LPEE Table of Contents
Lead Plaintiff Evidentiary Exhibits

Dates are formatted as year month day (yymmdd) throughout this index and in all file names.

BRMT Summary Description: Brain Remote Management Technology

1. This BRMT summary description identifies the essential functions, components, and operations of the prohibited Brain Remote Management Technology (BRMT) bioweapon and bioweapon delivery system. The illegal BRMT bioweapon and bioweapon delivery system is a weapon used to hijack the human brain, not a beneficial medical use of technology.

2. BRMT's continuing illegal secret development and existence was forensically reverse engineered by Lead Plaintiff in 2021-2022 using personal experience and access to open source (and sometimes deliberately blocked and/or hacked) information. This functional and operational summary of the illegal BRMT bioweapon system references independent explanations of the basic technologies used in field operation, shown at LP Evidentiary Exhibits pages 6645-6884. It includes limited examples of defendant UNITED STATES' illegal acts, violations and injuries against Lead Plaintiff during field operations which are illustrative of similar injuries to other members of this class of plaintiffs. No classified information has been used in this forensic process or in the development of this document nor in the Complaint it accompanies.

3. BRMT and all other bioweapons and bioweapons delivery systems were globally banned by 1972 Bioweapons Treaty, and its possession and operation are illegal under 18 U.S.C. § 175, which includes a prohibition on extra-territorial operations. Its continued use and development by Defendant UNITED STATES has and does violate the human, civil, and constitutional rights of its citizens (Complaint paragraphs 251-259, 322-327).

Origins of BRMT

4. BRMT's illegal biomedical experiments on human subjects from at least 1968 to the present without consent was preceded by the abject failures of CIA's MKUltra, a program of 149 similarly illegal medical experiments on human subjects using 100 million secretly administered doses of LSD on unsuspecting member of the public who were then left to their own devices in

public places while hallucinating, creating mayhem and violence to themselves and other members of the public. MKUltra was built by CIA on the Nazi Dachau Death Camp World War II era experiments on religious, ethnic, political, and "social deviant" prisoners. US and Aliied nation prosecutors sought and secured death, life imprisonment, and long prison sentences for participating Nazi doctors at the Nuremberg Trials in 1946-1947. CIA's MKUltra, was a 20 year program (1953-1973) of surreptitious illegal LSD druggings of US and Canadian citizens and soldiers by CIA (Science Directorate) and ARMY (Bioweapons Lab), which made CIA the world's largest drug dealer during the 10-15 most active years of that illegal program. When MKUltra was abandoned after 20 years of abject failure, mayhem, injury, and death, it was replaced by the then evolving BRMT program.

5. The fifty-five or more year evolution of the prohibited BRMT bioweapon program has been built on successive generations of medical research and technological advances in semiconductors, computing, computer software, communications, and space-based systems. It has also been built on the systematic exploitation of human subjects without their consent, on forced behavioral patterns hijacked and manipulated to and including lethality attempts and deaths, and on racketeering crimes committed by federal police powers agencies acting well outside legal bounds with the knowing consent and willful blindness of defendant DOJ, by military services operating in secret among the general public in violation of posse comitatus and the Third Amendment, and by the intelligence community in broad violations of the Constitution, US laws, and international treaties. medical abuses, and a wide variety of indirect violence to US persons and their families.

Evolution of BRMT

6. Early versions of BRMT in the late 1960s and into the 1980s caused hormone driven behavioral changes ranging from moderate effects of hormonal overdoses (1968, Complaint paragraph 417) and other imbalances (such as sleep, lust, depression, and bipolar mood swings, Complaint paragraph ??) to extreme forms of human emotion, which give rise to blood lust and murder (Complaint paragraph ??). See LP Evidentiary Exhibits pages 6686-6699 for an explanation of human hormones which regulate emotions among many other bodily functions. These early BRMT devices were relatively cumbersome and heavy locally operated tube-based systems in an equipment box in the late 1960s. This locally operated device has gradually evolved from that analog technology to an analog device locally placed which could be remotely triggered by a cell phone signal in the mid-1980s, through the development and further miniaturization of semiconductors, reduced power consumption and computing and software technologies.

7. Modern BRMT operation is a fully remote operation using pulsed energy precisely delivered from afar to a space-based burst style precision aimed weapons system which can operated fully remotely through either live video feeds or an encrypted local device about the size and complexity of a cell phone. Using modern technologies and massive advances in neuroscience research, BRMT hijacks and commands the victim's brain with tightly choreographed sequences to orchestrate a broad array of artificially contrived manipulations. The prohibited BRMT bioweapon and bioweapon delivery system can emulate or interrupt virtually any sequence of human activity from the lowest level of involuntary body functions such as breathing, heart rate, and heart rhythm, to the highest levels of consciousness, reasoning, and executive functioning.

8. Neuroscience research has dramatically advanced scientific understanding of the connections between the brain and unconscious functions like breathing and heart rhythms, and with conscious functions like thinking, reasoning, problem solving, and playing golf. See LP Evidentiary Exhibits pages 6645-6685 and 59-139 for basic explanations of neuroscience and recent advances in brain-to-computer interfaces. An early stage commercial version was approved for human trials by FDA in 2021 and first implanted by Synchron in 2022, see LP Evidentiary Exhibits pages 11-25. NeuraLink, an Elon Musk company, implanted its first similar device in January 2024. These are legally permitted brain to computer interfaces, beneficial medical devices to assist disabled persons in everyday tasks, such as for quieting ALS tremors and operating personal computers using thought only. BRMT is an internationally prohibited illegal bioweapon built on Nazi style illegal medical experiments on human subjects, without their consent.

9. Development of the prohibited BRMT bioweapon and bioweapon delivery system is more than five decades and billions of dollars ahead of the beneficial commercial implants from Synchron and NeuraLink. Its illegal evolution of uses follows the same pattern as GPS, which was used in classified service by the military in the 1960s, and did not become common in commercial navigation for ships, aircraft and vehicles until the late 1980s, before it appeared on your smartphone in the last ten years or so. But most importantly, while commercial medical and BRMT both use the same basic neuroscience and some shared technologies, the prohibited BRMT is a computer-to-brain offensive weapon system which commands the victim, NOT a beneficial brain to-computer interface controlled by the user for their own personal benefit,

Normal Brain Pathways Are Hijacked By Brain Remote Management Technology

10. The modern version of the prohibited BRMT bioweapon system is used by Defendant

UNITED STATES to command (hijack) brain and central nervous system connections and functions. The brain and a supercomputer both work in roughly similar, though certainly not identical, manner. Consider the jerky, gross motor movements of a tiny infant, as compared with the much more subtle movements of a teenage high school basketball star to understand the progression of coordination as learned through experience and practice by the human brain using eyes, trial and error and muscle sensations to develop hand-eye coordination.

11. BRMT development has progressed in similar fashion across its generations of development. Myriad simultaneous brain and central nervous system interactions occur to, for example, move your little finger a specific distance. The physical movement is accomplished by the transfer of biological chemicals (tiny amounts of energy) in brain cells on one side of a cellular boundary across a gap to other cells to command a specific muscle manipulation for example. Vastly oversimplified, this biochemical transfer from a brain cell generates a tiny bit of energy (a signal) in a receiving nerve cell which in turn generates a biochemical message (a set of commands) which travel, using routing instructions, through the central nervous system (similar to a network of cables) to specific muscle receptors in the little finger. The muscle receptor tells the muscle or muscles to contract or relax a certain distance at the desired speed to complete the desired movement. All while you don't spill your coffee, as you watch an infant learn how not to spill their plastic cup of milk at the dinner table.

Forensic Reverse Engineering Of BRMT

12. Lead Plaintiff's knowledge of the prohibited BRMT system is based on thought experiments used to repeat and verify the existence of this technology and repeatability of these thought experiments. He was then able forensic reverse engineering and to validate the evolution of the illegal BRMT system using his years of unwitting participation as an illegally hijacked

victim of these medical experiments on humans without their consent; his university science and technology education; his decades of professional experience in computer systems and technology, technology integration, national security sensitive facilities and applications, government and commercial organizations and practices; and legal research into the decades of persistent constitutional violations by defendant UNITED STATES; and the compelling necessity of his developing counterintelligence skills; all integrated to decipher and decode the methods used against him by defendant UNITED STATES over the past fifty years, to create this forensic reconstruction of the illegal BRMT system, its evolution, and its contemporary form. This process occurred mostly in 2021-2022, In 2023, he was able to connect this technology to the specific identities of the federal perpetrators in Summer and Fall 2023. Fraudulent concealment by defendant UNITED STATES' specific suppressions of publicly available information dramatically slowed early progress.

BRMT System Description - Illegal Brain Hijacking System: 18 U.S.C. § 175 and Ratified 1972 Bioweapons Treaty

13. The contemporary BRMT system integrates six key elements across a space-based hyper-focused pulsed energy system to deliver commands from ground-based command and control:

A. *Hardware Platform:* Supercomputer system supporting ultra-high rate floating point operations, BIOS (digital basic input output system), operating system which translates user-level software commands to BIOS, and monitors hardware system integrity.

B. *Software System:* Command system (user application) software used to pre-assemble operational sequences and support on-the-fly remote field improvisations; supports motion predictive analytics and behavioral predictive analytics; provides development and test platform to support analytics. Operational software system used for foreground and background operations, including brain hijacking command sequences execution with extreme precision as to intensity, timing, frequency and hyper-precision location instruction in a single command set sequence to the bioweapon platform; victim target tracking to support automated and direct pico-second cycle time remote system aiming and burst sequences; software system to monitor and trap field feedback on system stability, security, integrity, and accuracy for operational support, diagnostics, and analytics.

C. *Augmented Hyper-Precision Location Accuracy System:* integration with proximate ground-based augmentation systems inputs (cell phone towers are precisely located, for example) to enhance precision aiming of the satellite-based or other remotely located pulsed signal (energy) source.

D. *Pulsed Directional Transmission to Victim*: Command sequences delivered using software sequencing technology control of pulsed variable energy nanometer wavelength signals (energy) with dynamic hyper-precision location accuracy (similar to burst communications used in narrowcast highly directional espionage communications systems used for satellite-based communications with intelligence assets where direct human contact is too high risk but regular communication s essential).

E. *Artificial Intelligence Platform:* software system for testing, analysis, learning and refinement of hijacking command sequences, to monitor and enhance system efficiency and test incremental software and system components enhancements, support fail-safe operational integrity. Supports continual system software upgrades using advanced research in neuroscience and field tests observations to enhance granularity and accuracy e.g., moving a command set from initial crude on/off control to intensity variations (like a dimmer switch) and to intermittent operational outcomes (sporadic episodic sequencing).

F. *Systems Integration:* Advanced earth based platforms and space based platforms are integrated by leveraging DOD command and control technologies (such as communications and encryption systems) and physical platforms (such as dispersed earth-space communications system nodes and satellite constellations used for fail-safe operations across the various components of DOD – air, land, sea, and space).

Technologies Adapted For Prohibited Brain Remote Management Bioweapon System

14. The five base technologies and the sixth element, systems integration, which comprise this illegal bioweapon and bioweapon delivery system are summarized as follows:

A. Hardware Platform: A supercomputer and its operating system, programmed with a familiar style of user interface for human management similar to a Windows or MacIntosh operating system on personal computer platform hosing user applications like MS-Word and Excel. The supercomputer converts basic operator commands to the specific sequence of hijacking commands and precise timing using its operating system, which are sequenced using its internal clock and/or cues from the victim's environment, to effect a particular command sequence in a particular precise moment of action. For example, dropping a victim's foot onto a curb or step to cause the victim to fall into vehicle traffic lanes or to somersault on a set of stairs (both occurred to Lead Plaintiff in late 2022, see Complaint Interline Exhibit 14, page 127 for the latter incident).

A1. The supercomputer orchestrates these types of preprogrammed sets of brain hijacking commands (external biochemical hijacking interrupts of the victim's normal brain function) based upon the operator's desired outcomes. These brain hijacking commands can include branching options in a specific sequence or randomized series of brain hijacking commands, and/or can respond to environmental cues by processing and reacting to a remote sensing feed using neural networking and/or artificial intelligence. Numerous supercomputers centers currently operated in the Department of Defense and other Defendant UNITED STATES departments and agencies can process three quadrillion operations per second, equal to about 30% of the brain's processing power. A supercomputer with the processing power of a human brain is scheduled for completion this year at Argonne National Laboratory. See LP Evidentiary Exhibits pages 6700-6714.

B. Software System: The modern version of BRMT has extremely complex software providing the commands used to hijack the executive functions like thinking and speech, the more basic functions like voluntary muscle movements, and the involuntary functions like the hearing, vision, swallowing, and breathing of the hijacked victim to orchestrate the operator's commanded non-autonomous reality or outcome directed at the victim, or even at a third party through the hijacked acts of the victim on that third party. The complexity of this software is similar to the complexity of, for example, global weather simulation models or modern econometric models, which require supercomputer processing power to model billions to quadrillions of operations in seconds.

C. Augmented Hyper-Precision Location Accuracy System: Precision location technology is used to enhance the accuracy of a remotely located signal source. Prior generations of this technology likely required specific placement of a ground-based signal source to provide adequate location accuracy. Today, commercially available location augmentation technology like precisely located cell phone towers make it practical to use a space-based signal source with the current generation of BRMT. For example, commercially available RTK augmentation technology for farming currently provides about one-third inch in one mile accuracy, that is, 1 inch in 63,360 inches, at a distance of up to 25 miles from the RTK tower site. BRMT can reference a fixed point on the victim, so it is possible to apply this same level of precisely augmented location accuracy to a human head, even as the head moves in normal activity. This level of augmented location precision as applied to the head is about 2/1,000ths of an inch, 5,080 nanometers. Classified versions of commercial technologies are typically several generations ahead of commercial versions. Since an individual brain cell is 2,000 to 5,000 nanometers, it is straightforward to locate very specific addresses in the victim's brain. See LP Evidentiary Exhibits pages 6739-6810.

D. Pulsed Directional Transmission to Victim: A human hair is 80,000 to 100,000 nanometers in diameter. A typical brain cell is 2000-5000 nanometers in size. Nanometers scale signals (which are invisible forms of energy just like x-rays and radio signals) are used to send commands to specific brain addresses to activate or block biochemical messages. The short wavelength of nanometer signals allows them to easily penetrate concrete, dirt, rock, bone, etc., to reach the victim's brain virtually anywhere on earth using Defendant United States' global coverage satellite constellation and precision location augmentation (a highly advanced and encrypted form of GPS such as used for other modern military applications). See LP Evidentiary Exhibits pages 6739-6810.

E. Artificial Intelligence Platform: BRMT uses its accumulated set of learned patterns of the victim reactions to command sets to drive many small experiments on some victims to advance the encyclopedia of knowledge used to command human brains. These incremental experiments, which can be conducted in millions of variations by supercomputer in relatively short periods of time (all prohibited by law and treaty) are imposed on the unwitting victim without their consent, to grow the body of knowledge and commands which can be used in various combinations and in various settings to achieve the desired outcomes of the commander of this prohibited bioweapon system. See LP Evidentiary Exhibits pages 6715-6738.

E1. Continuing enhancements support additional developments by further abuses of unwitting research victims: MRI enhanced knowledge of research victims' fine brain structure can be used to further development of prohibited BRMT bioweapon use against a high-value target, and to advance general bioweapon capabilities. Lead Plaintiff was subjected to this baseline MRI brain mapping as a result of a potentially lethal fall during his second colonoscopy in two months in a New Jersey hospital in April 2022. See Complaint Subordinate Count L-13, pages 335-339. The Lead Plaintiff has had several such MRI image scans over the years in hospital settings, including in preparation for nasal surgery in the 1990s. These stored digital MRI images are easily accessible to medical researchers through the use of intelligence and police powers facilities, both through certain legal and extra-legal means.

F. Systems Integration: Billions of dollars and years of research and development are required to build such complex integrated systems. Moment to moment operations are managed by artificial intelligence and/or neural networks, so BRMT can simultaneously and sequentially execute instructions and issue hijacking commands to the victim on the millisecond level time intervals required to generate complex nonautonomous patterns of human thinking, speech, and involuntary actions. See LP Evidentiary Exhibits pages 6811-6814.

Body/Mind Manifestations of Biochemical Disruptions of Normal Brain Activity Using BRMT

15. The prohibited BRMT bioweapon and bioweapon delivery system can be used to hijack any function of any brain, including human brains. It can disturb normal body rhythms and processes, including balance, muscle responses, sleep rhythms, vision, and hearing. It can

disturb, disrupt or induce thoughts and movement patterns. For example, prior to a planned motion it can detect and disrupt or change that motion; during the thought process it can erase or block that thought or instill another thought in short-term memory; it can activate the central nervous system to paralyze or enhance body rhythms, activities, or movements; it can send pain signals and other messages to the brain. BRMT can induce sustained excess or deficient production of biochemicals, causing brain chemical imbalances to produce mental illness symptoms, such as depression or schizophrenia.

16. All these are toxic interventions in the brain which violate 18 USC § 178(2) and the 1972 *Convention on the Prohibition of the Development, Production and Stockpiling of Bacteriological (Biological) and Toxin Weapons and on Their Destruction.* Toxin is legally defined as:

> "the term "toxin" means the toxic material or product of plants, animals, microorganisms (including, but not limited to, bacteria, viruses, fungi, rickettsiae or protozoa), or infectious substances, or a recombinant or synthesized molecule, whatever their origin and method of production, and includes—
> (A) any poisonous substance or biological product that may be engineered as a result of biotechnology produced by a living organism; or
> (B) any poisonous isomer or biological product, homolog, or derivative of such a substance;"

The underlined words above precisely describe the means of toxic production used by the BRMT bioweapon when it hijacks the human victim's brain as an excess production of any substance by this artificial means poisons (disrupts the normal organic functioning of) the brain's delicate biochemical system.

17. BRMT does not, nor does it need to, replace all brain functions. Instead, it uses specifically addressed and precisely delivered brain hijacking commands to interrupt, delay,

accelerate, magnify, distort, and/or diminish specific selected brain functions, ranging from a single function to a few dozen at a time. For example, breathing, speech, or body movements can be momentarily disrupted with a few commands, as the brain continues its normal processing of all other body functions such as muscle movement, speech, respiration, balance, heart rhythm, vision, smell, etc. So, it does not turn the victim into a completely controlled robot, it just hijacks what it needs to control, kind of like a parasite uses its host, or a bank robber uses a hostage.

18. Select examples of BRMT central nervous system disruptions and distortions:

i. Body pains – induced arm, leg, torso, pains and headaches;

ii. Muscular control – induced twitches, tremors, yawns, coughs, itches, grip/grasp;

iii. Loss of balance - induced falls and collisions with objects or people;

iv. Body rhythms – induced heart, breathing irregularities, disturbed walking pace, sleep patterns;

v. Organ function disruptions - bowel movements, sexual organs, kidney pain;

vi. Aural and visual distortions – induced voices, floating visual distortions, visual cloaking, and visual nerve images;

vii. Induced thinking and speech disturbances – thinking and executive function disruptions such as distraction, erasure, modifications, distortions of concepts and ideas, garbling of phrases, sentences;

viii. Induced obsessions – including sexual urges, appetite, operating aircraft doors inflight, attraction to inappropriate targets, including repeated failed efforts to induce misconduct, such as, for example, assaults and child sexual abuse.

19. As forensically reverse engineered, these BRMT hijacking attempts and distortions have been directly experienced by Lead Plaintiff over many years. Lead Plaintiff has been forced to strongly resist any act on many of these BRMT bio-hijacking commands and distortions by defendant UNITED STATES' human operator's commanding this illegal system so as to avoid harms to others or to himself, including two long-running torturous sequences which led to suicide ideations (Complaint paragraphs 604, 606 HEXP-1, 3) and innumerable attempts to provoke assaults against undercover officers also acting to provoke at the same time, or to innocent third parties such as the elderly and children. Not all BRMT hijacking victims would have the necessary skills and self-control to avoid these types of harm to others or to themselves.

Select Examples Of BRMT Violations Of Lead Plaintiff By Defendants

20. Lead Plaintiff suffered induced mental illness from stress, brain distortions due to chemical imbalances, and the deprivation and functional blocking of medical interventions, with symptoms typical of a range of mental incapacity from mood disturbances in college to alleged symptoms of schizophrenia ascribed by psychiatrists when Lead Plaintiff accurately reported his symptoms in 2010. Lead Plaintiff is actually highly emotionally stable, according to independent tests as shown at LP Evidentiary Exhibits pages 193-236.

21. Lead Plaintiff suffered numerous programmed falls in varying locations ranging from mountain trails to sidewalks to ladders to beds, to hospital recovery rooms, beginning in the 1990s and continuing into the present. Each and every fall risked a collision by the Lead Plaintiff's head with some intervening object which could have caused a disabling or fatal head, neck, or spine injury. See LETHL-2, 6, 7, 8, 10, 12, 13, and 15 in the Complaint. Many more examples of injuries resulting from Defendants malign acts using BRMT are related through the violations in the Complaint and LP Evidentiary Exhibits. The number of individual BRMT brain

hijacking sequences per day range from dozens to thousands against the Lead Plaintiff alone. These prohibited BRMT bioweapon system hijackings are conducted with and enhanced by other physical and psychological operations of Defendants in all kinds of public places, from grocery stores and shopping malls to sidewalks and street crossings, to buses, planes, trains, and subways. Any time they wish, anywhere on earth. Bear in mind that these are only a tiny selection of examples from more than 18,000 days of prohibited BRMT brain hijacking.

Defendant United States Originates and Orchestrates Lawless Abuses Using BRMT

22. Illegal “state secrets” abuses and abusive classification strategies are used by Defendant United States to claim improper “national security,” “police powers,” and “qualified immunity” exemptions. These are used as sword and shield by defendant United States and its coconspirator governmental Defendants to hide their patterns of racketeering acts and civil rights violations under the color of law. These fraudulently claimed exemptions perpetuate broad patterns of violations of rights, laws, and the Constitution by departments and agencies, by individual agents, officers, confidential informants and other permitted criminal actors which acts and injuries are not pursued by police powers operations as required by law. These acts, violations, and injuries perpetrated by defendant UNITED STATES and its co-conspirators violate constitutional rights, domestic and extra-territorially asserted U.S. law, ratified international treaties, and state laws in the numerous states where they have occurred.

Synchron Announces First Human U.S. Brain-Computer Interface Implant

- First U.S. Human Procedure Performed at Mount Sinai Health System in New York City

Stentrode™ is implanted within the motor cortex of the brain via the jugular vein in an endovascular procedure.

July 19, 2022 08:00 AM Eastern Daylight Time

NEW YORK--(BUSINESS WIRE)--Synchron, an endovascular brain-computer interface (BCI) company, today announced the first human BCI implant in the United States. This procedure represents a significant technological milestone for scalable BCI devices and is the first to occur in the U.S. using an endovascular BCI approach, which does not require invasive open-brain surgery.

The procedure was performed at Mount Sinai West in New York, led by clinical investigator Shahram Majidi, MD, assistant professor of neurosurgery, neurology and radiology at the Icahn School of Medicine at Mount Sinai. The procedure was performed in the angiography suite with a minimally invasive, endovascular approach. Mount Sinai's Department of Rehabilitation and Human Performance helped coordinate the procedure.

The procedure marks the first U.S. patient implant in Synchron's COMMAND trial, which is being conducted under the first investigational device exemption (IDE) awarded by the FDA to a company assessing a permanently implanted BCI. The U.S.-based trial is being conducted with support from the NIH Neural Interfaces Program.

The COMMAND study will assess the safety and efficacy of the company's motor BCI technology platform, including the Stentrode™, in patients with severe paralysis with the goal of enabling the patient to control digital devices hands-free. Study outcomes include the use of brain data to control digital devices and achieve improvements in functional independence.

“This is an incredibly exciting milestone for the field, because of its implications and huge potential,” said Shahram Majidi, MD, the neurointerventional surgeon who performed the procedure, and assistant professor of neurosurgery, neurology and radiology at the Icahn School of Medicine at Mount Sinai. “The implantation procedure went extremely well, and the patient was able to go home 48 hours after the surgery."

“We are beyond excited to get to work with our patient, guiding them through the training process as they learn to use this device to live more independently and, most importantly, communicate with their family and friends,” said David Putrino, PhD, PT, Director of Rehabilitation Innovation for the Mount Sinai Health System and a Principal Investigator of the COMMAND study.

“The first-in-human implant of an endovascular BCI in the U.S. is a major clinical milestone that opens up new possibilities for patients with paralysis,” said Tom Oxley, MD, PhD, CEO & Founder, Synchron. “Our technology is for the millions of people who have lost the ability to use their hands to control digital devices. We’re excited to advance a scalable BCI solution to market, one that has the potential to transform so many lives.”

The Stentrode is implanted within the motor cortex of the brain via the jugular vein in a minimally-invasive endovascular procedure. Once implanted, it detects and wirelessly transmits motor intent using a proprietary digital language to allow severely paralyzed patients to control personal devices with hands-free point-and-click. The trial will assess the impact of everyday tasks such as texting, emailing, online shopping and accessing telehealth services, and the ability to live independently. The FDA granted Breakthrough Device designation to Synchron in August 2020.

Synchron will continue to advance enrollment in its COMMAND trial as the industry-first FDA-approved clinical trial for a permanently implanted BCI in the U.S. Recently reported long-term safety results have demonstrated this technology to be safe in four patients out to 12 months in Synchron’s SWITCH trial in Australia, as reported at the 2022 American Academy of Neurology Conference.

About the Stentrode™

Synchron’s flagship technology, the Stentrode, is an endovascular brain implant designed to enable patients to wirelessly control digital devices through thought and improve functional independence. Synchron’s foundational technology, a motor neuroprosthesis (MNP), or motor BCI, is implanted via the jugular vein using neurointerventional techniques commonly used to treat stroke, and does not require drilling into the skull or open-brain surgery. The system is designed for patients suffering from paralysis as a result of a range of conditions. It is designed to be user friendly and dependable for patients to use autonomously.

About Synchron, Inc.

Synchron, an endovascular brain interface company, is a leader in implantable neural interface technology. The clinical-stage company is developing a neuroprosthesis for the treatment of paralysis and the first endovascular implantable neuromodulation therapy. Future applications include the potential to diagnose and treat conditions of the nervous system, including Parkinson’s disease, epilepsy, depression, and hypertension. Synchron is headquartered in New York City, with R&D facilities in Melbourne, Australia. For more information, visit www.synchron.com. Follow us on Twitter @synchroninc.

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Synchron on Twitter

Synchron on LinkedIn

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THE SCIENCE

Introducing Neuro EP

A new frontier in the treatment of neurological disorders.

The brain is complex.

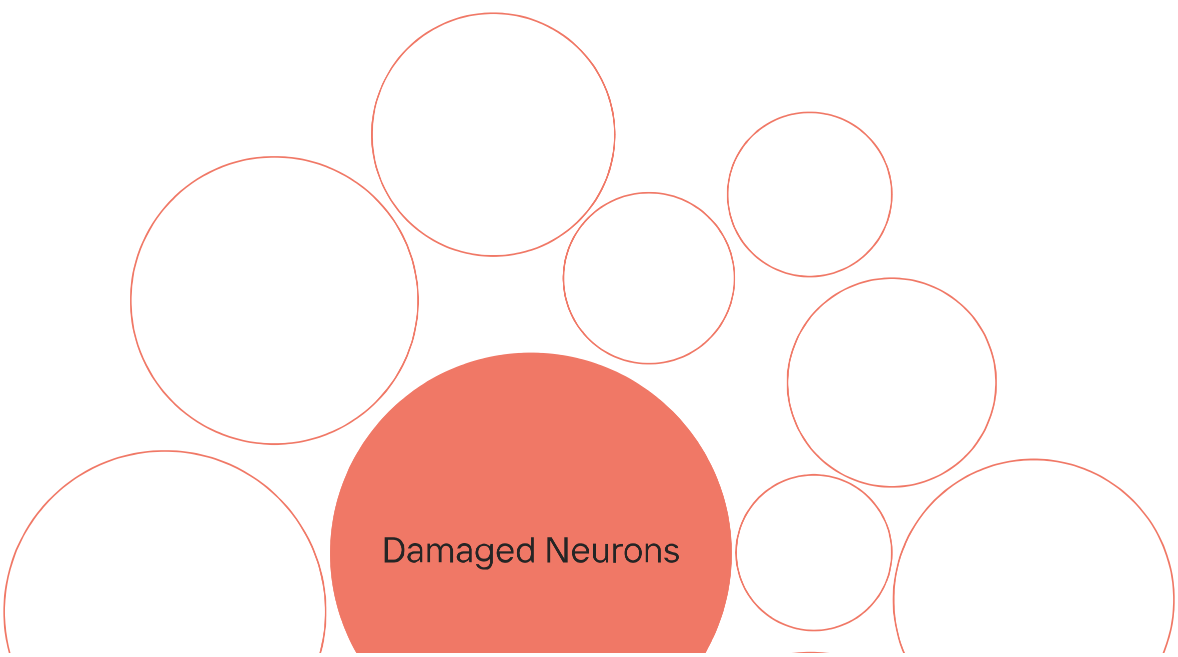
synchron

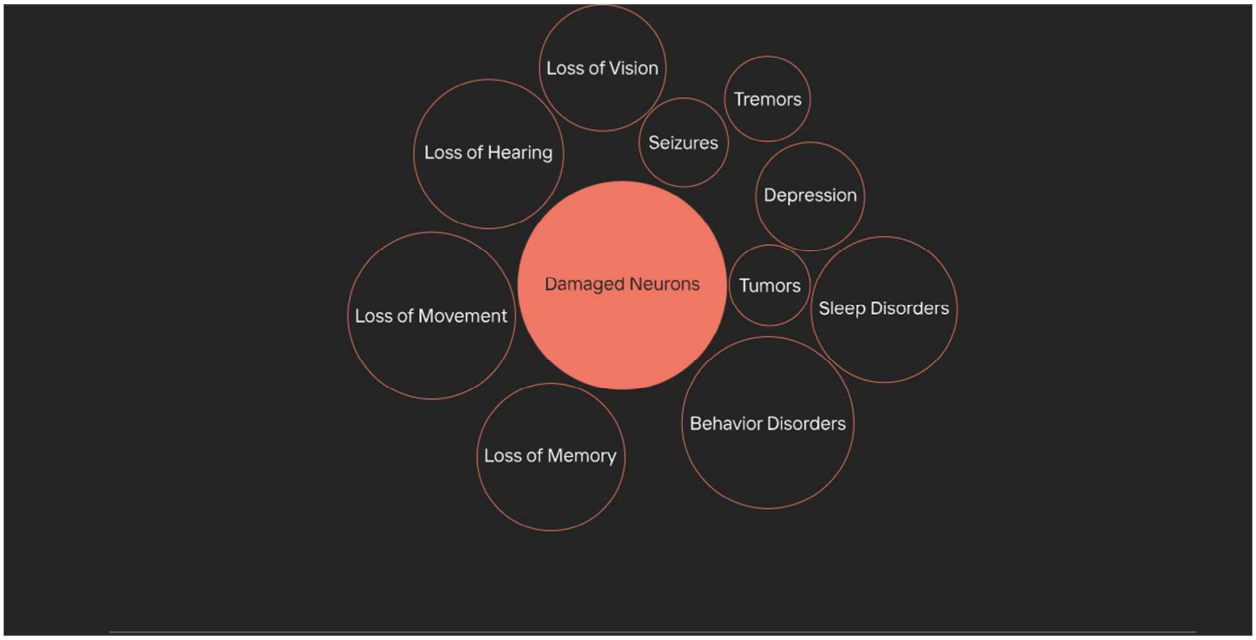
The brain is complex.

There are billions of inaccessible neurons and over 400 miles of blood vessels that navigate every part of the brain.

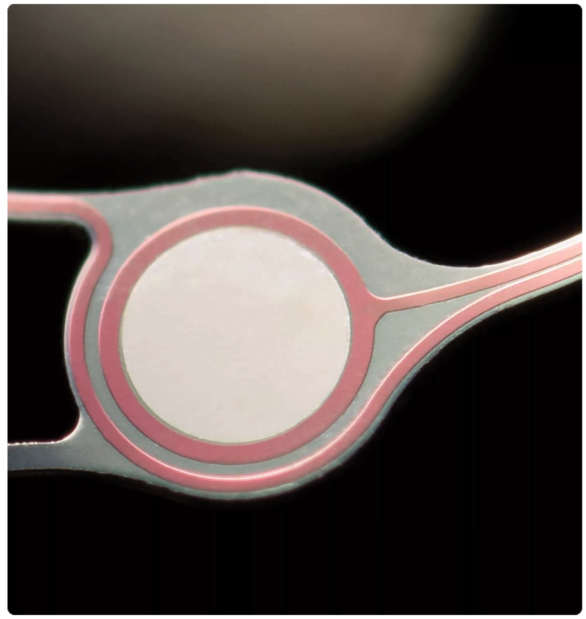
The Challenge

Damaged neurons can wreak havoc on our bodies and lives.




Loss of Vision
Tremors
Seizures
Loss of Hearing
Depression
Damaged Neurons
Tumors
Sleep Disorders
Loss of Movement
Behavior Disorders
Loss of Memory

The Endovascular Solution



Our team has collectively spent decades studying these pathways and the

application of our technology with an endovascular surgical procedure. We have solved how to deliver electronics into the wall of the blood vessel, giving us access to an unprecedented amount of data from untouched areas of the brain. Applications of Neuro EP will fundamentally change how we study, diagnose, and treat the brain.

Neuro EP

The science of restoring, treating, and mapping the

Neuroprosthetics

The restoration of a lost brain function, e.g loss of movement or vision.

Neuro EP

The science of restoring, treating, and mapping the electrical activities of the brain.

Neurointerventional Electrophysiology (Neuro EP) is a new field of medical science that combines and elevates three existing areas of research: neuroprosthetics, neuromodulation, and neurodiagnostics.

Neuroprosthetics

Neuromodulation

Neurodiagnostics

180,000,000[1]

People with severe disabilities

1. World Health Organization Fact Sheets

ABOUT US

Radically outpacing traditional BCI.

Our mission is to create an endovascular implant that can transfer information from every corner of the brain at scale.

In the News

synchron

OUR STORY

Innovating an Industry

Since 2012, we have been developing a solution that avoids the need for open brain surgery by using a minimally-invasive procedure.

Quick facts about us

Quick facts about us

01

The device, the stentrode™, is 8mm in diameter and made from a flexible alloy called nitinol. It is inserted into Superior Sagittal Sinus in the brain via the jugular vein.

02

Initial grant funding was provided to a lab in the University of Melbourne by the U.S. Defense Advanced Research Projects Agency (DARPA) and Department of Defense (DoD).

03

In 2020, FDA awarded the stentrode™ the Breakthrough Device Designation. In 2021, Synchron became the first company to receive an FDA IDE to conduct trials of a permanently implantable BCI.

04

Series B funding was led by Khosla Ventures, with total capital raised now of $70M, including support from the

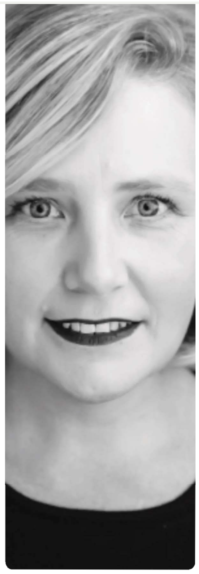
05

Synchron is headquartered in Brooklyn, New York, and has an office in Melbourne, Australia.

synchron

Amanda Zwarenstein

Director, Product



Chloe Brown

Director, Strategic Marketing

Kimberly Ha

Communications Lead

Awards

Partners

Board

TIME

The Best Inventions of 2021

Time Magazine 2021

FAST COMPANY

Next Big Things in Tech

Fast Company 2021

synchron

Awards

Partners

Board

Advisors

TIME

The Best Inventions of 2021

Time Magazine 2021

FAST COMPANY

Next Big Things in Tech

Fast Company 2021

Newsweek

Most Disruptive Innovator Award

Newsweek 2021

SVIN SOCIETY OF VASCULAR AND INTERVENTIONAL NEUROLOGY

Innovation Award

Society of Vascular and Neurointerventional Neurology 2021

BCI AWARD 2021 WINNER 1st PLACE www.bci-award.com

BCI Award

BCI Award Foundation 2021

Science, Technology Assessment, and Analytics

SCIENCE & TECH SPOTLIGHT:

BRAIN-COMPUTER INTERFACES

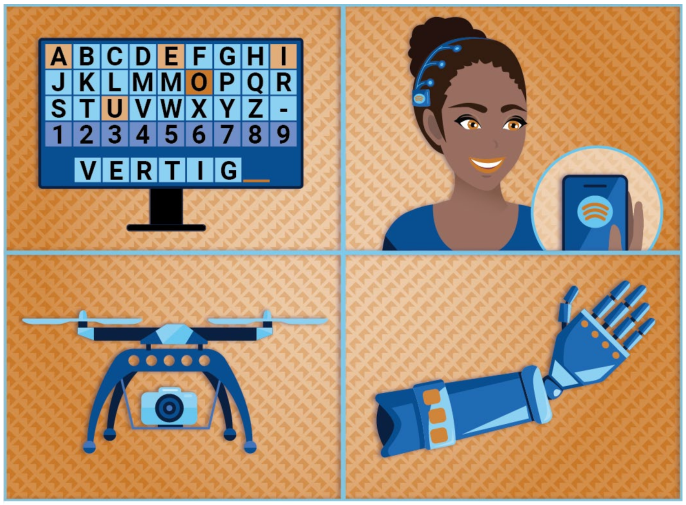
SEPTEMBER 2022

WHY THIS MATTERS

Brain-computer interfaces allow people to control machines using their thoughts. These interfaces can help people with disabilities as well as enhance human-computer interactions. For example, warfighters might operate a drone hands-free on the battlefield. However, the technology remains largely experimental, and it raises questions about security, ethics, and equity.

/// THE TECHNOLOGY

What is it? A brain-computer interface (BCI) enables a person to control an external device using brain signals. BCIs could aid people with disabilities and improve national defense capabilities, among other uses. For example, researchers are developing BCIs that allow people with paralysis to spell words on a computer screen or regain control of their limbs. In addition, researchers are developing BCI-controlled robotic limbs that can provide users with a sense of touch. BCIs could also augment human capabilities by allowing people to control computerized machinery using their thoughts, for example (see fig. 1).



Source: GAO analysis (data). emojoez/svitlana/titaporn/stock.adobe.com (images). | GAO-22-106118

Figure 1. Examples of BCI applications include a speller for communication, a smartphone interface, a BCI-operated drone, and a robotic limb.

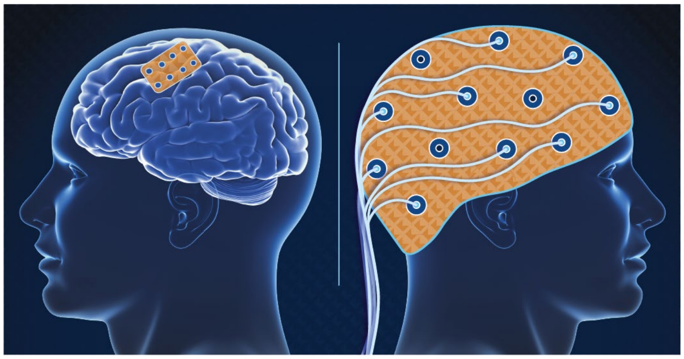
How does it work? New BCI users often undergo an iterative training process. The user learns to produce signals the BCI will recognize, and the BCI translates the signals to operate a device using machine learning.

Generally, BCIs connect to the brain in two ways: through implanted or wearable devices (see fig. 2). Implanted BCIs are often surgically attached directly to brain tissue. They may be more appropriate for users with severe neuromuscular disorders or physical injuries. For example, a person with paralysis could use an implanted BCI that is attached to specific neurons to regain precise control of a limb. Implanted BCIs measure signals directly from the brain, reducing interference from other tissue. However, they pose surgical risks, such as infection and rejection.

Some implanted BCIs reduce risk by placing electrodes on the surface of the brain, a method called electrocorticography (ECoG).

Wearable BCIs often require a cap containing conductors that measure brain activity detectable on the scalp. A wearable BCI may be appropriate for purposes like augmented and virtual reality, gaming, or controlling an industrial robot. Most wearable BCIs use electroencephalography (EEG) to measure the brain's electrical activity. An emerging method—functional near-infrared spectroscopy (fNIRS)—shines near-infrared light through the skull to measure blood flow, which can indicate information such as the user's intentions.

To enhance mobility, researchers are developing BCIs that use portable methods to acquire data—for example, wireless EEG. These methods allow users to operate a smartphone or other device while moving freely.



Source: GAO analysis (data). koya979/stock.adobe.com (images). | GAO-22-106118
Note: Connections between brain and device may be wired or wireless.

Figure 2. Examples of implanted (left) and wearable (right) BCIs.

How mature is it? Most BCIs are experimental. Researchers first tested a wearable BCI in the early 1970s and implanted a BCI in a human for the first time in the late 1990s. BCI research has increased significantly in the 21st century resulting in the publication of thousands of research papers. According to one leading BCI company, fewer than 40 people worldwide have implanted BCIs, all of them experimental. One of the main obstacles to BCI development is that each person generates unique brain signals. Another is the difficulty of measuring those signals.

Historically, BCI research has focused on biomedical applications, such as helping people disabled by a stroke, physical injury, or neurological disorder. In April 2021, a device that uses a wireless EEG headset to help stroke patients regain arm and hand control became the first wearable BCI for rehabilitation to receive market authorization from the Food and

Drug Administration. A number of other wearable and implanted BCIs for medical uses are currently in clinical trials.

Researchers are also developing applications for military use and for systems whose proper operation is critical to safety. For example, researchers at the National Aeronautics and Space Administration have used BCIs to help detect when pilots and air traffic controllers are more likely to make mistakes. The Department of Defense has funded research on BCIs for hands-free control of drones. And the Federal Aviation Administration has looked into how to medically certify pilots who may one day use BCIs to control airplanes.

What are some concerns? Some researchers have noted possible legal and security implications of BCIs. For example, cyberattacks are a concern because hackers could use malware to intercept brain signal data stored on a smartphone. The Department of Commerce is currently reviewing whether exporting BCIs could pose national security concerns. For example, foreign adversaries could obtain a military or intelligence advantage. Its decision could affect how the technology is used and shared overseas.

Researchers have also pondered societal and ethical implications. Reported costs of wearable BCIs range from hundreds to thousands of dollars, which may result in unequal access. Additionally, learning to use some types of BCIs requires training, which may burden users. Researchers have also suggested that translation of brain signals to speech by a BCI could cause harm if it is not accurate. For example, inaccurate translation might indicate legal or medical consent that the person did not intend to give.

/// OPPORTUNITIES

- **Help people with disabilities.** People paralyzed by physical injuries or neurological disorders could use BCIs to communicate and regain control of their limbs.
- **Augment human capabilities and human-computer interactions.** BCIs could accelerate and simplify interactions between humans and machines in fields like defense and space. Also, some researchers have suggested that BCI-controlled robots could assist people in hazardous environments, such as coal mines.
- **Facilitate brain research.** Scientists could use BCIs to improve understanding of the brain. Some researchers have used a BCI to detect the emotions of patients in a vegetative or minimally conscious state.

/// CHALLENGES

- **Technical and user challenges.** Each person generates unique brain signals, which are difficult to measure clearly. Also, learning to use a BCI can require substantial training.
- **Ethical framework.** BCIs may raise questions about what constitutes consent and about potential unfair advantages conferred by certain human enhancements.
- **Security and privacy.** BCIs could be vulnerable to cyberattacks that expose brain data or interfere with a device's function.

/// POLICY CONTEXT AND QUESTIONS

- As BCIs develop toward commercial and patient use, will they be accessible to all, and who will bear the cost?
- How should BCIs that augment human capabilities be regulated, if at all?
- What ethical issues might BCIs raise, and what applications might constitute unethical or controversial use of BCIs?
- What steps might help to mitigate potential security and privacy risks associated with the acquisition of brain signal data?

/// SELECTED GAO WORK

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This document is not an audit product and is subject to revision based on continued advances in science and technology. It contains information prepared by GAO to provide technical insight to legislative bodies or other external organizations. This document has been reviewed by Timothy M. Persons, PhD, the Chief Scientist of the U.S. Government Accountability Office.

Breakthrough Technology for the Brain

JOIN THE TEAM

WATCH THE UPDATE

Understanding the Brain

FIG. 1

SCIENCE

Interfacing with the Brain

FIG. 2

APPROACH

Engineering with the Brain

FIG. 3

APPLICATIONS

Create the Future with Us

Every day we're building better tools intended to communicate with the brain. With the right team, the potential applications for this technology are limitless.

REACH OUT

Understanding the Brain

A web of communication that allows you to move, think, feel and sense.

PLAY VIDEO

There Are 86 Billion Neurons in Your Brain

Neurons send and receive information. Although neurons come in many different types, they generally have three parts: a dendrite which receives a signal, a cell body called a soma which computes the signal, and an axon which sends a signal out.

Neurons Are Connected Through Synapses

The neurons of your brain connect to each other to send and receive signals through axon-dendrite connections called synapses.

Neurons Communicate Through Electric Signals

Action potentials cause synapses to release neurotransmitters. These small molecules bind to receptors on dendrites, opening channels that cause current to flow across the neuron's membrane. When a neuron receives the 'right' combination of spatiotemporal synaptic input, it initiates an action potential.

We Can Record Electrical Signals in the Brain

We place electrodes near neurons in order to detect action potentials. Recording from many neurons allows us to decode the information represented by those cells. In the movement-related areas of the brain, for example, neurons represent intended movements. There are neurons in the brain that carry information about everything we see, feel, touch, or think.

Learn More

WHY DO ELECTRODES NEED TO BE CONNECTED DIRECTLY TO THE BRAIN? ×

Neural activity can be monitored from outside the head using non-invasive techniques such as EEG. With these non-invasive techniques, each channel records the summed activity of millions of neurons, which means the details are blurred away. Imagine experiencing a sports event through a microphone placed outside the stadium. From the roars or groans of the crowd you can tell when something good or bad happens to the home team, but you'll have a hard time distinguishing whether they scored or made a great defensive play and you certainly wouldn’t be able to hear what individual people were saying about the game. The same is true for recording from the brain: recordings made at a distance provide some useful, high-level information, but to access fine-scale information, you need to be close to the source. Here, that means recording action potentials, or “spikes,” from individual neurons. Currently, that can only be done by placing electrodes inside the brain.

HOW DOES NEURAL STIMULATION WORK? +

Interfacing with the Brain

OUR APPROACH

Interfacing with the Brain

Innovation pushing the boundaries of neural engineering.

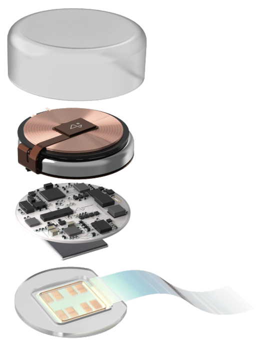
FROM NEURON TO COMPUTER

The Link

We're aiming to design a fully implantable, cosmetically invisible brain-computer interface to let you control a computer or mobile device anywhere you go.

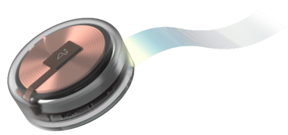
Micron-scale threads would be inserted into areas of the brain that control movement. Each thread contains many electrodes and connects them to an implant called the "Link."

NEURAL IMPLANT AND ELECTRODE ARRAY



LINK

Sealed, implanted device that processes and transmits neural signals.



NEURAL THREADS

Each small and flexible thread contains many electrodes for detecting neural signals.

CHARGER

Compact inductive charger wirelessly connects to the implant to charge the battery from the outside.

NEW APPROACH TO NEUROSURGERY

Precision Automated Neurosurgery

The threads on the Link are so fine and flexible that they can't be inserted by the human hand. Instead, we are building a robotic system that is designed to reliably and efficiently insert these threads exactly where the neurosurgeon wants them to be.

REGAINING INDEPENDENCE

The Neuralink App

The Neuralink app is being designed to allow you to control your keyboard and mouse directly with the activity of your brain, just by thinking about it.

BE IN CONTROL

The Neuralink app would guide you through exercises that would teach you to control your device.

SIMULATION.
NOT FDA-APPROVED OR AVAILABLE.

BE AUTONOMOUS

With a Bluetooth connection, you would be able to potentially control any mouse or keyboard with your thoughts.

Learn More

WHAT IS NEURALINK DEVELOPING?

Neuralink is building a fully integrated Brain Computer Interface (BCI) system. Sometimes you'll see this called a brain-machine interface (BMI). Either way, BCIs are technologies that enable a computer or other digital device to be controlled directly with brain activity. For example, prior research has demonstrated that a person with paralysis can control a computer mouse or keyboard just by thinking about how they want to move. Our goal is to build a system that is safe, fully implanted and cosmetically invisible, available at home or out and about, and usable without assistance. Our device, called the Link, aims to record from 1024 electrodes and is being designed to meet these criteria.

WHAT ARE THE BIGGEST CHALLENGES IN MAKING A SCALABLE BCI? +

HOW DOES THE NEURALINK SYSTEM DIFFER FROM OTHER BCI DEVICES? +

Engineering with the Brain

APPLICATIONS

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WHAT ARE THE BIGGEST CHALLENGES IN MAKING A SCALABLE BCI?

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Neuralink's technology builds on decades of BCI research in academic labs, some of which is currently being tested in ongoing clinical studies. The BCI systems used in these aforementioned studies have no more than a few hundred electrodes with connectors that pass through the skin. Their use also requires laboratory equipment and personnel to be present. Our challenge is to build a safe and effective BCI that is wireless and fully implanted, scales up the number of electrodes, removes the need for external equipment (other than the device being controlled), and that users can take anywhere and operate by themselves. Recent engineering advances in the field and new technologies developed at Neuralink are paving the way for progress on each of these key technical hurdles.

ELECTRODES

In order to optimize the compatibility of our threads with the surrounding tissue, we believe that they should be on the same size scale as neighboring neurons and as flexible as possible. The threads also have to resist corrosion from fluid in the tissue. Therefore, we microfabricate the threads out of thin film metals and polymers. To meet these criteria, we've developed new microfabrication processes and made advances in materials science. These include the integration of corrosion-resistant adhesion layers to the threads and rough electrode materials that increase their effective surface area without increasing their size.

CHIPS

Our Link needs to convert the small electrical signals recorded by each electrode into real-time neural information. Since the neural signals in the brain are small (microvolts), the Link must have high-performance signal amplifiers and digitizers. Also, as the number of electrodes increases, these raw signals become too much information to upload with low power devices. Scaling our devices requires on-chip, real-time identification and characterization of neural spikes. Our custom chips on the Link meet these goals, while radically reducing per-channel chip size the Link meet these goals, while radically reducing per-channel chip size and power consumption compared to current technology.

HERMETIC PACKAGING

The Link needs to be protected from the fluid and salts in the brain. Making a water-proof enclosure can be hard, and it's even harder when that enclosure must be constructed from biocompatible materials, replace the skull structurally, and allow over 1,000 electrical channels to pass through it. To meet this challenge, we are developing innovative techniques to build and seal each major component of the package. For example, by replacing the connection of multiple components with a process that builds them as a single component, we can decrease device size and eliminate a potential failure point.

NEUROSURGERY

Our threads are too fine to be manipulated by hand and too flexible to go into the brain on their own (imagine trying to sew a button with thread but no needle). Yet, we need to safely insert them with precision and efficiency. We are innovating on robot design, imaging systems, and software to build a robot that can precisely and efficiently insert many threads through a single 25 mm skull opening while actively avoiding blood vessels on the surface of the brain.

NEURAL DECODING

Neural spikes contain a lot of information, but that information has to be decoded in order to use it for controlling a computer. Academic labs have designed computer algorithms to control a virtual computer mouse from the activity of hundreds of neurons. Our device is intended to record from over an order of magnitude more neurons, which we hope will provide more precise and naturalistic control of electronic devices. To accomplish this, we are building on recent advances in statistics and algorithm design to improve the efficacy and robustness of neural decoding. One challenge is to design adaptive algorithms that maintain reliable and robust performance while continuing to improve over time. Ultimately, we want these algorithms to run in real time on the implanted device itself.

WHAT ARE THE BIGGEST CHALLENGES IN MAKING A SCALABLE BCI?

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HOW DOES THE NEURALINK SYSTEM DIFFER FROM OTHER BCI DEVICES?

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There are currently only a few approved BCI devices that record from and/or stimulate the human brain, including devices for deep brain stimulation (DBS), which can treat neurological disorders such as Parkinson's disease, and devices for the detection and disruption of seizures. These approved devices are designed to modulate neural activity over large brain areas, not to transfer information to and from the brain. Therefore, they generally have a small number of electrodes (less than 10), and these electrodes are much larger than our threads. For example, DBS leads have only 4-8 electrodes and are about 800 times larger in diameter.

There are also non-Neuralink BCI devices being tested in pilot clinical trials. However, none of these devices have more than a few hundred electrodes, and they are all either placed on the surface of the brain or in fixed arrays of single rigid electrodes. The Link is being designed with an order of magnitude more electrodes and with flexible threads that are individually placed to avoid blood vessels and to best cover the brain region of interest.

We are also designing the Link to provide unprecedented scale, with over 1024 channels of information from the brain. The Link is also being designed to perform real-time spike detection on every channel and to send this data wirelessly.

Engineering with the Brain

APPLICATIONS

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Engineering with the Brain

Working towards improving lives.

REGAINING CONTROL

A Direct Link Between the Brain & Everyday Technology

The initial goal of our technology is to help people with paralysis regain independence through the control of computers and mobile devices. Our devices are therefore currently being designed to one day give people the ability to communicate more easily via text or speech synthesis, to follow their curiosity on the web, or to express their creativity through photography, art, or writing apps.

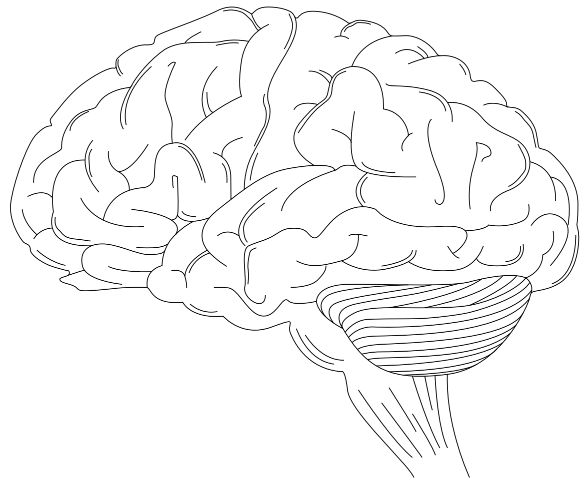
RECONNECTING THOUGHT TO ACTION

The Future of Neural Engineering

The Link is a starting point for a new kind of brain-computer interface. As our technology develops, we want to be able to increase the channels of communication with the brain, accessing more brain areas and new kinds of neural information. We believe this technology has the potential to treat a wide range of neurological disorders, to restore sensory and motor function, and eventually to expand how we interact with each other and experience the world around us.

FIG. 1

FIG. 2



VISUAL CORTEX

+

AUDITORY CORTEX

+

SOMATOSENSORY CORTEX

+

MOTOR CORTEX

+

Learn More

WHAT WILL THE LINK DO?

We are designing the Link to connect to thousands of neurons in the brain, so that it may one day be able to record the activity of these neurons, process these signals in real time, and translate intended movements directly into the control of an external device. As a first application of our technology, we hope to help people with quadriplegia by giving them the ability to control computers and mobile devices directly with their thoughts. We would start by recording neural activity in the brain's movement areas. As users think about moving their arms or hands, we would decode those intentions, which would be sent over Bluetooth to the user's computer. Users would initially learn to control a virtual mouse. Later, as users get more practice and our adaptive decoding algorithms continue to improve, we expect that users would be able to control multiple devices, including a keyboard or a game controller.

WHO WILL THE LINK HELP?

WILL THE LINK BE SAFE?

WILL THE LINK OR FUTURE SYSTEMS BE AVAILABLE TO THE GENERAL POPULATION?

HOW WILL YOU ADDRESS DEVICE SECURITY?

Learn More

WHAT WILL THE LINK DO? +

WHO WILL THE LINK HELP? ×

We hope our first application will enable people with quadriplegia to control a point-and-click computer cursor. We believe there are many other potential future applications for the Link. These may include restoring motor, sensory, and visual function, as well as treatment of neurological disorders.

WILL THE LINK BE SAFE? +

WILL THE LINK OR FUTURE SYSTEMS BE AVAILABLE TO THE GENERAL POPULATION? +

HOW WILL YOU ADDRESS DEVICE SECURITY? +

Expanding Our World

Learn More

WHAT WILL THE LINK DO? +

WHO WILL THE LINK HELP? +

WILL THE LINK BE SAFE? ×

We have not yet begun clinical trials, and so we do not have safety data in humans, but safety has been at the core of the design process. In particular, the Link includes technical innovations intended to improve the safety of the surgical procedure compared to existing BCI devices or traditional neurosurgery. Here are a few examples:

There is always risk associated with general anesthesia, and that risk is reduced by shortening the time of the procedure. We're designing the Neurosurgical Robot so that it will be capable of efficient and reliable electrode insertion. Also, the robot is being designed to insert threads through a hole in the skull as small as 25 mm in diameter. Combined with other advancements in robotic surgical tooling, this may eventually allow us to eliminate general anesthesia and implant the device under conscious sedation.

Inserting a device into the brain always carries some risk of bleeding. We are trying to reduce that risk by using micron-scale threads, inserted with a needle whose diameter is about the size of many neurons in the brain. Furthermore, because each thread is individually inserted, the Neurosurgical Robot is being designed so that it will aim each thread to avoid damaging blood vessels at or near the surface of the brain.

Learn More

WHAT WILL THE LINK DO? +

WHO WILL THE LINK HELP? +

WILL THE LINK BE SAFE? +

WILL THE LINK OR FUTURE SYSTEMS BE AVAILABLE TO THE GENERAL POPULATION? ×

Neuralink is currently focused on developing medical devices. We believe these devices have the potential to help people with a wide range of injuries and neurological disorders, and we hope to develop treatments for many of these conditions in the coming years. We expect that as our devices continue to scale, and as we learn to communicate with more areas of the brain, we will discover new, non-medical applications for our BCIs. Neuralink's long-term vision is to create BCIs that are sufficiently safe and powerful that the general population would want to have them.

HOW WILL YOU ADDRESS DEVICE SECURITY? +

Learn More

WHAT WILL THE LINK DO? +

WHO WILL THE LINK HELP? +

WILL THE LINK BE SAFE? +

WILL THE LINK OR FUTURE SYSTEMS BE AVAILABLE TO THE GENERAL POPULATION? +

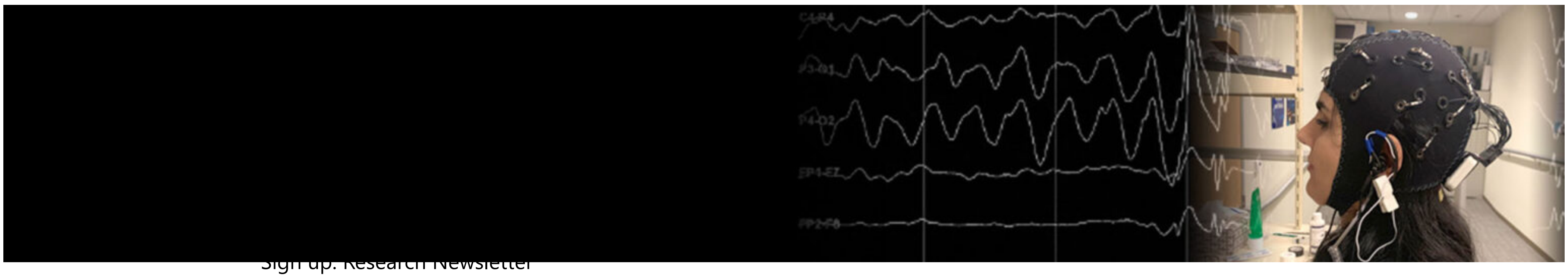
HOW WILL YOU ADDRESS DEVICE SECURITY? ×

We understand that medical devices need to be secure and it takes serious engineering to prevent unwanted access to such devices. Security will be built into every layer of the product through strong cryptography, defensive engineering, and extensive security auditing.

Expanding Our World

Expanding Our World

ABOUT US



Brain-Computer Interfaces

Established: June 29, 2018

Overview People Publications Videos Groups

Brain-Computer Interface (BCI) is a system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves the natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment. BCI is direct communication pathway between an enhanced or wired brain and an external device.

The Brain-Computer Interfaces (BCI) project in Microsoft Research aims to enable BCI for the general population. This means non-intrusive methods, fewer number of electrodes and custom-designed signal picking devices. We go towards interactive BCI, which means response times within seconds and using EEG signals.

Activity of CNS

Direct measurement:

- Electroencephalographic signals (EEG)
- Functional Near Infrared Spectroscopy (fNIRS)
- Magnetoencephalography (MEG)
- Functional Magnetic Resonance Imaging (fMRI)
- Positron Emission Tomography (PET)

Indirect indications:

- heart rate, pupil dilation, galvanic skin resistance (GSR)
- gaze dynamics, gesture/posture/gait dynamics

Neuroimaging modalities:

Recording method	Abbr.	SNR	Temporal resolution	Spatial resolution	Probably portable	Invasive
Electrocorticography	ECoG	High	High	High	Yes	Yes
Electroencephalography	EEG	Mid to low	High	Mid to low	Yes	No
Magnetoencephalography	MEG	Mid	High	Mid	No	No
Function MRI	fMRI	Mid	Low	High	No	No
Function Near-Infrared Spectroscopy	fNIRS	Low	Low	Mid	Yes	No

Electrical activity of the brain

Action potentials:

- Single neuron electrical activity
- Spikes 40 mV/1-2 ms/0-1,000 Hz

Local field potentials (LFP):

- Group of neurons

- 50-350 μV, up to 350 Hz

Electrocorticography (ECoG):

- Electrodes on the surface of the brain (4-32)
- 100 μV/200 Hz

Electroencephalography (EEG):

- Electrodes on the skull (16-256): dry, gel, saline solution
- 1-10 μV/50 Hz

Frequency bands:

Band	**Frequency, Hz**
Delta	< 4
Theta	from 4 to 8
Alpha	from 8 to 14
Beta	> 14

Types of BCI

Passive BCI:

- Monitoring the human state: emotion, attention, cognitive load

Interactive BCI:

- Direct EEG decoding
- Imaginary/inducted/stimulated movements, typically from the motor cortex
- Attention decoding to audio or video
- Evoked potentials: steady state video, or audio, or haptic, or …
- Event related potentials: P300

Active BCI:

- All the above
- Induction of stimulae

Evoked potentials

One of the approaches in the interactive BCI
Types of evoked potentials:

- Visual: steady state visual evoked potentials (SSVEP)
- Audio: auditory steady state response (ASSR)
- Haptic: steady-state somatosensory evoked potential (SSSEP)

BCI as type of HMI

BCI can be treated as another input modality of the human-machine interface. As such it should be used where it is more convenient or there are no other alternatives. Examples here are scenarios with augmented or virtual reality (AR/VR) glasses and hand-busy/eyes-busy situations. Such situation can arise on the manufacturing floor when hands are holding tools or are in protecting gloves (no gesture input) and it is too noisy (no voice input).

Our current research directions

We target general population (non-intrusive pickup with low number of electrodes) in interactive BCI (signal limited to EEG or MEG) scenarios. The most promising applications include augmenting the UI of AR/VR glasses with BCI components.

RAND CORPORATION OBJECTIVE ANALYSIS. EFFECTIVE SOLUTIONS.

ARTICLE

Brain-Computer Interfaces Are Coming. Will We Be Ready?

August 27, 2020

Illustration by Alyson Youngblood/RAND Corporation

OVERVIEW

Humans controlling machines with their minds may sound like something from a sci-fi movie, but it’s becoming a reality through braincomputer interfaces. Understanding this emerging technology now can help ensure that effective policies are in place before BCI becomes a part of everyday life.

Three drones lift off, filling the air with their telltale buzz. They slowly sail upward as a fleet—evenly spaced and level—and then hover aloft.

On the ground, the pilot isn't holding a remote control. In fact, he isn't holding anything. He's just sitting there calmly, controlling the drones with his mind.

This isn't science fiction. This is a YouTube video from 2016.

In the clip, a mechanical engineering Ph.D. candidate at Arizona State University (ASU) sports an odd piece of headwear. It looks a bit like a swim cap, but with nearly 130 colorful sensors that detect the student's brain waves. These devices let him move the drones simply by thinking directional commands: up, down, left, right.

Today, this type of brain-computer interface (BCI) technology is still being developed in labs like the one at ASU in 2016, which has since moved to the University of Delaware. In the future, all kinds of BCI tech could be sold to consumers or deployed on the battlefield.

The fleet of mind-controlled drones is just one real-life example of BCI explored in an initial assessment of BCI by RAND Corporation researchers. They examined current and future developments in the world of BCI and evaluated the practical applications and potential risks of various technologies. Their study is part of RAND's Security 2040 initiative, which looks over the horizon and explores new technologies and trends that are shaping the future of global security.

“That video of the drones really struck me as we were researching,” said Anika Binnendijk, a political scientist at RAND and an author of the report.

“Some of this technology seems to be the stuff of science fiction. But it was intriguing to see

what has actually been achieved thus far in a laboratory setting, and then to think in a structured way about how it might be used outside of the lab.”

If today's achievements in brain-computer interface technology already seem unbelievable,

It stands to reason that BCI breakthroughs in the not-too-distant future could be truly momentous.

Share on Twitter

then it stands to reason that BCI breakthroughs in the not-toodistant future could be truly momentous. And that means we need to start thinking about them now.

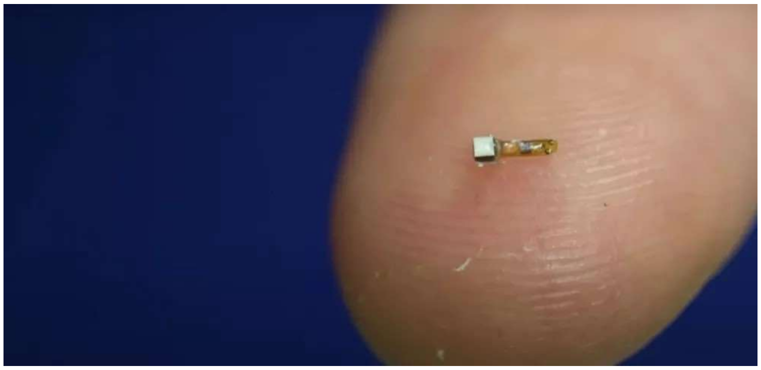
How Do BCIs Work?

BCI technology allows a human brain and an external device to talk to one another—to exchange signals. It gives humans the ability to directly control machines, without the physical constraints of the body.

Binnendijk and her colleagues analyzed existing and potential BCI tools that vary in terms of accuracy and invasiveness, two qualities that are closely related. The greater the proximity of an electrode to the brain, the stronger the signal—like a cerebral cell phone tower.

Non-invasive tools often use sensors applied on or near the head to track and record brain activity, just like the swim cap the ASU student used. These tools can be placed and removed easily, but their signals may be muffled and imprecise.

Invasive BCI would require surgery. Electronic devices would need to be implanted beneath the skull, directly into the brain, to target specific sets of neurons. BCI implants currently under development are tiny and can engage up to a million neurons at once. For example, a research team at the University of California, Berkeley, has created implantable sensors that are roughly the size of a grain of sand. They call these sensors “neural dust.”



A "neural dust" implantable sensor developed by researchers at UC Berkeley. Image from UC Berkeley / CC BY 3.0

Invasive methods would likely result in a much clearer and more accurate signal between the brain and the device. But as with any surgery, the procedures required to implant them would come with health risks.

A World of Possibilities

By creating the ability for humans to communicate directly with machines, BCI has the potential to influence all facets of life. But Timothy Marler, a senior research engineer at RAND and coauthor of the report, says that it makes sense to start by studying an emerging technology like BCI through a military lens. Why? Because war is one of the most fraught and complicated scenarios imaginable.

“If I can use it in a war, I could probably use it during a natural disaster like a tsunami or an earthquake. And frankly, I could use it more to save lives,” said Marler. “Those are good things.

But we aren’t necessarily advocating the use of these technologies. We're testing the viability of their use.”

Most BCI technologies are still in the early stages of development and are actively being researched and funded by the Defense Advanced Research Projects Agency (DARPA), the Army Research Lab, the Air Force Research Laboratory, and other organizations. With the power of BCI tools, the U.S. military could potentially enhance the physical and cognitive power of its personnel.

BCI could also provide major medical benefits in the military and civilian worlds. For instance, amputees could directly control sophisticated prosthetic limbs. And implanted electrodes could improve memory for people dealing with Alzheimer's disease, stroke, or head injuries. Binnendijk, recalling a young neighbor who currently controls her mobility by using a joystick, is hopeful that the technology might one day revolutionize the girl's ability to navigate the world.

Based on their analysis of current BCI development and the types of tasks that future tactical military units might face, the RAND team created a toolbox that catalogs how BCI might be useful in the coming years. Some BCI functions may be available within a relatively short time (within a couple of decades or so). But others, especially those that transfer more complicated data, could take much longer to mature. The team then tested this toolbox by bringing together neuroscientists and

individuals with operational warfighting experience to play a national security game.

A Systematic Approach

RAND researchers developed a path for determining where BCI technology stands now and where it could potentially go. They applied a comprehensive method that could be applied to other emerging technologies.

Step 1: Analysis

Conduct a literature review and interviews with experts.

Step 2: Toolbox

Break the technology down into practical tools.

Step 3: Tabletop Game

Facilitate a structured discussion of how and where to use those tools.

Step 4: Recommendations

Encourage developers to create products that respond to users' real needs.

Researching Tomorrow's Technology Today

As with any emerging technology, BCI carries many risks and unknowns. Before BCI matures, it's important for developers to plan ahead and consider the ethical and policy issues surrounding complicated and potentially frightening scenarios.

For instance, advanced BCI technology could be used to reduce pain or even regulate emotions. What happens when military personnel are sent into battle with a reduced sense of fear? And when they return home, what psychological side effects might veterans experience without their “superhuman” traits? Now may be the perfect time to think through these scenarios and ensure that there are guardrails in place ahead of time.

"There can be a knee-jerk reaction to emerging technology—that it will take jobs away or it will be militarized," said Marler. "But BCI is not that different than the automobile; it can be dangerous, but it can be very helpful.

As BCI developers prepare, they should carefully weigh the opportunities against the risks.

Share on Twitter

"I wish we had these policy discussions about artificial intelligence and robotics 20 years ago because, in many ways, folks are now being reactive. People fear what they don't understand. We all need to understand BCI, so we can ensure that we're not reckless with it."

As BCI developers prepare, they should carefully weigh the opportunities against the risks.

hing Potential Opportunities and Risks of BCI

gmented human ities

er information sharing and oved situational awareness d lead to **more rapid and rate decisions**.

ple could **control machines their thoughts**.

ple's **memory, attention s, and cognitive**

ormance could be oved.

Better understanding of human experience

People could **monitor for excessive stress or cognitive workload**.

People could develop a **better understanding of how physiological states affect** cognitive and motor **performance**.

Improved ability to succeed in challenging circumstances

Search-and-rescue operations in remote or otherwise inaccessible environments **could be improved**.

People could communicate silently and without risk of radio interference.

New health trea options

People who are una limbs could walk, m physical objects, or s interactions with pros exoskeletons.

Pain, depression, posttraumatic stres severe anxiety coul without pharmaceutic

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misused for of
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Better understanding of human experience

Interpersonal **relationships may be profoundly altered**.

People may be psychologically harmed if "superhuman" capabilities are revoked—for example, at the end of military service.

Long-term mental effects are unknown.

Ethical impacts and inequity

In war, **combat speed could outpace human decisionmaking speed**. Rapidly sharing information between people and machines raises ethical issues of accountability in war.

Unequal access to BCI technology could **widen existing social, political, and economic inequities**.

Physical harm

Implants introduce **hemorrhaging, infec brain damage**

Long-term physical unknown.

ris

The report highlights recommendations for the U.S. government, including planning to address a lack of trust in BCI technologies among the service members who may be expected to use them, and guidance to ensure ethical applications. The researchers also stress the importance of creating tools that respond to actual needs, rather than falling in love with "an exquisite technology," as Binnendijk put it, and developing something just because it's possible. These and other considerations could help reduce risks as BCI capabilities mature.

The thought-powered drones that first intrigued Binnendijk when she began this study may eventually be the ancestors of hands-free swarms of drones, robots, or even vehicles.

Binnendijk says it's important to analyze emerging technologies from a policy perspective to understand how they might be useful in the future.

“We have an opportunity to get ahead of the game. This is something we should be thinking about now, before BCI technologies become a reality in the everyday world.”

Project Credits

STORY: Marissa Norris

DESIGN AND DEVELOPMENT: Alyson Youngblood

More about this research

The research on which this article is based was conducted by RAND researchers. The full report, Brain-Computer Interfaces: U.S. Military Applications and Implications, An Initial Assessment (by Anika Binnendijk, Timothy Marler, and Elizabeth M. Bartels, 2020), was peer-reviewed and published to rand.org; it is free to read online or download for personal use. Learn more about RAND copyright and permissions.

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Brain-Computer Interface: Advancement and Challenges

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Sung-Phil Kim, Academic Editor

Abstract

Brain-Computer Interface (BCI) is an advanced and multidisciplinary active research domain based on neuroscience, signal processing, biomedical sensors, hardware, etc. Since the last decades, several groundbreaking research has been conducted in this domain. Still, no comprehensive review that covers the BCI domain completely has been conducted yet. Hence, a comprehensive overview of the BCI domain is presented in this study. This study covers several applications of BCI and upholds the significance of this domain. Then, each element of BCI systems, including techniques, datasets, feature extraction methods, evaluation measurement matrices, existing BCI algorithms, and classifiers, are explained concisely. In addition, a brief overview of the technologies or hardware, mostly sensors used in BCI, is appended. Finally, the paper investigates several unsolved challenges of the BCI and explains them with possible solutions.

Keywords: brain-computer interface, signal processing, biomedical sensors, systematic review

1. Introduction

The quest for direct communication between a person and a computer has always been an attractive topic for scientists and researchers. The Brain-Computer Interface (BCI) system has directly connected the human brain and the outside environment. The BCI is a real-time brain-machine interface that interacts with external parameters. The BCI system employs the user's brain activity signals as a medium for communication between the person and the computer, translated into the required output. It enables users to operate external devices that are not controlled by peripheral nerves or muscles via brain activity.

BCI has always been a fascinating domain for researchers. Recently, it has become a charming area of scientific inquiry and has become a possible means of proving a direct connection between the brain and technology. Many research and development projects have implemented this concept, and it has also become one of the fastest expanding fields of scientific inquiry. Many scientists tried and applied various communication methods between humans and computers in different BCI forms. However, it has progressed from a simple concept in the early days of digital technology to extremely complex signal recognition, recording, and analysis techniques today. In 1929, Hans Berger [1] became the first person to record an Electroencephalogram (EEG) [2], which shows the electrical activity of the brain that is measured through the scalp of a human brain. The author tried it on a boy with a brain tumor; since then, EEG signals have been used clinically to identify brain disorders. Vidal [3] made the first effort to communicate between a human and a computer using EEG in 1973, coining the phrase "Brain-Computer Interface". The author listed all of the components required to construct a functional BCI. He made an experiment room that was separated from the control and computer rooms. In the experiment room, three screens were required; the subject's EEG was to be sent to an amplifier the size of an entire desk in the control area, including two more screens and a printer.

The concept of combining brains and technology has constantly stimulated people's interest, and it has become a reality because of recent advancements in neurology and engineering, which have opened the pathway to repairing and possibly enhancing human physical and mental capacities. The sector flourishing the most based on BCI is considered the medical application sector. Cochlear implants [4] 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 [5]. Every application based on BCI follows different approaches and methods. Each method has its own set of benefits and drawbacks. The degree to which a performance can be enhanced while minute-to-minute and day-to-day volatility are reduced is crucial for the future of BCI technology. Such advancements rely on the capacity to systematically evaluate and contrast different BCI techniques, allowing for the most promising approaches to be discovered. In addition, this versatility around BCI technologies in different sectors and their applications can seem so complex yet so structured. Most of the BCI applications follow a standard structure and system. This basic structure of BCI consists of signal acquisition, pre-processing, feature extraction, classification, and control of the devices. The signal acquisition paves the way to connecting a brain and a computer and to gathering knowledge from signals. The three parts of pre-processing, feature extraction, and classification are responsible for making the associated signal more usable. Lastly, control of the devices points out the primary motivation: to use the signals in an application, prosthetic, etc.

The outstanding compatibility of various methods and procedures in BCI systems demands extensive research. A few research studies on specific features of BCI have also been conducted. Given all of the excellent BCI research, a comprehensive survey is now necessary. Therefore, an extensive survey analysis was attempted and focused on nine review papers featured in this study. Most surveys, however, do not address contemporary trends and application as well as the purpose and limits of BCI methods. Now, an overview and comparisons of the known reviews of the literature on BCI are shown in Table 1.

Feedback

Table 1

A summary of recent surveys/reviews on various BCI technologies, signals, algorithms, classifiers, etc.

Ref.	Purposes	Challenges
[6]	Advantages, disadvantages, decoding algorithms, and classification methods of EEG-based BCI paradigm are evaluated.	Training time and fatigue, signal processing, and novel decoders, shared control to supervisory control in closed-loop.
[7]	A comprehensive review on the structure of the brain and on the phases, signal extraction methods, and classifiers of BCI	Human-generated thoughts are non-stationary, and generated signals are nonlinear.
[8]	A systematic review on the challenges in BCI and current studies on BCI games using EEG devices	Biased within the process of search and classification.
[9]	A well-structured review on sensors used on BCI applications that can detect patterns of the brain	The sensors are placed in the human brain when neurosurgery is needed, which is a precarious process.
[10]	A brief review on standard invasive and noninvasive techniques of BCI, and on existing features and classifiers	To build brain signal capture systems with low-density electrodes and higher resolution.
[11]	This paper briefly describes the application of BCI and neurofeedback related to haptic technologies	This study only covers a small domain of BCI (haptic technology)
[12]	This survey mainly focuses on identifying emotion with EEG-based BCI, with a brief discussion on feature extraction, selection, and classifiers	There are no real-life event datasets, and the literature could not sense the mixed feelings simultaneously.
[13]	This paper refers to applying only noninvasive techniques on BCI and profound learning-related BCI studies	This study exclusively covers noninvasive brain signals.
[14]	This review focused on popular techniques such as deep learning models and advances in signal sensing technologies	Popular feature extraction processes, methods, and classifiers are not mentioned or reviewed.

Abiri, R. et al. [6] evaluated the current review on EEG-based various experimental paradigms used by BCI systems. For each experimental paradigm, the researchers experimented with different EEG decoding algorithms and classification methods. The researchers overviewed the paradigms such as Motor imagery paradigms, Body kinematics, Visual P300, Evoked potential, and Error related potential and the hybrid paradigms analyzed with the classification methods and their applications. Researchers have already faced some severe issues while exploring BCI paradigms, including training time and fatigue, signal processing, and novel decoders; shared control to supervisory control in closed-loop; etc. Tiwari, N. et al. [7] provided a complete assessment of the evolution of BCI and a fundamental introduction to brain functioning. An extensive comprehensive revision of the anatomy of the human brain, BCI, and its phases; the methods for extracting signals; and the algorithms for putting the extracted information to use was offered. The authors explained the steps of BCI, which consisted of signal acquisition, feature extraction, and signal classification. As the human brain is complex, human-generated thoughts are non-stationary, and generated signals are nonlinear. Thus, the challenging aspect is to develop a system to find deeper insights from the human brain; then, BCI application will perform better with these deeper insights. Vasiljevic, G.A.M. et al. [8] presented a Systematic Literature Review (SLR) conclusion of BCI games employing consumer-grade gadgets. The authors analyzed the collected data to provide a comprehensive picture of the existing reality and obstacles for HCI of BCI-based games utilizing consumer-grade equipment. According to the observations, numerous games with more straightforward commands were designed for research objectives, and there was a growing amount of more user-friendly BCI games, particularly for recreation. However, this study is limited to the process of search and classification. Martini, M.L. et al. [9] investigated existing BCI sensory modalities to convey perspectives as technology improves. The sensor element of a BCI circuit determines the quality of brain pattern recognition, and numerous sensor modalities are presently used for system applications, which are generally either electrode-based or functional neuroimaging-based. Sensors differed significantly in their inherent spatial and temporal capabilities along with practical considerations such as invasiveness, mobility, and maintenance. Bablani, A. et al. [10] examined brain reactions utilizing invasive and noninvasive acquisition techniques, which included electrocorticography (ECoG), electroencephalography (EEG), magnetoencephalography (MEG), and magnetic resonance imaging (MRI). For operating any application, such responses must be interpreted utilizing machine learning and pattern recognition technologies. A short analysis of the existing feature extraction techniques and classification algorithms applicable to brain data has been presented in this study.

Fleury, M. et al. [11] described various haptic interface paradigms, including SMR, P300, and SSSEP, and approaches for designing relevant haptic systems. The researchers found significant trends in utilizing haptics in BCIs and NF and evaluated various solutions. Haptic interfaces could improve productivity and could improve the relevance of feedback delivered, especially in motor restoration using the SMR paradigm. Torres, E.P. et al. [12] conducted an overview of relevant research literature from 2015 to 2020. It provides trends and a comparison of methods used in new implementations from a BCI perspective. An explanation of datasets, emotion elicitation methods, feature extraction and selection, classification algorithms, and performance evaluation is presented. Zhang, X. et al. [13] discussed the classification of noninvasive brain signals and the fundamentals of deep learning algorithms. This study significantly gives an overview of brain signals and deep learning approaches to enable users to understand BCI research. The prominent deep learning techniques and cutting-edge models for brain signals are presented in this paper, together with specific ideas for selecting the best deep learning models. Gu, X. et al. [14] investigated the most current research on EEG signal detection technologies and computational intelligence methodologies in BCI systems that filled in the loopholes in the five-year systematic review (2015–2019). The authors demonstrated sophisticated signal detecting and augmentation technologies for collecting and cleaning EEG signals. The researchers also exhibited computational intelligence techniques, such as interpretable fuzzy models, transfer learning, deep learning, and combinations for monitoring, maintaining, or tracking human cognitive states and the results of operations in typical applications.

The study necessitated a compendium of scholarly studies covering 1970 to 2021 since we analyze BCI in detail in this literature review. We specialized in the empirical literature on BCI from 2000 to 2021. For historical purposes, such as the invention of BCI systems and their techniques, we selected some publications before 2000. Kitchenham [15,16] established the Systematic Literature Review (SLR) method, which is applied in the research and comprises three phases: organizing, executing, and documenting the review. The SLR methodologies attempted to address all possible questions that could arise as the current research progresses. The recent study's purpose is to examine the findings of numerous key research areas. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines were used to put together the essential materials for this study, which consists of four parts: identification, scanning, eligibility testing, and inclusion. We gathered 577 papers from a variety of sources and weeded out duplicates and similar articles. Finally, we carefully chose 361 articles and sources for monitoring and review. The PRISMA process is presented in Figure 1.

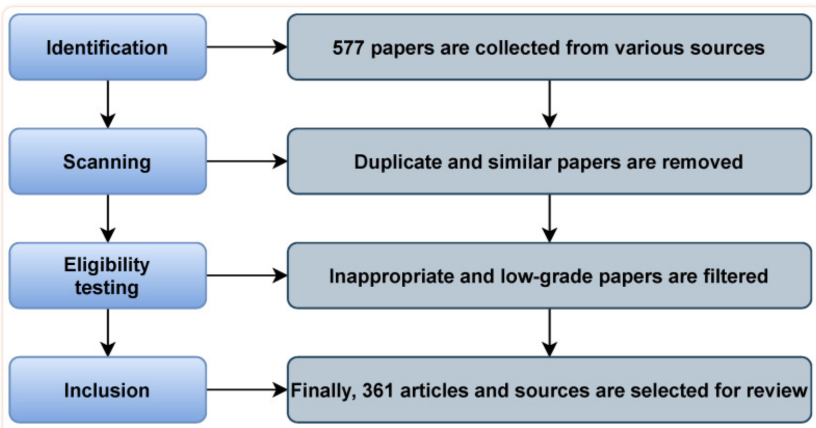

Figure 1

The PRISMA process that is followed in this article.

However, this research looks at the present challenges and difficulties in this BCI field. Furthermore, this study generates ideas and suggestions for future research subjects. The following are the research's total contributions:

- The paper explicitly illustrates Brain-Computer Interface's (BCI) present, past, and future trends and technologies.
- The paper presents a taxonomy of BCI and elaborates on the few traditional BCI systems with workflow and architectural concepts.
- The paper investigates some BCI tools and datasets. The datasets are also classified on different BCI research domains.
- In addition, the paper demonstrates the application of BCI, explores a few unsolved challenges, and analyzes the opportunities.

After reading this section, one should understand BCI and how to get started with it. Our motivation to work with BCI started from a desire to learn more about this domain. Furthermore, the BCI has a bright future ahead of it, as it has a lot to offer in the medical field and in everyday life. BCI can change one's incapability and can make life and work easy, as detailed in the following section. The applications, problems, future, and social consequences of BCI have also fueled our enthusiasm for this research.

The remainder of the paper is constructed as follows. The motivation of this work and diverse applications of BCI systems are illustrated in Section 2. Section 3 describes the structure of BCI and briefly reviews the most popular techniques of BCI. In Section 5, different categories of datasets available publicly are displayed. In Section 7, the most widely used methods for signal enhancement and feature extraction of BCI are discussed. The most commonly known classifiers are reviewed in Section 8. A broad discussion on the evaluation metrics for BCI is given in Section 9. The challenges faced most commonly during the BCI process are reviewed in Section 10. Lastly, this paper provides a conclusion in Section 11.

2. Applications of BCI

BCIs may be used for various purposes and the application determines the design of a BCI. According to Nijholt [17], applications based on BCI have two methods of usability. One can command whether the other one can be observed or monitored. The majority of command applications concentrate on manipulating brain impulses using electrodes to control an external device. On the other hand, applications that involve observation focus on recognizing a subject's mental and emotional state to behave appropriately depending on their surroundings. Some applications of BCI [18] based on usability are described below:

2.1. Biomedical Applications

The majority of BCI integrations and research have been focused on medical applications, with many BCIs aiming to replace or restore Central Nervous System (CNS) functioning lost with sickness or by accident. Other BCIs are more narrowly targeted. In diagnostic applications, on treatment and motor rehabilitation following CNS disease or trauma, BCIs for biological purposes are also employed in affective application domains. Biomedical technologies and applications can minimize extended periods of sickness, can provide supervision and protection by empowering persons with mobility difficulties, and can support their rehabilitation. The necessity to build accurate technology that can cope with potentially abnormal brain responses that might occur due to diseases such as brain stroke is a significant challenge in developing such platforms [19]. The following subsections go through each of these applications in further detail.

2.1.1. Substitute to CNS

These substitution means that it can repair or replace CNS functioning lost due to diseases such as paralysis and spinal cord injury due to stroke or trauma. In addition, due to changed brain functions, individuals with such illnesses might suffer and developing such technology can be difficult.

Myoelectrics, known as a motor action potential, which captures electrical impulses in muscles, is now used in several robotic prosthetics. Bousseta, R. et al. [20] provided an experimental technology for controlling the movement of a robotic prosthetic arm with mental imagery and using cognitive tasks, which can move in four directions like left, right, up, and down.

Feedback

2.1.2. Assessment and Diagnosis

The usage of BCIs in a clinical context can also help with assessment and diagnosis. Perales [21] suggested a BCI for assessing the attention of youngsters with cerebral palsy while playing games. Another research [22] looked into using BCI to capture EEG characteristics as a tool for diagnosing schizophrenia. There are also various diagnostic methods such as the detection of brain tumors [23], the identification of breast cancer [24], parkinson's disease [25] etc. Diagnoses of several diseases in children including epilepsy, neurodegenerative disorders, motor disabilities, inattentiveness, or different types of ADHD [26] are possible. Assessment and diagnosis technologies are essential to patient well-being. Their functioning must be fine-tuned to guarantee that they are safe, acceptable, and accurate to industry standards.

2.1.3. Therapy or Rehabilitation

BCI is being used in therapeutic applications besides neurological application and prosthetics nowadays. Among the many applications, post-stroke motor rehabilitation shows promising results using BCI. Stroke is a disease that causes long-term disability to the human body and hampers all kinds of motor or vigorous activity due to an impediment of blood flow. Stroke rehabilitation application has promised to aid these activities or user imaginations through a robot or other types of machinery [27,28,29]. Some other applications treat neurological disorders such as Parkinson's disease (PD), cluster headaches, tinnitus, etc. Deep Brain Stimulation (DBS) is an established treatment for PD as it delivers electrical impulses to a targeted area of the brain responsible for the symptoms [30]. Some stimulation BCI devices are used to process calmness during migraine attacks and cluster headaches. Lastly, a CNS disorder known as tinnitus is also in development to provide treatment by identifying brain patterns that are changed due to the disease [31]. Lastly, treatment for auditory verbal hallucinations (AVHs), best known as schizophrenia, is a possibility besides diagnosis [32,33].

2.1.4. Affective Computing

Users' emotions and state of mind are observed in affective computing BCIs, with the possibility of altering their surrounding environment to improve or change that emotion. Ehrlich, S. et al. [34] created a closed-loop system in which music is generated and then replayed to listeners based on their emotional state. Human emotional states and sensory connections can be studied with a device that is related to BCI system. Patients suffering neurological diseases also can benefit from affective computing to help them convey their feelings to others [35].

2.2. Non-Biomedical Applications

BCI technologies have shown economic promise in recent years, notably in the field of non-biomedical applications. Most of these applications consist of entertaining applications, games, and emotional computation. In comparison, researchers focus on robustness and high efficiency in medical and military applications, and innovations targeted at leisure or lifestyle demand a greater emphasis on enjoyment and social elements. The most challenging aspect of this entertainment application is that it must be a user favorite to be commercially successful. As an example, some of the most popular forms of amusement are as follows:

2.2.1. Gaming

BCIs focused mainly on the gaming sector have grown in importance as a research topic. However, gaming BCIs are currently a poor substitute for standard game control methods [36]. BCI in gaming is an area where further research is needed to make games more user-friendly. In some cases, EEG data make BCI games more utilizable and increase engagement, and the system tracks each player's enthusiasm level and activates dynamic difficulty adjustment (DDA) when the players' excitement drops [37]. When developing such systems, fine-tuning the algorithms that regulate the game's behavior is a big challenge. Some other games are based on BCI, as it is not visually intense and the graphics are not compatible with the recent generation. With setbacks, there is an engaging future for an Adaptation of P300 based Brain-Computer Interface for Gaming [38], which is gaining more popularity as these are very flexible to play.

2.2.2. Industry

EEG-based BCIs can also be used in industrial robotics, increasing worker safety by keeping people away from potentially demanding jobs. These technologies could substitute the time-consuming button and joystick systems used to teach robots in industrial applications; can detect when a person is too tired or ill to operate the machinery; and can take the necessary precautions to avoid injury, such as stopping the machinery [38].

2.2.3. Artistic Application

The four types of artistic applications recognized by BCIs are passive, selective, direct, and collaborative. Passive artistic BCIs need not require active user input to use the user's brain activity to determine which pre-programmed responses to produce. Every user has had some limited control over the process within selective systems. Still, they will never be in charge of the creative product. Direct artistic BCIs provide users with far more flexibility, generally allowing them to choose items from extensive menus, such as brush type and managing brush stroke movements [39]. Lastly, the collaborative system is controlled by different users [40].

2.2.4. Transport

BCI is used in transportation monitoring which tracks awareness to assess driver weariness and to enhance airline pilot performances. In the BCI system, mistakes can be costly regarding lives and monetary obligations on the entities involved when such technologies are utilized in critical applications [41,42].

3. Structure of BCI

Feedback

The BCI system operates with a closed-loop system. Every action taken by the user is met with some feedback. For example, an imagined hand movement might result in a command that causes a robotic arm to move. This simple movement of this arm needs a lot of processes inside it. It starts from the brain, which is one of our body's most extensive and most complicated organs. It is made up of billions of nerves that link billions of synapses to communicate. The processes from taking signals from the human brain to transforming into a workable command are shown in Figure 2 and described below:

- Signal acquisition: In the case of BCI, it is a process of taking samples of signals that measure the brain activity and turning them into commands that can control a virtual or real-world application. The various techniques of BCI for signal acquisition are described later.
- Pre-processing: After the signal acquisition, the pre-processing of signals is needed. In most cases, the collected signals from the brain are noisy and impaired with artifacts. This step helps to clean this noise and artifacts with different methods and filtering. That is why it is named signal enhancement.
- Feature extraction: The next stage is feature extraction, which involves analyzing the signal and extracting data. As the brain activity signal is complicated, it is hard to extract useful information just by analyzing it. It is thus necessary to employ processing algorithms that enable the extraction of features of a brain, such as a person's purpose.
- Classification: The next step is to apply classification techniques to the signal, free of artifacts. The classification aids in determining the type of mental task the person is performing or the person's command.
- Control of devices: The classification step sends a command to the feedback device or application. It may be a computer, for example, where the signal is used to move a cursor, or a robotic arm, where the signal is utilized to move the arm.

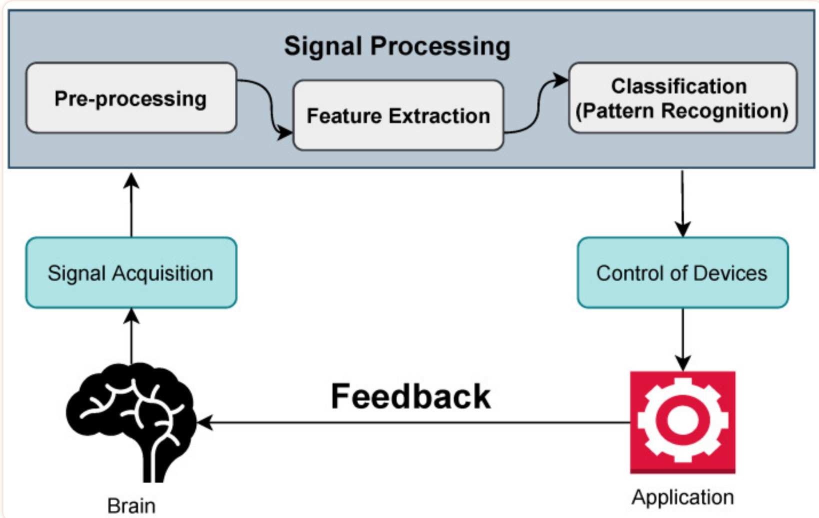

Figure 2

Basic architecture of a BCI system.

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. The BCI techniques are discussed in following parts.

From the above Figure 3, we can classify BCI from different aspects such as dependability, invasiveness, and autonomy.

- Dependability: BCI can be classified as dependent or independent. Dependent BCIs necessitate certain types of motor control from the operator or healthy subjects, such as gaze control. On the other hand, independent BCIs do not enable the individual to exert any form of motor control; this type of BCI is appropriate for stroke patients or seriously disabled patients.
- Invasiveness: BCI is also classified into three types according to invasiveness: invasive, partially invasive, and non-invasive. Invasive BCIs are by far the most accurate as they are implanted directly into the cortex, allowing researchers to monitor the activity of every neuron. Invasive varieties of BCI are inserted directly into the brain throughout neurosurgery. There are two types of invasive BCIs: single unit BCIs, which detect signals from a single place of brain cells, and multi-unit BCIs, which detect signals from several areas. Semi-invasive BCIs use Electrocorticography (ECoG), a kind of signal platform that enables electrodes to be placed on the attainable edge of the brain to detect electrical impulses originating from the cerebral cortex. Although this procedure is less intrusive, it still necessitates a surgical opening in the brain. Noninvasive BCIs use 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 noninvasive techniques used it to analyze the brain. However, because of the low cost and portability of the gear, EEG is the most commonly used.

- Autonomy: BCI can operate either in a synchronous or asynchronous manner. Time-dependent or time-independent interactions between the user and system are possible. The system is known as synchronous BCI if the interaction is carried out within a particular amount of time in response to a cue supplied by the system. In asynchronous BCI, the subject can create a mental task at a certain time to engage with the system. Synchronous BCIs are less user-friendly than asynchronous BCIs; however, designing one is substantially easier than developing an asynchronous BCI.

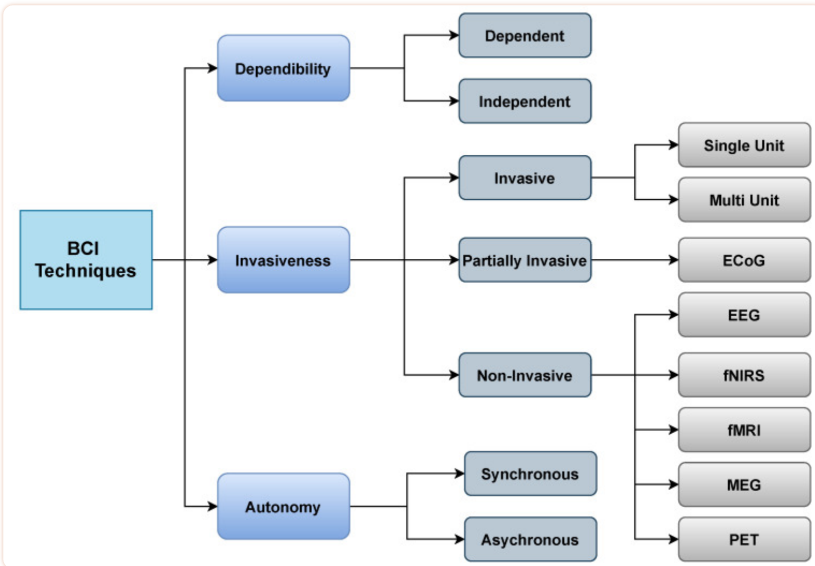

Figure 3

The classification/taxonomy of the BCI system.

As the motive of this research work is to focus on advancements of BCI, the most advanced and mostly used techniques that is based on invasiveness are described in the following part. Based on invasiveness, BCI is classified into three categories that are more familiar. In the consequent section, we address these three categories and describe them elaborately.

3.1. Invasive

The types of BCI that are invasive are inserted directly into the brain with neurosurgery. Invasive BCIs seem to be the most accurate even though they are implanted directly into the cortex as it is allowed to track every neuron's action. Invasive BCI also has two units rather than parts. The first unit is single-unit BCIs that detect signals from a single location of brain cells, whereas multi-unit BCIs detect numerous areas, the second unit [43]. However, the neurosurgery treatment has various flaws, such as the possibility of scar tissue formation. The body responds to the foreign object by forming a scar around the electrodes, leading the signal to deteriorate. Since neurosurgery is a dangerous and costly procedure, invasive BCI is mainly used on blind and paralyzed patients.

3.2. Partially Invasive

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Although this approach is not as intrusive, it still involves brain surgery. Electrocorticography (ECoG) is a sort of partially invasive BCI monitoring system that places electrodes in the cortex surface of the brain to produce signals with electrical activity. For example, blinking allows your brain to discharge electrical activity. When investigating signals, though, these involuntary actions are generally not of interest since they are in the way of what we search for. It is a form of noise. ECoGs are less considered with noise than non-invasive BCI, making interpretation easier [44].

Electrocorticography (ECoG)

Electrocorticography (ECoG) [45] is an partially invasive method that measures the brain's electrical activity. In another sense, the participant's skull must be evacuated, and the electrodes must be placed right at the brain's service. Consequently, this electrode is located on the skull. The particular resolution of the recorded signals is considerably better than EEG. The signal-to-noise ratio is superior compared with the closer proximity to cerebral activity. Furthermore, motion artifacts such as blinks and eye movement have a significantly lower impact on ECoG signals. However, ECoG would only be helpful in the accessible brain area and is close to impossible to utilize outside of a surgical setting [46].

3.3. Noninvasive

Noninvasive neuroimaging technologies have also been used as interfaces in human research. Noninvasive EEG-based BCIs account for the vast bulk of published BCI research. EEG-based noninvasive technologies and interfaces have been employed in a considerably more comprehensive range of applications. Noninvasive apps and technologies are becoming increasingly popular in recent years since they do not require any brain surgery. In the noninvasive mode, a headpiece or helmet-like electrode is utilized outside the skull to measure the signal by causing electrical activity in the brain. There are some well-known and widely used ways for measuring these electrical activity or potentials, such as Electroencephalography (EEG), Magnetoencephalography (MEG), Functional Magnetic Resonance Imaging (fMRI), Facial Near Infrared Spectroscopy (fNIRS), and Positron Emission Tomography (PET). An elaborate description of BCI techniques is given below:

3.3.1. Electroencephalography (EEG)

EG monitors electrical activity in the scalp generated by activating a few of the brain's neurons. Several electrodes implanted on the scalp directly, mainly on the cortex, are often used to record these electrical activities quickly. For its excellent temporal resolution, ease of use, safety, and affordability, EEG is the most used technology for capturing brain activity. Active electrodes and passive electrodes are indeed the two types of electrodes that can be utilized. Active electrodes usually feature an integrated amplifier, whereas passive electrodes require an external amplifier to magnify the detected signals. The prime objective of implementing either embedded or external amplifiers is to lessen the impact of background noise and other signal weaknesses caused by cable movement. One of the issues with EEG is that it necessitates the use of gel or saline solutions to lower the resistance of skin-electrode contact. Furthermore, the signal quality is poor, and it is altered by background noise. The International 10–20 system [47] is often used to implant electrodes over the scalp surface for recording purposes. The electrical activities across various frequency bands are used to describe EEG in general.

3.3.2. Magnetoencephalography (MEG)

The magnetic fields created by current flow in the brain are measured using MEG (Magnetoencephalography). Electric fields have significantly more interrupted travel via the skull than magnetic fields, therefore it has superior spatial resolution than EEG. A functional neuroimaging technique is applied to measure and evaluate the brain's magnetic field. MEG operates on the outside of the head and is now a part of the clinical treatment regularly. David Choen [48,49] was the first to invent it in 1968 by utilizing a conduction copper detector inside a shielded chamber to reduce background noise. Improved MEG signals have recently been produced using more sensitive sensors such as superconducting quantum interference devices (SQUID) [50]. MEG has become significant, especially for patients with epilepsy and brain tumors. It may aid in detecting regions of the brain with average function in individuals with epilepsy, tumors, or other mass lesions. MEG operates with magnetic waves rather than electrical waves so that it could contribute additional information to EEG. MEG is also capable of capturing signals with high temporal and spatial resolution. Therefore, to detect cerebral activity that creates tiny magnetic fields the scanners must be closer to the brain's surface. As a result, specific sensors are required for MEG, such as superconducting quantum interference (SQUID) sensors [51].

3.3.3. Functional Magnetic Resonance Imaging (fMRI)

Noninvasive functional magnetic resonance imaging (fMRI) is used to evaluate the fluctuation in blood oxygen levels throughout brain activities. fMRI has an excellent spatial resolution, which makes it ideal for identifying active areas of the brain [52]. The time resolution of fMRI is comparatively low, ranging from 1 to 2 s [53]. It also has low resolution when it comes to head movements, which could result in artifacts. In the 1990s, functional magnetic resonance imaging (fMRI) was created. It is a noninvasive and safe technology that does not include the use of radiation, is simple to use, and has great spatial and temporal resolution. Hemoglobin in capillary red blood cells in the brain transports oxygen to the neurons. As a result of the increased demand for oxygen, blood flow increases. If haemoglobin is oxygenated, its magnetic properties vary. The MRI equipment, which is a cylindrical tube with a strong electromagnet, can determine which regions of the brain are activated because of this difference. That is how fMRI works. There is also a specific application or software known as diffusion MRI, which generates images from the data or results that use water molecules' diffusion. Diffusion-weighted and diffusion tensor imaging (DWI/DTI) facilitates this exploration of the microarchitecture of the brain. Diffusion-weighted magnetic resonance imaging (DWI or DW-MRI) imaging renders picture variation depending on variances in the degree of diffusion of water particles inside the brain. Diffusion depicts the stochastic thermic mobility of particles. Diffusion inside the brain is defined by several agents, including representing particles beneath study, the temperature, and the microenvironmental structure in which the diffusion occurs [54]. Diffusion tensor imaging (DTI) investigates the three-dimensional form of the diffusion, also recognized as diffusion tensor. It is a powerful MRI modality that produces directional knowledge about the water motion in a voxel. It exhibits noninvasively microscopic tissue features that surpass the ability of any other imaging methods [55].

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3.3.4. Functional Near-Infrared Spectroscopy (fNIRS)

The infrared radiation is projected into the brain using fNIRS equipment [53,56] 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. fMRI is a technique that monitors variations in oxygen levels caused by various activities. 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.

3.3.5. Positron Emission Tomography (PET)

PET (positron emission tomography) is a sophisticated imaging tool for examining brain activities in real-time. It enables noninvasive measurement of cerebral blood flow, metabolism, and receptor binding in the brain. Due to the relatively high prices and complexity of the accompanying infrastructure, including cyclotrons, PET scanners, and radio chemistry laboratories, PET was previously only used in research. PET has been widely employed in clinical neurology in recent years due to technological improvements and the proliferation of PET scanners to better our understanding of disease etiology, to help in diagnosis, and to monitor disease progression and response to therapy [57]. PET medications such as radiolabeled choline, fluciclovine (18F-FACBC), and compounds targeting prostate-specific membrane antigen are now being researched and explored to improve noninvasive prostate cancer localization diagnostic performance [58].

4. Brain Control Signals

The brain-computer interface (BCI) is based on signal amplification that comes directly from the brain. Several of these signals are simple to extract, while others are more difficult and require additional preprocessing [53]. These control signals can be classified into one of three groups: (1) evoked signals, (2) spontaneous signals, and (3) hybrid signals. A detailed overview of the three categories is given below. The control signals classification is shown in Figure 4.

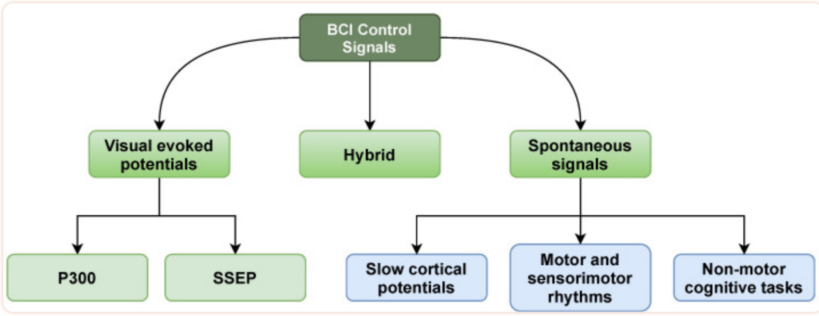

Figure 4

The basic architecture of BCI control signals.

4.1. Visual Evoked Potentials

Electrical potentials evoked by short visual stimuli are known as VEPs. The visual cortex's potentials are monitored, and the waveforms are derived from the EEG. VEPs are generally used to assess the visual pathways from the eye to the brain's visual cortex. Middendorf et al. published a procedure for measuring the position of the user's gaze using VEPs in 2000 [59]. The user is confronted with a screen that displays several virtual buttons that flash at varied rates. The frequency of the photic driving reflex over the user's visual brain is determined after the user focuses their gaze on a button. Whenever the frequency of a shown button equals the frequency of the user, the system concludes that the user wants to pick it. Steady-State Evoked Potentials (SSEP) and P300 are two of the most well-evoked signals. External stimulation is required for evoked signals that can be unpleasant, awkward, and exhausting for the individual.

4.1.1. Steady-State Evoked Potential (SSEP)

SSEP signals are produced when a patient experiences periodic stimuli such as a flickering picture, modulated sound, or even vibrations [60,61]. The strength of the EEG signal in the brain must grow to meet the stimulus frequency. Signals in many brain locations are observed in terms of the sensory process. SSEP signals of different forms, such as steady-state visual potentials (SSVEPs), somatosensory SSEP, and auditory SSEP, are found. SSVEP is widely used in a variety of applications. These are normal brain reactions to repeating stimuli, which vary depending on the frequency with which they are presented. Although there are instances of BCI paradigms utilizing somatosensory (SSSEP) or auditory (SSAEP) stimuli, they are generally induced using visual stimuli (steady-state visually evoked potentials, SSVEP) [62].

4.1.2. P300 Evoked Potentials (P300)

The peaks in an EEG generated by infrequent visual, auditory, or somatosensory inputs are known as P300 evoked potentials. Without the need for training to use P300-based BCI systems. A matrix of symbols, in which selection is dependent on the participant's gaze, is a prominent use of P300-based BCI systems. Such a signal is typically produced using an "odd-ball" paradigm. The user is asked to respond to a random succession of stimuli, which is less frequent than others [63]. The P300-based EEG waves are triggered when this unusual stimulus is significant to the person. P300 does not reasonably require any subject training, although, it does need repetitive stimulation, which may tire the subject and may cause inconsistencies.

4.2. Spontaneous Signals

With no external cues, the person produces random signals willingly. These signals are produced without any external stimuli (somatosensory, aural, or visual). Motor and sensorimotor rhythms, Slow Cortical Potentials (SCPs), and non-motor cognitive signals are some of the most prominent spontaneous signals [53].

4.2.1. Motor and Sensorimotor Rhythms

Motor activities are linked to motor and sensorimotor rhythms. Sensorimotor rhythms are rhythmic oscillations in electrophysiological brain activity in the mu (Rolandic band, 7–13 Hz) and beta (13–30 Hz) frequencies. Motor imagery is the process of converting a participant's motor intentions into control signals employing motor imagery conditions [64]. The left-hand motion, in an instance, may result in EEG signals in the and rhythms and a decrease in certain motor cortex areas (8–12 Hz) and (18–26 Hz). Depending on the motor imagery rhythms, various applications can be used such as controlling a mouse or playing a game.

4.2.2. Slow Cortical Potentials (SCP)

SCP is indeed an EEG signal with a frequency less than 1 Hz [65]. It is a low-frequency potential observed in the frontal and central portions of the cortex and depolarization level variations throughout the cortical dendrites. SCP is a highly gradual change in brain activity, either positive or negative, that can only last milliseconds to several seconds. Through operant conditioning, the subject can control the movement of such signals. As a result, extensive training may be required in addition to that needed for motor rhythms. Many studies no longer choose SCP, and motor and sensorimotor rhythms have taken their place.

4.2.3. Non-Motor Cognitive Tasks

Cognitive objectives are utilized to drive the BCI in non-motor cognitive tasks. Several tasks, such as musical imagination, visual counting, mental rotation, and mathematical computation, might be completed [66]. Penny, W.D. et al. [67] used a pattern classifier with unclear parameters. The individual performed simple subtraction in one of their non-motor cognitive activities.

4.3. Hybrid Signals

The term "hybrid signals" refers to the utilization of a mixture of brain-generated signals for control. As a result, instead of measuring and using only one signal in the BCI system, a mix of signals is used. The fundamental goal of using two or more types of brain signals as input to a BCI system is to increase dependability while avoiding the drawbacks of each signal type [68].

Some research is addressed that the types of brain signals are classified into two categories [10]. These are event-related potentials and evoked brain potential. Three varieties are organized for evoked brain potential: Visual Evoked Potential (VEP), Tactile Evoked Potential (TEP), and Auditory Evoked Potential (AEP) [69].

5. Dataset

While analyzing the literature on BCI systems, we discovered various often used datasets that researchers used while implementing these techniques. In terms of the research, EEG is now the most frequent method for collecting brain data in BCI. As this is a noninvasive method and has convenient handling for most datasets, an EEG signal is used. However, for a variety of reasons, EEG does not provide a comprehensive method of data collection. It needs a variety of fixed things to acquire the data. Firstly, the signal must be acquired and stored by some subject, participants, or patients. It is unsuitable when only one subject requires the same arrangement as multiple subjects to obtain data. After the subjects are prepared, the electrodes (a gear mounted on the scalp) are attached to the individuals to capture and measure data. This data collection method lasted for several sessions, with a particular recording period determined by the work's purpose. The saved data in these sessions and recordings are primarily brain signals measured by a brain's action on a sure thing, such as a video or a picture. EEG signals differ from one participant to the next and from one session to the next. In this section, the datasets as well as the subjects and electrodes, channels, and sessions are described. The explanation is tabulated in Table 2, Table 3, Table 4, Table 5, Table 6, Table 7 and Table 8. In Table 2, some popular motor imagery datasets are illustrated. The most beneficial option for creating BCIs is motor imagery (MI) impulses captured via EEG, which offers a great degree of mobility. It enables people with motor disabilities to communicate with the device by envisioning motor movements without any external stimuli generated from the motor cortex. A few datasets based on error-related potentials (ErrPs) are exhibited in Table 3 . ErrPs is an EEG dataset that utilizes a P300-based BCI speller to boost the performance of BCIs. Detecting and fixing errors of the neuronal signature of a user's knowledge linked to a brain pattern is known as error-related potentials (ErrPs). Affective computing improves human–machine communication by identifying human emotions. Some mostly used emotion recognition datasets are shown in Table 4. Various EEG-based BCI devices can detect the user's emotional states to make contact effortless, more useable, and practical. The emotions extracted in emotion-recognition datasets are valence, arousal, calm, positive, exciting, happy, sad, neutral, and fear. In addition, it is certainly clear by now that brain signals or memory are a mixed emotion. The part where all of these mixed emotions are gathered from different body parts is known as a miscellaneous part of the brain. Therefore, miscellaneous datasets include memory signals, brain images, brain signals, etc. Some miscellaneous datasets are represented in Table 5. In EEG-based BCI, the signals can detect eye movement such as eye blinks, eye states, etc. The BCI datasets of eye blinks or movements include voluntary and involuntary eye states, blinks, and activities are illustrated in Table 6. Subsequently, the electrical response in the brain to a specific motor or cognitive event such as a stimulus is known as an event-related potential (ERP). An unwanted sound, a sparking light, or a blinking eye can be an example of a stimulus. BCI utilizing ERPs attempts to track attention, weariness, and the brain's reaction to this event-related stimulus. Table 7 is encapsulated with popular ERP datasets around. Moreover, the visual information-processing mechanism in the brain is reflected in Visually Evoked Potentials (VEPs). Flashing objects in the form of shifting colors or a reversing grid are frequent visual stimulators. The CRT/LCD monitor or flash tube/infrared diode (LED) is utilized for stimulus display in VEP-based BCIs. Frequently used VEP-based datasets with these utilized objects are represented in Table 8.

Table 2

A table of different types of motor imagery datasets of BCI.

Dataset Name	Subject (S)/Electrodes (E)/Channels (C)	Used in
Left or Right Hand MI [70]	S: 52	[71,72,73,74,75]
Motor Movement or Imagery Dataset	S: 109 E: 64	[76,77,78,79]
Grasp and Lift EEG [80]	S: 12	[81,82,83,84,85]
SCP data of Motor-Imagery [86]	S: 13 Recordings: 60 h	[87,88,89,90,91,92]
BCI Competition III [93]	S: 3 C: 60	[94,95,96]
BCI Competition IV-1	S: 7 C: 64	[97,98,99,100,101]
BCI Competition IV-2a	S: 9 E: 22	[102,103,104,105,106]
BCI Competition IV-2b	S: 9 E: 3	[107,108,109,110,111,112]
High-Gamma Dataset [113]	S: 14 E: 128	[114,115,116,117,118,119,120]
Left/Right Hand 1D/2D movements	S: one E: 19	[86,121,122,123]
Imagination of Right-hand Thumb Movement [124]	S: one E: 8	[83,125,126,127,128]
Mental-Imagery Dataset	S: 13	[129,130,131,132,133,134,135]

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Table 3

A table of different types of Error-Related Potentials (ErrP) dataset of BCI.

Dataset Name	Subject (S)/Electrodes (E)/Channels (C)	Used in
BCI–NER Challenge [136]	S: 26 C: 56	[137]
ErrP in a target selection task	S: E: 64	[138,139,140,141,142,143,144]
ErrPs during continuous feedback [145]	S: 10 E: 28	[146,147,148]

Table 4

A table of different types emotion recognition dataset of BCI.

Dataset Name	Subject (S)/Electrodes (E)/Channels (C)	Used in
DEAP [149]	S: 32 C: 32	[150,151,152,153,154,155,156,157]
Enterface'06 [158]	S: 5 C: 54	NA
HeadIT	S: 31	[159]
NeuroMarketing [160]	S: 25 E: 14	[161,162]
SEED [163]	S: 15 C: 62	[12,164,165,166,167,168,169]
SEED-IV	S: 15 C: 62	[170,171,172,173,174,175]
SEED-VIG [176]	E: 18	[137,177,178,179]
HCI-Tagging	S: 30	[180,181,182,183,184,185,186]
Regulation of Arousal [187]	S: 18	[52,130,188,189,190]
EEG Alpha Waves [191]	S: 20	[192]

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Table 5

A table of different types of miscellaneous datasets.

Dataset Name	Subject (S)/Electrodes (E)/Channels (C)	Used in
MNIST Brain Digits	S: Single Recordings: 2 s	[193,194]
Imagenet Brain	S: Single Recordings: 3 s	[195,196,197,198,199,200]
Working Memory [201]	S: 15 E: 64	[202,203,204,205]
Deep Sleep Slow Oscillation [201]	R: 10s	[206]
Genetic Predisposition to Alcoholism	S: 120 E: 64	[124,207,208,209,210,211,212]
Confusion during MOOC [213]	S:10	[214,215]

Table 6

A table of different types of eye-blink or movement datasets in BCI.

Dataset Name	Subject (S)/Electrodes (E)/Channels (C)	Used in
Voluntary-Involuntary Eye-Blinks [216]	S: 20 E: 14	[217]
EEG-eye state [124]	Recordings: 117 s	[218,219,220,221]
EEG-IO [222]	S: 20 Blinks: 25	[222,223]
Eye blinks and movements [222]	S: 12	[222,224]
Eye State Prediction [225]	S: Single Recordings: 117 s	[130,218,219,226,227,228]

Table 7

A table of different types Event-Related Potential (ERP) datasets in BCI. These datasets are collected from [229].

Dataset Name	Subject (S)/Electrodes (E)/Channels (C)	Used in
Target Versus Non-Target (2012)	S: 25 E: 16	NA
Target Versus Non-Target (2013)	S: 24 E: 16	[230]
Target Versus Non-Target (2014)	S: 71 E: 16	[231]
Target Versus Non-Target (2015)	S: 50 E: 32	[232,233,234]
Impedance Data	S: 12	[86,94,235,236,237,238]
Face vs. House Discrimination [239]	S: 7	[240,241]

Table 8

A table of different types of Visually Evoked Potential (VEP) datasets in BCI. These datasets are collected from [229].

Dataset Name	Subject (S)/Electrodes (E)/Channels (C)	Used in
c-VEP BCI	S: 9 C: 32	[242,243,244]
c-VEP BCI with dry electrodes	S: 9 C: 15	[243,245,246,247,248]
SSVEP	S: 30 E: 14	[249,250,251,252,253]
Synchronized Brainwave Dataset	Video stimulus	[254,255]

However, the dataset covers information recorded from the beginning of BCI. To extract information from datasets, feature extraction methods are necessary, which is reviewed in the following section.

6. Signal Preprocessing and Signal Enhancement

In most situations, the signal or data measured or extracted from datasets are filled with noise. With a natural human activity such as eye blinks and heartbeats, the collected data might become noisy. These noises are eliminated during the pre-processing step to produce clean data that may subsequently process the feature extraction and classification. This pre-processing unit is also known as signal enhancement since it cleans the signal in BCI. Some methods are used for signal enhancement in the BCI system, and these are explained elaborately in the following subsections.

6.1. Independent Component Analysis (ICA)

The noises and EEG signals are isolated in ICA by treating them as distinct entities. Furthermore, the data are retained during the removal of noises. This method divides the EEG data into spatially fixed and temporally independent components. In the case of computing and noise demonstrable, the ICA shows more efficiency [256].

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6.2. Common Average Reference (CAR)

It is most commonly employed as a basic dimensionality reduction technique. This approach decreases noise across all recorded channels, but this does not address channel-specific noise and may inject noise into an otherwise clean channel. It is a spatial filter that can be thought of as the subtraction of shared EEG activity, retaining only the idle action of each EEG particular electrode [256].

6.3. Adaptive Filters

The adaptive filter is a computational device for mathematical processes. It connects the adaptive filter's input/output signals iteratively. There are filter coefficients that are self-adjusted utilizing an adaptive algorithm. It works by altering signal properties depending on the characteristics of the signals under investigation [257].

6.4. Principal Component Analysis (PCA)

PCA is a technique for detecting patterns in data represented by a rotation of the coordinate axes. These axes are not aligned with single time points, but they depict a signal pattern with linear combinations of sets of time points. PCA keeps the axes orthogonal while rotating them to maximize variance along the first axis. It reduces feature dimensions and aids in data classification by completing ranking. In comparison with ICA, PCA compresses separate data better whether noise is eliminated with it or not [258].

6.5. Surface Laplacian (SL)

SL refers to a method of displaying EEG data with a high spatial resolution. SL can be generated using any EEG recording reference scheme as their estimates are reference-free. Based on the volume conductor's exterior shape, it is a general estimate of the current density entering or exiting the scalp through the skull, and it does not require volume conduction details. The advantage of SL is that it improves the spatial resolution of the EEG signal. However, SL seems not to demand additional operative neuroanatomy premises as it is sensitive to spline patterns and artifacts [259].

6.6. Signal De-Noising

Artefacts frequently corrupt EEG signals taken from brain. These artifacts must be removed from EEG data to obtain valuable information from it. The technique of eliminating sounds or artefacts from EEG signals is known as de-noising [260]. Some de-noising methods are given below:

- Wavelet de-noising and thresholding: The multi-resolution analysis is used to transfer the EEG signal to the discrete wavelet domain. The contrasting or adaptive threshold level is used to reduce particular coefficients associated with the noise signal [261]. Shorter coefficients would tend to define noise characteristics throughout time and scale in a well-matched wavelet representation. In contrast, threshold selection is one of the most critical aspects of successful wavelet de-noising. Thresholding can isolate the signal from the noise in this case; hence, thresholding approaches come in several shapes and sizes. All coefficients underneath a predetermined threshold value are set to zero in hard thresholding. Soft thresholding is a method of reducing the value of the remaining coefficients by a factor of two [262].
- Empirical mode decomposition (EMD): It is a signal analysis algorithm for multivariate signals. It breaks the signal down into a series of frequency and amplitude-regulated zero-mean signals, widely known as intrinsic mode functions (IMFs). Wavelet decomposition, which decomposes a signal into multiple numbers of Intrinsic Mode Functions (IMFs), is compared by EMD. It decomposes these IMFs using a shifting method. An IMF is a function with a single maximum between zero crossings and a mean value of zero. It produces a residue after degrading IMFs. These IMFs are sufficient to characterize a signal [263].

Most of our datasets mentioned in the previous section are a part of various BCI paradigms and follow these signal enhancement techniques as well. The motor imagery datasets represent paradigms such as sensorimotor activity or rhythms. In addition, error-related potentials datasets and datasets such as event-related potentials or visually evoke potentials signify their own BCI paradigm. Some other paradigms, such as overt attention, eye movement, miscellaneous, and emotion recognition, identify their datasets. Indeed, these paradigms become bigger in number as the measurement of different brain movements and emotions are attempted. More than 100 BCI designs are required to use signal enhancement techniques to extract features from the signal. In comparison, Reference [264] shows that 32% of BCI designs use surface Laplacian (SL) to extract features, principal component analysis (PCA) or independent component analysis (ICA) was used in 22%, and common spatial patterns (CSP) and common average referencing (CAR) techniques are used in 14% and 11%, respectively.

7. Feature Extraction

Now, it is necessary to understand what the features represent, their qualities, and how to use them for a BCI system to select the best appropriate classifier. A classification system's accuracy or efficiency is primarily determined by the feature(s) of the samples to be categorized [265]; therefore, feature extraction has been crucial stage in BCI. The majority of noninvasive BCI devices use neuroimaging techniques such as MEG and MRI. However, EEG is the most widely utilized method, owing to its high temporal resolution and inexpensive cost [266]. The EEG signal feature extraction method is one of the essential components of a BCI system because of its involvement in successfully executing the classification stage at discriminating mental states. Nevertheless, the feature extraction methods based on both EEG and ECoG are discussed elaborately in the subsequent section.

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7.1. EEG-Based Feature Extraction

Typically, BCI focuses on identifying acquired events using various neuroimage techniques, the most common of which is electroencephalography (EEG). Since its involvement in successfully executing the classification stage at discriminating mental states, the EEG signal feature extraction method is one of the essential components of a BCI system. According to [267] on EEG, three types of feature extraction are discussed in detail in the following sections. These features are the time domain, the frequency domain, and the time–frequency domain. The following subsection address the feature domains elaborately.

7.1.1. Time Domain

The time–frequency domain integrates analyses in the time and frequency domains. It depicts the signal energy distribution in the Time–Frequency plane (t-f plane) [268]. When it comes to deciphering rhythmic information in EEG data, a time–frequency analysis comes in handy. EEG's time-domain properties are straightforward to fix, but they have the disadvantage of containing non-stationary signals that alter over time. Features are usually derived using signal amplitude values in time-domain approaches that can be distorted by interference as noise during EEG recording.

- Event related potentials: Event-related potentials (ERPs) are very low voltages generated in brain regions in reaction to specific events or stimuli. They are time-locked EEG alterations that provide a safe and noninvasive way to research psychophysiological aspects of mental activities. A wide range of sensory, cognitive, or motor stimuli can trigger event-related potentials [269,270]. ERPs are useful to measure the time to process a stimulus and a response to be produced. The temporal resolution of event-related potentials is remarkable, but it has a low spatial resolution. ERPs were used by Changoluisa, V. et al. [271] to build an adaptive strategy for identifying and detecting changeable ERPs. Continuous monitoring of the curve in ERP components takes account of their temporal and spatial information. Some limitations of ERPs are that it shows poor spatial resolution, whether it is suitable with temporal resolution [272]. Furthermore, a significant drawback of ERP is the difficulty in determining where the electrical activity originates in the brain.
- Statistical features: Several statistical characteristics were employed by several scholars [273,274,275] in their research:
    - Mean absolute value:

$$MAV = \frac{1}{N}\sum_{n=1}^{N}|x_n| \tag{1}$$

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- Power:

$$P = \frac{1}{N} \sum_{n=1}^{N} |x_n|^2 \tag{2}$$

- Standard deviation:

$$SD = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (x(n) - \mu_n)} \tag{3}$$

- Root mean square (RMS):

$$\mathrm{RMS} = \left(\frac{1}{N} \sum_{i=1}^{N} x_i^2 \right)^{1/2} \tag{4}$$

- Square root of amplitude (SRA):

$$\mathrm{SRA} = \left(\frac{1}{N} \sum_{i=1}^{N} \sqrt{|x_i|} \right)^2 \tag{5}$$

- Skewness value (SV):

$$\mathrm{SV} = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{x_l - \bar{x}}{\sigma} \right)^3 \tag{6}$$

- Kurtosis value (KV):

(7)

$$\mathrm{KV} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_l - \bar{x}}{\sigma}\right)^4$$

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where $x(n)$ is the pre-processed EEG signal with N number of samples; μ_n refers to the meaning of the samples. Statistical features are useful at low computational cost.

- Hjorth features: Bo Hjorth introduced the Hjorth parameters in 1970 [276]; the three statistical parameters employed in time-domain signal processing are activity, mobility, and complexity. Dagdevir, E. et al. [277] proposed a motor imagery-based BCI system where the features were extracted from the dataset using the Hjorth algorithm. The Hjorth features have advantages in real-time analyses as it has a low computation cost. However, it has a statistical bias over signal parameter calculation.
- Phase lag index (PLI): The functional connectivity is determined by calculating the PLI for two pairs of channels. Since it depicts the actual interaction between sources, this index may help estimate phase synchronization in EEG time series. PLI measures the asymmetry of the distribution of phase differences between two signals. The advantage of PLI is that it is less affected by phase delays. It quantifies the nonzero phase lag between the time series of two sources, making it less vulnerable to signals. The effectiveness of functional connectivity features evaluated by phase lag index (PLI), weighted phase lag index (wPLI), and phase-locking value (PLV) on MI classification was studied by Feng, L.Z. et al. [278].

7.1.2. Frequency Domain

When analyzing any signal in terms of frequency instead of just time, the frequency domain properties are considered. Any signal's frequency domain representation displays how much of it falls inside a specific frequency range. The frequency domain properties are commonly acquired using power spectral density (PSD). The discussion about these properties is presented below in the following section.

1. Fast fourier transform (FFT): The Fourier transform is a mathematical transformation that converts any time-domain signal into its frequency domain. Discrete Fourier Transform (DFT) [279], Short Time Fourier Transform (STFT) [280,281], and Fast Fourier Transform are the most common Fourier transform utilized for EEG-based emotion identification (FFT) [282]. Djamal, E.C. et al. [283] developed a wireless device that is used to record a player's brain activity and extracts each action using Fast Fourier Transform. FFT is faster than any other method available, allowing it to be employed in real-time applications. It is a valuable instrument for signal processing at a fixed location. A limitation of FFT is that it can convert the limited range of waveform data and the requirement to add a window weighting function to the waveform to compensate for spectral leakage.
2. Common spatial patterns (CSP): It is a spatial filtering technique usually employed in EEG and ECoG-based BCIs to extract classification-relevant data [284]. It optimizes the ratio of their variances whenever two classes of data are utilized to increase the separability of the two

classes. In the case of dimensionality reduction, if a different dimension reduction phase precedes CSP, it appears to be better and has more essential generalization features. The basic structure of the CSP can be described by the Figure 5.

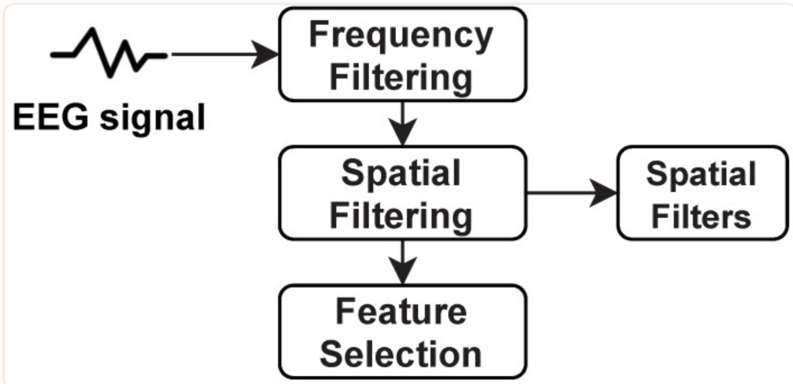

Figure 5

The basic structure of CSP [286].

In Figure 5, CSP provides spatial filters that minimize the variance of an individual class while concurrently maximizing the variance of other classes. These filters are mainly used to choose the frequency from the multichannel EEG signal. After frequency filtering, spatial filtering is performed using spatial filters that are employed to extract spatial information from the signal. Spatial information is significantly necessary to differentiate intent patterns in multichannel EEG recordings for BCI. The performance of this spatial filtering depends on the operational frequency band of EEG. Therefore, CSP is categorized as a frequency domain feature. However, CSP acts as signal enhancement while it requires no preceding excerpt or information of sub-specific bands.

3. Higher-order Spectral (HOS): Second-order signal measurements include the auto-correlation function and the power spectrum. Second-order measures operate satisfactorily if the signal resembles a Gaussian probability distribution function. However, most of the real-world signals are non-Gaussian. Therefore, Higher-Order Spectral (HOS) [285] is an extended version of the second-order measure that works well for non-Gaussian signals, when it comes into the equation. In addition, most of the physiological signals are nonlinear and non-stationary. HOS are considered favorable to detect these deviations from the signal's linearity or stationarity. It is calculated using the Fourier Transform at various frequencies.

$$HOS = X\left(K\right)X\left(l\right)X^{*}\left(k+l\right) \tag{8}$$

where $X(K)$ is the Fourier transform of the raw EEG signal $x(n)$ and l is a shifting parameter.

7.1.3. Time–Frequency Domain

In the time-frequency domain, the signal is evaluated both in the time and frequency domains simultaneously. The wavelet transform is one of many advanced approaches for analyzing the time-frequency representation. There are some other widely used models for utilizing the time-frequency domain. These models are addressed with a proper explanation in the subsequent section

1. Autoregressive model: For EEG analysis, the Autoregressive (AR) model has been frequently employed. The central premise of the autoregressive (AR) model is that the real EEG can be approximated using the AR process. With this premise, the approximation AR model's order and parameters are set to suit the observed EEG as precisely as possible. AR produces a smooth spectrum if the model order is too low, while it produces false peaks if it is too high [287]. AR also reduces leakage and enhances frequency resolution, but choosing the model order in spectral estimation is difficult. The observational data, denoted as $x(n)$, results from a linear system with an $H(z)$ transfer function. Then, $x(n)$ encounters an AR model of rank p in the formula [288].

$$x\left(n\right) = -\sum_{i=1}^{p} ap\left(i\right) x\left(n-i\right) + v\left(n\right) \tag{9}$$

   The AR parameters are $ap(i)$, the observations are $x(n)$ and the excitation white noise is $v(n)$. Lastly, the most challenging part of AR EEG modeling is choosing the correct model to represent and following the changing spectrum correctly.

2. Wavelet Transform (WT): The WT technique encodes the original EEG data using wavelets, which are known as simple building blocks. It looks at unusual data patterns using variable windows with expansive windows for low frequencies and narrow windows for high frequencies. In addition, WT is considered an advanced approach as it offers a simultaneous localization in the time-frequency domain, which is a significant advantage. These wavelets can be discrete or continuous and describe the signal's characteristics in a time-domain frequency. The Discrete Wavelet Transform (DWT) and the Continuous Wavelet Transform (CWT) are used frequently in EEG analysis [289]. DWT is now a more widely used signal processing method than CWT as CWT is very redundant. DWT decomposes any signal into approximation and detail coefficients corresponding to distinct frequency ranges maintaining the temporal information in the signal. However, most researchers try all available wavelets before choosing the optimal one that produces the best results, as selecting a mother wavelet is challenging. In wavelet-based feature extraction, the Daubechies wavelet of order 4 (db4) is the most commonly employed [290].

7.2. ECoG-Based Features

Electrocorticography (ECoG) generates a reliable signal through electrodes placed on the surface of the human brain, which decodes movement, vision, and speech. Decoding ECoG signal processing gives immediate patient feedback and controls a computer cursor or perhaps an exoskeleton. The ECoG signal feature extraction approach is a crucial element of the BCI system since it is involved in accomplishing the classification phase during decoding. Some of the widely used feature extraction methods are discussed below.

7.2.1. Linear Filtering

It is typically employed to filter out noise in the form of signals that are not in the frequency range of the brain's messages. Low-pass filters and high-pass filters are the two types of linear filters. This typical linear filtering is used to removed ECOG, EOG, and EMG artifacts from EEG signals. Low pass filtering is used to remove EMG artifacts, and high pass filtering is used to remove EOG artifacts [291]. These artifacts are noises produced by either physiological processes such as muscle, eye, or other biological movement or exogenous (external) sources such as machinery faults. There are three approaches for dealing with artifacts in EEG signal acquisition. Avoiding artifacts by keeping an eye on the subject's movements and the machine's operation. Contaminated trials are discarded due to artifact rejection. Pre-processing techniques are used to remove artifacts. The advantage of linear filtering is that signals are considered a controlled scaling of the signal's frequency domain components. High pass filtering is used to raise the relative importance of the high-frequency components by reducing the features in the frequency domain's center.

7.2.2. Spatial Filtering

Spatial filtering is a technique for improving decoding by leveraging information about the electrode positions. The spatial filter aims to lessen the influence of spatial distortion in the raw signal; various ECoG channels are treated as coordinates for multivariate data sampling through spatial filters. The filtering transforms that coordinate system to facilitate decoding. Spatial filtering can use to minimize data dimensionality or to increase the dissimilarity of various observations. The referencing systems used during ECoG recordings are frequently utilized for preliminary spatial filtering. Equation (10) determines the spatial filter [292].

$$x' = \sum_{i}^{n} (x_i) * (w_i) \tag{10}$$

where x' is the spatially filtered signal, x_i is the EEG signal from channel i, and w_i is the weight of that channel. With the aid of relevant information acquired from multiple EEG channels, spatial filtering contributes to recovering the brain's original signal. Simultaneously, it reduces dimensionality by lowering EEG channel size to smaller spatially filtered signals.

Thus far, feature extraction involves extracting new features from existing ones to minimize feature measurement costs, to improve classifier efficiency, and to improve classification accuracy. Now in the following section, the extracted feature classifiers are briefly described.

8. BCI Classifiers

BCI always needs a subject to use its device, and similarly, the subject must produce several types of data to use a BCI device. In addition, to use a BCI system, the subject must develop various brain activity patterns that the system can recognize and convert into commands. To achieve this mentioned conversion, some regression or classification algorithms can be used. The classification step's design comprises selecting one or more classification algorithms from a variety of options. In this section, some commonly known classifiers [293], which are classified in Figure 6, as well as some new classifiers [294] are described below.

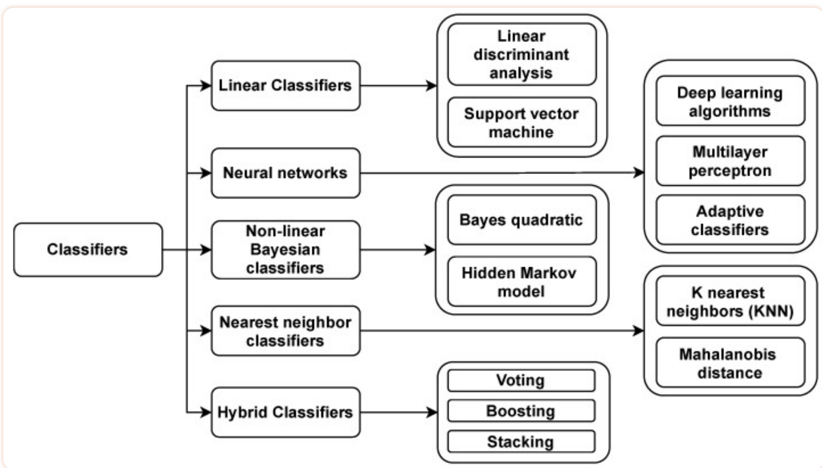

Figure 6

Classification of commonly used classifiers in BCI.

8.1. Linear Classifiers

Linear classifiers are discriminant algorithms that discriminate classes using linear functions. It is most likely the most widely used algorithm in BCI systems. Two types of linear classifiers are used during BCI design: linear discriminant analysis (LDA) and support vector machine (SVM).

8.1.1. Linear Discriminant Analysis (LDA)

The objective of Linear Discriminant Analysis is to separate data from diverse classes using a hyperplane. The side of hyperplane determinded through the category of a feature vector in a two-class problem. LDA requires that the data has a normal distribution and that both classes have the same covariance matrix. The separation hyper-plane is based on looking for a projection that maximizes the margin between the means of two classes while minimizing intraclass variance [295]. Furthermore, this classifier is straightforward to apply and generally produces excellent results and soundly implemented in various BCI system, including MI-based BCI, P300 speller, multiclass, and asynchronous BCI. The disadvantage of LDA is its linearity, which might lead to unsatisfactory results when faced with various nonlinear EEG data.

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8.1.2. Support Vector Machine (SVM)

A Support Vector Machine (SVM) uses a discriminant hyperplane to identify classes. The determined hyperplane in SVM is the one that maximizes the margins, i.e., the distance between both the nearest training samples. The ability to generalize is believed to improve when margins are maximized [296]. Linear SVM [297] is a type of SVM that allows for classification utilizing linear decision bounds. This classifier has been used to solve a substantial number of synchronous BCI tasks with tremendous success. The SVM classifier also works by projecting the input vector X onto a scalar value f(X), as shown in Equation (11).

$$f\left(X\right)=\sum_{l=1}^{N}a_1y_lK(X_l,X)+b \qquad (11)$$

Gaussian SVM or RBF SVM is the term applied to the equivalent SVM. RBF and SVM have also produced remarkable outcomes in BCI applications. SVM is used to solve multiclass BCI problems that use the OVR approach, similar to LDA.

8.2. Neural Networks (NN)

Neural networks (NN) and linear classifiers are the two types of classifiers most usually employed in BCI systems, considering that a NN is a collection of artificial neurons that allows us to create nonlinear decision limits [298]. The multilayer perceptron (MLP) is the most extensively used NN for BCI, as described in this section. Afterward, it briefly discusses other neural network architectures utilized in BCI systems.

8.2.1. Deep Learning (DL) Models

Deep learning has been widely used in BCI applications nowadays compared with machine learning technologies because most BCI applications require a high level of accuracy. Deep learning models perform better in recognizing changing signals from the brain, which changes swiftly. Some popular DL models such as CNN, GNN, RNN, and LSTM are described below:

- Convolutional Neural Network (CNN): A convolutional neural network (CNN) is an ANN intended primarily to analyze visual input used in image recognition and processing. The convolutional layer, pooling layer, and fully connected layer are the three layers that comprise

CNN. Using a CNN, the input data may be reduced to instant response formations with a minimum loss, and the characteristic spatial relationships of EEG patterns can be recorded. Fatigue detection, sleep stage classification, stress detection, motor imagery data processing, and emotion recognition are among the EEG-based BCI applications using CNNs. In BCI, the CNN models are used in the input brain signals to exploit the latent semantic dependencies.

- Generative Adversarial Network (GAN): Generative adversarial networks are a recent ML technique. The GAN used two ANN models for competing to train each other simultaneously. GANs allow machines to envision and develop new images on their own. EEG-based BCI techniques recorded the signals first and then moved to the GAN techniques to regenerate the images [299]. The significant application of GAN-based BCI systems is data augmentation. Data augmentation increases the amount of training data available and allows for more complicated DL models. It can also reduce overfitting and can increase classifier accuracy and robustness. In the context of BCI, generative algorithms, including GAN, are frequently used to rebuild or generate a set of brain signal recordings to improve the training set.
- Recurrent Neural Network (RNN): RNNs' basic form is a layer with the output linked to the input. Since it has access to the data from past time-stamps, and the architecture of an RNN layer allows for the model to store memory [300,301]. Since RNN and CNN have strong temporal and spatial feature extraction abilities in most DL approaches, it is logical to mix them for temporal and spatial feature learning. RNN can be considered a more powerful version of hidden Markov models (HMM), which classifies EEG correctly [302]. LSTM is a kind of RNN with a unique architecture that allows it to acquire long-term dependencies despite the difficulties that RNNs confront. It contains a discrete memory cell, a type of node. To manage the flow of data, LSTM employs an architecture with a series of "gates". When it comes to modeling time series of tasks such as writing and voice recognition, RNN and LSTM have been proven to be effective [303].

8.2.2. Multilayer Perceptron (MLP)

An Multilayer Perceptron (MLP) [304] comprises multiple layers of neurons along with an input layer, one or more hidden layers, and an output layer. The input of each neuron is linked to the output of the neurons in the preceding layer. Meanwhile, the output layer neurons evaluate the classification of the input feature vector. MLP and neural networks can approximate, meaning they can compare continuous functions if they have sufficient neurons and layers. The challenging factor behind MLPs is that they are susceptible to over-training, particularly containing noisy and non-stationary data. As a result, significant selection and regularization of the architecture are necessary. Perceptron is a multilayer with no hidden layers comparable with LDA. It has been used in BCI applications on occasion [293]. Sunny, M.S.H. et al. [305] used Multilayer Perceptron (MLP) to distinguish distinct frequency bands from EEG signals to extract features more effectively.

8.2.3. Adaptive Classifiers

As new EEG data become accessible, adaptive classifiers' parameters, such as the weights allocated to each feature in a linear discriminant hyperplane, are gradually re-estimated and updated. Adaptive classifiers can use supervised and unsupervised adaptation, that is, with or without knowledge of the input data's real class labels. The true class labels of the receiving EEG signals are obtained using supervised adaptation. The classifier is either reassigned on the existing training data, enhanced with these updated, labeled incoming data, or updated solely on this new data. Supervised user testing is essential for supervised BCI adaptation. The label of the receiving EEG data is vague with unsupervised adaptation. As a result, unsupervised adaptation is based on class-unspecific adaptation, such as updating the generalized classes EEG data mean or a co-variance matrix in the classifier model or estimating the data class labels for additional training [306].

8.3. Nonlinear Bayesian Classifiers

This section discusses the Bayes quadratic and hidden Markov models (HMM), two Bayesian classifiers used in BCI. Although Bayesian graphical networks (BGN) have been used for BCI, they are not covered here since they are not widely used [307].

8.3.1. Bayes Quadratic

The objective of Bayesian classification is to provide the highest probability class to a feature vector. The Bayes rule is often used to calculate the a posteriori probability of a feature vector assigned to a single class. The class of this feature vector can be calculated by using the MAP (maximum a posteriori) rule with these probabilities. The Bayes quadratic assumption is that the data have a distinct normal distribution. The result is quadratic decision boundaries that justify the classifier's name [308]. Although this classifier is not extensively utilized for BCI, it has been successfully used to classify motor imagery and mental tasks.

8.3.2. Hidden Markov Model

A Bayesian classifier that generates a nonlinear cost function is known as a Hidden Markov Model (HMM). An HMM is a statistical algorithm that calculates the chances of seeing a given set of feature variables [309]. These statistical probabilities from HMM are generally Gaussian Mixture Models (GMM) in case of BCI [310]. HMM may be used to categorize temporal patterns of BCI characteristics (Obermaier, B. et al. [302]), even raw EEG data, since the EEG elements required to control BCI have particular time sequences. Although HMM is not widely used in the BCI world, this research demonstrated that they could be helpful to classification on BCI systems such as EEG signals [311].

8.4. Nearest Neighbor Classifiers

In this section, some classifiers with distance vectors are described. Classifiers such as K nearest neighbors (KNN) and Mahalanobis distance are common among them as they are nonlinear discriminative classifiers [312].

8.4.1. K Nearest Neighbors

K nearest neighbor method aims to identify the dominant class amongst an unseen point within the dataset habituated for training. Nearest neighbors are typically estimated using a metric that has some intervals during the signal acquisition of BCI. KNN can construct nonlinear decision boundaries by evaluating any function with enough training data with an inflated k value. The usability of KNN algorithms is less in the BCI field as their condescending sensitivity hampers the capacity, which causes them to fail in multiple BCI research. KNN is efficient in BCI systems with some feature vectors, but low power can cause failure in BCI research [313].

8.4.2. Mahalanobis Distance

For each prototype of class *c*, Mahalanobis distance-based classifiers [314] assume a Gaussian distribution $N(c, Mc)$. Subsequently, using the Mahalanobis distance *dc*, a feature vector *x* is allocated to the class that corresponds to the closest prototype (*x*).

$$d_c(x) = \sqrt{(x - \mu_c) M_c^{-1} (x - \mu_c)^T} \tag{12}$$

This results in a basic yet reliable classifier; it has been shown to work in multiclass and asynchronous BCI systems. Considering its excellent results, it is still rarely mentioned in BCI literature [315].

8.5. Hybrid

In several BCI papers, classification is implemented with a single classifier. Furthermore, a current tendency is to combine many classifiers in various ways [316]. The following are indeed the classifier combination strategies utilized in BCI systems:

8.5.1. Boosting

Boosting is the process of using multiple classifiers in a cascade, and each focused on the errors made by the one before it. It can combine numerous weak classifiers to form a powerful one; thereforem it is unlikely to overtrain. Moreover, it is susceptible to mislabeling, illustrating why it failed in one BCI trial [293].

8.5.2. Voting

Multiple classifiers are employed for voting, each of which allocates the input feature vector to a class. The majority class becomes the final class. In BCI systems, voting is the most preferred process of combining classifiers due to its simplicity and efficiency [293].

8.5.3. Stacking

Stacking is the process of utilizing multiple classifiers to categorize the input feature vector. Level-0 classifiers are what it is named. Each one of these classifiers' output would then feed into a "meta-classifier" (or "level-1 classifier"), which makes a final decision [293].

Aforementioned in this section, some other classifiers are utilized in the recent BCI research. Since 2016 transfer learning is used for using MI classification tasks [317]. Some ground-breaking architectures are established in recent years, such as EEG-inception, an end-to-end Neural network [318], cluster decomposing, and multi-object optimization-based-ensemble learning framework [319]; RFNet is a fusion network that learns from attention weights and used in embedding-specific features for decision making [179].

Now, a better understanding of the performance of commonly known classifiers with some popular datasets are given in Table 9.

Table 9

Comparison of classifiers based on popular datasets and features.

Ref.	Dataset	Feature	Classifier	Accuracy
[102]	BCI competition IV-2b	CWT	CNN	Morlet- 78.93%, Bump-77.25%
[320]	BCI competition III	CSP	SVM	Evolved Filters: Subject 1—77.96%, Subject 2—75.11%, Subject 3—57.76%
[321]	BCI competition III	WT	SVM	85.54%
[321]	BCI competition III	WT	NN	82.43%
[322]	BCI competition III	WT	LDA	MisClassification Rate: 0.1286
[323]	BCI competition III	WT	CNN	86.20%
[324]	BCI competition IV-2a	Single Channel CSP	KNN	62.2 ± 0.4%
[324]	BCI competition IV-2a	Single Channel CSP	MLP	63.5 ± 0.4%
[324]	BCI competition IV-2a	Single Channel CSP	SVM	63.3 ± 0.4%
[324]	BCI competition IV-2a	Single Channel CSP	LDA	61.8 ± 0.4%

9. Evaluation Measurement

To evaluate the performance of BCI systems, researchers employed several evaluation metrics. The most common is accuracy, commonly known as error rate. Although accuracy is not always an acceptable criterion due to specific rigorous requirements, various evaluation criteria have been offered. An overview of BCI research evaluation criteria is provided below.

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9.1. Generally Used Evaluation Metrics

In this section, we sorted the most commonly used evaluation metrics for measuring the BCI system performances. The evaluation measures are explained carefully in the following subsections.

9.1.1. The Confusion Matrix

The confusion matrix represents the relationship between the actual class's user-intentioned output classes and the actual predicted class. True positives rate (TPR), False negative rate (FNR), False positives rate (FPR), Positive predictive value (PPV), and negative predictive value (PPV) are used to describe sensitivity or recall, specificity, (1-specificity), precision, etc. [325].

9.1.2. Classification Accuracy and Error Rate

Classification accuracy is one of the important metrics in BCI systems; this study evaluates performance using classification accuracy as well as sensitivity and specificity. This measure determines how frequently the BCI makes a right pick or what proportion of all selections are accurate. It is the most obvious indicator of BCI accomplishment, implying that it increase in a linear fashion with decision time, so it takes a long time. The following is the mathematical formula for calculating accuracy:

$$\text{Classification accuracy} = \frac{\text{Correctly classified test trials}}{\text{Total test triols}} \times 100 \quad (13)$$

9.1.3. Information Transfer Rate

Shannon [326] proposed the Information Transfer Rate (ITR) as the rate that makes up both of these metrics. This rate represents the quantity of data that may pass through the system in one unit of time. In [327], the information transmission rate in bits per minute ($bits/min$) and accuracy (ACC) in percentage (%) were used to evaluate performance. They made demographic data (age and gender) as well as the performance outcomes of 10 participants, and the ITR was computed using the Formula (14), which is as follows:

$$B_t = \log_2 N + p \log_2 p + (1-p) \log_2 \left[\frac{1-p}{N-1} \right], \quad (14)$$

where N is the number of targets and p is the classification accuracy (ACC). Based on four cursor movements and the choose command, this resulted in a N of 5. Bits per trial were used to compute B_t.

According to ITR [328] also has some important parameters that are used to evaluate BCI. A description of them is given below:

1. Target detection accuracy: The accuracy of target identification may be enhanced by increasing the Signal-to-Noise Ratio (SNR) and the separability of several classes. Several techniques, such as trial averaging, spatial filtering, and eliciting increased task-related EEG signals, are employed in the preprocessing step to reduce the SNR. Many applications utilize trail averaging across topics to improve the performance of a single BCI. These mental states may be used to lower the SNR [53].
2. Number of classes: The number of classes is raised and more sophisticated applications are built with a high ITR. TDMA, FDMA, and CDMA are among the stimulus coding techniques that have been adopted for BCI systems [243,329]. P300, for example, uses TDMA to code the target stimulus. In VEP-based BCI systems, FDMA and CDMA have been used.
3. Target detection time: The detection time is when a user first expresses their purpose and when the system makes a judgment. One of the goals of BCI systems is to improve the ITR by reducing target detection time. Adaptive techniques, such as the "dynamic halting" method, might be used to minimize the target detection time [330].

9.1.4. Cohen's Kappa Coefficient

Cohen's Kappa measures the agreement between two observers; it measures the contract between the proper output and the command of BCI domain in a BCI-based AAC system. Cohen's kappa coefficient resolves many of the accuracy measure's objections [331]. The general agreement $p_0 = ACC$, which is equivalent to the classification accuracy and the chance agreement p_e, with n_i and n_{i_i} being the column $i_t h$ and row $i_t h$, correspondingly, are used to calculate K.

$$p_e = \frac{\sum_{i=1}^{M} n_{ii} n_{i:}}{N^2} \tag{15}$$

where posteriori and priori probability are $n : i, ni :$ respectively. The estimated kappa Coefficient K and standard error $e(K)$ are acquired by

$$\kappa = \frac{p_0 - p_e}{1 - p_e} \tag{16}$$

When there is no correlation between the expected and actual classes, the kappa coefficient becomes zero. A perfect categorization is indicated by a kappa coefficient of 1. If the Kappa value is less than zero, the classifier offers an alternative assignment for the output and actual classes [332].

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$$\sigma_e(\kappa) = \frac{\sqrt{\left(p_0 + p_e^2 - \sum_{i=1}^{M}\left[n_{:i} n_{i:}\left(n_{:i} + n_{i:}\right)\right] / N^3\right)}}{(1 - p_e)\sqrt{N}} \tag{17}$$

9.2. Continuous BCI System Evaluation

Continuous BCI performance was measured using a variety of parameters. Different measures may be even more appropriate depending on whether the study is conducted online or offline. The section goes through some of the most commonly used metrics in this field, including the correlation coefficient, accuracy, and Fitts's Law [333].

9.2.1. Correlation Coefficient

The correlation coefficient could be a useful statistic for determining whether an intracortical implant receives task-relevant neurons. There are two essential stipulations: one is scale-invariant, which implies that the cursor might miss the mark substantially while still generating high values if the sign of the actual and anticipated movements coincide [334]; the other is that a decoder can yield a high value if it simply generates a signal that fluctuates with the repetitions [333].

9.2.2. Accuracy

Task characteristics such as target size and dwell time have a significant impact on accuracy. As a result, it is more of a sign that the task was is good enough for the subject and modality than a performance measure [333].

9.2.3. Fitts's Law

Fitts's law asserts that the time taken for a person to move a mouse cursor to a targeted object of the target's distance is divided by its size. The longer it takes, the greater the distance and the narrower the target [335,336]. Fitts's law requires using a method to calculate the "index of difficulty" of a particular change.

9.3. User-Centric BCI System Evaluation

Users are an essential element of the BCI product life cycle. Their interactions and experiences influence whether BCI systems are acceptable and viable. The four criteria or User Experience (UX) factors are used to evaluate user-centric BCI systems. These are usability, affects, ergonomics, and quality of life, shown below in the following subsection.

9.3.1. Usability

The amount that can be utilized to fulfill specific objectives with effectiveness, efficiency, learnability, and satisfaction in a given context is referred to as usability [337]. In usability measure, we can include four metrics, such as,

1. Effectiveness or accuracy: It depicts the overall accuracy of the BCI system as experienced from the end user's perspective [333].
2. Efficiency or information transfer rate: It refers to the speed and timing at which a task is accomplished. Therefore, it depicts the overall BCI system's speed, throughput, and latency seen through the eyes of the end user's perspective [333].
3. Learnability: The BCI system can make users feel as if they can use the product effectively and quickly learn additional features. Both the end-user and the provider are affected by learnability [338].
4. Satisfaction: It is based on participants' reactions to actual feelings while using BCI systems, showing the user's favorable attitude regarding utilizing the system. To measure satisfaction, we can use rating scales or qualitative methods [333].

9.3.2. Affect

Regarding BCIs, it might refer to how comfortable the system is, particularly for long periods, and how pleasant or uncomfortable the stimuli are to them. EEG event-related possibilities, spectral characteristics, galvanic skin responses, or heart rates could be used to quantitatively monitor user's exhaustion, valence, and arousal levels [339].

9.3.3. Ergonomics

Ergonomics studies are the study of how people interact with their environments. The load on the user's memory is represented by the cognitive task load, a multidimensional entity. In addition, physiological markers including eye movement, EEG, ERP, and spectral characteristics could also be employed to evaluate cognitive stress objectively [340].

9.3.4. Quality of Life

It expresses the user's overall perception of the system's utility and acceptance and its influence on their well-being. The Return on Investment (ROI) is an economic measure of the perceived benefit derived from it. The overall quality of experience is a measure of how satisfied a user is with their expertise [333].

Other assessment methods, such as Mutual Information, Written symbol rate (WSR), and Practical bit rate (PBR), are utilized to a lesser extent.

10. Limitations and Challenges

The brain-computer interface is advancing towards a more dynamic and accurate solution of the connection between brain and machine. Still, few factors are resisting achieving the ultimate goal. Therefore, we analyzed a few core research on BCI in this section and found the limitations exhibited in Table 10. Then, we demonstrated the significant challenges of the BCI domain.

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Table 10

A summary of some research papers proposing new methods of BCI.

Model	Novelty	Feature Extraction	Architecture	Limitations
P300, ERN, MRCP, SMR [200]	Compact Convolutional neural network for EEG based BCI	Band pass filtering	EEGNet	The proposed approaches only work effectively when the feature is accustomed to before.
WOLA [254]	Dynamic filtering of EEG signals	CSP	Embedded-BCI (EBCI) system	This model is not updated yet for eye blinking or muscle activities.
xDAWN [255]	Enhance P300 evoked potentials	Spatial Filtering	P300 speller BCI paradigm	There is room for improvization and enhancements.
SSVEP, P300 [341]	BCI-based healthcare control system	P300 detector Kernel (FDA+ SSVEP)	Self- paced P300 healthcare system with SSVEP	SSVEP stimulation paradigm can be used to enhance accuracy.
LSTM, pCNN, RCNN [342]	Online decoding of motor imagery movements using DL models	CSP, log-BP features	Classify Motor Imagery movements	The data used in proposed models are limited.
MDRM and TSLDA [343]	Classification framework for BCI-based motor imagery	Spatial filtering	MI-based BCI classification using Riemannian framework	Computational costs are faced while implementing this proposed framework.
SVM [344]	Fatigue detection system	FFT	Train driver Vigilance detection	NA
Gaussian, polynomial kernel [345]	MKELM-based method for motor imagery EEG classification	CSP	MKELM-based method for BCI	Improvement of accuracy and extension of the framework is needed.
Bimodal NIRS-EEG approach [346]	Bimodal BCI using EEG and NIRS	Low pass filter and Savitzky–Golay (SG)	SSVEP paradigm	Only used in EEG and fNIRS channels.

The challenges and difficulties of the BCI domain are divided into three categories: challenges based on usability, technical challenges, and ethical challenges. The rest of the section briefly explains these challenges.

10.1. Based on Usability

This section describes the challenges that users have in accepting BCI technology [350]. They include concerns relating to the requisite training for class discrimination.

Feedback

10.1.1. Training Time

Usually, training a user, either leading the user through the procedure or the total quantity of the documented manual, takes time. The majority of the time, the user also requests the system to be simpler to use. The users often despise a complicated system that is difficult to manage. It is a challenging effort to create such a sophisticated, user-friendly system [351].

10.1.2. Fatigue

The majority of present BCIs generate a lot of fatigue since they need a lot of concentration, focus, and awareness to a rapid and intermittent input. In addition to the annoyance of weariness of electrodes, BCI may fail to operate because the user cannot maintain a sufficient degree of focus. As in BCI, mental activity is continually monitored and the user's attention point alters the input. The concentration necessary for stimuli results in a combination of input and output [352,353]. Rather than relaxing, the user must concentrate on a single point as an input and then look at the outcome. At some point, the interaction has a forced quality to it, rather than the natural quality that would be there if the user could choose whatever part of the visual output to focus on [6].

10.1.3. Mobility to Users

Across most situations, users are not allowed to move around or to have mobility in BCIs. During the test application, users must stay motionless and quiet, ideally sitting down. However, in a real-world setting, a user may need to utilize BCI while walking down the street, for example, to manage a smartphone. Additionally, BCIs cannot ensure user comfort. Usually, the EEG headset is not lightweight and easy to carry, which hampers the user experience.

10.1.4. Psychophysiological and Neurological Challenges

Emotional and mental mechanisms, cognition-related neurophysiology, and neurological variables, such as functionality and architecture, play vital roles in BCI performance, resulting in significant intra- and inter-individual heterogeneity. Immediate brain dynamics are influenced by psychological elements such as attention; memory load; weariness; conflicting cognitive functions; and users' specific characteristics such as lifestyle, gender, and age. Participants with weaker empathy engage less emotionally in a P300-BCI paradigm and generate larger P300 wave amplitudes than someone with greater empathy involvement [354].

10.2. Technical Challenges

Non-linearity, non-stationarity, and noise as well as limited training sets and the accompanying dimensionality curse are difficulties relating to the recorded electrophysiological characteristics of brain impulses.

10.2.1. Non-Linearity

The brain is a very complex nonlinear system in which chaotic neuronal ensemble activity may be seen. Nonlinear dynamic techniques can thus better describe EEG data than linear ones.

10.2.2. Non-Stationarity

The non-stationarity of electrophysiological brain signals to recognize human recognition is a significant challenge in developing a BCI system. It results in a constant shift in the signals utilized with time, either between or within transition time. EEG signal variability can be influenced by the mental and emotional state backdrop across sessions. In addition, various emotional states such as sadness, happiness, anxiety, and fear can vary on daily basis that reflects non-stationarity [355]. Noise is also a significant contribution to the non-stationarity problems that BCI technology faces. Noises and other external interferences are always present in raw EEG data of emotion recognition that is most robust [356]. It comprises undesired signals generated by changes in electrode location as well as noise from the surroundings [357].

10.2.3. Transfer Rate of Signals

In BCIs, the system must continuously adjust to the signals of the user. This modification must be made quickly and precisely. Current BCIs have an extremely slow information transfer rate, taking almost two minutes to “digitalize” a single phrase, for example. Furthermore, BCI accuracy does not always reach a desirable level, particularly in visual stimulus-based BCI. Actions must sometimes be repeated or undone, producing pain or even dissatisfaction in using interactive systems using this type of interface [358].

10.2.4. Signal Processing

Recently, a variety of decoding techniques, signal processing algorithms, and classification algorithms have been studied. Despite this, the information retrieved from EEG waves does not have a high enough signal-to-noise ratio to operate a device with some extent of liberty, such as a prosthetic limb. Algorithms that are more resilient, accurate, and quick are required to control BCI.

10.2.5. Training Sets

In BCI, the training process is mainly impacted by usability concerns, but training sets are tiny in most cases. Although the subjects find the training sessions time-consuming and challenging, they give the user the required expertise to interact with the system and to learn to manage their neurophysiological signals. As a result, balancing the technological complexity of decoding the user's brain activity with the level of training required for the proper functioning of the interfaces is a crucial issue in building a BCI [359].

Feedback

10.2.6. Lack of Data Analysis Method

The classifiers should be evaluated online since every BCI implementation is in an online situation. Additionally, it should be validated to ensure that it has low complexity and can be calibrated rapidly in real-time. Domain adaptation and transfer learning could be an acceptable solution for developing calibration-free BCIs, where even the integration of unique feature sets, such as covariance matrices with domain adaptation algorithms, can strengthen the invariance performance of BCIs.

10.2.7. Performance Evaluation Metrics

A variety of performance evaluation measures are used to evaluate BCI systems. However, when different evaluation metrics are used to assess BCI systems, it is nearly impossible to compare systems. As a result, the BCI research community should establish a uniform and systematic approach to quantify a particular BCI application or a particular metric. For example, to test the efficiency of a BCI wheelchair control, the number of control commands, categories of control commands, total distance, time consumed, the number of collisions, classification accuracy, and the average success rate need to be evaluated, among other factors [360].

10.2.8. Low ITR of BCI Systems

The information transfer rate is one of the extensively used processes for the performance evaluation metrics of BCI systems. The number of classes, target detection accuracy, and target detection time are all factors of this rate. By increasing the Signal-to-Noise Ratio (SNR), it can improve the target detection accuracy [53,328]. Several techniques are typically used for the preprocessing phase to optimize the SNR. When a high ITR has been attained, more complicated applications can be created by expanding the number of classes available. CDMA, TDMA, and FDMA [243,361] are only a few of the stimulus coding schemes that have already been developed for BCI systems. TDMA was used with P300 to code the required stimuli, while CDMA and FDMA have been used with BCIs that interact with VEP. Furthermore, the essential aspect of BCIs is reducing the target recognition period, which helps to increase the ITR. Adaptive techniques, such as "dynamic stopping", could be an effective option for accomplishing this.

10.2.9. Specifically Allocated Lab for BCI Technology

Most of the BCI systems are trialed in a supervised lab rather than in the actual surroundings of the users. When designing a BCI system, it is essential to think about the environment in which the technology may be used. It is critical to thoroughly investigate the system's requirements, environmental factors, circumstances, and target users mostly during the system design phase.

10.3. Ethical Challenges

Feedback

There are many thoughts surrounding the ethical issues behind BCI as it considers physical, psychological, and social factors. In biological factors, BCI always finds a human body to identify signals that must be acquainted with electrodes. As humans need to wear these electrodes, it is always risky for them and can harm the human body to some worse extent. BCI also requires strict maintenance of the human body during signal acquisition, so the subject must sit for a long time in his place. Adding to that, a user or participant must act what the electrodes need, so they cannot do anything willingly. This fact can have a substantial impact on the human body.

11. Conclusions

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. The fundamental principles of BCI techniques are discussed elaborately. It describes the architectural perspectives of certain unique taxons and gives a taxonomy of BCI systems. The paper also covered feature extraction, classification, evaluation procedures, and techniques as the research continues. It presents a summary of the present methods for creating various types of BCI systems. The study looks into the different types of datasets that are available for BCI systems as well. The article also explains the challenges and limitations of the described BCI systems, along with possible solutions. 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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