the behaviour of signal within a few milliseconds. One of the biggest advantages of EEG is that it captures the cognitive process in the period in which cognition happens. The cerebral cortex of the human brain is divided into four lobes; temporal, frontal, parietal, and occipital. Different brain regions are capable of performing different functions and controlling different actions. The EEG signal is often a combination of many base frequencies that are known to describe the cognitive, affective, or attentional states. These frequencies are based on particular ranges or bands. The EEG signal frequency range is 0–100 Hz, which is divided into five classes according to their frequency (Delta, Theta, Alpha, Beta, and Gamma).
 Delta band (1 – 4 Hz)
 Theta band (4 – 8 Hz)

Alpha band (8 – 12 Hz)

Beta band (13 – 25 Hz)

Gamma band (> 25 Hz)

These frequencies are illustrated in figure 3. Moreover, different regions of the brain associated with different frequencies are given below:

Table 2: Brain Locations to Record Specified Signals

Rhythm	Frequency Range	Location
Gamma	Above 25 Hz	Occipital
Beta	12-25 Hz	Frontal, Central
Alpha	8-12 Hz	Frontal, Occipital
Theta	4-8 Hz	Temporal, Midline
Delta	1-4 Hz	Frontal

Conclusion

The brain-computer interface is a communication method that joins the wired brain and external applications and

devices directly. The BCI domain includes investigating, assisting, augmenting, and experimenting with brain signal activities. Due to transatlantic documentation, low-cost amplifiers, greater temporal resolution, and superior signal analysis methods, BCI technologies are available to researchers in diverse domains. Moreover, it is an interdisciplinary area that allows for biology, engineering, computer science, and applied mathematics research. However, an architectural and constructive investigation of the brain–computer interface is exhibited in this article. It is aimed at novices who would like to learn about the current state of BCI systems and methodologies with special emphasis laid upon the common techniques of EEG used in BCI. The fundamental principles of BCI techniques are discussed elaborately. It presents a summary of the present methods for creating various types of BCI systems. The study looks into the different modes of signal acquisitions from the brain while simultaneously throwing light on the physical areas from where various signals can be obtained using any of the mentioned methods. Lastly, BCI technology advancement is accomplished in four stages: primary scientific development, preclinical experimentation, clinical investigation, and commercialization. At present, most of the BCI techniques are in the preclinical and clinical phases. The combined efforts of scientific researchers and the tech industries are needed to avail the benefit of this great domain to ordinary people through commercialization.

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