Brain Computer Interface System, Performance, Challenges and Applications

Zhu Jiping
Department of Modern Mechanics, University of Science and Technology of China, Hefei, Anhui province, China.
jipingmech@ustc.edu.cn

Correspondence should be addressed to Zhu Jiping: jipingmech@ustc.edu.cn

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Abstract – Using electrodes placed on the scalp, a Brain-Computer Interface (BCI) may read electric activity in the brain and interpret it into orders to be sent to output devices. Artificial neuromuscular output channels are not used in BCIs. People with neuromuscular illnesses such as cerebral palsy, amyotrophic lateral sclerosis, spinal cord or stroke might greatly benefit from BCI since it can help them regain or maintain the abilities they once had. Standardized technological platforms have been developed as a result of massive multinational research efforts; and these platforms have the potential to be utilized to tackle intractable issues such as feature selection and segmentation, as well as the brain's incredibly complex dynamics. Researchers working on BCIs face additional challenges from the impact of time-variable psycho-neurophysiological fluctuations on brain signals, which must be overcome before the technology can be used in a plug-and-play fashion in daily life. This article provides a concise summary of the decades of research and development that have gone into BCIs so far, as well as a discussion of the most pressing issues yet to be solved.

Keywords – Brain-Machine Interface (BMI), Brain-Computer Interface (BCI), Electrocorticography (ECoG), Electroencephalogram – EEG.

I. INTRODUCTION

A Brain-Computer Interface (BCI) or Brain-Machine Interface (BMI) is a method of transmitting information between a person's brain and a machine, often a microprocessor or robotic limb. In most cases, BCIs are used to study, map, aid, enhance, or restore some aspect of human cognition or sensorimotor performance. Based on the proximity of the electrodes to the brain tissue, BCI implementations may be classified as either non-invasive (Electroencephalogram – EEG, EOG, MEG, MRI) or partially-invasive (ECoG, endovascular). Jacques Vidal of UCLA started studying BCI in the 1970s with the help of a National Science Foundation grant and then a contract from DARPA. The term "brain-computer interface" was first used in a scholarly article written by Vidal in 1973 [1]. The amazing plasticity of the brain may allow for the processing of signals from inserted prostheses in a manner similar to that of natural detector or effector pathways after some adaption. After many years of testing on animals, the first neuroprosthetic devices intended for human implantation were available in the mid-1990s.

The term "Brain-Computer Interface" (BCI) [2] refers to a digital framework, which is capable of receiving brain transmissions, decode them, and then transmit the resultant commands to a console to generate the intended outcome. That is because BCIs bypass the brain's typical output channels, which include the limbs and the musculature. Under this definition, BCI may only refer to devices that detect and process brainwaves or other neural activity. Therefore, a communication system that relies on voice activation or muscle activation is not a BCI. An EEG device cannot be viewed as BCI since it typically records the signals from the brain and does not issue an output, which impacts the environment of users. The famous myth and misconception that BCI can "read your mind" is unfounded. The objective of developing BCIs is not to "read the minds" in the sense of surreptitiously gleaning data of the user without their knowledge or permission, but rather to enable individuals to interact with their surroundings by means of brain signals rather than muscular. The user and BCI are able to work in concert with one another.

When properly trained, the user is able to generate brain signals that contain intention, and the BCI is able to decode these signals and turn them into commands for a console to execute out the user's goal. Is it possible to use detectable electrical brain impulses as data conduits in human-computer interaction or for the regulation of prosthetics? To what end? Vidal asked back in 1973. In an effort to assess whether or not computers might function as a prosthetic extension of the brain, he initiated the Brain-Computer Interface Project. The ability to utilize impulses from individual cortical neurons to move a meter needle was first shown in the late 1960s in monkeys, but systematic human research didn't begin until the 1970s [3]. Human BCI research progressed slowly at first due to limitations imposed by both technological constraints and our limited knowledge regarding the psychology of the brain. In 1980, Nusier and Alawneh [4] showed that people could not effectively control upward movements of rocket images on movable TV screens by applying neurofeedback on slow cortical possibilities in EEG activity.

Using the P300 event-based potential, Sellers, Arbel, and Donchin [5] demonstrated in 1988 that healthy volunteers could type sentences onto a computer. Since the 1950s, movements and their simulations have been connected to sensorimotor oscillations (mu and beta waves) documented throughout the sensorimotor cortex. In the late 1970s, Tato" Sokhadze [6] demonstrated that EEG biofeedback training had the potential to enhance the mu rhythm. Using this information as a springboard, Ross and Balasubramaniam [7] guided study participants through the process of controlling the amplitudes of sensorimotor rhythms in order to accurately move a pointer in one- or two - dimensional on a computer screen. A microelectrode collection was integrated into a young man's foundational motor cortex in 2006 once he suffered C3/C4 spinal injuries, which rendered him with full tetraplegia. This form of electrode array was linked to BCI system that allowed the patient to do basic tasks such as opening and closing a prosthetic hand, controlling a television, sending and receiving simulated emails, and operating a robotic arm. By using Electrocorticography (ECoG) to capture signals from the brain's surface, Witham et al. [8] demonstrated in 2022 that a BCI can successfully translate these signals into keyboard input. Over the last three decades, there has been a fundamental increment in the number of articles devoted to studying brain-computer interfaces (see **Fig 1**).

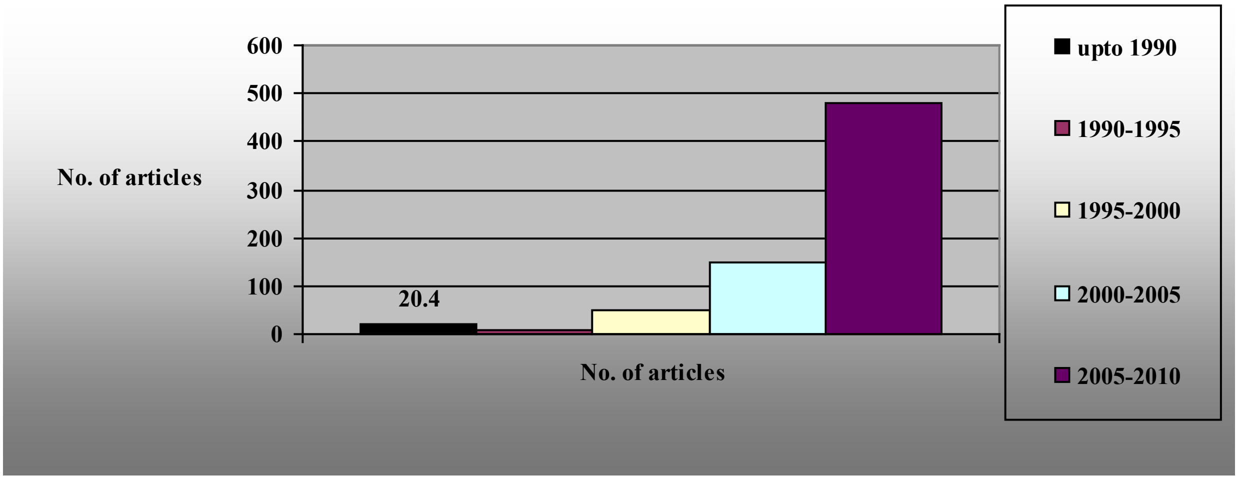

Fig 1. The brain-computer interface as discussed in scholarly journals over the last three decades

Within the last 40 years, BCI research—which was formerly conducted only in a few of labs—has exploded into a thriving and fast expanding area of study. The majority of articles are from the last five years. Interface between the computer system and the human brain.

The Brain/Neural Computer Interaction (BNCI) project [9]funded by the European Commission purposes to centralize the BCI research on six fundamental software themes: restoration (such as regaining access to a locked room), replacement (such as a BCI-controlled neuroprosthesis), augmentation (such as enhanced user knowledge and experience in games consoles), supplementation (such as virtual reality glasses), improved performance (such as upper limb regeneration after cerebrovascular accident), and data analysis (e.g., decoding). Many issues and developments in the BCI industry are covered in this review. We look to the most recent literature for in-depth analyses of specific BCI areas (in **Fig 2**).

The data came from a PubMed search using the term "brain computer interface" in the query bar. Only publications that were indexed as of December 4, 2020, have been taken into consideration. More articles have been published in this decade than in the previous one, suggesting a growing interest in BCI technology and highlighting its increasing relevance. Section II presents an overview of Brain-Computer Interfaces (BCI) where details about the representation of BCI systems and factors affecting BCI performance are discussed. Section III focuses on the neurological/psychological and technological challenges facing BCI. Section IV reviews the neuroplasticity, signal processing, and applications of BCI. Lastly, Section V draws final remarks on the paper as well as directions for future research.

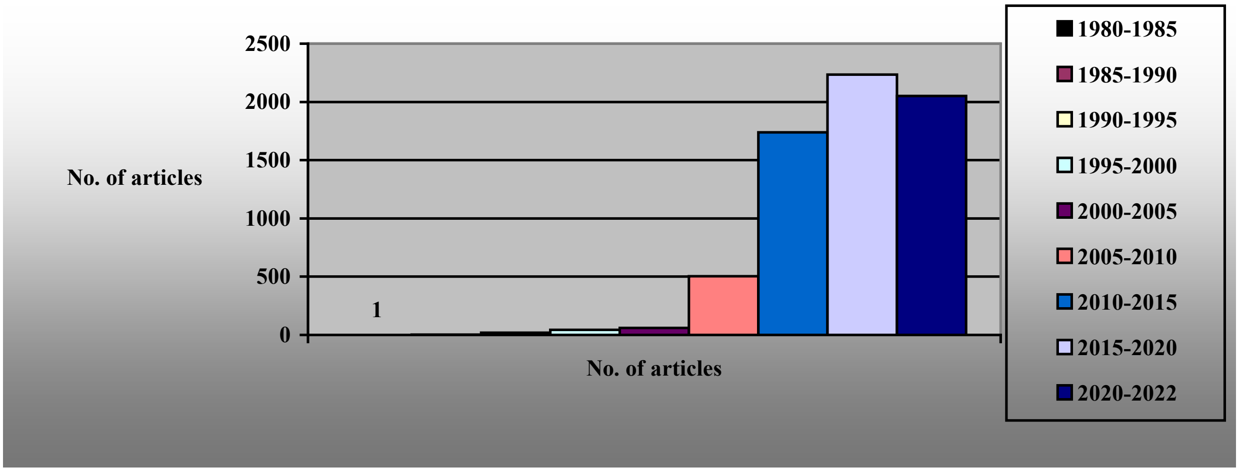

Fig 2. The total number of works published throughout the last 40 years.

II. OVERVIEW OF BRAIN-COMPUTER INTERFACES

Representation of BCI Systems

Intra-cortical Brain-Computer Interface (BCI) devices might help people with paralysis control their prosthetics and other assistive technologies by translating their brain activity. In recent years, it has been shown that BCIs can operate a wide range of equipment, including computer mouse, robotic arms, communication devices, and even the individuals' own paralyzed limbs. When transitioning BCI systems from presentations in the lab to clinical usage, it is important to keep the end user's goals in mind. User studies indicate that speed, flexibility, and accuracy are among the most valued characteristics of a BCI system. Building BCI systems with these considerations in mind might speed up their widespread clinical use.

The quality of the neural decoding element of a BCI system determines its precision, speed of response, and utility. The decoding algorithm's job is to figure out what kind of function the users want to do according to the signals they're sending from their brain. Therefore, the decoding method is dependent on not only the accuracy and speed with which functions/actions can be retrieved, but also the quantity of operations that can be decoded. Also, the BCI user's sense of agency depends heavily on the response time, which is the time it takes for the BCI to register the user's desire to act (perception of agency over BCI operation).

The first stage in developing a decoder that meets BCI users' expectations for accuracy, response time, and number of functionalities is determining what those expectations are. Huggins, Moinuddin, Chiodo, and Wren [10] conducted a poll of people with Spinal Cord Injury (SCI) SCI who would utilize a BCI and discovered that the vast majority said they would be happy with an accuracy rate of 90% or higher. Accuracy may signify various things depending on the BCI-enabled task; however this can be used as a minimum acceptable requirement. Several measures, including the degree of agreement between expected and actual cursor movement, may be used to assess the efficacy of BCIs for continual cursor control (R2). However, conventional classification accuracy is often employed to assess BCIs for discrete control system like "on," "off," or "left," "right," etc. Therefore, the level of accuracy required to pass muster as a BCI may vary from one job to the next.

The authors in [11] also discovered that the people they surveyed wanted BCI communication systems to be able to process at a rate of at least 20 to 24 characters in a single minute (2.5 to 3 s each answer). There are no established latency standards for BCI systems that attempt to restore hand function at this time. Ferreira et al. [12] have shown that even with delays as small as 750 milliseconds, able-bodied users using EEG-based BCI technologies to move the cursor with imaginary hand gestures experience a decrease in their feeling of autonomy. Finally, despite being a key need for potential users, the polls did not specify a target amount of BCI functionalities that users would consider appropriate. If no data is available, we will attempt to optimize the number of features while still achieving the desired levels of accuracy and speed.

One can classify BCI systems according to the mental processes they employ: In passive BCI, the user's unconscious feelings and thoughts are decoded, whereas in active BCI, the user's intention-based brain activity is directly engaged. Brain-computer interfaces that are "reactive" read brain waves that occur in response to something happening in the outside world. One application of passive BCI is detecting driver drowsiness to prevent traffic accidents. Active BCI refers to systems that are driven by the user's intentional Motor Imagery (MI), while reactive BCI refers to systems that are driven by visually evoked P300 caused by external stimulation. Invasive and non-invasive BCIs have been classified based on their signal-acquisition modalities. Although EEG-based non-invasive BCIs have been used extensively, more recent developments have seen the implementation of functional transcranial Doppler ultrasonography, functional near infrared spectroscopy (fNIRS), functional magnetic resonance imaging (fMRI), and magnetoencephalography (MEG). However, electrocorticography (ECoG) and intrusive intracortical sensors have been utilized to offer a higher signal-to-noise ratio and pinpoint the precise location of brain activity.

Inducing plasticity, or the modification of neurosynaptic organization, requires both the decoding of neuronal activity and the delivery of environmental cues into specific regions of the brain. Rehabilitative applications of BCIs and other neuroscientific fields rely on the brain and nervous system's natural plasticity. Some BCIs actively activate particular regions of the brain using external stimulation techniques like repetitive transcranial magnetic or transcranial stimulation, while others just convert brain data into computer instructions. The bidirectional design of a BCI consists of two brains or a single brain plus a feedback modality. Transcranial instantaneous current stimulus controlled by EEG signals associated to MI alters the connections in sensori-motor systems in healthy persons. The bidirectional BCI architecture also shows promise for developing direct brain-to-brain communications. Proprioceptive responses and efficient electric stimulations stimulated by neural activities as response for boosting and recovering auxiliary motor activities are two examples of the supplementary modalities required by certain BCI applications.

Factors Affecting BCI Performance

Although brain-computer interfaces (BCIs) show a lot of promise, they are currently plagued by low dependability. Guidance of users to develop BCI control mastery is an intriguing research field since it complements but does not replace efforts to improve brain signal processing. Because of this, we provide here a collection of cognitive and motivational aspects that might impact the learning process and should be taken into account to enhance the overall efficiency of BCI users. Keller's integrative theories of motivation, volition, and execution served as a foundation for this research. This theory seeks to explain what helps human users learn and execute effectively regardless of the task by taking into account both motivational (affective) and cognitive elements. Learning environments, like BCI training regimens, may be developed with these considerations in mind.

According to the idea, increased user effort and quality performance result from optimizing four motivational factors: attention (piqueing interest), relevance (being congruent with an individual's aims or ideals), confidence (success expectations), and satisfaction (extrinsic and intrinsic incentives). More effective skill acquisition is also achieved by accounting for the user's cognitive components, such as his or her limited memory retention (which necessitates reducing the skill-unrelated data), the manner in which data is actively handled by him or her (which requires making pertinent information salient), and the knowledge already stored in his or her good memory (which requires relating the to-be-learned expertise to existing knowledge). In most cases, designers of brain-computer interfaces (BCIs) neglect to take into account important elements.

Possible improvements in user BCI control might result from optimizing motivating elements while still taking into account cognitive restrictions. Although brain-computer interfaces (BCIs) show a lot of promise, they aren't particularly dependable just now. One promising avenue of study goes beyond just enhancing brain signal processing to instead teach users how to become BCI control masters. Our goal here is to help BCI users enhance their overall performance by presenting a collection of cognitive and motivational aspects that may affect the learning process. Messina et al. [13] explain what helps human users learn and perform well regardless of the job at hand by drawing on Keller's integrative psychology of motivation, volition, and achievement, which blends motivational (affective) and cognitive components.

Training environments, such as brain-computer interface (BCI) training protocols, may be designed with these considerations in mind. Based on this hypothesis, users are more likely to put forth their best effort because they are more interested in what they are doing, have higher expectations for success, and are more satisfied with the outcomes of their efforts (thanks to both intrinsic and extrinsic incentives). It is more effective to learn a new skill when the learner's cognitive factors are taken into account. A few examples of these factors include the user's limited cognitive function (which calls for a reduction in the amount of non-skill-related data), the way data is proactively analyzed by the student (which calls for the elevation of important material), and the learner's prior knowledge. In most cases, designers of brain-computer interfaces (BCIs) neglect to take into account important elements. Possible improvements in user BCI control might result from optimizing motivating elements while still taking into account cognitive restrictions.

There are three main requirements for BCI to be used in the medical field: (1) a user-friendly signal acquiring device, (2) widespread system validation, and (3) the potential and reliability of BCI. BCI performance is enhanced when invasive intracortical recordings are used to restore motor function in patients with motor disabilities, as compared to non-invasive methods like EEG. How well a patient completes a motor task or communicates with an external device depends on how well they perform. For patients who are unable to leave their homes, invasive modalities may be an option because the potential gains (a vastly enhanced quality of life) justify the potential drawbacks of implantation. After a year of observation, the pilot study's subjects showed no signs of surgery-related or tissue-reaction-related complications. Individuals with otherwise-normal neurological systems are often discouraged from having invasive BCI because to the hazards involved with surgery.

However, external auditory recordings from non-invasive modalities may be better explained with the use of invasive measurements and the usage of spatially explicit inner cortex movements. Considering the underpinning cortical-subcortical networks is crucial to improving BCI performance, which is influenced by a wide variety of factors. The ideal places to capture MI-induced signals are in the brain's most active regions, which include primary motor cortex, supplementary motor area, the premotor cortex, and the ventral striatum and basal forebrain of the subcortical parts. The electroencephalogram (EEG) measures activity in predictor and motor regions, whereas intracortical electrodes capture signals from the brain stem and thalamus.

BCI efficiency may be severely hampered by a number of problems. To get reliable results from non-invasive long-term recordings, the signal-to-noise ratio must be kept above a certain threshold. Brain oscillations triggered by an external stimulus are dynamic and stimulated by Resting-State Networks' (RSN) degree of stability [14]. Unreliable RSN estimation is caused by time-variant psychophysiological, neuroanatomical, and user-basic trait variables, leading to long- and short-term signal variance in and across people. For BCI devices to work, users must undergo a laborious and frequently irritating calibration exercise due to these inherent signal fluctuations. The principle of inter-subject associativity might be utilized toward inter-subject operable BCI, eliminating the need for subject-specific training, as shown in prior research in the situation of natural sight and natural musical listening.

Recent research suggests that people with similar brain dynamics may soon be able to use a BCI based on their sensory rhythms to communicate with one another. Inter-subject BCI offers the greatest potential for healthy persons and software for tireless monitoring, lie detection, and gaming, but the rehabilitative BCI should account for the degree and characteristics of certain impairments. Transfer training might aid in reducing the impacts of session-to-session and subject-to-subject differences by employing systems trained on data from different individuals to take advantage of similarities and reduce training demands.

III. CHALLENGES

Neurological and Psychophysiological Challenges

BCI performance varies significantly across and among individuals on account of factors including psychological and emotional processing, neurophysiology connected to intelligence, and neurological characteristics (i.e., architecture and functions). Dynamic brain activity in the present is affected by a variety of personal and contextual variables, including but not limited to the user's attention, memory load, weariness, and competing cognitive processes, and their fundamental traits like lifestyle, gender, and age. Individuals with poorer empathy, for instance, have stronger ability to generate P300 waves of larger amplitude in a P300-BCI scenario and exhibit less emotional engagement in the task overall. Results on the P300-BCI are also correlated with levels of intrinsic motivation.

Resting-state physiological factors, such as frequency-domain properties of heart-rate variability at rest, are correlated with BCI performance alongside psychological attributes. The benchmarks of RSNs are also dynamic, meaning that they may instantly change the look of any cortical signature. The reactivity of sensory neurons (RSNs) and the cognitive processes they're linked to change as people age. When RSN effects mask cortical reactions to events, it becomes more challenging to adjust to RSNs that change over time. Furthermore, the functioning neural networks are influenced by the intrinsic complexity and variety of human brain development, which in turn creates highly variable neuronal connection over time and between persons. More generalized systems can only be made possible with a BCI that can withstand the inevitable physiological changes that occur over time.

Research linking to the performance of BCI with psychological, electrophysiological and neuroanatomical aspects has shown a correlation between gray matter density in somatosensory cortical areas and BCI success. Research into sensorimotor rhythm-based BCI has shown correlations between physiological metrics e.g., spectrum complexities and energy spectral density from BCI performance and EEG recordings [15]. Additionally, sensorimotor rhythm-based BCI effectiveness is correlated with psychological factors like focus and drive. The degree of corticospinal excitability may also serve as a valid indicator of BCI efficacy. By considering the human skull as a whole, BCI performance is improved.

There are between 15 and 30 percent of the population whose brains just cannot generate the strong enough impulses to run a BCI. BCI ignorance might be reduced by learning more about neurophysiological processes. The problem of BCI ignorance might be mitigated with the use of an adaptive machine learning strategy that takes into account neurophysiological and psychological characteristics. Users' inability to generate signals is only one of several factors that contribute to their lack of BCI knowledge. Sometimes technical constraints prevent necessary characteristics from being extracted for effective BCI functioning. For instance, a person's unique brain anatomy, such as a folded cortex or a large distance from the scalp to the cortex, may prevent reliable task-specific signals from being recorded using scalp EEG/MEG.

More case-specific investigation into the neuro-psycho-physiological variables impacting BCI performance is urgently required. Stroke survivors need precise localization of the lesion in order to get optimal rehabilitation, since brain responses vary depending on their precise anatomical position. Although current neuroimaging techniques are helpful in identifying stroke lesion areas, rehabilitative therapies need a case-specific BCI architecture that takes into account remaining brain function. The widespread implementation of BCI-driven therapy for neurological diseases is hindered by its highly personalized design.

Technological Challenges

Although not all BCI applications benefit from any particular method for detecting cognitive signatures, some have been proposed. These methods include steady-state visual evoked potential (SSVEP), auditory evoked potential (AEP), event related potential (ERP), motor imagery (MI) and somatosensory evoked potential (SSSEP). ERPs and SSVEPs, for instance, are able to zero in on a specific target and elicit a response; When ERPs are evoked only by visual stimulation, however, they cannot be utilized for interactivity by patients who are physically restrained and have visual processing impairments. If the ability to process sound is unaltered, an ERP might be performed. The SSVEP technique provides the fastest data transmission speed for an EEG-based BCI that does not need invasive brain surgery. The SSVEP method has its drawbacks, such as the potential for eye strain from prolonged exposure to a flickering display.

The control signal in this method may be random and counter-intuitive, but this may depend on the specifics of the experiment. To use an SSVEP-based BCI speller, one might stare at the letter "A," which flickers at a rate of 10 hertz. In order to interrelate with a computer, the control message is typically arbitrarily mapped, so that no particular significance is attached to the fact that "A" is correlated with 10 Hz. The ability to explicitly map brain signals related to a given task is a significant benefit of a MI-based BCI. MI, however, appears too sluggish for action control, making them unsuitable for operating VR environments or videogames. Recent proposals for hybrid BCIs, such as SSVEP/ERP and SSVEP/MI, which combine the use of multiple fingerprints, seem to provide more robust capabilities. Poor performance persists even when asynchronous BCI is considered, in which the user decides to stimulate an instruction only when absolutely essential.

Challenges to developing effective BCI systems stem from the brain's inherent neurophysiological instability. The brain-computer interface (BCI) consists of three main parts: the sensor, the processor, and the effector device (see Table 1 for further descriptions). Neuroimaging techniques have been used in numerous attempts to measure the automated or hemodynamic annotations of cortical activities, but none of these efforts has yet demonstrated commercial viability for a BCI system, which accomplishes the four vital requirements of affordability, portability, minimum maintenance, and negligible surgical treatment. When compared to other data logging modalities, EEG-based BCI more closely meet the aforementioned requirements (see **Table 1**).

Table 1. Requirements for EEG-based BCI

EEG-based BCI Requirement	
Signal Acquisition	Signal acquisition is the method used to measure brainwaves using a certain sensor modality (For instance, fMRI may detect metabolic activity, as can scalp or brain sensors for electrophysiologic operation). The signals are enhanced by an amplifier to enable electronic processing (and they could also go through filtering to get rid of electrical interference or other undesired signal features, such 60-Hz power line disturbance.). The digital signal is received by a computer.
Feature Extraction	The phrase "feature extraction" is used to describe the action of assessing digitalized signals to retrieve insightful signal features, such as signal properties linked to an individual's objectives, from the noises and determine them in a compact form suitable for translating into an output instruction. Strong correlations should exist between these features and the user's intended outcomes. Due to the transient or oscillatory nature of most of the significant (i.e. strongly linked) brain activities, the most extracted signal features currently. The BCI process integrates time-oriented ECoG or EEG response latencies and amplitudes, intensity within a particular ECoG or EEG frequencies, or the rates of discharge of individual cortical neuron. Reliable measures of brain signal parameters are obtained by eliminating or reducing environmental and physiological aberrations, such as electromyographic signals.
Feature Translation	The characteristics extracted from the signal are then sent into features translating techniques that translate them into insightful instructions from the output device. A decrease in power in a particular range of frequency might amount to an upward shift of the cursor, and P300 prospective might be employed to select the letter linked with it. For the users' available range of feature value to integrate the range of device controls, the translation approach needs to be flexible to react and accept to learnt or spontaneous changes in the signal characteristics.
Device Output	The features translation system issues instructions that cause the external device to work, allowing the user to do things like pick letters, control a robotic arm, move a cursor, and so on. The users obtain feedback on the device's performance while it operates, completing the feedback loop.

EEG's non-invasive scalp recordings give it lower spatial resolution than fMRI but superior temporal resolution. While high density EEG modeling improves spatial resolution, it comes at a high supercomputing cost and requires extra work to keep the signal-to-noise ratio acknowledge in different channels. Considering that electroencephalography (EEG) only records brain activity linked with an electric field, BOLD (blood-oxygen level-dependent) activity evaluation in parallel might enhance the performance of BCI. The fMRI is normally employed to capture the activity of BOLD; nonetheless, this approach is impractical for most BCI application because of their larger size and high cost. With its lack of invasiveness, portability, and low cost, functional near-infrared spectroscopy (fNIRS) is a viable alternative to other neuroimaging methods for capturing BOLD activity. Despite the slow information transmission rate caused by hemodynamic delays, classification performances can be greatly improved by integrating fNIRS with EEG. A recent study found that fNIRS alone does not provide sufficient performance, but that it can be merged with EEG to improve results. However, ongoing technological advancements may ultimately establish fNIRS as the gold standard in neuroscience research and BCI development.

Another significant limitation of scalp-based sensors like EEG is that they cannot probe sources in cortico-subcortical networks. The so-called inverse problem, which requires reconstructing task-induced networks, presents a formidable obstacle. In order to identify the anatomical basis of MI-oriented sources and boost classification accuracy, EEG data was analyzed using a two-equivalent-dipole model. In order to learn more about the sources of MI and how they affect BCI performance, Feng, Li, Li, and Liu [16] posited a wavelet-based source location strategy. Magnetic permeability is consistent in the cerebrospinal fluid, the skin, and the skull whereas neuronal potentials attenuate as they travel through multiple tissue layers with more complex analytics and varied electrical feature. For this reason, MEG is superior to EEG in terms of signal capture quality. However, because the magnetic field generated by the brain is so tiny, MEG requires expensive, stationary recording equipment despite providing superior spatiotemporal resolution to EEG. There are two main concerns that need to be addressed in the design of the BCI classifier. First, depending on the classifier's features, the number of measurements of the functionality set used to calculate the prototypes variables should be determined for best performance. Second, it is important to think about the bias-variance trade-off, which may require regularizing the parametric estimation.

When the features taken from the training set are different from the features in the test set, a phenomenon known as covariate shift occurs, which negatively affects classification accuracy. For the compensation of feature space transitions due to covariate shift, adaptive approaches are needed. With the unsupervised subdomain learning approach, data may be shared across subjects and sessions to improve BCI functionality. In both online and offline BCI applications, the typical geographical patters, the supervised strategy, has seen widespread usage. When adopting such a data-driven approach, it is easy for the model's parameters to become over-fit to the training sets, leading to inaccurate predictions being made when applied to the test data. Recent research has included a wide variety of methodologies into prospective transfer learning models for BCI, e.g., spatially filtered (such as typical spatial patters), Euclidean alignment, domain adaptation, Riemannian geometries and deep learning-based approaches.

IV. NEUROPLASTICITY, SIGNAL PROCESSING, AND APPLICATIONS

In order to create a functional BCI, it is necessary to take advantage of neuroplasticity, construct high-fidelity and individualized brain sensors, use sophisticated signal processing, and use machine learning strategies. Signal collection mode, experimental methodology, data processing and pattern classification, application area, and importance are only few of the features of BCI infrastructure and applications.

Neuroplasticity and Cognitive Rehabilitation

Nikolaidou et al. [17] originally showed that the brain's adaptability is anchored in the time-varying dynamics of synapses within large neural networks. Neurorehabilitation relies heavily on neuroplasticity because of its role in facilitating cognitive and perceptual development. The success of a neurofeedback method to produce desired activity patterns may hinge on the degree of plasticity of the target brain region. There is evidence that the visual cortex is malleable enough to generate strong neural signals for perceptual learning after biofeedback. Differential alpha activity between the right and left hemispheres during neurofeedback training has been linked to visual data processing and motor movements, suggesting that these differences govern spatial attention. Functional MRI (magnetic resonance imaging) is used in neurofeedback training sessions to bring about changes in attention-related behavior. Clinical implications imply that neurofeedback may be useful in the treatment of attention deficit. Recently, Azarpaikan and Taheri Torbati [18] have employed neurofeedback to induce strong somatosensory oscillations, which are linked to human perception.

Closed-loop BCIs in conjunction with neurofeedback have been shown to be effective in re-organizing cortical-subcortical neural network models and teaching people to self-regulate particular brain rhythms, although the processes behind these modifications to neural substrate is not critically comprehended. One of the example include the covert visuo-motor training using a brain-computer interface (BCI), which modifies connected neural substrates, the consequences of which are seen during the relevant motor task. Extensive research on the efficacy of brain-computer interfaces (BCIs) has demonstrated that they may facilitate considerable learning in overt movement-related activities, suggesting that BCIs play a vital role in enhancing increased motor learning needed for effectively operating neuro-prosthetics. For example, intra-cortical electrode can be integrated to enhance particular motor-control parts of the brain. Restoring control of tissue engineering or upper limb functions may be possible via training-induced neuroplasticity, which BCI may help by re-exciting the relevant neural substrates during therapeutic motor rehabilitation. Similarly, a brain-computer interface operated exoskeleton might boost worker efficiency.

Several factors influence the extent to which a BCI induces plasticity. These include (1) the choice of image acquisition modality, which is essential for analysing neural signals, (2) the model of input treatment approach that has clear and specific relationship with the neural message categorization findings, (3) the evaluation of application-based response interruptions, and (4) the application of effective feedback method of treatment. The use of many signal collection modalities, including functional magnetic resonance imaging (fMRI), electroencephalography (EEG), and magnetoencephalography (MEG) has led to a shift from single-unit recordings toward recordings of brain ensembles. Since behavioural actions are linkely to be distributed spatially in the entire cortical-subcortical systems, it is doubtful that single unit recordings will be able to catch them all.

Utilizing and promoting neuroplasticity is the purpose of rehabilitative BCI. This may be done in a variety of methods, such as by attaching neural prostheses to a body part that has been damaged or by re-stimulating the synaptic networks that were destroyed. For stroke patients with paralyzed muscles and no remaining finger movement, therapy using BCI-driven orthoses displays enhanced neuromuscular coherence that is fundamental for restoring the controls of movement. BCI may also play a role in rehabilitation via the use of functional electric stimulation controlled by movement-related signals derived from electroencephalography. There is evidence of plasticity generated by electrical stimulation in paretic muscles, as measured by increased electromyographic activity. Controlling the prosthetic or stimulation modality in BCI-based rehab in a real-world setting relies heavily on distinguishing between task-induced and resting-state activities.

The use of electric or magnet fields to activate the affected parts of the brain from the outside is an effective approach as a stroke rehabilitation therapy. Neuroplasticity within the white matter and the cortical procedures after prolonged stroke was induced using functional magnetic resonance imaging and transcranial instantaneous current stimulation. Cortical activity may be enhanced in stroke patients through the use of electrical stimulation of particular brain areas regulated by a brain-computer interface. Training must be individualized because of the wide range of post-rehabilitation neuroplasticity. Motor rehabilitation through a brain-computer interface is challenging to accomplish for patients who are unable to interact with the device. Furthermore, BCI-driven rehabilitation has been used in the fields of transcranial magnetic stimulations for the diagnosis of critical depressive disorders and the optimizations of deep brain stimulation environments for Parkinson's disease patients.

Patients with illnesses such ALS (Amyotrophic Lateral Sclerosis), spinal cord injury, downs syndrome, brainstem stroke, chronic peripheral neuropathies and muscular dystrophy could benefit from BCI either through the absolute authority of assistive technologies or through direct neuro-stimulations. The quality of life for persons with impairments is greatly enhanced when supplementary degrees of freedom are made available to them. Wheelchairs might be controlled by thought alone. A tetraplegic patient was able to successfully complete the grasping challenge with the help of a prosthetic limb thanks to the incorporation of BCI initiatives and a vision-based autonomous framework. There has been talk of controlling 3D neuroprosthetics using an implanted microelectrode array.

Signal Processing, Signal Acquisition, and Modeling

Many new investigations are looking at how to improve existing BCI systems by merging different kinds of signal capture. By taking use of the superior temporal precision of EEG and superior spatial resolution of fMRI, simultaneous methods like these may provide complementing features. Hybrid EEG/fNIRS signals improved classification performance on multiclass sensorimotor tasks, suggesting the significance of characteristics collected from both hemodynamic and electric activity. Combining MEG with EEG is a viable option since MEG may record dipole origins in cortical-subcortical networks, providing valuable context for EEG readings. While some may still be skeptical, a growing body of research suggests that EEG and MEG may pick up brain processes that originate in the brain's subcortical regions. Recent efforts have focused on maximizing BCI performance by integrating several signal collection techniques.

The ability to convert brain signals into commands for computers and other devices relies heavily on the marriage of signal processor and machine learning techniques. Understanding the physiological significance of BCI findings requires representing the signals within a time-frequency spacing. The FT (Fourier Transform) and vector auto-regression modelling are some of the deployments within the time domains, whereas the time-frequency models short-time FT as well as the wavelet transform are deployments in the time domain. Generally speaking, the Laplacian filter, independent components analysis, and the common geographic distribution are the most well-liked methods of spatial filtering. The real sources projected onto the 3D cortical-subcortical systems may be identified using a wide variety of inverse theories. Several different linear and non-linear categorization techniques may be used to interpret the extracted characteristics. Linear discriminant evaluation and SVMs (Support Vector Machine, non-linear kernel-oriented) are two examples of classifier models that may be thought of as either linear or non-linear.

Since its first publication in the year 2000, common spatial structure has been frequently utilized to characterize multichannel EEG data including spatial components. As a data-oriented approach, it necessitated a larger number of learned cases in order to determine the parameters of screening. Regularized covariance estimation has the potential to outperform the traditional method when working with a small sample size of training data. Electroencephalogram (EEG) data projection through spectral division and sparse representation of raw signals by filter banks are two examples of how spatial filtering has been modified. In general, geographical filtering works well in subject-oriented BCI enhancement, even if prior researches have advised using a subject's data to derive the filter parameters and then applying those parameters to a subject who did not provide a training sample. There are several well-known data-oriented approaches, e.g., SVMs, LDA (Linear Discriminant Analyses), and PCA (Principle Component Analysis).

Due to extraordinary advancements in computer capacity over the past year, deep learning BCI frameworks, which facilitate the assessment of big data, might soon become trendy. In contrast, autonomous analytical approach is a non-supervised technique for separating sources. When estimating the components of a signal independently, we rely on the signals' innate statistical properties. However, the true cortical inputs are modeled as polarisation in the complex brain architecture, a method that aims to mitigate the inverse issue. One of the most recent techniques for source localization, wavelet-oriented maximum entropy on the mean-first convert EEG and MEG data into geographical representations by representing the signals as significant time-frequency contents. Variation in localized sources is especially noticeable when comparing results from various inverse algorithms and toolboxes. Knowing the precise sources that need to be modelled using EEG/MEG is also not easy. For instance, due to sparse (spatial) sampling, the ground truth founded by electrodes that have been implanted might not be completely trustworthy. This is because fMRI is an indirect method of measuring brain activity. Despite this, inverse approaches have shown a great deal of promise in the development of several BCI models.

State-of-the-Art for Neurosensors

Multiple neuronal actions get support from deeper brain areas, such as the subcortical and cerebellar regions. Understanding the cells to scalp layers and RSNs scattered over the brain's 3D space is crucial for guiding BCI development. Customized sensors are being created to improve brain signal collecting methods. Electrical, optical, chemical, and biological components may all go into the building of a neurosensor. It is widely held that the signal-to-noise ratio of the dry EEG sensor is inferior to that of its wet equivalents, despite the fact that they are more convenient to use. Wet electrodes utilize conductive gel and necessitate the skin to be appropriately prepared to decrease the skin-electrode impedance, which might be problematic for certain users. However, research into BCIs that employ dry electrodes has shown that, with some careful circuit design, these electrodes may be used to capture high-quality data.

More research is needed to support the use of dry electrodes with wirelessly devices that might provide the same signal quality as wet electrodes. Taking use of the mechanical qualities of polymer, quasi-dry electrodes may collect signals at a level equivalent to commercial Ag/AgCl electrodes, combining the best features of both types of electrodes. Rolfe [19] have developed an ultra-dense sensing model of 700 to 800 electrodes to enhance EEG's spatial resolution. There was a twofold improvement in signal-to-noise ratio against high-density EEG, which may employ up to a maximum of 256 gold-coated sensors. It was suggested that an auricle electrodes with a stretchy connection might not only make recordings more convenient but also more mobile. As the skin's electrical and mechanical qualities change, so does the electrode's ability to adapt.

Biocompatibility is a need for invasive sensors. Sensing neural impulses from the brain's outside is now possible thanks to an unique organic electrochemical transistor-based sensor. This sensor has a far better signal-to-noise ratio than standard ECoG because its transistor-based construction enhances recorded signals locally. This sensor is physically malleable and is safe for biological use. The signal quality may be improved by covering the electrodes with carbon nanotubes, which reduces their resistance and increases charge transfer. Another invasive biocompatible device with data transmission is being developed to record spectra of vast neuron populations that have been unavailable till now.

Due to remarkable developments in nanotechnology, nanowire Field Effect Transistors as well as other p/n junction devices may soon be used as a neuro-sensing approach for the intra-cellular recording, even within the deeper regions of the brain system. Invasive stent-electrodes arrays (stentrode) have been suggested by Strokov, Schander, Stemmann, TeBmann, Lang, and Kreiter [20]. Stentrode placement into brain arteries and veins is possible with the use of computer-guided catheter angiography. With this technique, the risks associated with craniotomy may be greatly reduced because of the high-fidelity cortical impulses it captures. Recent research confirms the strentrode can be implanted in people to record brain signals over an extended period of time. Strentrode-based BCI had a similar rate of information transmission as Iredale et al.' [21] seminal work using implanted electrodes. Access to neural data may also be obtained wirelessly by means of an entrenched ECoG plotter dubbed Wireless Implantable Multi-channel Acquisition system for Generic Interface with Neurons (WIMAGINE). Long-term dataset collection reliability and craniotomy risk have both recently been assessed on the WIMAGINE.

Small-scale neuronal activity recording are essential for studying the activities and intra- and inter-neurons interactions in brain circuits, alongside large-scale recording models such as MEG and EEG. To move neuroengineering and BCI further, it is essential to represent every cognitive process as a function of both local and global neural connections. A high-density array of silicon probes serves as a neurosensor, and optogenetics allows for single-unit recordings in this context. A unique multi-plane two-photon microscope was suggested, which would allow for the cellular-level capture of multi-layer neuronal architecture and process. Calcium imaging and improved microscopes with chronically inserted lenses are two more imaging techniques that might be used to study cell signaling. With the use of designer receptors that are only triggered by designer medications, Eroğlu [22] now have a powerful chemogenetic tool with which to study cell-signaling processes, such as electrical activity in molecularly clustered groups of cells. Millimeter-scale recordings of electromyograms and electroneurograms are now possible thanks to a novel ultrasonic-based wireless device termed neural dust.

Complex Computing, Robotics, Gaming, and Miscellaneous Applications

Computer systems in the future are thought to acquire psychological and perceptual skills, which would boost their usage beyond only supporting people and into decision-making. Using data from the body and the mind, computers may soon be able to identify and make sense of people's true feelings. Recent research has shown that brain-computer interfaces (BCIs) may be utilized to evaluate complex states, extending its use into the field of psychology. Paranjape, Dhabu, Deshpande, and Kekre [23] propose a BCI oriented on EEG, which can identify whether a given visual input elicited a favorable or negative emotional response.

As a subset of BCI, "artistic BCI" refers to the practice of incorporating creative expression into the technology. David Rosenboom started exploring neural correlates of musical creativity, form recognition, and bodily musical awareness in the late 1960s. Affective state detection, video gaming, and virtual/augmented reality environment control are further instances of creative BCI. In a number of studies, Martišius and Damaševičius [24] have shown that the SSVEP-BCI may be used to control a video game entirely. The concept of a cooperative game, (in which numerous players work together to make decisions about the game's state), has been the subject of other research. As was shown in a different research, the combined brain signals of two intelligence analysts may be superior to those of a single analyst when it comes to making important decisions. The reason for this may lie in the fact that people vary in their level of intelligence and their ability to perceive the world around them. User collaboration with an emphasis on diversity and inclusion may aid in decision making for individual users. Expanding the use of BCIs in sociology, a tweaked arrangement might examine how individuals interact in a variety of social circumstances.

A combination of BCI and V/AR technologies has the potential to provide immersive experiences with several applications, such as in the arts and neurofeedback. By reading brain signals, a user may create a virtual canvas on which to draw a line, opening up a new form of communication for those whose motor abilities have been compromised. They've created a VR brain painting program. An additional piece of study has shown the potential of VR-BCI for measuring cognitive burden in the service of neuroergonomics. The employment of virtual reality (VR) has been studied as a viable neurofeedback alternative to the traditional computer screen, with positive results for BCI precision. Spicer, Anglin, Krum, and Liew [25] have developed a platform for motor rehabilitation called REINVENT that combines VR and BCI concepts. In a similar vein, BCI combined with AR may be employed to operate robots remotely to aid in the rehabilitation of children with attention-deficit/hyperactivity syndrome.

BCI-driven robotic controllers provide cutting-edge assisting technology for those with mobility constraints, and may significantly improve human ergonomic performance in healthy participants. Mobile robotic or wheelchair controllers powered by BCIs based on EEG data have shown the technology's promise in the robotics sector. In dangerous circumstances, such as sending robots into coal mines to carry out a job that may be harmful to a person, a BCI can be utilized to manage the robot remotely via EEG. To track astronauts' energy levels and power an exoskeleton, BCI has potential applications in space. Work becomes more difficult and uncomfortable without gravity. At addition, astronauts' time in the office is invaluable. The use of BCI-powered technologies to enhance astronauts' performance, productivity, and safety is a plausible future goal.

Experiments with brain-to-brain interfaces (BBIs) have been conducted recently, with the goal of translating a sender's mental state into a set of instructions for stimulating a recipient's brain. A direct BBI device was built in 2013 to allow one rat to transfer sensorimotor data to another rat. The intended brain regions of the recipient were stimulated using intracortical macrostimulation. In an early effort to create BBI between two human individuals, Lee et al. [26] suggested using non-invasive EEG and transcranial magnetic activation to produce sensorimotor rhythm-based BBI. Many other proposals for completely non-invasive BBI investigations include human participants exchanging and decoding words encoded in pseudo-random binary streams while playing cooperative games.

Regardless of the scientific progress made in the area, the advantages to users and societal consequences of BCI research should be maximized by taking into account key aspects pertaining to security, ethics, confidentially protection and information secrecy, community acknowledgment, and economic considerations. BCI Researchers may have trouble communicating with patients wearing BCIs and gaining their ethically sound informed consent. There should be a greater focus on ethics policies and a heightened level of public understanding to increase the likelihood that patients will receive sufficient data.

BCI users' psychological and bodily well-being must be prioritized. Deep brain stimuli and intracortical microelectrode variety are examples of invasive procedures that can have lasting psychological and neurological effects in the postoperative period. Also, the implanted sensors may need to be removed or maintained if bleeding or diseases occur. Guidelines are required to ensure the safe development of neurotechnology’s like BCIs, which might affect behavior and pose risks to an individual's emotions, personality, and memory. By considering the importance of responsible application of this technology, one can establish a ceiling for the scope of studies involving human brain-to-brain interface requests. Because of the multifaceted roles played by both the sender and the receiver, the intended result may be affected by the sender's deliberate manipulation of brain signals. Ethical concerns concerning improving human cognitive and maybe moral ability are raised by the lack of knowledge about the reversibility and effectiveness of the cognitive alterations.

In addition to the unknown risk factors, which can reduce the benefit of using BCI, users may be disappointed when they fail to achieve the additional or extended degrees of freedom they had hoped for. People who worry about becoming too reliant on technology could benefit from education about BCI technology if it were more widely disseminated. It is critical, however, to perform robust clinical investigations of cutting-edge devices like strentrode and WIMAGINE in order to establish their potential advantages, particularly for those with cognitive impairments of any kind. Large-scale adoption among healthy consumers should not be too challenging to obtain given that EEG electrodes might allow long-term method of a BCI setup with minimum maintenance.

For BCI to be used legally and for personal information to be protected, a lawful framework must be put in place. Recently published research has shown that consumer-grade BCI may be used to decode passwords or recognize faces, raising concerns about unauthorized access to and usage of users' raw data. A user's emotional and moral dispositions are shaped by their affective moods. Therefore, it is crucial to restrict the uses of emotional BCI in order to protect private data. To prevent unauthorized users from gaining access to sensitive information or breaking the system, preliminary efforts should develop application-specific BCI frameworks. Recent occurrences, such as the illegal usage of a wireless BCI-oriented limb and the manipulative reconfigurations of computer-aided neuro-stimulations, have underlined the requirement of defining effective safeguards to the employment of BCI. To ensure that a user's private data remains private, cryptographic methods have been suggested as built-in features of BCI. The advancement of BCI would be slowed if the commercialisation of BCI occurred before social, economic, ethical, and policy concerns were thoroughly examined.

V. CONCLUSION AND FUTURE RESEARCH

Building a common network infrastructure for Brain-Computer Interfaces (BCI) researchers throughout the world is essential for speedy creation of a full list of universal principles, which is crucial to continued progress in the domain of BCI. In order to further our understanding of the nervous and the brain system, these researchers have formed alliances to work on projects together e.g., the Human Brain Initiative, which is a joint European Union and university effort. The White House has also made an announcement on an initiative called the Brain Initiative. The design, performance, and use of BCIs of the future will depend, in our view, on our increased knowledge of fundamental neuroscientific processes. Recent developments in computational tools and neuro-sensors provide a significant insight for developing BCI devices that need minimal maintainability and are easy for their users to learn to use. In addition to improvements in high-fidelity signal collection, developments in signal processing and machine training techniques, as well as increases in computing mobility and power have all had a significant impact to the development of BCI technology. However, addressing these crucial issues is crucial for the development of BCI technology in the future. (i) Determining what psychological and physiological variables may have an effect on BCI accuracy. (ii) Creating less intrusive sensors that nevertheless acquire and resolve signals reliably while also being portable, low-maintenance, and inexpensively. (iii) Simulating how data moves between sessions and across people, such that more generic BCI models may be proposed with little or no calibration, and (iv) Building widespread agreement on how to responsibly use this technology to the social and economic realms.

Data Availability

No data were used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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