CONTRIBUTED PAPER

Brain–Computer Interface—A Brain-in-the-Loop Communication System

This article discusses brain–computer interface (BCI) technologies from a communication perspective, highlighting critical components of the BCI communication system and discusses the challenges and opportunities.

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ABSTRACT | The brain–computer interface (BCI) establishes a direct communication system between the brain and a computer or other external devices. Since the inception of BCI technology half a century ago, it has advanced rapidly and developed into an active area of frontier research in modern applied science and technology. This article provides a comprehensive survey on BCI with respect to a brain-in-the-loop communication system. In the present work, we first introduce the underlying architecture of the BCI system from the theoretical and methodological perspectives of communication systems. The key technologies are then detailed, including the construction of BCI system, brain-to-computer (B2C) communication, computer-to-brain (C2B) communication, and multiuser BCI systems. Additionally, this article discusses the various applications of BCI and the challenges they face. Finally, this article discusses BCI's future development, with an emphasis on the convergence of human intelligence (HI) and artificial intelligence (AI), and the interaction of BCI with wireless communication and the metaverse.

KEYWORDS | Artificial intelligence (AI); bidirectional communication; brain–computer interface (BCI); brain-in-the-loop; coadaptive communication; communication system; decoding; encoding; human augmentation; human intelligence (HI); metaverse; neural rehabilitation; neuromodulation; sixth generation (6G).

I. INTRODUCTION

The brain–computer interface (BCI), also known as the brain–machine interface (BMI), enables direct communication between the brain and a computer or other external devices. In a broader sense, any system that directly communicates with the brain and an external device can be considered a BCI system [1]. Since its inception half a century ago, BCI technology has introduced a wide variety of paradigms and applications. The primary objective of BCI study is to establish a new nonmuscular communication pathway between the brain and the computer to facilitate communication and control for individuals with severe motor impairment. Increased interest in interdisciplinary collaboration across disciplines such as neuroscience, engineering, computer science, and psychology

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has expanded the scope of BCI beyond communication and control to include a suite of generalized BCI tasks [1]. The BCI system enables a new alternative and augmentative communication mode for disabled and non-disabled users by measuring and translating brain signals related to sensation, perception, and cognition into commands or objective reports. BCI research, in particular, has exploded in popularity over the last two decades of the 21st century. The technology has made remarkable progress, demonstrating great promise in various practical applications, including neural rehabilitation, human enhancement, and entertainment. Currently, the BCI is one of the most active research areas and continues to push the boundaries of cutting-edge technology [2].

Broadly speaking, the BCI system is a communication system. BCI and modern communication technologies are inextricably linked and work in concert. On the one hand, modern communication technology has accelerated the development of the BCI consistently and profoundly. Specifically, a variety of BCI paradigms have emerged due to the methodology of modern communication technology, such as the principle of multiple access [3]. Furthermore, modern wireless communication enables fast and reliable wireless communication between a brain and a machine, enabling a diverse range of portable BCI applications [4]. On the other hand, the BCI advocates for low-energy wireless technology with a high data rate, thereby contributing to the advancement of modern communication technology. Recently, BCI technology was highlighted as one of the key applications that will power the upcoming sixth-generation (6G) wireless communications standard [5]. Additionally, the advent of next-generation technology will create opportunities for the interaction of BCI and modern communication technology, such as the emergence of BCI in future metaverse applications [6].

In particular, BCI is a brain-in-the-loop communication system, i.e., a bidirectional closed-loop communication system that comprises both brain-to-computer (B2C) and computer-to-brain (C2B) directions. In this loop, human intelligence (HI, i.e., the brain) and artificial intelligence (AI, i.e., the computer) are organically integrated to form a highly intelligent communication system. In the B2C direction of communication, due to the involvement of the brain, the BCI achieves intelligent control of external devices [4], [7], [8], [9] and also enables a higher level of intelligent decision-making [10], [11]. In the C2B direction of communication, the AI systems can send effective commands to the brain, thus regulating the state and function of the brain. A computer–brain interface (CBI) writes messages or commands onto the brain without sending them through the brain's normal input pathways [12], [13], [14]. Such brain modulation methods not only enable neural rehabilitation and therapy [15], [16], [17], [18] but also facilitate the intelligence augmentation of healthy people [15], [19], [20], [21]. In addition, the organic integration of HI and AI can also effectively enhance human efficacy by ergonomics [22], [23], [24], and the interaction of the two yields far better results than working in a single mode. Furthermore, as a brain-in-the-loop communication system, when BCI is integrated into future advanced network communication, the brain will act as a node in the network, enabling a new brain-type communication in the future Internet of Things (IoT) [25].

While modern communication technology has become an integral part of the BCI system, the BCI literature has paid little attention to it. In terms of the review, while there is a substantial body of recent work on BCI that offers a variety of novel perspectives [26], [27], [28], [29], [30], a review elucidating the essence of BCI from the perspective of communication system theory and practice is still lacking. To address this deficiency, this survey provides an in-depth and comprehensive review of BCI technology over the last 50 years within the context of modern communication technology. To emphasize the critical role of communication technology in the BCI domain, this article discusses a wide variety of BCI technologies from a communication perspective, highlights critical components of the BCI communication system, and provides new insights into the challenges and opportunities beyond the current state of the art.

The following outlines the topics addressed in this review. First, Section II introduces the BCI configuration as a communication system. Then, in Sections III–VI, the key technologies underlying BCI systems are discussed, including the construction of BCI system, B2C communication, C2B communication, and multiuser BCI. Section VII describes a variety of BCI applications. The grand challenges and prospects of BCI are discussed in Sections VIII and IX, respectively. Finally, this article is concluded in Section X.

II. BCI AS A COMMUNICATION SYSTEM

A. Definition of BCI Communication

The term "BCI" first appeared in official publications half a century ago. Vidal [31] developed a visual evoked potential (VEP)-based BCI system in his laboratory in the 1970s and called it the BCI system. There is no universally accepted scientific definition of BCI at the moment, but the overwhelming majority of literature cites the definition proposed by Wolpaw and Wolpaw [32]. According to this definition, a BCI system replaces, restores, enhances, supplements, or improves the natural output of the central nervous system (CNS) by measuring it and converting it to artificial output, thereby gradually altering the way the CNS interacts with its external or internal environment. The emphasis in this definition is on the fact that BCI measures signals from the CNS, which is distinct from the peripheral nervous system (PNS) and consists of the brain and spinal cord.

BCI is highly analogous to well-known communication systems in terms of system structure. In most modern communication systems, the source data to be transmitted, for example, the text message, are first encoded by an encoder.

Encoding is used to convert transmitted data to a signal suitable for transmission over a channel, such as the binary symbol 0 or 1. The encoded signal is transmitted over a specific communication channel and is recovered at the receiver by a decoder. The encoded source signal must be modulated onto a radio carrier for atmospheric transmission, while the received signal must be demodulated and then decoded to recover the original signal [33], [34]. Due to the inevitable mixing of the source signal with various noises during encoding, transmission, and decoding, the system typically requires acquisition measures to suppress noise and improve decoding accuracy.

BCI serves as a communication system, and its basic framework is very similar to that of modern communication systems, which consist of two primary components, an encoder and a decoder [35]. In BCI, the source information we wish to transmit is the user's intentions or wishes, which are converted by the brain, the BCI system's encoder, into stable and distinguishable characteristic brain signals. Specifically, the so-called characteristic brain signals can be the cerebral cortex's characteristic neuroelectric activity or metabolically related blood oxygen signals. Since the characteristic brain signal is a physiological signal, it must be converted into a measurable and calculable physical signal before being fed into the computer for analysis. Generally, existing conversion methods include electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and so on, with the converted physical signal being either a time-varying electrical signal or an image with spatial distribution characteristics. This conversion process is fundamentally related to encoding, as it converts the user's intentions or wishes into a tangible and deliverable form of expression that can be fed into the communication channel. After the computer receives the incoming brain activity data, it can use feature extraction and classification to recover information about the user's intentions or wishes. In this case, the computer acts as a decoder. It is critical to remember that the BCI system's encoding, transmission, and decoding stages are inevitably mixed with various noises. For instance, the scalp EEG signal contains numerous spontaneous EEG signals with "noise" characteristics in addition to task-related brain signals. Thus, to enhance the communication system's channel capacity, it is critical to minimize noise at each stage.

B. Brain-in-the-Loop Communication System

Under normal circumstances, the brain's output signal is transmitted via the PNS to effector cells to perform the corresponding function, which is an efferent process. Meanwhile, there is an afferent process counterpart in which the terminal sensory receptor transmits information about the surrounding environment to the brain via the sensory neuron. The efferent and afferent pathways form a closed-loop control system that ensures the effectiveness and stability of human behavior.

As a substitute for the natural neural control system, BCI must also incorporate both "efferent" and "afferent" pathways and be structured in a closed-loop fashion. A typical bidirectional BCI communication system is the motor imagery (MI) BCI system. Physiological studies have demonstrated that when subjects imagine their body movements (without actually moving their bodies), a decrease or increase in the power of brain signals in specific frequency bands can be detected in the primary motor cortex (M1) region. The terms event-related desynchronization (ERD) and event-related synchronization (ERS) refer to this phenomenon [36]. The MI BCI utilizes this phenomenon to record the neural signals associated with motor intention from M1 and converts them to control commands via neural signal decoding. The translated commands are then used to control the advanced movement of the prosthetic hand. Meanwhile, feedback information about grasp, touch, and proprioception is captured by sensors embedded in the prosthetic actuator and encoded into a stimulus train directed at a sensory region of the brain, such as the primary somatosensory cortex (S1). These bidirectional pathways constitute a closed-loop BCI and serve as the basis for an effective and efficient control [37].

The terms "efferent" and "afferent" pathways in BCI refer to the two directions of communication between the brain and the computer, i.e., B2C and C2B communication, respectively. Similarly, the bidirectional BCI system bears a strong resemblance to the duplex communication system. In B2C communication, the transmitted information, i.e., the user's intentions or wishes, is first converted into a specific brain activity signal. Different signal patterns represent different intents or wishes, with the brain acting as the encoder. Brain activity signals that have been encoded can be acquired in various ways and then transmitted to the computer at the receiver. After the computer analyzes and processes the signals, the computer recognizes and recovers the various patterns of brain signals. In this communication system, the computer acts as the decoder (see the upper portion of Fig. 1). The computer acts as an encoder in C2B communication. The computer first encodes the transmitted source signal to enable the brain to recognize the various stimulus signals. Then, the encoded signal must be delivered to the brain using instrumentation such as transcranial magnetic stimulation (TMS), transcranial electrical stimulation (TES), or focused ultrasound stimulation. After the subject's brain receives the signal, he or she can consciously comprehend it and restore the originally transmitted signal (see the lower portion of Fig. 1).

It is critical to note that BCI entails the interaction of biological and physical systems. Without a doubt, the brain is the most advanced intelligent system currently available, and its intervention causes the BCI system to operate in a highly adaptive mode. This intelligence-based adaptation is the most salient distinction between BCI and conventional physical communication systems, highlighting BCI's uniqueness. Two adaptive controllers, namely, the user's brain and the BCI system, are critical in this adaptation.

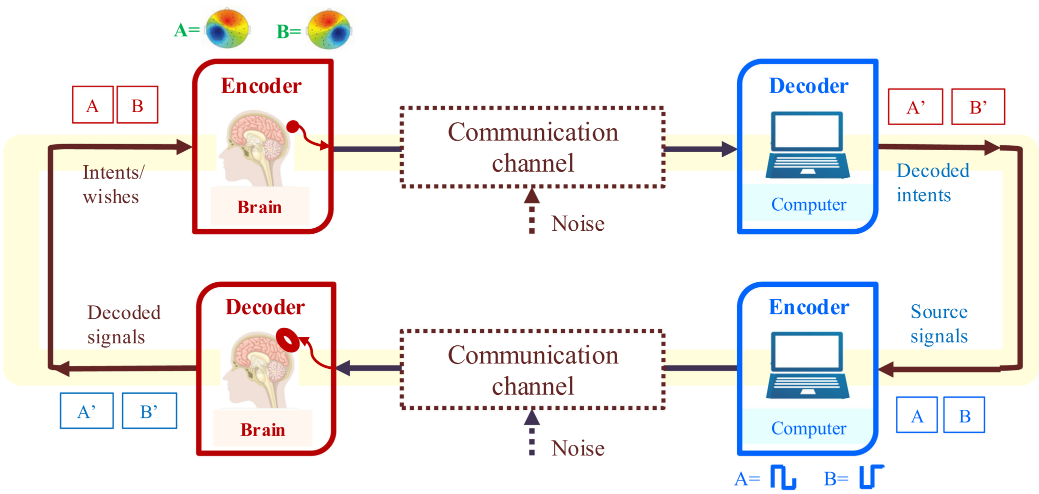

Fig. 1. ***Brain-in-the-loop communication system. A bidirectional BCI modeled as a duplex system with efferent (B2C) and afferent (C2B) pathways. The brain encodes motor intent signals, which are decoded by the computer for control. Feedback signals are then encoded by the computer and delivered to the brain via stimulation, forming a closed-loop, coadaptive system.***

The brain generates signals for the BCI system and the BCI decoding feedback for the brain [38], [39]. A BCI system that achieves the interaction of two adaptive controllers is called a coadaptive BCI system, which involves key technologies that we will describe in detail in Section V-B.

Summary: As a communication system, BCI possesses many mature technologies and methods used in modern communication. Surprisingly, advancements in communication technology have aided in the development of BCI. At the same time, the brain's involvement has endowed brain-in-the-loop communication systems with intelligent characteristics that distinguish them from traditional physical communication systems. This intelligence-based characteristic of BCI enables a broader range of applications in various domains, ranging from communication and control to human augmentation, neural rehabilitation, neuromarketing, and so on.

III. CONSTRUCTION OF BCI SYSTEM

The BCI system is an integrated technology that directly interfaces with the brain, and it is constructed by a comprehensive pipeline designed to acquire, process, and interpret brain signals, thereby enabling the brain-in-the-loop communication. The BCI system is a melting pot of a wide spectrum of disciplines, with its design process in hardware and software particularly demanding a profound integration of neuroscience and engineering. On the hardware side, the design of BCI system should be aligned with neuroscience principles and, in particular, tailored to the neurophysiological properties of brain signals while ensuring usability and safety. On the software side, the BCI system should leverage neuroscience principles to accurately interpret brain signals and infer user intent while achieving real-time processing with high efficiency. Enhancing the performance of BCI system demands a comprehensive approach to both software and hardware to fully maximize channel capacity in BCI communication.

A. Brain Signals for BCI

Various brain signals generated by neuronal activity in the brain can be used to build BCI systems. How to obtain these brain signals is crucial. The term "brain signal" in this section specifically refers to measurable physical signals, such as EEG and event-related potential (ERP), derived from the neuronal activity of the cerebral cortex. The processes underlying the generation of various signals are detailed in the relevant literature [40].

Brain signal acquisition techniques in BCI can be broadly classified into invasive and noninvasive techniques (see Fig. 2). Electrocorticography (ECoG), multiunit activity

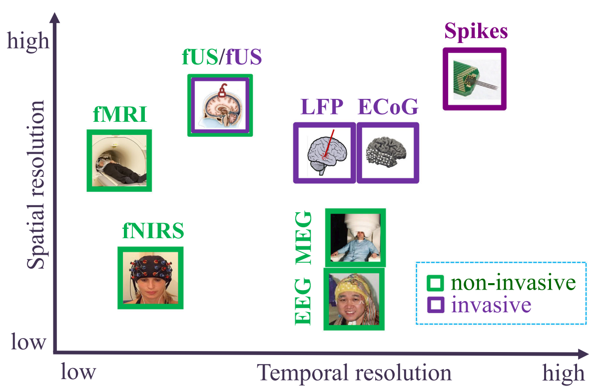

Fig. 2. ***Brain signals for BCI [41], [42], [43], [44], [45]. Overview of commonly used brain signals in BCI, categorized by spatial and temporal resolution. Noninvasive and invasive techniques offer tradeoffs in resolution and safety for BCI applications.***

(MUA), local field potentials (LFPs), and single-neuron action potentials (spikes) are all brain signals measured from traditional invasive techniques. Recently, cerebral blood volume (CBV) signals related to neurovascular coupling can be measured by functional ultrasound (fUS) neuroimaging in a portable and less invasive way [45], [46], [47]. Generally, these signals have a significant advantage in terms of spatial and temporal resolution, which is advantageous for later-stage high-precision decoding. However, invasive methods incur the cost of clinical surgery and expose recorded neural signals to degradation due to biocompatibility concerns. Besides, it is important to note that the high spatial resolution in invasive recordings is only achievable when measuring a specific brain region, and simultaneous recordings across the entire brain with such a high resolution are still infeasible. At the same time, noninvasive techniques include EEG, magnetoencephalography (MEG), fMRI, functional near-infrared spectroscopy (fNIRS), and so on. Due to their noninvasive nature, which ensures the safety of participants, these methods are better suited for applications in large populations. The acquired brain signals are further classified into two categories based on their physiological properties: electrophysiological signals and metabolism-related signals, the former of which includes EEG, ECoG, LFP, and spikes, and the latter of which includes fMRI, fNIRS, fUS, and so on [27], [40], [46], [48].

Given the noninvasive nature of EEG and the low cost of equipment, as well as the fact that it is currently the most frequently used signal in BCI research, this article will focus on EEG-based BCI systems.

According to neuroscience principles, the brain signals used in BCI can also be classified into three distinct categories, namely, sensation, perception, and cognition. Specifically, a sensation signal refers to the signal transmitted to the brain through the human sensory organs. This category of the signal includes those elicited by external visual, auditory, somatosensory, olfactory, or other sensory stimuli. Generally, the BCI system developed based on the sensation signal has a high communication rate. Perception signals are generated when a subject becomes aware of changes in the external environment. For instance, the perception signal is usually related to an ERP, which is a brain response time-locked to specific events or stimuli and consists of ERP components that reflect a specific neural or psychological process [49]. Among the ERP components, a well-known perception signal is P300 that occurs in the parietal region of the brain as a positive deflection approximately 300 ms after a subject is presented with an unusual stimulus. This perception signal has been successfully applied in the P300-based BCI paradigm. Finally, cognition signals refer to the brain signals generated by a subject during the completion of a cognitive task, e.g., decision-making [32], [50].

Generally, the aforementioned brain signals occur on various temporal and spatial scales. Sensation signals are generated immediately after stimulus onset; perception signals are typically generated several hundreds of milliseconds after stimulus onset [51]; and cognition signals are generated during the user's completion of the mental task, which may take seconds. These signals also originate from distinct brain regions on a spatial scale (see Fig. 3). The brain regions associated with sensation signals are determined by the stimulus signals' properties. VEPs occur in the occipital lobe's visual cortex, auditory evoked potentials (AEPs) occur in the temporal lobe's auditory cortex, and somatosensory evoked potentials (SEPs) occur in the parietal lobe. P300 signals associated with perception can be recorded in the brain's parietal lobe. Additionally, the frontal lobe produces a variety of cognitive signals associated with mental tasks. A thorough understanding of the spatiotemporal properties of brain signals while performing specific tasks is required to design BCI systems [52].

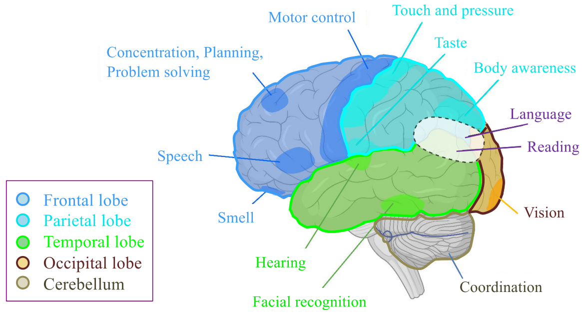

Fig. 3. *Cortical areas of interest for BCI recordings or stimulation. Functional brain regions associated with sensation (e.g., vision, hearing, and touch), perception (e.g., language and reading), and cognition (e.g., planning and decision-making). These areas serve as key targets for BCI signal acquisition, depending on task demands.*

B. BCI Hardware

BCI hardware primarily provides a physical means to acquire, store, and analyze brain signals, including sensors for detecting brain signals, an analog front end (AFE) for signal amplification and analog-to-digital conversion, and a computer for brain signal processing and control command transmission [53], [54].

Brain signals can be broadly classified into electrophysiological and metabolic signals based on their acquisition mode. As a result, the sensors and acquisition devices used to detect and acquire each signal are distinct [55]. Metabolic signals can be measured specifically using fNIRS and fMRI devices. However, due to the complexity of the acquisition device system and its relative lack of real-time performance, devices based on metabolic signals are rarely used in real-world applications. Additionally, electrophysiological signals can be acquired extracranially (e.g., scalp EEG) or intracranially (e.g., ECoG, MUA, LFPs, or spike; see Fig. 4) [56]. Extracranial EEG is a completely noninvasive technique that involves placing electrodes on the scalp surface. The EEG signal is derived from the activity

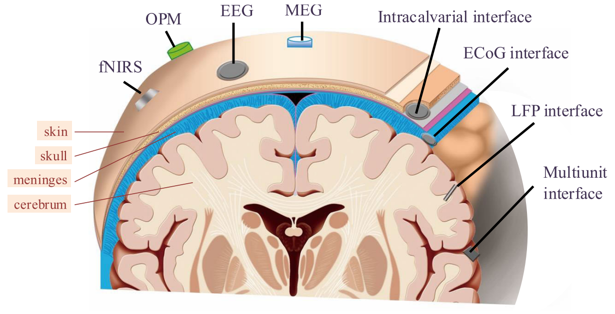

Fig. 4. ***Anatomic locations of the representative BCI sensors. Illustration of sensor placement across scalp, skull, and brain layers for various BCI modalities. Noninvasive sensors (e.g., EEG, MEG, fNIRS, and OPM) are positioned extracranially, while invasive interfaces (e.g., ECoG, LFP, and multiunit) penetrate the skull to access intracranial activity. Each modality offers tradeoffs in signal fidelity, spatial resolution, and invasiveness.***

of millions of neurons beneath the electrodes, resulting in a signal with a relatively low spatial resolution. Notably, most current EEG systems utilize "wet electrodes," which require the injection of gel between the electrodes and the scalp during preparation to reduce contact impedance, which virtually always results in user discomfort. For intracranial EEG measurements, a high spatial resolution is possible to obtain more precise information about brain activity, which is extremely beneficial for the subsequent interpretation of brain signals. However, the electrode implanting procedure is traumatic, which inevitably increases the risk of wound infection. The electrodes' long-term effectiveness and biocompatibility also remain a technical challenge. Due to the natural coexistence of electricity and magnetism, the generation of neuroelectric signals is accompanied by the generation of weak magnetic signals that can also be measured outside the skull. During transmission from intracranial to extracranial, the magnetic signal is unaffected by the conduction medium, e.g., cerebrospinal fluid, skull, and scalp. As a result, the magnetic brain signal has a higher signal-to-noise ratio (SNR) than the EEG signal. Multichannel MEG systems currently available are complicated and expensive, limiting their application. Recently, a simple MEG device capable of operation at room temperature, the optically pumped magnetometer (OPM), has been used in BCI systems on a preliminary basis [57].

The amplified and digitized brain signals are then transmitted to a computer for further analysis. Various brain signals are transmitted wirelessly due to recent advancements in wireless communication technology. This enables BCI users to move freely while using the device, thereby increasing the device's usability [4], [58].

Beyond signal acquisition for BCI systems, a brain-in-the-loop system also facilitates C2B communication through the direct writing of information into the brain. This write-in capability imposes substantial demands on hardware systems, which must be engineered to both record brain signals and deliver precise stimulation. Notably, a category of stimulation electrodes has been specifically designed to fulfill this dual role, for instance, the PiStim electrode for TES [59] and the sputtered iridium oxide film (SIROF) electrode for intracortical microstimulation (ICMS) [60]. These brain-in-the-loop hardware components have exhibited robust performance in delivering write-in signals, providing a substrate for a broad array of neuromodulation applications, as detailed further in Section V-A.

Because the EEG system's hardware is relatively simple, inexpensive, and simple to operate, and a basic experimental platform can be readily constructed quickly, the vast majority of BCI research currently reports EEG-based BCI systems. Therefore, this article will feature a particular emphasis on EEG-based BCI technology.

C. BCI Software

BCI software is composed of four main modules: data acquisition, signal analysis, and output, as well as a system-level operating protocol [32] (see Fig. 5).

1) Data Acquisition: This module's function is to record and store the brain signal via the sensor. This module configures the sampling rate, the number of channels, the reference type, and the buffer size. The buffer size determines the number of sampling points in each batch that is transferred in real time to the signal analysis module. These parameters vary according to the experimental paradigms and applications used in BCI.

2) Signal Analysis: This module is responsible for decoding brain signals and converting them to control commands. This module is typically divided into two steps, namely, feature extraction and classification. The first step is to extract features and patterns that are closely related to the user's intent. Then, the extracted patterns are classified, and the predicted result is translated into control commands for external devices. Section IV-B will discuss the specific algorithm for decoding brain signals in detail.

3) Output: This module's purpose is to send the corresponding control commands to external devices or provide user feedback. The feedback can be in the form of the

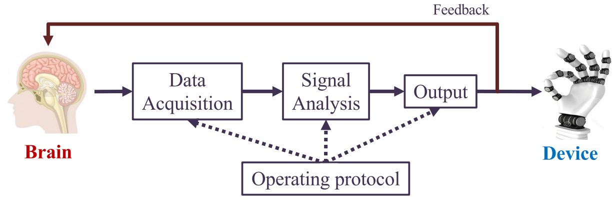

Fig. 5. ***BCI software platform. Core modules of a BCI software system, including data acquisition, signal analysis, and output execution, are coordinated by a system-level operating protocol. A feedback loop enables closed-loop interaction between the brain and external devices.***

control performance of external devices or other data pertinent to the BCI's operation. To operate optimally, most BCI systems require some form of feedback.

4) Operating Protocol: The function of this module is to coordinate the operation of the entire BCI system. As the BCI system's core module, it defines the parameters used in the three preceding modules and also controls the system's timing, e.g., the onset, offset, and timeline of trials.

To assist BCI developers, particularly those who are new to the field, in quickly establishing their own experimental platforms, engineers have developed numerous general-purpose BCI software platforms that have been widely used [61].

BCI2000 is one of these well-known software platforms [62]. Since the platform's inception in 2000, it has provided an open-source C++ program that supports a variety of development environments. The operator, source, signal processing, and user application modules can all be adapted for use with various online BCI paradigms. BCI2000 is well documented, and users can refer to the book for detailed documentation [63].

OpenViBE is an open-source BCI platform designed for use in both real-world and virtual environments [64]. OpenViBE's defining feature is its high modularity, which makes it an ideal fit for virtual reality (VR) and 3-D display, as well as its user-friendliness for a variety of user types. Nonprogrammers can quickly set up a complete BCI system using OpenViBE without having to write any code. Additionally, the platform is optimized for various real-time BCI applications, particularly in VR scenes.

BCILAB, an open-source toolbox based on the MATLAB environment, is another well-known software platform. BCILAB provides a comprehensive set of machine learning and signal processing methods, all of which are accessible via a graphical user interface and extensive documentation, allowing for rapid prototyping of new BCI implementations. The BCILAB, as a versatile toolbox, is compatible with a variety of other data acquisition and experimentation environments [65].

BCI platform research is a rapidly expanding field, and a variety of other BCI software platforms are available, including OpenBCI, BCI++, xBCI, BF++, and PyfF. Readers can refer to the relevant literature to delve into their characteristics [40], [66].

D. Channel Capacity in BCI Communication

The channel capacity of a communication channel is the maximum data rate at which data can be reliably transmitted across it. The channel capacity of the BCI communication system can be quantified using information transfer rate (ITR), a metric derived from Shannon channel theory [67] under certain mild conditions of memorylessness, equiprobability, and so on. Wolpaw et al. [38], [68] proposed the ITR, which quantifies the amount of information transferred by the BCI per symbol or unit time by considering the number of targets N and the average

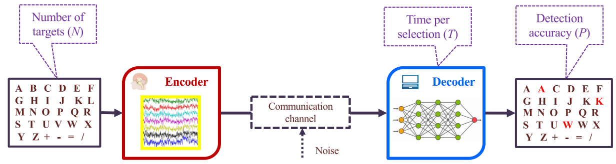

Fig. 6. ***ITR. Illustration of key parameters influencing BCI communication efficiency: the number of targets (N), time per selection (T), and detection accuracy (P). These parameters jointly determine the ITR, which quantifies the effective data throughput of the BCI system.***

detection accuracy P. The following defines the ITR in bits per symbol:

$$B = \log_2 N + P\log_2 P + (1 - P)\log_2 [(1 - P) / (N - 1)]. \tag{1}$$

Based on (1), the ITR in bits per min (bits/min) enjoys widespread adoption

$$B_t = B * (60/T) \tag{2}$$

where T denotes the average selection time for a target in seconds. It is worth noting that T should encompass the total amount of time required for signal acquisition and decoding, i.e., $T = T_A + T_D$.

To achieve a high ITR from a communication system perspective, the system must have ultrahigh reliability, low latency, and a large number of targets to ensure a large P, small T, and large N, respectively (see Fig. 6) [69], [70], [71], [72].

Over the last two decades, significant progress has been made in improving the ITR of BCIs. For example, continuous efforts have been made to optimize the steady-state VEP (SSVEP)-based BCIs, with the best-performance ITR increasing from ~0.9 bits/s in 2002 [73] to ~6.3 bits/s in 2018 [74]. Nonetheless, insufficient channel capacity continues to be a significant barrier to real-world BCI applications. There is room for improvement in channel capacity and ITR to close the transfer rate gap between BCI and traditional human–computer interfaces (HCIs) [75].

IV. B2C COMMUNICATION

A. Brain Signal Encoding

Brain signal encoding is the process of converting a user's intentions or wishes into the corresponding brain signals. This can be accomplished endogenously or exogenously. The endogenous approach, in particular, refers to the fact that subjects generate specific brain signals when they voluntarily complete a mental task. For instance, when subjects imagine limb movements, ERD and ERS signals can be recorded in the primary motor cortex (M1) region [36]. By contrast, the exogenous approach to brain signal encoding requires the subject to be stimulated with a specific stimulus (such as visual, auditory, or tactile

Table 1 BCI Paradigms (1)—Active Mode

Paradigm	Encoding method	Reference
Motor imagery (MI-SMR)	Sensorimotor rhythms (SMR) paradigms: Subjects imagine the kinesthetic movements of different body parts, e.g., hands, feet, and tongue, which modulates mu (8-12 Hz) and beta rhythms (18-26 Hz) and causes the phenomenon of event-related desynchronization (ERD) and event-related synchronization (ERS) in sensorimotor cortex.	[78-86]
Motor imagery (MI-IBK)	Imagined body kinematics (IBK) paradigms: Occasionally referred to as natural imaginary movement, this paradigm makes use of the low-frequency (<2 Hz) kinematic information contained in EEG signals in the motor cortex when subjects perform continuous imagined movement of a single body part in multi-dimensional space.	[87-92]
MRCP	Movement-Related Cortical Potential (MRCP): The movement planning and execution process are accompanied by a gradual decrease in EEG amplitude lasting more than 500 milliseconds. This is referred to as the MRCP, which is composed of readiness potential, motor potential, and movement-monitoring potential.	[93-94]
Non-motor mental imagery	Non-motor mental imagery paradigm: EEG signals are recorded during non-motor imaginary tasks, e.g., math calculation.	[95]
SCP	Slow cortical potentials (SCP) paradigm: SCP signals are slow non-movement potential changes in the EEG that reflect changes in cortical polarization associated with mental relaxation or preparation. The signals last between 300 ms and a few seconds.	[96-100]
Attention	Overt/Covert attention paradigm: The covert attention paradigm requires subjects to fixate on a central point and attend to another point without moving their eyes overtly, whereas the overt attention paradigm allows for overt eye movement.	[101-107]
CVSA	Covert visuospatial attention (CVSA) paradigm: In the CVAS paradigm, subjects draw attention to different visual field regions by overtly not moving their eyes.	[108-109]
Discrete movement attention	Discrete movement attention paradigm: The discrete movement attention paradigm decodes a subject's intended movement using pre-movement EEG signals and converts the output for environment control.	[110-113]
Articulatory movements	Articulatory movements paradigm: The articulatory movements paradigm refers to the process of automatically performing speech recognition by using articulatory information in neural signals, which decodes articulatory trajectories or formant frequencies.	[114-115]

stimulation) via an external signal. The subject's response to the external stimulus signal is the required characteristic brain signal [3].

Different methods for encoding brain signals have shaped the existing BCI paradigms [28]. In general, BCI paradigms fall into three categories in terms of how brain signals are encoded, namely, active BCIs, reactive BCIs, and passive BCIs (see Fig. 7) [76]. Additionally, a hybrid BCI can be formed by combining multiple BCI paradigms [77].

1) Active BCI: An active BCI system is defined as one whose output is derived directly from the user's conscious control of brain activity and is not dependent on external events to control an application [76].

There are many approaches to generating stable and distinct brain signals voluntarily, including motor or mental imagery, overt or covert attention, and articulatory movements (see Table 1). Among them, the MI BCI is one of the most widely used experimental paradigms. Active MI can be used to generate distinguishable brain signals in the motor regions of the cerebral cortex in patients with quadriplegia and loss of motor function, and the signals can be converted into corresponding control commands to control wheelchairs and even rehabilitation devices.

The advantage of the active BCI paradigm is that no external stimulation equipment is required, and the user can achieve control while moving freely. The disadvantage is that subjects must train extensively prior to using the BCI system, and the system's overall performance, e.g., communication rate, is relatively low. Nonetheless, such a paradigm is required for completely paralyzed patients, such as those who lack the ability to control their eye movements to focus on external stimulus targets or users with impaired sensory systems.

2) Reactive BCI: A reactive BCI is defined as a BCI system whose output is derived from brain signals generated in response to external stimuli and whose signals are modulated by the user to control the application indirectly [76].

External stimuli are used to generate characteristic brain signals in reactive BCI. The stimulus signal is applied to the user's visual, auditory, tactile, or olfactory sensory pathways during the experiment, eliciting distinct characteristic

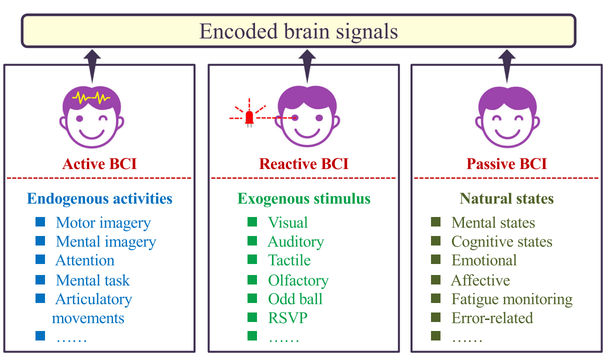

Fig. 7. ***BCI paradigms. Brain signal encoding strategies are grouped into active (endogenous mental tasks), reactive (brain responses to external stimuli), and passive (spontaneous state monitoring), laying the foundation for single- and hybrid-mode BCIs.***

Table 2 BCI Paradigms (2)—Reactive Mode

Paradigm	Encoding method	Reference
P300	P300 paradigm: The P300 paradigm is based on the P300 signal, which is a positive deflection of the ERP (amplitude: 5-10 mV, latency: 220-500 ms) in response to unusual stimuli, such as visual, auditory, or tactile stimuli.	[51], [116-121]
f-VEP (SSVEP)	Steady-state VEP (SSVEP) Paradigm: The SSVEP is a frequency-tagged response elicited by a flickering stimulus with a constant frequency between 1-3.5 Hz and 75-100 Hz. Many modified SSVEP-based BCI paradigms exist, including multi-focal SSVEPs (mfSSVEPs) and phase-frequency SSVEPs (pfSSVEPs).	[7], [74], [122-125]
m-VEP (motion-onset stimulus)	Motion-onset VEP Paradigm: Motion-onset VEP is defined by three prominent P1, N2, and P2 peaks. N2 is the most motion-specific peak, occurring 160-200 ms after the motion begins.	[126-128]
c-VEP (code stimulus)	Code Stimulus Paradigm: In the c-VEP BCI, the stimulus signal consists of pseudorandom sequences, such as the most frequently used m-sequence generated by maximal linear feedback shift registers.	[129-132]
Auditory stimulus	Auditory Paradigm: To elicit EEG signals, the auditory paradigm employs an external sound stimulus, which has potential applications for aural prostheses.	[133]
Tactile stimulus	Somatosensory Evoked Potential Paradigm: Tactile stimuli stimulate different body parts with varying frequencies, eliciting somatosensory evoked potentials for classification and command control.	[134-136]
Olfactory stimulus	Olfactory Paradigm: Different EEG patterns can be induced by olfactory stimuli, e.g., smelling or remembering an odor.	[137]
RSVP	Rapid Serial Visual Presentation (RSVP) Paradigm: In the RSVP paradigm, subjects were presented with a rapid stream of images and instructed to search for an infrequent target. At the same time, their EEGs and ERPs were recorded and detected in real-time to aid in the selection of relevant information.	[138-139]
Statement presentation	Reflexive Semantic Conditioning Paradigm: The presentation of various statements modifies the EEG signals in the reflexive semantic conditioning paradigm, which is primarily used for communication purposes in ALS and CLIS populations.	[140-144]

brain signals. The stimulus signal can take on a variety of paradigms, for example, frequency/phase/time/code-modulated stimulus and oddball stimulus (see Table 2). The P300 and SSVEP-based BCI paradigms are the most frequently used reactive BCI paradigms. Both of these systems have a high rate of communication and can be used by the vast majority of populations.

The advantage of the reactive BCI paradigm is that most subjects can use it to achieve extremely high accuracy within minutes of calibration. However, because the reactive BCI paradigm requires a high level of attention, it has the disadvantage of subject fatigue or discomfort when they pay attention to external stimulus signals for extended periods of time. Additionally, brain signals are typically detected based on the stimulus's onset time in reactive BCI systems. Thus, synchronization protocols between external stimulation devices and brain signal recording devices are frequently required in such systems, increasing their complexity. Notably, the reactive BCI system outperforms all other BCI systems in terms of system performance. Due to a large number of candidate targets, the relatively high recognition accuracy of brain signals, and the relatively short recognition time, reactive BCIs can typically achieve a high ITR.

3) Passive BCI: A passive BCI is defined as a BCI system whose output is derived from arbitrary brain activity and is used to augment implicit information in human–computer interaction, rather than for voluntary control [145], [146].

Affective BCI, mental state assessment BCI, and error-related potential (ErrP)-based BCI are all examples of typical passive BCI systems (see Table 3). These systems do not require subjects to perform any behavioral or cognitive tasks during operation, nor do they require subjects to be exposed to any external stimuli, and users remain entirely in their natural state.

Passive BCI systems can be used in various scenarios where subject mental states must be monitored, most notably for the detection of cognitive load states in personnel performing high-stress jobs, such as air traffic controllers [159]. The ErrP can be used to rectify errors that occur during the BCI system operation.

4) Hybrid BCI: A hybrid BCI system is one that combines two or more physiological measures in which at least

Table 3 BCI Paradigms (3)—Passive Mode

Paradigm	Encoding method	Reference
Mental state assessment	Mental state assessment paradigm: The EEG can be used to assess a subject's mental state, including attention, emotion, workload, stress, and performance capability.	[22], [147-148]
Affective BCI	Affective BCI: Human affect can be estimated using brain signals in affective BCIs that are classified as emotion recognition or emotion regulation.	[149-153]
Error-related potential	Error-related Potential: The mismatch between a subject's intention and the task outcome elicits an ERP component called error-related potential (ErrP), which has a latency of 200–700 ms and can be used to correct BCI errors.	[154-158]

Table 4 BCI Paradigms (4)—Hybrid Mode

Paradigm	Encoding method	Reference
EEG/fNIRS	This hybrid paradigm simultaneously measures electrical and hemodynamic brain activity and provides more detailed information about brainwave activity via feature combination.	[161-162]
P300/SSVEP	This hybrid BCI combines time division multiple access (TDMA) and frequency division multiple access (FDMA) technologies from P300 and SSVEP to create a high-speed BCI.	[163-168]
MI/SSVEP	SSVEPs are integrated into motor imagery BCIs in this hybrid BCI to provide effective continuous feedback to motor imagery training subjects.	[169-170]
Mu Rhythm /SSVEP	By decoding variations in mu rhythm or event-related synchronization, this hybrid BCI provides a switch for SSVEP-based BCIs (ERS).	[171-172]
EMG/SSVEP	This hybrid BCI employs an EMG-based multi-selection strategy in conjunction with SSVEP-based BCI to increase the number of targets and ITR.	[173]
Mu/beta Rhythm/P300	This paradigm combines motor imagery-based BCI and P300-based BCI to create a two-degree-of-freedom BCI control system, i.e., independent and simultaneous control of a cursor in horizontal and vertical directions.	[174-175]
EMG/EEG	The combination of EEG and electromyographic (EMG) activity enables a more stable control for disabled BCI users with residual muscle activity.	[176]
ERP/EOG	The hybrid BCI combines data from the EOG, which detects eye movements (e.g., blinks), and the EEG, which decodes ERPs (e.g., P300).	[177-178]
ERD/EOG	The hybrid BCI incorporates eye movement data from an eye tracker into a self-paced BCI to minimize false positive rates in text-entry applications.	[179]
MI/eye-tracking	The hybrid BCI paradigm combines motor imagery and eye movements to enable three-dimensional BCI control of a quadcopter.	[180]

one is brain signal [77], [144], [159], [160]. Integrating two distinct BCI paradigms is a frequently used approach for developing a hybrid BCI (see Table 4). Since hybrid BCI leverages the advantages of multiple paradigms, it typically outperforms a single paradigm.

The hallmark feature of the hybrid BCI system is that it fuses the advantages of different paradigms to compensate for the shortcomings of a single paradigm, thus effectively improving the overall performance of BCI.

B. Brain Signal Decoding

The decoding of brain signals is a critical component of the BCI system. The primary objective of the decoding process is to convert brain signals to commands and then provide feedback to BCI users.

Typically, decoding brain signals can be divided into three steps: preprocessing, feature extraction, and classification (see Fig. 8). Preprocessing is primarily used to remove noise from the recorded signal. The purpose of feature extraction is to compactly and meaningfully express the original recorded brain signal as a set of features for subsequent classification by a classifier. The classifier is responsible for classifying the received features into distinct patterns and then converting the classification results into control commands for the external device issued by the user [35], [181].

As an important branch of machine learning, transfer learning (TL) harnesses the power of shared knowledge from distinct yet related domains to improve the classification performance [182]. TL is emerging as a promising solution in BCI decoding, addressing the traditionally onerous calibration needs due to the high variability and low SNR of brain signals. By bridging the gaps between source and target domains, TL in BCI decoding can effectively utilize auxiliary brain signals transferred across subjects, sessions, devices, and tasks [183]. This approach can significantly reduce calibration burden and enhance the practical usability of BCI systems.

1) Preprocessing Methods: Neurophysiologically, the BCI system records very low-amplitude brain activity, whereas the accompanying artifacts are prominent. Preprocessing is primarily concerned with removing all types of interference noise and laying the foundation for feature extraction and classification.

Using the EEG signal as an example, interference noise is generated in part by the external environment, including accumulated static charge, faulty electrode contact, and ambient noise [30]. Apart from external interference, EEG signals are frequently and significantly contaminated by various physiological activities occurring within the human body, such as spontaneous EEG, EOG, electromyogram (EMG), and movement artifacts. Additionally, some interfering noises, such as artifacts from ocular, cardiac, and muscular activities, whose frequency range (0.5–15 Hz) coincides with the frequency range of the brain signals that we intend to leverage in BCI, making noise removal more difficult.

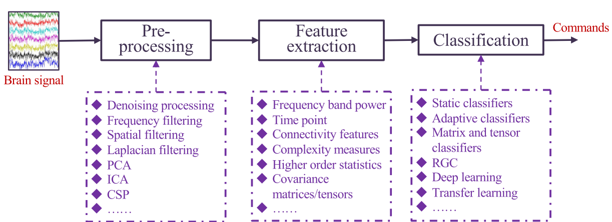

Fig. 8. ***Brain signal decoding. Overview of the standard BCI decoding pipeline comprising preprocessing, feature extraction, and classification. The decoding pipeline uses distinct techniques at each stage to denoise signals, extract neural features, and generate control commands for real-time brain–computer interaction.***

Spectral filtering and spatial filtering are frequently used denoising techniques in preprocessing, and the filter parameters must be configured according to the various BCI experimental paradigms. Additionally, signal decomposition and transformation techniques are frequently used to eliminate artifacts in EEG [184]. Independent component analysis (ICA) [185], regression analysis [186], and empirical mode decomposition [187] have been used to remove noise from EEG. These methods exhibit superior performance in removing artifacts with minimal distortion to the EEG signal and achieving high artifact selection accuracy.

2) Feature Extraction: Feature extraction aims to convert the received EEG signal into compact EEG features that subsequent classifiers can classify. Typically, BCIs select EEG features to highlight the critical subset of characteristic features that are highly relevant to a particular type of brain activity [30].

There are two types of features that are frequently used in BCI systems: spectral features that utilize frequency band power and temporal features that utilize time-point data. Many BCI systems exhibit specific rhythmic variations, which are reflected in the power characteristics of the frequency bands [20], [188], in response to changes in the user's brain signal. In another type of BCI paradigm, a strong time-locked relationship exists between the brain signal response and the onset of the stimulus event. For instance, the brain signals in ERP-based BCIs exhibit distinct time-point features [189], [190]. In practical applications, combining multiple features also helps improve the final classification.

As a result of the brain signal's complexity and significant nonstationarity, features extracted directly from the EEG may exhibit temporal or spatial overlap. The extracted features are further refined by a feature selection session [191], and redundant components are removed. Additionally, reducing the number of features simplifies classifier design and enables the researcher to deduce the neural correlates of these features [181].

3) Classification Methods: The classification algorithm is a critical component of decoding brain signals. Existing classifiers include methods such as static classifiers, adaptive classifiers, matrix and tensor classifiers, and deep learning [181], [192].

a) Static classifiers: Static classifiers are typically nonadaptive classifiers whose parameters are kept constant throughout the system's operation. Linear classifiers [support vector machine (SVM) and linear discriminant analysis (LDA)] and nearest neighbor classifiers (k-nearest neighbor (kNN) and Mahalanobis distance classifiers) are the most widely used static classifiers. Other static classifiers, such as neural networks [multilayer perceptron (MLP)] and nonlinear Bayesian classifiers (hidden Markov models (HMMs) and Bayes quadratic classifiers), have also been studied in the context of BCI classification [193]. They are incapable of dealing with the EEG's nonstationarity.

b) Adaptive classifiers: Adaptive classifiers adjust and update decoding model parameters incrementally, for example, weights in the LDAs, ensuring an optimal classifier for ongoing EEG data. This classifier is extremely adaptable to possible rapid changes in feature distribution and the ubiquitous nonstationarity and variability found in EEG [194], [195], [196], [197]. Adaptive CSP [198], [199], adaptive LDA [200], [201], and adaptive Gaussian classifier [202], [203] are a few representative methods. Additionally, a deep learning classifier can also be used as an adaptive classifier when there are adaptive layers in the deep neural network (e.g., a batch normalization layer, which gets the running mean and the running variance from the test set).

c) Matrix and tensor classifiers: Matrix and tensor classifiers do not employ spatial filtering or feature selection, but instead, decode the input data (i.e., two or higher dimensional array) directly. The Riemannian geometry classifier (RGC) is a successful application that maps raw data directly to a geometrical space quantified by a suitable metric [204], [205], [206]. The geometric subspace enables various EEG data processing operations, including smoothing, averaging, extrapolating, interpolating, and classifying [181], [207].

d) Deep learning: Deep learning learns the features and classifiers simultaneously in an end-to-end manner [208], [209], [210], [211], [212], [213]. Convolutional neural networks (CNNs) and Transformers are two popular approaches for deep learning in BCI [214], [215], [216]. Deep learning has the advantage of alleviating the burden of handcrafted feature engineering and converting brain signals to high-level features and latent representations.

4) TL in BCI Decoding: Due to the high sensitivity of recorded brain signals (e.g., EEG) to noise and various interferences, nonstationarity of signals within or between subjects frequently occurs in BCI systems. As a result, it is difficult to design a general decoding method that performs optimally across subjects, trials, devices, and tasks. When working with a new subject or task, it is frequently necessary to collect some training samples for calibration to determine the so-called optimal decoding scheme before moving on to the actual testing phase. This procedure is frequently lengthy. TL is the process of leveraging previously acquired similar or pertinent information about a future task to assist the designed decoder in adapting to the environment of new subjects or tasks. This can significantly reduce the time and effort required for system calibration [217]. TL techniques used in existing EEG-based BCI systems can be classified according to their transferability across sessions, subjects, devices, and tasks (see Fig. 9) [183].

a) Cross-session transfer: The source and target domains are distinct sessions, and the information contained in the brain signals from the previous sessions can

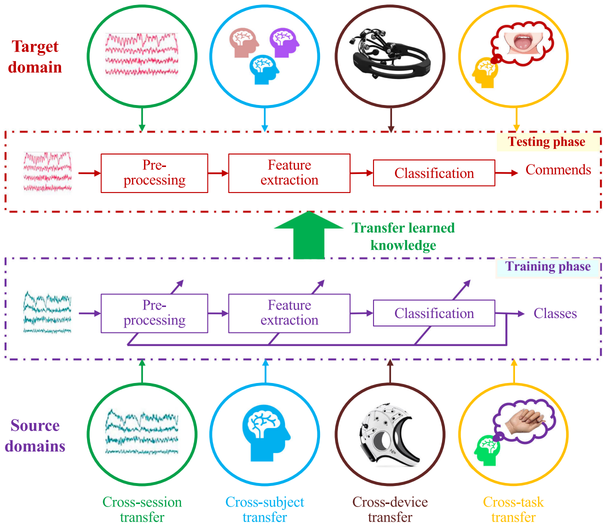

Fig. 9. ***TL for brain signal decoding. In the training phase, knowledge is learned from a source domain across sessions, subjects, devices, or tasks and transferred to optimize decoding in the target domain. The oblique arrow indicates which processing stages are adapted. This approach reduces calibration effort and improves the generalization of BCI systems for practical applications.***

be transferred to the subsequent sessions for classification. The cross-session transfer is exemplified by the cross-day transfer, in which the time interval between the training and test sessions is several days. Typically, cross-session studies use the same subject, acquisition device, and BCI task [218], [219].

b) Cross-subject transfer: The source and target domains come from different subjects, and the decoding model from other subjects is transferable to a new subject. TL reduces intersubject variability in cross-subject transfer. The cross-subject studies are usually based on the same acquisition device and BCI task [220], [221].

c) Cross-device transfer: The source and target domains come from different acquisition devices. Brain signals acquired from one device can be used to aid in the decoding of BCI signals for a new device. TL mitigates the domain gap associated with switching acquisition devices in cross-device transfer. Typically, cross-device studies use the same subject and BCI task [222].

d) Cross-task transfer: The source and target domains originate from distinct BCI tasks, and discriminative information is shared between them to facilitate BCI decoding. For instance, in MI BCIs, EEG data associated with the left and right MI can be used to classify feet and tongue MI. The majority of cross-task studies use the same subject and acquisition device [85], [223].

C. Successful Application: Multiple Access Method

Source encoding and multiple access are the core technologies in modern communication and also the key to BCI systems. Given that most existing BCI systems are discrete, the purpose of source encoding is to convert a collection of users' distinct wishes or choices (which this article refers to as targets) into a set of distinguishable brain signals. Additionally, because the brain signals encoded in different tasks must be transmitted via the same pathway of brain signal acquisition and decoding to the computer, multiple access remains an issue that must be resolved.

VEP-based BCI (VEP-BCI) is the most technically mature system at the moment. We will use VEP-BCI as an example in this article to demonstrate channel access methods in BCI (see Fig. 10) [224], [225]. Compared with the summary of the multiple access methods of visual and auditory BCIs in [3], here we highlight the concepts of encoding and decoding associated with communication systems.

1) Frequency Division Multiple Access: When a subject is presented with multiple selection targets, we can configure different targets to flicker at various frequencies $(f_1,\ f_2,\dots,f_N)$, resulting in characteristic EEG signals carrying different frequency components $[T(1),T(2),\dots,T(N)]$. After the computer receives these distinctive brain signals, we can infer the fixated target by performing a spectrum analysis [226], [227]. This is typically a frequency division multiple access (FDMA) system within the context of a communication system.

2) Time Division Multiple Access: A negative deflection and a positive deflection in the subject's visual cortex can be recorded approximately 200 ms after motion onset of a moving target. To select from multiple targets, we can configure different moving targets to appear at different moments $(t_1,\ t_2,\dots,\ t_N)$. As long as a common time reference is established, the receiver can infer the target selected by the subject based on the EEG deflection $[T(1),T(2),\dots,T(N)]$ [126], [228]. This is typically a time division multiple access (TDMA) system within the context of a communication system.

3) Code Division Multiple Access: Different stimulus codes $(\text{code}_1,\ \text{code}_2,\dots,\text{code}_N)$ can be assigned to different flicker targets, thereby eliciting different characteristic brain signals $[T(1),T(2),\dots,T(N)]$. The m-sequence pseudorandom coding technique has been the most frequently used [229]. The computer compares the received characteristic signals to previously stored templates throughout the operation to identify the subject's selected target [129], [145]. This is typically a code division multiple access (CDMA) system within the context of a communication system.

4) Phase Division Multiple Access: When distinct stimulus targets are assigned distinct phase labels $(\varphi_1,\ \varphi_2,\dots,\varphi_N)$, this phase difference will appear in the VEP to characterize different stimuli [230]. As a result, the computer can distinguish between distinct targets based on phase characteristics [231]. This is typically a phase division multiple access (PDMA) system within the context of a communication system.

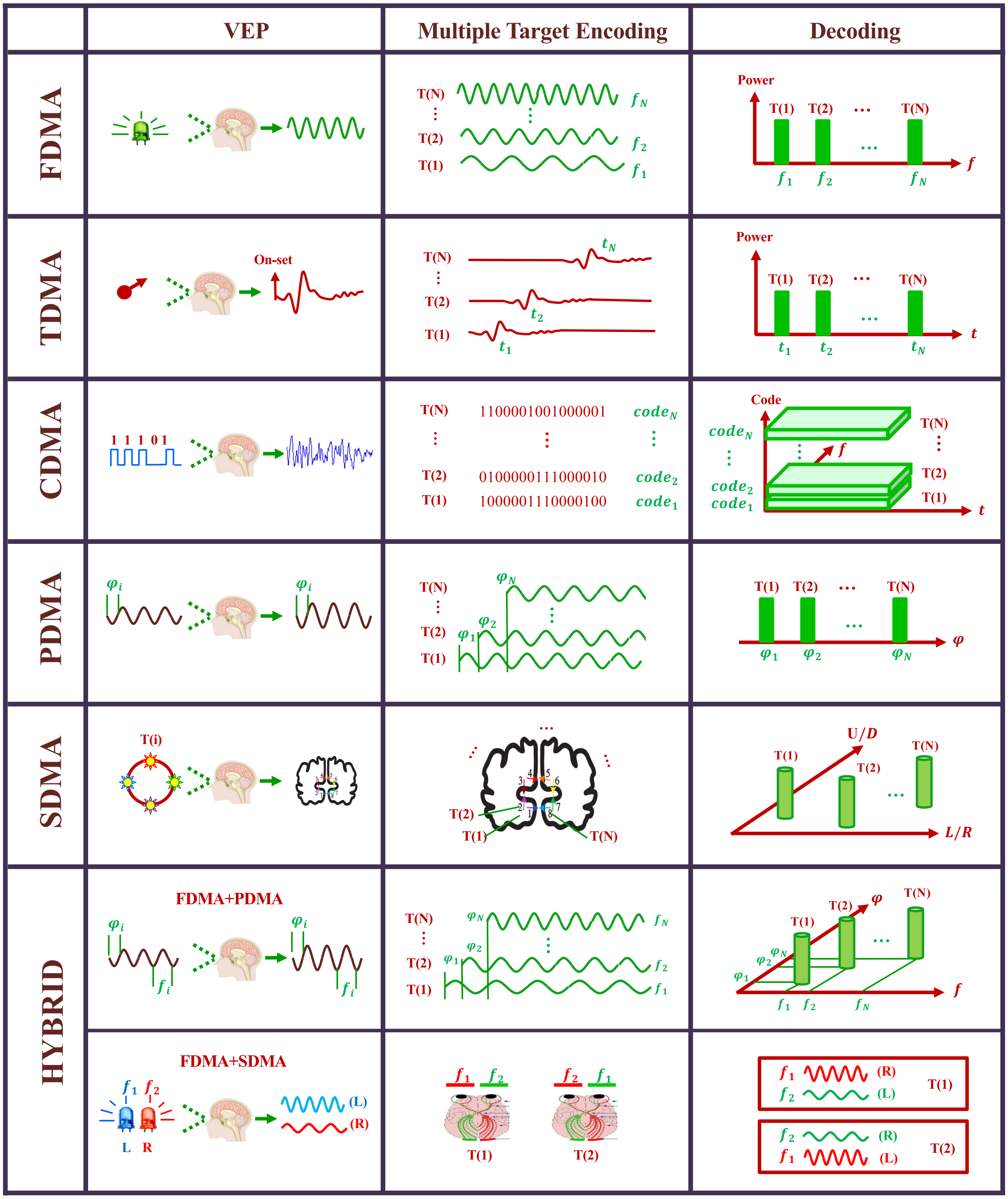

Fig. 10. *Taxonomy of visual BCI based on multiple target access methods. Illustration of six paradigms inspired by communication system strategies: FDMA, assigning distinct frequencies to targets; TDMA, separating targets by stimulus onset times; CDMA, employing unique pseudorandom codes; PDMA, differentiating targets by phase; SDMA, utilizing spatially distinct cortical activations; and hybrid methods combining multiple strategies to enhance encoding efficiency and decoding accuracy.*

5) Spatial Division Multiple Access: According to retinotopic mapping in the primary visual cortex (V1) [232], when subjects receive stimuli from various spatial locations, the resulting VEPs are mapped to a variety of locations in the visual cortex. In other words, based on the location of the signal in the visual cortex, it is possible to discriminate between target signals in different spatial locations. This is typically a spatial division multiple access (SDMA) system within the context of a communication system.

6) Hybrid Multiple Access Methods: Hybrid coding is a more complex technique that combines two or more distinct coding methods. In existing BCI systems, FDMA-based coding has been successfully combined with other coding methods (e.g., FDMA/PDMA [7], [233] and FDMA/SDMA [234], [235]) to improve the coding efficiency.

The experimental paradigm of BCI, which is inspired by modern communication technology, extends beyond the examples presented above. For instance, the frequency shift keying (FSK)-based BCI system developed by Kimura et al. [236] is also a successful example. It is envisioned that this line of research will propel the development of novel BCI experimental paradigms in the future.

V. C2B COMMUNICATION

A. Brain Neuromodulation

A closed-loop BCI system is an advanced form of BCI system that enables bidirectional communication between the brain and the computer. One such pathway is B2C communication, which converts brain signals into control commands for external devices. The other pathway is C2B communication, which directly transmits information from the outside world to the brain. C2B communication is typically used for the following multiple purposes: 1) to directly inform the brain of external information; 2) to alter the functional state of the brain for neurorehabilitation; 3) to provide feedback to the brain from controlled external devices in a closed-loop BCI system; and 4) to regulate affect state in affective BCIs.

Brain neuromodulation is a type of neural technology that alters the activity or plasticity of the brain by delivering various stimulations or chemical agents to the appropriate neurological region in the body. The application of neuromodulation to the brain can be broadly classified into two categories. One method is to administer specific energy directly to the brain, thereby altering the brain's operating state. The other is subject to self-regulation. The former employs stimulation techniques such as magnetic, electrical, ultrasound, and light stimulation, whereas the latter employs neurofeedback (NFB) training to promote self-regulation [237] (refer to Fig. 11).

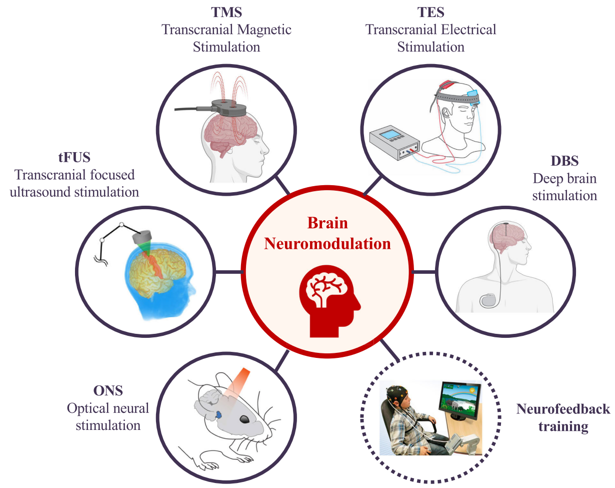

Fig. 11. ***Brain neuromodulation. Brain neuromodulation techniques such as TMS, TES, DBS, tFUS, optical neural stimulation (ONS), and NFB training support C2B communication for information delivery, neurorehabilitation, device feedback, and affective regulation.***

1) Electrical Stimulation: Electrical stimulation has a long history of research and clinical application [237], and it is frequently used in clinical practice to treat and rehabilitate patients suffering from psychiatric disorders [238]. Electrical stimulation can be delivered in various ways, which can be broadly classified as extracranial and intracranial stimulation modalities.

Cortical surface stimulation can be accomplished epidurally or subdurally, with electrodes placed on the dura or directly on the cortex. Because the electrodes are in direct contact with the cortex, subdural stimulation allows for more precise stimulation with less current. However, surgery to open the dura increases the risk of infection. Epidural stimulation requires a higher stimulation current to reach the cortex, as it must pass through the dura and cerebrospinal fluid. Not only is cortical stimulation used clinically to treat various neurological diseases, but it is also used during craniotomy to locate sensorimotor and speech areas, thereby avoiding intraoperative injury to critical functional cortical areas. ICMS is another method of cortical stimulation in which direct electrical stimulation is delivered to the cerebral cortex using microelectrodes [60]. Typically, these electrodes are encased in an insulating material, with only a small portion of the electrode material exposed for more precise stimulation.

Deep brain stimulation (DBS) is another intracranial electrical stimulation device that has been widely used in clinical practice [239], [240]. Three components comprise the DBS device: an implanted pulse generator (IPG), a lead, and an extension. DBS has been successfully used to treat various neurological disorders, including Parkinson's disease.

In addition to intracranial electrical stimulation, electrical stimulation can be performed extracranially by transcranial current stimulation (TCS). Transcranial direct current stimulation (tDCS) and transcranial alternating current stimulation (tACS) are both frequently used methods. To achieve neuromodulation, tDCS delivers a constant and low direct current into the skull via scalp electrodes. In contrast, tACS modulates electrical current with a fixed frequency and a constant or zero offset. Additionally, tDCS and tACS technologies are frequently used clinically to treat various psychiatric disorders, including major depressive disorder.

2) Transcranial Magnetic Stimulation: TMS is a noninvasive brain stimulation technique that employs electromagnetic induction to impose a changing magnetic field and induce an electrical current targeted at a particular brain region [241]. Typically, a TMS system consists of a magnetic coil wrapped around the scalp and an electrical pulse generator or stimulator. Specifically, the magnetic coil induces a magnetic field driven by the generator's changing electrical current, eliciting an endogenous electrical charge in the brain.

TMS technology is promising for diagnosing and treating CNS disorders and demonstrates potential clinical utility in a variety of neurologic disease states [242].

3) Transcranial Focused Ultrasound Stimulation: Transcranial focused ultrasound stimulation (tFUS) is a novel noninvasive brain stimulation technique that delivers low-intensity ultrasound to nervous system tissue and transiently modulates neural activity [243].

A specific ultrasound frequency can pass through the scalp and skull and into the brain. Additionally, the focused approach concentrates the incident ultrasound energy into a small, circumscribed region. Using a variety of stimulation parameters, tFUS can either stimulate or inhibit cellular activity. In comparison to DBS, tFUS is noninvasive; compared to TMS and TCS, tFUS has a sharp spatial focus [244]. tFUS is expected to be a valuable diagnostic and therapeutic tool in neurology and neuropsychiatry.

4) Optical Neural Stimulation: Optogenetic neuromodulation is a technique that involves the expression of light-sensitive ion channels (referred to as opsins) in neurons and their activation by photic stimulation. Compared with conventional neuromodulation techniques, optogenetic neuromodulation enables spatially and temporally precise activation or inhibition of neural circuitry, with temporal precision of milliseconds and spatial precision of a single cell [245].

Optogenetic neuromodulation, which incorporates genetic engineering, achieves selective and specific neuronal activation or inhibition, making it a promising neuromodulation technology [246].

5) Neurofeedback: NFB is a type of biofeedback technology that provides real-time feedback to the user based on brain activity, thereby reinforcing healthy brain function via operant conditioning [247], [248]. In a typical NFB system, noninvasive EEG monitoring of brain activity is used to provide feedback in the form of a video display or sound. Although NFB has not yet become standard medical practice, it has been used for decades, and substantial evidence has emerged to support the nonpharmaceutical treatment of mental disorders through neurotherapy.

There is a variety of established NFB protocols, some of which use fMRI or quantitative EEG (qEEG) to aid in identifying and treating individuals. Notably, certain NFB protocols incorporate metabolic measurements, such as hemoencephalography (HEG), fNIRS, and fMRI.

Neuromodulation of the brain is widely used to treat various neurological and psychiatric disorders. Closed-loop NFB training has numerous successful applications in neural rehabilitation and human augmentation in the field of BCIs [15]. Additionally, brain neuromodulation demonstrates significant promise for brain-to-brain and C2B communication [249].

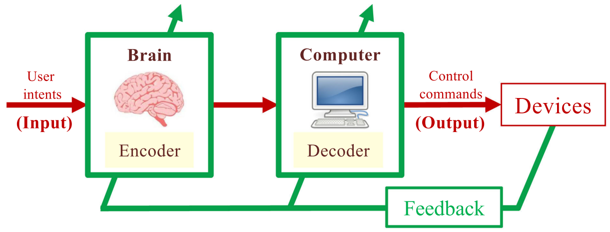

Fig. 12. ***Architecture of coadaptation BCI. Illustration of a closed-loop coadaptive BCI system in which both the brain (encoder) and computer (decoder) continuously learn and adapt. The computer decodes neural signals into control commands for external devices, while feedback from the devices helps the user adjust neural output, forming a dynamic interaction between human and machine.***

B. Brain–Computer Coadaptation

Not only do the brain signals of different users differ significantly during the operation of the BCI system, but the brain signals of individual users also change over time and exhibit noticeable signal variability. This necessitates the BCI system's decoder to adapt to changes in brain signals and maintain a stable output. At the same time, when the external device's control state is presented to the brain as feedback, the brain will adjust its own output, either intentionally or unintentionally, to maintain the external device's stable control state. Thus, to ensure the normal operation of the entire BCI system, both the user and the machine must adapt to one another. This section discusses brain–computer coadaptation, a critical technology for system optimization [250].

1) Framework of Coadaptive BCI: The basic architecture and theoretical framework of coadaptive BCI are depicted in Fig. 12 [251]. The cornerstone of the coadaptive BCI system is still a closed-loop system. After learning and training, the computer decodes and converts the received brain signals into control commands for external devices. Following the external device's action, it will provide feedback to the user in various forms, including audio, visual, and sensory information. The user's output is then adjusted in response to changes in the external environment. In other words, both the brain and the computer have the ability to adapt and learn in this closed-loop system. Specifically, the brain learns how to manipulate the external device and modulate its state of mind to perform the BCI task more effectively. Simultaneously, the computer adapts the system to optimally interpret the command issued by the brain. The combination of these two adaptive systems is referred to as a coadaptive BCI system [252].

Additionally, the coadaptive BCI system is a classic two-learner problem. Müller et al. [253] proposed a mathematical model and a theoretical formulation for the study of coadaptive BCI to address this issue.

2) Machine Learning: Machine learning algorithms are used in coadaptive BCI to enable algorithms to adapt to the nonstationarity of brain signals [181], with adaptive signal processing and pattern classification as the primary methods [194], [254]. Numerous experiments have demonstrated that using adaptive features in the data and adaptive classifiers in the model can significantly improve BCI performance both offline and online [255].

3) Human Learning: Human learning is used in coadaptive BCI to assist users in consistently generating stable and distinguishable brain signals during brain–computer coadaptation. The generation of distinctive brain signals is associated with the user's psychological components, including mood, motivation, abilities, and personality traits. Thus, in contrast to machine learning, which is based on algorithms, human learning is accomplished through NFB training in the system. In the operation of a coadaptive BCI, the user continuously adjusts his output in response to received feedback to maximize the effectiveness and efficiency of the external device's control.

A well-designed feedback loop is critical for any closed-loop system. The feedback loop's intricate design enables users to increase their intrinsic motivation and progress under the tutor's guidance [256]. Similarly, in coadaptive BCI, an elaborate feedback loop design can effectively facilitate the user's motivation and learning, resulting in superior performance on the BCI task [257].

4) System Optimization: The purpose of developing a coadaptive BCI is to optimize its performance. The implementation of coadaptation BCI can take a variety of forms. For instance, one can fix one of the encoders (brain) or decoders (computer) on a reasonable timescale and leave the other to learn to obtain an optimized system [258]. Alternatively, both the encoder and decoder can learn and optimize simultaneously, resulting in high BCI performance [251].

Additionally, the system optimization method based on the two-learner problem is worth noting. Two types of learners are considered to be the brain and computers with adaptive functions. The two learners can be combined into a joint loss function by assuming a simple linear model. This approach establishes a computational mathematical model for coadaptive BCI systems [253].

It is self-evident that the process of brain learning would result in variability in brain signals in coadaptive BCI. A thorough understanding of the pattern of brain plasticity during learning will not only improve the performance of existing coadaptive BCI systems. However, it will also enable the application of BCI in various emerging fields, including neurorehabilitation, memory enhancement, and brain augmentation [39].

VI. MULTIUSER BCI

Multiuser BCI is also referred to as multibrain BCI, multisubject BCI, or multimind BCI. All of these terms refer to BCI systems that incorporate multiple users [259].

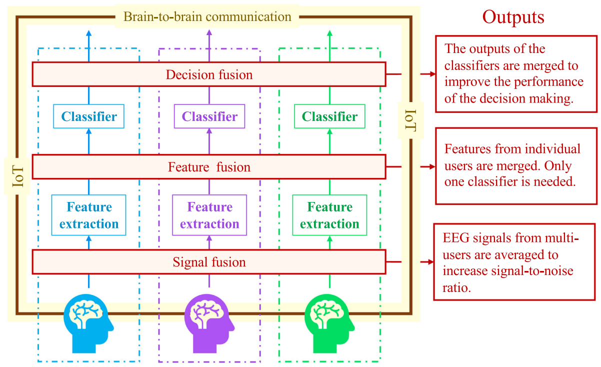

Fig. 13. ***Information flow diagram in multiuser BCI. EEG signals from multiple users are first combined to enhance the SNR (signal fusion), followed by merging extracted features to reduce redundancy (feature fusion), and finally integrating individual classifier outputs to improve decision accuracy (decision fusion). This structure supports collaborative brain-to-brain communication via the IoT.***

Generally, multiuser BCI performs better than single-user BCI [260]. Multiuser BCI systems have been evaluated in various applications, including target detection, device control, and monitoring of brain state.

Integration of multiuser BCI data can be accomplished on various levels, depending on the application. As shown in Fig. 13, data from various users are processed through the appropriate decoding procedures, including signal acquisition, feature extraction, and classification. In multiuser BCIs, information from multiple users can be integrated at various stages, including the raw brain signal, extracted features, and the final decision stage, potentially enhancing the SNR or recognition accuracy.

According to different applications, multiuser BCI can also be categorized into, among other types, collaborative multiuser BCI, competitive multiuser BCI, passive multiuser BCI, and brain-to-brain communications.

A. Collaborative Multiuser BCI

When multiple users collaborate on a common goal in a multiuser BCI system, the system is referred to as a collaborative multiuser BCI or collaborative BCI. The collaborative BCI's primary objective is to enhance human performance [261]. By combining brain signals from multiple users for decoding, the overall BCI performance, e.g., decoding accuracy, can be significantly increased.

Multiple-user participation raises several technical issues in terms of system implementation, most notably in terms of hardware and software design. First, data collection for multiple users should be conducted independently and concurrently. Second, multiuser recording systems must adhere to the requirement of synchronization with respect to common events. Third, the overall process of data recording and processing should occur in real time for multiple users [261].

Communication and control remain the mainstay in BCI applications. Due to the weakness of brain signals, BCI systems based on a single user frequently perform poorly in single-trial recognition. The ensemble average of signals collected over multiple trials improves system performance but degrades the communication rate. By aggregating signals from multiple users, the collaborative multiuser BCI system significantly improves the communication system's performance without increasing the signal acquisition time [261]. In the context of device control, collaborative multiuser BCI not only enhances the system's robustness for a single task but also enables multiple users to independently control different components of the external device, enabling simultaneous multidimensional control [260].

B. Competitive Multiuser BCI

When multiple users in a multiuser BCI system are in a competitive relationship with one another or must complete individual goals without collaboration, the system is referred to as competitive multiuser BCI or competitive BCI [262].

Currently, competitive multiuser BCI is mostly used in video games [263], [264]. This is because multiple users can compete for game control, which benefits users' attention levels [265].

C. Passive Multiuser BCI

When passive BCI is used to monitor the brain activity of multiple subjects, the system is referred to as passive multiuser BCI, alternatively called a hyperscanning system [266].

Hyperscanning was originally developed for the purpose of measuring neurological activity during social interaction. The practice of hyperscanning of multiple users was later applied to passive multimind BCIs [267], [268], revealing remarkable intersubject correlation in a natural vision scene [269].

D. Brain-to-Brain Communications

Brain-to-brain interface (BBI) or brain-to-brain communication is another novel experimental paradigm in multiuser BCI systems. By systematically integrating BCIs and CBIs, BBI establishes a multisubject system to transmit neural information between users via brain imaging and brain neuromodulation technologies [270], [271], [272], [273]. In BBIs, the main task of the BCI part is to extract and digitize the brain activities of the sender, typically achieved through detecting neurophysiological indicators to discern the sender's intention. Conversely, the CBI part is responsible for transmitting these digitized brain activities to the receiver's brain. This process utilizes technologies such as TMS and tFUS to input instructions into the CNS.

Despite the fact that BBI research is still in its infancy, a wide variety of BBI systems have already been reported. Based on the mode and direction of information transfer, BBIs can be categorized into four types: indirect unidirectional, direct unidirectional, indirect bidirectional, and direct bidirectional [273]. The distinction between indirect and direct systems lies in whether the information transfer is achieved through a neural modulation device, while the difference between unidirectional and bidirectional systems is whether the information can be reciprocally transmitted between two brains. Specifically, the direct BBI can be combined with the muscle-to-muscle interface (MMI) to create a new type of closed-form human interaction [274].

Based on the number of senders and receivers, BBIs can be classified into 1:1, N:1, and N:N models. The 1:1 model refers to a simple configuration involving only one sender and one receiver, which is the most commonly used approach in the current literature [271], [275], [276], [277]. The N:1 model involves multiple senders transmitting information to a single receiver. For example, Jiang et al. [249] extracted the intentions of two senders on whether to rotate a block in a Tetris game and delivered this information via magnetic stimulation to the brain of one receiver to make the final decision. The N:N model refers to a BrainNet that involves multiple senders and receivers. For instance, Pais-Vieira et al. [280] recorded and analyzed the cortical neuronal activity of four rats in real-time and exchanged the information among them via ICMS. They found that BrainNets consistently performed as well as, or better than, individual rats in tasks such as storing and retrieving tactile information. BBIs are capable of transmitting various types of information, including motor, visual, tactile, auditory, and memory information. For example, by selectively stimulating specific areas of the nigrostriatal pathway in rats through the SSVEP-BCI system, humans can guide the rats to turn left or right in a maze [275]. By controlling an MI BCI, one human subject was able to determine whether to stimulate another human subject's visual cortex via TMS, thereby inducing visual phenomena and enabling the transmission of pseudorandom binary flows encoding words [271]. The transmission of tactile information can be achieved by combining a BCI that recognizes a human subject's imagined left or right hand movements with an fUS device that stimulates the somatosensory area of another subject [276]. It is equally fascinating that speech information can be processed by a guinea pig's auditory system and successfully transferred to a human cochlear implant user, enabling cross-species transmission of lexical data [277]. Hippocampal firing patterns encoding memory can also be extracted from trained animals and transferred via electrical stimulation to untrained animals, effectively enhancing the latter's task performance [278]. Based on the type of subjects involved, BBI can be categorized into cross-species systems and same-species systems. Cross-species systems typically involve human subjects controlling the movement trajectories of animals like mice or cockroaches [275], [279], while same-species systems often focus on enhancing cooperative performance in interactions [280].

Recently, the Internet of Brain was proposed as a way to better understand the interaction of cyberspace and thinking space. The Internet of Brain has a dual meaning. First, it enables efficient mapping of choices, ideas, and thoughts in cyberspace. Second, at a more advanced stage, the Internet of Brain enables entities in cyberspace to mimic human thought through the use of bionic technology [281].

Multiuser BCIs contributed to the advancement of BCIs beyond assistive BCIs, such as communication and control for the motor disabled, and toward augmentative BCIs, such as decision-making facilitation [10], interaction performance enhancement [282], and neuromarketing [283]. Additionally, brain-to-brain communication ushers in a new era of unprecedented brain-type communication [25]. Additionally, due to the simplicity and low cost of EEG equipment, it is relatively simple to implement multiuser BCI. However, other devices, such as fNIRS, can also be used to implement multiuser BCI [284].

VII. BCI APPLICATIONS

In the early stage of BCI research, the main focus was on providing augmentative communication and control tools for people with motor disabilities. As BCI technology becomes increasingly sophisticated, the scope of BCI applications has expanded dramatically. Apart from serving disabled people in the medical domain, BCI applications have been used to benefit the general population [27], [285].

A. Communication and Control

Patients with quadriplegia and complete loss of motor function, such as those with amyotrophic lateral sclerosis (ALS) or severe CNS damage, are the initial target users of BCI. These patients are unable to breathe, swallow, or even make facial expressions in the advanced stages of the disease. At this point, their only means of communication with the outside world is through the BCI [144], [286]. Besides, for individuals with Broca's aphasia or those who speak different native languages, BBI can establish an innovative communication platform [270].

A brain speller based on BCI is a critical tool for establishing communication between the brain and the outside world. Various BCI experimental paradigms, including SSVEP, P300, and MI, are technically compatible with the speller [7], [287]. As BCI and CBI technologies advance, future devices may replace traditional communication methods, enabling the transmission of more abstract and complex thoughts and emotions.

Control of devices in the surrounding environment via BCI systems will undoubtedly and significantly improve the ability of paralyzed patients to care for themselves. The BCI system has been used successfully to control various external devices, including wheelchairs, robot arms, and household appliances. Additionally, BCIs can leverage state-of-the-art VR technology to interact with and control the IoT [4], [8].

For non-disabled individuals, the application of BCI enhances control performance in certain work environments by adding a new dimension of control [9]. Additionally, many people benefit from brain-controlled games [288]. Furthermore, BBIs have been shown to synchronize participants' behavior without any PNS cues, thereby enhancing collective performance in complex tasks [280].

B. Neural Rehabilitation and Therapy

Most stroke patients experience sequelae of temporary loss of motor function due to the stroke. Therefore, rehabilitation training is critical for patients' motor function improvement. However, current rehabilitation training methods, which include a variety of forms of assistive exercise, are incapable of producing satisfactory results. Rehabilitation systems based on BCI use the principle of brain reorganization and emphasize top-down rehabilitation. During training, these systems require the patient to actively imagine the limb's movement (even though the paralyzed limb cannot move) and employ techniques such as functional electrical stimulation (FES) to actually move the paralyzed limb. This method of active training has been demonstrated in practice to be a relatively effective method of stroke rehabilitation [16], [17], [289], [290]. Besides, the BBI technology enables rehabilitation therapists to transmit motor commands to patients during recovery, assisting in the reconstruction of damaged neural pathways and further enhancing the efficiency of rehabilitation exercises [273].

Mental illnesses such as attention deficit hyperactivity disorder (ADHD), autistic spectrum disorders (ASDs), anxiety disorders, and schizophrenia pose serious threats to human health and a significant burden on society. However, modern medicine continues to lack adequate means and methods for treating mental illnesses. NFB training based on the BCI system has gained increasing interest in recent years, as it provides a new avenue for clinical treatment of neurological disease [15], [18], [291].

C. Human Augmentation

Human augmentation is a term that refers to the process of enhancing human capabilities through medical or technological means [292]. Human augmentation research is frequently concerned with sense, action, and cognitive augmentation [1]. Human enhancement is also a primary focus of BCI research and application. For disabled individuals, augmentation refers to the ability to restore or replace lost function; for non-disabled individuals, augmentation refers to the ability to enhance existing functions [293], [294].

Cognitive augmentation is frequently used to refer to the process by which people acquire and generate knowledge while performing a high-level task. Cognitive augmentation technology has implications for various cognitive processes, such as problem-solving, language, memory, attention, reasoning, and computation [19].

Decision-making is a necessary component of human cognitive capability. Individuals or groups can make decisions in a variety of ways. Regardless of the approach, the goal is to make the best decisions possible. Identifying and correcting errors in decision-making on a timely basis is one method for increasing decision-making effectiveness. When a subject's intention to perform a task does not match the actual outcome, ErrP occurs. ErrP can be used to gauge a decision maker's confidence level. Passive BCI can monitor for ErrP occurrences at any time and thus correct them in a timely manner. A group-based decision-making system involving multiple participants can be used to further enhance decision-making performance. Group decision-making has been shown to outperform individual decision-making [295], [296]. Moreover, BBI can achieve the aforementioned goals by networking multiple brains, creating a connected system that not only enhances individual capabilities but also significantly improves collaboration among individuals [297].

BCI is a closed-loop interactive system. By continuously monitoring the subject's brain activity and providing appropriate feedback throughout the training process, it is possible to accelerate the trainee's learning rate [21], [28], [298].

D. Mental State Monitoring

Excessive workload or stress on operators can result in decreased efficiency or even incorrect operation in some critical jobs, such as air traffic controllers at airports. As a result, it is critical to monitor operators' mental states (e.g., workload) in real time [22], [23]. BCIs can monitor a user's mental state by continuously recording and analyzing brain activity data, such as workload, stress, emotion, and vigilance [24]. Furthermore, BBIs allow the dynamic allocation of tasks to individuals based on their cognitive levels, improving overall performance and enabling seamless collaboration even across different locations [299].

Traditional methods of assessing mental state are frequently conducted a posteriori via questionnaires and cannot be assessed in real-time online. Because no conscious intention on the part of the subject is required for mental state monitoring, BCI-based mental state monitoring is typically implemented using a passive BCI system. After analyzing the recorded raw brain signals, the BCI system can obtain a continuous or discrete quantification of mental states, enabling a data-driven assessment of subject-specific brain states.

Mental state monitoring has revealed significant application values in studies such as human factors and neuroengonomics.

E. Security and Authentication

Authentication is undoubtedly critical in today's information society for ensuring information security. Among the various authentication methods, biometric authentication systems that are based on a person's physiological and biological structure provide a higher level of security than traditional password authentication methods. Physiological biometrics already exist and include fingerprints, face, iris or retina, hand, and DNA. However, these biometric features are susceptible to falsification, fabrication, manipulation, and compulsion. Recent biometric authentication systems based on EEG signals have been proposed to address these issues by interpreting collected brain activity data for identification [300].

Existing biometric authentication systems based on BCIs typically acquire information about brain activity via EEG signals, either spontaneous EEG or evoked potentials following external signal stimulation. This is because EEG signals are relatively stable, and intersubject variability is significant. Additionally, because EEG is a brain signal generated by living individuals, biometric features are unlikely to be stolen after an individual's death [301].

Along with EEG signals, brain structure information can be used to identify individuals. Similar to a fingerprint, each individual's brain structure is unique, which is referred to as a brainprint. Unlike a fingerprint, a brainprint is a secret biometric technique that cannot be duplicated or falsified. A biometric system based on a brainprint can be built using structural brain images obtained via existing imaging techniques [302] or on brain connectivity graphs [303].

F. Neuromarketing

Neuromarketing is a relatively new advancement in marketing research that exists at the intersection of neuroscience and marketing. Traditionally, marketing research has relied heavily on subjective measurements such as questionnaires, individual and group interviews, and observational efforts to elicit feedback on merchandize, which is a time-consuming and expensive process. Additionally, consumers providing subjective feedback may conceal their true preferences, introducing bias into the evaluation process and resulting in inaccurate conclusions. Neuromarketing addresses this issue by analyzing consumers' cognitive and affective brain activity in response to marketing stimuli using noninvasive BCI technology, such as EEG recording. This procedure can be carried out in an unspoken and objective manner, thereby transforming traditional marketing research [283], [304].

Neuromarketing studies are typically designed to present a series of stimulus signals to subjects, such as information about the product, price, and promotion, based on marketing strategies while simultaneously recording and analyzing the subjects' brain signals to ascertain true consumer preferences. Most neuromarketing studies use EEG as the acquisition device, but others use fMRI, MEG, and so on. The brain regions involved in the process are mainly the frontal and prefrontal cortex, which are responsible for cognitive and emotional inquiries [304].

G. Entertainment

Various game platforms for entertainment can be devised based on the BCI platform. Given that the BCI platform enables brain–computer interaction, BCI games can be used for purposes other than entertainment, such as education [305], health care, advertisement, training, and other scientific purposes [306].

The cost of BCI equipment is decreasing, particularly for the EEG-based BCI system. This enables readily available BCI games to revolutionize our understanding of how players interact with games by introducing enhanced immersion, accessibility, and game experience via BCI games [307], [308].

VIII. CHALLENGES

Since the first publication of the BCI in the published literature half a century ago [31], the development of BCI has focused on increasing communication rates, decreasing transmission latency, improving decoding algorithms, decreasing BCI illiteracy, and expanding the range of BCI applications. We continue to face many difficulties and obstacles in achieving this goal. Given that BCI is a synthesis of multiple disciplines, we will discuss the major challenges in developing BCI from three perspectives: neuroscience, engineering, and application.

A. Challenge in Neuroscience

A practical issue that has arisen during the development of BCI is the conflict between the expectation of a high-performance BCI system and the limited knowledge of neuroscience. Successful design is inextricably linked to a prior comprehensive understanding of the relevant physiological processes throughout the relatively mature BCI experimental paradigms. The experimental paradigms based on SSVEP, P300, and MI are determined by extensive research on VEPs, ERPs, and motor cortex function. As a result, the continued development of novel BCI systems will require a greater understanding of neuroscience.

Among the many factors impeding the practical application of BCI, those relating to the subjects (people) are extremely important. For example, it has been demonstrated that approximately 15%–30% of subjects, even after a standard training period, are unable to meet the fundamental requirements for operating a BCI system or are unable to operate an existing BCI system at all. This is referred to as BCI illiteracy [309]. Individual differences are one plausible explanation for the BCI illiteracy phenomenon. If such individual differences exist, we would appear to have to abandon BCI in this population to avoid the costly, exhausting, and frustrating training. However, recent research indicates that the use of methods such as coadaptive learning may be able to "cure" BCI illiteracy to a certain extent [309]. This may imply that so-called "individual differences" actually refer to more fundamental neurophysiological differences between populations, including structural and functional differences in the brain. The neurophysiological differences result in a mismatch between the user's physiology and the BCI system's actual requirements [310]. In other words, the fundamental solution to the problem of BCI illiteracy continues to rely on the neurophysiological understanding of the problem. Only by elucidating the neurological causes of BCI illiteracy, can we develop BCI systems that are tailored to the unique characteristics of each individual.

Individual differences have a significant impact on the performance of the BCI application system in a variety of ways. Stroke patients frequently experience motor impairment as a result of their stroke. Motor rehabilitation for stroke patients using sensorimotor rhythms (SMR) is a significant area of application for BCI at the moment. It is obviously critical to know the intracranial stroke lesion locations in stroke patients, as the intracranial injury will directly cause fluctuations in brain signals. However, knowledge of the damage's spatial location alone is insufficient, as temporal information also plays a significant role in the individual difference. Specifically, the temporal information in SMR changes over time and across subjects, a phenomenon known as intrasubject and intersubject variability, which makes model transfer across sessions or subjects difficult due to covariate shifts in data distributions [311]. It is more critical to choose the optimal neuropsychophysiological parameters for each patient based on their residual brain function status and thus design a highly personalized rehabilitation intervention program. Indeed, the NFB approach to neurorehabilitation is predicated on the assumption of cerebral cortex neuroplasticity. Without an in-depth study of the principles of plasticity, it is difficult to ensure the long-term effectiveness of training.

Instantaneous brain dynamics are typically mediated by physiological and psychological factors relating to the user. Gender-, age-, and lifestyle-related characteristics are considered physiological factors [312], whereas attention, fatigue, memory load, and cognitive processes are considered psychological factors [313], [314], [315]. The challenges we face are adapting the decoder to changes in brain signals and developing a personalized BCI system.

BCI is a multidisciplinary field of research, and the advancement of neuroscience lays the groundwork for its development. Arguably, the state of neuroscience research will significantly impact the success or failure of BCI research and its application.

B. Challenge in Engineering

From the standpoint of system components, a BCI consists primarily of three components: acquisition of brain signals, decoding of brain signals, and control and feedback of external devices. The challenge for the development of BCI is to enhance and improve the performance of these components. Besides, the advancement of CBI hinges on the development of noninvasive, high-precision brain stimulation techniques, which will ultimately shape the scope and effectiveness of future CBI applications.

Current approaches to brain signal acquisition can be broadly classified into two categories: invasive and noninvasive (see Fig. 2). Several of these techniques have a high temporal resolution but a low spatial resolution (e.g., EEG). In contrast, others have a high spatial resolution but a low temporal resolution (e.g., fMRI). While electrode implantation achieves high temporal and spatial resolution, it is difficult for most users, particularly normal healthy human users, to accept because the electrode implantation process causes some trauma to the human body. Additionally, the electrode material's biocompatibility and long-term effectiveness following implantation in the cerebral cortex remain unresolved issues. Future research should prioritize the development of implantable electrode systems that require no surgery or minimal trauma, as well as the wireless transmission of high-throughput signals. In general, invasive methods can obtain higher quality signals due to their direct contact with the cerebral cortex, thereby achieving higher data transmission speeds. Conversely, noninvasive methods need to obtain brain signals through the scalp and skull, and the signals are weaker and susceptible to interference, resulting in lower ITR. Acquiring high-quality brain signals will greatly facilitate subsequent brain signal decoding. To obtain high-quality brain signals, factors such as noise, interference, and artifacts from external sources must be considered. In recent years, technologies such as adaptive filtering, artifact rejection algorithms, and advanced sensor designs have provided support for improving the quality and reliability of brain signals.

The inherently low SNR of EEG signals has long posed a significant challenge. Leveraging multichannel EEG acquisition to spatially boost the signal quality presents a promising approach to addressing this limitation. Recent studies have demonstrated that increasing the number of EEG channels offers richer neural information, thereby enhancing the performance of BCIs [316], [317], [318]. For example, Sun et al. [316] employed the high-density 256-channel EEG to enhance the angular resolution of VEP stimuli to 1°, achieving significantly higher ITR compared to configurations with 64- or 128-channel densities. Wang et al. [317] also found that emotion recognition performance improved with higher density electrode setups covering the full scalp (128 electrodes versus 60 electrodes). Similarly, Lee et al. [318] achieved precise decoding of individual finger movements using 256 channels placed over the contralateral sensorimotor cortex. Besides, increasing the sampling rate also has the potential to enhance the ability to capture high-frequency oscillations including ripples (80–250 Hz) and fast ripples (250–500 Hz), as well as auditory brainstem responses, which typically have a frequency band of interest roughly ranging from 20 Hz to 20 kHz [319]. It is foreseeable that as the number of channels and sampling rates increases, future noninvasive BCI systems will offer users greater operational freedom, and the applications will transform from efficient interaction to natural interaction.

The benefits of increasing EEG channel density are complemented by advancements in spatial sampling theory and practical considerations for electrode placement. Srinivasan et al. [320] estimated the "spatial Nyquist rate" of EEG based on an idealized head model and demonstrated that at least 128 sensors are required to adequately sample the entire scalp surface. Grover et al. [321] refined the analysis and estimated that 600–1000 electrodes are necessary to achieve the Nyquist rate by recovering 98% of the signal energy. They also suggested that increasing the number of electrodes would still aid in more accurate localization of brain sources. In practical applications, electrodes only need to be placed in the target brain regions and the appropriate number of electrodes can be selected according to task complexity. For instance, in the VEP paradigm, effective signals are concentrated in the parieto-occipital region. Additionally, as the size of the stimuli decreases and the number of targets increases, the required number and density of electrodes will increase accordingly [316]. As the number of electrodes increases, a major challenge arises in ensuring the efficient wearability of arrays comprising hundreds or even thousands of electrodes. To address this issue, flexible electrode arrays and adjustable helmet-type devices need to be developed to accommodate different head shapes and facilitate electrode placement [322]. Additionally, electrophysiological source imaging offers a strategy to further enhance EEG spatial resolution by leveraging high-density EEG devices, precise head models, and advanced algorithms to solve the inverse problem [323]. The differential channel EEG recording method effectively suppresses common-mode noise, significantly enhancing signal quality, and has been extensively utilized in BCI systems. With the continuous advancements in multichannel signal acquisition, transmission, and processing technologies, EEG will continue to play a significant role in the field of BCI, particularly in consumer-grade BCI applications, due to its affordability, portability, and noninvasiveness.

The core technologies in BCI systems are encoding and decoding brain signals. The encoding process modulates the user's intention into a detectable brain signal, while the decoding process unveils and analyzes the relationship between the recorded brain signal and the user's real intention. The nonlinear and nonstationary characteristics of brain signals require special consideration during this process. Nonlinearity originates physiologically in the complex system of the brain, which is teeming with chaotic neuronal activity. The nonlinear nature of brain signals, therefore, deserves special consideration during data processing. Additionally, the nonstationary characteristics of brain signals should be taken into account. Nonstationarity is caused by both internal physiological activities of the human body and disturbances in the external environment. Internally, nonstationary brain states, such as fatigue and varying degrees of attention, significantly affect the recorded brain signals. External noises such as electrode shift, motion artifacts, and ambient noise significantly affect the recorded brain signals.

The composition of the feedback mechanism used by the BCI system during operation is a particularly difficult issue. On the one hand, there are few methods for directly applying external feedback signals to the CNS, and the available results are insufficient. On the other hand, coadaptation of brain–machine interaction in a closed-loop system also presents a significant challenge. Coadaptation is an open question on a platform where HI and AI coexist.

While invasive CBI devices are commonly used in rodent models, they are less favored in human studies due to associated complications. Noninvasive CBI devices, such as tDCS, TMS, and tFUS, are actively researched for their clinically friendly attributes. In particular, tFUS shows great promise due to its superior spatial selectivity and penetration depth [299]. However, the mechanisms of tFUS neuromodulation remain unclear, making the selection of optimal ultrasound parameters challenging. Different sonication settings can either excite or inhibit neural activity, adding complexity to the software control of CBI systems [273]. Moreover, the interaction between ultrasound waves and the skull leads to sound attenuation and distortion, posing significant hardware challenges for tFUS CBI systems, especially when targeting specific brain regions with high precision [324].

Engineering and technical issues for BCI and CBI span multiple disciplinary domains, including material science, computer science, electronics, and control technology. It is reasonable to assume that the rapid advancement of engineering technology will incentivize BCI to enter a new stage of development.

C. Challenge in Application

BCI is fundamentally different from traditional physical-world-based communication systems. BCI aims to establish a channel of communication between biological and physical systems. Indeed, there is a fundamental distinction between biological and physical systems. The cerebral cortex contains approximately 10^{11} neuronal cells, and each neuron is connected to thousands of other neurons via synapses. In comparison, state-of-the-art technology in the physical world can only simultaneously capture information from thousands of neurons [325]. At a functional level, the brain has a slow processing speed and a limited storage capacity, significantly slower than the processing speed and storage capacity of computers in the physical world. Coordinating them in a consistent manner is challenging. At the operational level, information transfer between biological neurons is accomplished by using an ionic current or chemical transmitter. In contrast, in the physical world, it is accomplished through the use of an electronic current. Apparently, a suitable medium is required to convert them from ionic to electronic current. The difficulty and challenges of putting these two strikingly different systems on a single platform to work synergistically are self-evident.

While numerous BCI paradigms have been developed, none are claimed to be perfect. Even the three more mature noninvasive technologies, namely, MI-BCI, P300-BCI, and SSVEP-BCI, are insufficient. MI-BCI systems typically require extensive training before use, and some users are unable to achieve the desired result after training and must withdraw from further use. Additionally, MI-BCI is slow for motor control and is incompatible with VR environments or video games. P300-BCI is typically based on externally applied visual-specific stimuli and is therefore incompatible with individuals who have a visual impairment. While SSVEP-BCI currently has the highest ITR [7], prolonged viewing of a flickering screen can cause visual fatigue. Both the P300-BCI and MI-BCI systems operate with a high degree of concentration, resulting in user fatigue. For us, the challenge is to create a more sophisticated, user-friendly BCI system.

The system's ease of use also acts as a barrier to the widespread adoption and use of BCI systems. Currently, most EEG-based BCI systems use a so-called "wet electrode" system to ensure a high SNR, which requires injecting conductive gel between the electrodes and the scalp. This procedure is time-consuming and inconvenient for the user. Additionally, most testing continues to take place in a laboratory setting under strictly controlled conditions, and the developed systems are not yet suitable for use in everyday life. In practice, we require BCI systems that are cost-effective, portable, simple to maintain, and require minimal surgery. BCI should be designed in such a way that it fully considers environmental factors and the needs of target users.

The low rate of communication is a significant impediment to the promotion and application of BCI. Currently, the ITR of BCI systems based on noninvasive technology is less than 6 b/s, which is significantly lower than the rate of voice communication (39 b/s). Improving encoding and decoding efficiency is the foundation for increasing the communication rate from a communication system design perspective. Among the existing BCI paradigms, some take several seconds to generate the required characteristic brain signals. The number of optional targets is also limited, for example, the MI-based BCI system. Other systems, such as the P300-based BCI system, require numerous repetitions of the experiment to extract useful information. The abovementioned inefficient encoding process stymies the BCI system's communication rate. The received signal is contaminated with significant noise during the decoding process. The signal is frequently incomplete due to the small number of channels acquired, which frequently results in an incorrect decoding outcome. Repeated error correction has a noticeable effect on the system's communication rate. To address the issues mentioned above, it is necessary to advance neuroscience research and develop additional experimental paradigms with efficient coding capabilities. On the other hand, it is critical to improve the performance of advanced decoding algorithms available in the field of engineering technology [326].

Current BBI research predominantly focuses on unidirectional and 1:1 collaboration models, with little exploration of bidirectional neuromodulation or complex multisender systems. However, complex systems hold significant potential in real-world applications, especially in scenarios that require advanced teamwork. A collaborative BrainNet capable of multiparty information exchange could play a crucial role in managing complex tasks and enhancing collective decision-making. The CBI part of BBI systems also faces significant safety challenges. For instance, in tFUS-based CBIs, monitoring and evaluating the ultrasound beam within the target brain region is crucial to improving experimental success rates and reducing risks. However, current studies often overlook mentioning safety measures such as imaging guidance, temperature, and neural response monitoring [273].

In addition to the aforementioned technical challenges, the ethical challenges of using BCI and CBI in practice cannot be neglected. Physical, psychological, and social factors all play a role in the ethical issues raised by BCI applications. Particular emphasis should be placed on the short- and long-term effects of cortically implanted electrodes on human subjects. Besides, CBI systems have the potential to access and alter brain information, raising concerns about unauthorized information transmission. The complexity of these issues is heightened in multiperson BBI systems, where managing informed consent and potential adverse effects becomes more challenging [327]. Additionally, members of a BBI network may find their decision-making autonomy heavily influenced by other participants, further complicating the ethical landscape.

IX. PROSPECTS

BCI technology has advanced significantly over the last decade due to the development of many related science and technology fields. Not only has communication technology aided in the development of BCI in the past, but it will also be a major driver of BCI development in the future. Today, the application of BCI has begun to expand beyond the medical domain, where it provides communication tools for people with motor disabilities, to all spheres of life for healthy people, and it will undoubtedly become a new focus of science and technology in the future. As medical advances reduce the risks of invasive surgery, the use of BCI technology may change significantly. Noninvasive BCIs are expected to achieve performance breakthroughs and continue dominating the consumer market (e.g., entertainment, education, and health monitoring) due to their safety and convenience [55]. With advancements in medical technologies, particularly in minimally invasive surgery and biocompatible materials, invasive BCIs may emerge as the preferred technology for high-precision control tasks such as prosthetic control and play a significant role in improving the quality of life for patients with severe neurological diseases (e.g., ALS and brain injuries). As surgical risks decrease, some healthy individuals may opt for invasive BCIs to enhance their cognitive or physical abilities, and invasive BCIs will be more widely used. These developments will promote the application of BCI technology in multiple fields such as medical care, consumer electronics, and industrial control, bringing more benefits to human health and life.

A. BCI—Convergence of HI and AI

In the BCI loop, the "brain" is an intelligent system in the biological sense, namely, HI, while the "computer" has the properties of AI. There is no doubt that both HI and AI are at the frontiers of science and technology that have received widespread attention today.

In recent years, with the rapid development of AI technology, it has achieved great success in many fields, including intelligent robotics, computer vision (CV), and natural language processing (NLP). However, it is inevitable that the application of AI technology is still very limited. It can usually only address well-defined issues or execute tasks in preset parameters, and AI cannot tackle dynamically varying and complicated problems as humans can. Although efforts are being made to provide AI with more human-like intelligence, it is difficult to fully accomplish this in practical applications. This is probably because the brain (HI) and the computer (AI) are completely distinct in both structure and behavioral characteristics. Moreover, humans have some unique complex cognitive functions, e.g., the emotional quotient (EQ) and social quotient (SQ), the creative quotient (CQ) and innovative quotient (INQ), and the moral and ethical quotient (MQ). Thus, it is very difficult to understand the formation mechanism of these complex cognitive functions and imitate them.

HI undoubtedly represents the highest level of intelligence. The human brain is a highly developed intelligence that has evolved over time to possess advanced intelligence behaviors such as language, learning, understanding, abstraction, judgment, and planning. Most of these behaviors and capabilities are not available in existing AI systems and are difficult to imitate. Of course, compared with AI systems, HI also has obvious disadvantages. Due to physiological constraints, the brain itself has small storage space and low computational speed, which is significantly inferior to AI systems. This makes it difficult to process massive amounts of big data quickly and to achieve efficient retrieval and management of the vast amount of information that is ubiquitous today.

Obviously, both HI and AI have their own innate strengths and inevitable weaknesses, but there is a clear complementarity between the two strengths. If we fuse HI and AI systems together to form a so-called hybrid or collaborative intelligence system, we can take advantage of their respective strengths and thus optimize the performance of the whole system.

A typical BCI system is a brain-in-the-loop communication system, which operates on a unified platform integrating HI and AI. On this platform, HI and AI communicate

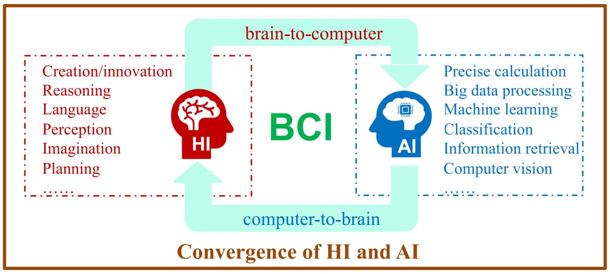

Fig. 14. ***Convergence of HI and AI. Illustration of BCI enabling real-time interaction between HI and AI. HI excels in creation, reasoning, language, and imagination, while AI offers strengths in computation, data processing, and pattern recognition. BCI facilitates collaborative intelligence by integrating their complementary capabilities.***

and interact with each other in real time and can thereby learn, evaluate, and adapt their strategies continuously for interaction throughout an ongoing communication (see Fig. 14). This also provides the system with the foundation for collaborative intelligence. The term collaborative intelligence in this context refers to the capacity for coordination, cooperation, and/or collaboration and exchange of knowledge or even high-level wisdom. Unlike existing offline interaction approaches, e.g., brain-inspired computing techniques to improve the performance of AI systems, collaborative intelligence enables HI and AI to converge dynamically. Because it fully integrates the advantages of HI and AI, collaborative intelligence can often show significantly better processing results than single-mode HI or AI.

Collaborative intelligent communication systems enable a variety of potential applications, e.g., intelligent decision-making [10], [11], human factor engineering [22], [23], [24], and HI enhancement [15], [19], [21], [295]. Taking the decision-making problem as an example, usually, the problems we face in decision-making are very complex, and oftentimes, we can be troubled by situations such as uncertainty, equivocality, and complexity [328]. Advanced AI techniques with quantitatively, computationally, and analytically superior capabilities can handle complex big data and thus provide more evidence for human decision-making. However, facing those ambivalent problems with high uncertainty makes AI techniques difficult to deal with due to ill-defined decision rules. The complementary relationship is formed in a way that although human is not good at big data computational processing, he/she will deal with uncertainty and equivocality more rationally based on his/her own experience, and sometimes humans can even make a correct judgment on the problem by intuition. Based on the above analysis, the advantages of both HI and AI can be integrated together to obtain better decisions than any single model. The so-called cortically coupled CV is a typical example of such a successful application [329]. It combines the human's superior intuitive perception and judgment with the AI's high-speed capacity in gathering and analyzing information to achieve an efficient target image retrieval task [139].

With the advancement of BCI technology, collaborative intelligence has shown its potential application in a broad array of fields. It is foreseeable that collaborative intelligence or hybrid intelligence will become the mainstream development direction of the next generation of BCI [330].

B. BCI and Wireless Communications

In the development and application of BCI, the support of wireless communication is indispensable. On the other hand, the advancement of BCI technology also accelerates the advancement of wireless communication. Presumably, it pushes it to a new era of Internet of Everything (IoE, thing-to-thing) or brain-type communication.

Brain activity data can be acquired in various ways, both invasive and noninvasive. Signal transmission can be accomplished via both wired and wireless methods. From a practical utility standpoint, wireless communication has exploded in popularity because it enables subjects to perform tasks while moving freely. At the moment, both EEG and neuronal activity information can be wirelessly transmitted to a computer and decoded by the computer to enable control of external devices [4], [58], [331].

The number of channels in the multichannel EEG signal recorded noninvasively on the scalp is relatively small, ranging from a few to no more than 512. Each channel has a low sampling rate, typically less than a few kilohertz. As a result, the volume of data transmitted in real time is quite small. Numerous existing EEG acquisition systems include wireless computer communication. However, implanted electrode arrays typically have hundreds or even thousands of channels and a sampling rate of up to tens of kilohertz. As a result, wired communication was widely used in the past. Simeral et al. [58] developed the world's first BCI system with wireless communication for implanted electrodes in 2021. The system consists of two implanted electrode arrays with a total of 192 electrodes, a sampling rate of 20 kHz per channel, and 12 bits per sample. It is designed to transmit wirelessly at a rate of 3.3/3.5 GHz, allowing for the reception of brain signals from multiple patients. The system has been successfully tested on two patients, one of whom was subjected to testing for up to 24 h. The test results indicate that the wireless communication system's data quality is comparable to that of the previous wired communication system.

Musk and Neuralink [325] launched a platform for BCI integration. The platform made use of a novel type of flexible electrode called "threads," which consisted of arrays of 96 threads, each with 3072 electrodes. They also developed a neurosurgical robot tool capable of inserting six threads or 192 electrodes per minute for electrode implantation. The electrode signals are processed and then transmitted to the outside of the body via a custom-designed low-power chip. The platform has been demonstrated to be effective in rat experiments. The system was recently tested in live pig experiments and human experiments. Clearly, this technology has great potential if surgical risks can be mitigated and issues such as electrode biocompatibility can be addressed.

Intracranial implantable neural sensors should present the following characteristics: 1) miniaturized—the sensor's size should be extremely small; 2) biocompatibility—to ensure long-term effectiveness, the sensor should be extremely biocompatible; 3) safety—the sensor should be easily implanted via minimally invasive surgery or nonsurgical methods to ensure safety; 4) batteryless—ideally, the device will not require implanted batteries; and 5) wireless—the collected signal can be wirelessly transmitted at a high rate of speed. Theoretically, assuming that the human brain contains approximately 100 billion (10^{11}) neurons, each neuron fires at a rate of 200 times/s, providing only a binary 1-bit signal. Each neuron is connected to approximately 1000 others, and the generated data from human brain flops will reach approximately 20 000 Tb/s (10^{11} neurons $\times$ 200 flop/s $\times$ 10^3/neuron $=$ 20 $\times$ 10^{15} flop/s $=$ 20 petaflops/s $\times$ 1 bit/flop $=$ 20 000 Tb/s) [332], which is an incredibly enormous amount of data. Admittedly, the generated data volume is much lower due to the neurophysiological constraints on brain activity. Nevertheless, as soon as the terabit-per-second magnitude is reached, current 5G systems will no longer be able to meet the demand.

Most existing BCI systems are discrete in nature, interpreting and converting characteristic brain signals into a series of discrete control commands. For instance, when left-/right-hand movements are imagined, the resulting characteristic brain signals can be interpreted and converted into ON/OFF control of an electrical appliance. This type of control not only renders BCI unnatural in practice but also has a direct effect on the system's communication rate. Indeed, the source signal we wish to transmit in a BCI system is the user's intention or wishes, which possess semantic and goal-oriented properties. Suppose decoding can be accomplished directly at the semantic level. In that case, it will not only improve the naturalness of the interaction between brain and computer but will also significantly improve communication efficiency. Naturally, to achieve semantic communication in BCI research, the problem of semantic encoding and decoding must be addressed. This requires converting the specific semantic concepts a user is focusing on or thinking about into a unique brain signal and decoding it at the receiver [333], [334], [335]. From a communication technology perspective, a semantic communication system does not place a premium on ensuring the correct reception of every transmitted bit. Rather than that, it is more concerned with the impact on the interpretation of the meaning of the received bits in relation to the transmitter's intent or with the accomplishment of a joint goal. As a novel mode of communication in the age of intelligence, the application of semantic communication in BCI systems has the potential to improve the efficiency and naturalness of human–computer interaction. From the perspective of communication systems, semantic communication is likely to be a future solution for approaching the Shannon limit [336].

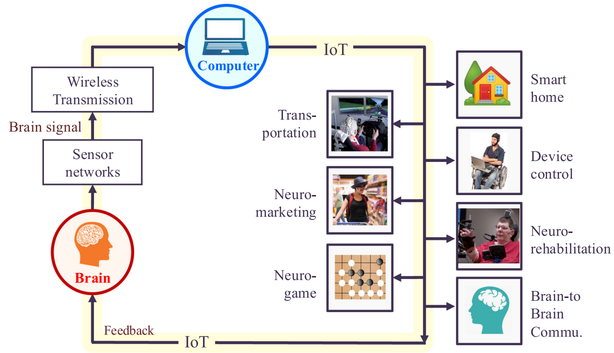

Fig. 15. ***BCI in wireless communications. A wireless BCI framework is illustrated, in which brain signals are acquired through sensor networks, wirelessly transmitted, and decoded by a computer to control various external applications, including smart homes, device control, neurorehabilitation, neuromarketing, gaming, and brain-to-brain communication, within the IoT ecosystem.***

Remote control of BCI has long been a reality due to the rapid development of network technology (see Fig. 15). Apart from remote control of external devices [8], [337], the most exciting development is the successful implementation of brain-to-brain communication [249], [271], [338].

The IoT technology has advanced significantly, and a large number of devices are now connected daily, significantly expanding the scope of BCI systems in controlling external devices, such as remotely controlled smart homes [339], [340], [341], [342]. Furthermore, Grau et al. [271] and Rao et al. [338] achieved Internet-based brain-to-brain communication. Not only was B2C communication established on this platform, but also C2B information transfer. Later on, Rao et al. [338] further developed a multiperson brain-to-brain communication system, providing a new platform for multiperson collaborative problem solving [249]. Internet-based brain-to-brain communication has facilitated the transition of wireless communication technology from human-to-machine communication to a new era of brain-to-brain communication [25].

Compared to conventional communication systems, brain-type communication has far-reaching implications and places greater demands on communication systems' performance. Human-environment communication is extremely diverse and complicated. People use their five senses of sight, smell, hearing, taste, and touch to perceive and interact with their environment. Future wireless communication systems could transmit the five senses' data remotely. Not only that, humans are endowed with emotions. Subjects' joys and sadnesses are also expected to be transmitted online via affective BCI. It is possible that human brains will become an integral part of a future

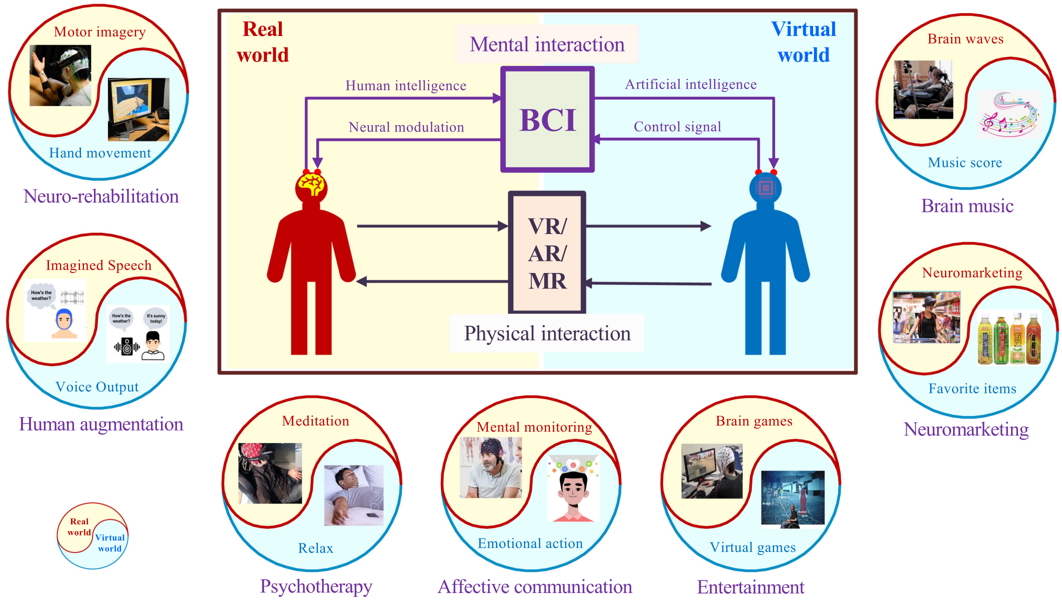

Fig. 16. ***BCI and metaverse. BCI acts as a bridge enabling seamless integration between the real and virtual worlds through both physical and mental interaction. By decoding user intent via MI, imagined speech, and neural feedback, BCI expands metaverse applications into neurorehabilitation, human augmentation, psychotherapy, affective communication, entertainment, and neuromarketing.***

brain-type communication system. The brain is capable of communicating directly and seamlessly with artificial devices and other brains [25]. At that point, the IoE will have truly arrived. To this end, existing systems' performance must be enhanced further, particularly in terms of data rate, system capacity, latency, and service quality.

Apart from the high-performance wireless networks required to support wireless BCI systems, there are numerous applications that will drive the development of a future 6G mobile network system, including multisensory extended reality (XR) applications, blockchain, and distributed ledger technologies, connected robotics, and autonomous systems. Indeed, these applications are frequently intertwined, requiring highly reliable uplink and downlink data transfer with low latency for heterogeneous devices. We anticipate the rapid deployment of advanced 6G wireless communication networks, which will provide the technological foundation for the prospect from wirelessly connecting things to connecting intelligence [5], [25], [343].

C. BCI and Metaverse

Until now, no unified scientific definition of the metaverse has been proposed [344]. In a broad conceptual sense, the metaverse refers to the digital world that exists alongside our physical world and provides us with a means of living, working, and playing [345], [346].

The metaverse's implementation requires the creation of an avatar or digital twin in the virtual world, in which a physical object or process is mapped in real time into a virtual embodiment. The human avatar already has the appearance and image of a real person in the physical world in the existing metaverse. Additionally, it exhibits adaptable behavioral movements similar to those of a real person. However, it lacks HI as a substitute for the living creature. Without a doubt, human nature is unique due to biological and psychological differences between individuals, which are the most salient distinctions between a human being and a machine, as well as between one human being and another [347]. This implies that the avatar in the metaverse world should not only be a robot that closely resembles and follows you but also a humanoid embodiment with HI. The indispensable so-called HI should encompass a range of quotients, including the physical quotient (PQ), the intellectual quotient (IQ), the EQ and SQ, the INQ, the CQ, and the MQ [348].

From the perspective of technology, the metaverse bridges the gap between the real and virtual worlds in an integrated, interactive, and intertwined fashion. In the existing metaverse paradigm, avatars can realistically mimic the external appearance of individuals in the real world, including their body shape, appearance, and even skin, by utilizing VR/augmented reality (AR)/XR technologies. Additionally, they can mimic the behavioral actions of real-world individuals, including body behavior and speech patterns. At the same time, the perception and behavior of the avatar in the virtual world can be provided in real time to the real-world individual, for example, tactile feedback. However, the interactions described above are typically limited to physical interactions that provide people with a surreal experience of partial senses rather than an entire spectrum of senses, including the mind.

To create an intelligent avatar, it is necessary to transcend physical interaction and achieve mental or intelligence interaction (see Fig. 16). Only through mental interaction are avatars in the virtual world capable of displaying genuine HI and establishing social relationships with one another. Through participation in social, economic, cultural, and political activities, avatars can cultivate social relationships, transforming the metaverse into a truly self-sustaining, independent, and interoperable virtual world that exists alongside the physical world. To accomplish this ultimate goal, direct communication between the human brain and the physical world must be established, and this technology is described in this article as the BCI technology. By connecting the human neural world to the external physical world, BCI decodes and translates individual brain activity into commands that can be interpreted by computing devices, spatially aggregating the virtual world with the real world seamlessly [345].

Indeed, existing BCI research has resulted in the development of several techniques for implementing interactions at the level of intelligence in the metaverse, thereby bringing mind reading to reality [8]. For instance, users can imagine limb movements to control the motion of exoskeletal prostheses using MI BCI systems [83], [85]; brain signals associated with human speech can be directly interpreted and converted into corresponding speech or text messages [6], [349], [350], [351], [352], [353], [354]; and spontaneous brain signals associated with the human brainprint can even be used as a feature signal in identity recognition [300], [302]. Because BCI technology enables players to directly interface and interact with the outside world or virtual world, it is more likely that BCI will become the primary mode of interaction in the era of the upcoming metaverse, as opposed to the current VR/AR headsets. We can be certain that achieving interaction at the level of intelligence will undoubtedly result in a more natural, intuitive, effective, and immersive interaction between the real and virtual worlds. At that point, it may be difficult to distinguish the real world from the metaverse.

Currently, the metaverse's applications are largely limited to the gaming industry. The integration of BCI into the metaverse has the potential to rapidly expand the applications of the metaverse to human augmentation, neuro-rehabilitation, psychotherapy, and other fields (see Fig. 16). Recent publications (e.g., neurorehabilitation [15], [355], human augmentation [6], psychotherapy [16], [289], effective communication [298], neuromarketing [283], [304], entertainment [307], [308], and brain music [356]) discuss related technologies. These applications will significantly impact the metaverse's future development and transform it into a truly beneficial platform of information technology for humans [357].

The applications mentioned above of BCI in the metaverse environment suggest that BCI is expected to play a critical role in the metaverse's development. Naturally, advanced wireless communication, such as 6G, is a critical underlying technology for accomplishing all of this. Future wireless communication will hopefully push the boundaries of VR and BCI, expanding the scope of service from conventional physical connections to fairly dense connections between humans, machines, things, and the virtual environment, paving the way for the future metaverse.

X. CONCLUSION

Technologies such as BCI, AI, IoT, VR/AR/XR, and wireless communication are unquestionably the most cutting-edge research priorities in the field of modern information science and technology. Interdisciplinarity and concerted effort drive the advancement of modern information technology, thereby significantly increasing social productivity and living standards. To this end, a comprehensive understanding of the inherent relevance and complementarity of these state-of-the-art technologies is critical for anyone involved in information technology research and development.

Unlike previous BCI reviews, this article not only covers all aspects of BCI technology in detail but also elaborates on the inextricable connection between BCI and fields of information science, particularly modern communication technology. To address the issue of real-time wireless communication between brain signals and computers, the BCI system makes use of a broad spectrum of advanced wireless communication technology. Many experimental paradigms in BCI are derived fundamentally from the technology and methodology of modern communication systems, particularly the channel access method used in modern communication technology. BCI technology is inspired by communication in some ways, and conversely, the advancement of BCI research has accelerated the advancement of communication technology. Due to the demand for high-speed real-time wireless communication in big data, BCI is the driving application for developing the next 6G technology [5]. Combining BCI and communication will undoubtedly enable new applications in the future, including the development of the metaverse, as BCI has the potential to be one of the best forms of interaction in the future metaverse era. ■

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