From Mind to Machine: A Comprehensive Review of Brain-Computer Interfaces

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Abstract

The world of Brain-Computer Interfaces (BCIs) is a captivating journey, merging neuroscience, engineering, and human-computer interaction. This paper embarks on a comprehensive exploration of BCIs, spanning their historical evolution, diverse applications, signal acquisition methods, and the formidable challenges they encounter.

Beginning with a historical perspective, we trace the evolution of BCIs, highlighting their pivotal role in reshaping human-computer interaction. We delve into the significance of BCIs, emphasizing their transformative impact on assistive technology, medical fields (ranging from prevention to diagnosis and rehabilitation), as well as their immersive applications in virtual reality and gaming.

Understanding BCIs necessitates a look into their diverse types. We dissect non-invasive and invasive BCIs, unveiling the technologies that bridge the mind-machine interface.

Signal acquisition is the lifeline of BCIs, and our exploration extends into electrophysiological methods, including EEG, MEG, ECoG, and IEEG, along with neuroimaging techniques such as fMRI, NIRS, PET, and SPECT.

The odyssey through BCIs brings us face-to-face with multifaceted challenges—usability and functionality hurdles that demand creative solutions. We propose strategies such as artifact removal algorithms, real-time feedback mechanisms, data augmentation, and transfer learning to surmount these obstacles.

In this enigmatic landscape, we find a confluence of technology, innovation, and the boundless capabilities of the human mind. As we navigate the ever-expanding horizon of BCIs, we uncover a future brimming with possibilities—a world where the boundaries between thought and action blur, and where BCIs hold the promise of enhancing lives in ways previously unimagined.

1 Introduction

1.1 Brief Definition

Brain-computer interfaces science is a science that aims to make the human able to translate his thoughts and imagination into a machine language or commands that are understandable by computers.

1.2 The Historical Evolution of BCIs

Since the discovery of brain currents in 1920, and discovering that these currents can be measured on the scalp by electrodes which is now known as electroencephalography (EEG) 1929, human has been searching for ways to diagnose and dodge neuro-pathogens. With the development of the EEG, scientists started to think of the brain as a channel to contact devices 1968 [1]. Many trials have been made with real-time feedback. After 5 years, exactly 1973, a Belgium researcher at the University of California called Jacques J.Vidal first acknowledged the concept of Brain-Computer interfaces. He described BCIs as "utilizing the brain signals in a man-computer dialogue" and "as a mean of control over external processes such as computers or prosthetic devices" [2], [3]. this crucial acknowledgment opened the way for researchers to try to develop a direct way of contact between the brain and computers. The study of BCIs continued to evolve from just an idea to the first successful BCI: "P300-speller", which could spell some words based on an Event-Related Potential(ERP) 1988 [4]. Not long after, both in the USA and in Europe, researchers developed BCIs based on SensoriMotor Rhythms (SMR), i.e., based on the oscillatory EEG activity and notably the mu rhythm (7-13Hz) over the sensorimotor part of the cortex. In the USA, Jonathan Wolpaw and his colleagues developed a BCI for 1D cursor control based on operant conditioning which enabled people to move a ball up and down using their brain signals [5]. In Europe, in the same period, researchers were working on another type of SMR that could translate the thinking of human hand movement to a machine language that can be read by a computer [3]. This project defined imaginary BCIs. In Europe also and during the same period, scientists invented a device that can translate a paralyzed man's thoughts and help him communicate with brain activity only after some complicated processes explained in the paper mentioned [6]. According to [3] "While it did not get as much visibility at that time and even after, Jose Principe and his colleagues also developed an ERP-based BCI at that time in the USA. They developed the so-called "cortical mouse", which enables a user to select one command among two based on the N400 response to a congruent or incongruent stimulus sentence" [3].

At the beginning of the new century, many search groups joined the efforts, and New BCI paradigms were proposed, such as BCIs based on Steady-State Visual Evoked Potentials (SSVEP). Scientists used signals or flickering visual stimuli to stimulate the brain and move a plane to the right and the left using these fixed flickering stimuli on its sides in a flight simulator. after that the study of invasive BCIs began to appear and more teams began to conduct experiments on rats and then monkeys to control robotic arms by electrodes implanted inside the brain cortex [7], [8], [3]. In modern history, many crucial changes happened: new visual and auditory BCIs were invented, invasive BCI became valid on humans and sort of successful [9], [10]. The journal "Brain-Computer Interfaces" was created in 2013, and according to [3] '"The international BCI society was also created in 2015, in order to "to foster research and development leading to technologies that enable people to interact with the world through brain signals"' [11].

1.3 The Importance of BCIs

Brain–computer interface (BCI) systems are a fast-growing technology involving hardware and software communication systems that control external devices through brain activity. One of the important applications of BCI technology is to provide assistance to disabled people like paralytic patients. And other applications like allowing normal humans to communicate with computers which can in turn ensure a better quality of life.

1.4 The Objective and Scope

After knowing the historical evolution and the importance of BCIs we are now going to explain briefly the objective and the scope of the review. This review aims to provide readers with a comprehensive understanding of BCIs, showcasing their multifaceted applications, technological advancements, challenges, and the ethical considerations that accompany their development. Through this exploration, the review contributes to the ongoing discourse surrounding BCIs and their role in shaping the future of human-computer interaction and human augmentation.

2 Applications of BCIs

BCIs have contributed to many fields as shown in 1,[12]. It contributes to the fields of assistive technologies, medical fields, neuroscience, gaming, education, aerospace, and many other fields.

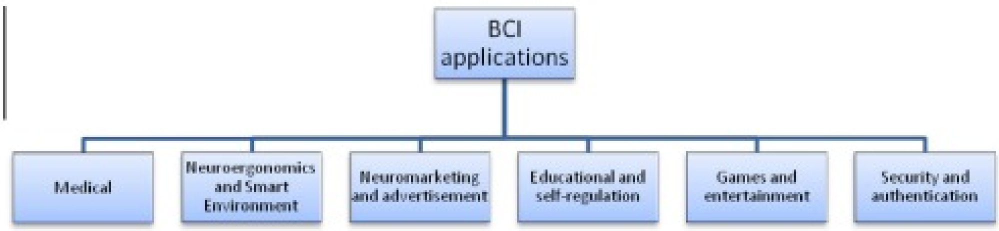

Figure 1: Figure 2: applications of BCIs

2.1 Assistive Technology

Brain-computer interfaces (BCIs) have emerged as transformative tools in the field of assistive technology. They allow individuals to communicate, regain mobility, and control their environment using their brain signals [13]. Brain–computer interface(BCI) technology “gives their users communication and control channels that do not depend on the brain’s normal output channels of peripheral nerves and muscles.” [14], and can allow a completely paralyzed individual to communicate with the surrounding environment. One of the applications of BCIs in the field of communication is the spelling device created by [6] to face amyotrophic lateral sclerosis(ALS) disease, which involves progressive degeneration of all the motor neurons of the somatic motor system. The device used the slow cortical potentials (SCPs) to allow the totally paralyzed patients- after some training - to be able to communicate again and simply express their desires.

Another application in this field is the Brain Gate system. Brain Gate utilizes implanted electrode arrays that record neural signals directly from the motor cortex of the brain. These neural signals are then decoded into commands that enable users with paralysis or mobility impairments to control computer cursors, robotic arms, and even type messages. This technology empowers individuals to regain independence, communicate with loved ones, and interact with the world in ways that were once considered impossible. For someone who has lost the ability to move or speak due to spinal cord injuries or neurological disorders, BCIs offer a lifeline to a more fulfilling and connected life [15].

2.2 Medical Fields

The integration of Brain-Computer Interfaces (BCIs) into the medical field represents a groundbreaking paradigm shift in healthcare. The applications of BCIs in the medical field are 3 types as shown in 2. These applications include prevention, detection, diagnosis, rehabilitation, and restoration.

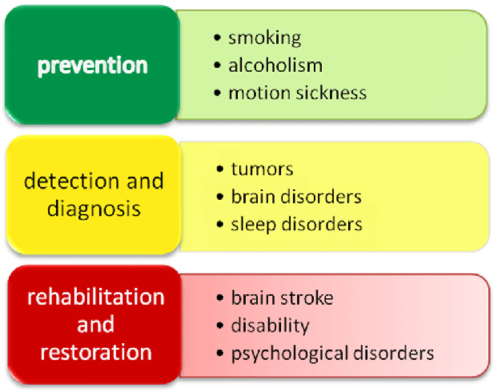

Figure 2: Uses of BCIs in the medical fields

2.2.1 Prevention

BCIs, with their ability to facilitate direct communication between the brain and external devices, are ushering in innovative approaches to early detection, risk assessment, and personalized preventive measures. These interfaces are poised to revolutionize how we approach the prevention of neurological conditions, mental health disorders, and cognitive decline.

BCIs provide a unique opportunity for tailoring preventive measures to individual needs such as Neurofeedback Training: BCIs can offer neurofeedback training, allowing individuals to learn to self-regulate their brain activity. This personalized approach can help individuals reduce stress, improve focus, and enhance mental well-being, thereby preventing mental health disorders. Also, BCIs can assist in assessing an individual's risk for neurological conditions and provide guidance on lifestyle modifications to reduce that risk as it can assess an individual's brain health by analyzing neural patterns. Based on this assessment, individuals can receive personalized recommendations for lifestyle changes such as diet, exercise, and cognitive activities that promote brain health and reduce the risk of neurological conditions [16].

BCIs also can solve one of the most popular and important causes of death as claimed in [17] as they can do all the following:

1- Detect Cognitive Distractions.

Distracted driving, often stemming from activities like texting, eating, or daydreaming, remains a leading cause of accidents. BCIs offer a cutting-edge approach to detecting cognitive distractions in real-time. How do they work? BCIs continuously monitor brainwave patterns and can discern shifts in attention away from driving-related tasks. When cognitive distractions are identified, BCIs can activate alarms, issue warnings, or even limit non-driving-related activities, ensuring that drivers remain fully focused on the road.

2-Combating Drowsy Driving

Drowsy driving, a silent yet perilous contributor to road accidents, often goes unnoticed until tragedy strikes. BCIs can become a potent ally in preventing accidents caused by driver fatigue. By monitoring a driver's level of alertness through the analysis of brainwave patterns linked to drowsiness, BCIs can alert drivers when signs of fatigue are detected. These alerts can prompt drivers to take rest breaks or, in advanced systems, engage driver assistance features to compensate for their reduced vigilance.

3-Preventing Impaired Driving

Driving under the influence of alcohol or drugs remains a stubbornly persistent issue contributing to accidents. BCIs can be employed as a crucial tool in preventing accidents involving impaired drivers. Through biometric analysis, BCIs can integrate data such as blood alcohol levels or drug metabolites into their assessments. When a driver is found to be impaired, BCIs can take decisive action, immobilizing the vehicle or alerting law enforcement, thereby thwarting impaired driving and the potential for accidents [18].

4-Personalized Driver Assistance

One of the most exciting aspects of BCIs in accident prevention is their capacity for personalization. BCIs can offer a highly individualized approach to enhancing road safety, tailoring assistance based on the driver's cognitive states and behaviors. Through adaptive driver support, BCIs can dynamically adjust vehicle features, like adaptive cruise control and lane-keeping assist, based on the driver's cognitive state. For example, if a driver becomes distracted, these features can engage automatically to compensate for their reduced attention.

5-Real-Time Data Insights

BCIs are not only about real-time interventions but also about data insights that can reshape road safety strategies. By analyzing driver behavior data collected by BCIs, authorities and researchers can gain valuable insights into distracted or risky driving patterns. Armed with this knowledge, targeted interventions, and awareness campaigns can be developed to promote safer driving practices and reduce accidents. It can also determine the destination and thus it will enhance the accessibility to vehicle controls [19].

6-Enhanced Emergency Response

In the unfortunate event of an accident or a medical emergency, while driving, BCIs can be the lifeline that accelerates emergency response. Automatic distress signals triggered by BCIs can expedite emergency services, potentially preventing secondary accidents or providing critical medical assistance, ultimately saving lives.

2.2.2 Diagnosis and Detection

The continuous monitoring of brain signals while using BCIs helps diagnose brain signal abnormalities such as brain tumors, seizures, swelling, and sleep disorders. The BCI acquisition methods which are much cheaper than tumor scans can work as an alternative to CT scans and detect cancer as claimed in [12]. Some researchers in [20] were thinking of ways to use EEG in the early detection of breast cancers. They found out that: When cancer cells proliferate, they alter the local tissue environment, causing changes in electrical conductivity and impedance. These alterations can be picked up by EEG electrodes placed on the skin's surface, even at a considerable distance from the tumor site.

As severe as tumors, Dyslexia is one of the important diseases that can cause massive impacts when it's late diagnosed. It is characterized by difficulties in reading, spelling, and writing, despite normal intelligence and adequate instruction. Early diagnosis is crucial for implementing effective interventions and support, yet dyslexia often remains hidden until children struggle academically. In [21] Fadzal and his group have likely explored the use of EEG-based BCIs to analyze brainwave patterns in individuals with dyslexia and compared them to neurotypical individuals. These patterns may reveal differences in brain activity during reading-related tasks, forming the basis for dyslexia diagnosis.

2.2.3 Rehabilitation and Restoration

"Stroke is one of the principal causes of morbidity and mortality in adults in the developed world and the leading cause of disability in all industrialized countries" [22]. Stroke severity is no doubt one of the highest severities of all diseases and survivors can suffer several neurological deficits or impairments, such as hemiparesis, communication disorders, cognitive deficits or disorders in visuospatial perception [23, 22]. BCIs can be used to restore motor functions in stroke survivors. By decoding brain signals associated with movement intention, BCIs can control exoskeletons, robotic limbs, or functional electrical stimulation (FES) devices, allowing stroke survivors to regain control over their affected limbs. In worst cases, BCIs will be able to replace the affected limb and allow the paralyzed patient to restore his ability to use it again. In cases of cognitive deficits, BCIs can assist in cognitive rehabilitation by providing neurofeedback to enhance cognitive functions such as attention, memory, and problem-solving. Training tasks can be tailored based on individual cognitive deficits[22]. BCIs can also facilitate neuroplasticity in stroke survivors. By engaging in repetitive and targeted tasks controlled by BCIs, individuals can stimulate neural reorganization and recovery of damaged brain regions.

2.3 Virtual Reality and Games

BCIs can be added to the field of games not only to help people with implementations who can't use mice, controllers, or keyboards but also to enhance the experience of gaming and make the brain fully involved in this entertaining experience.

till now scientists have reached for ways to play anti-stress pinball games as in [24]. Pinball game is one of the easiest games to play with BCIs and scientists are searching for ways to insert BCIs into more advanced games like those we see today [25].

BCI is a thriving field and its applications are far greater than what humans have ever thought of. A simple theory of what BCIs can do In games is what was shown in the movie named "Ready Player One" and we hope one day we can overcome the obstacles holding us back from seeing the fascinating magic of BCIs.

3 Types of BCIs

3.1 Non-invasive BCIs

The first feature that distinguishes between BCIs is whether they are invasive or non-invasive. The non-invasive method is connecting the brain to cursors or other devices without brain surgeries or electrode implantation in the brain. it mainly depends on many signal acquisition methods as shown in 3 [26].

Table 1 Non-invasive BCI acquisition methods

Sl no.	*Non-invasive method*	*Description*
1	Electroencephalogram (EEG)	Electrical signals are recorded using flatmetal discs
2	Magnetoencephalography (MEG)	Magnetic fields are recorded using neuroimaging method
3	functional magnetic resonance imaging (fMRI)	Measures the variation of blood oxygen level during brain activities
4	Positron emission tomography (PET)	Imaging technique used to observe the metabolic process in body
5	Near-infrared spectroscopy (fNIRS)	Near-infrared spectroscopy uses electromagnetic spectrum to diagnose physiological diseases
6	Fetal magneto encephalography (fMEG)	Study of brain activity of fetus in uterus
7	Single photon emission computed tomography (SPECT)	Neuro tomographic imaging which is based on gamma rays

Figure 3: figure 1

While EEG stands out as the most widely used signal acquisition method in Brain-Computer Interfaces (BCIs) due to its accessibility and safety, its effectiveness can be limited by the weak signal strength and resolution caused by multiple layers of tissue the neural signals must traverse [27]. In applications such as controlling robotic limbs with intricate movements, the transfer rate of 5-25 bit/sec, as reported by [9], can prove to be inadequate. However, it excels in tasks where precision and speed are not the sole factors, such as cursor manipulation or experiencing touch sensations in robotic limbs through neural commands.

EEG-based BCIs have undergone transformative developments since their inception. Various classes of EEG-based systems have emerged, each catering to specific applications. Visual Evoked Potentials (VEPs) and P300 Evoked Potentials have been utilized to create BCIs that enable communication through gaze direction and choice selection. Slow cortical potentials and mu/beta rhythms have empowered users to control computer cursors, enabling basic interactions.

These systems often require extensive training, involving visual feedback and the integration of biofeedback or classifier algorithms.

Despite its limitations, EEG-based BCIs have demonstrated their safety and non-invasiveness, obviating the need for skull penetration or cortical tissue damage. These characteristics have positioned EEG as a valuable tool for interfacing between the human brain and machines. Whether utilizing original motor imagery or responding to external stimuli, EEG remains an appealing option [28].

Another approach to signal acquisition is Magnetoencephalography (MEG). MEG measures the magnetic fields generated by brain activity. MEG has higher signal quality than EEG, but it is more expensive and requires a more specialized setup. MEG is often used to study the brain activity of people with epilepsy and other neurological disorders [29, 9]. And another new method is Functional near-infrared spectroscopy (fNIRS). fNIRS measures changes in blood oxygen levels in the brain. fNIRS is a relatively new technique that has the potential to be used in portable applications. However, it has lower signal quality than EEG and MEG. fNIRS is often used to study the brain activity of people who are performing cognitive tasks. Despite its weakness,fNIRS has the potential to lead the way to portable BCIs [30]. Non-invasive BCIs have the potential to facilitate the lives of millions of paralyzed people and we are looking forward to seeing the future development of this revolutionary advancement.

3.2 Invasive BCIs

The invasive BCI is mainly: implanting electrodes on the surface of the brain to collect the neuro signals directly and convert them to machine languages. There are two types of invasive BCIs which are: 1- collecting data from single brain cells and 2- collecting data from multiple ones and so-called as multi-units. The first invasive Brain-Computer Interface (BCI) is often attributed to the pioneering work of Dr. Jose Delgado, a Spanish-American neuroscientist and professor. In the 1960s, Delgado conducted groundbreaking experiments involving direct brain stimulation and control of animals using implanted electrodes.

One of his most notable experiments was conducted in 1963, where he implanted electrodes into a bull's brain. Delgado used this setup to remotely control the bull's movements, including stopping it in its tracks during a charging motion. He referred to this system as a "stimoceiver," a combination of "stimulation" and "receiver" [31]. In this experiment, he used a remote to deliver a sudden pulse to a specific place in the bull's brain while it was charging towards him and stopped it. The experiment achieved great success but it also generated a lot of discussions about ethical considerations and how to use this technology to benefit human beings.

Now, after a lot of development in the field of BCIs as mentioned in the introduction 1 neura link -Elon Musk's BCIs company- is trying to create a multi-functional bi-dimensional BCI that can be directly placed inside the brain and computers can exchange signals wirelessly with it. It aims to enhance cognitive capabilities and facilitate the usage of the rising AI field.

Invasive Brain-Computer Interfaces (BCIs) represent a pioneering frontier in neurotechnology, offering remarkable potential for restoring lost function and enhancing human capabilities. These interfaces, though invasive, hold the promise of profound breakthroughs in fields such as neuroprosthetics and neural rehabilitation. By directly interfacing with the brain, they enable precise control of external devices, offering new hope for individuals with severe disabilities. However, invasive BCIs also come with challenges related to safety, ethical considerations, and the need for surgical procedures. As research continues to advance, invasive BCIs remain at the forefront of innovation, holding the potential to reshape the future of human-machine interactions.

4 Methods of Signal Acquisition

We mentioned some signal acquisition methods in 3, and in this section we are going to discuss every method thoroughly. Signal acquisition methods are classified into 4 main categories as shown in 4, Each method focuses on a specific way of collecting signals as we are going to discuss.

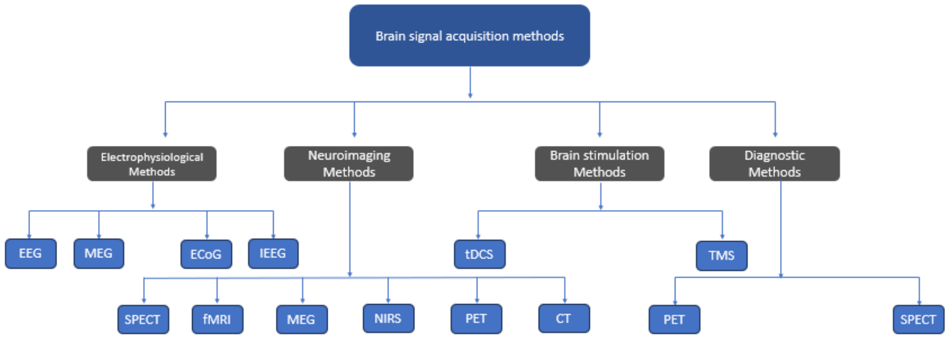

Figure 4: The different types of acquisition methods

4.1 Electrophysiological Methods

As shown in 4 signal acquisition methods are classified to electrophysiological, neuroimaging, brain stimulation, and diagnostic methods. Firstly, we will start discussing the electrophysiological methods. Electrophysiological methods are a class of techniques used to measure and record electrical activity within biological systems, particularly the nervous system. These methods are instrumental in understanding the functioning of neurons, neural circuits, and the brain as a whole. Electrophysiological methods offer high temporal resolution, allowing researchers to capture the rapid changes in electrical signals that occur in living organisms.

4.1.1 EEG

EEG or Electroencephalography measures the Brain activity caused by the flow of electric currents in the neurons and it's extremely sensitive to the effect of secondary currents [32]. EEG signals are recorded with no harm by electrodes placed right on the scalp for that, it's the most widespread method used worldwide. Although it has the advantage of non-invasiveness it is a very poor method of collecting data as it has to go through many layers of skull and it can be easily affected by background noise generated either inside the brain or externally over the scalp [33].

EEG system consists of electrodes, amplifiers, A/D converter, and a recording device. The electrodes acquire the signal from the scalp, the amplifiers process the analog signal to enlarge the amplitude of the EEG signals so that the A/D converter can digitalize the signal in a more accurate way. Finally, the recording device, which may be a personal computer or similar, stores, and displays the data [33].

EEG measures different types of brain waves, each associated with distinct mental states and activities: Alpha Waves (8-12 Hz): Alpha waves, oscillating at a frequency of 8 to 12 cycles per second, are most prominent when an individual is awake but in a state of relaxation, often with closed eyes. These waves exhibit a consistent rhythm and relatively high amplitude. Alpha waves are closely associated with wakeful relaxation, a state often experienced during meditation or quiet reflection. Their presence signifies a mind at ease, free from excessive cognitive demands.

Beta Waves (12-30 Hz): In contrast to the tranquil alpha waves, beta waves thrive in the hustle and bustle of active cognition. With a frequency ranging from 12 to 30 Hz, beta waves dominate when a person is awake and engaged in cognitive tasks. They are characterized by their rapid, desynchronized pattern, reflecting heightened mental activity. Beta waves are the companions of alertness, concentration, problem-solving, and active thinking. The higher end of this spectrum may indicate intense mental engagement.

Theta Waves (4-7 Hz): Theta waves, with a frequency range of 4 to 7 Hz, emerge during drowsiness, light sleep, or deep relaxation. They manifest as a slower rhythm compared to alpha and beta waves. Theta waves invite us into the realm of daydreams, creativity, and intuitive thinking. Often seen during meditation and deep relaxation exercises, they are thought to play a role in memory consolidation, particularly during sleep.

Delta Waves (0.5-4 Hz): Delta waves reign supreme in the deepest realms of slumber. With a frequency of 0.5 to 4 Hz, they are the slowest of all brain waves. Delta waves are predominantly observed during deep non-REM (rapid eye movement) sleep stages. Their defining characteristic is their towering amplitude, dwarfing the other waves. During this phase, delta waves orchestrate the symphony of restorative sleep, both physically and mentally. It's worth noting that the presence of delta waves in waking adults may be a cause for concern, potentially indicating brain injury.

Gamma Waves (¿30 Hz): At the high-frequency end of the spectrum lies gamma waves, with frequencies surpassing 30 Hz. They are associated with the most demanding cognitive tasks, including perception, problem-solving, and conscious awareness. Gamma waves are recognizable by their rapid, synchronized patterns. These waves are believed to serve as the glue that binds together various aspects of perception and cognitive processing. They are essential for higher-order brain functions, often accompanying moments of insight and profound awareness[33].

4.1.2 MEG

MEG or magnetoencephalography is a powerful technique in collecting brain signals. It is based on the principle of electromagnetic induction, a phenomenon discovered by Michael Faraday in the 19th century. When neurons in the brain become electrically active, they generate small electrical currents. According to Faraday's law, these electrical currents produce associated magnetic fields [34]. MEG detects and records these magnetic fields using highly sensitive sensors called superconducting quantum interference devices (SQUIDs).

Its system consists of SQUIDs which are ultra-sensitive detectors that can measure extremely weak magnetic fields. MEG systems contain an array of these sensors placed around the head to capture the magnetic fields generated by neural activity and Head Positioning System. Precise localization of brain activity is crucial in MEG. Head positioning systems help ensure that the sensors are accurately aligned with the brain's anatomy. EMG offers: 1-High Temporal Resolution as it provides exceptional temporal resolution, allowing researchers to capture the millisecond-by-millisecond dynamics of neural processes. This is particularly valuable for studying rapid cognitive and perceptual events. 2-Direct Measure of Neural Activity: MEG directly measures the magnetic fields produced by neural currents. Unlike fMRI, which measures blood flow changes as a proxy for neural activity, MEG provides a more direct and immediate measure of brain function. Localization as it can accurately pinpoint the sources of neural activity, providing detailed information about where specific brain processes are occurring. This localization is crucial for mapping brain functions and planning neurosurgical procedures [35].

4.1.3 ECoG

ECoG is a technique where the signals are measured by electrodes planted directly on the brain surface. It has high temporal and spatial resolution and higher amplitudes with less vulnerability to artifacts when compared to EEG and MEG [36]. It is based on the principle that the brain's outermost layer, the cerebral cortex, generates electrical activity during various cognitive and motor processes. By placing electrodes directly on the cortical surface, ECoG captures these electrical signals with high precision. However, ECoG requires surgical operations and carniotomy to plant the electrode on the brain which in turn causes high risks to the patient and that's why it was first studied on animals [33].

ECoG consists of Electrode Grids or Strips. It involves surgically implanting grids or strips of electrodes onto the brain's surface. These electrodes are made of biocompatible materials and are positioned strategically over specific brain regions. It also consists of Amplifiers and Data Acquisition Systems: The electrical signals picked up by the electrodes are amplified and transmitted to data acquisition systems. These systems record and process the neural signals for analysis. Aside from its high resolution more recent experiments with monkeys have shown that ECoG can perform at a high level for months without any drift in accuracy or recalibration [37, 33].

4.1.4 IEEG

Intracranial Electroencephalography, commonly referred to as iEEG, is a neuroimaging method that involves placing electrodes directly within the brain's parenchyma or on the surface of the cortex. This technique provides a great view of neural activity, allowing for highly localized and precise monitoring of brain functions. It operates on the same fundamental principle as traditional EEG. It measures electrical potentials generated by the brain's neurons during their activity. However, iEEG takes this measurement from within the brain tissue itself, offering advantages in terms of spatial and temporal precision [38].

IEEG system consists of electrodes which are implanted right on the brain surface. These electrodes can be grids, strips, or depth electrodes, depending on the specific clinical or research objectives. Also it requires amplifiers and data acquisition systems to capture the data. IEEG provides high temporal and spatial resolution which makes it a vital tool for mapping the exact locations of brain functions and identifying critical areas during neurosurgical procedures. And it also can capture neural events with millisecond precision. Which is crucial for studying rapid cognitive and motor processes [39].

Despite their advantages, iEEG and ECoG present some challenges, including their invasive nature, which necessitates surgery for electrode placement. Additionally, they carry a risk of infection and bleeding, making them suitable primarily for clinical and research contexts with proper ethical considerations.

4.2 Neuroimaging Methods

4.2.1 fMRI

Functional Magnetic Resonance Imaging, commonly known as fMRI, is a powerful non-invasive neuroimaging technique that detects the change in the oxygenated blood. It operates on the principle that when a specific brain region becomes active, it requires more oxygenated blood to fuel its metabolic demands. In response to increased neuronal activity, blood flow to that region increases, leading to changes in the local concentration of oxygenated and deoxygenated hemoglobin. fMRI detects these changes and creates images that represent brain activity.

fMRI system consists of MRI scanners which apply electromagnetic fields of strength in the order of 3T or 7T, Magnet and Radiofrequency Coils that are positioned inside the scanner during the scan to generate the brain images, and data processing software which processes the signals and highlight the active areas during the scan. Its main advantage is the high spatial resolution that is offered by it. However, fMRI has a low temporal resolution of about 1 or 2 seconds. Additionally, the hemodynamic response introduces a physiological delay from 3 to 6 seconds [40]. Along with all the mentioned disadvantages fMRI is very expensive and the scanners aren't always available. "fMRI appears unsuitable for rapid communication in BCI systems and is highly susceptible to head motion artifacts" [33].

4.2.2 NIRS

NIRS or near infrared spectroscopy is a method that employs infrared light to characterize fluctuations in cerebral metabolism during neural activity. NIR light easily penetrates biological tissue and allows for detection of changes in specific light-absorbing chromophores in humans. The NIRS signal in human tissue is derived predominantly from the absorption of light by hemoglobin (Hb) in small arterioles, capillaries and venules. The vascular specificity of the signal is due to the differential light absorption between large and small blood vessels [41]. When neurons become active, there is an increased demand for oxygenated blood in those regions. NIRS systems use optical fibers to emit near-infrared light into the brain and detect the light that is scattered back. Changes in the absorption of this light provide information about oxygenation levels and, by extension, brain activity.

NIRS system consists of Light Sources: systems that employ light-emitting diodes (LEDs) to produce near-infrared light of specific wavelengths, Detectors: Photodetectors capture the scattered light and measure changes in its intensity, and Fibers: These fibers deliver light to the scalp and collect the reflected light, allowing for precise localization of brain activity. NIRS main advantage is its non-invasiveness and portability as it can be portable and relatively compact. Its main limitation is the limited penetration depth (mostly limited to the outer cortex), susceptibility to motion artifacts, and challenges in precisely localizing deeper brain structures.

4.2.3 PET

Positron Emission Tomography, or PET, is a sophisticated imaging technique that allows researchers and clinicians to observe metabolic and functional processes within the human brain and other tissues. By tracing the distribution of radioactive tracers in the body, PET provides invaluable insights into various aspects of physiology and pathology. it relies on the detection of positron-emitting radioactive isotopes. These isotopes are incorporated into biologically active compounds, such as glucose or neurotransmitters. When a positron is emitted during the isotope's decay, it encounters an electron, leading to mutual annihilation. This results in the emission of two gamma-ray photons in opposite directions. PET scanners detect these photons, enabling the reconstruction of images that highlight areas with higher tracer uptake.

The key components of the system are Radioactive Tracers which are Various radioactive isotopes can be used, with fluorine-18 (18F) commonly employed in brain imaging, PET Scanner: The scanner consists of multiple detectors that surround the body or the area of interest. It records the gamma-ray emissions from the radioactive tracers, Computer System: Specialized software processes the data collected by the detectors and generates three-dimensional images of tracer distribution [42]. There are many advantages of PET represented in: Quantitative Assessment: PET provides quantitative data about the concentration and distribution of radiotracers, making it suitable for studying physiological processes, such as glucose metabolism and neurotransmitter activity, Functional Insights: It enables the study of dynamic processes, including blood flow, glucose utilization, and receptor binding, allowing researchers to investigate brain function in real time, Clinical Applications: PET is widely used in clinical settings for diagnosing and staging diseases, including cancer, Alzheimer's disease, and epilepsy. It aids in treatment planning and assessing treatment responses, and Whole-Body Imaging: While often associated with brain imaging, PET can also examine other organs and tissues throughout the body, providing a comprehensive view of systemic processes.

4.2.4 SPECT

Single-Photon Emission Computed Tomography, or SPECT, is a nuclear imaging technique that allows healthcare professionals to visualize the internal structures and functions of organs, most commonly the brain and the heart. By tracing the distribution of radiotracers emitting gamma rays, SPECT provides valuable diagnostic information, particularly in the fields of cardiology and neurology. It operates on the principle of gamma ray detection. Patients are injected with a radiotracer, a compound that emits gamma rays. These gamma rays are detected by gamma cameras, which are equipped with special collimators to focus on the area of interest. As the gamma camera rotates around the patient, it captures images from multiple angles. These images are then reconstructed to create detailed three-dimensional views of the organ being studied.

SPECT system consists of Radiotracers: Different radiotracers are used for specific organs and conditions. For cardiac imaging, thallium-201 or technetium-99m sestamibi is commonly employed. In neuroimaging, iodine-123 IMP or technetium-99m HMPAO is used, Gamma Camera: This is the primary imaging device, which detects and records gamma ray emissions from the radiotracers, and Computer System: Specialized software processes the data collected by the gamma camera and creates cross-sectional and 3D images for interpretation. It is mainly used for its 1-Functional Imaging as it provides functional information about the targeted organ, revealing blood flow, metabolic activity, and receptor binding, making it invaluable for assessing organ function, 2-Versatility: While commonly used for cardiac and neurological applications, SPECT can be adapted for imaging other organs, such as the lungs, liver, and bone, depending on the radiotracer used, 3-Clinical Utility: SPECT is widely used in clinical practice for diagnosing conditions like coronary artery disease, Alzheimer's disease, and epilepsy. It assists in treatment planning and monitoring, 4-Safety as The radiation exposure from SPECT is relatively low and considered safe for most patients.

5 Challenges and Suggested Solutions

5.1 Challenges

Despite all the advantages and solutions proposed by BCIs. This field is surrounded by many challenges that are hindering the evolution of it. These challenges can be said to be three types: usability challenges, ethical challenges, and functionality challenges [12].

5.1.1 Usability Challenges

They are challenges that face the users during using BCIs. "They include the issues related to the training process necessary for classes' discrimination. Information transfer rate (ITR) is one of the system evaluation metrics that combines both performance and acceptance aspects" [12].

Training Process Users of BCIs often face a significant challenge in the form of a steep learning curve. Learning to operate a BCI effectively can be a demanding and time-consuming process. It typically involves extensive training to familiarize users with the BCI system, teach them how to generate specific brain signals, and refine their control over the interface [43]. For individuals with physical disabilities or other impairments, this learning curve can be even more formidable. The complex nature of BCI technology, along with the need to decipher and translate intricate brain signals, can lead to mental fatigue and frustration during the initial stages of learning. Thus, addressing this challenge involves the development of user-friendly BCIs with intuitive interfaces, streamlined training protocols, and adaptive learning mechanisms to minimize the time and effort required for users to become proficient.

Signal Calibration and Adaptation Signal calibration poses a significant usability challenge for BCIs. Each user's brain generates unique signals, and precise calibration is essential for accurate BCI performance. This calibration process can be time-consuming, requiring users to perform specific tasks to establish a baseline for their brain signals. Furthermore, users' brain signals may change over time due to factors like fatigue, distractions, or fluctuations in cognitive states. This necessitates frequent recalibration to maintain reliable BCI functionality. Addressing this challenge involves simplifying the calibration process, possibly through automated or semi-automated methods, and exploring techniques for continuous adaptation that allow BCIs to adjust to users' changing brain patterns without the need for repeated calibration sessions.

5.1.2 Functionality Challenges

They are challenges related to recorded electrophysiological properties of the brain signals which include non-linearity, non-stationarity and noise, small training sets and the companying dimensionality curse.

Non-linearity Electrophysiological properties of brain signals often pose significant challenges due to their non-linearity, non-stationarity, and susceptibility to noise. Unlike linear systems, the brain's neural networks exhibit complex, nonlinear behaviors that make signal analysis and interpretation intricate. Additionally, brain signals are inherently non-stationary, meaning they change over time due to various factors like cognitive states, emotions, and external stimuli. This dynamic nature makes it challenging to establish stable baselines and track meaningful signal changes accurately. Moreover, brain signals can be contaminated by various types of noise, such as electrical interference or muscle artifacts, which can obscure the underlying neural information. To address these challenges, advanced signal processing techniques like nonlinear modeling, adaptive filtering, and artifact removal algorithms are essential. These methods aim to disentangle the non-linearities, mitigate non-stationarity, and enhance signal-to-noise ratios for more reliable BCI performance [44, 45].

Small Training Sets One of the persistent challenges in working with brain signals is the limited availability of training data, which is particularly pronounced in some medical and research contexts. Effective BCIs often require substantial amounts of labeled training data to build accurate models for signal decoding. However, acquiring such data can be challenging, especially for rare medical conditions or specific cognitive tasks. The scarcity of training data can lead to overfitting, where BCIs perform well with the training data but struggle with real-world applications. Addressing this challenge involves developing techniques for data augmentation, transfer learning, and semi-supervised learning. These methods aim to leverage small training sets more effectively by extracting relevant information from limited data while preventing overfitting [12, 46].

Dimensionality Curse The dimensionality curse is a pervasive challenge in working with brain signals, primarily due to the high-dimensional nature of neural data. Brain signal recordings often involve multiple channels, sensors, or electrodes, each capturing data at high temporal resolution. This results in massive datasets with high dimensionality, making it computationally intensive and challenging to process and analyze efficiently. The dimensionality curse can lead to increased computational complexity, slower processing speeds, and the risk of overfitting models. To combat this challenge, dimensionality reduction techniques such as principal component analysis (PCA) and feature selection algorithms are employed to reduce the number of dimensions while retaining essential information. These techniques help streamline signal processing, enhance BCI performance, and make it more feasible to work with large-scale electrophysiological datasets [47, 48].

5.2 Proposed Solutions

Advanced Signal Processing Techniques Develop and apply advanced signal processing techniques specifically designed to handle non-linear, non-stationary, and noisy brain signals. This includes employing adaptive filters, time-frequency analysis methods, and nonlinear modeling algorithms to better capture and interpret the underlying neural information while reducing the impact of noise.

5.2.1 Artifact Removal Algorithms

Implement robust artifact removal algorithms that can identify and remove noise sources such as muscle artifacts or electrical interference. Combining multiple signal acquisition modalities (e.g., EEG and fNIRS) can help reduce noise and improve signal quality.

5.2.2 Real-Time Feedback and Adaptation

Incorporate real-time feedback mechanisms that continuously adapt signal processing parameters based on the changing characteristics of brain signals. Adaptive algorithms can help account for non-stationarity and maintain signal accuracy over time.

5.2.3 Data Augmentation

Employ data augmentation techniques to artificially expand the training dataset. This involves creating additional training samples by introducing variations in existing data, such as applying different transformations or perturbations to the signals.

5.2.4 Transfer Learning

Utilize transfer learning approaches that leverage pre-trained models from related tasks or domains to bootstrap BCI systems with limited training data. Transfer learning can help extract relevant features and patterns from existing knowledge.

5.2.5 Semi-Supervised Learning Explore

semi-supervised learning methods that make the most of both labeled and unlabeled data. These techniques can utilize unannotated data to improve model generalization while still benefiting from the limited labeled training data available.

5.2.6 Feature Selection and Extraction

Apply feature selection techniques to identify the most informative and relevant features within high-dimensional datasets. This reduces dimensionality while preserving crucial information for accurate signal decoding.

5.2.7 Dimensionality Reduction Algorithms

Utilize dimensionality reduction algorithms like Principal Component Analysis (PCA) or t-distributed Stochastic Neighbor Embedding (t-SNE) to transform the data into lower-dimensional spaces, where computational complexity is reduced while retaining essential patterns.

5.2.8 Sparse Coding and Compression

Implement sparse coding techniques and data compression methods to represent high-dimensional data more efficiently. These approaches aim to represent the data in a more compact form while minimizing information loss.

5.2.9 Hardware Acceleration

Leverage hardware acceleration technologies such as Graphics Processing Units (GPUs) or specialized hardware designed for signal processing tasks. This can significantly speed up computations related to high-dimensional data.

By incorporating these proposed solutions, BCIs can become more robust in handling non-linear, non-stationary, and noisy brain signals, more adaptable to small training datasets, and more efficient in managing the dimensionality curse, ultimately enhancing their usability and performance across various applications.

6 Conclusion

In conclusion, this research has delved into the multifaceted realm of Brain-Computer Interfaces, elucidating the profound implications and promising prospects they offer in the realms of healthcare, assistive technology, and human-computer interaction. The challenges associated with BCIs, from signal acquisition complexities to usability constraints, have been thoroughly examined. Through innovative signal processing techniques, advanced machine learning algorithms, and the incorporation of neuroimaging modalities, significant strides have been made in enhancing the robustness and accuracy of BCI systems.

This study has underscored the critical role of collaboration among multidisciplinary teams of researchers, encompassing neuroscientists, engineers, and clinicians. Such partnerships are imperative in translating BCI advancements into practical applications that can ameliorate the lives of individuals with disabilities, facilitate neurorehabilitation, and even extend the boundaries of human cognition.

As BCIs continue to evolve, it is incumbent upon the scientific community to address the remaining challenges, including those related to signal quality, data privacy, and ethical considerations. Moreover, further exploration into emerging neuroimaging modalities, such as functional near-infrared spectroscopy (fNIRS) and invasive techniques like electrocorticography (ECoG), holds promise for unlocking new frontiers in brain-computer communication.

In closing, the journey of Brain-Computer Interfaces is an unfolding narrative of innovation and human potential. While many questions remain, the trajectory is clear: BCIs are poised to revolutionize our interaction with technology and reshape our understanding of the human brain. Through sustained research and development efforts, BCIs have the potential to empower individuals, transform healthcare, and bridge the gap between mind and machine, ushering in a new era of human-computer symbiosis.

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