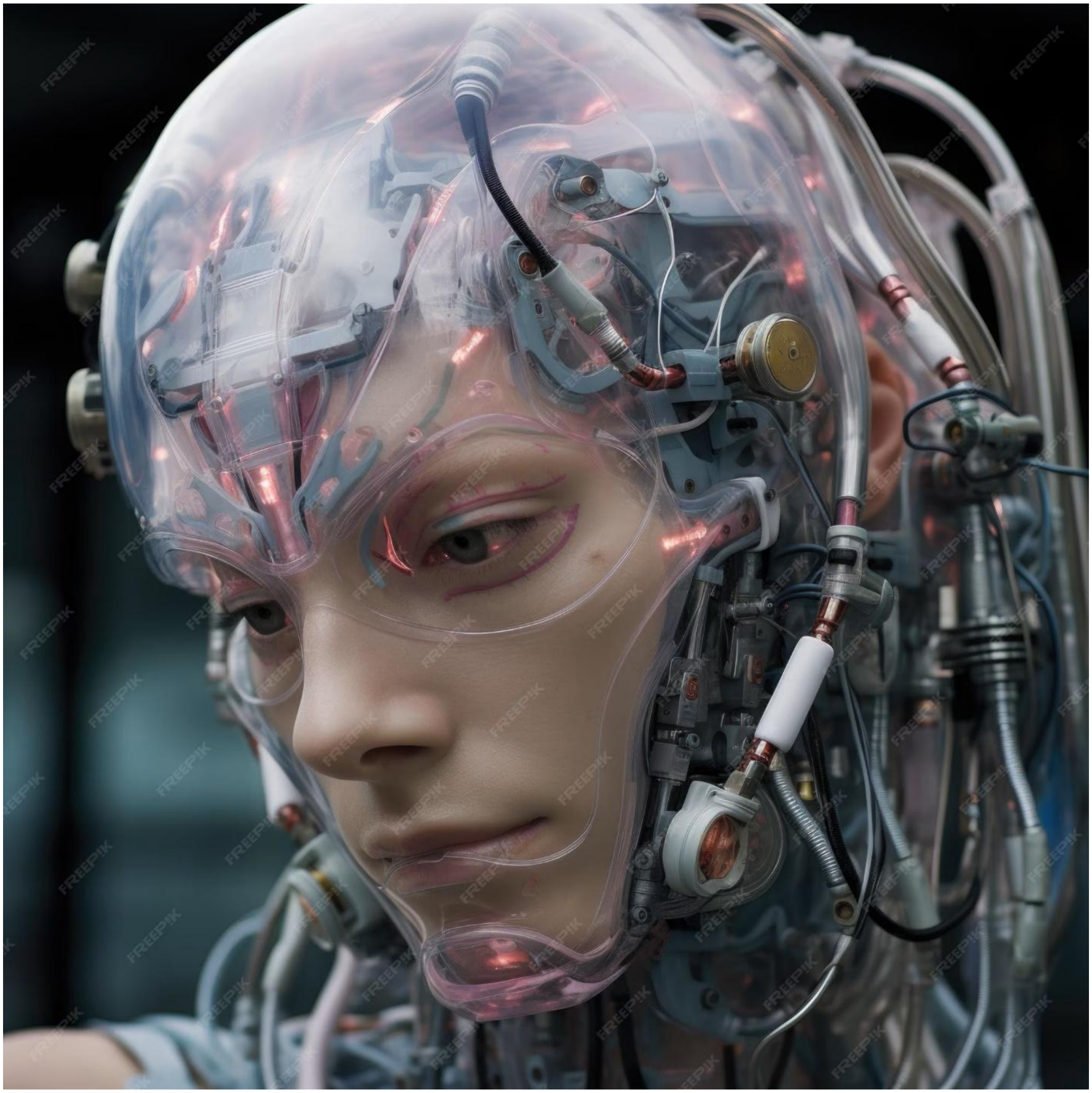
NON-INVASIVE BCI



First Ever Non-invasive Brain-Computer Interface Developed

| Original story from Carnegie Mellon University

A team of researchers from Carnegie Mellon University, in collaboration with the University of Minnesota, has made a breakthrough in the field of noninvasive robotic device control. Using a noninvasive brain-computer interface (BCI), researchers have developed the first-ever successful mind-controlled robotic arm exhibiting the ability to continuously track and follow a computer cursor.

Being able to noninvasively control robotic devices using only thoughts will have broad applications, in particular benefiting the lives of paralyzed patients and those with movement disorders.

BCIs have been shown to achieve good performance for controlling robotic devices using only the signals sensed from brain implants. When robotic devices can be controlled with high precision, they can be used to complete a variety of daily tasks. Until now, however, BCIs successful in controlling robotic arms have used invasive brain implants. These implants require a substantial amount of medical and surgical expertise to correctly install and operate, not to mention cost and potential risks to subjects, and as such, their use has been limited to just a few clinical cases.

A grand challenge in BCI research is to develop less invasive or even totally noninvasive technology that would allow paralyzed patients to control their environment or robotic limbs using their own "thoughts." Such noninvasive BCI technology, if successful, would bring such much needed technology to numerous patients and even potentially to the general population.

However, BCIs that use noninvasive external sensing, rather than brain implants, receive "dirtier" signals, leading to current lower resolution and less precise control. Thus, when using only the brain to control a robotic arm, a noninvasive BCI doesn't stand up to using implanted devices. Despite this, BCI researchers have forged ahead, their eye on the prize of a less- or non-invasive technology that could help patients everywhere on a daily basis.

Bin He, Trustee Professor and Department Head of Biomedical Engineering at Carnegie Mellon University, is achieving that goal, one key discovery at a time.

"There have been major advances in mind controlled robotic devices using brain implants. It's excellent science," says He. "But noninvasive is the ultimate goal. Advances in neural decoding and the practical utility of noninvasive robotic arm control will have major implications on the eventual development of noninvasive neurorobotics."

Using novel sensing and machine learning techniques, He and his lab have been able to access signals deep within the brain, achieving a high resolution of control over a robotic arm. With noninvasive neuroimaging and a novel continuous pursuit paradigm, He is overcoming the noisy EEG signals leading to significantly improve EEG-based neural decoding, and facilitating real-time continuous 2D robotic device control.

Using a noninvasive BCI to control a robotic arm that's tracking a cursor on a computer screen, for the first time ever, He has shown in human subjects that a robotic arm can now follow the cursor continuously. Whereas robotic arms controlled by humans noninvasively had previously followed a moving cursor in jerky, discrete motions--as though the robotic arm was trying to "catch up" to the brain's commands--now, the arm follows the cursor in a smooth, continuous path.

In a paper published in Science Robotics, the team established a new framework that addresses and improves upon the "brain" and "computer" components of BCI by increasing user engagement and training, as well as spatial resolution of noninvasive neural data through EEG source imaging.

The paper, "Noninvasive neuroimaging enhances continuous neural tracking for robotic device control," shows that the team's unique approach to solving this problem not enhanced BCI learning by nearly 60% for traditional center-out tasks, it also enhanced continuous tracking of a computer cursor by over 500%.

The technology also has applications that could help a variety of people, by offering safe, noninvasive "mind control" of devices that can allow people to interact with and control their environments. The technology has, to date, been tested in 68 able-bodied human subjects (up to 10 sessions for each subject), including virtual device control and controlling of a robotic arm for continuous pursuit. The technology is directly applicable to patients, and the team plans to conduct clinical trials in the near future.

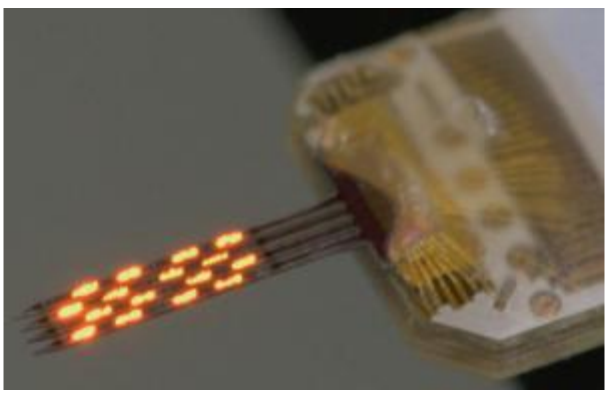
"Despite technical challenges using noninvasive signals, we are fully committed to bringing this safe and economic technology to people who can benefit from it," says He. "This work represents an important step in noninvasive brain-computer interfaces, a technology which someday may become a pervasive assistive technology aiding everyone, like smartphones."

Reference: Edelman, B. J., Meng, J., Suma, D., Zurn, C., Nagarajan, E., Baxter, B. S., … He, B. (2019). Noninvasive neuroimaging enhances continuous neural tracking for robotic device control. Science Robotics, 4(31), eaaw6844. https://doi.org/10.1126/scirobotics.aaw6844

The year of brain–computer interfaces

With advances in capabilities coming hand in hand with calls for regulation, 2023 is proving to be a critical year for brain–computer interfaces.

Back in February, we announced that brain–computer interfaces were our technology of the year for 2023. The interfaces, which provide a direct communication link between the brain and an external device, can record, decode and stimulate neural activity. They are of potential use in a variety of profound applications — from treating neurological disorders to enhancing human capabilities — and they have been the topic of a series of powerful research demonstrations in recent years.



Photograph of an optical probe developed by Malte Gather, Kenneth Shepard and colleagues with 512 of the 1,024 OLEDs illuminated. Credit: Reproduced under a Creative Commons licence CC BY 4.0

These capabilities have continued to develop throughout 2023. In August, for instance, two reports were published in *Nature* on brain–computer interfaces that can translate neural signals into sentences at speeds close to that of normal conversation (around 150 words per minute)[1,2]. In one approach, intracortical microelectrode arrays were used to collect signals, which — with the help of a recurrent neural network and a language model — could be decoded at an average rate of 62 words per minute, and with a word error rate of 23.8% for a 125,000-word vocabulary[1]. In the other approach, an electrocorticography electrode array was used to collect signals, which — again, with the help of a recurrent neural network and a language model — could be decoded at a median rate of 78 words per minute, and with a word error rate of 25.5% for a 1,024-word vocabulary[2]. (See also our Research Highlight on the two papers.)

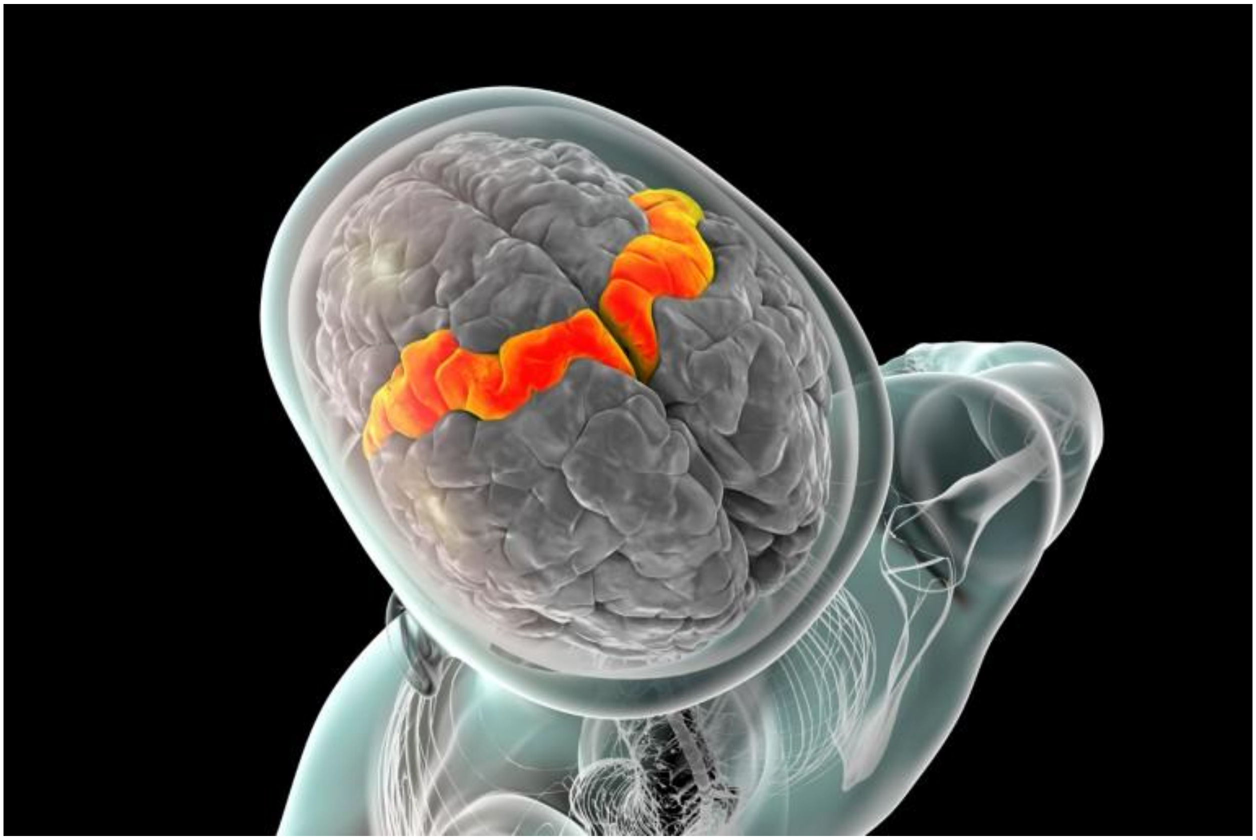
Developments in the underlying devices have also continued. In this issue of *Nature Electronics*, for example, Baibhab Chatterjee, Shreyas Sen and colleagues at Purdue University report a wireless communication technique for neural implants. In this approach — which is termed biphasic quasistatic brain communication — the implants transmit information to a wearable headphone-shaped hub, and this hub sends power and programming bits to the implant; all of which is done using fully electrical signals that should avoid transduction losses.

In a Comment article back in our February issue, Rikky Muller and colleagues at the University of California, Berkeley argued that the future of brain–computer interfaces could be entirely optical[3]. For now, and in an Article elsewhere in this issue, Malte Gather, Kenneth Shepard and colleagues report device developments focused on creating optical probes for neural stimulation. The researchers — who are based at Columbia University, the University of Cologne, the University of St Andrews, the Massachusetts Institute of Technology and Stanford University — have integrated organic light-emitting diodes (OLEDs) with silicon complementary metal–oxide–semiconductor (CMOS) control circuitry. The resulting implantable probes incorporate 1,024 OLEDs with two different colours and can be used to selectively activate individual neurons in mice. (See also the accompanying News & Views article on the work.)

Our decision to select brain–computer interfaces as our 2023 technology of the year was also based on the fact that we felt this was a critical moment to consider the potential consequences and direction of the technology. In July, the United Nations Educational, Scientific and Cultural Organization (UNESCO) released a report on neurotechnology[4], a field that brain–computer interfaces lie at the heart of. The organization also called for global regulation for the technology and proposed to develop a universal ethical framework for it[5], similar to what it has done in the past for the human genome (in 1997), human genetic data (in 2003) and artificial intelligence (in 2021)[6]. Such developments are likely to be as important for the future of brain–computer interfaces as the technological advances themselves.

World first: brain implant lets man speak with expression — and sing 13 June 2025

Device translates thought to speech in real time.



The motor cortex (orange, illustration). Electrodes implanted in this region helped to record the speech-related brain activity of a man who could not speak intelligibly. Credit: Kateryna Kon/Science Photo Library

A man with a severe speech disability is able to speak expressively and sing using a brain implant that translates his neural activity into words almost instantly. The device conveys changes of intonation when he asks questions, emphasizes the words of his choice and allows him to hum a string of notes in three pitches.

The system — known as a brain–computer interface (BCI) — used artificial intelligence (AI) to decode the participant's electrical brain activity as he attempted to speak. The device is the first to reproduce not only a person's intended words but also features of natural speech such as intonation, pitch and emphasis, which help to express meaning and emotion.

In a study, a synthetic voice that mimicked the participant's own spoke his words within 10 milliseconds of the neural activity that signalled his intention to speak. The system, described today in *Nature*[1], marks a significant improvement over earlier BCI models, which streamed speech within three seconds or produced it only after users finished miming an entire sentence.

"This is the holy grail in speech BCIs," says Christian Herff, a computational neuroscientist at Maastricht University, the Netherlands, who was not involved in the study. "This is now real, spontaneous, continuous speech."

Real-time decoder

The study participant, a 45-year-old man, lost his ability to speak clearly after developing amyotrophic lateral sclerosis, a form of motor neuron disease, which damages the nerves that control muscle movements, including those needed for speech. Although he could still make sounds and mouth words, his speech was slow and unclear.

Mind-reading devices are revealing the brain's secrets

Five years after his symptoms began, the participant underwent surgery to insert 256 silicon electrodes, each 1.5-mm long, in a brain region that controls movement. Study co-author Maitreyee Wairagkar, a neuroscientist at the University of California, Davis, and her colleagues trained deep-learning algorithms to capture the signals in his brain every 10 milliseconds. Their system decodes, in real time, the sounds the man attempts to produce rather than his intended words or the constituent phonemes — the subunits of speech that form spoken words.

"We don't always use words to communicate what we want. We have interjections. We have other expressive vocalizations that are not in the vocabulary," explains Wairagkar. "In order to do that, we have adopted this approach, which is completely unrestricted."

The team also personalized the synthetic voice to sound like the man's own, by training AI algorithms on recordings of interviews he had done before the onset of his disease.

Editorial: Advances in artificial intelligence (AI) in brain computer interface (BCI) and Industry 4.0 for human machine interaction (HMI)

Editorial on the Research Topic

Advances in artificial intelligence (AI) in brain computer interface (BCI) and Industry 4.0 for human machine interaction (HMI)

Introduction

The convergence of Artificial Intelligence (AI) and Brain-Computer Interface (BCI) has witnessed substantial advancements, particularly in the domains of emotion recognition and cognitive screening. This comprehensive editorial delves into the latest developments presented in the Research Topic "*Advances in Artificial Intelligence (AI) in Brain-Computer Interface (BCI) and Industry 4.0 for Human-Machine Interaction (HMI)*" of Front. Hum. Neurosci., Sec. Brain-Computer Interfaces. Over the past decade, noteworthy industrial progress has transpired in computerized control and monitoring applications, further catalyzing the integration of advanced technologies such as BCIs empowered by artificial intelligence. Modern BCIs are situated at the confluence of data acquisition, signal processing, artificial intelligence, and cyber-physical systems (CPS). Innovations in algorithms, particularly in cognitive computing, are fueling the continuous infusion of artificial intelligence into realms like BCIs, Industry 4.0, and Surgery 4.0 (healthcare), with the aim of establishing a robust industrial artificial intelligence ecosystem. Industry 4.0, a swiftly evolving sector, seeks to revolutionize traditional industrial methods through the deployment of digital tools such as artificial intelligence and brain-computer interfaces. Sophisticated artificial intelligence algorithms, including machine and deep learning, play a pivotal role in enhancing the performance of a BCI system, facilitating more effective management of real-life challenges. BCI-based solutions are gaining traction in bolstering industrial performance, from precise assessment to optimizing neuroergonomic systems, accurately evaluating the mental and cognitive workload of industrial operators, facilitating human-robot interactions, robot-assisted surgeries, and ensuring safety in critical conditions.

BCIs offer a methodology for manipulating computers and external mechatronic devices based on brain signals. Recently, the modern industrial sector has exhibited a growing interest in BCI-operated machines. The research and development of innovative BCIs, coupled with advancements in AI, may eventually give rise to a robust artificial intelligence-centric industry. Studies suggest that BCIs may find applications outside of laboratories and in ecologically relevant settings. However, deploying BCI systems in real-world ecological applications poses various challenges, including the need for accurate recognition of human mental states and emotions. Addressing these challenges in emotion detection, mental workload, and mental state recognition may require sophisticated approaches based on novel machine or deep learning models. In modern industry and healthcare, efforts are underway to develop hardware, software, machines, and devices with human-like intelligence.

This issue serves as a platform to share ideas, approaches, opinions, and comments on the latest research in AI and BCI, emphasizing challenges pertinent to the future deployment of intelligent AI-based BCI applications for Industry 4.0. Additionally, it aims to provide a forum for researchers to investigate the role of these AI methods in enhancing the performance of existing BCI applications. Four papers are included in this Research Topic, comprising three original research papers and one review. The contributions of these papers underscore the significance of advanced technologies like AI-augmented BCIs in modernizing and improving the quality of life and related applications.

In the first original research paper, Liang et al. introduce two primary contributions. The first is a multi-source joint-domain adaptation network proposal that addresses the challenge of cross-domain generalization in electroencephalography (EEG) emotion recognition. The second involves extensive cross-subject and cross-session transfer experiments on a publicly available emotion EEG dataset, validating the effectiveness of the proposed method. The second original research paper, by Ran et al., presents three key contributions. First, the authors propose a simplified style transfer mapping method based on the instance selection (SSTM-IS) algorithm, which enhances the accuracy and speed of cross-subject emotion recognition by selecting informative instances and simplifying the update strategy of hyperparameters in style transfer mapping. Second, the proposed algorithm is validated on both public and self-collected datasets, demonstrating higher accuracy in a shorter computing time for real-time emotion recognition applications. Third, the authors design and implement a real-time emotion recognition system that integrates EEG signal acquisition, data processing, emotion recognition, and result visualization. In the third original research paper, Li et al. introduce a novel model, STGATE, which combines a Transformer Learning Block (TLB) and a Spatial-Temporal Graph Attention (STGAT) mechanism. The TLB leverages 2D convolutional layers and a transformer encoder to extract time-frequency information, while the STGAT incorporates spatial and temporal attention mechanisms to capture connections between brain regions and temporal information. The authors' approach treats EEG signals as graph data and integrates them into graph neural networks to capture correlations between EEG channels. In their review, Sirilertmekasakul et al. focus on the application of three AI implementations: machine learning (ML) and deep learning (DL), computer vision, and automatic speech recognition (ASR). The authors discuss the advantages and limitations of digitized cognitive screening tests.

Conclusion

The Research Topic "*Advances in Artificial Intelligence (AI) in Brain-Computer Interface (BCI) and Industry 4.0 for Human-Machine Interaction (HMI)*" collectively signifies the dynamic evolution of AI-BCI applications, ranging from real-time emotion recognition to the digitization of cognitive screening tests. These advancements not only contribute to understanding human emotions through EEG signals but also pave the way for accessible and efficient cognitive assessments. The interdisciplinary nature of these studies underscores the potential of AI-BCI in shaping the future of healthcare and human-machine interaction. This Research Topic serves as an invaluable resource for readers seeking in-depth knowledge and understanding of the intricacies of these modern technologies and their significance in contemporary life.

A brain-actuated robotic arm system using non-invasive hybrid brain-computer interface and shared control strategy

Linfeng Cao [1], Guangye Li [1], Yang Xu [1], Heng Zhang [1], Xiaokang Shu [1], Dingguo Zhang [2]
Affiliations Expand

- PMID: 33862607

- DOI: 10.1088/1741-2552/abf8cb

Abstract

*Objective.*The electroencephalography (EEG)-based brain-computer interfaces (BCIs) have been used in the control of robotic arms. The performance of non-invasive BCIs may not be satisfactory due to the poor quality of EEG signals, so the shared control strategies were tried as an alternative solution. However, most of the existing shared control methods set the arbitration rules manually, which highly depended on the specific tasks and developer's experience. In this study, we proposed a novel shared control model that automatically optimized the control commands in a dynamical way based on the context in real-time control. Besides, we employed the hybrid BCI to better allocate commands with multiple functions. The system allowed non-invasive BCI users to manipulate a robotic arm moving in a three-dimensional (3D) space and complete a pick-place task of multiple objects.*Approach.*Taking the scene information obtained by computer vision as a knowledge base, a machine agent was designed to infer the user's intention and generate automatic commands. Based on the inference confidence and user's characteristic, the proposed shared control model fused the machine autonomy and human intention dynamically for robotic arm motion optimization during the online control. In addition, we introduced a hybrid BCI scheme that applied steady-state visual evoked potentials and motor imagery to the divided primary and secondary BCI interfaces to better allocate the BCI resources (e.g. decoding computing power, screen occupation) and realize the multi-dimensional control of the robotic arm.*Main results.*Eleven subjects participated in the online experiments of picking and placing five objects that scattered at different positions in a 3D workspace. The results showed that most of the subjects could control the robotic arm to complete accurate and robust picking task with an average success rate of approximately 85% under the shared control strategy, while the average success rate of placing task controlled by pure BCI was 50% approximately.*Significance.*In this paper, we proposed a novel shared controller for motion automatic optimization, together with a hybrid BCI control scheme that allocated paradigms according to the importance of commands to realize multi-dimensional and effective control of a robotic arm. Our study indicated that the shared control strategy with hybrid BCI could greatly improve the performance of the brain-actuated robotic arm system.

Keywords: Bayesian fusion; computer vision; hybrid brain–computer interface; intention inference; robotic arm; shared control.

Similar articles

- Shared Three-Dimensional Robotic Arm Control Based on Asynchronous BCI and Computer Vision.

  Zhou Y, Yu T, Gao W, Huang W, Lu Z, Huang Q, Li Y.IEEE Trans Neural Syst Rehabil Eng. 2023;31:3163-3175. doi: 10.1109/TNSRE.2023.3299350. Epub 2023 Aug 7.PMID: 37498753

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Chen X, Zhao B, Wang Y, Gao X.J Neural Eng. 2019 Apr;16(2):026012. doi: 10.1088/1741-2552/aaf594. Epub 2018 Dec 3.PMID: 30523962

- [Robotic arm control system based on augmented reality brain-computer interface and computer vision].

  Chen X, Li K.Sheng Wu Yi Xue Gong Cheng Xue Za Zhi. 2021 Jun 25;38(3):483-491. doi: 10.7507/1001-5515.202011039.PMID: 34180193 **Free PMC article.** Chinese.

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  Vilela M, Hochberg LR.Handb Clin Neurol. 2020;168:87-99. doi: 10.1016/B978-0-444-63934-9.00008-1.PMID: 32164870 Review.

- Analyzing and computing humans by means of the brain using Brain-Computer Interfaces - understanding the user - previous evidence, self-relevance and the user's self-concept as potential superordinate human factors of relevance.

Neuralite: Enabling Wireless High-Resolution Brain-Computer Interfaces

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Neuralite: Enabling Wireless High-Resolution Brain-Computer Interfaces

Pages 984 - 999

Abstract

Intracortical brain-computer interfaces (iBCIs) promise to sense brain activity at an unprecedented scale and resolution. However, unlocking this potential for practical, untethered applications remains an unsolved challenge. The major barrier is the significant wireless bandwidth required to stream high-resolution brain signals. Existing approaches rely on extensive on-device processing, which is severely constrained by the limited resources of iBCI devices, the complexity of brain signals, and the dynamic nature of neural activity. This paper introduces *Neuralite*, a wireless iBCI system that integrates high-fidelity brain signal models and effective brain sensing mechanisms within an efficient server-driven streaming framework. By thoroughly characterizing brain signal variability, Neuralite adaptively optimizes streaming under dynamic neural conditions, minimizing bandwidth consumption without imposing excessive burdens on resource-constrained iBCI devices. Experimental results demonstrate that Neuralite significantly reduces bandwidth consumption while preserving neural decoding precision across key iBCI components and representative applications.

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Brain–computer interface: trend, challenges, and threats

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Brain Informatics **volume 10**, Article number: 20 (2023) Cite this article

Abstract

Brain–computer interface (BCI), an emerging technology that facilitates communication between brain and computer, has attracted a great deal of research in recent years. Researchers provide experimental results demonstrating that BCI can restore the capabilities of physically challenged people, hence improving the quality of their lives. BCI has revolutionized and positively impacted several industries, including entertainment and gaming, automation and control, education, neuromarketing, and neuroergonomics. Notwithstanding its broad range of applications, the global trend of BCI remains lightly discussed in the literature. Understanding the trend may inform researchers and practitioners on the direction of the field, and on where they should invest their efforts more. Noting this significance, we have analyzed 25,336 metadata of BCI publications from Scopus to determine advancement of the field. The analysis shows an exponential growth of BCI publications in China from 2019 onwards, exceeding those from the United States that started to decline during the same period. Implications and reasons for this trend are discussed. Furthermore, we have extensively discussed challenges and threats limiting exploitation of BCI capabilities. A typical BCI architecture is hypothesized to address two prominent BCI threats, privacy and security, as an attempt to make the technology commercially viable to the society.

1 Introduction

Naturally, humans use their peripheral nerves and muscles to interact with the outside physical environments in carrying out the desired actions. This necessity and premise for survival comes with a cost for people with severe neurological diseases, including amyotrophic lateral sclerosis and brainstem stroke. These people cannot control external devices, thus requiring assistance from healthy people that may not always be available. Challenged by the limitation, scientists and researchers have developed a brain–computer interface (BCI) technology that can transform brain signals into human actions independent of the peripheral nerves or muscles.

BCI, also called brain–machine interface, provides direct communication between brain and external devices, such as computers and robotic limbs [1,2,3,4]. Bypassing the conventional communication channels for different tasks (e.g., vision, movement, and speech), BCI links the brain's electrical activity and the external world to augment human capabilities in interacting with the physical environment [1]. BCI provides a non-muscular communication channel and facilitates acquisition, manipulation, analysis, and translation of brain signals to control external devices or applications.

Since its conception in 1973 by Vidal [5], BCI has remained an active area of research with enormous promising opportunities [6,7,8,9,10,11,12,13,14]. Researchers have, for instance, reported remarkable achievements demonstrating that BCI can efficiently restore capabilities of people with disabilities, such as those with schizophrenia symptoms (psychosis, emotional disturbances, and cognitive dysfunction) [15,16,17,18,19,20,21]. Generally, BCI applications can be classified depending on the industry: gaming and entertainment [22,23,24], security and authentication [25], healthcare [21], education [26,27,28], advertisement and neuromarketing (commercial marketing using principles of neuroscience and cognitive science) [29,30,31,32,33], and neuroergonomics (application of neuroscience to ergonomics) [34, 35]. Given its cross-cutting nature across many aspects of developments, BCI may remain an attractive and a competitive research area over a longer period.

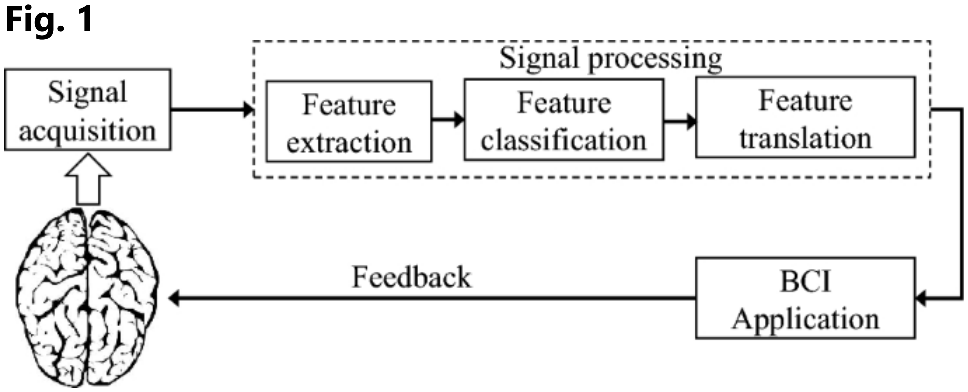
Despite the promising applications of BCI, there has been a paucity of studies on the future of this technology and its possible threats when applied to humans. The present study covers typical BCI threats, including medical safety, privacy, ethics, and security. We stimulate discussions within the scholarly community on the readiness to adopt the BCI technology and accommodate its challenges and potential threats. Furthermore, because the natural working principles of the brain are not comprehensively understood, recommendations have been provided for researchers to focus more on the short- and long-term impacts of BCI on the general welfare of humans. In addition, our study surfaces several research opportunities in the field of brain–computer interface. Researchers and practitioners may capitalize on these opportunities to develop safe BCI products that advance humanity and improve quality of our lives.

Lastly, we extracted 25,336 metadata from Scopus to analyze patterns and trend of BCI research. Results show an exponential growth of BCI publications, China being the leading country between 2019 onwards followed by the United States within the same period. This observation signals the significance of BCI to the community, but raises critical questions on the potential BCI threats to humans.

2 Fundamental components of BCI system

The BCI system comprises three fundamental components that serve specific roles: signal acquisition, signal processing, and application (Fig. 1). These components are interconnected and work together to allow the flow of brain signals to the target BCI application (e.g., robotic arm). In particular situations, control signals from the BCI application may be sent back to the brain to stimulate some common human functionalities, such as vision and hearing.

Fig. 1



Main components of the brain–computer interface (BCI) system

2.1 Signal acquisition

This component comprises an electronic device with electrodes for acquiring brain signals (oscillating electrical voltages caused by biological activities of the brain) that define its neurophysiological states. Signal acquisition involves capturing of electrophysiological signals that represent specific activities of the brain (e.g., movement, speech, hearing, and vision). Most BCI systems, including the commercial ones, deal with the following electrophysiological signals: electroencephalography, brain's electrical activity measured with electrodes placed on the scalp [36, 37]; electrocorticography [38,39,40], electroencephalographic signals measured directly with electrodes placed on the surgically exposed cerebral cortex; local field potential [41], electric potential measured around the neuron's extracellular space; and neuronal action potential [42, 43], rapid and temporary change in the neuron's membrane potential. Before being presented to the next BCI component, the captured brain signals undergo filtering, amplification, and digitization [21]. The overall performance of the BCI system depends heavily on the quality (signal-to-noise ratio) of the acquired brain signals.
Depending on the signal acquisition method, BCI can broadly be categorized into two types: invasive (electrodes implanted under the scalp to record signals directly from the brain) and non-invasive (electrodes implanted on the scalp). Invasive BCI provides a more accurate reading of brain signals, but requires surgery; non-invasive BCI does not require surgery, but suffers from weak brain signals (poor signal-to-noise ratio) that require expensive amplification hardware and sophisticated signal processing techniques.

2.2 Signal processing

2.2.1 Feature extraction

In this stage, the BCI system extracts critical electrophysiological features from the acquired signals to define brain activities, and hence encoding of the user's intent [21]. Similar to the previous stage, feature extraction should be executed accurately, ensuring that the features reflect high correlation with the user's intent to enhance the effectiveness and performance of the BCI system. Typical BCI systems employ time-domain or frequency-domain features [44,45,46,47,48,49,50,51] that take different characteristics: amplitude or latency of event-evoked potentials (e.g., P300), frequency power spectra (e.g., sensorimotor rhythms), or neuronal firing rates [21]. Therefore, before designing the BCI system, the domain transform and characteristics of features should be established. Also, confounding artifacts contained in the features that can negatively impact the subsequent stages of the BCI system should be eliminated.

2.2.2 Feature classification

The extracted features represent brain activities intended for desired actions. The classification process helps to recognize patterns of the features corresponding to these actions. For example, we can recognize features representing an instruction for moving a robotic arm. This component is usually implemented using machine learning and classification methods [52,53,54].

2.2.3 Feature translation

In this signal processing stage, the classified features are translated and transformed into actual commands to operate an external device (BCI application). Examples of the outputs given after feature extraction include commands for cursor movement on the computer screen, volume control on the audio device, or text writing. One important attribute of an algorithm for feature translation is adaptability [55, 56]: ability of the translation algorithm to adaptively track changes of the features and generate an appropriate output.

2.2.4 BCI application

Feature translation generates commands that can control external devices (BCI applications): cursor [57,58,59,60] for letter and text selection on the computer screen [44, 45, 61], wheelchair [62, 63], and robotic arm [64, 65]. For BCI restoration problems, the control signals from the BCI application may be transmitted to the brain or other body organs.

3 Applications and future of brain–computer interface

In this contemporary society, scientists and engineers have been striving to apply advanced technologies in improving quality of human life [144]. Of the available technologies, BCI has gained considerable attention in medicine for its ability to restore emotional and physical strength of people with missing or damaged body parts. The BCI technology allows physically challenged people to control machines using their thoughts. This advantage gives such people a revealing experience to interact with the external environment and accomplish different activities without dependence from healthy people.

The BCI field is moving fast with a number of promising outcomes that can significantly improve human lives. Researchers require regular updates to address challenges hindering further advancement of the BCI technology.

More importantly, given the multidisciplinary nature of brain–computer interface, scientists and engineers should work together to develop new and advanced BCI applications. Recently, the technology has found numerous industrial merits in a range of fields, including mining and education. Combined with fourth industrial revolution, researchers have demonstrated that BCI may accelerate the evolution of robots and neurophysiological discoveries [98, 99, 150]. Other applications of the BCI technology include decoding of thoughts, extension of human memory, telepathy communication, automation and control, intelligence sharing, brain energy harvesting, and optimized (targeted) treatment of damaged body parts.

3.1 Decoding of thoughts

The brain, being a complex human organ, generates and controls our thoughts and other physiological parameters: emotion, touch, breathing, hearing, motor skills, hunger, temperature, memory, and anger. Some parameters, such as anger and changes of breathing rate, may be manifested outside through physical expressions or actions. However, most parameters can only be manifested internally (inside the brain) without the knowledge of other people. The current technologies cannot, for example, predict with an acceptable accuracy the thoughts of an individual. While this internalization of human thoughts—represented as brain signals in a BCI system—may have advantages, some situations may demand us to accurately decode such thoughts. In criminology, for example, policemen would like to understand whether a suspected criminal speaks the truth. Recently, researchers have been investigating how BCI can improve the performance of polygraphs that measure the degree of truth in the arguments from a person (e.g., criminal) [2, 66,67,68]. Perhaps the promising results in this direction may be achieved by combining BCI and artificial intelligence techniques.

Can the BCI application facilitate translation of human thoughts accurately into a readable text? How can the accuracy of the translated text be measured? Can our imaginations be mapped into real objects, such as pictures and texts printed on a piece of paper? Can events in the dreams be accurately decoded by the BCI system? Can we extend the applications of BCI to develop wearable devices that monitor thoughts or sleeping patterns [69,70,71]? Can we extract a will directly from the thoughts of a dying person? Can we print physical documents by sending command signals and data from the brain, through the BCI system, to the printer? These interesting questions need further scientific inquiry.

This study envisages that future developments of brain–computer interface will include sophisticated products that can directly map human thoughts into physical objects. We believe that, with the growing trend of BCI, people (especially those with physical disabilities) will drive and control machines (e.g., drones, vehicles, and airplanes) remotely using their thoughts [72]. The advanced developments of BCI may surface critical security and privacy issues, and hence the technology needs to be well-regulated through universal standards [73, 74].

3.2 Extension of human memory

Stephen Hawking theorized the possibility of uploading the human mind into a computer [75]. This philosophical argument, despite its focus on the human mind (consciousness), raises a critical question on whether BCI may be a promising future technology to realize the concept. Specifically, how do we extract memory signals from the brain and decode them for storage into a computer (memory extension)? If successfully implemented, humans will be able to upload their memories into the computer for quicker processing, retrieval, and transmission of information, or for control of external devices.

In the recent developments of brain–computer interface, scientists have generated outstanding results showing that brain signals can be harvested and converted into data reflecting human intended actions [76, 77]. Future studies on BCI may advance these results to investigate how BCI may be used to harvest behaviors and traits from humans for research and scientific study purposes. But this inquiry should be pursued under strict ethical guidelines, a component that has not been well-captured by the BCI researchers.

The sensitive information from the brain, if accurately harvested, may be stored into and retrieved from the external physical memory. Imagining the future of BCI, we envisage that scientists and practitioners may develop portable flash drives (or other variations of physical memories) that may be plugged into the BCI device to extract information from (or introduce information into) the brain. One may question a possible area that may apply the proposed idea. Imagine a counselling psychologist armed with accurate information (obtained through a BCI device) on the behaviors and traits of a person. Evidently, this expert may be expected to provide a well-informed advice and conclusion, giving an appreciable impact to a person being counseled. Achieving this scientific endeavor requires an intensive multidisciplinary research.

3.3 Telepathy communication

Rao et al. demonstrated that BCI, in conjunction with the computer–brain interface (CBI) [78, 79], may allow individuals to communicate without physical interaction or sensory channels [80], a process called telepathy communication. Integration of BCI and CBI forms brain–brain interface that is still in early stages of research and development [81,82,83,84]. In future, we expect more work in this direction to expand the applications of telepathy communications in various science and engineering fields. As an example, researchers may investigate how human brains can be interconnected over the Internet of Things (IoT) network to enhance exchange of information and experiences among individuals. While few studies demonstrate the possibility of interfacing BCI and IoT [85,86,87,88,89,90], linking brains and IoT over the network remains an open-ended challenge that deserves attention of researchers. Furthermore, integration of BCI-IoT and other communication modalities, such as mind–mind interface and mind–machine interface, need further investigation to explore additional capabilities and functionalities on human–machine–human communications. All these technological advancements should, however, be made in parallel with adherence to ethical principles of humanity.

3.4 Automation and control

The promising developments in BCI suggests that the technology may be useful in automation and control industries [91,92,93,94,95,96]. Currently, BCI has received a significant deal of attention in home automation and control [97]. In this scenario, the technology assists physically challenged people to automate their daily home activities, making it possible for such people live independently. As the technology advances, we expect positive impacts of BCI in the industrial manufacturing processes. In essence, researchers may attempt to investigate the role of BCI in the fourth industrial revolution [98, 99]. For instance, the BCI application may be connected over a secure wireless network to automate processes in the manufacturing industry. Considering sophistication and rapid development in the sensor technology, BCI may be applied in non-contact control and automation industrial systems. This research direction requires intensive investigation to overcome inherent limitations of the BCI technology and ensure seamless interaction with intelligent sensors.

3.5 Intelligence sharing

Can the BCI, in conjunction with the CBI, help to reprogram the brain, hence allowing sharing of intelligence between individuals? Although it may be imagined as a fiction, the fundamental principles of the technology suggest that brains may be reprogrammed artificially. Achieving this milestone, however, requires solid understanding on the nature and functioning of our brains—a stage that has not been reached by the current state of knowledge.

3.6 Brain energy harvesting

The human brain takes only 2% of the body's mass and, for an average adult in a normal state, consumes 20% of the whole body energy budget to execute its activities [100]. This proportion of energy consumption makes it the third most energy-hungry body organ [101]. We hypothesize that the BCI technology may be combined with other advanced technologies to harvest portion of this enormous amount of energy for powering low-energy external devices. Studies are needed to realize the idea, investigating how much energy can a typical BCI system harvest from the brain.

3.7 Localized brain–computer interface

In BCI, the process of brain signals acquisition is not discriminatory. Virtually, the electrodes acquire all the available signals within the vicinity of its location (under or on the scalp). Consequently, a huge amount of signals and noise are collected for a single intended task (e.g., movement of the artificial leg), making the processing of such signals rather difficult. We can, however, tap the specific signals intended to control a targeted body part by localizing the BCI system. For example, considering a person with speech problems, the BCI system may be placed in an area that directly receives speech control signals from the brain. This advancement may improve the performance of the BCI system and reduce its size.

4 Trend of BCI research

In analyzing the trend of BCI research, we, on 26 August 2022, extracted metadata of 25,336 publications from Scopus.[Footnote1] The search string used was "brain computer interface" that, as per the Scopus research rules, includes other similar string variations: brain-machine interface; Brain Computer Interface; Brain-Computer Interfaces; Brain-computer Interface; Brain Machine

Interface; Brain-computer Interface (BCI); Brain Computer Interfaces (BCIs); Brain-computer Interfaces; Brain-machine Interface; Brain Computer Interface (BCI); and Brain-Computer Interface. Next, some publications incorrectly classified as related to BCI were omitted. In our extended dataset,[Footnote2] all the extracted metadata were organized into continents, regions, and countries[Footnote3] for analysis. The VOSviewer[Footnote4] served a purpose of organizing and analyzing the bibliographic networks of the investigated BCI publications.

Our analysis reveals that the BCI field has constantly been evolving over the years, with publications ranging from theories and fundamental principals to practical applications. Studies demonstrate that BCI may significantly improve the quality of life for physically challenged people [77, 102]. Given its broad applications in many fields, researchers have invested more time to address practical challenges in BCI systems. Analyzing previous BCI studies, we have observed an exponential growth of the BCI field to date (Fig. 2a). Within a 5-year interval (between 2016 and 2021), for instance, the number of BCI publications increased steadily by approximately 1.5 times. This trend suggests an increasing demand of BCI to the scientific and general community, an indicator calling for a need to conduct advanced BCI research.

Figure 2b, c shows that Asia, specifically the Eastern region, has generated more BCI publications over the years. China demonstrates a steadily growing trend of the publications on brain–computer interface, topping other countries from 2019 onwards (Fig. 2d). This interesting trend may be caused by an increased research funding and support by the China government to undertake advanced research [103, 104]. In the *Made in China 2025* [105] strategy, China has established ambitious plans to become a leading superpower by 2049. The strategy, coupled with a higher population size and an increased number of academic and research institutions, could be a driving factor for China to achieve a remarkable achievement in BCI research.

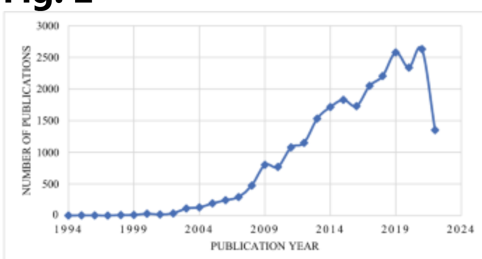
The United States, however, remains a leading country in terms of the overall number of BCI publications (Fig. 3). Given the higher technological and economical muscle of the United States, this observation would be expected. Perhaps an intriguing question for future inquiry would be on why the number of BCI publications for this country started to decline from 2019 onwards. One way that the United States may improve the trend of BCI publications is to promote co-authorship with Chinese universities and research institutions (Fig. 4).

Figures 4 and 5 show five countries with higher volume of BCI publications: United States, China, Germany, Japan, and India. Authors from these countries collaborate to foster the development of BCI research. Given the value of BCI technology in human socio-economic development, we recommend the efforts to be adapted in other countries, specifically those in the global south. Institutions from low-income economies, as defined by the World Bank, should be empowered to conduct advanced BCI research with a focus on addressing the third sustainable development goal, "good health and well-being".

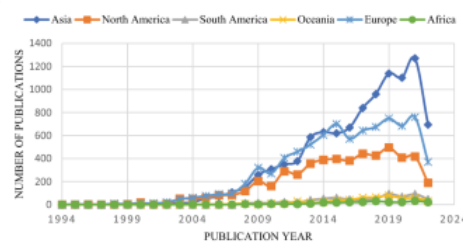
Africa lags behind in BCI research (Fig. 2b), generating only 0.95% of all the BCI publications globally. This small proportion may be attributed to insufficient funding for supporting and advancing BCI research (Fig. 5). Funding organizations may need to observe Africa as a potential continent for BCI research. With an estimated population of 1.426 billion people by 2022[Footnote5]—approximately three times that of Europe[Footnote6]—and with more than 2,000 universities and institutions,[Footnote7] Africa can significantly contribute in BCI research. The methods and results from studies on BCI can improve the quality of life for millions of Africans. According to statistics from the United Nations, more than 80 million people in Africa are disabled, including those with severe mental health conditions and physical impairments that may be beneficiaries from BCI results. Therefore, supported by funding organizations and governments, African researchers and innovators should exploit the capabilities of BCI technology to address the existing practical challenges in Africa. Another possible reason causing low number of BCI publications in Africa could be the inadequate level of technology to undertake BCI research that requires advanced equipment and complex infrastructure. Collaboration with the developed world, especially China and United States, in undertaking BCI research may be an effective and a feasible strategy for Africa to achieve the desirable output in BCI research.

Generally, the BCI research opens up several interesting problems that demand attention within the scholarly community. Our study discovered that countries address the BCI problem differently depending upon their local contexts. For example, while BCI studies from developed countries focus on the industrial applications of the technology, those from developing countries mostly deal with how the technology contributes in improving life quality of humans (e.g., increasing life expectancy). United States and China, which have shown significant advances in BCI research, provide promising prospects of BCI in the fourth industrial revolution [98, 99] with, however, a serious concern of the potential threats that the technology may impose if misused. These countries have, in fact, practically applied BCI in the real-world to advance humanity. Critically analyzing metadata of the 25,336 reviewed articles, we observed sophisticated BCI research laboratories[Footnote8], [Footnote9], [Footnote10] that generates results with positive practical impacts. Developing countries, such as those in Africa, lack a support infrastructure for BCI research. Therefore, it may be relatively challenging in these countries to comprehensively explore competitive advantages of the BCI technology.

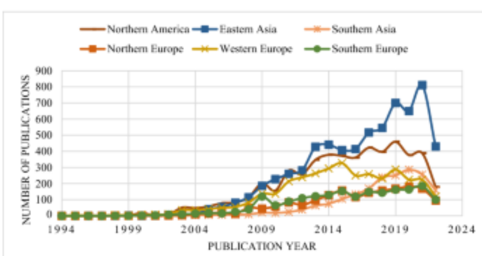
Fig. 2



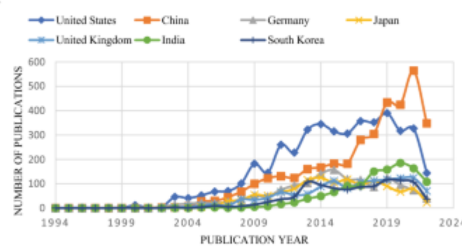
(a) Overall publication trend



(b) Continental publication trend



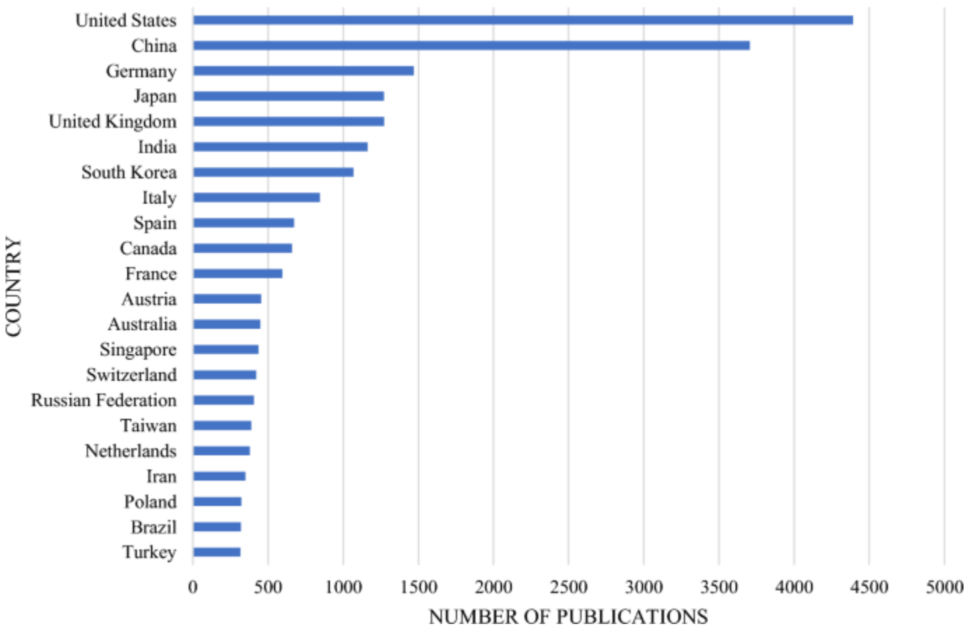
(c) Regional publication trend



(d) Publication trend per top countries

Evolution of brain–computer interface publications. (Data collected from Scopus on 26 August 2022.)

Fig. 3



Number of publications on brain–computer interface per country. (Data collected from Scopus on 26 August 2022.)

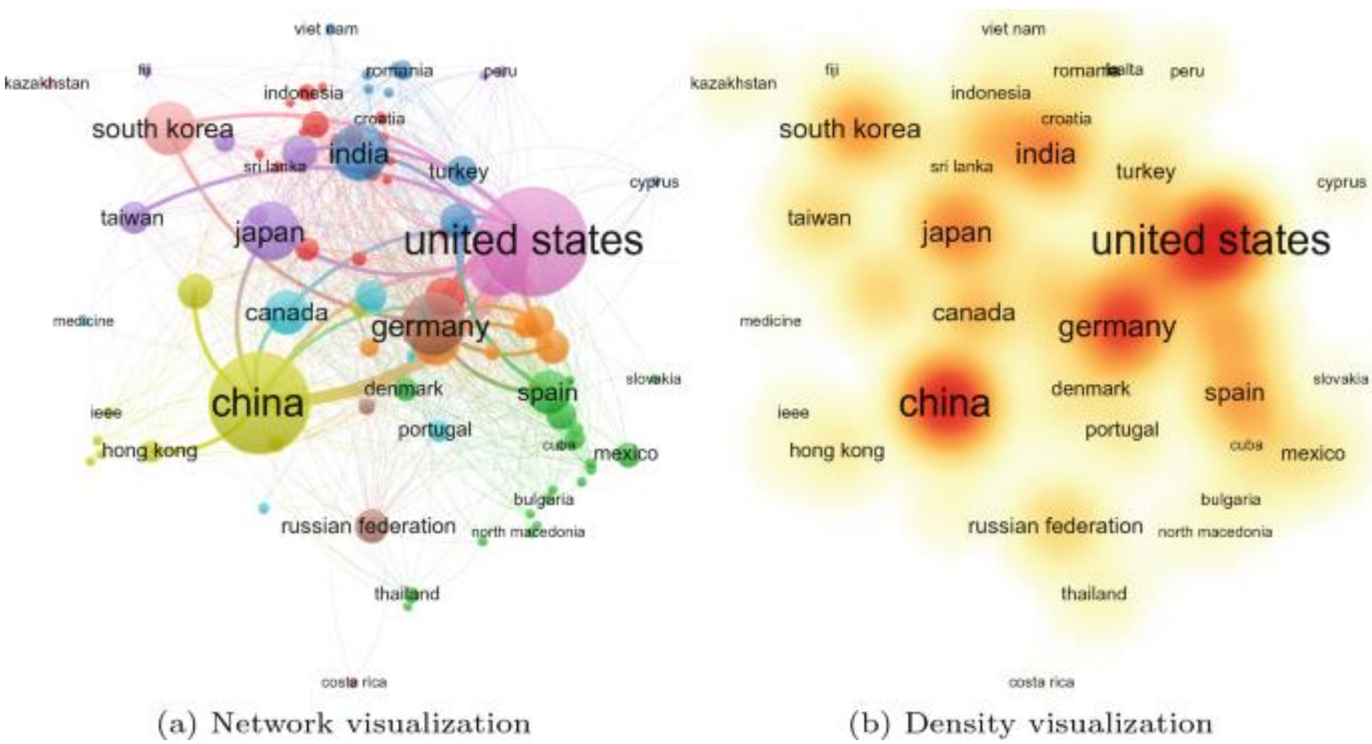
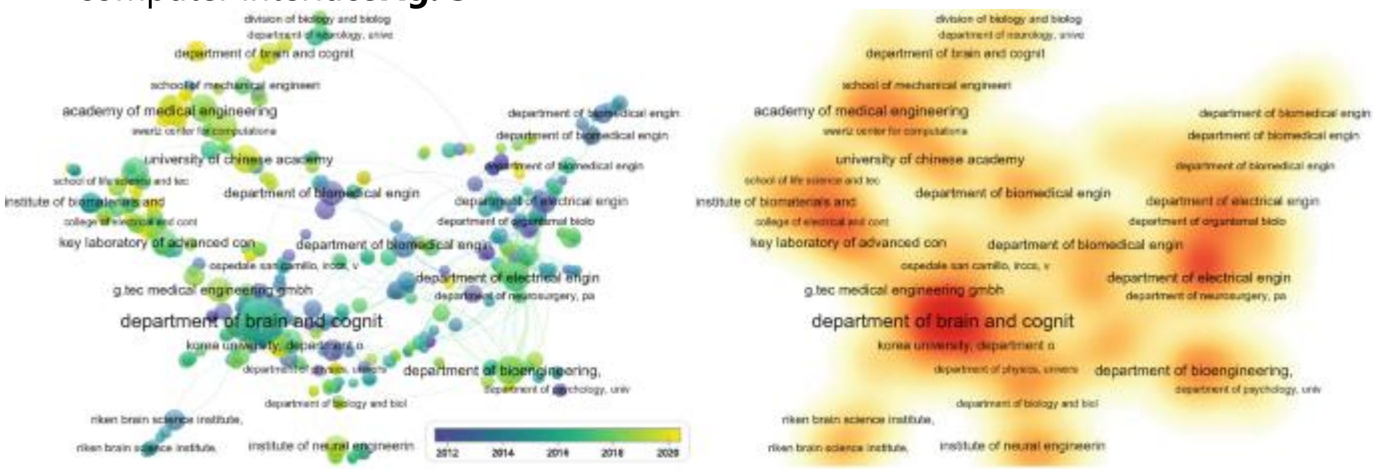


Fig. 4

Collaboration network among countries based on publications in brain–computer interface**Fig. 5**



(a) Network visualization (b) Density visualization

Collaboration network of organizations supporting research on brain–computer interface. (Data collected from Scopus on 26 August 2022.)

5

Challenges and potential threats of brain–computer interface

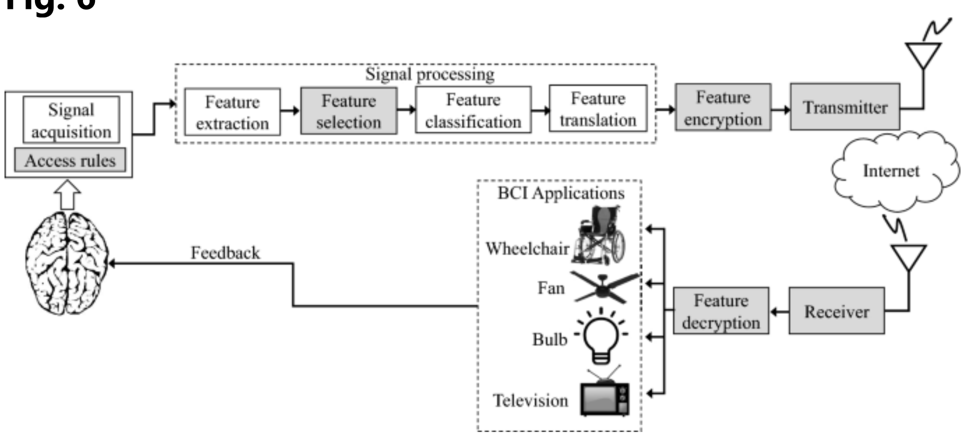
The BCI technology, despite its broad applications, poses threats to humans that need to be addressed. As we strive to make the technology friendly and useful, researchers should develop BCI applications that resonate with the standard principles of humanity. In essence, a better technology should enhance our lives while considering human factors, including convenience, ease-of-use, privacy, security, and safety [106,107,108]. Before adopting the BCI technology for use by the community, researchers and practitioners are obliged to engage users and ensure that the technology has passed predefined quality standards.

5.1 Privacy

In the article by Luigi Bianchi,[Footnote11] the author informs lack of specific standards that govern development of BCI applications. This challenge, as noted by Takabi et al. [109], has resulted in BCI applications with unrestricted access to brain signals. The authors' results show that these applications may, as a consequence, extract sensitive information from users without their knowledge. As an attempt to address privacy concerns, standards should be established to define acquisition methods, access control protocols, and encryption techniques, among other attributes. Klein and Ojemann suggest that the privacy concerns and other threats may be addressed through adherence to best practices when developing BCI systems and incorporating such concerns into the informed consent protocols [110].

In this work, we have hypothesized a functional model of the BCI system that accounts for privacy and security issues (Fig. 6). This model, which extends the work of Mason and Birch [111], contains components that may prevent unauthorized access of sensitive personal information without the user's awareness. Recalling Fig. 6, before acquisition of brain signals, the BCI system engages the user with predefined access rules to ensure high integrity and privacy of information. In the signal processing block, a component "Feature selection" retains quality features intended for classification and translation. Next, for BCI applications linked with networked devices over the Internet, we propose encryption of the translated features (control commands) before transmission. This process prevents attackers from altering the control commands, a consequence that may threaten the user's safety. Other advanced technologies, including blockchain [112], may also be used to prevent unauthorized access of the control commands by the attackers. Lastly, the model contains a feature decryption block that decodes the encrypted control commands for use by the BCI applications.

Fig. 6



Brain–computer interface (BCI) system with encryption and decryption components for enhancing privacy

5.2 Security

The field of BCI has made a significant progress in the development of medical applications and products to improve the patients' quality of life (e.g., restoration of damaged sight or hearing) [113]. However, given the increasing demand for BCI-internet communications, security concerns have emerged [114,115,116]. The advancement of brain–computer interface creates opportunities for cyber attackers to intervene in the normal operations of the BCI application [117]. The attackers may alter commands derived from the feature translation component (Fig. 1) and cause adverse effects to the target subject. Therefore, researchers should investigate security threats and vulnerable BCI components that can be easily attacked, then find robust solutions.

5.3 Safety

Safety concerns can generally be observed in invasive BCI types. Because of being implanted into the brain tissue, invasive BCI can damage nerve cells and blood vessels, hence increasing the risk of infection.[Footnote12] Additionally, the natural defence system of the body may reject the implant, treating it as a foreign entity (biocompatibility concern). Another safety concern of invasive BCI is the possible formation of scar tissue after surgery, a consequence that may gradually degrade the quality of the acquired brain signals. Addressing this challenge requires a comprehensive knowledge on how the human body works and interacts with foreign matters. The knowledge should be used by BCI scientists and engineers to develop safe and quality BCI applications. This knowledge should, in addition, equip neurosurgeons with more accurate information on specific brain regions to implant BCI electrodes.

5.4 Ethical, legal, and social concerns

The BCI research raises a number of ethical, legal, and social concerns on privacy, security, safety, accountability, and accessibility [118]. The society would prefer the BCI technology that addresses their questions. For example, should people be concerned by privacy and security of the BCI applications? Does the technology guarantee safety? Does the society get equal access to the technology? In a situation of negative technological or technical impacts, who will be accountable and what are the legal implications? These questions require careful considerations and further research before administering this technology to the society.

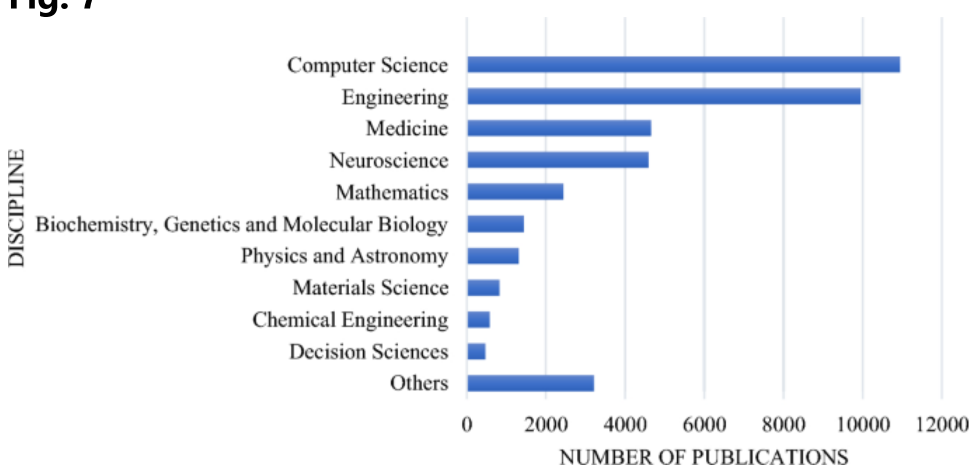
5.5 Convenience and flexibility

Most BCI applications require calibration data to reverse undesirable changes caused by neural plasticity or micromovements of the electrode arrays [77]. This necessity calls for frequent decoder retraining, an inconvenient and time-consuming process that unnecessarily burdens the user. Willett et al. [77] highlight the challenge in their seminal work on brain-to-text communication through handwriting. Despite the promising performance achieved by the authors' model, daily decoder retraining was unavoidable. Future studies may investigate more effective techniques for decoder training without physically engaging the user. In essence, the BCI application should operate adaptively with respect to the stochastic changes in the neural activities of the brain. Automatic self-calibration approaches may be employed to update operation of the BCI application accordingly, hence promoting convenience and flexibility.

5.6 Multidisciplinarity

The BCI field involves multiple disciplines that should be linked to establish advanced principles and more effective BCI applications. In our analysis from Scopus, we observed that some important disciplines have not been adequately engaged in the BCI research (Fig. 7). For example, only 1% of the BCI-related publications originate from psychology, a discipline dealing with study of human mind and behavior. Psychology, when combined with other disciplines, may provide a milestone to develop even better and practical BCI systems that can revolutionize humanity positively. Establishing research teams from varied disciplines may require strategic plans and funding, but such multidisciplinary teams are important to fully harness the BCI promising capabilities.

Fig. 7



Number of brain–computer interface publications per discipline

5.7 Big data

The brain stores an enormous amount of information serving different human tasks. In addition, this central body organ generates a vast amount of electrical signals that control, monitor, and regulate human activities. Evidently, BCI raises a big data problem that needs sophisticated techniques to address. Unfortunately, because of insufficient knowledge on the brain working principles, BCI researchers may not have collected and utilized all the brain data and signals. Researchers need to understand key neurological features, including neuroplasticity that flexibly allows re-organization of neurons in learning or injury recovery [119]. In non-invasive BCI, researchers should determine resolution of the electrode network on the scalp for optimal collection of brain signals. Similarly, invasive BCI requires electrodes optimally positioned under the scalp.

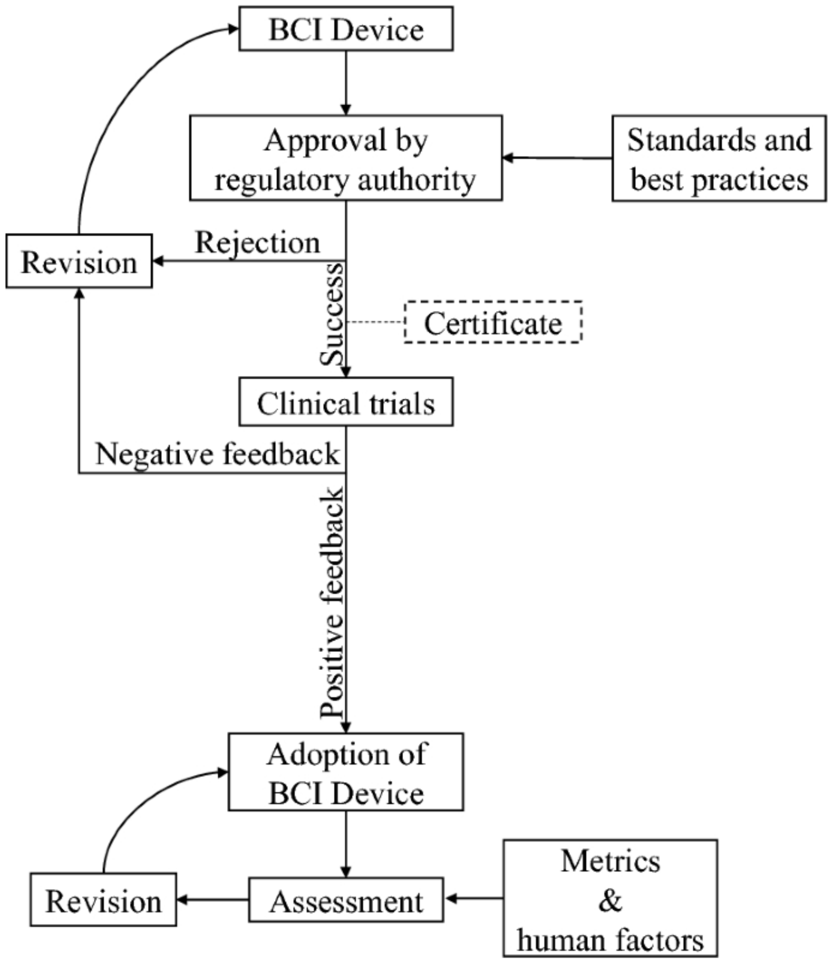
5.8 Availability of participants for clinical trials

BCI, being an emerging and a relatively new technology, offers promising opportunities to several disadvantaged groups. Most people, especially those from developing countries, are unaware of the merits and demerits of the technology as evidenced from a smaller number of BCI publications collected from such countries (Fig. 2b). Therefore, engaging an acceptable number of people in testing the BCI medical products may be relatively challenging. Following ethical guidelines, people should express their consent to accept, adopt and use the BCI technology. In this work, we noted limited attempts to start clinical trials of BCI devices. On 28 July 2021, Synchron became the first BCI company to receive approval from the United States Food and Drug Administration for conducting (investigational device exemption) clinical trial of a permanently implanted device, Stentrode[Footnote13] [120]. Other initiatives for clinical trials of BCI products can be observed at the University of Pittsburgh[Footnote14] (sensorimotor microelectrode brain–machine interface) and the United States National Library of Medicine[Footnote15] (e.g., BrainGate2[Footnote16] [121] and BCI device from the University of Grenoble [122, 123]). Morinière et al. introduced a dual-arm exoskeleton for evaluating BCI products in clinical trials [124]. Despite these initiatives, including those from startups and companies, the number of participants involved in the clinical trials seems insufficient for generalization across the global community. We recommend diversification and increased number of participants for clinical trials from different countries, considering cultural and traditional values. Furthermore, studies may be needed to understand acceptance of the BCI technology to the society. In this work, we located a few studies that attempt to determine human behavioral factors towards acceptance of BCI devices [125, 126]. Our recommendation is that, despite the advantages that this technology provides, the development of such devices should consider the factors.

5.9 Standardization and approval by regulatory authorities

We have witnessed an increasing number of initiatives to develop BCI devices with advanced features[Footnote17], [Footnote18] [119, 127]. Startups and companies have been developing commercial BCI devices for use by the society. Our study found ongoing efforts for developing universal standards governing neurotechnologies for BCI devices.[Footnote19] These efforts should be accelerated to match with the increased commercial demands of the BCI devices. Currently, people may raise concerns on the practical suitability of the BCI technology with respect to general quality and ethical guidelines. In addition, guided by the best practices for developing and administering medical devices, information on clinical trials for the commercially viable BCI devices remains unclear. We could locate from public medical databases only a few clinical trials with limited number of participants. Considering the delicacy and possible long-term impact of BCI technology to humans, approval procedures from respective regulatory authorities seem necessary before commercialization of BCI devices (Fig. 8). This necessity, however, introduces another challenge that some developing countries may be inadequately equipped with advanced facilities and expertise to test and approve BCI devices.

Fig. 8



Proposed procedures for practical administration of brain–computer interface devices

5.10 Battery lifetime

Implantable BCIs require materials that can sustainably operate over longer periods of time, preferably decades, without deterioration [119, 128,129,130]. The warm aqueous nature of our brains, however, affects the power-retention capability of the implants. Water (cerebrospinal fluid), being a powerful solvent, gradually corrodes the insulating materials of the electrodes. Over time, short circuits may be created, increasing crosstalks between electrodes. This challenge reduces battery lifetime and limits the amount of signals collected by electrodes. Researchers need to study different insulating materials to understand how they interact with the brain relative to the BCIs battery lifetime. In addition, computationally efficient algorithms should be developed to ensure optimum utilization of battery power. Even more importantly, alternative energy sources (e.g., micromovements inside the brain) for powering implantable BCIs should be investigated.

5.11 Affordability and portability

Commercially available BCI devices can hardly be afforded by the general public because of their prohibitively high costs [131,132,133,134], perhaps due to their sophistication and construction materials. Also, the current BCI systems are complex and bulkier, making them suitable only in laboratory and industrial settings. Researchers should develop cost-effective and portable BCI systems for ordinary people, potential users of the technology. This solution will be more useful for people in developing countries.

6 Conclusion

In this study, insights have been given on the perspective of the brain–computer interface. Inspired by its benefits, the society needs to seize the available opportunities that the technology advocates. To maximize the benefits and increase usability of the BCI technology across the society, researchers and scientists should address the potential threats of the technology highlighted in our work. We can fully exploit the benefits and capabilities of the technology through multidisciplinary efforts to address limitations of the current BCI systems.

In view of the BCI components, five possible research directions can be taken: cognitive psychology, medicine, biomedical electronics, signal processing, and engineering. These directions necessitate multidisciplinary research where researchers work closely to address the BCI sub-challenges. Psychologists and medical doctors should provide the fundamental working principle of the brain; scientists should develop effective signal acquisition devices along with algorithms for processing brain signals (extraction, classification, and translation of features); and engineers should develop physical BCI applications and evaluate their performance based on the predefined standards.

We assert that the BCI field has many research opportunities that have not been explored. From all the reviewed literature, an observation was made that the existing challenges in brain–computer interface have received little attention. The research community is recommended to address the challenges and extend the capabilities that BCI offers, including development of BCI-Internet and BCI-CBI communication devices. In addition, researchers may explore how mind–body intervention methods, such as hypnotherapy, can improve BCI systems [135,136,137]. In whatever situation of development, however, the primary goal of BCI should be to advance humanity by improving the quality of people's lives.

Notwithstanding the promising capabilities and merits of BCI, a significant number of challenges and threats have not been adequately addressed. In addition, the current number of participants in the clinical trials seems low and undiversified, making generalization of the results questionable. Furthermore, global standards should be established to develop safe and quality BCI products with threats significantly minimized. In this regard, although BCI unlocks our future for well-being, this emerging technology requires intensive research, including many clinical trials, for practical applications. With the existing challenges and threats unsatisfactorily addressed, the technology may not be ready for consumption by the society. This conclusion is partly supported by a few other studies [138,139,140,141,142,143,144] and scholarly communications.[Footnote20]

Our future work will be focused on addressing some threats originating from the middle BCI component, signal processing. Using the publicly available dataset[Footnote21], [Footnote22] [145,146,147,148,149], we will develop computationally inexpensive algorithms for encrypting, extracting, classifying, and translating features from the brain. Measures of accuracy will be established to ensure that the developed algorithms give computer commands that accurately emulate users' actions. Note that there has been no universally acceptable standards for measuring the accuracy of BCI applications, and we will attempt to narrow this research gap.

The functional differentiation of brain–computer interfaces (BCIs) and its ethical implications

- Xiao-yu Sun &
- Bin Ye

Abstract

The growth of research and applications of brain–computer interfaces (BCIs) has spurred extensive discussion about their ethical implications. However, most existing research has primarily examined ethical issues related to BCIs from a general perspective, with little attention paid to the specific functions of the technology. This has resulted in a mismatch between governance and ethical issues, due to the lack of differentiation between write-in and read-out BCIs. By providing detailed descriptions of the functions and technical approaches of both write-in and read-out BCIs, we argue that ethical governance of BCIs should follow the principle of precise governance and develop refined governance strategies for different functional types of BCIs.

Introduction

Since its inception, brain–computer interface (BCI) technology has sparked significant interest and debate regarding its ethical implications. Concerns have been raised that the use of BCI technology may infringe upon users' rights to safety, privacy, and informed consent. For instance, Tamara Bonaci has asserted that despite claims of performance, reliability, and security guarantees by current engineering practices for BCI technologies, they still pose significant risks to physical safety and privacy, due to the lack of standards and guarantees (Bonaci et al., 2014). Eran Klein has similarly warned that BCI may compromise the privacy and security of patients' brain information (Klein et al., 2015), while other studies have shown through a BCI game (Flappy Whale) that BCI technology can be used to collect users' private and sensitive data, leading to potential violations of privacy and a hindrance to users' right to informed consent (Ienca et al., 2018).

In addition to the risks associated with BCI technology, many studies have shown that it raises significant ethical issues regarding personal identity, responsibility, and social justice/fairness. For example, a qualitative study conducted by Erika Versalovic et al. found that BCI devices can impact users' self-conceptions and how others perceive them (Versalovic et al., 2020). Similarly, Schmid et al. discovered through an online survey that there is widespread support among the public for holding BCI users accountable for the consequences of their behavior and that users cannot avoid taking responsibility (Schmid et al., 2021). Sasha Burwell et al. have identified personal identity, responsibility, and fairness as the most important ethical issues arising from BCI technology, but note a lack of concrete proposals to address them (Burwell et al., 2017). Emily Postan has conducted research on the influence of neurotechnologies like BCIs on identity and has presented a normative framework regarding identity to assist in crafting narratives that constitute identity (Postan, 2016; 2020). The impact of BCI technology on patient autonomy and agency has been a key concern for many scholars. For instance, Michael Abbott and Steven Peck suggest that patients with total locked-in syndrome, who entirely rely on BCI-related functions and lose voluntary muscle control, may face ethical issues related to the technology replacing patients' own decision-making abilities (Abbott and Peck, 2017). Likewise, Frederic Gilbert et al. have highlighted concerns regarding the potential for BCIs to alter patients' agency (Gilbert et al., 2019).

However, the above-mentioned studies have not considered the way the technology is implemented, i.e., most of them ignore the fact that different functional types of BCI technologies rely on different technological approaches. Because of the differences in their approaches, it results in different ethical consequences, i.e., the ethical issues and implications arising from write-in and read-out BCIs are different (Mazurek and Schieber, 2021), and thus a universal or general strategy of governance may not be applicable to all types of BCIs and may even hinder the further development of BCIs.

This paper provides in the second section an overview of two functional types of BCIs: read-out BCIs and write-in BCIs, outlining their current state of development, with a specific focus on highlighting the differences between the two technologies. In the third section, we investigate the ethical challenges associated with both read-out and write-in BCI technologies. To address these challenges, we argue that a precise governance approach is required, and we further propose the need to refine the current governance model. Based on these established governance measures, the paper concludes by offering recommendations and countermeasures for the technical and ethical issues faced by the two types of BCIs.

Write-in and read-out BCIs

BCI is defined uniformly in current studies. Stephen Scott regards BCI as a mechanism that deciphers our thoughts into action, providing brain-damaged patients with an opportunity for direct communication with the external environment (Scott, 2006). John Donoghue believes that BCI permits interaction between external devices and the brain by decoding appropriate neural signal characteristics, which controls external devices (Donoghue, 2008). A standard BCI framework consists of an acquisition system, a signal processing system, and an effector. The acquisition system aims to obtain and record brain signals through electrode arrays. The signal processing system extracts features of brain signals and translates these feature signals into various intentions - for instance, speech, movement, and cognition. The effector is responsible for converting and implementing various intentional actions of the users (Bonaci et al., 2014; Santhanam et al., 2006).

However, such a definition of BCI focuses solely on the read-out aspect. This could be due to the mature technology of read-out BCIs, which offers a broad range of benefits, allowing patients to control robotic arms, wheelchairs, and use voice synthesis devices and word processors as tools to communicate with the outside world (Chaudhary et al., 2016; Anumanchipalli et al., 2019; Mudgal et al., 2020). Yet based on BCIs' different technical approaches and functions, they can be classified into write-in and read-out BCIs.

Write-in BCIs

Write-in BCIs are those that send signals to neural tissue through electrical or optical stimulation. For example, Deep brain stimulation (DBS), which is an invasive brain stimulation method that entails the implantation of electrode arrays under the deep cortex of the brain to stimulate certain target sites, with stimulation parameters controllable by external devices to treat symptoms such as Parkinson's disease, tremor, or other refractory disorders (Kringelbach et al., 2007; Lyons and Pahwa, 2008; Volkmann, 2004).

Write-in BCIs are designed to manipulate brain activity with the aim of either stimulating or inhibiting specific responses (Rafferty, 2021). These BCIs find extensive application, primarily in therapeutic contexts. For example, the cochlear prosthesis, an artificial implant, restores auditory function by stimulating auditory nerves, enabling individuals with hearing impairments to regain their ability to hear (Andersen, 2019). DBS offers therapeutic possibilities for a range of neurological conditions and disabilities, including Parkinson's disease (Limousin and Foltynie, 2019; Weaver et al., 2012; Fasano et al., 2012; Pal et al., 2022), tremors (Lozano, 2000; Bekar et al., 2007), and dystonia (Anderson and Lenz, 2006), among other movement disorders. Additionally, DBS is utilized in the management of specific psychiatric conditions, such as Alzheimer's disease (Laxton et al., 2010; Sankar et al., 2015), treatment-resistant depression (Bewernick et al., 2010; Schlaepfer et al., 2014), and severe obsessive-compulsive disorder (Greenberg et al., 2006; Visser-Vandewalle et al., 2022).

From a technical perspective, there are certain issues associated with write-in BCIs. First, there are safety concerns related to write-in BCIs. Implanting electrode arrays often requires craniotomy, which can cause a range of issues, such as hardware infection and damage to adjacent brain structures, such as intracranial hemorrhage (Volkmann, 2004). Additionally, electrode array stimulation parameters, such as frequency and voltage, are often generalized based on animal studies, rendering safety uncertain and human application highly risky (Bjånes and Moritz, 2019; Kim et al., 2015; Negi et al., 2010). Optimal electrode array size must be selected to improve signal accuracy in write-in BCI devices (Negi et al., 2010). Prolonged stimulation times on write-in BCIs can degrade brain signal quality and potentially alter the responsiveness of nerves to electrical stimulation, thereby elevating safety risks to brain nerves (Hughes et al., 2021; Tehovnik and Slocum, 2009; DeYoe et al., 2005).

Second, the exact mechanism of write-in BCIs is not well understood, and further investigation is needed to fully comprehend it. There is no way to predict which brain tissues will be affected by electrical stimulation or to what extent it will be damaged (Benabid, 2015; Gershon et al., 2003). Moreover, it is difficult to determine the precise target location for electrode array implantation and which areas of the brain can be used to "write" information (Mazurek and Schieber, 2021).

Third, the feasibility of BCIs is a critical concern that warrants investigation. The implantation of BCI electrodes in the cerebral cortex leads to a range of inflammatory reactions and gliosis, which raises long-term feasibility concerns (Lee and Fried, 2017; Davis et al., 2012). Furthermore, the reliability and flexibility of current write-in BCIs are considerably limited (Buller, 2021). Of utmost significance, patients may need to rely on write-in BCIs for extended periods, yet the impact of long-term use of this technology on the brain remains unclear. As such, the capacity of write-in BCIs to meet the users' needs is questionable, calling into question their technical feasibility (Bensmaia and Miller, 2014).

Read-out BCIs

Read-out BCIs receive and record brain signals, decode them using algorithms and decoders, and convert them to various representations of intentional activities that can be used to control effectors such as prostheses or wheelchairs (Andersen, 2019). Electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI) are technologies that "read" brain signals. Among these, EEG-based BCI technology is more advanced and involves recording brain signals using an array of electrodes placed on the scalp. (McFarland and Wolpaw, 2017) These signals can then be used to control external robotic arms and other devices for the detection of brain function and diseases such as sleep disorders (Demene et al., 2017; Stevner et al., 2019).

The primary function of a read-out BCI is to retrieve neural data generated by the brain, assess and analyze brain activity, with the aim of deducing alterations in intentions, behaviors, perceptions, and cognitive states based on brief data snapshots (Rieger et al., 2008; Schicktanz et al., 2015). Additionally, it can transmit or report neural data for various purposes (Rafferty, 2021). Read-out BCIs designed to restore motor and language functions serve as common examples (Rieger et al., 2008; Schicktanz et al., 2015). For instance, through direct transmission of mental commands to relevant devices, monkeys can manipulate limb movements through their thoughts (Ifft et al., 2013). These devices are similarly employed for individuals with severe paralysis, where electrode signals can decode their motor intentions (Aflalo et al., 2015), allowing them to control robotic arms for tasks such as bringing a bottle to their mouth and drinking through a straw (Hochberg et al., 2012). Furthermore, read-out BCIs have applications in real-time language translation and mood detection for individuals who have lost their speech and communication abilities (Moses et al., 2019; Wu et al., 2017). Moreover, some scholars speculate that these BCIs may eventually find application in lie detection, deception detection, and even in uncovering intricate and potentially subconscious or concealed brain information (Roelfsema et al., 2018).

From a technical perspective, there are also certain issues associated with read-out BCIs. Firstly, read-out BCIs are generally non-invasive, less costly and pose fewer safety risks compared to write-in BCIs (Volkova et al., 2019; Van Steen and Kristo, 2014). Secondly, the mechanism of read-out BCIs is easy to comprehend. Signals generated by intentional brain activity are recorded with scalp electrode arrays, and specialized algorithms decipher these signals into recognizable representations. Thirdly, these representations are converted into external actions via dedicated devices. Technically, read-out BCIs require only minimal apparatus attached to the scalp, which enhances the feasibility of utilizing them for 24-hour periods or extended periods (Bensmaia and Miller, 2014). Lastly, the efficiency of read-out BCIs is limited by some challenges. The EEG-based technology has some limitations, as it is subject to interference from tissue layers such as the scalp and skull (Nicolas-Alonso and Gomez-Gil, 2012; Lebedev and Nicolelis, 2006). Consequently, the accuracy of signals and the transmission rate is relatively low, compromising the ability to translate the user's intentions into external activities. Moreover, it is impossible to extract signals generated by individual fascicles, which contributes to errors in decoding the neurological activity resulting in incorrect external activity outcomes (Xu et al., 2018). This might negatively impact users, and in severe cases, may lead to harm. There is also the danger of malicious attackers exploiting vulnerabilities, potentially compromising the confidentiality of brain information (Xu et al., 2018).

From the previous description of read-out and write-in BCIs, we can identify the differences between these two technologies. Firstly, read-out BCIs interpret the users' intentional activity and translate it into actual actions where the users take control of these activities. On the other hand, write-in BCIs input intended action into users, and stimulate them to generate intentional action brain signals, whereby the device is the initiator of the intention-generating activity, not the users. Secondly, while read-out BCIs involve electrode arrays on the users' scalp to record and analyze brain activity, write-in BCIs require implanting an electrode array in the brain to electrically stimulate a target site, generating cognitive, verbal, or motor intentions in the users, controlled by an external device based on their needs or medical condition. While some write-in BCIs function by stimulating specific areas of the scalp using induced currents, the accuracy, and achievement of all the desired outcomes may be minimal. In conclusion, while both read-out and write-in BCIs can convert user intentions into actual activities, the former is a self-generated activity by the users, while the latter is a device-initiated activity that raises technical challenges and ethical considerations that differ from those of read-out BCIs.

Ethical challenges of write-in and read-out BCIs

According to the technical differences and different functions between write-in and read-out BCIs, the ethical issues posed by each are distinct. While there may be some common concerns, the impact of these ethical issues varies significantly. Therefore, it is necessary to distinguish between ethical issues caused by these two types of BCIs in order to fully comprehend the ethical implications of each. A comparison of the ethical issues present in write-in and read-out BCIs, the need for differentiation, and the varying levels of impact are provided in Table 1 below.

Table 1 A comparison of ethical challenges of write-in and read-out BCIs. Table 1 highlights the distinct ethical challenges associated with write-in BCIs and read-out BCIs. This paper summarizes these challenges into seven key aspects: safety, privacy, identity, autonomy and agency, responsibility, fairness, and informed consent. Below, this paper provides a detailed analysis of the ethical issues and implications of write-in and read-out BCIs.

Ethical challenges of write-in BCIs

Safety

As can be seen from the second section: the safety of users is a primary concern with the implementation of write-in BCIs. Technical uncertainties surrounding the devices and their lack of a reliable mechanism may result in harm to the user's body (Benabid, 2015; Gershon et al., 2003). Unavoidable risks from surgery and electrical stimulation can also create damage to brain tissues, and unexpected situations may lead to risks to the user's life.

Identity

Identity refers to the enduring nature of a person's self, remaining stable over a period of time without transformation into a distinct persona. Scholars concur that specific criteria determine whether someone's identity has been modified. These are personality, beliefs, thoughts, perceptions, behaviors, emotions, and sense of self (Coleman and Williams, 2013; Postan, 2016; Pugh, 2020; Postan, 2020). The use of write-in BCIs may change users' cognition, behaviors, and self-perception, thereby affecting their identity (Gilbert et al., 2017). Researchers have delved into the connection between BCIs and identity, investigating the potential for BCIs to modify a user's identity and induce psychological changes, among various other factors (Tamburrini, 2009; Klein, 2015; Glannon, 2016; Gilbert et al., 2018; Aggarwal and Chugh, 2020).

According to a qualitative study by F. Gilbert et al., in which semi-structured interviews were applied to patients using write-in BCIs, patients perceived the devices as an extension of their bodies, materializing into a portion of themselves. These machines impacted their desired goals and improved daily activities (Gilbert et al., 2017). The change in identity can create varied effects: both positive and negative. For instance, if a write-in BCI encourages users to set proper ideal goals in life, it has a positive effect, users possess the capacity to comprehend their own selves, identify valuable aspects, strategize for and sustain enduring projects, commitments, and relationships (Postan, 2020). Conversely, when this leads to the embrace of erroneous values, detrimental consequences ensue.

Autonomy and agency

Autonomy and agency are vital for individuals' ability to control their daily activities spontaneously, particularly since this behavior is independent of the external environment's influence and manipulation (Buss and Westlund, 2018). Autonomous agents freely act as per their choices and plans (Schlosser, 2019). Agency's realization primarily relies on agents' autonomy, and this can only be possible with the ability of agents to decide independently about their activities (Schlosser, 2019). Write-in BCIs offer the potential to alter users' agency and autonomy. On the one hand, they can restore users' autonomy and agency, while on the other hand, they can impair them (Friedrich et al., 2018). A user with Locked-in syndrome (LIS), for instance, may use a write-in BCI to enhance her or his cognitive ability and decide and perform routine activities independently, thus restoring autonomy and agency (Fenton and Alpert, 2008; Vukov, 2017). However, if a user receives signals through write-in BCIs to perform behaviors that she or he cannot control, it erodes their autonomy and agency. As an illustration, BCIs could potentially find applications in interrogation contexts or even for the purpose of pacification, ultimately eroding the autonomy of individuals (Munyon, 2018).

Ethical challenges of read-out BCIs

Read-out BCIs pose fewer ethical concerns due to their functional and methodological differences. The most apparent ethical challenge that arises with read-out BCIs is privacy concerns. To illustrate, read-out BCIs have the capability to acquire not only the user's brain data but also various other data types, including physiological and behavioral information. Subsequently, these systems can formulate specific inferences about the user's brain activities or thoughts, individually or in combination, thereby presenting a potential risk to the privacy and security of the user (Postan, 2020). These concerns associated with read-out BCIs stem not only from the devices themselves but also from malware attacks like malicious algorithms, "brain spyware," among others

(Bonaci et al., 2014). Attackers carefully design "brain spyware" malware to locate and tap into user's private data, including their financial and facial information, raising severe ethical concerns (Martinovic et al., 2012).

Users' privacy security could be seriously threatened when attackers misuse the private information generated by users' brains and predict their mental activities, intentions, beliefs, health information, and personality traits (Inzlicht et al., 2009; Chaudhary and Agrawal, 2018). Landau et al. (2020a, 2020b) illustrated that the collection of EEG data via BCI applications constitutes an encroachment upon privacy. Furthermore, they established that personality traits can be deduced from this EEG data.

Exploitation of such information could lead to users being manipulated or coerced into performing malicious behaviors. As BCI technology advances, the ability to monitor users' thoughts will continue to improve. For instance, researchers have developed a GPT-based language decoder that is similar to the ChatGPT model. This decoder records and decodes brain activity information using non-invasive fMRI, achieving an accuracy rate of up to 82% in speech perception (Tang et al., 2023; Reardon, 2023).

Users' raw and predicted private information could be exploited for commercial advertising and marketing purposes, or even to harm and manipulate them, posing a threat to their physical and mental well-being and overall safety (Bonaci et al., 2014). For instance, a malicious attacker might obtain private information about an individual with epilepsy and purposely send them unwanted messages with rapidly flashing, horrific, and hateful animated images designed to trigger seizures (Ertl, 2007; Poulsen, 2008). Users of read-out BCIs are often physically disabled, and access to their private information, coupled with inference and predictions of other information, could significantly threaten their physical and mental well-being, along with various other aspects of their lives.

Common ethical challenges of write-in and read-out BCIs

Responsibility

BCI technology, both write-in and read-out, is faced with ethical issues concerning responsibility (Rainey et al., 2020); however, write-in BCIs have more significant implications. The use of write-in BCIs may cause the user's personal identity to change, resulting in altered personality, emotions, and perceptions before and after usage - a transformation into a different person (Jebari and Hansson, 2012). However, the responsibility for any unethical or illegal actions is controversial, since the user is not the same person as before using the write-in BCI. It becomes challenging to determine who should be responsible, especially if the user behaves wrongly due to being a different person or acquiring a nervous disorder. Consequently, owing to the convergence of identity and responsibility, the ethical responsibility linked to the actions of BCIs becomes notably intricate (Klein et al., 2015).

Furthermore, alterations in users' autonomy and agency can diminish their capacity to exercise autonomy independently, thereby introducing further complexities in ascertaining accountability. Moreover, BCIs can respond to users' subconscious thoughts, an arena where users possess neither consciousness nor control (O'Brolchain and Gordijn, 2014). In light of this scenario, the pivotal query emerges: whether users should assume complete responsibility for all consequences produced by the BCIs (Klein et al., 2015).

Privacy violations caused by read-out BCIs create a responsibility problem. If a user's privacy is breached, and they are manipulated or forced to commit illegal activities or suffer harm due to leakage (Bonaci et al., 2014), attributing responsibility for any wrongdoing and harm caused by manipulation becomes challenging. Furthermore, this responsibility issue for read-out BCIs extends beyond identifying the responsible party and involves determining how to hold the user accountable while also identifying the party responsible for privacy violations. As a result, multiple parties may be involved, necessitating more effective ways of attributing responsibility.

Social Fairness

The issue of social fairness is critical for both types of BCIs but has various implications. Write-in BCIs may use electrical stimulation to enhance users' cognitive abilities, actions, and other functions, creating social inequality (Khan and Aziz, 2019). Low affordability of write-in BCI devices to a large number of people can create differences in abilities between those who use and those who do not use them, leading to more class antagonism and social division (Vlek et al., 2012). In contrast, read-out BCIs have a relatively low social impact since they mainly focus on restoring hearing, speech, motor functions, etc., although they could still create some social inequalities. To illustrate, in the case of a BCI gaming, the input comprises EEG scan data obtained from users. Simultaneously, hospitals and healthcare institutions house vast datasets of patient EEG scan data and associated personal information. In a concerning scenario, if malicious actors were to gain access to both the EEG scan data from the gaming environment and hospital records, they could conduct comparative analyses to extract intricate user details. This, in turn, has the potential to result in discriminatory practices against specific populations, with implications for fairness (Landau et al., 2020a, 2020b).

Informed consent

The concept of informed consent is an important ethical concern in both types of BCIs and numerous other research domains (Grübler et al., 2013; Versalovic et al., 2020). It is crucial to obtain and provide consent from BCI users before utilizing it and ensure that they comprehend all potential consequences. Nevertheless, acquiring informed consent may be complicated for people lacking the ability to make autonomous decisions. In these circumstances, it is essential to brief their guardians on all the information so that they can make an informed decision.

Write-in BCIs raise ethical issues concerning user security, personal identity, autonomy, and agency, whereas read-out BCIs primarily concern privacy. Both categories pose challenges regarding responsibility, social equitability, and informed consent. It is crucial to differentiate personal identity, autonomy, and agency, and privacy for each type of BCIs. While responsibility and social equity issues have different impacts on users and society, they need not be distinguished since they arise from similar causes and require the same governance measures. Informed consent issues do not demand differentiation as they have comparable impacts on users and society. Although write-in BCI technologies are still in their nascent stages, current research on ethical concerns in BCI technologies prioritizes write-in BCIs. Neglecting to distinguish between the two categories of BCIs may cause unwarranted concerns about read-out BCI products currently in use, emphasizing the need for precise governance of ethical issues concerning BCIs. Although current research has put forth many governance measures and ethical principles concerning BCIs, it has yet to establish a distinct differentiation between write-in BCIs and read-out BCIs, thereby imposing certain constraints. Consequently, there exists a demand for precise governance to augment and fine-tune ongoing research pertaining to the ethical governance of BCIs.

Suggestions for governance

The current approaches for the ethical governance of BCIs

This article, following a comprehensive review of pertinent literature, identifies that the current approaches to governance concerning ethical aspects in BCIs can be broadly classified into two levels: ethical and legal.

Ethical level

The application of BCI technology has given rise to a multitude of ethical challenges with significant implications. Certain scholars contend that established ethical guidelines, such as the *Declaration of Helsinki* and the *Belmont Report*, may not offer adequate solutions to contemporary ethical dilemmas (Yuste et al., 2017). In response to the ethical quandaries stemming from BCI technology, numerous international organizations, and governmental bodies have implemented pertinent ethical initiatives and governance measures. As an illustration, UNESCO has published the "Report on Ethical Issues of Neurotechnology," which advocates for responsible innovation (International Bioethics Committee (IBC), 2022). Remarkably, China has introduced, for the first time within the BCI domain, a proposal emphasizing that BCI development should align not only with the principles of respecting, non-harming, benefiting, and justice in bioethics to preventing harm to users, but also with the principles of non-harming, respecting autonomy, protecting privacy, ensuring transparency, and upholding fairness and justice

(Chinanews, 2023). Additionally, several scholars have proposed a range of recommendations pertaining to ethical issues in BCIs. These recommendations encompass the establishment of rights such as “neurofreedom” and “neuroprivacy,” enhancements in informed consent procedures, regulation of brain data collection, constraints on brain data sharing, the recognition and mitigation of biases, and the advancement of fairness in neurotechnology (McCullagh et al., 2014; Goering et al., 2021; Doya et al., 2022).

Legal level

At the legal level, it is noteworthy that only a limited number of countries have enacted legislation and regulations aimed at safeguarding the integrity of the human mind or have incorporated neural data into their personal data protection laws (UNESCO, 2023). For instance, Chile’s constitutional amendments have paved the way for the safeguarding of citizens’ mental privacy and their freedom of will (Guzmán, 2022). Spain has introduced the “Digital Rights Charter,” which mandates that the utilization of neural technology must ensure each individual’s control over their identity, sovereignty, and self-determination, while also guaranteeing the security and confidentiality of acquired neural data. Moreover, it regulates the deployment of technologies that may impact physical or mental integrity (AOC blog, 2021). France, among others, has issued a “Charter for the responsible development of neurotechnologies.”

In summary, while some governance approaches have been established, the research on the governance of ethical issues related to BCIs remains incomplete due to the ongoing development of BCI technology. Existing governance approaches exhibit certain limitations. Besides potential delays in the legal domain and the abstract nature of ethical aspects (Mittelstadt, 2019), a pivotal concern arises from the fact that current governance measures do not distinguish between write-in BCIs and read-out BCIs. Instead, they address ethical issues in BCIs at a macroscopic level. This approach may lead to confusion in practical applications, potentially governing non-existent ethical issues while overlooking genuine ethical concerns.

To effectively manage ethical challenges encountered by the aforementioned BCI types, precisely targeted recommendations and governance measures are necessary for specific ethical dilemmas unique to each type of BCIs. Precision governance (PG) is an approach that incorporates the preferences and contexts of individuals and collectives into policy decision-making. This governance method also includes the potential preferences and needs arising from specific circumstances and experiences, thereby enhancing the precision and personalization of decision-making (Hondula et al., 2018). Write-in BCIs and read-out BCIs face distinct challenges at ethical and technical levels. Ethical concerns regarding write-in BCIs encompass user safety, identity, autonomy, and agency, while read-out BCIs primarily entail significant privacy risks. On the technical level, write-in BCIs primarily confront issues of feasibility and uncertainty in operational mechanisms, whereas the effectiveness of the technology represents the primary concern for read-out BCIs. Therefore, ethical and technological governance diverge. Ethical governance primarily addresses the ethical challenges associated with BCIs, encompassing specific social and societal values, whereas technological governance primarily concentrates on the technical obstacles encountered by BCIs, encompassing practical rules in design, development, and deployment. Consequently, the general governance strategy mentioned earlier is inappropriate for addressing the multifaceted issues stemming from BCIs. Instead, precise governance is imperative, offering distinct governance measures tailored to the specific issues of write-in BCIs and read-out BCIs, meeting unique preferences and needs, achieving fine-grained and personalized governance, and compensating for the shortcomings of the general governance approach.

The approach of precise governance

To effectively govern ethical issues of BCI technology, it is imperative to apply precise governance principles by pinpointing specific issues and tailoring recommendations and governance measures for the unique ethical considerations of write-in and read-out BCIs. Problem-targeted governance measures should address key ethical issues, including security for write-in BCI and performance for read-out BCI. Governance measures should restrict write-in BCI use until establishing high levels of security and promoting use only after achieving the highest security standards. To deploy effective governance measures, implementing PG whereby ethical issues are classified, and effectively resolved is necessary. Current governance measures may lead to impractical solutions, misguided guidance, and improper resource deployment, impeding further BCI technology development and improvement.

PG for write-in BCIs

Technology governance

The safety of BCI technology is crucial, particularly for write-in BCIs that are still in their early stages of scientific and clinical development. Uncertainty about the safety, feasibility, and effectiveness of write-in BCIs exists, and prolonged use may be required to maintain their intended functions and effects, posing further concerns about their long-term impact on the brain. Additionally, the level of medical care significantly affects the use of write-in BCIs, making it necessary not only to enhance the quality of medical care but also to utilize write-in BCI technologies reasonably. Improving their safety is essential to protect the lives of users and promote the development and advancement of BCI technology.

Ethical governance

The utmost importance must be given to safeguarding users' identity and autonomous decision-making rights when developing write-in BCI technology. Malicious attackers can exploit mind control over the user, generating impulsive or harmful thoughts and behaviors. Distinguishing the origin of such actions, either from the user or the attacker, can be challenging, leading to a loss of personal identity and autonomy. Therefore, write-in BCI technology must take into account user needs and values, tailoring the design accordingly while implementing relevant review standards and audit mechanisms to protect the user and others from harm.

PG for read-out BCIs

Technology governance

Enhancing the effectiveness of read-out BCI technologies is critical when considering interference or external environmental attacks. Although there is no immediate security risk, deviations from user-intended actions can occur, and the timeliness and accuracy of the device can be affected, ultimately harming the user. Therefore, additional improvements are necessary to ensure accurate and timely translation of user intention into an external device activity.

Ethical governance

Protecting user privacy is of paramount importance from an ethical standpoint. As read-out BCI technologies become more popular and mature, they become increasingly integrated into users' daily lives. However, over-involvement in users' lives poses a significant risk to privacy and security. Malicious access to, collection, and use of private information can cause harm to individuals and society, with potentially life-threatening results. Therefore, establishing technology specifications, enhancing and upgrading security mechanisms, and developing and updating privacy and security monitoring mechanisms in a timely manner becomes critical. It is vital to explain and prevent all possible harms resulting from read-out BCI technology and to establish privacy protection technologies. Supervising the product development process and enforcing ethical principles, laws, and regulations for privacy protection are of utmost importance to ensure user privacy.

PG for the common ethical issues of write-in BCIs and read-out BCIs

It is vital to improve relevant systems and regulations and reinforce policy protection

Responsibility attribution relies on clarification of the source of information driving the intentional behavior. If users generate it, they are responsible for any impulsive behavior. On the other hand, technical issues causing harm make the manufacturer accountable. The legal systems must be enhanced and policy protection strengthened to facilitate the market use of BCI technology. Specific mechanisms to handle recourse cases must be identified, and the right to informed consent protected. Furthermore, vendors must not obtain, store, or share user's personal privacy information without proper consent.

Enhancing social distribution systems is essential to promoting distributive justice

Generally, BCI products are costly, rendering them inaccessible to many patients, particularly those in impoverished areas where these products may be unavailable. Therefore, the state should allocate resources reasonably, and control BCI product prices. Additionally, pricing standards and allocation systems should be region and user-group-specific. It is worth noting that the development and utilization of BCIs may exhibit global variations, particularly in remote and resource-constrained areas. Thus, the governance of ethical issues related to BCIs in these regions should be adapted to their unique contexts. It is commonly recommended to engage local communities and researchers while fostering collaboration with other regions (Pickersgill, 2021; Shen et al., 2021). Furthermore, R&D and production companies should receive subsidies to develop BCI products, allowing them to forgo economic benefits while remaining profitable. These steps aim to ensure that everyone in society has an equal opportunity to access and utilize BCI technologies.

Conclusion remarks

BCIs bring about convenience and ethical concerns intrinsic to their function and mechanism. It is, therefore, necessary to differentiate BCI technologies by function and discuss technical and ethical issues separately. Write-only BCIs face technical safety, mechanism uncertainty, and low feasibility problems; technical effectiveness problems persist with read-out BCIs. Write-in BCIs give rise to problems in user security, personal identity, autonomy, and agency issues while privacy and security are chiefly problematic with read-out BCIs. Therefore, effective governance of ethical issues posed by BCIs requires precise governance measures for different technical and ethical problems to attain effectiveness and accuracy. The application of precise governance to the various technical and ethical concerns of BCIs will significantly enhance governance effectiveness in the field of BCIs. One limitation of this paper is in the definition of identity, which is a complex concept with multiple controversies in academia, thus relying on a general concept. In the future, BCIs will combine write-in and read-out techniques, emphasizing the need for increased research, clinical attention, and investment in this area.

A review of research on non-invasive brain-computer interface technology

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A review of research on non-invasive brain-computer interface technology

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Abstract

Brain-computer interface (BCI) is a new technology, especially non-invasive BCI. A large number of scholars at home and abroad have carried out relevant research. This paper has read a large number of references, first of all, the definition of BCI and its system composition are summarized, and then the classification of BCI, the definition of each part, principles, advantages and disadvantages are introduced. This paper studies and analyzes the research status of non-invasive BCI at home and abroad, and summarizes the common non-invasive BCI systems. Bci can be widely used in medical treatment, entertainment, games, education and training, military and security fields, and plays a very important role in daily life and work.

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Directly wireless communication of human minds via non-invasive brain-computer-metasurface platform

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Abstract

Brain-computer interfaces (BCIs), invasive or non-invasive, have projected unparalleled vision and promise for assisting patients in need to better their interaction with the surroundings. Inspired by the BCI-based rehabilitation technologies for nerve-system impairments and amputation, we propose an electromagnetic brain-computer-metasurface (EBCM) paradigm, regulated by human's cognition by brain signals directly and non-invasively. We experimentally show that our EBCM platform can translate human's mind from evoked potentials of P300-based electroencephalography to digital coding information in the electromagnetic domain non-invasively, which can be further processed and transported by an information metasurface in automated and wireless fashions. Directly wireless communications of the

human minds are performed between two EBCM operators with accurate text transmissions. Moreover, several other proof-of-concept mind-control schemes are presented using the same EBCM platform, exhibiting flexibly-customized capabilities of information processing and synthesis like visual-beam scanning, wave modulations, and pattern encoding.

1 Introduction

To directly inspect and distinguish human's will, brain-computer interface (BCI) is presented to establish the communication between brain and devices. By collecting spontaneous or specifically evoked electro-encephalography (EEG) signals from the scalp via non-invasive electrodes, BCI can decode operator's intentions and send commands to the controlled objects, without any requirements for the operator's muscle activity [1,2,3]. P300 potentials, steady-state visual evoked potentials [4] (SSVEPs), and sensorimotor rhythms are three typical brain patterns in EEG-based BCIs. The P300-based BCIs, which identify the operator's intention from the P300 potentials evoked by flashes of the corresponding buttons on the control panel, have been frequently used [5,6,7] to assist the handicapped [8] or medical applications [3].
Metamaterials and metasurfaces have showcased unparalleled electromagnetic (EM) regulating capabilities, enabling various novel phenomena on EM wave manipulations like the anomalous diffraction [9], invisibility cloaking [10, 11], lensing [12], and imaging [13, 14]. Recently, digital coding metasurfaces, incorporating with PIN diodes [15], varactors [16, 17], micro-electromechanical systems [18] and amplifiers [19, 20], have enabled active, real-time, and programmable controls over the EM functionalities [21,22,23], which used to be static or quite limited in conventional passive counterparts. This powers up abundant sub-directions like time-coding and space–time-coding metasurfaces [24, 25], self-adaptively smart metasurfaces [26,27,28], programmable holograms [29, 30], and direct information processing [31].
In this work, we cast a roadmap fusing the reprogrammable EM metasurfaces with BCIs. We firstly propose an electromagnetic brain-computer-metasurface (EBCM) to flexibly and non-invasively control the information syntheses and wireless transmissions. We then design and demonstrate the wireless text-communications between two BCI operators by using a 2-bit programmable metasurface, under the brain control. A P300-based BCI is applied to translate

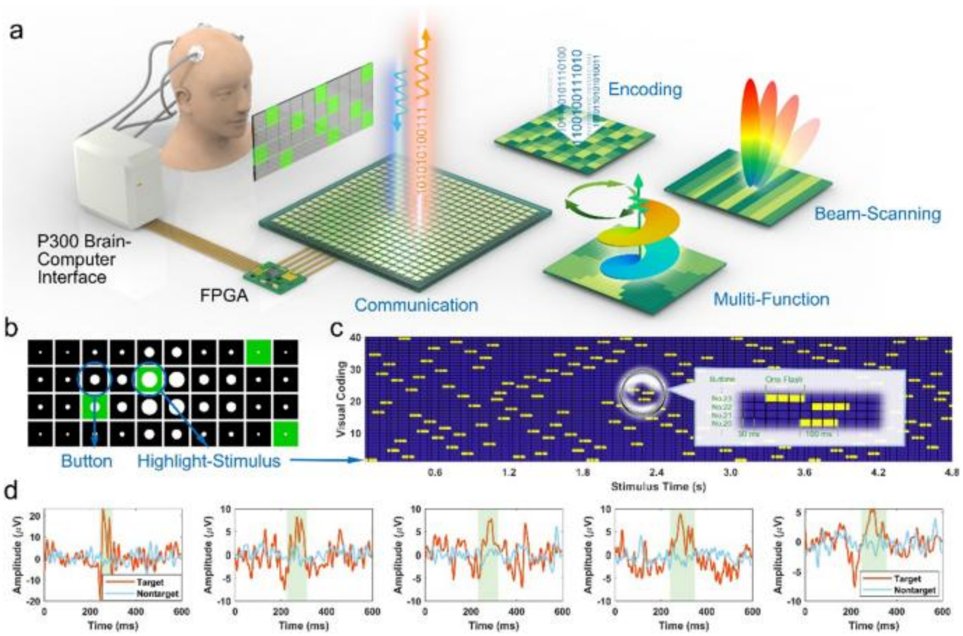
the operator's brain messages to EEG signals, and further to computer commands, which are fed into the electrical control system of the programmable metasurface. After that, the digital messages are wirelessly transmitted and received by two programmable metasurfaces to fulfill the text communication in experiments. In addition, three typical applications are also designed and experimentally verified, including visual-beam scanning, wave modulations, and pattern encoding. The measured data of multiple scattering modulations have shown good consistence with the operator's intention, which can be well reflected from the recorded EEG. We envision that the programmable metasurface system will become an incubator that can integrate the artificial intelligence and human brain intelligence to form more advanced intelligent systems.

2 Results

2.1 Principle of the EBCM

We witnessed impressive advancements in the programmable metasurfaces [25, 32, 33]. On the other hand, BCI has been captivated a popular notion of enabling brain signals to directly deliver the physical actions. With non-invasive electrodes [5, 6], the P300 potentials can be identified from the brain signals under a certain time sequence of visual stimuli. In this work, we intuitively combine the P300 coding characteristics with the programable information metasurface, and experimentally demonstrate a robust P300-based EBCM to showcase the robust control of EM wireless information (e.g., synthesis, manipulation, and encoding/decoding) with only inputs from the brain signals and the designed functions, as shown in Fig. 1a.

Fig. 1



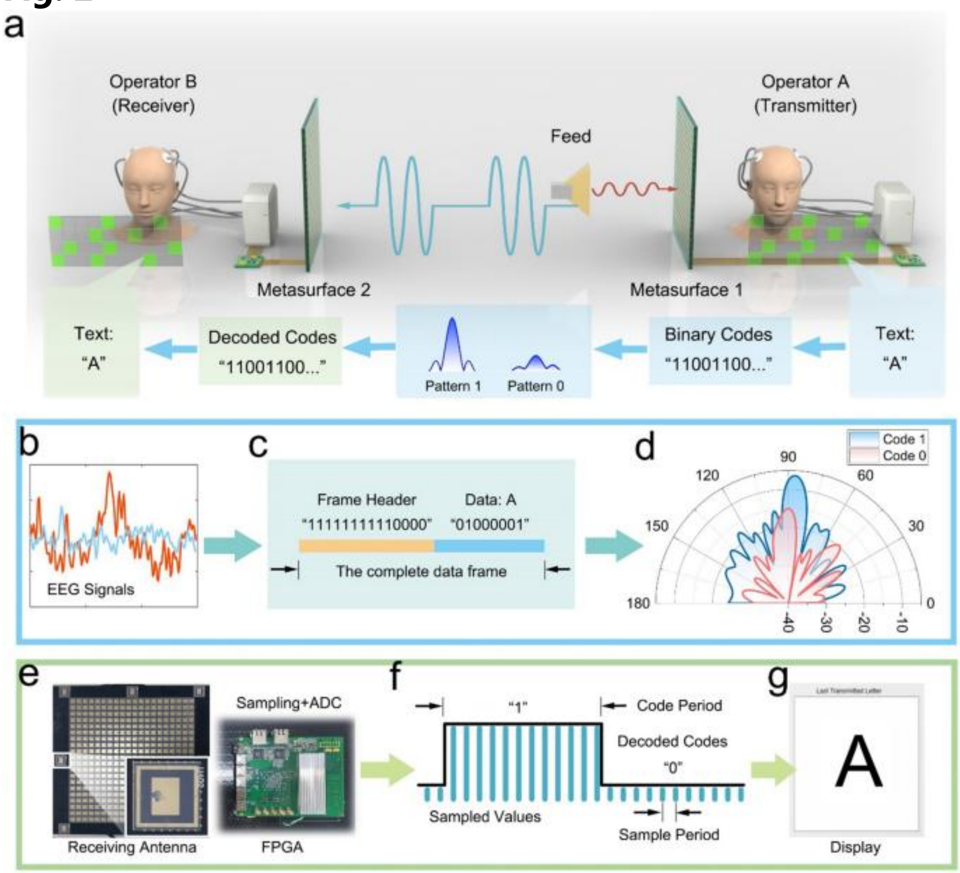
The EBCM platform. **a** The system architecture of EBCM. The operator equipped with electrodes and P300 BCI device can directly instruct the metasurface with diverse EM functions under visual stimulus with the specific temporary coding sequences. Four typical schemes including brain-wireless communications, coding pattern encoding, beam scanning, and multi-function of EM modulations are demonstrated. **b** The graphical user interface of the beam deflection scheme. The buttons with different circles represent different beam scattering directions, where the highlight stimulus is green blocks. **c** Schematic diagram of the stimulus sequence, in which 40 rows represent the 40 buttons, and the yellow blocks mark the highlights of the buttons, each of which lasts for 100 ms. **d** The experimentally measured EEG signals of five button operations, where obvious amplitude peaks occur at about 300 msA displayer is placed in front of the operator to show the graphical user interface (GUI), and there is a virtual button matrix, as exhibited in Fig. 1b. Different buttons correspond to different coding-pattern operations of EBCM. Each trial corresponds to one command sending, and the buttons start to flash successively in a random order for about 5 rounds, each of which contains one flash for each button. The flash sequence is randomly generated before each trial. Figure 1c presents the flashing sequence of 40 buttons (40 rows) in the beam-scanning scheme, where the yellow squares indicate the starting point of the stimulus. The vertical axis represents the number of buttons from 1 to 40, while the horizontal axis represents the 160 sequential stimulus flashes marked by yellow bars in Fig. 1c. Each marked block in Fig. 1c represents a duration of 30 ms and each flash lasts for 100 ms, which will span slightly more than 3 blocks. In Fig. 1c, we further show a zoom-in view of three flashes to illustrate the stimulus time sequences of different buttons more clearly.

The operator's attention is focused on the button corresponding to the command that he/she would like to issue (i.e., the target). When the target flashes, due to the oddball effect, a positive potential may be detected from EEG after approximately 300 ms, dubbed P300 potential [34]. Such a P300-based BCI has been experimentally proved effective for the brain to directly control the external devices [5, 35]. To present the brain signals for two stimulus types (target and nontarget), we exhibit the measured EEG signals in Fig. 1d, where the red and blue curves correspond to the signals for target and nontarget stimulus, respectively. In each subfigure of Fig. 1d, the signals corresponding to both target and nontarget buttons are averaged across multiple flashes. For each button flash in a trial, a segment of EEG signal from 0 to 600 ms after the flash onset is extracted and corrected with a baseline extracted from 200 ms before the flash onset. Next, we exploit this sequential stimulus to directly control the field programmable gate array (FPGA) to execute the related instructions in the operators' mind, and successfully realize the paradigm shift from the brain signal to EM scattering manipulations. As a proof-of-concept demonstration of EBCM, we present wireless text communications between two operators by the minds. By designing specific rules between EEG and EM signals, the transmitted text in mind is accurately received and decoded in experiments. To exhibit more functions realized by the same EBCM, we also demonstrate three applications, which include (1) EM-beam scanning; (2) multiple scattering-beam switching; and (3) metasurface pattern encoding. More details of the EBCM platform are provided in Additional file 1: Supplementary Note S1 [36].

2.2 Wireless text communication by mind based on EBCM

To fully exhibit the application of EBCM, we design and experimentally demonstrate wireless text communications by mind, as illustrated in Fig. 2a. A text GUI is provided for the BCI operator (see Additional file 1: Supplementary Note S2 [36]), in which the visual button is encoded directly as a specific coding sequence composed of '0' and '1', related to two coding patterns. Here we employ a single-beam pattern with high gain and a scattering-reduction pattern for amplitude discrimination, respectively corresponding to ‘1’ (high amplitude) and ‘0’ (low amplitude). As a proof of prototype, we show the text wireless transmissions by mind from one operator to another within our EBCM communication system. The operator A, as the text transmitter, sends the letters by visually staring at the character button on the GUI of EBCM. When the target letter is decoded from the EEG signals, a coding sequence based on the ASCII codes is implemented on FPGA to switch the time-varying patterns.

Fig. 2



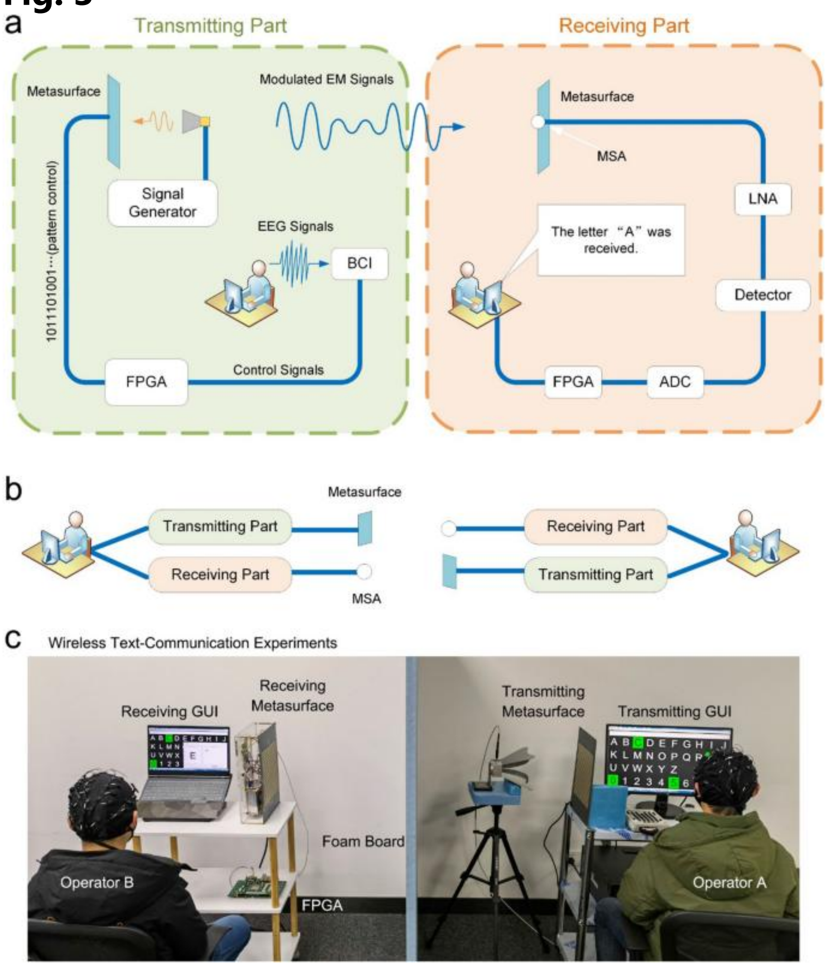
The wireless text-communication using EBCM. **a** The system architecture of the text-communication system as well as the coding and decoding process. **b**–**d** The encoding process from EEG signals to the transmitted EM signals, where the EEG signals shown in **b** are first detected by BCI and translated into the digital sequence in **c** for wireless transmission, then radiated by the metasurface with different pattern amplitudes in **d**. **e**–**g** The decoding process of wireless communication, where the antenna and FPGA in **e** firstly receive and sample the signals from space and convert them into the digital signals. The sampled data are discretized into 0/1 codes for decoding, as depicted in **f** and finally translated into the text for displayIn the encoding process, since the buttons representing the related text characters have the corresponding ASCII codes, the selected button is directly translated to the binary ASCII codes with the frame header “11111111110000”, as illustrated in Fig. 2c. Then according to the final code, the metasurface reflects the high or low intensity to the space. In the decoding process, we firstly collect the spatial EM energy using the receiving channel, including a microstrip antenna embedded beside the metasurface, as shown in Fig. 2e, as well as a low-noise amplifier (LNA) and a high-speed analog-to-digital convertor (ADC) controlled by FPGA. The collected data stream is a series frame set, which represents the sampled intensity at the acquisition rate of 10 MHz. We use the decoding algorithm to locate the position of the frame header to determine the starting point of the data frame, as illustrated in Fig. 2f. Then the sampled data are transferred into the binary ASCII codes, and we display the text in the GUI (provided in Additional file 1: Supplementary Note S2).

Four text sequences are sent and received successfully by mind using the EBCM platform, including “HELLO WORLD”, “HI, SEU”, “HI, SCUT”, and “BCI METASURFACE”. A recorded video is provided in Additional file 2: Supplementary Movie S1. The average inputting time of each character is about 5 s using the P300-based BCI by a skillful BCI operator. Since the programmable metasurface can achieve the “0/1” code transmitting speed of at least 1 Mbps, the maximum character transmitting speed for the metasurface is about 5×10^4 characters per second (20 bits each sequence). Hence the final text-transmitting speed is about 12 characters per minute. It is worth mentioning that the P300-based BCIs yield great accuracies and robustness among various noninvasive BCIs [5, 6]. It is possible to improve the text input speed by applying some quick-spelling paradigms [7, 37].

2.3 Experiment implementation and results of wireless communications

The detailed illustration of the communication system is depicted in Fig. 3a, in which the transmitting and receiving parts are marked in orange and green. In the transmitting part, the EEG signals are firstly detected and processed with the BCI devices and translated into the corresponding control signals of FPGA. The control signals follow the signal coding principle of the corresponding interface shown in Fig. 2b–d. The FPGA executes the coding pattern arrangements and drives the PIN diodes to the desired states. In the receiving part, the microstrip antenna (MSA) beside the metasurface obtains the EM signals from the transmitter and sends it into the LNA and detector. The detector samples the analog amplitude, which is further converted to the digital codes for FPGA. The presented process is unidirectional but the communication system of EBCM is bidirectional since the transmitting and receiving fronts are respectively the metasurface and MSA, as illustrated in Fig. 3b, which enables simultaneous transmission and reception of EBCMs by the same operator. When one metasurface sends a signal, the MSA next to the other metasurface receives and demodulates it. A similar process can also be performed in reverse simultaneously.

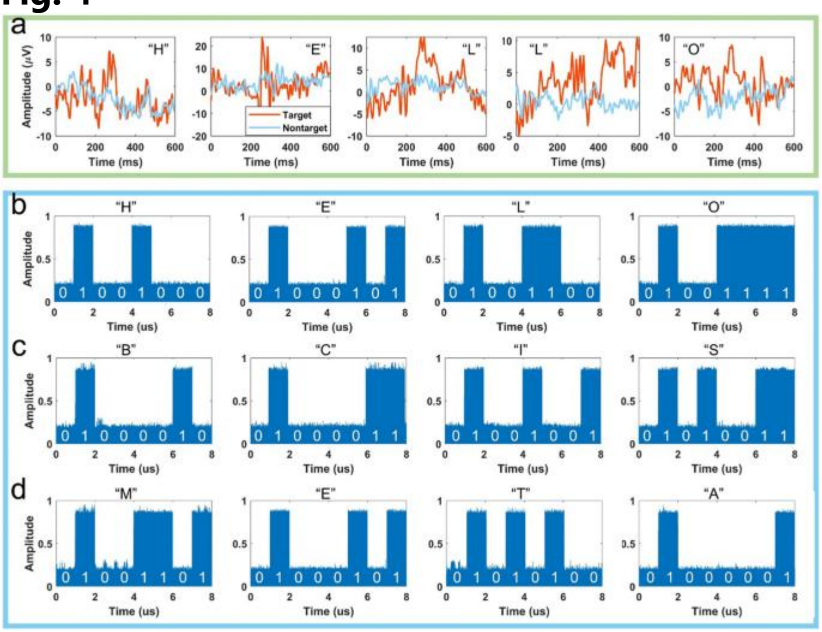
Fig. 3



Experimental implementation of the wireless text-communication. **a** The system architecture of the wireless text-communication experiment. **b** The illustration of the working mechanism of transmitting and receiving parts. **c** The experiment scenario of the wireless text-communications directly through EBCM, where a foam board is placed between two operators to verify the wireless propertiesThe experimental scenario is exhibited in Fig. 3c, in which Operator A executes the text transmitting task and Operator B receives and reads the text. The distance between transmitting and receiving metasurfaces is about 1.3 m, in which the transmitting metasurface is excited by a broadband antenna with a distance of 0.3 m, and the receiver is an antenna integrated near the receiving metasurface, which is connected to an LNA and a high-speed detector, as well as an ADC, controlled by another FPGA. The received and demodulated letters and text are finally displayed on the designed GUI. The experiment process of the wireless text communications is recorded in Additional file 2: Movie S1.

Figure 4a illustrates the processed EEG responses of the channel OZ to two stimulus types (target and nontarget) when the subject is spelling the word “HELLO”. In each subfigure corresponding to the spelling of one character, for each of the two stimulus types, the event-related potential (ERP) waveforms are extracted by the time-locked average of the EEG signals across all flashes of the target or one of the nontarget buttons in a trial. Compared to the nontarget data, high amplitude is clearly observed at about 300 ms after the stimulus. According to the EEG signals, EBCM produces the amplitude-modulated EM signals of different letters using the ASCII code.

Fig. 4



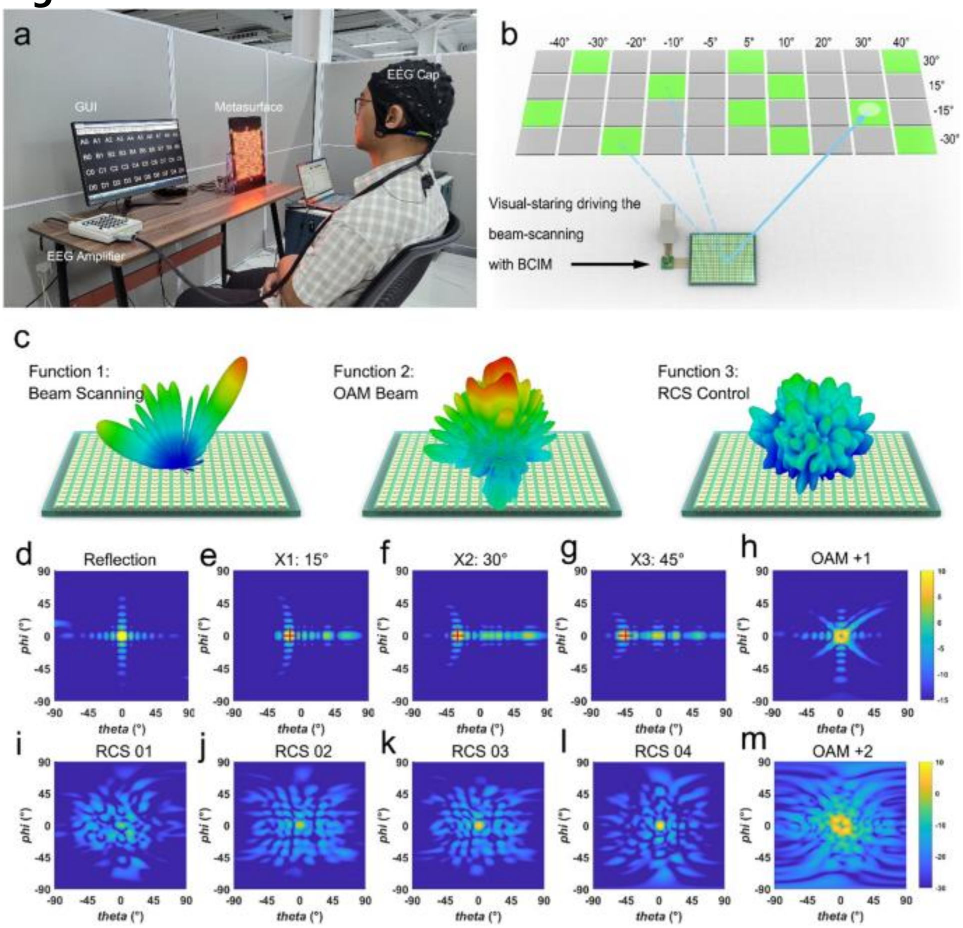
The experimental results of the wireless text-communications using EBCM. **a** The experimentally measured EEG signals in the text communication scheme. The EEG segments corresponding to five letters “HELLO” are presented for demonstration. **b**–**d** The measured EM signals of the letters ‘HELO’, ‘BCIS’, and ‘META’. The normalized amplitude-modulated signals present the ASCII codes of these letters, where high and low amplitudes mean ‘1’ and ‘0’To fully demonstrate the wireless communications, we further provide 12 segments of the measured EM signals, including the letters ‘H, E, L, O, B, C, I, S, M, E, T, A,’ as showed in Fig. 4b–d, where the high and low amplitudes respectively mean ‘1’ and ‘0’ in the ASCII code.

The presented data are collected by an EM detector and then normalized. Each detection generates an amplitude pulse and numerous amplitude pulses to compose the presented data, where the high and low amplitudes respectively mean the codes 1 and 0. The ASCII codes of these letters are clearly observed according to Fig. 4b–d. Please note that the EEG signal waveform of the same test subject at different times and different states are not the same even when test the same letter. The EEG detection based on the P300 is aimed at the test subject having a clear peak at 300 ms after being stimulated, to prove that the corresponding key is triggered.

2.4 More functions of wavefront syntheses by EBCM

To further demonstrate more functions of wavefront syntheses by the brain signals, we design three typical applications including the visual-beam scanning, multiple EM modulations, and coding pattern input. Here, we establish a demonstration prototype of EBCM, in which the metasurface is replaced by the light emitting diode (LED) version instead of PIN diode, as shown in Fig. 5a. Since the coding patterns on the metasurface directly determine the EM functions, we embed LEDs to intuitively visualize the pattern control in the EBCM verification system (see Additional file 1: Supplementary Note S3). In the visual-beam-scanning scheme, we wish that the operator can direct the EM beam scanning accordingly using EBCM by simply staring at various directions in the sky, as depicted in Fig. 5b. We design a beam-scanning GUI with a sky background in Additional file 1: Fig. S7, and the detailed descriptions are provided in Additional file 1: Supplementary Note S4. We record a video of the visually-controlled beam scanning towards multiple directions, as presented in Additional file 3: Supplementary Movie S2. We envision that this scheme can be further integrated with the augmented reality (AR) technique and finds more applications in adaptive mind-text wireless communications and intelligent radar detections.

Fig. 5



More functions of versatile wavefront syntheses using EBCM. **a** The experiment photograph of the pattern encoding scheme. **b** The illustration of beam scanning by EBCM. The visual-staring of BCI operator directly drives the metasurface to adjust the scattering direction to the desired angle. Each button relates to a specific scattering direction as labelled. **c** Three typical EM functions including beam scanning, OAM-beam generation, and RCS control. **d**–**g** The simulated results of four kinds beam-scanning fields, where the measured result of the main direction is marked with the red cross, as listed in Supplementary Note S6 [36]. The scattering beam is deflected from 0° to 45° along the x-axis. **g**–**j** The simulated field results of RCS control, where '01' to '04' indicate the four levels of reflection intensity. **k**, **l** The far-field simulation results of OAM modes + 1 and + 2. The central null is clearly observedTo realize multiple EM modulations by EBCM, we design a specific interface to show that the operator can directly drive the EBCM for diverse EM functions (see Additional file 1: Supplementary Note S4), including beam deflections, orbital-angular momentum (OAM) beam generations, and radar cross section (RCS) controls, as shown in Fig. 5c. The simulated results of these functions are presented in Fig. 5d–m. For example, we illustrate the result of vertically-reflected single beam generated by the uniform phase pattern in Fig. 5d, and the results of three deflecting angles in Fig. 5e–g, where the simulated data clearly indicate the scattering directions of 15°, 30°, and 45°, suggesting great consistency with the measured directions marked in the red cross. More results are given in Additional file 1: Supplementary Note S5. In the RCS level control, four RCS buttons from '01' to '04' will generate the scattered fields presented in Fig. 5i–l, showing the scattering levels of − 15 dB, − 12 dB, − 9 dB, and − 6 dB, respectively. For the OAM-beam generation, we exhibit two scattered fields of two OAM modes (+1 and +2) in Fig. 5h and m, in which the central amplitude null is clearly observed.

For experimental verification of the multiple EM modulations by EBCM, we recorded the controlling process of three representative EM functions, as shown in Additional file 4: Supplementary Movie S3. The related coding patterns of 10 deflecting directions are given in Additional file 1: Supplementary Note S6. The measured results presented in Additional file 1: Supplementary Note S7 [36] show good agreements with the simulations in visual-beam scanning and multiple EM modulations. The related 30-channel EEG signals are also listed in Additional file 1: Supplementary Note S8 [36], where the P300 waves are successfully captured from the EEG signals when the target button flashes. In addition, we perform the metasurface pattern coding scheme using EBCM. We show that the 2-bit phase coding patterns of the metasurface can be directly input from the brain signals to generate various EM functions. More details are illustrated in Additional file 1: Supplementary Note S9 and Additional file 5: Movie S4.

3 Discussion and conclusion

We present an EBCM platform for direct mind-text wireless communications and diverse EM manipulations under non-invasive brain signals. We establish a new control manner from the operator consciousness to the metasurface pattern and realize EM functions by combining the P300 BCI device and the programmable metasurface. We propose and experimentally verify a wireless text-communication demo to directly transmit information from mind to mind based on EBCM between two operators. We show that the operator no longer needs any muscle-involved actions but only stares at the specific visual button for related sequential stimulus, which can be recognized by the EBCM and translated into the corresponding EM signals for communications. We also demonstrate three typical schemes with distinct functions, including visual beam scanning, multiple EM function switching, and metasurface pattern input, which contains more than 20 coding patterns for different single-beam scanning, multi-beam forming, OAM-beam generation, and RCS control. The presented work, combining the EM wave space and BCI, may further open up a new direction to explore the deep integration of metasurface, human brain intelligence, and artificial intelligence, so as to build up new generations of bio-intelligent metasurface systems.

4 Methods and materials

4.1 The brain signal analysis based on P300 scanning

A 40-channel EEG amplifier NuAmps (Compumedics, Neuroscan, Inc., Australis) and a 30-channel EEG cap (LT 37) that followed the extended 10–20 system are used to collect the EEG signals, and the signals are referenced to the right mastoid. All electrode impedances are maintained below 5 kΩ during the data collection. Before manipulating the metasurface, the operator is instructed to perform a calibration stage, during which the EEG signals are collected to build up a training set, which is used to train a model for prediction in online manipulation stage. The calibration stage consists of 30 trials, and each trial consists of 10 rounds of button flashes. In each trial, the operator is instructed to focus on one target button, which is specified by the BCI program rather than freely determined by the operator.

The collected 30-channel EEG signals then undergo the preprocessing and feature extraction processes. Specifically, the EEG signals are firstly bandpass-filtered at 0.5–20 Hz. Then for each button flash (i.e., epoch) in a trial, a segment of EEG signal from 0 to 600 ms after the flash onset is extracted and baseline-corrected with a baseline extracted from the 200 ms before the flash onset. For each flash, the segment of EEG signal is subsequently down-sampled at a rate of 6. Since the sampling rate of the EEG signals is 250 Hz, there are 250 Hz × 600 ms/6 = 25 sampling points for each channel per flash. Last, the segment of each flash is normalized along each channel using z-score normalization. Each obtained segment of signal, for example, segment corresponding to the flash of the *b*-th button in *r*-th round, forms a 30 × 25-dimensional matrix, and all rows of the matrix are concatenated together to form a vector, denoted as $\mathbf{x}_{r,b}$, as the feature vector of this fragment. To improve the signal-to-noise ratio (SNR), we average the feature vectors corresponding to the first *R* rounds of each button in a trial as follows:

$$\bar{x}_{R,b}=\frac{1}{R}\sum_{r=1}^{R}x_{r,b} \quad (1)$$

For each trial, a segment is labeled as a positive one if and only if the corresponding button is the target of the current trial, which indicates the presence of the P300 potential.

For each trial of the calibration data, we average the feature vectors over all the 10 rounds as in Eq. (1) to build up the training set, which is subsequently used to train a Bayesian linear regression model to decode the EEG segments, i.e., to distinguish the segments between with and without the presence of P300 potential.

In the online manipulation stage, to achieve a better balance between the accuracy and the speed of giving commands, the number of flash rounds is determined adaptively according to the confidence in making a decision. Similar to the calibration stage, the real-time collected EEG signals undergo the preprocessing and feature extraction processes to obtain feature vectors. After each round of button flashes, i.e., different values of *R*, the feature vectors are averaged as in Eq. (1). The averaged feature vectors corresponding to different commands are respectively fed into the trained decoder, and the outputs of the decoder are regarded as the confidence scores of the presence of P300 potential. When the score difference between the command with the highest score and the command with the second highest score is greater than a preset threshold (0.2 in this study), the command with the maximum score is sent; otherwise, the BCI proceeds to the next round of button flashes until the score difference reaches the threshold, or the number of flash rounds reaches the upper limit (10 rounds in this study).

4.2 The coding and decoding methods on text communications

In the text communication scheme, once the text from the operator's brain signal is detected by the BCI device, the FPGA should receive the text through the serial port and produce a binary sequence based on the ASCII code of the character. Taking character 'A' for example, the final coding sequence, composed of the frame header and the ASCII code of 'A', is encoded as '1111111000000001000001'. This coding sequence is also the switching sequence for FPGA, in which '0' and '1' respectively are the pattern for low and high reflection intensity. Here we employ an RCS reduction pattern and a single beam pattern as '0' and '1'. FPGA always monitors the serial port and switches the metasurface patterns for one sequence period when receiving a letter.

In the receiving part, the microstrip antenna integrated around metasurface undertakes the receiver to detect the transmitted energy. The coupled energy is firstly amplified by an LNA and sent into a detector with high accuracy. The detector performs sampling at 10 times the frequency of the modulator to recover the transmitted signals. The detected voltage is converted into digital within an ADC and then processed by a receiving FPGA. According to our coding rules, the decoded text is finally displayed on the screen of the operator B.

4.3 EM experiment configurations

The EM measurements are performed in a standard microwave chamber room, including the beam deflections, RCS reductions, and OAM-beam generations. The far-field measurement system consists of a rotatable table, two standard horn antennas, a signal generator (Keysight E8267D), a spectrum analyzer (Keysight E4447A), and an LNA. The feeding horn and the metasurface sample are both fixed on the rotatable table for far-field tests. In measuring the OAM phase distribution, the measurement is performed in a near-field measurement system, which is composed of a two-dimensional scanning frame, a vector network analyzer (Agilent N5230C), a probe and an LNA. In the communication scheme, a signal generating module (LMX 2594) and an LNA is applied to excite the metasurface. The receiving detector samples at the frequency of 10 MHz. It should be noted that the experimental verification of the EBCM control and the EM function modulation is not performed together in the chamber room since the BCI device and operator have interference to the EM measurement.

Supplementary Information

Additional file 1.

Supplementary information.

Additional file 2. The wireless text-communication process is presented in this movie. The transmission of five letters 'HELLO' are exhibited. The last received letter is shown on the receiver's screen.

Additional file 3. The visual beam-scanning experiment is presented in this movie. The operator directly achieves the desired beam-scanning direction by visually staring at the specific direction. The executed coding pattern for the related beam-scanning direction is exhibited on the LED-version metasurface after the EBCM detects the operator's EEG. Four typical patterns are shown in this movie.

Additional file 4. The versatile wavefront synthesis of five typical EM functions within the EBCM is presented in this movie, including one RCS reduction, two beam-deflections and two OAM beams. The related coding pattern is displayed on the metasurface after the EEG detection.

Additional file 5. The pattern encoding process with EBCM is presented in this movie. The operator inputs the desired code by staring the specific button. The inputted codes that detected by EBCM are displayed on the screen with yellow blocks. The last code 'C4' is a stop instruction to end the encoding process and command FPGA calculate the final coding pattern. After that, the EBCM executes the calculated coding pattern, as exhibited on the LED-version metasurface.

Technological Advancements in Brain-Computer Interfaces (BCIs): Translating Thoughts into Text

The domain of Brain-Computer Interfaces (BCIs) has witnessed groundbreaking advancements, especially in translating human thoughts into text. This article delves into the latest developments in this field, with a particular focus on non-invasive techniques that are reshaping communication paradigms.
In recent years, the convergence of neuroscience and artificial intelligence has propelled BCIs to the forefront of technological innovation. These interfaces have transcended the realm of science fiction, becoming a reality that holds immense promise for humanity.

This article delves into the latest developments in this field, with a particular focus on non-invasive techniques that are reshaping communication paradigms. As we explore the remarkable journey of Brain-Computer Interfaces(BCIs), we will uncover the transformative power they hold in enabling individuals to communicate, interact, and express themselves in ways previously unimaginable.

The Evolution of Brain-Computer Interfaces(BCIs)

The Evolution of BCIs has been nothing short of extraordinary, reflecting the relentless pursuit of enhancing human-machine communication. In its early stages, BCIs primarily relied on invasive methods that necessitated surgical implants. These pioneering efforts laid the foundation for what was to come, with early examples such as cochlear implants proving to be a lifeline for individuals with hearing loss. However, the invasive nature of these technologies presented limitations and risks.

In recent years, a remarkable shift has occurred in the field of Brain-Computer Interfaces(BCIs), marking a pivotal moment in their development. A significant Transition to Non-Invasive Methods has taken place, driven by advances in sensor technology and our growing understanding of brain signals. Non-invasive BCIs have emerged as a game-changer, eliminating the need for surgical interventions. Instead, they utilize external devices like EEG caps, which are placed on the scalp to capture neural signals. This transition has democratized access to BCIs, making them more accessible and less intimidating for users.

The move towards non-invasive Brain-Computer Interfaces(BCIs) represents a fundamental shift in the field, opening up new avenues for research, development, and application. As we explore the latest developments in non-invasive BCIs, it becomes evident that these technologies are not only reshaping communication paradigms but also fostering a more inclusive and user-friendly approach to human-computer interaction.

Non-Invasive Techniques

Electroencephalography (EEG): Electroencephalography (EEG) has emerged as a cornerstone in the field of Brain-Computer Interfaces (BCIs). These EEG-based Brain-Computer Interfaces(BCIs) operate by recording the electrical activity of the brain through electrodes strategically placed on the scalp. The electrodes pick up the faint electrical signals generated by neurons firing in the brain, and this data is then processed and analyzed by advanced algorithms. What makes EEG-based BCIs particularly remarkable is their non-invasive nature, as they eliminate the need for surgical procedures or implants, making them accessible to a wider range of users.

Functional Near-Infrared Spectroscopy (fNIRS): Functional Near-Infrared Spectroscopy (fNIRS) stands as a promising and emerging technique in the ever-evolving landscape of Brain-Computer Interfaces (BCIs). Unlike traditional BCIs that rely on electrodes placed on the scalp, fNIRS takes a different approach to measuring brain activity. This innovative method detects changes in blood flow in the brain by employing near-infrared light. When neurons in the brain become active, they require more oxygen, leading to increased blood flow to that region. fNIRS capitalizes on this physiological response, making it a non-invasive yet highly effective tool for monitoring brain activity.

AI Integration in BCIs

Machine Learning Algorithms:

Machine Learning(ML)Algorithms have emerged as the linchpin in the domain of Brain-Computer Interfaces (BCIs), enabling the translation of intricate neural signals into meaningful information. These algorithms are instrumental in decoding the complex language of the brain, offering a bridge between our thoughts and external communication. What makes them particularly remarkable is their capacity to discern subtle differences in neural patterns associated with various words or thoughts.

Imagine a scenario where an individual’s thoughts are translated into text or speech with remarkable accuracy. This feat is made possible by the capability of machine learning algorithms to distinguish between distinct neural patterns. For instance, these algorithms can identify the unique brain activity associated with thinking about different words or concepts. This means that, in practical terms, a BCI user can think about a word like “apple,” and the algorithm can recognize the corresponding neural signature, converting it into written text or audible speech.

Real-Time Processing:

Real-Time Processing powered by advanced AI marks a pivotal advancement in Brain-Computer Interfaces (BCIs), revolutionizing the way individuals with speech impairments communicate. This cutting-edge technology has the transformative capability to instantaneously translate thoughts into text or speech, offering a lifeline to those who have faced barriers to effective communication. One notable example that showcases the power of real-time processing is the groundbreaking work of researchers at Stanford University. They developed an AI system that, when coupled with Brain-Computer Interfaces(BCIs), enabled a paralyzed individual to communicate with remarkable effectiveness.

Imagine the profound impact of this technology on someone unable to speak due to paralysis or other speech-limiting conditions. With real-time processing, the delay between forming a thought and expressing it is virtually eliminated. As the user thinks, the AI system rapidly translates their thoughts into spoken words or written text, allowing for fluid and natural communication. This achievement not only enhances the quality of life for individuals facing speech impairments but also empowers them to engage more fully in social interactions, express their desires and needs, and participate actively in various aspects of life.

Breakthroughs in Thought-to-Text Translation

Case Studies: A Transformative Milestone
One of the most remarkable and transformative breakthroughs in the field of Brain-Computer Interfaces (BCIs) has been the successful demonstration of thought-to-text translation in individuals with severe speech impediments. These groundbreaking case studies have exemplified the potential of BCIs to profoundly impact the lives of those facing significant communication challenges. By providing individuals with a means to translate their thoughts directly into written text or spoken words, BCIs have effectively dismantled barriers to expression.

In several notable cases, individuals with conditions such as amyotrophic lateral sclerosis (ALS) or complete paralysis have been able to communicate fluently and effectively using BCIs. These case studies serve as powerful testaments to the capabilities of BCIs and the life-changing opportunities they offer to those in need. Moreover, they highlight the collaborative efforts of researchers, engineers, and individuals with disabilities, underscoring the importance of innovation and inclusivity in the development of assistive technologies.

Accuracy and Speed: Advancing Practicality and User-Friendliness
Another critical dimension of breakthroughs in thought-to-text translation lies in the continuous improvements in accuracy and speed. In the early stages of BCI development, accuracy could be a limiting factor, causing frustration for users attempting to convey their thoughts accurately. However, through relentless research and innovation, BCIs have seen substantial enhancements in their ability to precisely interpret neural signals and convert them into coherent text or speech. This increase in accuracy not only reduces errors but also boosts user confidence and satisfaction. Furthermore, Brain-Computer Interfaces(BCIs) have made significant strides in terms of speed, allowing for a more natural and seamless flow of communication.

The faster translation of thoughts into text or speech has made these systems more practical and user-friendly in real-world scenarios. Users can now engage in dynamic conversations, express their thoughts swiftly, and keep pace with the rapid exchanges of everyday communication. These advancements have not only improved the quality of life for individuals with speech impairments but have also expanded the potential applications of BCIs in various professional, social, and educational contexts.

Applications and Impact

Medical Applications: Medical Applications of Brain-Computer Interfaces (BCIs) represent a beacon of hope for individuals facing the challenges of stroke recovery and neurodegenerative diseases. BCIs have emerged as powerful tools in the field of rehabilitation, offering innovative solutions to address motor and communication impairments. For stroke victims, BCIs hold the promise of aiding in the recovery process by facilitating neuroplasticity and motor skill reacquisition. By allowing individuals to control external devices or prosthetics through neural signals, BCIs enable stroke survivors to regain mobility and independence.

Moreover, for individuals grappling with neurodegenerative diseases such as Parkinson's or amyotrophic lateral sclerosis (ALS), BCIs offer a lifeline by providing a means of communication when traditional methods fail. These medical applications signify a profound shift in how we approach rehabilitation and care for those with neurological conditions. BCIs not only enhance the quality of life for patients but also pave the way for personalized and effective therapeutic interventions, bringing new hope to those on the journey toward recovery and improved well-being.

Enhancing Communication: Enhancing Communication for individuals grappling with conditions like Amyotrophic Lateral Sclerosis (ALS) represents one of the most profound and life-changing applications of Brain-Computer Interfaces (BCIs). ALS is a devastating disease that gradually robs individuals of their ability to move, speak, and communicate. In the face of such challenges, BCIs emerge as beacons of hope. By translating thoughts into text or speech, BCIs effectively dismantle the communication barriers that ALS imposes. These individuals, often trapped within their bodies, can now express their thoughts, feelings, and needs with remarkable fluency and precision.

The transformative impact of BCIs in this context cannot be overstated; they offer a lifeline of connection to the outside world, enabling individuals to engage in conversations, make choices, and regain a sense of agency and independence. The ability to communicate effectively is not merely a convenience but a fundamental human right, and BCIs are revolutionizing the landscape for individuals who have long yearned for a means to express themselves and connect with their loved ones, caregivers, and the world at large.

Challenges and Future Directions

Ethical and Privacy Concerns: As Brain-Computer Interfaces(BCIs) become more advanced, they raise important questions about privacy and the ethical use of thought data.
Technological Limitations: Current limitations include the need for more accurate and faster interpretation of complex neural signals.
Future Innovations: Ongoing research focuses on enhancing the portability, affordability, and user-friendliness of BCIs.

Conclusion

The advancements in non-invasive Brain-Computer Interfaces(BCIs), especially in translating thoughts into text, mark a significant leap in technology and healthcare. As we continue to refine these interfaces, they promise not only to revolutionize communication for those with impairments but also to offer profound insights into the workings of the human brain. The future of BCIs holds limitless potential, bridging gaps between the human mind and the external world through the power of technology.

State-of-the-Art on Brain-Computer Interface Technology

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Abstract

This paper provides a comprehensive overview of the state-of-the-art in brain–computer interfaces (BCI). It begins by providing an introduction to BCIs, describing their main operation principles and most widely used platforms. The paper then examines the various components of a BCI system, such as hardware, software, and signal processing algorithms. Finally, it looks at current trends in research related to BCI use for medical, educational, and other purposes, as well as potential future applications of this technology. The paper concludes by highlighting some key challenges that still need to be addressed before widespread adoption can occur. By presenting an up-to-date assessment of the state-of-the-art in BCI technology, this paper will provide valuable insight into where this field is heading in terms of progress and innovation.

1. Introduction

Brain–computer interfaces (BCIs) are a rapidly evolving technology that has the potential to revolutionize how humans interact with computers [1,2,3,4]. BCIs measure brain activity and translate it into commands for a computer or other device, allowing users to control machines and devices using only their thoughts. Neurogadgets, ranging from moving robotic spiders and balls to more practical applications, are increasingly being used for entertainment purposes. However, what is more important is that neurogadgets are also being developed to assist people with disabilities, such as those with paralysis of the limbs [5,6,7,8,9,10].

BCIs are typically divided into unidirectional and bidirectional categories based on the direction of their action. Unidirectional BCIs either receive signals from the brain or send them to it, while bidirectional BCIs allow for information exchange in both directions, enabling control of external devices by the brain.

Research into feedback methods is ongoing, with the aim of developing technologies that can transform external commands into electrical signals transmitted via the nervous system. For instance, it could be used to enable electrical stimulation of leg muscles in people with spinal cord injuries, allowing them to regain mobility by controlling their movements through a tablet device [11].

The utilization of neural networks and other learning algorithms in signal processing is commonplace, as brain activity varies between individuals. Consequently, these systems require lengthy training sessions to enable the BCI to accurately interpret commands from a particular user. The duration of the training depends on the number of commands received by BCI.

While this technology is still in its early stages of development, recent advances have shown great promise for applications ranging from medical rehabilitation to gaming and entertainment. This paper will provide an overview of the current state-of-the-art in BCI technologies, discussing various platforms, techniques, and applications currently being explored.

2. Platforms

The operation of the interface is typically structured in this manner: electrodes detect brain signals, which are then processed by an BCI microcontroller to remove any noise or artifacts caused by both external and device-specific factors. Subsequently, the obtained signal is analyzed to identify the corresponding command; artificial neural networks are often utilized for this purpose due to their high data processing and adaptation capabilities.

The detected command is usually sent to an external device for further processing according to a pre-programmed algorithm, although highly specialized systems may assume this task themselves. Ultimately, the received command is interpreted as per its specific characteristics on the controlled device (**Figure 1**). The principles underlying BCI operation are described in [12,13,14,15].

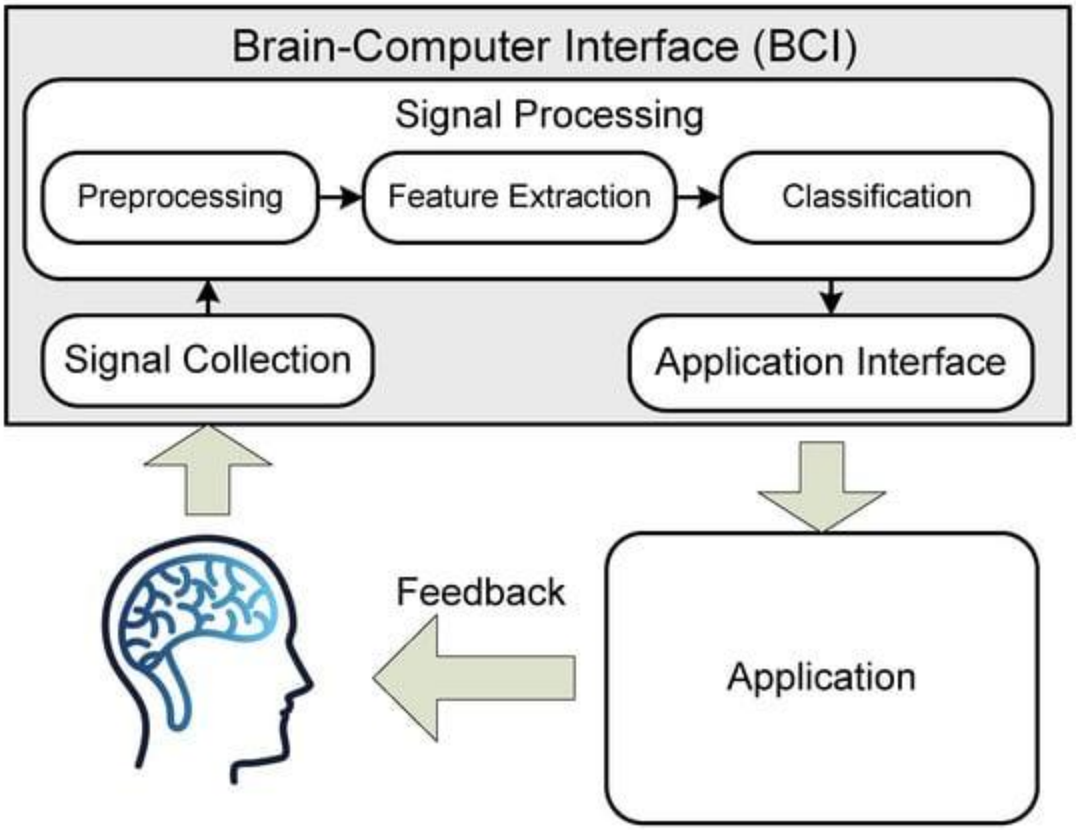

Figure 1. BCI operation principle.

According to the degree of invasiveness, neural interfaces are divided into three categories: invasive, non-invasive, and semi-invasive. Invasive neural interfaces require direct implantation of intracortical microelectrodes (IM) into the human brain, providing the highest efficacy but posing a greater risk. Non-invasive neural interfaces analyze brain activity from the surface of the head by using electroencephalography (EEG), magnetoencephalography (MEG), or functional magnetic resonance imaging without implanting electrodes. Semi-invasive BCIs have electrodes located under the skull bone on the surface of the brain, such as electrocorticography (ECoG) (**Figure 2**).

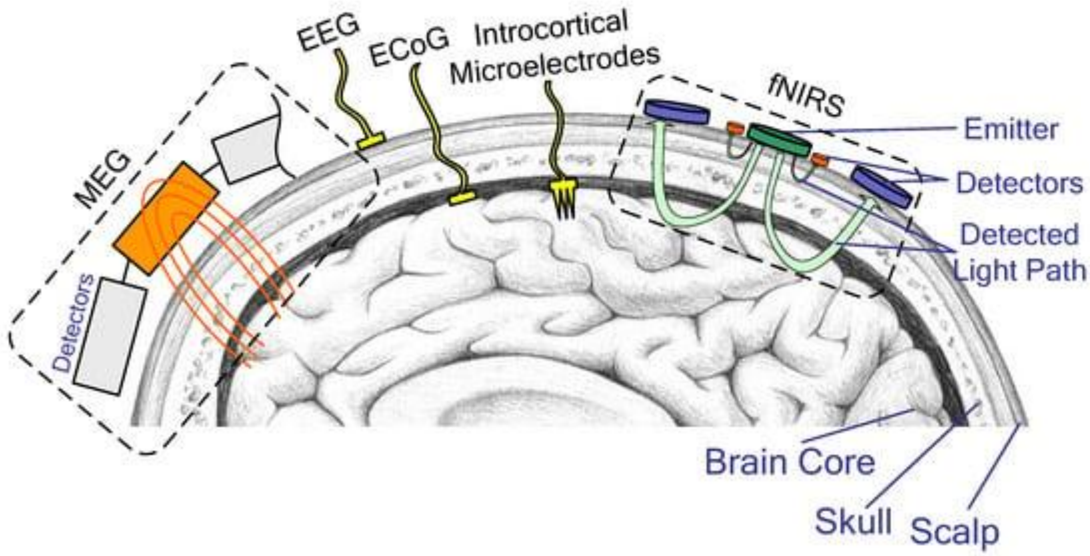

Figure 2. BCI sensor mounting types: invasive (IM), semi-invasive (ECoG), and non-invasive (MEG, EEG, fNIRS).

At present, invasive and semi-invasive neurointerfaces are mainly utilized in medical contexts to enhance the wellbeing of individuals with disabilities. Additionally, these devices are also being used to correct and prevent a variety of diseases. On the other hand, non-invasive neural interfaces have been gaining traction in the gaming industry [16,17,18,19]. As more types of neurogadgets become available, it is possible that this sector will experience a revolution. It is envisaged that smartphones may be able to record human thoughts in the foreseeable future; research into this area has been ongoing [20,21].

The most common platform used for BCI research is electroencephalography [22,23,24,25,26]. EEG measures electrical signals produced by neurons within the brain through electrodes placed on the scalp, providing researchers with detailed information about neural activity associated with different cognitive functions. Other platforms commonly used include functional near-infrared spectroscopy (fNIRS) [27,28,29,30,31,32,33], magnetoencephalography [34,35,36], and electrocorticography [37,38,39]. These methods measure different types of neural signals than EEG but can still be useful in developing effective BCI systems due to their higher temporal resolution or ability to detect deeper sources of brain activity.

All these platforms have their own pros and cons, which are analyzed below.

2.1. EEG Platform

The electroencephalogram is a widely used tool for monitoring electrical activity in the brain. EEG signals, which are a visual representation of the frequency activity of the human brain [40,41], are commonly used as inputs for BCI systems. It has been used to diagnose and treat neurological diseases, monitor sleep patterns, and study cognitive processes such as attention and memory. In recent years, advances in technology have enabled the development of EEG sensors that are smaller, more accurate, and easier to use than ever before. Due to its non-invasive data collection principle and relatively simple signal interpretation, this platform is one of the most commonly used BCI techniques nowadays.

EEG sensors measure electrical activity produced by neurons in the brain using electrodes placed on the scalp or other parts of the body. By monitoring this activity over time, clinicians can detect changes associated with different mental states, such as sleep or alertness. Additionally, certain types of abnormal brain activity can be detected through EEG readings; these may include seizures or evidence of stroke-related damage. The data collected from EEG recordings can also be analyzed to assess cognitive abilities such as attention span or memory recall speed.

Figure 3 illustrates that there are four distinct "rhythms" of the human brain, which can be categorized based on their frequency: δ delta (0.1–4 Hz), θ theta (4–7.5 Hz), α alpha (7.5–12 Hz), β beta (12–30 Hz), and γ gamma (over 30 Hz). It is important to note that these rhythms differ in amplitude as well as frequency.

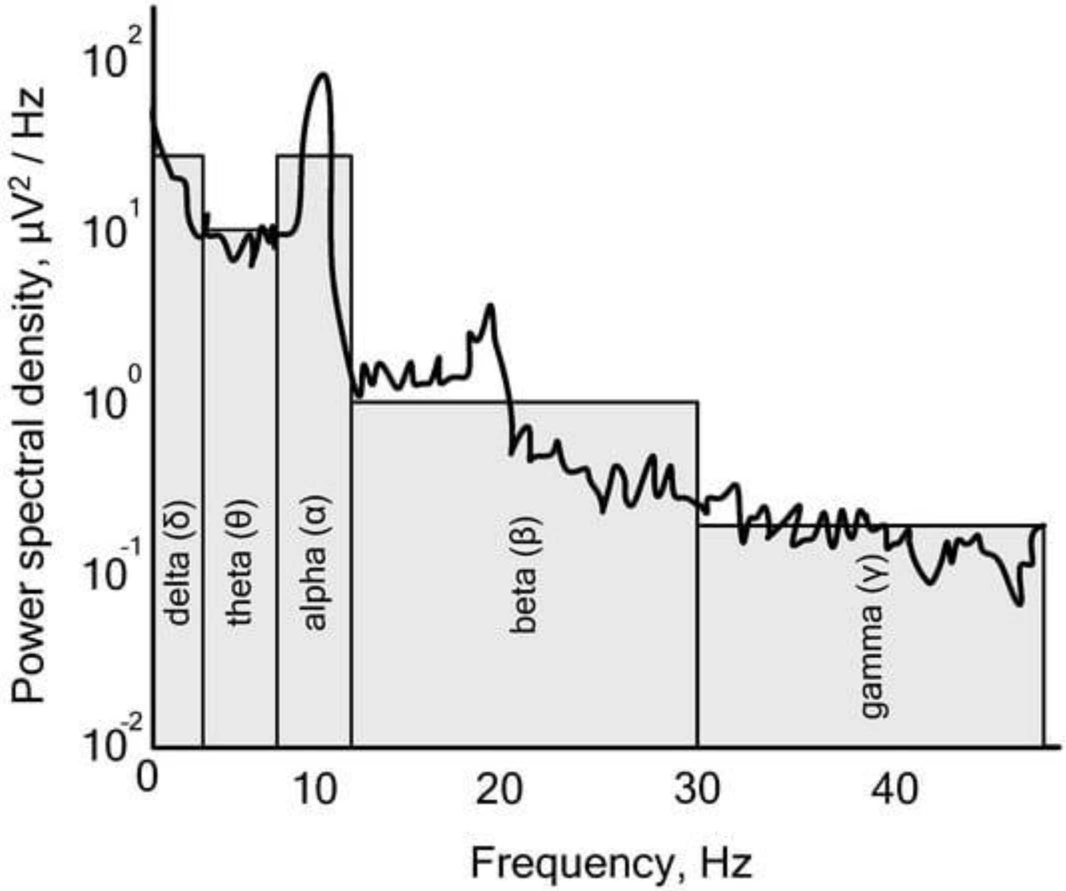

Figure 3. An example of the frequency spectrum of a human brain electroencephalogram.

Recent advances in EEG sensor technology have made them smaller, lighter, and cheaper than ever before while still providing high levels of accuracy and reliability when compared to traditional systems [25,26,42]. Moreover, newer systems often make use of dry electrode designs, which eliminate the need for conductive gels that were previously required for proper functioning [43,44,45,46,47]. Furthermore, many new portable devices exist now that allow users to easily record their own EEG signals without having to visit a clinic [9,48,49,50,51]. These devices typically employ Bluetooth connectivity so that they can transmit their data wirelessly directly to computers for analysis. Recent advancements have also led to improvements in signal processing algorithms, which enable better detection and analysis techniques [52,53,54]. For example, it is now possible to detect subtle changes within short periods of time, leading to improved diagnosis capabilities. Additionally, some algorithms are able to identify distinct features within each individual's recordings, allowing personalized treatment approaches [55,56]. Finally, artificial intelligence techniques are being explored that could help automate certain aspects of processing raw data, resulting in faster diagnostic times [57,58,59,60].

The overall quality of an EEG signal is affected by both the quantity and placement of electrodes. Increasing the electrode count can improve spatial resolution, allowing for more detailed analysis. Additionally, a greater number of electrodes allows for better noise reduction techniques such as averaging or interpolation. However, increasing electrode count also increases the cost and complexity associated with recording equipment; thus, it is important to consider tradeoffs between benefits in accuracy versus the burden imposed by additional hardware requirements when choosing an optimal sensor configuration.

In addition to overall quantity, positioning plays a critical role in determining signal quality during EEG recordings. Different positions provide varying levels of information about different parts of the brain; therefore, careful consideration must be taken when selecting which sites should be used for data acquisition. Furthermore, differences in skull thickness across individuals may require adjustments from standard placements due to potential changes in impedance at various locations relative to one another. It is also important that all channels are placed symmetrically with respect to each other so that any artifacts generated from movement will cancel out. Finally, proper reference placement is necessary since it serves as a "ground" against which all other signals can be compared. The effectiveness of an EEG system relies heavily on the selection, number, and arrangement/placement of the sensors being used. Careful consideration must be given to these factors so that optimal results can be achieved while minimizing costs associated with hardware requirements. With advances in technology continuing apace, it will become increasingly possible to optimize sensor configurations, further improving BCI performance capabilities over time.

2.2. Other Platforms

Functional near-infrared spectroscopy is a non-invasive brain imaging technique that uses light to measure changes in the concentration of oxygenated and deoxygenated hemoglobin in the brain [28,30,31,33,61]. fNIRS can be used to measure both regional and global activity in the cortex, allowing for real-time monitoring of neural activity. The technology has been applied to BCI applications such as motor imagery, language processing, affective state recognition, and EEG/ERP source localization. As with EEG, the number and arrangement of sensors are important considerations. If too few sensors are used, then not enough information may be collected to accurately assess brain activity; conversely, if too many sensors are employed, they may interfere with each other or saturate certain areas due to excessive light intensity. The placement and orientation of each sensor must be carefully considered so that it is able to detect meaningful signals from its target area without being overly influenced by nearby sources. Placing one sensor too close to another could lead to interference between them or cause one sensor's signal strength to dominate over another's. Furthermore, depending on the type of task being performed during an experiment, there may be different requirements regarding how many channels should be monitored at once as well as where those channels should be located relative to each other. Therefore, careful consideration must go into deciding how many channels should be included in any given experiment and where they should be best placed in order to ensure accurate data collection while avoiding unnecessary noise or saturation effects.

Magnetoencephalography is a non-invasive brain imaging technique that measures magnetic fields generated by electrical currents inside neurons [12,35,36,62,63]. It provides high temporal resolution with excellent spatial accuracy and can be used to track changes in neural activity related to cognitive processes such as attention or memory formation over time. MEG has been used for auditory BCI research but also shows potential for visual BCIs as well as multimodal approaches combining MEG with other modalities such as EEG or fMRI. One of the important factors affecting signal resolution is sensor density: more sensors mean more accurate localization of neural activity within the brain, allowing better control over output devices such as robotic limbs or computer cursors. Increasing sensor density above 30–50 sensors per cm^3 can significantly improve spatial resolution and accuracy when compared to lower densities. However, this must be balanced against increased costs associated with higher numbers of sensors as well as any potential interference between closely spaced elements due to mutual inductance. In addition to sensor density, placement also plays an important role in determining signal fidelity. Ideally, each individual's head should be modeled before placing electrodes so that they are optimally positioned based on their unique anatomy. Furthermore, optimal placement may vary depending on what type of information one wants to extract from recorded data. For example, if one wishes to study motor cortex activation, it would make sense to place electrodes near primary motor areas, while studying visual cortex activation might require different locations. Using multiple layers of overlapping grids can help reduce noise levels caused by external sources such as power lines or electronic equipment, although further research into this area is still needed before definitive conclusions can be drawn about its efficacy.

Electrocorticography is an invasive brain imaging technique that records electrical signals from the surface of the cerebral cortex directly through implanted electrodes placed on top of the cortical surface [**38**,**39**,**64**,**65**]. ECoG offers high temporal resolution (~milliseconds), excellent signal quality, very low noise levels, and direct access to underlying neuronal sources, which makes it particularly suitable for decoding complex mental states such as speech production or intention decoding from motor areas. However, due to its invasive nature, this method requires surgery, which limits its widespread use outside clinical settings. As well as with previously described platforms, increasing the total number of ECoG electrodes generally improves the overall accuracy rate across all task types, regardless of whether they are placed at random locations or at regular intervals around the cortex. However, accuracy rates do not improve significantly when more than eight regularly distributed electrodes are used. Furthermore, even though traditional EEG systems have higher overall accuracy rates than any individual ECoG setup due to their greater electrode coverage area, they are still outperformed by some smaller-scale ECoG setups under certain conditions—particularly when dealing with multi-task classifications involving complex patterns such as visual stimuli recognition.

2.3. BCI Platforms Comparison

Based on the provided analysis, we can draw the following conclusions.

EEG is a non-invasive technique that measures electrical activity in the brain via electrodes placed on the scalp. It has good temporal resolution, allowing it to detect changes in neural activity within milliseconds. EEG is relatively inexpensive and portable, making it well suited for use in BCI systems. EEG's key issues are the following:

- Signal quality: EEG signals are highly sensitive to noise and artifacts, so it is important to ensure that the signal quality is optimal for BCI applications;
- Feature extraction: the ability to accurately extract meaningful information from raw EEG data is a key issue in BCI research as this determines how effective the system will be at recognizing user intentions and commands;
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- Classification accuracy: designing efficient algorithms for classifying EEG signals into different categories (e.g., left vs. right hand movement) is an important issue in BCI research as it determines how well the system can recognize user commands or intentions.
- User interface design: designing user interfaces that are intuitive and easy to use is an important issue in EEG-based BCIs as it can determine how easily users can interact with the system;
- Adaptability: developing algorithms that can adapt to individual users' brain activity and recognize subtle changes in EEG patterns is an important research topic for creating robust BCI systems;
- System reliability: ensuring reliable performance of a BCI system over long periods of time with minimal calibration or setup requirements is an important challenge in EEG-based BCIs due to the dynamic nature of brain activity and its variability across users and sessions.

fNIRS uses light to measure changes in oxygenated hemoglobin levels associated with neural activity. fNIRS offers excellent spatial resolution and can be used to monitor multiple areas of the brain simultaneously, but its temporal resolution is limited compared to other techniques such as EEG. The key issues of the fNIRS platform are the following:

- Signal quality: fNIRS signals are relatively weak and affected by noise, making it difficult to accurately detect changes in brain activity;
- Spatial resolution: the spatial resolution of fNIRS is limited due to the limited number of sources and detectors, which may lead to incorrect interpretations of the data;
- Temporal resolution: fNIRS has a relatively slow response time compared with other BCI modalities such as EEG or MEG, meaning that more complex cognitive tasks may not be suitable for this technology;
- Cost: while fNIRS systems are becoming increasingly affordable, they remain significantly more expensive than EEG or MEG systems and require specialized training in their use and interpretation of results;
- Safety: fNIRS systems operate by sending light into the head, which could potentially lead to eye damage if not used correctly.

MEG is an imaging technique that records magnetic fields produced by electrical activity inside the brain using superconducting sensors placed outside of the head. MEG provides very high temporal resolution and an excellent signal-to-noise ratio, making it useful for detecting subtle changes in neuronal firing patterns associated with BCI tasks. However, MEG systems are expensive and require specialized hardware not usually found outside research laboratories or hospitals. MEG's key issues are described below:

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- Good signal-to-noise ratio: MEG signals are relatively strong and easy to detect reliably, making them beneficial for BCI applications;
- High cost of equipment: the cost of equipment necessary for MEG is high, limiting its practicality in many settings;
- Limited spatial resolution: the spatial resolution of MEG is limited compared to other imaging technologies such as EEG, making it difficult to accurately map brain activity patterns with a single scan;
- Long acquisition times: the data acquisition times for MEG can be quite long, making it difficult to measure dynamic processes such as those involved in motor control tasks used in BCI systems;
- Head motion artifacts: head motion artifacts can significantly interfere with the accuracy of the recorded signal and lead to false positives or negatives, which could confuse the user's experience with the system or even cause harm if medical decisions were made based on incorrect information from an artifactually contaminated signal.

ECoG involves placing electrodes directly onto the surface of the cortex during neurosurgery procedures such as epilepsy treatment or tumor removal operations. ECoG has excellent temporal and spatial resolutions due to its direct contact with cortical neurons; however, this comes at a cost—invasive surgery carries risks such as infection or bleeding, which may outweigh any potential benefits from using ECoG for BCI applications. Key issues with the ECoG platform are listed below:

- Signal acquisition: ECoG signals have relatively low amplitudes and might contain a certain degree of noise; therefore, reliable signal acquisition is essential for successful BCI applications;
- Data interpretation: properly interpreting the data collected from ECoG recordings can be challenging due to the complexity of neural activity as well as the need to distinguish between different types of brain activity (e.g., motor vs. non-motor);
- Safety concerns: since ECoG involves implanting electrodes directly onto the surface of the brain, there are potential safety risks that must be taken into consideration when designing an ECoG-based BCI system;
- Ethical considerations: the ethical implications associated with using invasive technology such as ECoG must also be considered when developing a BCI system for clinical use or research purposes.

Pros and cons for each technology are presented in **Table 1**.

Table 1. BCI platforms pros and cons.

The choice of a platform depends on several factors, such as the research goals, cost of equipment, patient comfort level, etc. EEG is widely used due to its low cost and portability. It has good temporal resolution but lacks spatial resolution, making it less suitable for some applications. fNIRS offers a non-invasive option with higher spatial resolution than EEG but lower temporal resolution. MEG offers excellent temporal and spatial resolutions with high accuracy; however, it comes at a much higher cost compared to other platforms. ECoG provides very high temporal and spatial resolutions but requires invasive surgery for the implantation of electrodes, which limits its use to certain clinical scenarios.

EEG is the most commonly used BCI platform in practice because of its relatively low cost, easy setup, and portability compared to the other mentioned platforms. Additionally, EEG provides excellent temporal resolution and can detect brain signals with millisecond accuracy. This makes it an ideal choice for real-time feedback systems such as those used in motor imagery or P300 speller implementations. In addition, this technique does not require any invasive procedures or radiation exposure, so it can be safely used on a wide variety of users, including children or elderly people who may have difficulty tolerating more intrusive monitoring methods.

The choice of BCI platform should be based on the research goals and other considerations such as cost of equipment or patient comfort level, rather than assuming one platform is better than another in general terms.

3. Classical Paradigms in BCI Systems

The most common types of BCIs are based on classical paradigms such as P300, steady-state visual evoked potentials (SSVEP), and motor imagery (MI).

The P300 paradigm uses EEG recordings from the scalp electrodes to measure event-related potentials generated when a user recognizes an important stimulus in a series of stimuli presented on a computer screen. It is one of the oldest BCI paradigms, developed in the 1980s [66]. It uses electrical signals from the brain to detect when a user is focusing on a particular stimulus or event. When this happens, an EEG signal called the P300 wave appears around 300 milliseconds after the event occurs. This wave can be used to measure how interested or involved someone is in what they are seeing or experiencing, and it can be used as input for BCIs. When presented with multiple stimuli on a computer screen, users typically respond more quickly when they recognize one particular target stimulus among them. This reaction time difference generates an EEG signal known as the P300 waveform, which can then be detected using scalp electrodes placed over different regions of the head. By monitoring this signal over time, it is possible to detect which stimuli were recognized by the user and thus infer their intentions. The P300 paradigm has a wide range of applications, ranging from medical rehabilitation, helping disabled patients regain movement through robotic prosthetics, to assistive communication, helping those who cannot speak communicate via text messages, security authentication, verifying identity without needing passwords, gaming, enhancing interactive experiences through mental commands, and cognitive assessment, evaluating patients mental states such as attention span and fatigue levels.

Steady-state visual evoked potentials (SSVEPs) utilize flicker frequencies, which present monitors generate periodic EEG patterns that correlate directly with the user’s gaze direction towards specific target screens [67]. By presenting rapidly changing colored squares in various locations of the display monitor, participants were instructed to focus their gaze onto each square in order to elicit a unique neural signature corresponding to the frequency of light being emitted from the object, thus allowing researchers to accurately track their eye movements around the environment without the need for any additional hardware equipment, such as cameras, or tracking their head movements manually. Furthermore, because flickering lights tend to remain visible longer than typical flashes, human eyes become accustomed to their frequency, easily reducing the possibility of errors arising from distractions outside the scope of the experimenter's control while also increasing the maximum allowable response speed significantly compared to alternative methods such as P300. SSVEPs prove highly useful in a diverse range of fields, particularly ones involving virtual reality simulations, industrial robotics, advanced gaming technologies, artificial intelligence research, automated surveillance, biological engineering, etc. All benefiting greatly from improved response times, increased bandwidth, and offered protocols, along with the robustness factor brought to the table thanks to the simple yet reliable design structure operating behind the scenes. Other areas include, but are not limited to, medical diagnostics, psychological analysis, military operations, environmental monitoring, etc.

Motor imagery (MI) is a BCI paradigm where users are asked to imagine themselves performing certain movements without actually moving any body parts [68]. This type of system relies on EEG recordings from the scalp electrodes to measure changes in electrical activity within the brain that occur when a user imagines making specific motor actions. These changes can then be used to infer the intentions of the user and allow them to control external systems with just their thoughts. MI has been used for applications such as controlling wheelchairs, robotic arms, or other prosthetic devices, but it has also been applied in more novel ways, such as allowing people to play computer games using only their mind and even allowing paralyzed individuals to communicate by spelling out words letter-by-letter using mental commands alone. MI still has a wide range of uses today, including medical rehabilitation, helping patients regain lost limb functions through artificial prosthetics, gaming, enhancing interactive experiences through thought-controlled commands, communication aiding those who cannot speak via text messages, security authentication verifying identity without passwords, cognitive assessment evaluating patients mental states such as attention span fatigue levels, and finally, robotics, providing new ways to control machines remotely utilizing only brain power.

Advantages and disadvantages of these classical paradigms are summarized in Table 2.

Table 2. BCI classical paradigms pros and cons.

4. BCI Signal Processing Techniques

A variety of signal processing techniques are employed when constructing a BCI system, including feature extraction algorithms such as independent component analysis (ICA), wavelet transformations, and autoregressive modeling; classification algorithms such as support vector machines (SVM); pattern recognition approaches such as hidden Markov models; machine learning models such as artificial neural networks; and optimization methods such as genetic algorithms or particle swarm optimization.

A key component of BCI's signal processing is synchronization and asynchronization, which are methods used to establish a connection between the user's brain signals and the computer system. Synchronization involves establishing an exact match between two signals, while asynchronization involves allowing for some variation in timing.

Synchronization is typically used when there is an exact time relationship required between two events or signals; this ensures that all data collected by one device is accurately transferred to another device at exactly the same moment it was acquired from its source. This type of synchronization requires precise timing control over both devices so that they remain synchronized throughout the duration of the data transfer. To achieve this level of accuracy, certain hardware components, such as clocks, must be employed to ensure accuracy over long periods of time without drift occurring due to environmental factors such as temperature changes or electrical interference from nearby devices. Synchronized data acquisition has been shown to improve signal detection accuracy compared to non-synchronized techniques since any temporal differences between acquisitions can be accounted for during analysis [69]. Additionally, synchronizing multiple channels allows EEG measures such as coherence values or event-related potentials (ERPs) to be measured across different electrode sites within each channel.

Asynchronous operations involve allowing some degree of variation in timing. Different from synchronized operations, where two events must happen simultaneously, asynchronous operations do not require absolute precision but rather permit some leeway when it comes to timing discrepancies [70,71]. This type of operation may also include elements such as buffering, which helps reduce latency issues associated with transmitting large amounts of data quickly across networks. Asynchronous methods have been shown to be effective for reducing false alarm rates in BCI applications since they allow more flexibility when dealing with erroneous inputs caused by noise contamination. They also provide better scalability than synchronous approaches since they do not need additional hardware components such as clocks, which can increase cost and complexity. However, asynchronous methods tend not to perform well in situations where real-time responses are essential, thus limiting their usage mainly to offline applications only.

Both synchronous and asynchronous techniques have been successfully applied to various types of BCIs, including motor imagery-based systems, P300 spellers, hybrid systems combining both EEG and EMG features, etc.

Each BCI signal processing technique has its own advantages depending on the application's specific requirements, but all aim to accurately interpret user input from raw sensory data collected by sensors attached directly to the user's head or body.

4.1. ICA Use in BCI Systems

Independent component analysis (ICA) is a powerful statistical technique used to identify and separate independent sources of information from data streams. It can be used in brain–computer interface (BCI) systems to improve the accuracy of EEG signal processing by separating useful signals from noise or artifacts. ICA helps extract meaningful information, such as event-related potentials, which are then further processed for better understanding brain activity patterns during tasks. Additionally, ICA can be used for artifact removal purposes, allowing BCI applications to reduce false-positive detections caused by movement artifacts or other interference signals.

Independent Component Analysis (ICA) has been employed to decompose multichannel datasets into independent components based on certain assumptions [72]:

- The number of independent components must not exceed the number of electrodes used in recording EEG signals;

- Neuronal and artifact sources are considered to be linearly mixed yet independent from each other;
- A negligible signal propagation delay is assumed between brain sources and electrodes.

The objective of ICA is to identify a linear projection that maximizes mutual independence, which can be mathematically expressed as:

$$x(k) = As(k),\ k = 1, 2, 3, \ldots, N, \tag{1}$$

where: $x(k)\in\Re^{M\times 1}x(k)\in\Re^{M\times 1}$ are recorded EEG signals, $s(k)\in\Re^{M\times 1}s(k)\in\Re^{M\times 1}$ are corresponding independent components, $A(k)\in\Re^{M\times M}A(k)\in\Re^{M\times M}$ is unknown M full rank mixing matrix, k—discrete time, and M is the number of electrodes.

Independent components can be represented as

$$s_i(k)=w^T_i x(k),\ k=1, 2, 3, \ldots, N, s_i(k)=w_i^T x(k),\ k=1, 2, 3, \ldots, N, \tag{2}$$

where i is the electrode ordinal number (i = 1, 2, 3, …, M), $w_i w_i$ is the column vector.

After evaluating each w_i, the independent components can be calculated [73] as:

$$s_i(k)=Wx(k),\ W\approx A^{-1}, s_i(k)=Wx(k),\ W\approx A^{-1}. \tag{3}$$

The ICA models utilized by algorithms such as Infomax, JADE, FastICA, and RADICAL assume that the sources of independent components are either non-Gaussian or a single source is Gaussian. These approaches do not consider the temporal structure of the signal or extract components with a Gaussian distribution. To address this limitation, time series-based ICA models implemented in TDSEP/SOBI, and AMUSE can select independent components with a Gaussian distribution [74]. Extended-Infomax ICA has the capacity to remove both super-gaussian artifacts (eye blinks) and sub-gaussian signals (power noise interference), whereas regular Infomax ICA is limited to the removal of super-gaussian artifacts only.

ICA algorithms have been found to have numerous drawbacks, including ambiguity regarding the origin of sources, uncertainty with regards to component dispersion, and dependence on data set size; in particular, ICA algorithms are characterized by inadequate performance when operating on small data sets [75].

4.2. Wavelet Transformations and Autoregressive Modeling in BCI

Wavelet transformations and autoregressive modeling are used in BCI systems to identify patterns in brain signals. The wavelet transform can be used to decompose the EEG data into its frequency components, allowing for an analysis of different frequencies associated with cognitive tasks. Autoregressive modeling uses a linear regression model to estimate the current value of a signal based on past values, which can then be used in conjunction with classification algorithms such as support vector machines or neural networks to detect subtle changes in EEG signals that may indicate certain mental states. Together, these two methods provide powerful tools for understanding how our brains interact with technology and allow us to develop better BCI systems that respond more accurately and effectively to user inputs.

The wavelet transform (WT) is a one-dimensional technique that decomposes an electroencephalographic signal into a set of coefficients representing its similarity with the waveform of a parent wavelet at certain scales. This transformation can be expressed mathematically as selecting a subset of scales (j) and time shifts (k) of the parent wavelet (t):

$$\Psi_{j,k}(t)=2^{j2}\Psi(2^{j}t-k),\Psi j,k(t)=2j2\Psi(2jt-k), \tag{4}$$

where j and k are integers.

The Discrete Wavelet Transform (DWT) is a method for calculating the scaling and detail components of a waveform by low- and high-frequency filtering, where the waveform is discretely sampled in time.

The use of DWT for artifact removal is often achieved through thresholding the decomposed coefficients and reconstructing the remaining signal components, channel by channel [76]. A disadvantage of DWT is that it cannot completely remove artifacts when the spectral properties of the signal being studied overlap with those of the artifacts.

The temporal dispersion, which is the main DWT disadvantage, is eliminated in the stationary wavelet transform (SWT) algorithm, which does not involve downsampling. SWT has been shown to enable the tracing of changes in the harmonic components of EEG signals over time [77].

Regression analysis has been demonstrated to be relatively straightforward to use; however, specific assumptions must be adhered to in order for accurate results [78]. (1) The native EEG signal is a combination of genuine neuronal activity and extraneous activity (an artifact); (2) true neuronal activity and extraneous activity of the EEG signal are uncorrelated; (3) artifacts should not contain components related to brain activity; otherwise, they may be lost during artifact removal.

Regression algorithms necessitate exogenous reference channels (e.g., EOG, ECG) for artifact detection; however, it is challenging to identify the most suitable reference signal for myographic and other non-biological artifacts, hence constricting the use of regression methods for artifact removal.

The use of temporal auto-tuning for EEG signal activity has proven to be an effective method for detecting artifacts among evoked brain activity, yet it does not account for background activity. Regression methods can identify oculographic artifacts but are limited in their ability to reduce bilateral contamination between EEG and EOG [79]. To address this issue, low-pass filtering before applying Bayesian adaptive regression splines has been proposed as a solution [80], as the high-frequency content of the recorded EOG typically refers to neural activity, which can be filtered out to significantly reduce bidirectional pollution effects.

The literature overview showed a lack of consensus on the best low-pass filtering of EOG signals. In contrast, some researchers have suggested that all frequency bands in the EOG signal are associated with neuronal activity [81].

Despite their shortcomings, regression methods are regarded as the "gold standard" for evaluating the effectiveness of new artifact detection algorithms.

4.3. SVM in BCI Systems

SVMs are used in BCI systems for classification tasks, such as recognizing patterns in EEG signals. SVMs can be used to identify features from the raw EEG data and classify them into different categories or classes. For example, an SVM may be used to distinguish between different brain states, such as sleep states or mental workload levels. Additionally, SVMs can be trained on specific tasks, such as imagined hand movement recognition and motor imagery-based BCI control. The high accuracy of SVM algorithms makes them well suited for use in BCI applications where accurate classification is essential.

SVM, proposed by V. Vapnik and A. Chervonenkis [82], is a method of linear classification that divides the sample into classes using an optimal separating hyperplane with the following general equation form:

$$f(x)=[\omega,\varphi(x)]+b, f(x)=[\omega,\varphi(x)]+b, \tag{5}$$

where $\omega=\sum_{i=1}^{N}\lambda_i y_i \varphi_i(x_i)$ $\omega=\sum i=1N\lambda iyi\varphi i(xi)$, and the coefficients λ_i λi depend on the vector of labels y_i yi, and on the scalar products $\varphi_i(x_i)$ $\varphi i(xi)$. To find the decision function, knowledge of these scalar products is necessary. Data transformations are determined by a kernel function: $K(x,y)=[\varphi(x), \varphi(y)]$ $K(x,y)=[\varphi(x), \varphi(y)]$.

In 1992, a non-linear Support Vector Machine (SVM) classification method was proposed by utilizing a non-linear kernel function [82,83]. This approach enables the search for the optimal separating hyperplane in the transformed feature space. The radial Gaussian basis function can be used as a kernel function:

$$K(x_i,x_j)=\exp(-\gamma\|x_i-x_j\|^2), \text{ for } \gamma>0. K(xi,xj)=\exp(-\gamma\|xi-xj\|2), \text{ for } \gamma>0. \tag{6}$$

The classifier is divided into two stages: training and testing. The data are first split into a training set with assigned class labels and a test set without them. During the first stage, the classifier builds a model based on the training sample and divides it into given classes. In the second stage, the constructed model is tested by feeding in the test sample (without class labels) to determine if EEG patterns belong to possible classes. The classification accuracy (the ratio of correctly determined samples over the total number of samples expressed as a percentage) then measures how effective the classifier was.

4.4. HMM's for BCI

Hidden Markov models (HMMs) are used in BCI systems to recognize user intentions based on their brain signals. HMMs can be trained to detect patterns in EEG signals, such as movement intent or mental arithmetic tasks, and classify them into different classes. The model is then able to predict the user's intention from the observed data and use it to control a computer system or robotic device. In addition, HMMs can be used for decoding motor imagery activities, which allow users with severe disabilities to interact with computers using only their minds.

The HMM method, based on the Bayesian posterior probability maximization approach, has been successfully employed to classify time series, with states at any given time t being affected by states at the previous time (t − 1). This technique has shown its utility in resolving speech recognition problems and is widely used for signal analysis, classification, modeling, and control purposes [84].

The solution of three fundamental problems is required to construct a Hidden Markov Model (HMM) for the given sequence of observed states:

1. The evaluation problem can be stated as follows: Given an HMM with transition probabilities a_{ij} and b_{jk}, determine the probability that a particular sequence of visible states (VT) was generated by this model.
2. Decoding problem. Given an HMM and a set of observations (V^T), we need to determine the most probable sequence of hidden states ω^T that result in these observations.
3. The learning problem. Given an enlarged structure of the model with a specified number of states and visible states but without knowledge of transition

probabilities a_{ij} and b_{jk}, learning can be performed by determining the most plausible model from a training sample of visible states.

Problems 1 and 2 are solved at the decoding stage using forward procedures or Viterbi algorithms [84]. Problem 3 is tackled in the learning process by employing an iterative procedure for finding a local maximum, such as the Baum–Welch algorithm [84], or utilizing global optimization algorithms, e.g., simulated annealing [85].

HMMs can be utilized in BCIs as probabilistic automata that calculate the likelihood of a given sequence of feature vectors. Each state of the automaton models the probability distribution for observing a particular feature vector, with Gaussian models being commonly used in BCI applications [83].

The use of HMMs for classifying time series has been demonstrated to be effective due to their inherent nature. As the EEG contains distinct features that can be distinguished in the temporal domain, the HMM method was utilized for EEG classification in BCI [86,87,88]. However, HMMs have not seen widespread application in BCI development yet, despite the relatively high success rates reported by known studies. One major obstacle is the necessity of identifying an invariable set of observable states related to an event, which may prove difficult when analyzing EEG signals; for example, while studying induced desynchronization as reported in [80] across different channels. If signals associated with close localized events and similar dynamics are being analyzed, it becomes hard to identify stable observable states; requiring instead the identification of process attractors related only to classified events without including background nervous system activity. A further exploration into EEG signals and neurophysiological brain functioning fundamentals could possibly provide such an opportunity, thus increasing the relevance of using HMMs significantly.

4.5. Neural Network Algorithms for BCI Systems

Machine learning models such as artificial neural networks (ANNs) are used in BCI systems to help interpret and classify the brain signals that they receive [89,90,91]. By utilizing ANNs, a BCI system can be trained to recognize patterns in EEG data, which can then be used to detect changes in states of consciousness or other types of mental activities. This allows BCI systems to respond more accurately and quickly than traditional methods would allow. Additionally, by using ANNs for pattern recognition tasks, it is possible for a BCI system to adapt over time as new patterns emerge from the EEG data. This ability makes them especially useful for applications involving long-term monitoring of patients with neurological disorders such as epilepsy or dementia.

Convolutional neural networks (CNN) are most commonly used for this task. CNNs have been proposed by LeCun [92] as a type of artificial neural network architecture for efficient pattern recognition in images. CNNs are composed of convolutional layers and pooling layers, which enable the extraction of features from input data while reducing the amount of processed information and preserving task-specific information.

When working with EEG signals, convolutional networks can be used to reduce the problem of image classification by feeding spectrograms into their inputs. Alternatively, one may use an adaptation of the FBCSP method as an input architecture; for example, ShallowNet is described in [93] and illustrated in **Figure 4**. The layers composing this architecture and their respective functions are detailed as follows: A 1 × 25 time convolution is implemented to highlight characteristic peaks in the signal, followed by a spatial filtering of all electrodes similar to that of the FBCSP algorithm. Subsequently, an element-wise squaring is performed on the matrix values before proceeding with a 1 × 75 windowed time pooling operation, wherein the average value of each window element is taken. A natural logarithm transformation then follows for each element, which is equivalent to calculating the logarithm of signal dispersion as seen in FBCSP. Finally, these features are classified by combining fully connected and softmax layers.

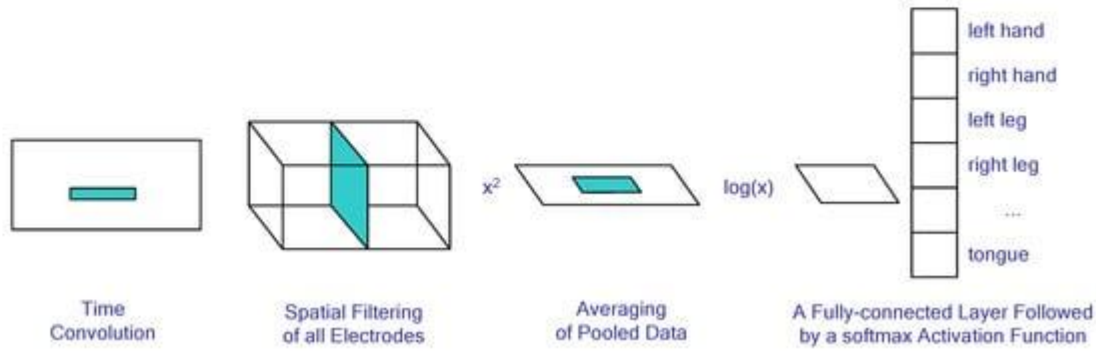

Figure 4. The CNN architecture in BCI analysis.

Deep learning methods are reliant on the amount of data available; as more data is used, better generalization occurs. To counter this issue, augmentation methods have been utilized.

4.6. Genetic Algorithms and Particle Swarm Optimization in BCI

Genetic algorithms (GA) and particle swarm optimization (PSO) are optimization methods that can be used to optimize or tune the parameters of a BCI system. GA is an evolutionary algorithm that uses concepts such as mutation, crossover, and selection to find optimal solutions. PSO is an iterative algorithm inspired by social behavior in which particles move around in search space with velocities that are influenced by their own best position and the global best position found so far. Both algorithms can be used to automatically adjust model parameters within a BCI system, thereby improving its performance. For example, they could be used to optimize feature extraction techniques for EEG signals or adaptively select appropriate stimuli for brain–computer interfaces based on user feedback.

GAs use the principles of natural selection and genetics to find solutions to complex optimization problems. They are used for tasks such as finding the optimal parameters for a machine learning model or finding the shortest route from one point to another in a network. GAs have been increasingly used in BCI systems as they offer an effective way to optimize BCI performance by automatically searching through a large space of potential parameter values and selecting those that yield better results [94,95,96,97,98]. As advantages of Gas could be mentioned, their robustness. Gas are able to handle noise, nonlinearities, and outliers without much difficulty. This makes them particularly well suited for BCIs, where there is often considerable uncertainty due to biological variability between users or individuals with different levels of expertise using the system. Another advantage is their efficiency. Gas can be implemented quickly and easily compared to other optimization techniques such as gradient descent or simulated annealing, making them ideal for real-time applications such as online control systems where speed is essential. Finally, due to their flexibility, GAs can be applied to many different types of problems, including classification, regression, clustering, etc., making them applicable across many different domains within BCI research.

On the other hand, these methods are known for their computational complexity. While GAs provide efficient solutions compared to other methods, they require more computational resources than some alternative approaches such as grid search or random search, which may limit their applicability on certain platforms with limited memory or computing power available, e.g., embedded devices used in mobile applications. In addition, they are limited in their interpretability. Due to their nature as black box models, it can be difficult to interpret why certain decisions were made by the algorithm, which could lead to issues when trying to debug any errors during the development stages or if unexpected behavior occurs while using the system live.

PSO in BCI has been used for feature selection, parameter tuning, and model selection. Its strong sides are [99,100,101,102]:

- PSO is simpler than other optimizers since it does not require costly derivatives or linear algebra operations;
- PSO can be used with any type of problem formulation, such as discrete, continuous, constrained, or unconstrained optimization problems;
- PSO can find solutions faster compared to traditional algorithms because it uses parallel computing techniques that allow multiple particles to explore the search space simultaneously and cooperatively;
- The algorithm is easy to implement due to its simple structure and few parameters to adjust during its execution process.
- It does not require an initial guess from the user and thus can be useful in cases where one may not know what kind of solution they are looking for.

On the other hand, PSO's downsides are the following:

- The results obtained by using this method depend on the choice of parameters such as inertia weight, cognition factor, social factor, etc., so if these values are set too high or too low, then the result will also suffer accordingly.
- It may take more time than other methods since many iterations need to be done until a good solution is found;
- Some features may remain unexplored due to a lack of exploration strategies implemented in some versions of PSO algorithms, resulting in sub-optimal solutions being returned instead of optimal ones.

4.7. BCI Datasets and Benchmarking

In order to assess the performance and accuracy of different BCI techniques and methods for designing these interfaces, BCI datasets are typically used. These datasets are collections of data gathered from individuals using BCI systems and provided either by research organizations, BCI manufacturers, or individual researchers. Commonly used BCI datasets include NeuroSky Mindwave [103], Emotiv EPOC+ [104,105], OpenBCI Ganglion [106], Graz University EEG Motor Imagery Database [107], PhysioNet EEG Motor Movement/Imagery Dataset [108], etc. These datasets provide a variety of recordings, including raw EEG data as well as preprocessed information such as event-related potentials (ERPs).

The NeuroSky Mindwave dataset consists of recordings made during various cognitive tasks such as mental arithmetic and memory recall, while the Emotiv EPOC+ dataset contains recordings taken during emotional recognition tasks. The OpenBCI Ganglion dataset includes both resting state and motor imagery recordings, while the Graz University EEG motor imagery database provides detailed information on motor imagery-related activities performed by subjects in an experimental setting. Finally, PhysioNet's EEG motor movement/imagery dataset offers multiple types of motor imagery tasks along with corresponding scores indicating how accurately each task was performed by participants.

Another widely used BCI benchmark dataset is described in [109,110,111]. These datasets were initially used in BCI research competitions in the early 2000s, and could now be used to assess the performance and accuracy of novel BCI techniques and methods. These datasets typically consist of EEG signals recorded by participants as they perform various tasks. The most commonly used BCI benchmark datasets include [109,110,111]:

- BCI Competition IV Dataset 2a: This dataset consists of EEG and EOG recordings from nine subjects performing motor imagery tasks such as left/right hand or foot movement, imagining a circle or a line, and other more complex movements;
- The BCI Competition IV Dataset 2b: This dataset consists of EEG recordings from nine subjects performing motor imagery tasks while a visual cue was presented at different time points during the task;
- The BCI Competition IV Dataset 3: This dataset consists of MEG recordings from two subjects performing motor imagery tasks such as wrist movement in different directions;
- The BCI Competition IV Dataset 4: This dataset contains ECoG recordings from three subjects performing motor imagery tasks such as finger movement acquired with a data glove;
- The OpenMIIR Dataset [112]: This dataset includes EEG recordings from 20 healthy volunteers who were asked to imagine either moving their hands, feet, tongue, or eyes in order to control a virtual avatar on screen by using their thoughts alone;
- The High-Gamma Dataset (HGD) [113,114]: This dataset is composed of high-gamma-power EEG signals that can be used for studying the neural correlates associated with visual perception and memory encoding processes in humans using machine learning algorithms.

Thus, existing BCI datasets allow one to assess novel BCI techniques and algorithms, helping to improve their performance and accuracy.

4.8. Noise and Environmental Disturbances Impact on BCI Systems

As with any form of communication, noise and environmental disturbances can greatly reduce the efficiency of BCI systems. The most common type of external disturbance encountered by BCI systems is acoustic noise. This includes any sound produced by people or machines in close proximity to a BCI system user, such as conversations, typing noises, etc., that may interfere with accurate EEG signal acquisition or processing. Studies have shown that even low levels of background noise can significantly reduce accuracy when trying to distinguish different mental states (e.g., attention vs. relaxation). Furthermore, some studies also suggest that certain frequencies can be more disruptive than others depending on their similarity to those present in EEG signals; therefore, it is important to identify these frequencies prior to using a BCI system in order to minimize interference from external sources [115].

In addition to acoustic sources of interference, there are also numerous types of electromagnetic fields present in everyday life that may interfere with the proper functioning of a BCI system due to its reliance on electrical signals generated by neurons within the brain [116]. Common sources include power lines, radio waves emitted from cell phones or Wi-Fi routers, etc., all of which could potentially disrupt neural activity recorded via EEG electrodes, thus reducing overall accuracy when detecting specific mental states or commands given by users [117]. Therefore, it is essential that adequate shielding measures are taken during the design and implementation stages so as not to compromise performance due to unwanted outside influences [118].

Noise and environmental disturbances can severely affect the efficacy of BCI systems if left unchecked; however, appropriate measures taken during the development stages concerning both acoustic/mechanical interferences as well as electromagnetic ones should help ensure maximum efficiency when using such technologies going forward into future applications involving human–machine interactions.

5. Applications

BCIs have been proposed for use in many fields, including medicine, neuroscience research, education/training environments, human–computer interaction, and even gaming/entertainment applications where users can control virtual objects using only their thoughts without any physical movement required. In addition to these more traditional uses, there is also ongoing work exploring new areas such as thought-controlled wheelchairs, which allow disabled people greater freedom of mobility without relying on manual controls; prosthetic devices enabling amputees to have better manipulation capabilities than ever before; communication aids designed specifically for people suffering from severe speech impairments; remote monitoring systems that track vital signs while allowing patients greater independence at home rather than having them stay confined in hospitals; and even mind-controlled drones. The possibilities seem endless when considering what could be achieved if we were able to understand our brains better, so let us take a look at some examples where this technology has already made an impact.

5.1. Neuroprosthetics

BCIs are being used to create neuroprosthetic devices, which allow people with physical disabilities to control external devices such as wheelchairs and robotic arms using their own brain signals. For example, the BrainGate neural interface system is a device that can be implanted in the brain to record electrical activity from neurons and translate it into commands for controlling external devices.

The use of BCIs in neuroprosthetics is a rapidly growing field, with potential applications ranging from restoring communication to those who have lost it due to injury or illness to providing enhanced control of prosthetic limbs. BCI technology has been used for decades in the medical sector but only recently began being applied to the development of neuroprostheses [9,12,119,120].

One example of BCI technology being used in neuroprosthetics is brain-controlled robotic arms and hands [121,122,123,124,125]. These are designed to allow users with spinal cord injuries or amputations to move their prosthetic limb by simply thinking about it, rather than having to manually control it using switches or joysticks. This type of device can also be used as an assistive tool for people with limited motor skills, such as stroke victims or those suffering from degenerative diseases such as ALS (amyotrophic lateral sclerosis). By interpreting electrical signals produced by neurons in the user's brain, these devices can accurately predict what action they should take when given input from the user, allowing them greater independence and mobility.

Another application for BCI technology within neuroprosthetics is its use in restoring communication capabilities for those unable to speak due to paralysis caused by conditions such as ALS, stroke, or traumatic brain injury [126,127]. In this case, electrodes placed on the scalp detect electrical activity produced by neurons that would normally be associated with speech production and then translate this into words spoken through a computerized voice synthesizer. This allows individuals who cannot physically produce sound themselves to still communicate their thoughts and feelings without relying solely on writing them down or typing out messages using eye-tracking software programs—enabling them much more freedom than before.

Finally, neural implants are another form of BCI technology currently being explored within the realm of neuroprosthetics research—particularly as part of "neurohybrid" systems combining both biological components (such as nerves) and artificial ones (such as microprocessors) [121,128,129]. Neural implants involve surgically implanting electrodes directly into areas responsible for controlling movement so that they can receive direct commands from neuronal activity generated there instead—potentially resulting in even faster response times than traditional forms of BCIs, which rely on detecting signals transmitted through scalp electrodes alone.

Overall, BCI technology is an exciting new field with a wide range of potential applications within the realm of neuroprosthetics—from restoring communication capabilities to providing enhanced control over prosthetic limbs and beyond. As research continues to progress in this area, it can be expected that further advancements will be made that will allow individuals with disabilities greater independence and mobility than ever before.

5.2. Communication

BCI technology is also being used to develop new ways of communicating for people who have lost the ability to speak or write due to paralysis or other conditions. For example, BCI systems can be used to detect intentions from users' brain signals and then convert them into text messages or even speech output through computer algorithms [14,130].

BCIs have become increasingly popular in recent years as a way to enable communication between humans and machines. BCIs are devices that measure brain activity, such as electrical signals from the brain, and then use this information to control external objects or systems. BCIs can be used for a variety of applications, including controlling prosthetics, medical diagnosis, rehabilitation therapy, gaming, robotics control, and even communication.

This type of research is promising as it could be used to help people with disabilities who cannot communicate verbally or physically due to paralysis or other conditions.

Other studies have looked into how BCI technology can be used for more complex forms of communication, such as typing on a computer keyboard or giving speech commands via voice recognition software [131,132,133,134,135,136]. These types of applications could prove useful for helping individuals with severe motor impairments regain some level of independence when communicating with others. Additionally, there have also been attempts at developing interfaces that allow users to generate language through thought alone using EEG recordings. While these technologies are still relatively new and require further development before they can be widely adopted, they represent an exciting potential future application for augmenting human-machine interaction via BCI technology.

Overall, BCI technology has the potential to revolutionize communication as we know it. While there is still a lot of research and development needed before this technology can be widely adopted, the potential for enabling individuals with disabilities to communicate more effectively or even generate language through thought alone is an exciting prospect.

5.3. Gaming

BCIs are increasingly being used in gaming applications where players can interact with virtual environments using only their thoughts instead of traditional controllers such as keyboards and joysticks [137,138,139,140,141,142].

One example of a game that utilizes BCI is MindRDR, developed by the London-based startup This Place [143]. The game uses EEG sensors to measure players' emotional responses while playing. Players use their mental focus or concentration levels to control the direction and speed of an avatar on screen. As players become more emotionally engaged with the game, their avatar will move faster and farther across the screen than if they were not as focused or engaged with it.

Another example of a BCI-enabled video game is Brain Wars from NeuroSky Inc., which allows players to compete against each other using EEG headsets to measure brainwaves associated with concentration levels during gameplay [144,145]. Players must concentrate hard enough so that their brain waves reach certain thresholds in order to be able to progress through different levels in the game.

In addition, there are several research projects underway exploring how BCIs can be used for virtual reality gaming experiences [146,147].

Overall, BCIs offer great potential when it comes to enhancing gameplay experiences by providing gamers with new ways of experiencing games beyond just pressing buttons on controllers or keyboards—allowing them instead to tap into emotions and thought processes unique to themselves! With further advancements in technology, BCIs could become a major part of the gaming industry in the future.

5.4. Education

BCIs are being used to enhance the learning experience by providing real-time feedback about students' cognitive states and helping them focus better on their studies.

This technology has been used in various ways for educational purposes, ranging from helping students with special needs learn how to control their movements and communicate effectively to providing more immersive learning experiences for all learners [148,149,150,151].

Research on the use of BCI in education has shown positive results when it comes to improving student engagement and motivation. For example, one study found that using BCI-based games improved cognitive skills among students who had difficulty paying attention during traditional classroom activities. Additionally, research suggests that BCI can be used as an effective tool for teaching abstract concepts such as mathematics or foreign languages by allowing users to directly experience the material instead of relying solely on verbal instruction.

Furthermore, studies have demonstrated that the use of BCIs can reduce stress levels among students by providing them with a more natural way of interacting with computers than conventional input devices such as keyboards or mice. Finally, research indicates that BCIs may provide new opportunities for personalized learning since they allow teachers to tailor lesson plans according to individual students strengths and weaknesses based on real-time feedback from brain activity data.

Overall, research suggests that BCI technology has the potential to revolutionize education by providing more engaging and immersive learning experiences for students of all ages.

5.5. Mental Health

BCI technology is also being explored as a potential treatment for mental health conditions such as depression, anxiety, and addiction by allowing clinicians to monitor patients' brain activity in real time and provide targeted interventions when required [152,153,154,155].

In mental health care, BCI can be used to assess cognitive processes such as attention and memory; detect changes in emotional states; monitor progress in therapy; measure levels of stress or relaxation; provide feedback during biofeedback exercises; diagnose neurological disorders such as Alzheimer's disease or Parkinson's disease; improve motor skills after stroke or traumatic brain injury (TBI); help people suffering from depression manage their symptoms through self-regulation techniques; reduce anxiety associated with public speaking; and more. In addition, BCIs have been shown to be effective tools for helping patients develop better coping skills when dealing with difficult emotions such as anger or fear.

Research suggests that BCI could potentially revolutionize how we approach mental healthcare by allowing us to quickly identify psychological problems at an early stage and intervene before they become serious issues. For example, some research has suggested that EEG-based BCIs may be able to detect subtle signs of distress related to depression that would not normally be picked up by traditional methods of assessment such as questionnaires or interviews alone. Other research has demonstrated how portable EEG systems can be used in real-time settings outside of a clinical environment, providing clinicians with valuable information about the patient's condition without having the patient physically present in front of them.

5.6. Sleep Medicine

Recently, there has been an increasing interest in BCI's potential application for sleep medicine applications, such as improving sleep quality and diagnosing different psychiatric and neurodegenerative diseases by analyzing sleeping stages [156,157,158,159,160,161,162]. The use of BCIs could help individuals track their sleeping patterns more accurately than traditional methods.

One way this technology can be utilized is through EEG-based BCI systems, which measure electrical activity in the brain during different stages of sleep. These devices are able to detect changes in neural oscillations associated with rapid eye movement (REM) and non-REM sleep cycles, allowing accurate tracking of the user's progress throughout the night.

Another promising application for sleep BCIs is treating various types of insomnia by providing targeted neurostimulation therapies such as transcranial alternating current stimulation (tACS). tACS uses low-intensity electric currents delivered directly into specific areas of the brain believed to regulate wakefulness/sleep cycles, thus helping reset abnormal rhythms associated with poor sleeping habits or disruptions caused by stressors such as jet lag or shift work schedules.

Furthermore, research suggests that combining tACS with cognitive behavioral therapy might produce better results compared to either treatment alone when it comes to managing chronic sleeplessness conditions such as primary insomnia disorder or obstructive sleep apnea syndrome (OSAS).

Sleep brain computer interfaces offer great potential for improving our understanding of how we process information during restful states while also enabling more effective treatments for common problems related to the lack/disruption of adequate shut-eye—from mild cases involving occasional difficulty falling asleep all the way up to severe clinical disorders such as OSAS. As these technologies continue to advance over time, we should see further improvements both in terms of accuracy when monitoring physiological parameters related to slumber and in terms of efficacy when delivering personalized interventions meant to optimize one's overall wellbeing.

Overall, there is still much work needed before we can fully understand the potential benefits offered by this exciting new technology, but initial findings suggest it could dramatically improve our understanding of mental illness while offering patients access to more personalized treatments tailored specifically for their individual needs.

6. Conclusions

The paper presented the current state-of-the-art in brain-computer interface technologies. Main platforms used for BCI data collection, such as EEG, fNIRS, MEG, and ECoG, were reviewed, and their pros and cons were singled out. It was concluded that the choice of a platform depends on the research goals, cost of equipment, patient comfort level, etc., while it is not correct to say that one of the platforms is better than others in general.

The most widely used BCI signal processing techniques, such as ICA, wavelet transformation, SVM, hidden Makrov models, machine learning, and genetic algorithms, were reviewed. Brief principles of their operation and main application areas are highlighted.

Finally, the main BCI system application areas, such as neuroprosthetics, communication, gaming, education, and mental health care, were reviewed.

It was highlighted that BCI offers tremendous potential opportunities across multiple domains—both existing ones, such as medical treatment and monitoring, and entirely novel concepts, such as controlling drones via thought alone. There is still much progress needed, however, before these ideas become realities—further technological developments must continue alongside increased understanding about how our brains actually function so that reliable interactions between humans and machines can be established and maintained over time safely and effectively.

A New Frontier: The Convergence of Nanotechnology, Brain Machine Interfaces, and Artificial Intelligence

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Abstract

A confluence of technological capabilities is creating an opportunity for machine learning and artificial intelligence (AI) to enable “smart” nanoengineered brain machine interfaces (BMI). This new generation of technologies will be able to communicate with the brain in ways that support contextual learning and adaptation to changing functional requirements. This applies to both invasive technologies aimed at restoring neurological function, as in the case of neural prosthesis, as well as non-invasive technologies enabled by signals such as electroencephalograph (EEG). Advances in computation, hardware, and algorithms that learn and adapt in a contextually dependent way will be able to leverage the capabilities that nanoengineering offers the design and functionality of BMI. We explore the enabling capabilities that these devices may exhibit, why they matter, and the state of the technologies necessary to build them. We also discuss a number of open technical challenges and problems that will need to be solved in order to achieve this.

Keywords: nanotechnology, neuroscience, machine learning, artificial intelligence (AI), brain machine interface (BMI), brain computer interface, computational neuroscience

Introduction

A confluence of technological capabilities is creating an opportunity for machine learning and artificial intelligence (AI) to enable “smart” nanoengineered brain machine interfaces (BMI). The goal is for this new generation of technologies to be able to communicate with the brain in ways that support contextual learning and adaptation to changing functional requirements. This applies to both invasive technologies aimed at restoring neurological function, as in the case of neural prosthesis, as well as non-invasive technologies enabled by signals such as electroencephalograph (EEG). Advances in computation, hardware, and algorithms that learn and adapt in a contextually dependent way will be able to leverage the capabilities that nanoengineering offers the design and functionality of BMI. Eventually, these technologies will be able to carry out learning and adaptation in (near) real time, as external shifting demands from the environment and physiology require them. Ultimately, the goal is to produce personalized individual user experiences for applications such as gaming, and to allow the device to learn and adapt to changing disease requirements in clinical scenarios. In this commentary we explore the enabling capabilities that these devices may exhibit, why they matter, and the state of the technologies necessary to build them. We also discuss a number of open technical challenges and problems that will need to be solved in order to achieve this.

The Opportunity for “Smart” Brain Machine and Brain Computer Interfaces

Brain machine and brain computer interfaces (we use these terms interchangeably here) represent technologies designed to communicate with the central nervous system: the brain, spinal cord, and neural sensory retina. Clinically, depending on the design and intent of the technology, the goal can be to record and interpret neural signals in order to execute an intended neural command through an external device, or to achieve neural stimulation, often to restore neural function following disease or trauma, or both (Adewole et al., 2016; Choi et al., 2017; Slutzky and Flint, 2017; Rezeika et al., 2018). Some devices make use of feedback in an attempt to optimize performance, whether physiological or via patient specific intent and instructions (Widge et al., 2018). There is also a growing list of non-invasive brain machine interface technologies not meant for clinical use, primarily driven by innovative startup companies. These technologies are intended to augment the user experience and control interface for gaming and augmented (AR) and virtual reality (VR) applications. Although of course very different than technologies aimed at treating and restoring clinical function and quality of life to patients, this is a market that should not be ignored. Not the least of which because it could provide leveraging resources to the benefit of clinically related research. For example, advances in our understanding of the relevant neurophysiology, cognitive neuroscience, mathematical and engineering aspects of signal processing, and hardware, can significantly impact both the gaming industry as well as clinical devices and neural prosthesis. The brain machine interface market is projected to reach $1.46B by 2020, with a compound annual growth rate (CAGR) of 11.5% between 2014 to 2020 by one estimate (Allied Market Research, 2015), and a comparable $1.72B in 2022, with a predicted CAGR of 11.5% between 2012 and 2022 by another estimate (Grand View Research, 2018). Much of this projected growth will be due to non-invasive technologies, with the gaming industry as a market driver roughly on par with healthcare applications.

As significant as these numbers are, these projections primarily reflect enabling technologies for interfacing between neural control and sensory experiences with machines. They do not reflect opportunities that go beyond what is currently possible with the existing state of the art. BMI that can learn and adapt reflect the cutting edge of what is technologically possible, due to a confluence of BMI technologies, in particular nanotechnologies, machine learning and AI, alongside a continued increasing understanding of the relevant neuroscience. AI can provide opportunities to create “smart” BMI that contextually learn and adapt to changing functional requirements and demands. This has the potential to produce personalized individual experiences in gaming and AR/VR, and allow for the changing requirements associated with patient specific disease progression and evolution in clinical applications. This latter point cannot be overestimated, because not only would it accommodate the differing clinical demands of different neurological disorders, it would allow for patient specific adaptation of BMI functionality to the needs of different patients. And it would allow the technology to continue to adapt as disease progression evolves in individuals over time. One of the significant limitations of current state of the art BMI and neural prosthesis is the assumption of one size fits all. In in other words, the assumption that a technology operating under a specific set or range of functionality will properly treat all patients. While we are not aware (yet) of a device or technology that reflects the actualized integration of machine learning and nanotechnology applied to BMI, we argue that the potential and impact of doing make the subject worth exploring. Each on their own, machine learning and nanotechnology, are already being used in the design and function of BMI and neural prosthesis in a number of ways that align with the vision we propose here.

Integration of Bmi With Machine Learning

What advantages does machine learning and artificial Intelligence (AI) offer BMI? What exactly are machine learning algorithms learning, and how can they use that information to adapt in a meaningful way? What these algorithms can learn is information provided by feedback and telemetry from the hardware. This could be information about the current state of the output settings of the device, or any kind of external information measured by sensors in the BMI. For example, physiological measurements in response to stimulation, feedback from other algorithms external to the BMI-machine learning system, such as haptic or computer vision feedback, or the internal parameter settings of current stimulation or recording protocols to the device. In the case of internal parameters the algorithms have constant access to variables such as pulse durations and amplitudes, stimulation frequencies, energy consumption by the device, stimulation or recording densities, electrical properties of the neural tissues it is interfacing with (resistances, impedances), and continuous or near continuous levels of biochemical factors such as neurotransmitters or other metabolites. Of course, none of these are mutually exclusive, with multiple types and streams of information possibly being provided to the algorithms in parallel, albeit at likely different sampling resolutions. With this information, machine learning algorithms could then identify subtle and non-trivial patterns and phenomena in the data, ideally in (near) real time, in order to produce desired functional outcomes from the BMI that change dynamically as external (e.g., clinical or functional) requirements demand them. This would necessitate the development and training of machine learning models and algorithms offline as part of the design of the BMI system. The algorithms would need to learn a wide enough range of the parameter spaces in order to appropriately identify patterns in the data they encounter when online. Subsequent algorithms can then autonomously make decisions about how to use that data. This step does not necessarily have to be part of the brain machine interface system itself, and could be executed with algorithms computing in the cloud, if sufficient bandwidth was available. Or even offline following periodic data downloads, for example. Clearly though, on board decision algorithms that operate in real time with the machine learning algorithms that are identifying patterns in the data would be ideal. This would alleviate issues of data transfer delays, and bandwidth insufficiency. This could also allow for the need to store less data on the device, which could be limited due to physical constrains. Data would only have to be stored long enough for the system to make an autonomous decision, essentially as a moving window that matches the processing capabilities of the algorithms. Of course, it may still be valuable or necessary to store some data or types of data for offline analyses even though they may not be needed for the BMI system to make a decision. For example, in order to understand offline after the fact why the algorithms made the decisions they made and the clinical outcomes of those decisions. With this process complete we close the loop: information is provided to the machine learning algorithms, followed by learning, pattern identification, and subsequent executable autonomous decisions that in turn dynamically change the output of the brain machine interface and how it interacts with the external environment it is interfacing with. This could be the brain itself in the case of a neural prosthesis intended to restore clinical function, or software in a non-invasive BMI that is interfacing that is part of an AR or VR system.

While still early days, a number of research groups have recognized this potential, and are beginning to explore how machine learning could inform and integrate neural stimulation and feedback. Nurse and colleagues (Nurse et al., 2015) have developed a generalized approach that takes advantage of a stochastic machine learning method to classify motor related signals specifically for BMI applications. Importantly, their classifier does not need to rely on the use of extensive *a priori* data to train the BMI. Their algorithms outperformed other methods on the Berlin BMI IV 2008 dataset, and demonstrated high levels of classification accuracy when tested on datasets derived from EEG signals. In another recent study, Ortega et al. (2018) explored different data pre-processing strategies and convolution neural network architectures for classification tasks derived from EEG signals. Interestingly, they found that a rather straightforward network architecture, when combined with a pre-processing step that analyzed spectral power preserving features of the electrode arrangements, was sufficient to handle the analysis of the data. Their network consisted of a single convolution layer, one connection layer, and single linear regression classifier layer. Their approach allowed them to carry out co-adaptive training on the data to achieve on-line classification. A different study had explored a similar approach. Lawhern et al. (2016) carried have also explored a similar approach.

As discussed above, one of the biggest advantages machine learning may confer on BMI is the ability to achieve real-time or near-real-time modulation of output or stimulation parameters in response to active real-time feedback from physiological signals, the environment, or other internal cues from the system itself, such as possibly the output from other internal algorithms that have processed some amount of data. Most BMI's have a decoder component whose job it is to decode and make sense of neural signals in order to produce executable or actionable outputs. This typically necessitates extensive supervised training in order to optimize the interpretation of recorded neural signals before the decoder can properly correlate observed signals with desired outputs and commands. This training has traditionally required supervised feedback with a human in the loop, typically a technician or clinician often with input from the patient her/himself, thus making the process highly inefficient and intermittent.

Training and subsequent adjustments can only occur periodically and are typically time consuming. Furthermore, the mapping from neural signals to actionable outputs is limited to the training data the system is exposed to during the training. This then highly limits the ability of the BMI to respond to variable real world scenarios it may encounter when in use, thus severely limiting its functionality to the patient when such conditions arise. Early work relied on feedback from external sensory references to compute an error between the output of the system and desired supervised target. These included visual and auditory signals (Wessberg et al., 2000; Lebedev et al., 2005), mechanotransduction (Nicolelis and Chapin, 2002; O'Doherty et al., 2011), and direct cortical sensory stimulation (6 Bach-y-Rita and Kercel, 2003). But these approaches are severely limited due to their need for continuous information from an external reference target to adjust the mapping to the output of the BMI. More recent work has addressed some of these limitations by adapting output parameters to unsupervised learning methods such as Bayesian statistical methods and reinforcement learning that do not rely on an external reference (Vidaurre et al., 2011; Orsborn et al., 2012, 2014; Bryan et al., 2013; Huang and Rao, 2013; Bauer and Gharabaghi, 2015). Although in most cases they still require significant training periods. More recent studies have begun to investigate the use of endogenous neural signals directly as the training source in iterative closed feedback loops with the BMI that can respond and adapt in a much more direct way (Suminski et al., 2010; Carmena, 2013). For example, Prassad and colleagues are developing an approach they call Actor-Critic reinforcement learning that does not need to rely on a supervised error signal (Pohlmeyer et al., 2014; Prins et al., 2014, 2017).

In general, the BMI field in general and neural prosthesis field in particular are still exploring machine learning. One of the challenges is that key state of the art methods, such as deep learning, that have had huge successes in other applications may not be the best approach for the constraints imposed by the needs of BMI (Vidaurre et al., 2015). In a recent paper, Panuccio et al. (2018) do an excellent job summarizing the current state and challenges of neural engineering aimed at restoring neural function, including proposing a number of similar requirements discussed in the current paper, that emerging algorithms and machine learning will need to address in order to build a true adaptive BMI.

An important consideration that such machine learning approaches offer that other methods cannot is the opportunity to develop BMI that adapt to the scaling requirements, both spatial and temporal, necessitated to achieve targeted functional outcomes. In the context of neural stimulation, the optimal density of stimulation required to produce a target response in neuronal populations being stimulated is a complex consideration, and may not always be the highest stimulation density achievable by the device (Shepherd et al., 2013; Patil and Thakor, 2016). What the right stimulation density should be can be a complex question to answer, and often depends on specific physiological and pathophysiological considerations. In many situations we still do not fully understand what the right stimulation density should be and why. Furthermore, the optimal stimulation density is likely to vary from individual to individual even in the same disorder, and within an individual patient the disease can greatly evolve over time as the physiology changes and the body responds and adapts to altered conditions. This could be a function of age or exogenous perturbations such as a response to other treatments, diet, and the psychological state of the patient. Another consideration is that hardware or other algorithms that need to make use of recorded or measured neural data in order to interact with the brain could have different scaling requirements in the data. This would be dependent on what the external query is and how the neural data needs to be used. It reflects the technical capabilities and limitations of the external technologies requesting the data. Under sampling could lead to poor user interactions, for example, a frustrating or confusing AR/VR experience, or the inability of a disabled patient to communicate in a timely or accurate manner. Oversampling would waste computational resources and time. In a research setting, data scaling issues could affect the empirically determined accuracy of a computational model, or how a hypothesis is tested and interpreted. Clinically, it could impact treatment or other clinical decisions. Changing temporal and spatial scaling requirements demanded by exogenous considerations to the BMI present situationally unique challenges that the existing state of the art is not yet able to address in a substantive way. The integration of machine learning and AI with nanoengineered BMI offers the opportunity for these technologies to learn, adapt, and respond to their environments in order to address functionally challenging considerations such as dynamic scaling demands.

Beyond the Current State of the Art: Machine Learning Enabled Nanoengineered Bmi

In recent years there has been an explosion of work focused on the development and use of nanotechnologies aimed at interacting and interfacing with the brain and central nervous system generally (Silva, 2006, 2007a,b, 2008, 2010; Kotov et al., 2009; De Vittorio et al., 2014; Saxena et al., 2015; Badry and Mattar, 2017; Scaini and Ballerini, 2017; Rosenthal, 2018), and in the context of BMI and neural prosthesis in particular (Webster et al., 2003; Lovat et al., 2005; Fabbro et al., 2012; Nicolas-Alonso and Gomez-Gil, 2012; Seo et al., 2013; Avants et al., 2016; Ha et al., 2016; Scaini and Ballerini, 2017). Considerable recent effort has focused on nanoscale neurotechnologies aimed at recording from and stimulating from the brain at high densities. This has to a significant degree been motivated by federal research efforts in both the United States and the European Union through the Brain Initiative[1] and Human Brain Project,[2] respectively. We do not attempt to review this extensive literature here, but refer the reader to the references and published literature more broadly.

While the confluence of machine learning and nanoengineered BMI and neural prosthesis has not yet occurred, machine learning is playing an increasing role in other aspects of nanotechnology and related molecular-scale research (for example, see the review by Sacha and Varona, 2013). In one example, Albrecht et al. (2017) have written a tutorial for using deep learning convolution neural networks for analyzing and mining single molecule data from DNA sequencing experiments. Ju et al. (2017) recently showed they could use an atomic version of Green's function and Bayesian optimization to optimize the interfacial thermal conductance of Si-Si and Si-Ge nanostructures (Ju et al., 2017). Their method was able to identify optimal structures within a library of over 60,000 candidate structures. And in another striking recent study, Lin et al. (2018) were able to implement a deep learning architecture on an all-optical 3d printed Diffractive Deep Neural Network (D2NN) that were designed and optimized by deep learning. These researchers were able to carry out classification and other imaging tasks without the need or use of any power, except for the input light into their system. The opportunity for BMI and neural prosthesis lies in the ability of machine learning to "learn" (i.e., identify and classify patterns) in highly complex physical and chemical data derived from devices that have been engineered at the nanoscale in order to inform and optimize the design and functional outputs of the devices.

As already alluded to, however, an important consideration in this quest is the realization that existing machine learning and AI algorithms may not be optimal for such needs. Thus, there is a possible opportunity and need for the development of purposely developed machine learning algorithms specifically designed to take advantage of and control nanoengineered BMI devices. Current machine learning methods, in particular deep artificial neural networks (ANN's), are incredibly powerful and continue to show some spectacular progress. What is probably the most surprising is that at its most fundamental, the underlying learning rules responsible for the existing state of the art and success of ANN's are essentially all variants of gradient descent statistical learning methods. But like any method, there are theoretical and practical limitations. The data they operate on must therefore be able to accommodate these constraints. In particular, existing algorithms are dependent on exposure to enormous data sets to train them properly so they can learn (a form of model bias). They can only find associations and patterns in the data that already exist (model bias again). There is always a danger of over generalizing from a limited training set (model over fitting). A such, they display an almost complete lack of robustness and ability to adapt beyond the training sets they are exposed to. New data may not achieve further learning (model saturation). And because of these considerations these methods will miss outliers (data sparseness problem). Finally, they require large computational resources and the consumption of huge amounts of energy to properly identify learned patterns. These methods are limited by a set of fundamental engineering challenges inherent to statistical learning. Yet, even with these constraints in mind, and ignoring all the hype currently surrounding machine learning and AI, it is difficult not to be impressed by the accomplishments these methods are achieving. If the data and resources are appropriate to the task being presented to the algorithms, these methods can work remarkably well and it is likely impractical (and even unnecessary) to attempt to develop new methods to supersede them; at least for the foreseeable future. In some cases it is certainly plausible that the machine learning needs of nanoengineered BMI's could be amenable to the current state of the art (see references and discussion above). BMI can generate significant amounts of data, and the range of operating conditions of physiological signals, stimulation parameters, and recording densities specific to given functional tasks are sufficiently well understood, at least from the perspective of defining the extremes of those conditions. Thus, sufficient data over known and practical physiological operating ranges could allow existing machine learning to learn sufficiently in order to guide decision algorithms for adapting the interactions of the BMI with their targets. This is particularly true of nanoengineered brain machine interface's, whereby the degree of synthesis control over the material or device, and spatial and temporal stimulation resolutions and recording densities, can be engineered at the nanoscale. Conceivably, the quality and amount of information nanoengineered BMI could produce, along with the degree of functional control nanoscale engineering provides, are particularly well suited to take advantage of the state of the art in machine learning and AI in order to achieve smart integrated BMI.

At the same time, however, it is worth asking if machine learning and AI architectures designed to learn differently than existing algorithms could provide a degree of functionality and integration with BMI's that does not yet exist. In particular, machine learning methods that mathematically model and abstract specific neurobiological properties of interest. Empirical (i.e., data driven) statistical learning AI works well on problems where bias, sparseness, and saturation are not (or not yet) an issue that limit its learning. But it is precisely learning beyond these constraints that the biological brain excels at. In particular, the ability of the brain to adapt and extrapolate beyond data presented to it, and it is incredible computational and physical robustness to perturbations. These properties go beyond the current stage of the art in machine learning, but could be critical to the sophisticated integration of BMI with the brain. The biological brain represents, learns, and manipulates information very differently than the way existing artificial neural networks, machine learning, and statistical methods "learn" to find patterns in data. The brain primarily learns by analogy and by abstracting beyond the immediate training sets presented to it. It is capable of robustly adapting to different situations and contexts it may not have previously encountered with an incredible degree of plasticity. The computational flexibility, adaptation, and robustness of the brain exceed any existing machine. One extreme example of the human brain's incredible robustness and ability to adapt is evident in a neurological condition called Rasmussen's encephalitis, a rare pediatric chronic inflammatory neurological disorder that typically affects one hemisphere. It is typically characterized by severe and frequent seizures that result in loss of motor function, loss of speech, hemiparesis, encephalitis, and cognitive decline (Freeman, 2005; Varadkar et al., 2014; Venkatesan and Benavides, 2015). Most patients become refractory (stop responding) to medical treatment. In many cases the only effective treatment for seizures is hemispherectomy, whereby portions or the entire affected cortical hemisphere are surgically removed and the corpus callosum cut from the unaffected hemisphere. The corpus callosum is the high speed "ribbon cable" that connects our two sides of the brain. Yet, to varying degrees, the remaining side of the cortex in these patients is able to take up the functions of the excised cortical tissue to a remarkable extent. In many cases these patients are able to function cognitively and physically almost normally considering how much of their brains are removed. (Contrast that with what would happen if you remove even a handful of the transistors or circuits in a computer.) All of this is even more impressive given the computational and energy efficiency with which the brain achieves this - using about 20 watts of power, barely enough to power a dim light bulb, in about 3 lbs of "wetware" that occupies a volume equivalent to a 2 liter bottle of soda.

One final comment worth emphasizing is that although the biological brain exhibits computational properties and an ability to learn that we want to understand and leverage, this does not necessarily mean that we have to reverse engineer the brain to the point that we are modeling or emulating every aspect of how the biology itself implements the brain's internal algorithms. One approach is to abstract away the biological details and capture the core algorithms, i.e., rules, that underlie the property or system being studied in the brain that we want to build into the BMI. The end result are mathematical models that are independent of the underlying biological details, but which capture the functional mechanisms at an appropriate scale of abstraction in order to arrive at algorithmic descriptions that emulate those properties. Admittedly, where that line of abstraction is drawn can be more an art than a science.

Challenges and Open Problems

In this final section we briefly introduce some of the challenges and open problems associated with actually executing the vision discussed above. We do not elaborate in this paper, but leave them open for further discussion and dialog.

First, most (all) of the recent efforts in the development of neurotechnologies aimed at high density recording or stimulation have focused on the physics, chemistry, and engineering of the core nanotechnologies themselves. This is understandable because the fundamental technologies necessary to enable stimulation or recordings at the actual interface with the brain have to come first. They need to precede any methods or technologies intended to modify or make use of data and information such technologies provide. Beyond the actual interface itself, mechanical and operational stability and long term reliability of the devices is critical in order to ensure accurate recordings or stimulation. For example, if the electrodes move or there is excessive reactive gliosis it will severely affect the efficacy and accuracy of the devices, rendering any control or adaptation by machine learning algorithms irrelevant. These reflect fundamental engineering challenges that have attracted significant amounts of work. And while significant progress has been made, it very much remains highly active areas of research. We do not discuss these issues further in this paper (see for example Lega et al., 2011; Gilja et al., 2011; Lu et al., 2012).

Beyond these well-known issues surrounding the fabrication and functionality of BMI devices, there are open problems that have received comparatively less attention. Of particular relevance are questions surrounding how data from these devices can be accessed and used, which are of importance to any discussion about integrating machine learning as part of the overall system. At the nanoscale, the density of recording or stimulation can be so large that the telemetry problem of how do you keep track of all those signals becomes an issue. In other words, how do you keep track of where and when signals are coming from (in the case of recordings) or going to (in the case of stimulation). With high density recordings, e.g., many thousands of signals, it becomes physically impossible to follow the standard micro-scale strategy of having individual leads "read out" signals. Most of the nanotechnologies currently being developed for recording at such extreme densities are being engineered as individual standalone nanoscale devices that can then be deployed in large numbers. But even if each individual device is indeed able to faithfully record local signals, how does one extract that information globally across the entire population of sensors and how does one make sense of the resultant data? In the case of applications that necessitate spatial "corticotopic" information, this question is critical. We do not yet have a clear answer, but the impact of the problem cannot be overstated. Whatever the solutions end up being, they will almost certainly necessitate a combination of developments in nanotechnology, algorithms, and data analyses methods. The analogous problem with neural stimulation at nanoscales is how do you selectively target, i.e., turn on and off, nanoscale electrodes in controlled and coordinated spatial and temporal combinations according to defined optimized protocols to produce the most efficient clinically meaningful stimulation paradigms? As discussed above, these would likely differ from patient to patient and evolve over time in the same patient. Being able to accommodate such changes is at the core of the learning and adaptation machine learning methods applied to BMI and neural prosthesis could provide. The design of BMI devices from a materials and engineering standpoint should be aligned with the implementation and integration of machine learning intended to be deployed as part of the overall system.

Other important considerations are broader topics and go beyond just nanoengineered BMI integration with AI, but no less relevant or important. For example, we do not completely understand the neurophysiology, neural code, and intent of neural signals in the context of information processing. This makes it difficult or not yet possible to develop meaningful machine learning algorithms for controlling BMI. So even if the neural stimulation or neural recording interface technologies were perfected, and even if we could develop efficient and accurate machine learning for closed loop feedback control, it still is not clear what we should be optimizing for. We just do not understand how the brain works well enough to do this. With existing neural prosthesis technologies in particular, it is the brain that adapts to the engineered technology, and not the other way around. Other open problems reflect open engineering challenges, beyond the neuroscience. For example, how can machine learning and AI be efficiently implemented on board the device itself given limited form factors and local computational resources? If access to more significant computational resources on the cloud are required, the usual questions of insuring appropriate bandwidth access becomes important, in particular if such reliance was needed under clinically sensitive situations. Is edge computing a possible emerging alternative?

Finally, it is important to acknowledge and consider ethical challenges that arise from the development and use of these technologies. Neurotechnologies and AI on their own each have important ethical considerations. And in at least one recent commentary the ethical considerations of neuroscience, neurotechnologies, and AI were simultaneously discussed (Yuste et al., 2017). Those authors identified four principles that these technologies must adhere to and respect for each individual: privacy, identity, agency and equality. This needs to be an on-going and evolving conversation that tracks with the progress of the technology. The potential risks are too high to ignore or defer.

Concluding Comments

The integration of machine learning and AI with nanoengineered brain machine and brain computer interfaces offers the potential for significant advances in neurotechnology. BMI's that have the ability to learn and adapt from the environment and situational demands of external requirements offer tremendous possibilities to radically change the treatment and quality of life of patients. It also offers opportunities for non-invasive interactions and collaborations between humans and machines that at the moment are still in the realm of science fiction. It is conceivable that we are approaching an era of personalized individual experiences that will impact both clinical and non-clinical applications. Of course, as with any truly disruptive and paradigm changing progress, there remain many technical challenges that must be overcome, many in no way trivial or easy, and serious ethical questions that have to be thoughtfully considered and navigated. But it is hard not to be excited about the prospects, what it could mean for how we interact with and use technology and computers for everyone, and the life changing effects it could have on the quality of life and well-being of patients who stand to benefit the most.

We end with one last parting consideration. We have argued the position that the machine learning and AI algorithms that will be required to arrive at "smart" nanoengineered brain machine interface systems may include the use of existing state of the art algorithms, but also possibly new neural derived algorithms and machine learning architectures that more directly model computational and systems neuroscience. What we have not argued for, and what is in no way obvious, is a need for artificial general intelligence (AGI) as necessary to achieve this. Advanced applications such as smart adaptive BMI will almost certainly benefit from advanced algorithms that depend on new mathematical models and theory grounded in empirical neurobiological data. But such algorithms in isolation and out of context do not constitute AGI (although they could conceivably contribute to it). These algorithms need to be able to execute very sophisticated data analyses, pattern recognition, learning, and decision making, but only within the context and embodiment of the neurotechnologies they are supporting. The concept of a self-aware or conscious machine is not required, and should not be confused with the technical considerations that actually are needed, i.e., the discussion in this paper. This distinction is important, because the serious societal and ethical concerns and on-going conversations surrounding AGI are very different than the societal and ethical questions that we need to discuss involving neurotechnologies.

A Real-Time Non-Implantation Bi-Directional Brain–Computer Interface Solution Without Stimulation Artifacts

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Abstract:

The non-implantation bi-directional brain-computer interface (BCI) is a neural interface technology that enables direct two-way communication between the brain and the external world by both "reading" neural signals and "writing" stimulation patterns to the brain. This technology has vast potential applications, such as improving the quality of life for individuals with neurological and mental illnesses and even expanding the boundaries of human capabilities. Nonetheless, non-implantation bi-directional BCIs face challenges in generating real-time feedback and achieving compatibility between stimulation and recording. These issues arise due to the considerable overlap between electrical stimulation frequencies and electrophysiological recording frequencies, as well as the impediment caused by the skull to the interaction of external and internal currents. To address those challenges, this work proposes a novel solution that combines the temporal interference stimulation paradigm and minimally invasive skull modification. A longitudinal animal experiment has preliminarily validated the feasibility of the proposed method. In signal recording experiments, the average impedance of our scheme decreased by $4.59\ \mathrm{k}\Omega$, about 67%, compared to the conventional technique at 18 points. The peak-to-peak value of the Somatosensory Evoked Potential increased by 8%. Meanwhile, the signal-to-noise ratio of Steady-State Visual Evoked Potential increased by 5.13 dB, and its classification accuracy increased by 44%. The maximum bandwidth of the resting state rose by 63%. In electrical stimulation experiments, the signal-to-noise ratio of the low-frequency response evoked by our scheme rose by

8.04 dB, and no stimulation artifacts were generated. The experimental results show that signal quality in acquisition has significantly improved, and frequency-band isolation eliminates stimulation artifacts at the source. The acquisition and stimulation pathways are real-time compatible in this non-implantation bi-directional BCI solution, which can provide technical support and theoretical guidance for creating closed-loop adaptive systems coupled with particular application scenarios in the future.

Introduction

Brain-computer interface (BCI) technology is an expanding area of research within the field of neural engineering, defined as a communication system that bypasses the brain's normal output pathways of peripheral nerves and muscles [1]. Recently, the definition of BCI has expanded to encompass applications in medical, educational, and cognitive enhancement domains [2]. Unlike traditional BCIs, which represent the majority of the state-of-the-art, a bi-directional BCI enables complete interaction between the brain and an actuator, thus offering greater clinical and commercial potentials [3]. A bi-directional BCI is a device that capable of reading and writing data from the brain, enabling a complete linkage between the brain and an external device [4]. For instance, a bi-directional BCI can detect an epileptic seizure and stimulate the brain to prevent it [5], or provide tactile feedback to improve the control of a robotic arm [6]. Bi-directional BCIs hold significant promise in medical and cognitive enhancement domains.

The majority of current bi-directional BCI systems rely on implantable devices, such as electrocorticography (ECoG) and deep brain stimulation (DBS), which can acquire high-quality neural signals [7], [8]. However, implantable devices possess several drawbacks that limit their utility and application. First, they have a short lifespan, typically lasting only a few weeks to months [9]. Second, they can cause immune reactions and tissue damage, influencing neural signal stability and reliability [10], [11]. Third, they raise ethical concerns that challenge the research and application of implantable bi-directional BCI technology [12]. Despite recent advances in materials science that have improved the biocompatibility of implanted devices, these limitations still exist and require more effective solutions [13]. Consequently, there is a need to develop a high-performance non-implantation bi-directional BCI system, which would significantly enhance the usefulness and applicability of bi-directional BCI technology. In contrast to implantable devices, non-implantation technologies can offer excellent safety and ease of use while reducing patient pain and medical costs.

However, non-implantation bi-directional BCIs face a critical challenge in dealing with the significant interference caused by external stimuli on acquired signals. Conventional electrical stimulation, such as transcranial alternating current stimulation (tACS), generates rapid electric fields with frequencies close to physiological signals around the electrode. Moreover, the magnitude of these fields is usually much larger than the action potential, leading to the masking of crucial physiological information [14]. Furthermore, the presence of stimulus artifacts poses hardware design issues as it can saturate standard neural amplifiers [6]. Many approaches were invented to deal with this issue. These include blanking neural amplifiers during stimulation to prevent saturation, adopting alternating recording and stimulation intervals, recording in between every stimulus, and developing algorithms for extracting signals from mixed data [15]. Although those analytical methods can reduce stimulus artifacts in electroencephalogram (EEG) data, they often come at the cost of reduced decoding information or complete failure to fully restore the original signal [16]. Consequently, non-implantation bi-directional BCIs currently have limited capabilities for real-time feedback, with most studies focusing on post-stimulation effects.

To address the real-time feedback issue of non-implantation bi-directional BCIs, we present a novel solution. We draw inspiration from the temporal interference (TI) electrical stimulation method [17], known for mitigating stimulus interference by utilizing a high-frequency stimulus source to induce a low frequency. However, replicating this TI scheme in a non-implanted setting is challenging due to cranial obstructions [18], [19]. To overcome this cranial interference, we incorporate an ultrasonic drill to enable the interaction of internal and external currents, a technique known as local skull electrophysiological modification (MILEM) [20].

In our evaluation, we focus on testing event-related potentials known for their stable signal quality. Specifically, we examine the Steady-State Visual Evoked Potential (SSVEP) signal in the visual area and the Somatosensory Evoked Potential (SEP) signal in the motor area. Both signals exhibit stable evoked patterns and reproducibility, making them commonly used in electrophysiological research and clinical testing [21], [22]. Furthermore, to mimic the human body environment as closely as possible, we employ sheep as experimental subjects due to their similar skull size and skin thickness to that of humans.

In this study, we present a novel solution that effectively tackles cranial interference using the MILEM technique. Our approach utilizes two high-frequency stimulation sources to induce low-frequency stimulation in vitro, thereby minimizing stimulation artifacts and achieving complete isolation of stimulation and recording frequencies. Consequently, our system enables uninterrupted and simultaneous stimulation and recording, effectively surpassing this limitation. Moreover, our proposed method outperforms existing non-implantable techniques in terms of both recording and stimulation capabilities.

Methods

A. The Non-Implantation Bi-Directional BCI Solution

The solution comprises an electrical stimulation part and an electrophysiological recording part, as shown in Fig. 1a. The recording part uses external contact electrodes operating at $\leq 500\mathrm{Hz}$. The stimulation part uses two high-frequency sinusoidal stimulation sources with different frequencies and the same type of contact electrodes as the recording part, operating at $\geq 1\mathrm{kHz}$. These two parts operate in independent frequency bands and can work simultaneously in vitro. To enhance the access of the stimulation current to the target brain area and improve the recording part's signal quality, we performed local skull modifications by applying ultrasonic vibrations to a needle and disrupting the surrounding bone tissue. The surgical procedure is described in detail below.

Fig. 1.
(a) Schematic diagram of the non-implantation bi-directional BCI solution proposed in this study. The black line with the oval box represents the recording part, which operates at $\leq 500\mathrm{Hz}$, and the green line with the box represents the stimulation part, which operates at $\geq 1\mathrm{kHz}$. The small picture on the right side is a local zoom of the skull modification location in the occipital region. The red arrow represents the ionic current propagation path. (b) Schematic diagram before and after skull modification. The skull modification enhanced the intracranial and extracranial ionic currents. (c) 3D reconstruction of CT images in skull modification. (d) CT image of the cross-section in skull modification. The locations of the stainless-steel nails used in the surgery are outlined with red lines.
The electrical signals from the brain to the scalp have to cross multiple layers of different tissues. Among all the layers, the skull has the lowest electrical

conductivity and the most significant impact [18]. As shown in Fig. 1b, cranial modification can partially destroy the cranial tissue. In contrast, the tissue fluid in the organism will rapidly fill the cavity. This effectively reduces the resistivity along the path of ionic currents from the scalp to the brain, thus enhancing the energy of the incoming and outgoing currents. To confirm that our surgical procedure could indeed penetrate the skull, we performed Computed Tomography (CT) imaging. As shown in Fig. 1c and d, the visible length of the needle tip on the multiplanar reconstruction (MPR) image was $1.23\mathrm{cm}$. Knowing that the needle tip diameter was $0.5\mathrm{mm}$, which was smaller than a pixel ($0.7\mathrm{mm}$ isotropic), and that the overall length of the needle was $1.60\mathrm{cm}$, MPR results indicated that the needle tip passed through the skull by at least $0.37\mathrm{cm}$. The needle's potential wear during the procedure could lead to a reduction in length, resulting in a slightly smaller actual penetration depth, less than $0.37\mathrm{cm}$. No evident bleeding was during the procedure or on CT images.

B. Animal Models

We used 13-month-old male small-tailed sheep as the animal subject in this study. Before the experiment, the sheep were sedated with thioridazine, secured on a surgical table, and intubated. We shaved the hair from the head and neck of the sheep using a razor and hair removal cream and sterilized them with 70% ethanol. We maintained constant and stable anesthesia during the experiments and tests with a mixture of isoflurane and oxygen. The animals' health is continuously monitored by medical equipment. All experimental procedures were approved by the Laboratory Animal Management and Use Committee of the GATEWAY MEDICAL INNOVATION CENTER (IACUC No. BJ2022-05009).

C. Minimal-Invasive Skull Modification

We used ultrasound resonance for the modification in the skull modification section. Ultrasound in a specific frequency range can break covalent bonds and vaporize bone tissue without damaging the soft tissues [19]. We made contact with the skull by inserting a stainless-steel needle with a front end that was silicon carbide-plated into the scalp of the target remodeling area. Then The ultrasound was fed into the stainless-steel needle through a piezoelectric ceramic transducer with an output frequency range of $28{,}000\mathrm{Hz}$ to $35{,}000\mathrm{Hz}$ and an output power of $50\mathrm{W}$. The operation duration was controlled within $30\mathrm{s}$ without damaging the dura mater.
We measured the change in the electrical impedance value of current propagation channel before and after the modification using an LCR700

precision digital bridge (test frequency: $1000\mathrm{Hz}$, test AC signal: $0.63\mathrm{Vrms}$, accuracy: $\pm[0.3\%+1]$) produced by SANWA. We selected the parallel mode to measure the equivalent resistor value and connected the positive and negative electrodes of the digital bridge to two patch-type Ag/AgCl electrodes. We individually fixed the negative electrode above the sheep's right temporal region, moved the positive electrode onto the 18 points in the parietal and occipital regions, and recorded the readings.

D. Methods for Generating Evoked Potentials

In order to quantitatively assess the degree of improvement of electrophysiological recordings with our proposed protocol, we chose two evoked potentials, SSVEP and SEP, for comparison.

To induce SSVEP response. We presented periodic visual stimuli on a liquid crystal display (model: BENQ XL2720-B, size: 27 inches, resolution: 1920×1080 pixels, refresh rate: $144\mathrm{Hz}$) using the sampled sinusoidal stimulation method [24], [25]. We tested nine stimulation frequencies while avoiding breach rhythm [26] [$11\mathrm{Hz}$, $12\mathrm{Hz}$, $13\mathrm{Hz}$, $14\mathrm{Hz}$, $15\mathrm{Hz}$, $16\mathrm{Hz}$, $17\mathrm{Hz}$, $18\mathrm{Hz}$, $19\mathrm{Hz}$, $20\mathrm{Hz}$]. The stimulation form was:

$$B(f,i)=Round(255*0.5*\{1+\sin[2\pi fiRefreshRate]\})(1)$$

View Source where B represents the display's brightness, an integer between 0 and 255. f represents the stimulation frequency. i represents the serial number of each frame in the stimulus sequence. The round represents the rounding operation. $RefreshRate$ represents the screen's refresh rate, which was 144 in this study. This simulation scheme uses the impulse sequence with a time interval of $1/RefreshRate$ to perform a zero-order sampling hold operation on the sinusoidal signal.

We wrote the stimulation and interface program using MATLAB R2022a and Psychtoolbox-3 [27]. We displayed each frequency stimulus on the full screen (1920×1080 pixels). A single stimulus trial lasted 10 s, with a $5\mathrm{s}$ break between trials. We presented five trials for each stimulus frequency and randomly generated the presentation sequence of the trials by the computer. An event trigger was transmitted to the amplifier at the beginning of each stimulation to ease subsequent data analysis. We set the distance between the screen and the sheep to exactly $20\mathrm{cm}$ in the front. We fixed the eyelids of the sheep open to ensure watching while using saline to keep the eyes wet.

To generate SEP, we stimulated the median nerve of the right front leg of the sheep using a square wave electrical stimulation instrument produced by NEUSEN. We used two silver microneedles with a diameter of $350\ \mu\mathrm{m}$ as the stimulation electrodes and separated them by $5\mathrm{cm}$. The square wave signal generated by the instrument had a rising and falling period of $5\ \mu\mathrm{s}$ each. The monophasic stimulation pulse width was $200\ \mu\mathrm{s}$, the frequency was 5 Hz, and the current value was $15\mathrm{mA}$. We applied electrical stimulation for $200\mathrm{s}$ in each experiment, and $500\mathrm{ms}$ for each trial, with a total of 1000 trials. We observed apparent muscle twitches in the right forelimb of the sheep during the electrical stimulation.

E. Electrophysiological Recording and Electrical Stimulation In Vitro

This experiment used 20 patch-type Ag/AgCl electrodes (18 for signal leads, one for REF lead, and one for GROUND lead). For signal recording, we used the NEUSEN W wireless amplifier (sampling rate: $1\mathrm{kHz}$, standard mode rejection ratio: $120\mathrm{dB}$, AD conversion bit: $24\mathrm{bit}$, input noise: $\leq 0.4\mathrm{uVrms}$) produced by NEURACLE company. We placed the reference electrode on the right side of the forehead and the ground electrode on the left side and subsequently divided the signal leads into two groups of nine, each 3×3 array in the occipital and parietal regions. Adjacent electrodes were separated by $3\mathrm{cm}$. We controlled the contact impedance of each signal lead within $10\mathrm{k}\Omega$ during the acquisition process. The electrode locations were selected based on a specific criterion. As depicted in Fig. 2a, the electrodes were positioned along the median axis, aligning with the line between the occipital bone and the nasal bone. The spacing between each electrode was set at 2 cm.

Fig. 2.

Electrical impedance test results. (a) Point location diagram of the electrical impedance test experiment. The black origin represents the location of the 18 test points, which are arranged in a 3×6 array in the parietal and occipital regions. The red box marks the modified point location of experiment A, and the red circle box marks the modified point location of experiment B. The negative terminal of the digital bridge was fixed in the right temporal region of the sheep, and the values of each test site were obtained by sequential traversal. (b) Topographic maps of the electrical impedance decrease measured by the digital bridge, which is the pre-modification resistance value minus the post-modification resistance value in $\mathrm{k}\Omega$. The higher the decrease, the more the spot color is skewed toward red. The test frequency of the digital bridge was $100\mathrm{Hz}$, and the test mode was a parallel connection. (b) I. Impedance decreased values before and after the modification of the parietal region. The location of this modification point was the center of the parietal area, marked with a red box in the figure. (b) II. Impedance decreases values before and after the modification of the occipital region. The location of this modification point was the center of the occipital area, marked with a red circle box in the figure.

In Vitro Electrical Stimulation, we used $10\mathrm{Hz}$, $20\mathrm{Hz}$, and $40\mathrm{Hz}$ as the different frequencies for the stimulation. According to Grossman et al. a carrier of $1\mathrm{kHz}$ and above is necessary to ensure that the nerve cells are responding following the difference frequency rather than the carrier [17]. Therefore we used $1\mathrm{kHz}$ as the carrier wave. Using an external high-power resistance, we converted a dual-channel ATG-2082 power signal source (AIGTEK; voltage: $400\mathrm{Vp}$, current: $0 \mathrm{to} 40\mathrm{mAp}$, bandwidth: $\mathrm{DC} \mathrm{to} 200\mathrm{kHz}$, slew rate $\geq 356\mathrm{V}/\mu\mathrm{s}$) into a dual-channel current source with a synchronous output of $1(\pm 0.12)\mathrm{mA}$ sinusoidal signal. We placed the positive stimuli in the bilateral temporal regions and the two co-negative stimuli in the center of the occipital region. The stimulating electrodes were four Ag/AgCl electrodes. It is worth noting that while our technical approach drew inspiration from TI [17], we distinguish our work from the original by exclusively conducting the stimulation process in vitro. The three stimulation frequency combinations we applied were: $[1\mathrm{kHz}, 1.01\mathrm{kHz}]$, $[1\mathrm{kHz}, 1.02\mathrm{kHz}]$, and $[1\mathrm{kHz}, 1.04\mathrm{kHz}]$. Each stimulation lasted $10\mathrm{s}$.

F. Data Preprocessing and Analysis

We divided the data into segments based on the recorded trigger for the SSVEP analysis. The data segments with the same stimulation frequency were averaged. We further filtered the data using an IIR filter with $5\mathrm{Hz}$ to $20\mathrm{Hz}$ passbands and downsampled the filtered data to $250\mathrm{Hz}$. For the SEP analysis, we filtered the data using a high-pass IIR elliptic filter with a $50\mathrm{Hz}$ cut-off frequency [28], and averaged the recorded 1000 trials. For the resting state data, analysis was done by removing the DC and power frequency components using a comb-shaped IIR filter with a quality factor of 40. We then applied a high-pass FIR filter with an 8Hz cut-off frequency to the recorded signal. Any leads with obvious abnormal frequencies were substituted in the subsequent analysis by the mean of the adjacent leads. We implemented all filtering operations using the filtfilt() function in MATLAB R2022a.

In the SSVEP classification task, we used the FBCCA algorithm [29]. The method is divided into three main steps. The first step passes the preprocessed data through each of the five filters ($[6\mathrm{Hz}, 90\mathrm{Hz}]$, $[14\mathrm{Hz}, 90\mathrm{Hz}]$, $[22\mathrm{Hz}, 90\mathrm{Hz}]$, $[30\mathrm{Hz}, 90\mathrm{Hz}]$, $[38\mathrm{Hz}, 90\mathrm{Hz}]$) to get five data matrices. In the second step, five ρ-values for each of the ten stimulus targets are obtained using sine and cosine templates for each stimulus frequency to calculate the CCA correlation. In the third step, squares

of the five ρ -values are summed according to their weights. The highest result among the ten stimulus targets is selected as the predicted frequency.
In data analysis, we used broadband signal-to-noise ratio (SNR) [30], [31] as a metric to reflect the signal quality in physiological signal processing comprehensively. The main idea was to treat the energy component of the target frequency as a signal and the energy components of all other frequencies as noise. We calculated all SNR indicators in this paper according to broadband SNR. Its calculation formula was:

$$SNR=10*\log_{10}\left[\frac{N(f_{Target})}{\sum_{f=f_l}^{f_h}N(f)-N(f_{Target})}\right] \tag{2}$$

View Source where SNR represents the value of broadband SNR. f_{Target} is the target signal frequency, the stimulation frequency in SSVEP analysis, and the difference frequency in electrical stimulation analysis. $N(f)$ is the energy component at frequency f . f_h and f_l are the upper and lower limits of the frequency band.
To determine the PSD and maximum bandwidth of the resting state signal, we first applied the Welch technique for spectral estimation. A Hamming window was used as a window function with 50% overlap. The trend line was drawn using the moving average approach with a sliding window length of 30 points to make it easier to understand the PSD map before and after the skull modification. Following several earlier research, we utilized a statistical test and estimated the maximum signal bandwidth before and after the modification [32], [20]. We hypothesized that the signal obtained from in vitro measurements at approximately $100 Hz$ encompasses a significant amount of ambient noise components, outweighing the effective information. Therefore, we used the $85 Hz$ to $95 Hz$ band as the noise floor, as it was the highest $10 Hz$ band within $100 Hz$ that avoided both the powerline frequency and its harmonics. We performed a paired t-test between the energy value array of any $10 Hz$ band and that of the noise floor, and if the band's significance level was below 0.01, we deemed that the band contained effective information. We started from $0 Hz$ and traversed through all $10 Hz$ bands until the significance level was higher than 0.01. Then we regarded the starting frequency of this band as the highest valid frequency.

Results

A. Electrical Impedance

To investigate the impact of skull modification on the reduction of electrical resistivity, we conducted animal experiments to record changes in resistance values before and after modification. The recording sites were identified as shown in Fig. 2a. The instrumentation and experimental parameters used in the tests are described in the Methods section. Two sets of experiments targeting different brain regions were conducted in parallel to allow for a comprehensive comparison. In experiment A, we performed a skull modification at the central point of the parietal region, indicated by the red box in Fig. 2a. Following the modification, we observed a significant decrease in the electrical impedance values recorded at a total of 18 test sites in the parietal and occipital regions ($M=1.94k\Omega$,$SD=1.05$) as compared to the values prior to modification ($M=8.4k\Omega$,$SD=2.37$), $t(17)=9.95$, $p=.000000017\ll.01$. In experiment B, we conducted a skull modification at the center of the occipital region, as indicated by the red circular box in Fig. 2a. Similarly, a significant decrease emerged in resistance values recorded at the 18 tested sites after the modification ($M=2.28k\Omega$,$SD=0.83$) compared to those prior to the modification ($M=6.87k\Omega$,$SD=3.37$), $t(17)=6.04$, $p=.00000013\ll.01$. These results provide solid evidence to support the significance and validity of skull modification as a strategy to reduce electrical resistance values. The experimental findings reveal significant lateralization in the spatial distribution of the impedance reduction resulting from skull modification. To illustrate this effect, we plotted the topographic distribution of the electrical impedance reduction values (pre-modification electrical impedance values minus post-modification electrical impedance values in $k\Omega$) induced by skull modification, as shown in Fig. 2b. Specifically, Fig. 2b I. depicts the results of experiment A, with the modification site located in the parietal region, while Fig. 2b II. illustrates the results of experiment B, with the modification site located in the occipital area. Markers indicate the modification sites in both experiments in the figures. Notably, the electrical impedance reduction due to modification was more pronounced near the modification site, as demonstrated by the topographic maps.

B. Evoked Potential Recording for BCI

After demonstrating that skull modification reduces electrical impedance, this work further assessed its specific effects on electrophysiological recordings. In the two experiments mentioned in the Electrical Impedance section, we also performed evoked potential recordings before and after the modification. In the parietal region of experiment A, an electrical stimulus was given at the median nerve for recording the somatosensory evoked potential (SEP) before and after the modification. In experiment B for the occipital region, we recorded the SSVEP before and after the modification using cyclic visual stimulation in different frequencies. Fig. 3a. shows the locations of the recording electrodes and the modified sites. Fig. 3b. shows the SEP recorded at the center of the parietal region in experiment A (after averaging 1000 trials). A clear N20 and P23 component is visible, and the peak amplitude after the modification ($8.01\ \mu V$) is about 8% higher than before ($8.68\ \mu V$). In experiment B, Fig. 3C. and 3D. show the time-frequency representations of the signals recorded at the central occipital region under SSVEP stimulation at $11Hz$ before and after the modification, respectively, along with the spectrograms (the results of five 10-second trials averaged by superposition). The improvement of the SSVEP signal quality by the skull modification is evident in both time and frequency domains. The mean signal-to-noise ratio (SNR) of the SSVEP at the occipital region at each stimulation frequency after skull modification ($M=-10.47dB$, $SD=1.74$) was significantly higher than the one before modification ($M=-15.6dB$, $SD=2.78$), $t(9)=-6.88$, $p=.000072\ll.01$, as shown in Fig. 3e. The average increase was about $5.13dB$. To verify the effect of signal boosting on the performance of the BCI, we used the filter bank canonical correlation analysis (FBCCA) algorithm to classify the acquired data for SSVEP stimulation frequency prediction. Fig. 3f. and Fig. 3g. show the confusion matrix and the accuracy of the classification results, respectively. Fig. 3f I. shows the classification results after the modification and Fig. 3f II. shows the results before the classification. It can be seen that the skull modification has an obvious improvement in the classification performance of the BCI. The accuracy of SSVEP classification after the modification ($M=0.98$, $SD=0.06$) was significantly higher than that before the modification ($M=0.54$, $SD=0.37$), $t(9)=-3.6$, $p=.0057<.01$, as shown in Fig. 3g.

Fig. 3.

Electrophysiological recordings. (a) Recording sites. Eighteen recording electrodes are arranged in a 3×6 pattern in the parietal and occipital regions of the sheep. The red boxes and circles mark the locations of the modification sites in experiments A and B, respectively. (b) SEP was recorded after averaging 1000 trials. The red and blue curves show the results after and before cranial modification. The peak-to-peak amplitudes after and before the modification are also marked, with values of $8.68\mu V$ and $8.01\mu V$, respectively. (c) Time-frequency representation of the signal recorded at the central dotted lead of the occipital region under SSVEP stimulation at $11Hz$. The upper and lower panels show the results after and before the modification. The darker red color indicates low energy, and the more yellow color indicates high energy. (d) The amplitude-frequency representation of the signal recorded at the central point lead of the occipital region. The red and blue lines show the results after and before the modification. (e) the Broadband signal-to-noise ratio of the SSVEP recorded at each stimulation frequency. The result is the average of the 9-lead SNR across the occipital region. The red and blue bars show the results after and before modification. (f) I. is the confusion matrix of SSVEP classification prediction results after the modification, and II. is the confusion matrix before the modification. (g) red represents the SSVEP classification accuracy after the modification, and blue represents the accuracy before the modification.

C. Resting-State Frequency Band Enhancement

We analyzed the resting-state data before and after the modification to measure the change in the maximum effective bandwidth of the electrophysiological recording section. We first calculated the average PSD maps of the nine leads in the parietal region of experiment A and the nine leads in the occipital region of experiment B. Then we performed a statistical analysis to determine the maximum effective bandwidth. Fig. 4a. shows that for experiment A, the mean maximum effective bandwidth of the parietal region 9-lead after cranial modification ($M=50.7Hz$,$SD=16.85$) was significantly higher than before modification ($M=38.2Hz$,$SD=4.47$), $t(8)=-2.38$, $p=.044<.05$. The average increase was about 33%. Fig. 4b. shows that for experiment B, the maximum effective bandwidth of the occipital region 9-lead after cranial modification ($M=62.4Hz$,$SD=14.54$) was also significantly higher than before modification ($M=38.24Hz$,$SD=1.7$), $t(8)=-4.9$, $p=.0012<.01$. The average increase was about 63%. The occipital region's results may be better due to its greater distance from the Ground and Reference lead. These results suggest that skull modification enhances the effective bandwidth of the electrophysiological recording Section in the resting state. This phenomenon may indicate that as the local electric impedance of the skull decreases, more information can be transmitted from the brain to the scalp. It suggests more possibilities for non-implantation BCIs.

Fig. 4.

Resting-state electrophysiological recordings. (a) Average PSD maps in the parietal region before and after the modification. (b) Average PSD maps in the occipital region before and after the modification. The locations of the leads used for the analysis and the corresponding modification sites are indicated below. The light red and blue curves show the results after and before the modification. The red and blue lines show the moving averages of the PSD plots after and before the modification, respectively. The red and blue vertical dashed lines indicate the maximum effective bandwidth after and before the modification. The energy drops around $0Hz$, $50Hz$, and $100Hz$ due to the industrial frequency removal operation.

D. Bi-Directional in Vitro Implementation of AC Stimulation and Recording

Fig. 5a. shows the distribution of electrical stimulation and electrophysiological recording points. Because the frequency range used in our stimulation protocol was isolated from the frequency range of the electrophysiological recordings, we could record the effects of electrical stimulation in real-time. We performed three-point skull modifications to ensure the stimulation current could enter the brain and activate neurons. We tested three different stimulation combinations, which are [$1kHz\&1.01kHz$, $1kHz\&1.02kHz$, $1kHz\&1.04kHz$]. The specific parameters and technical details of the electrical stimulation are given in Methods. We calculated the SNR before and after the modification to quantify the enhancement of the electrical stimulation effect by the cranial modification. Fig. 5b. shows that the SNR of the frequency component at the differential frequency of two stimulus sources, Δf (for three combinations: $10Hz$, $20Hz$, $40Hz$), was significantly higher after skull modification ($M=-10.48dB$,$SD=0.33$) than before modification ($M=-18.52dB$,$SD=1.36$), $t(3)=-13.41$, $p=.005<.01$. The average increase was about $8.04dB$. Fig. 5c. shows the topographic distribution of the SNR increase at the Δf frequency component for the 18 leads. The values refer to the SNR differences before and after the modification in dB. This figure implies that the electric field distribution was more focused and had a higher spatial resolution after the skull modification. The amplitudes of the Δf frequency components we recorded in our experiments were on the order of microvolts. As shown in Fig. 5d, our electrical stimulation was on the order of millivolts, indicating that our stimulation protocol successfully induced clustered oscillations of neurons. Moreover, Fig. 5d. also shows that the amplitude of the Δf frequency component before skull modification did not exhibit a significant peak. This experimental observation suggests that the in vitro realization of the TI stimulation may not be achievable directly without skull modification. Thus, we posit that reducing the electrical impedance of the skull is imperative for successful TI stimulation in vitro. In other words, the induction of Δf through skull modification can be viewed as a transition “from absence to presence” rather than a mere enhancement.

Fig. 5.

Results of simultaneous electrical stimulation and electrophysiological recordings. (a) Distribution of leads for electrical stimulation and electrophysiological recording. The grey leads are used for electrical stimulation, and the black leads are used for electrophysiological recordings. The skull modification sites are marked with red circles. A sinusoidal cross-current stimulus with frequency f was applied between the right temporal and occipital regions for electrical stimulation. In contrast, a sinusoidal cross-current stimulus with frequency f+Δf was applied between the left temporal and occipital regions. (b) Change in SNR of Δf frequency component (from left to right, $10\mathrm{Hz}$, $20\mathrm{Hz}$, and $40\mathrm{Hz}$) before and after skull modification under the three stimulus combinations. The blue box shows the result before modification, and the red box shows the result after modification. (c) In dB, the topographic distribution of the SNR improvement of Δf frequency component (from left to right, $10\mathrm{Hz}$, $20\mathrm{Hz}$, $40\mathrm{Hz}$) under the three stimulus combinations before and after modification. The modification points are marked with red boxes in the figure. The redder the color, the higher the improvement. (d) The signal's spectrogram was recorded at the central point of the parietal region under the three stimulus combinations. The blue line shows the result before modification, and the red line shows the result after modification. Δf frequency component values and locations are indicated in the figure. (e) Comparison between direct low-frequency stimulation (Δf) and TI stimulation protocol. The green line illustrates the spectrogram of the signal recorded at the central potential electrode using direct low-frequency stimulation (Δf), whereas the red line depicts the spectrogram of the signal recorded during the application of the TI stimulation protocol.

Finally, in order to illustrate the superiority of the TI stimulation scheme, we conducted an experiment wherein both stimulation sources were directly stimulated at a frequency of Δf for low-frequency stimulation, and the resulting signals were recorded. Fig. 5e presents a comparison of the obtained results for the case when Δf is set to $10\mathrm{Hz}$. The figure clearly indicates that direct low-frequency stimulation leads to significant stimulation artifacts, completely overshadowing the electrical signals generated by neural activity, with their amplitude surpassing the neural signals by several orders of magnitude. In contrast, the TI stimulation scheme, depicted in red in Fig. 5e, effectively circumvents the interference caused by stimulation artifacts, enabling direct recording of the neural signals.

Discussion

This paper presents an innovative real-time, non-implantation, bi-directional BCI solution that enables simultaneous high-quality brain activity recording and precise modulation. This advancement offers new tools and methodologies for brain science and brain-computer interaction. Our approach relies on local skull electrical modification, achieved through the use of ultrasound resonance to evaporate specific skull tissue, thus reducing the electrical impedance of the targeted skull region. As a result, this technique mitigates the skull's blocking effect on electrical signals, enabling more accurate and sensitive measurement of electrophysiological signals through external electrodes. This represents a substantial improvement over conventional EEG techniques.

Furthermore, we leverage the reduced resistance in the current propagation path resulting from skull modification to design an in vitro TI scheme. This scheme involves applying two high-frequency AC currents with electrodes to induce low-frequency responses in targeted brain areas. Importantly, the stimulation frequency employed in this scheme does not overlap with the frequency of the electrophysiological signals we measure, avoiding any interference between the stimulation and the recordings. By integrating these innovations, we have successfully achieved a real-time bi-directional BCI solution, enabling simultaneous recording and stimulation in an in vitro setting. This approach opens up promising avenues for further research and application in BCIs and brain science.

A. The Significance of Real-Time

Unlike previous studies focusing on post-stimulation effects, our protocol enables a simultaneous bi-directional BCI, allowing us to obtain EEG signals during tACS [33]. We observed some interesting experimental results that have rarely been reported during the recording process. The most notable of these is that the EEG recordings evoked by the TI protocol show significant peaks not only at the difference frequencies (Δf) but also at their multiples. For example, in Fig. 5d., there is a higher peak at 20Hz in the recordings with a Δf of 10Hz and a significant peak at 40Hz in the experiments with a Δf of 20Hz. The underlying neural mechanism of this phenomenon is unknown, and it is unclear whether this is specific to TI or whether all tACS stimuli induce harmonics. Our bi-directional BCI scheme could be an essential tool for studying the physiological mechanisms of tACS in the future.

B. Application of Skull Modification in BCI

The skull modification, a pivotal component of our proposed scheme, acts as a "solid" spatial filter rather than a mere signal enhancer. This remarkable phenomenon is visually evident in Fig. 2b, where the method selectively enhances signals from local brain regions. This feature holds immense significance in BCI research, as most BCI tasks focus on specific brain regions [34]. For instance, the SSVEP paradigm targets the occipital regions [25], while motor imagery and handwriting recognition tasks concentrate on the parietal regions [35], [36].

The “solid” spatial filter attribute of the skull modification allows researchers to effectively eliminate interference from other brain regions, thus significantly improving the performance of the target task. As a result, the future of skull modification in the field of BCI looks promising, extending beyond studies limited to parietal and occipital regions to include BCI investigations in temporal and frontal regions. Nonetheless, it is essential to acknowledge that the efficacy of skull modification may be constrained for certain BCI tasks that target deeper brain regions, such as tactile and auditory processes, due to the associated risks and dangers of punching holes in the side or underneath the skull.

In conclusion, the development and application of skull modification in BCI research present valuable opportunities for enhancing brain signal analysis and fostering advances in neurotechnology. However, careful consideration of safety and appropriate utilization is necessary, particularly when dealing with tasks that involve deeper brain regions.

C. Security Considerations in Skull Modification

The use of ultrasound vibration to modify the skull entails certain risks that demand careful examination. To assess the extent of damage caused by skull modification, we conducted continuous CT monitoring on the sheep subjects involved in the experiment, as illustrated in Figure 6. The CT results revealed remarkably rapid healing of the sheep’s modified skulls, with no discernible holes visible in the CT images within a month. This contrasts with previous findings in rats, where similar holes failed to heal in larger crania [20]. We attribute this difference to the disparity in cranial size, as sheep possess larger crania, which subjects them to more stress. Consequently, the holes can be sealed through deformation within a short timeframe, thereby expediting the healing process. Moreover, throughout the continuous monitoring, the sheep maintained good health.

Fig. 6.
illustrates the process of cranial healing. (a) displays the CT image immediately after the skull modification, while (b) presents the CT image taken one-month post-surgery. The red circle highlights the region on the skull where the modification was performed.

Collectively, these findings lead us to conclude that the effects of skull modification on large mammals are minimal and reversible. Nevertheless, its practical application may be subject to individual variations and other factors. Therefore, conducting further clinical studies is imperative to validate the method's efficacy and safety, and to establish the optimal surgical protocol and parameter settings.

D. Comparison With Similar Technologies

Our work exhibits several advantages over traditional non-implantation electrical stimulation and recording. However, when compared to implantable technology, it does have some limitations in both recording and stimulation capabilities. For instance, a study revealed that the enhancement of SSVEP over EEG on ECoG can reach 7 dB and above [37], whereas our protocol achieves a maximum of only 5 dB. Furthermore, our enhancement of effective bandwidth for rsEEG falls short compared to implantable techniques such as stentrode [38].

Regarding stimulation, the accuracy of the TI scheme is influenced by the precision of the electric field and is not as proficient as techniques found in implantable DBS [19], [39]. Nevertheless, a significant advantage of our approach is the elimination of the need for electrode implantation, thereby mitigating numerous risks related to biocompatibility and ethics. We firmly believe that our scheme has the potential to partially replace implantable devices in the future, particularly in medical scenarios where exceptional precision is not a strict requirement.

Conclusion

Our solution presents a secure and convenient alternative to traditional invasive BCI technologies. The surgical procedure utilized in our approach is minimally invasive, involving a cranial opening diameter of only 500 μm , and the experimental cranial modification can be completed within a rapid 30 seconds. Notably, our solution does not require sensor implantation, thus mitigating the risks associated with biocompatibility. Moreover, in comparison to conventional non-implantation techniques, our solution offers superior signal quality and bandwidth for electrophysiological recording, potentially surpassing the performance limitations of current non-implantation BCIs.

The local impedance reduction resulting from the skull modification enables us to conduct TI protocols in vitro, thereby facilitating simultaneous electrical stimulation and electrophysiological recording. This groundbreaking feature opens up avenues for studying diseases and neural recordings, as well as future bi-directional closed-loop BCI investigations.

Connecting the Brain with Augmented Reality: A Systematic Review of BCI-AR Systems

by
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Abstract

The increasing integration of brain–computer interfaces (BCIs) with augmented reality (AR) presents new possibilities for immersive and interactive environments, particularly through the use of head-mounted displays (HMDs). Despite the growing interest, a comprehensive understanding of BCI-AR systems is still emerging. This systematic review aims to synthesize existing research on the use of BCIs for controlling AR environments via HMDs, highlighting the technological advancements and challenges in this domain. An extensive search across electronic databases, including IEEEXplore, PubMed, and Scopus, was conducted following the PRISMA guidelines, resulting in 41 studies eligible for analysis. This review identifies key areas for future research, potential limitations, and offers insights into the evolving trends in BCI-AR systems, contributing to the development of more robust and user-friendly applications.
Keywords:
augmented reality; **AR**; **brain–computer interface**; **BCI**; **EEG**; **HMD**; **PRISMA**; **systematic review**

1. Introduction

A brain–computer interface (BCI) is a system that directly interprets the intentions of a person based on their brain activity [1,2]. It enables users to manipulate or control objects [3] in their environment using only their thoughts. Typically, BCIs establish a direct connection between the electrical signals in the brain and an external device, such as a computer, an electric wheelchair, a head mounted display, or a robotic limb. These interfaces are primarily used for exploring, mapping, assisting, or enhancing human cognitive or sensory-motor functions. The main components of a brain–computer interface are usually the following:

1. Brain activity measurement device: This can take the form of a headset, cap, or headband equipped with specialized sensors. These sensors detect and record the signals emitted by the brain.
2. Computer system for processing and analyzing brain activity: The recorded brain signals are processed and analyzed by BCI software. This software employs specialized methods and algorithms to interpret the user's intended actions based on the brain activity.
3. Application control: Once the system has identified the user's desired action, it sends a signal to the relevant application or tool to execute that command.

There are many alternative techniques used to measure brain signals, and these can be categorized into invasive, semi-invasive, and non-invasive techniques. Invasive BCIs involve the direct implantation of devices into the brain's grey matter during neurosurgery. While these devices provide the highest quality of signals, they are prone to issues such as scar tissue formation, which can weaken the signals or trigger an immune response due to the presence of a foreign object in the brain.

Semi-invasive BCIs, on the other hand, are implanted inside the skull but positioned outside the brain's grey matter. These devices offer better signal resolution compared to non-invasive BCIs. In addition, the risk of scar tissue formation within the brain is lower in semi-invasive BCIs than in fully invasive ones.

The least invasive method is the use of a set of electrodes, typically known as an electroencephalograph (EEG), which are attached to the top of the head [**4**]. These electrodes can detect and record brain signals. Regardless of the placement of the electrodes, the underlying mechanism remains the same: the electrodes measure small voltage differences between neurons. The signal is then amplified and filtered. Although the electrical signal is partially blocked and distorted by the skull, this non-invasive method is more widely accepted due to its relative advantages over the other techniques mentioned. The most important advantage is the safety of the procedure, as the electrodes do not require surgery to be placed [**5**]. Additionally, non-invasive BCIs are widely accessible and easy to use, making them suitable for a larger population without requiring extensive training. They do not restrict mobility or physical movement, allowing users to engage in various activities while using the interface.

BCI systems examine the brain's electrical activity, which can be recorded using invasive, semi-invasive, or non-invasive techniques, such as electrodes positioned on top of the head. The signals are amplified and converted into digital form using preprocessing methods, and the applicable features of the signals are extracted, processed, and translated into commands capable of controlling external devices or applications. BCI systems can be categorized into three types: active, reactive, and passive. In active BCI systems, users participate in mental tasks that generate specific patterns of EEG signals. These patterns are then detected by the BCI system. The most commonly used method involves motor imagery (MI), where participants imagine moving body parts without physically carrying out the movements [**6**]. On the other hand, reactive BCI involves regulating brain activity in response to external stimuli provided by the BCI system. The prevalent paradigm in this category is the P300 speller, where symbols or letters are displayed sequentially on a screen, and participants focus their attention on the desired symbol. Passive BCI [**7**] involves solely monitoring the EEG activity of users without requiring them to engage in any mental tasks. In passive systems, the EEG activity is not intentionally manipulated for a specific purpose but rather used to extract information such as the user's emotional state. The BCI focus of this paper is presented in **Figure 1**.

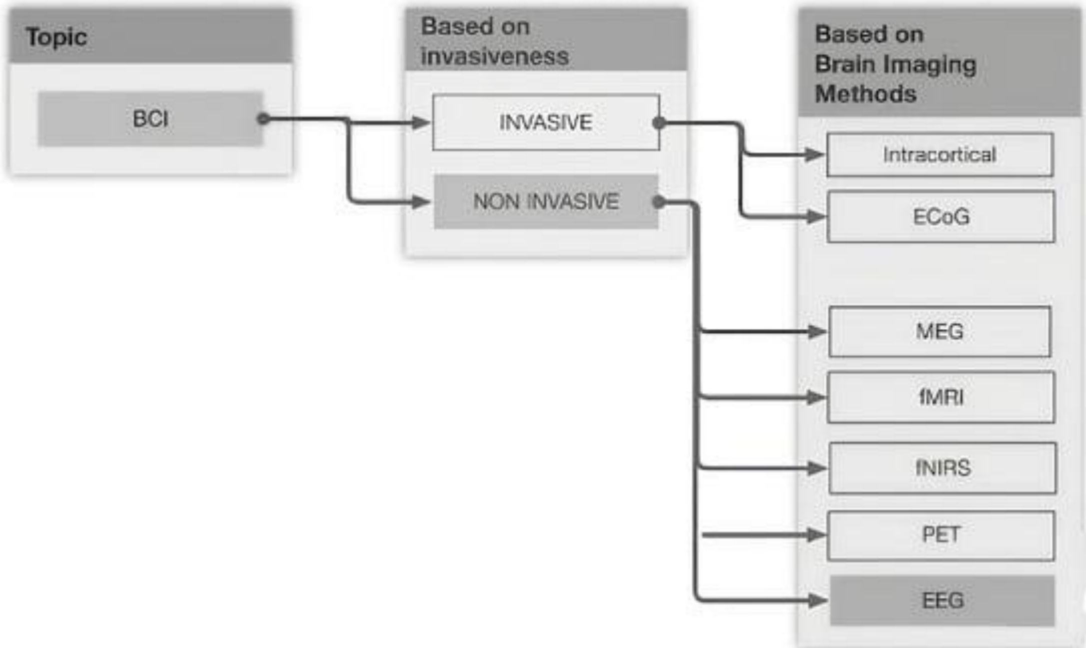

Figure 1. BCI focus of this paper.

Augmented reality (AR) is an interactive encounter with the actual surroundings in which computer-generated perceptual information enhances the objects present in the real world. This enhancement can involve multiple senses, such as sight, sound, and touch. AR can be described as a system that combines elements of the real and virtual worlds, allowing for real-time interaction and accurate 3D alignment between virtual and real objects. The additional sensory information can either enhance the natural environment (add virtual content in real-world elements) or mask it (hide or override real-world elements). The AR experience seamlessly blends with the physical world, creating an immersive perception within the real environment.

Smart glasses offer two primary methods for displaying AR content: optical see-through and video see-through. Video see-through systems utilize cameras embedded within the head-mounted device to present video feeds. This is the conventional approach employed by smartphones for AR applications. Video see-through is particularly advantageous when remote experiences are desired, such as controlling a robot to fix something from a distant location or virtually exploring a potential vacation destination. It is also beneficial for utilizing image enhancement systems like night-vision devices. On the other hand, optical see-through systems combine computer-generated imagery with a real-world view seen through the glasses via a semi-transparent mirror. This method is useful in scenarios where concerns arise about potential power failures. An optical see-through solution allows users to maintain visual perception in every situation. Additionally, if high image quality is a priority, portable cameras and fully immersive head-mounted displays cannot match the experience of direct viewing provided by optical see-through technology.

Various review attempts have been made in the literature to demonstrate the brain's connection with alternative realities. However, most of them focus on virtual reality and distinct applications like patient rehabilitation. A comparative analysis is presented in Table 1 to showcase the existing review attempts.

Table 1. Review articles on AR-BCI technologies.

Lotte et al. [8] conducted a review in 2012, highlighting the existing BCI-VR applications. The articles were categorized according to the neurophysiological signal used to drive the BCI (MI, P300, SSVEP).

Kohli et al. [9] reviewed the use cases of virtual and augmented reality-based BCI applications for smart cities. The review was conducted in 2022, and the papers included were divided into two main categories depending on the type of reality (virtual or augmented).

Angrisani et al. [10] provided a comprehensive picture of the current state-of-the-art SSVEP BCIs in AR environments. The search was conducted on the Scopus database using the AR and SSVEP keywords and covering the last 6 years (2018–2023). Out of the 56 articles retrieved, 20 of them were thoroughly compared based on EEG acquisition, EEG processing, and BCI application.

Nwagu et al. [11] conducted a systematic review focusing on EEG-based BCI applications in immersive environments. The search was performed in four online databases (ACM, IEEE Xplore, PubMed, and Scopus), resulting in 2982 papers. The final number of articles to be assessed was 76, and they covered the last decade (2012 to 2022). The structure of the results contained the following sections: trend by year, application domains, trend by country, features of the VR/AR application, BCI paradigms, EEG acquisition, EEG signal processing, BCI interaction tasks, system evaluation, study findings, and challenges.

This work presents a systematic review of EEG-based BCI applications in AR environments. To the best of our knowledge, this is the first systematic review focusing explicitly on immersive AR environments projected on HMDs. This review spans from 2012 to 2024 and exclusively includes applications involving only healthy participants. A search was performed in three online databases (IEEE Xplore, PubMed, and Scopus) retrieving 730 search results. The final 41 papers included for analysis were divided into three categories based on the BCI paradigm (reactive, passive, and active).

This systematic review investigates the progress and trends in the domain of BCI-AR systems. The primary goal is to conduct a comprehensive analysis of the existing literature and point out crucial discoveries and emerging patterns. The main objective is to identify innovative directions and potential future developments through the synthesis of available knowledge.

2. Research Methodology

A systematic review is an approach that involves the identification, evaluation, and interpretation of all relevant research findings referring to a specific research question or topic area. The primary objective is to synthesize the existing evidence in a reasonable, thorough, and unbiased manner. The authors implemented a comprehensive screening procedure to assess the eligibility of the articles and evaluated the risk of bias in all included studies. Discrepancies among the researchers were addressed through discussions, leading to an agreement.

2.1. Search Strategy

The preferred reporting items for systematic review and meta-analysis (PRISMA) [12] were used to direct the reporting of the search for articles, the extraction of data, and the synthesis of results. A broad search process was conducted in the following digital databases: IEEE Xplore (145), PubMed (139), and Scopus (446). The search was performed between June 2024 and early July 2024, covering 13 years of publication (2012–2024) to showcase the most recent BCI technology. The search string used to search for relevant literature was the following: ((“BCI” OR “brain-computer interface”) AND (“mixed reality” OR “augmented reality” OR “MR” OR “AR”)). The next step was to exclude duplicate publications using the Rayyan software [13] which is a free web tool designed to help researchers with systematic reviews.

2.2. Selection Criteria

During the review process, articles were assessed for inclusion based on specific criteria. The first requirement was that the articles described a BCI system that was designed using EEG technology. Additionally, the articles were only considered if they included a head-mounted device as the stimuli used in the study. Finally, only articles that involved participants who were healthy and had no history of disorders or pathology were included in the analysis.

Also, several exclusion criteria were applied to ensure that the included studies were relevant and met the requirements of the research question. First, review articles, case studies, qualitative research, and any other secondary articles were excluded. Studies that included participants with a pathological history were excluded, as were studies that did not involve mixed or augmented reality stimuli. Additionally, studies that used biological measures other than an electroencephalogram (EEG) as the primary research outcome were excluded from the review process. Finally, full texts that were published in languages other than English were excluded from the review.

2.3. Study Selection

A comprehensive search of databases (presented in **Figure 2**) and other sources yielded a total of 730 search results. After removing duplicate entries, 356 studies remained for a title and abstract screening, and their eligibility was assessed based on predefined inclusion criteria. From this screening process, 41 papers were identified for further analysis, and their full texts were thoroughly examined. The included papers comprise 15 from conferences and 26 from journals. Among the journal papers, the sources are diversified across 19 different journals, with 13 classified as Q1, 4 as Q2, and 2 as Q3. The papers were divided into three categories based on the type of BCI (active, reactive, or passive).

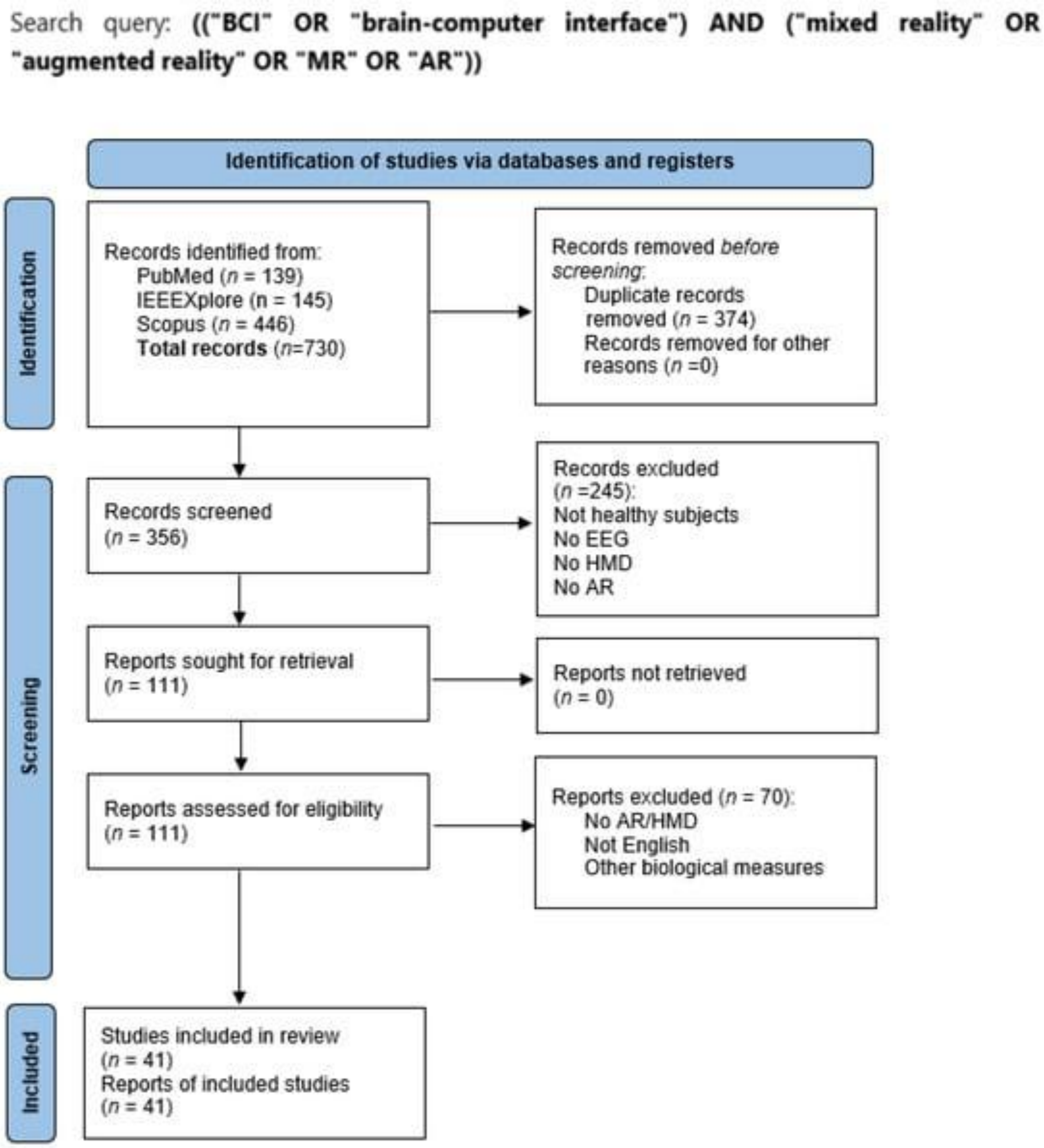

Figure 2. PRISMA flow chart with search query.

3. Study Statistics

3.1. Research Attributes

The following subsection presents graphs and statistics pertaining to the following attributes: publication year, number of participants, and BCI paradigm.

3.1.1. Publication Year

Articles included in the analysis were limited to those published from 2012 onward. However, none of the articles identified during the screening process prior to 2014 met the predefined criteria for inclusion. The median publication year (Figure 3) of the selected studies was 2022 (mean = 2020.73; SD = 2.42; range = 2012–2024).

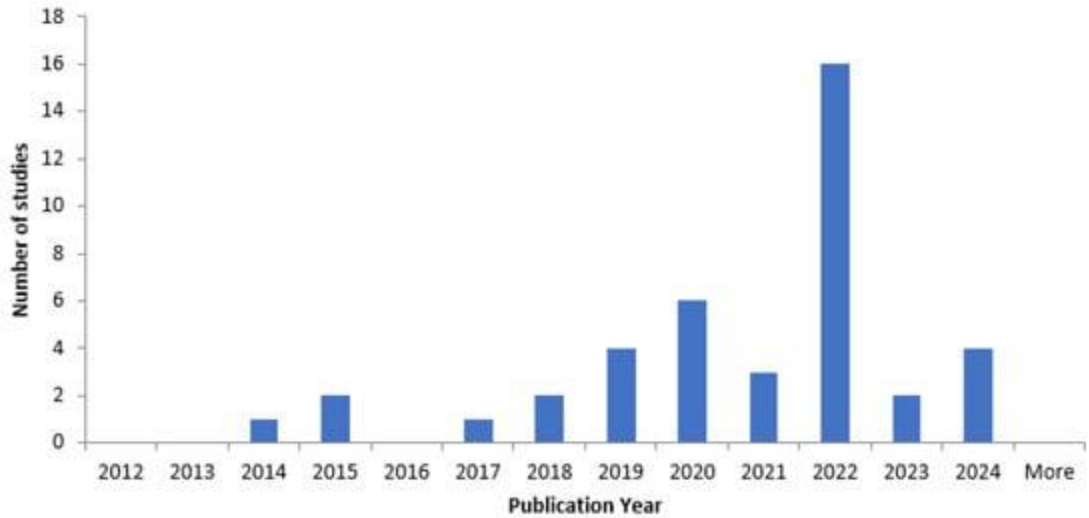

Figure 3. Publication year of the included studies.

3.1.2. Participants

The mean number of participants across all included articles (**Figure 4**) was 12.07 (SD = 7.03, range = 1–35).

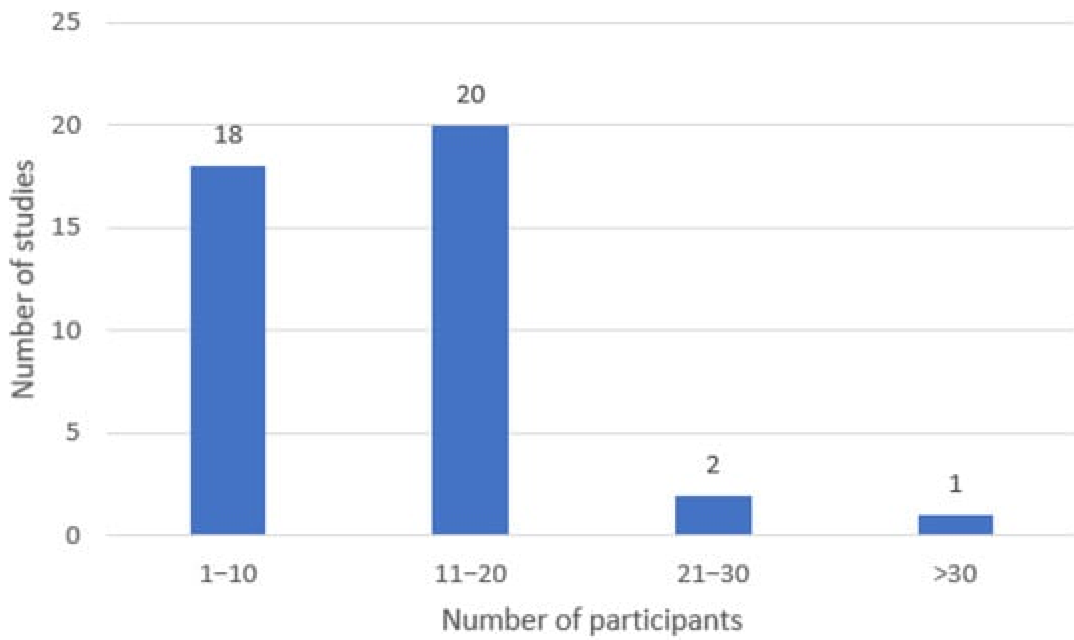

Figure 4. Distribution of participants.

3.1.3. BCI Paradigm

In this section, an overview of the distribution of studies based on the BCI paradigms is provided. **Table 2** summarizes the number of studies categorized under each paradigm, and **Figure 5** visualizes this distribution.

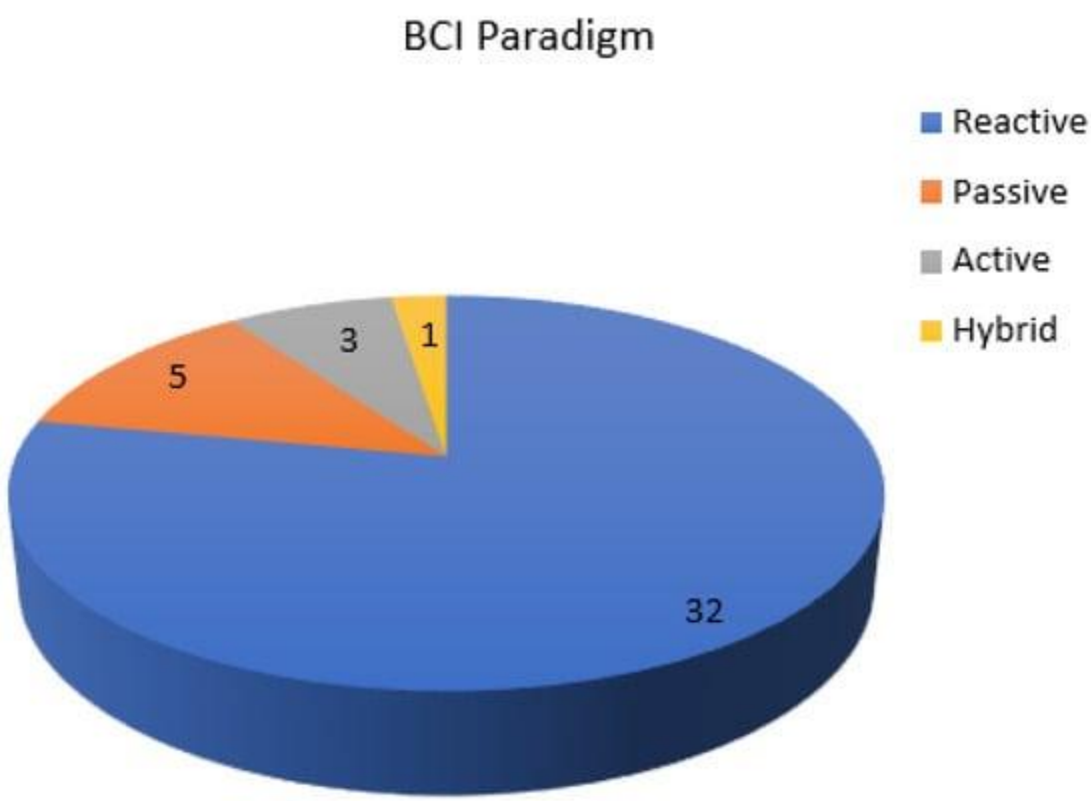

Figure 5. Distribution of the studies based on the BCI paradigm.

Table 2. Number of studies for each BCI paradigm.

3.1.4. EEG Devices

In addition to the participant statistics and BCI paradigms, it is also important to consider the EEG devices used across the studies. These devices vary in terms of electrode count and cost, which affect the precision and accessibility of brain signal recordings. **Table 3** provides a comparison of the EEG devices used in the included studies, classified by the number of electrodes and their approximate price.

Table 3. Comparison of EEG devices based on electrode count, price, manufacturer, city, and country.

4. Results

In this section, a comprehensive summary of the studies in the literature is presented. The results section is divided into three categories: reactive BCI, passive, and active BCI. For each category, a brief synopsis of each work is presented along with information about signal preprocessing, feature extraction methods, classification techniques, and evaluation metrics. One study, which employs a hybrid approach by incorporating elements of both active and reactive BCI, has been included in the active BCI category, as it primarily aligns with the characteristics of active BCI.

4.1. Reactive BCI

This category focuses on the reactive BCI systems and consists of 32 studies presented in **Table 4**, which will be classified into three categories: home automation and control, human–robot interaction and control, and IoT applications.

Table 4. Studies from the reactive BCI category.

4.1.1. Home Automation and Control

Putze et al. [14] developed the HoloSSVEP system that utilizes the HoloLens HMD's AR camera combined with an eye tracker to control a smart home. To record the EEG signals, a g.Nautilus headset was employed consisting of three electrodes. The EEG signal was filtered using a bandpass filter between 1–35 Hz and then processed with canonical correlation analysis (CCA). To evaluate the experiment, 12 subjects tried to control 4 different systems (office lights, window blinds, a TV, and a music player) with four different control options. Classification accuracy was the evaluation metric applied for this work. Although the accuracy of the system was high, users were concerned about the comfort of wearing two headsets. With a similar objective, Park et al. [15,29] implemented a home appliance control system by combining EEG-based BCI with HoloLens AR HMD. They tested four different stimulus types (three under an AR environment and one on an LCD monitor). A BioSemi ActiveTwo system with 33 electrodes was used to record the EEG data. Then, the EEG data were downsampled to 512 Hz, and a bandpass filter was applied between 2 and 54 Hz. The multivariate synchronization index (EMSI) was employed for the classification process. To evaluate their experiment, 17 participants took part in the online experiment, which consisted of controlling three home appliances with four available commands. Classification accuracy and information transfer rate (ITR) were the evaluation metrics for this experiment, with respective values of 92.8% and 37.4 bits/min. In a later attempt, they also integrated an eye tracker based on electrooculograms (EOGs) in their system. The system's performance and usability were assessed with 13 individuals over the age of 65. The EEG data were collected from 12 electrode positions using a BioSemi ActiveTwo system equipped with 12 active electrodes. Afterward, the data were downsampled at a rate of 512 Hz and subjected to bandpass filtering with cutoff frequencies of 2–54 Hz. An EMSI algorithm was used to classify the SSVEP responses. In this experiment, the evaluation criteria used were classification accuracy and ITR, achieving values of 88.8% and 34 bits/min, respectively.

4.1.2. Human–Robot Interaction and Control

Si-Mohammed et al. [17] also tested the combination of BCI-AR technology with four user studies and tested their results by controlling a mobile robot through the HoloLens device. To record the EEG data, a g.USB amplifier with six electrodes was used. The multi-class common spatial pattern (CSP) was used to filter the data, and linear discriminant analysis (LDA) was used to classify the signal into one of the three classes. The robot was controlled by the three directional commands: forward, rightward, and leftward.

Angrisani et al. made several attempts [18,23,31] to integrate BCI with AR. At first, they explored the viability of combining Epson Moverio BT-200 smart glasses with BCI to enhance human–robot interaction in the Industry 4.0 framework. Single-channel Olimex EEG-SMT was employed to acquire the EEG signals, and the fast Fourier transform (FFT) of the EEG signal was calculated and visualized for the frequency range of interest. One participant was tested on the two-class AR-BCI system featuring a simultaneous display of two flickering icons. In a later attempt, they proposed a wearable monitoring system for inspection in the framework of Industry 4.0. They combined Olimex EEG-SMT, using one electrode, with Epson Moverio BT-200 AR HMD (Epson, Suwa, Nagano, Japan). To process the EEG signal, a simple power spectral density (PSD) analysis was first conducted, followed by a digital bandpass finite impulse response (FIR) filter and a fast Fourier transform (FFT) for feature extraction. To evaluate the system, 20 participants tested the prototype and tried to control the system using two commands. The results indicated that the accuracy was better when the acquisition time for the SSVEP signals was higher. In their most recent attempt, they proposed the adoption of machine learning (ML) classifiers in order to improve the performance of highly wearable, single-channel BCIs. The EEG data were collected using the Olimex EEG-SMT (Olimex Ltd., Plovdiv, Bulgaria), featuring one active electrode, while the Epson Moverio BT-200 smart glasses were utilized to display the two flickering targets. To process the EEG signals, an FFT was performed in the frequency domain, followed by the application of a bandpass filter within the time domain, restricting the signal to frequencies between 5 and 25 Hz. For the classification process, the selected ML classifiers were support vector machine (SVM), k-nearest neighbor (KNN), and artificial neural network (ANN). The experiment involved the participation of 20 volunteers, and two evaluation metrics were utilized to assess performance: classification accuracy and acquisition time.

Chen et al. [22] designed a four-command SSVEP-BCI system combined with HoloLens to control a robotic arm. Nine channels from the Neuracle EEG amplifier were used in this study. EEG signals were downsampled to 250 Hz, and a notch filter at 50 Hz was applied. The FBCCA algorithm was used to classify the data. Twelve subjects participated in the online experiment, and the evaluation metrics employed for this study were the mean classification accuracy, ITR, and time to complete a freely controlled robot movement, with respective results of 93.96%, 14.21 bits/min, and 107.67 s.

Ke et al. [24] aimed to design and evaluate a high-speed online eight-class SSVEP-based BCI in an OST-AR environment and test it by controlling a robotic arm. The proposed hardware consisted of an eight-channel EEG device designed in their laboratory and a HoloLens HMD. The EEG signals were bandpass filtered from 7–90 Hz and notch filtered at 50 Hz. To classify their data, they used extended CCA and ensemble TRCA. A total of 10 subjects took part in the online robot arm control task, resulting in an ITR of 45.57 bits/min.

Fang et al. [30] designed a four-target AR-based BCI-SSVEP for human–robot interaction. The EEG signals were acquired using a Neuroscan (Compumedics Neuroscan, Abbotsford, Australia) device equipped with eight electrodes, while the AR display was facilitated by the utilization of HoloLens 2. For the preprocessing portion, three subfilters with different bandpass ranges were designed, running at 7–17 Hz, 16–32 Hz, and 25–47 Hz, respectively, while for the classification process, the filter bank convolutional neural network (FB-tCNN) was employed.

During the cue-guided task involving the robotic arm, all subjects demonstrated a grasping success rate of 87.50%. Additionally, ITR achieved a value of 159.40 bits/min.

De Pace et al. [43] explored the potential of a projected AR system combined with an SSVEP-based BCI to aid human–robot interaction. They employed the NextMind BCI device, which used NeuroTags as flickering visual stimuli in order to enable users to control a robotic arm for pick-and-place tasks. The system was tested with 22 healthy participants, evaluating usability and robustness through metrics such as the System Usability Scale (SUS) and NASA-TLX. The study found that the adaptive positioning of visual stimuli was significantly more effective and preferred over a nonadaptive linear approach.

4.1.3. IoT Applications

Kim et al. [16] investigated the feasibility of an AR-BMI system using grid-shaped (3 × 3) SSVEP flickering stimuli displayed on HoloLens HMD. A 32-electrode antiCAP was used to record the EEG signals, which were then classified into one of six classes using shrinkage-regularized linear discrimination analysis (shrinkage-rLDA) with 10-fold cross-validation. One subject participated in the evaluation portion, and the average classification accuracy, which was the evaluation metric for this experiment, was 30.51%.

Zhao et al. [19] designed four different display layouts and tested the different results by displaying them in HoloLens HMD and on a PC screen. SynAmps2 amplifiers with 64 electrodes were used to record the EEG data. A bandpass filter between 0.5–45 Hz was applied, and the signals were sampled at 1000 Hz. Power spectrum density (PSD) estimation was used to process the data, and CCA was used for the classification. Ten subjects participated in the experiment, and the evaluation metrics employed were classification accuracy, ITR, and power distribution topography. The results indicated that when the stimulus duration is more than 3 s, the AR-SSVEP achieves similar classification accuracy to PC-SSVEP. Apart from the performance variation attributed to display layouts, Zhang et al. [25] investigated the effect of ambient brightness on AR-BCI performance by testing five different light intensities on 18 subjects. The SynAmps2 amplifier, with 64 selected electrodes, and HoloLens HMD were the selected hardware for this study. In order to process and classify their EEG data, they used FFT, CCA, and FBCCA. To enable the SSVEP recognition algorithm to adjust to varying light intensities, they introduced a novel optimization algorithm called ensemble online adaptive CCA (eOACCA). The purpose of this algorithm was to enhance the adaptability of the SSVEP recognition algorithm when faced with changes in light intensity. The results indicated that as the light intensity increases, the response intensity of AR-SSVEP gradually decreases, and there is a corresponding decrease in recognition accuracy as well. Furthermore, the experimental outcomes proved that the proposed eOACCA algorithm outperforms FBCCA and CCA algorithms. In the same context, Du and Zhao [39] explored the impact of different visual stimulus colors on the classification accuracy of SSVEP-BCI. The researchers designed interfaces featuring four distinct colors (white, red, green, and blue) and conducted tests in a combined AR environment and on a conventional PC screen. The NeuSen W acquisition device with 32 electrodes was combined with HoloLens HMD. The classification results were found to be affected by both the visual stimulus colors and the duration of stimulation.

Liu et al. [20] designed an AR-BCI system with an eight-class SSVEP stimulus and studied the performance of different algorithms. The hardware used in this study was an eight-channel EEG device developed in their laboratories and the HoloLens HMD. EEG data were filtered by a notch, highpass, and lowpass filter. Extended filter bank canonical correlation analysis (FBCCA) and task-related component analysis (TRCA) were the two algorithms tested. Eight participants took part in the experiment, and the results showed that the extended FBCCA had the best overall performance.

Kerous and Liarokapis [21] developed a working prototype of BrainChat that featured two-person textual communication. HTC Vive HMD was used in combination with an eight-channel NeuroElectrics Enobio 32. EEG signals were processed and classified with the OpenVibe software. Two subjects tested the prototype system and managed to communicate using their EEG signals.

Heo et al. [26] conducted a study to evaluate the performance of BCI in various postures, including sitting, standing, and walking. They utilized a standard EEG cap with 31 electrodes in combination with the HoloLens HMD. For signal preprocessing, the researchers implemented several filters. A highpass filter was employed to eliminate frequencies above 0.5 Hz, while a lowpass filter was used to remove frequencies below 50 Hz. Additionally, another lowpass filter was applied to eliminate frequencies below 12 Hz. The linear support vector machine (SVM) classifier was utilized in terms of classification. To evaluate their system, six subjects took part in the experiment, and the performance metric was employed, which can be defined as the ratio of the number of trials for a correctly predicted target to the total number of trials for each posture. The results showed that there were no significant differences in BCI performance in regard to posture.

Zhang et al. [27] present a robot grasping experiment that was designed to verify the applicability of the AR-BCI. The Neuracle EEG Recorder, equipped with nine electrodes, was integrated with the HoloLens HMD to create the BCI-AR system. The FBCCA algorithm was used to classify the flickering stimuli. Twelve subjects participated in the online experiment, and they were able to successfully control the robot. The evaluation metrics employed for this study were classification accuracy and ITR. In a different study, Zhang et al. [41] created SSVEP flickering stimulation interfaces that featured four different numbers of stimulus targets to examine the impact of stimulus numbers on SSVEP-BCI within an AR context. SynAmps2 with 64 electrodes was used as the acquisition device, and a bandpass filter between 5 and 90 Hz was applied. The researchers employed CCA, FBCCA, and TRCA for the classification process. The results indicated that the recognition accuracy decreased as the number of stimuli increased in the AR-SSVEP setup. Also, in a later work, Zhang et al. [44] developed a BCI system based on SSVEP to enhance the practical application and interaction capabilities of prosthetic hands for disabled patients. The study introduced an asynchronous visual stimulus paradigm using AR with eight control modes (grasp, put down, pinch, point, fist, palm push, hold pen, and initial) and proposed a new pattern recognition algorithm, Center-ECCA-SVM, combining center-extended canonical correlation analysis and support vector machine. Additionally, an intelligent BCI system switch based on the YOLOv4 deep learning object detection algorithm was proposed to enhance user interaction. The results showed that the AR paradigm significantly improved the average SSVEP spectrum amplitude and SNR compared to the liquid crystal display (LCD) paradigm. The proposed Center-ECCA-SVM classifier achieved high asynchronous pattern recognition accuracy, and the YOLOv4-tiny model demonstrated effective real-time detection of the prosthetic hand. The system's practicality was validated through real-life task completion, showcasing its effectiveness and user acceptability.

Jang et al. [28] designed a biometric authentication system based on EEG by utilizing the rapid serial visual presentation (RSVP) paradigm with stimuli of photographs of people displayed on AR HMD. During the experimental trial, 10 photographs depicting faces were presented to the subjects in a randomized sequence. Within this set, one photograph portrayed a person familiar to the subject (referred to as the “target”), while the remaining nine photographs displayed faces of individuals unknown to the subject (referred to as “non-targets”). To obtain the EEG data, a 64-channel BioSemi ActiveTwo system was employed. The preprocessing stage consisted of downsampling the signal from 2048 Hz to 512 Hz and applying a bandpass filter from 0.1–50 Hz. To perform the classification stage, the researchers employed four distinct machine learning classifiers: linear SVM (LSVM), k-nearest neighbor (KNN), LDA, and decision tree (DT) models. A total of 20 participants actively participated in the experiment, and the results showcased exceptional performance and accuracy. The evaluation of this experiment involved two key metrics: the amplitude of event-related potentials (ERP) and the latency. These metrics assessed and measured the neural responses and time delays associated with the experimental task.

Apicella et al. [32,35] addressed the adoption of ML classifiers and CNN to improve the performance of highly wearable single-channel BCIs. The suggested system relied on classifying SSVEPs. They combined a single-channel EEG acquisition device with four different AR HMDs. The signal processing stage involved an FFT in the frequency domain and the appliance of a bandpass filter between 5–25 Hz in the time domain. Finally, the classification process involved three ML classifiers, specifically, SVM, KNN, and ANN. In the initial experiment, 20 subjects participated, while in the subsequent three experiments, there were nine subjects each. Furthermore, the first HMD featured two flickering targets, while the other three HMDs had four targets each. The evaluation metric utilized for this study was classification accuracy. In another attempt to improve the performance of highly wearable reactive BCIs, they proposed the adoption of an innovative algorithm (ANN) with a learnable activation function. In the experimental campaign, 20 volunteers participated, and each volunteer underwent single-channel EEG acquisition. Epson Moverio BT-200 smart glasses were used to display two flickering icons during the experiment. Classification accuracy was the evaluation metric employed for this study, and the results indicated that the ML classifier can outperform other processing strategies, such as CCA.

Sakkalis et al. [33] proposed an AR-based BCI-SSVEP system with three to four commands for wheelchair navigation. The system was composed of Epson Moverio BT-35E smart glasses and a four-channel g.MOBIlab+. The EEG signals were first subjected to a 0.5–100 Hz bandpass filter, and then the relevant features were extracted using CCA. For the classification stage, LDA, KNN, and SVM were employed. In the online experiment, 12 subjects participated, and the evaluation metrics used for assessing the system’s performance were classification accuracy and ITR. In a similar attempt, Mori et al. [45] developed a BCI system to control an electric wheelchair using audiovisual stimuli from MR goggles and virtual sound sources. The system components included an electric wheelchair (YAMAHA JWX-1), MR goggles (HoloLens2), wired earphones (ALPEX HR-3500BK), and four EEG electrodes (Polymate Mini AP108). The classifiers for visual and auditory stimuli were evaluated using leave-one-out cross-validation, achieving average classification accuracies above 70% and 50%, respectively. Online analysis showed target selection accuracies of 37.1% for visual markers and 25.7% for sound, with visual selection significantly higher than chance level. The lower online accuracy was attributed to marker flashing certainty and sound distinction difficulties for some participants.

Huang et al. [34] proposed a protocol for SSVEP-based neurofeedback training to alter attention with emotional biases using a portable AR-BCI. The five participants were instructed to focus their attention on the task-relevant stimulus, which was a semi-transparent Gabor patch, and to disregard the emotional distractor, represented by an angry or sad face. Each stimulus was flickering at a specific frequency (8.57 or 12 Hz). Signal acquisition was performed with an EEG cap containing 16 electrodes. FFT was used to detect the distinct response of visual stimuli tagged with specific frequencies.

Sugino et al. [36] designed an AR-BCI system that detected objects in a 3D space using depth sensors and ML. The EEG signals were acquired using the Polymate Mini AP108, which used two electrodes. On the other hand, for displaying the four stimuli, HoloLens 2 was utilized. Classification accuracy was the evaluation metric employed for this study.

Liu et al. [37] combined computer vision (CV) and AR with a brain-controlled wheelchair. They used five active electrodes to acquire the EEG signals and Epson BT-350 to display the stimuli. Twenty subjects tested the six-command semiautomatic mode, and the performance metrics employed for this experiment were classification accuracy, ITR, and the average time required to reach each designated target.

He et al. [38] developed a fast recognition method based on a separable convolutional neural network (SepCNN) in order to improve the accuracy and ITR of AR-BCI systems. An EEG cap with 32 electrodes was combined with HoloLens HMD in order to display the nine-target experiment. In their comparison, SepCNN was tested against four common ML classifiers: Bayesian LDA, LDA, SVM, and SWLDA. The results revealed that SepCNN demonstrated significant improvements in both ITR and classification accuracy.

Arpaia et al. [40] improved the classification accuracy of SSVEPs by combining the use of FFT and CCA in the time domain. To acquire the EEG data, the researchers employed the Olimex EEG-SMT system, equipped with two active electrodes. For the AR device comparison, they evaluated three different HMDs: Epson Moverio BT-350, Oculus Rift S, and Microsoft HoloLens. The proposed algorithm demonstrated higher performance in terms of classification accuracy compared to the classic CCA method. Among the AR devices evaluated, HoloLens exhibited the best overall performance.

Horii et al. [42] introduced a BMI system designed to determine the user's focus or attention on an object, enabling them to grasp it within the physical environment. An eight-channel EEG cap was combined with HMZ-T3 HMD to carry out the study. To assess the performance of the experiment, eight subjects took part in the experimental process, and the study utilized classification accuracy as the evaluation metric.

4.1.4. System Commands

The number of commands for the reactive BCI category varies from 2 [18,23,31,35] to 36 [21,41]. The most frequently used number of commands is four, and it appears in 10 studies, [14,15,19,22,26,29,30,36,39,40]. The authors of [20,24,27,44] designed a system with eight commands, while refs. [17,42] chose three commands for their system. In the works of [16,37], a six-command system was developed, whereas ref. [25] employed nine commands. Additionally, Refs. [32,33] designed systems incorporating three and four commands, while ref. [41] developed a system with 9, 16, 25 and 36 commands.

4.1.5. Signal Processing and Feature Extraction

The majority of the researchers applied a variety of bandpass filters: 1–35 Hz [14]; 2–54 Hz [15,29]; 0.5–45 Hz [19]; 1–20 Hz [21]; 7–90 Hz [24]; 0.1–50 Hz [28]; 7–17 Hz, 16–32 Hz, and 25–47 Hz [30]; 5–25 Hz [31,32,40]; 0.5–100 Hz [33] and 9–25 Hz [35]; 5–20 Hz [36]; 0.5–50 Hz [37]; 0.1–12 Hz [38]; 5–40 Hz [39]; 5–90 Hz [41]; 0.5–60 Hz [42]; 8–40 Hz [44]; and 0.5–30 Hz [45]. The researchers in [20] applied a highpass, a lowpass, and a notch filter, while those in [26] applied a highpass filter above 0.5 Hz and two lowpass filters below 50 and 12 Hz, respectively. Also, Refs. [20,22,24] applied a notch filter to remove the powerline noise. The authors of [19,23] calculated the PSD using FFT, while those of [25] applied only FFT. The CSP technique was used by [17].

To extract the desired features for the classifier, the vast majority of the researchers [14,32,33,35,41] used CCA. FFT was also employed by [18,23,32,42], while stepwise LDA was used by [37]. Finally, ref. [44] employed extended CCA and FFT for feature extraction.

4.1.6. Classification Techniques

Different classification techniques were used in these studies. Since the goal of many researchers was to improve the classification accuracy and the ITR of their systems, they employed more than one classification technique in order to compare the results. More specifically, ref. [20] used Extended-FBCCA and TRCA; Ref. [24] employed extended CCA and extended TRCA; Ref. [25] tested CCA, FBCCA, and eOACCA; Ref. [28] compared LSVM, KNN, LDA, and DT; Refs. [31,32] used SVM, KNN, and ANN; Ref. [38] employed BLDA, LDA, SWLDA, SVM, and SepCNN; Ref. [39] used CCA and FBCCA; Ref. [40] compared CCA with their proposed algorithm; Ref. [41] employed CCA, FBCCA, and TRCA; Ref. [44] utilized Center-ECCA and SVM; and Ref. [45] employed LDA and SVM. As for the rest of the studies that employed a single classification algorithm, KNN was used by [14], EMSI was tested by [15,29], shrinkage-rLDA was used by [16], LDA was employed by [17,21], FBCCA was utilized by [22,27], SVM was used by [26,42], FB-tCNN was employed by [30], FFT was used by [34], and ANN was employed by [35].

4.1.7. Evaluation Metrics

Several evaluation metrics were utilized by the authors in order to measure the effectiveness of their systems. The most common were the classification accuracy presented in 24 studies [14,15,16,19,20,22,23,24,25,27,29,30,31,32,33,35,36,37,38,39,41,42,44,45] along with the information transfer rate (ITR) presented in 12 studies [15,19,20,22,24,27,29,30,33,37,38,41]. In addition to these common performance metrics, some authors employed further evaluation metrics (EEG and time metrics) that were well suited to their respective systems. Those metrics were measured brain potentials [18], power distribution topography [19], time to complete a robot movement [22], performance [26], amplitude of ERP [28], acquisition time [31], SSVEP competition scores [34], average time to reach target [37], SUS, NASA-TLX questionnaires [43], and time to response [40]. It is worth mentioning that most authors employed more than one of the previously mentioned evaluation metrics for their systems.

4.2. Passive BCI

This section is dedicated to passive BCI systems and includes five studies presented in Table 5.

Table 5. Studies from the passive BCI category.

Olivieri et al. [46] proposed a novel AR-BCI framework to train the user to regulate his own mental state while performing surgery-like tasks using a robotic system. They combined Emotiv EPOC with Sony HMZ-T1 in order to present the AR-BCI scenario. Ten subjects participated in the experiment, in which they would operate an AR scalpel based on their cognitive value.

Vortmann et al. [47] designed an alignment experiment in order to classify user attention as internally or externally directed. They combined a 16-channel g.Nautilus with HoloLens to display the alignment task. To preprocess the EEG data, they used a lowpass filter at 50 Hz, a highpass filter at 1 Hz, and a notch filter at 50 Hz. LDA was utilized in the classification process, and the results of the analysis of 15 participants demonstrated that the classifier reliably predicts the type of attention. In another attempt, Vortmann et al. [48] explored the feasibility of categorizing a target as real or virtual by analyzing EEG signals using ML techniques. To acquire the EEG data, a g.Nautilus EEG headset with 16 active electrodes was used. The EEG data were bandpass filtered between 3 and 45 Hz and notch filtered at 50 Hz. Results showed that person-dependent classification based on EEG data is possibly better and works more reliably than the classification based on eye-tracking data.

Sanna et al. [49] developed a BCI–AR user interface based on the NextMind and the HoloLens 2. The experiment was structured into two distinct parts. In the first phase, participants were required to visually identify and select a specific component. Once this selection was made, the second phase involved the assembly of these components using a robotic arm. NASA-TLX and SUS questionnaires were used to evaluate the experiment.

De Massari et al. [50] combined BCI in mixed reality (MR) environments in order to decode users' mental states. To acquire the EEG data, a 64-channel actiCAP was utilized, while SVM and LDA classifiers were used for the classification process. The results suggest that LDA had the best accuracy.

4.2.1. Signal Processing and Feature Extraction

Different types of filters were used in this category to preprocess the EEG signals. Ref. [47] used a lowpass filter at 50 Hz along with a highpass filter at 1 Hz and a notch filter at 50 Hz. Ref. [48] employed a bandpass filter between 3 and 45 Hz and a notch filter at 50 Hz, while ref. [50] used a spatial filter. Finally, refs. [46,49] did not mention their preprocessing phase.

All of the researchers employed different approaches to extract features for their classifiers. Ref. [47] used PSD, ref. [48] employed FBCSP, and ref. [50] used spectral estimation.

4.2.2. Classification and Evaluation Metrics

LDA was the most-used classifier in this category, employed by [47,50]. CNN was used by [48], while ref. [50] also employed SVM along with LDA.

Quite a few evaluation metrics were used by the authors. Classification accuracy was employed by [47,48,50]. Test trial time was the evaluation metric used in [46], whereas ref. [49] employed SUS and NASA-TLX questionnaires to assess their experiment.

4.3. Active BCI

This category centers on the active BCI systems and consists of four studies presented in Table 6. One of the studies [51] features a hybrid BCI system that integrates active and reactive BCI technologies.

Table 6. Studies from the active BCI category.

Choi and Jo [51] designed a hybrid BCI-AR system that combines MI and SSVEP to navigate a quadcopter. EEG data were collected using actiCHamp with six electrodes, and a lowpass filter at 40 Hz was applied in collection. CCA was used for the SSVEP classification, while FBCSP was used for the MI classification. To test their system, two subjects took part in the experiment, and both of them managed to successfully navigate the quadcopter.

Horie et al. [52] developed two games utilizing the beta/alpha ratios of EEG signals as a degree of concentration. A single EEG channel in combination with HoloLens was employed for the two experiments. In the first game, users attempted to hit targets positioned in the mixed reality space using bullets controlled by hand gestures and concentration. Meanwhile, in the second game, the user had to focus on outperforming their opponent. One-way ANOVA was performed to evaluate the experiments.

Ji et al. [53] designed an active AR-BCI system that utilized voluntary eye blinks to control a robot. They developed an eye blink detection algorithm in order to identify the long blink and the double blink from the EEG data while effectively filtering out noise and the normal blink. The results indicated that the blink-based input method of the eye, as opposed to the gesture-based input, resulted in a reduced user input time.

Sun et al. [54] developed a brain-controlled robotic arm system based on MI using MR visual guidance to enhance training efficiency and EEG signal classification accuracy. The system integrated EEG signals for task switching and motor imagery to control the robotic arm, utilizing a combination of CSP and SVM for signal classification. Eight subjects participated in the experiment, using a 64-channel EEG cap with data processed through the actiCHamp amplifier. The results showed a significant improvement in classification accuracy after visually guided training, with an average increase of about 10% in accuracy and a notable enhancement in kappa values.

4.3.1. System Commands

The hybrid BCI system of [51] consists of four commands (one active and three reactive), while ref. [53] designed a system with two active commands. These commands allowed users to interact with the system efficiently, depending on the task complexity and the BCI paradigm employed.

4.3.2. Signal Processing and Feature Extraction

For the active BCI category, a low-pass filter at 40 Hz was applied by [51], while ref. [54] employed a bandpass filter between 13 and 30 Hz. To extract the desired features for the classifier, ref. [54] utilized CSP. The filtering and feature extraction techniques are crucial to enhancing signal quality and improving classification accuracy.

4.3.3. Classification

For the classification process, CCA and FBCSP were employed by [51], SVM was utilized by [54], and ref. [53] used their own proposed algorithm. Each classifier was selected based on its effectiveness in recognizing specific features within the EEG signals.

4.3.4. Evaluation Metrics

To evaluate their systems, the authors of this category employed two different evaluation metrics. Classification accuracy was employed by [51,53,54], while one-way ANOVA was utilized by [52]. These metrics provided insight into system performance and ensured the reliability of the results.

5. Discussion

The present systematic review analyzed research articles that use EEG signals in order to control an AR environment projected on HMDs. The study relies on the results obtained from three established scientific databases: IEEE Xplore, Scopus, and PubMed. The initial section of the review showcases the statistical outcomes of the articles, including the publication year, number of participants, and BCI paradigm. In the following section, the articles are grouped into three categories according to their BCI paradigm (reactive, passive, or active). For each category, a summary of each article is presented, along with an analysis of the number of system commands, feature extraction stage, classification techniques, and evaluation metrics employed.

The review yields numerous significant observations. The vast majority of the researchers (78.04% of the studies included) chose the reactive BCI paradigm. This may be attributed to the nature of reactive BCI techniques, such as SSVEP, which demand minimal to no training, making them well-suited for BCI-AR applications. Also, the literature showed that reactive BCI systems, and more specifically, SSVEP systems, provide the best accuracy and ITR. Another observation is the use of EEG caps instead of headbands. Since AR technology requires HMDs to render the environment, most commercial headbands are not a good solution because of their shape and size, which do not allow them to integrate with HMDs. Furthermore, the average number of participants was 12.14, which is a relatively small number. This phenomenon could have several explanations. First, most studies were conducted after 2019, coinciding with the COVID-19 pandemic, which made it challenging to gather volunteers. In addition, the physical discomfort of the systems plays a significant role in the limited number of volunteers since they need to wear both the BCI device and the HMD. Moreover, because the BCI-AR technology is still in its early stages of development, researchers primarily focus on the feasibility of the systems.

Regarding the classification process, the researchers utilized several algorithms (**Figure 6**). It is worth mentioning again that the researchers were aiming to enhance the performance of their systems; therefore, in the majority of the studies, multiple algorithms were employed. SVM, alongside CCA and its variations, was the most utilized algorithms, appearing in 11 studies. LDA was another prevalent choice, being utilized in 9 studies. Moreover, Neural Networks and KNN were employed in 5 studies.

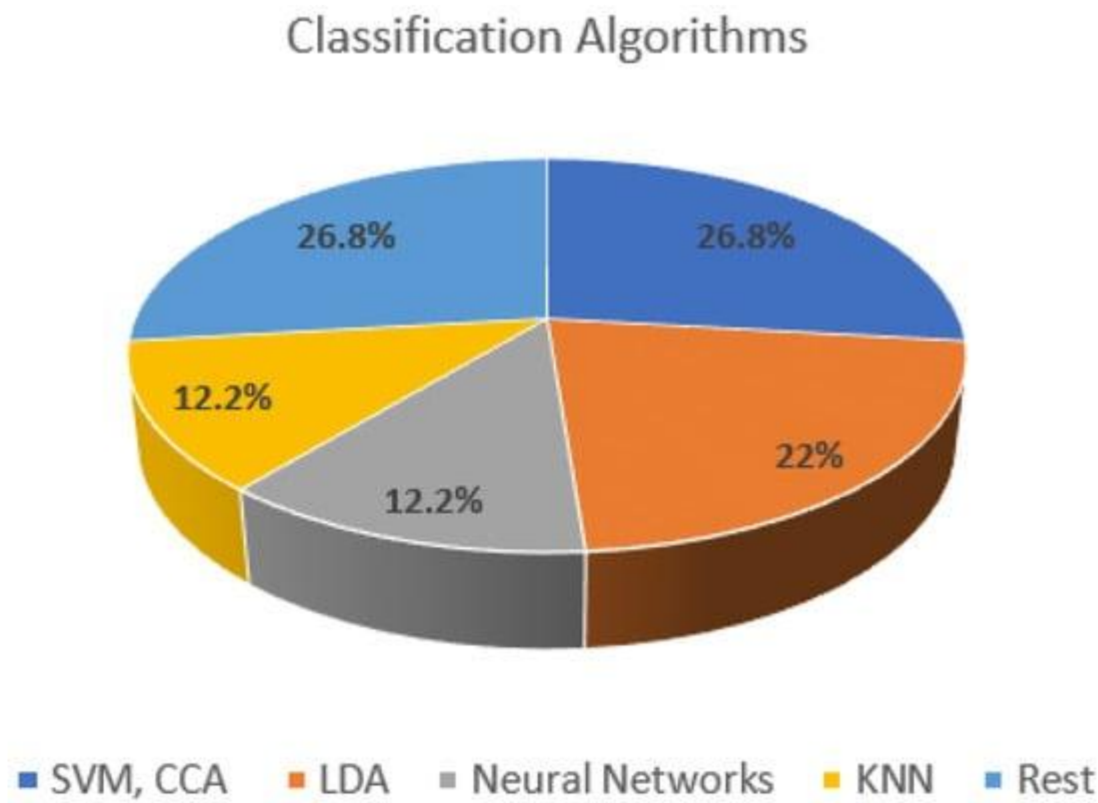

Figure 6. Classification algorithms employed in the studies.

Among the feature extraction methods (**Figure 7**), CCA was the most frequently used method to extract features for the classifier, being utilized in six studies. FFT ranked as the second most popular choice among researchers, being applied in five studies.

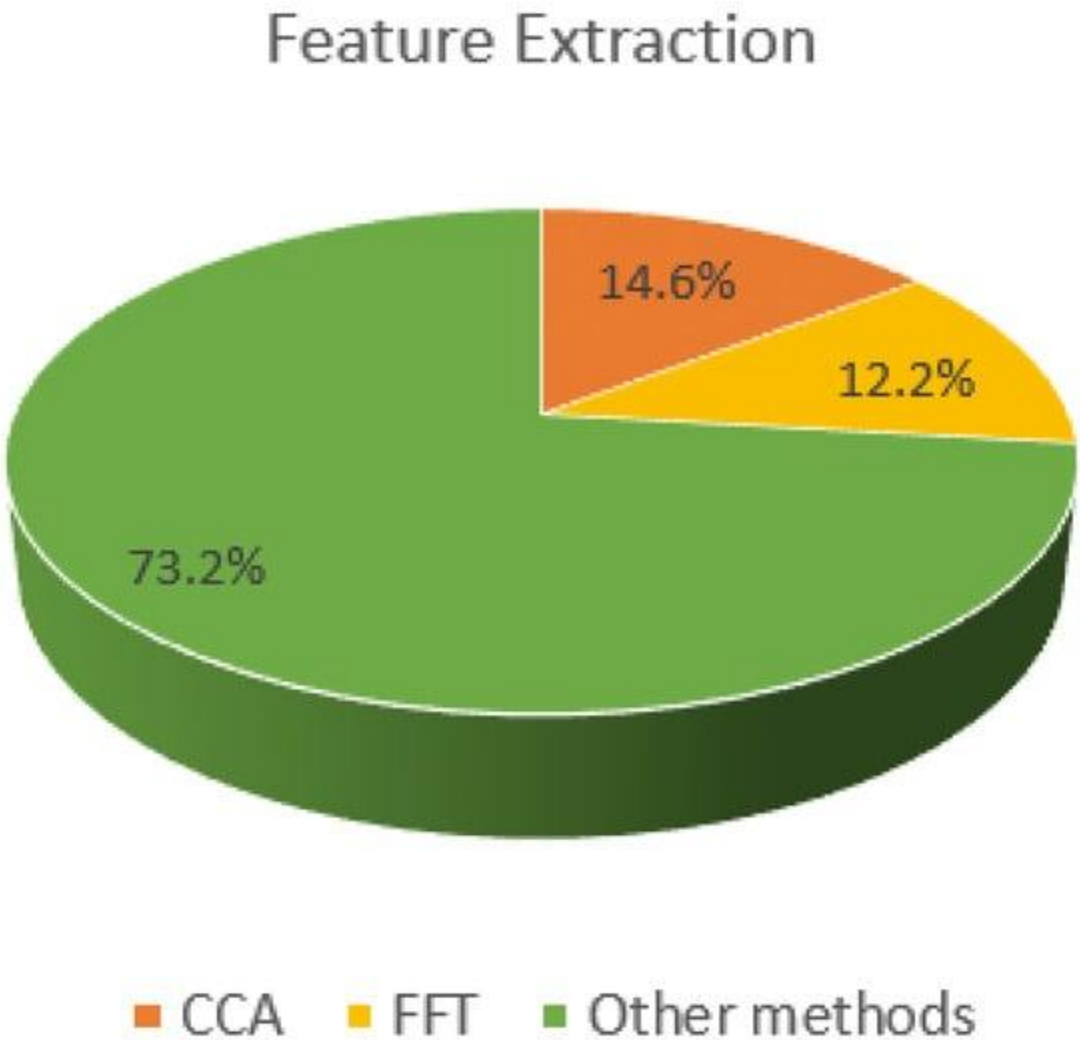

Figure 7. Feature extraction methods.

Figure 8 shows the number of system commands for BCI-AR systems from the literature. Most of the authors designed their systems with up to eight commands. Since most of the studies utilized the reactive BCI paradigm, the system commands were displayed in the HMD. Consequently, as the number of commands increased, the user's field of view decreased, resulting in a limited view of the environment for the user. Although the mean number of commands is 7.37, the median is much lower, being 4, since two studies [21,41] employed 36 commands for their systems. In summary, for this dataset, the median is a more representative measure of central tendency than the mean due to the presence of outliers.

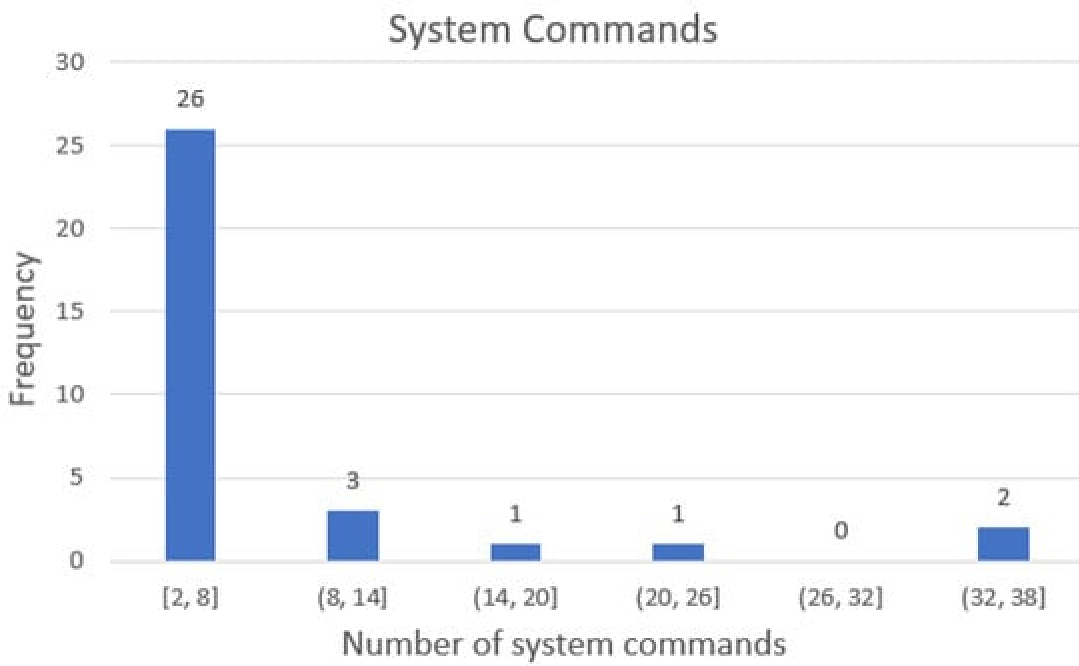

Figure 8. Number of system commands.

Future Trends

Many key points were identified throughout the course of this research. The most common aspect shared among studies was the relatively low number of participants. Since HMDs for AR are still in their early stages of development, they are not very comfortable for the user, especially when they have to be combined with a BCI. Hence, the rapid advancement of AR technology is expected to play a significant role in enhancing the comfort and usability of AR-BCI systems. Another future trend is the adoption of deep learning techniques to enhance the classification accuracy of the systems. Researchers are working on integrating different machine learning algorithms and constructing neural networks to improve the transfer rate of BCI systems. Yet another critical aspect that demands attention is finding the ideal stimulation and acquisition time for EEG signals in reactive BCIs. Various studies [19,20,23] that have examined the correlation between classification accuracy and different stimulation times indicate that an increase in stimulation time is associated with a corresponding rise in classification accuracy. In addition to stimulation time, ref. [39] highlighted the importance of determining the optimal color for visual stimuli. Their research findings indicated that varying stimulus colors can impact classification accuracy. One more important future trend to be considered is the development of hybrid BCI systems. This approach enables researchers to harness the benefits of each BCI paradigm while mitigating their respective limitations. As ref. [51] proposed, combining MI with SSVEP can result in decreasing the training time needed for BCIs relying on MI while expanding the range of usable classes without introducing additional visual complexity.

6. Conclusions

This systematic review presents an overview of BCI-AR systems, including studies from 2012–2024. The 41 studies were grouped into three main categories: reactive BCI, passive BCI, and active BCI. The review provides a summary of the conducted experiments, the obtained results, and the signal processing and classification techniques utilized. It also reveals several important contributions from the existing research on BCI-AR systems. The most significant finding is the consistent use of reactive BCIs, particularly SSVEP, which demonstrates high accuracy and ease of use, making it a valuable paradigm for controlling AR environments. Furthermore, the integration of BCI with AR through HMDs shows considerable potential for creating immersive, hands-free interaction systems. Despite these advances, there are key limitations in the current state of research. A major challenge is the discomfort associated with EEG caps, which not only limits user participation but also affects the long-term feasibility of BCI-AR systems. Using a wearable BCI-AR system that involves two separate devices placed on the head—such as an EEG cap and an HMD—further adds to the discomfort, making these systems less practical for extended use. Looking forward, several promising directions for future research have emerged. One key area involves developing more comfortable, user-friendly BCI devices that can seamlessly integrate with HMDs. The adoption of advanced machine learning and deep learning techniques is also expected to significantly enhance classification accuracy and improve system performance. Additionally, hybrid BCI systems, which combine multiple paradigms, can help increase functionality and expand applications. Addressing these challenges will be essential for advancing the field and unlocking the full potential of BCI-AR technologies.

Author Contributions

Conceptualization, M.G.T.; methodology, G.P., P.A., P.S., S.B. and M.G.T.; software, G.P. and P.S.; validation, G.P. and P.A.; data curation, G.P. and M.G.T.; writing—original draft preparation, G.P.; writing—review and editing, G.P., P.A., P.S., S.B. and M.G.T.; supervision, M.G.T.; project administration, M.G.T. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BCI	Brain–computer interface
AR	Augmented reality
HMD	Head-mounted display
EEG	Electroencephalograph
EOG	Electrooculogram
PRISMA	Preferred reporting items for systematic review and meta-analysis
CCA	Canonical correlation analysis
EMSI	Multivariate synchronization index
ITR	Information transfer rate
shrinkage-rLDA	Shrinkage-regularized linear discrimination analysis
CSP	Common spatial pattern
LDA	Linear discriminant analysis
FFT	Fast Fourier transform
FIR	Finite-impulse response
ML	Machine learning
ANN	Artificial neural network
KNN	k-nearest neighbor
SVM	Support vector machine

Brain-Computer Interfaces: Mind Control Technology

"The greatest trick the devil ever pulled was convincing the world he didn't exist." – Charles Baudelaire

This quote by Charles Baudelaire introduces us to **brain-computer interfaces** (BCIs). These "mind control" devices are changing how we interact with technology. They open new doors in communication, healthcare, and more.

Back in the 1970s, the first **brain-computer interfaces** were implanted. Now, they can help people with Parkinson's disease and paralysis. BCIs have huge potential, from playing games with your mind to helping with mental health.

Key Takeaways

- **Brain-computer interfaces** (BCIs) enable direct communication between the brain and external devices, unlocking new frontiers in human-machine interaction.
- BCIs have progressed from early implanted devices in the 1970s to advanced non-invasive technologies that can regulate tremors, restore movement, and even enable mind-controlled gaming.
- The consumer neurotechnology market has seen steady growth, indicating increasing interest in personal BCIs, while advancements in medical applications show promise for treating mental health conditions.
- Ethical considerations around the responsible development and use of BCIs must be carefully navigated to ensure the technology benefits individuals in need.
- The transformative potential of BCIs, compared to revolutionary technologies like the touchscreen, is captivating the imagination of scientists, entrepreneurs, and the general public alike.

Introduction to Brain-Computer Interfaces

Brain-computer interfaces (BCIs) blend neuroscience, engineering, and technology. They create a direct link between the brain and devices. These systems help people with neuromuscular disorders or disabilities.

What is a Brain-Computer Interface (BCI)?

A **brain-computer interface** (BCI) links the brain to devices like computers or robotic limbs. It captures and reads the brain's electrical signals. Then, it turns these signals into commands for devices.

This technology lets people interact with their world using only their thoughts. It helps them regain lost functions.

History and Early Developments

The story of BCIs started in the 1920s with Hans Berger's discovery of brain electrical activity. He used electroencephalography (EEG). In the 1970s, *Jacques Vidal* at UCLA introduced the term "brain-computer interface". He also experimented with using **EEG** to control devices. Since then, BCIs have made great strides. They've helped paralyzed people move again and opened new ways to interact with computers. The **future of BCIs** looks very promising.

"The history of the BCI field can be traced back to the pioneering work of Jacques Vidal*, who in the early 1970s coined the term 'brain-computer interface' and conducted the first experiments on using **EEG** signals to control external devices."*

As neuroscience and imaging technologies advance, BCIs could greatly improve our lives. They have a lot of potential to enhance human abilities.

Brain-Computer Interfaces: Mind Control Technology

The idea of controlling devices with just your thoughts has always fascinated people.
Now, brain-computer interfaces (BCIs) are making this a reality. They read the signals from our brains and turn them into commands for devices. This can be anything from moving a cursor to controlling robotic limbs.
This technology is changing how we interact with the world. It's helping people with limited mobility and making controlling devices with your mind easier. BCIs are set to change how humans and machines work together.

Advancements in BCI Capabilities

BCI technology has made huge leaps forward. Researchers can now read your thoughts and feelings using special machines. This means you can control devices just by thinking.

One example is Dennis DeGray, who controlled a cursor on his screen with his thoughts. Companies like Synchron are pushing BCI technology even further. This shows how promising the future of **mind control technology** is.

"Synchron's BCI can help patients text message, which is a significant emotional restoration of power for them."

BCIs let us control devices with our brain signals. This could change how we use technology and interact with the world. As BCIs get better, the possibilities of **mind control technology** will keep exciting us.

Neural Signals and Brain Activity

Brain-computer interfaces (BCIs) work by capturing and understanding the electrical signals from our brain, called **neural signals**. Electroencephalography (EEG) is a method that records these signals from the scalp without surgery. By looking at **EEG** signals, scientists can spot the brain's activity linked to different tasks, like moving or seeing things.

Decoding Neural Signals for BCI Control

Thanks to new tech in **machine learning** and signal processing, we can now understand these **neural signals**. This lets BCIs turn what the brain thinks into commands for devices. This decoding is key for making BCIs work well, letting our brains talk to machines easily.

TECHNIQUE	DESCRIPTION	APPLICATIONS
Electroencephalography (EEG)	Non-invasive recording of electrical **brain activity** from the scalp	Motor control, speech decoding, seizure prediction
Intracortical **Neural Recordings**	Direct recording of **neural signals** from within the brain using implanted electrodes	High-performance neuroprosthetic control, closed-loop neuromodulation
Electrocorticography (**ECoG**)	Recording of electrical activity from the surface of the brain using implanted electrodes	Point-and-click communication, motor rehabilitation

From EEG to more invasive methods like intracortical recordings, we've found ways to decode many brain signals for BCIs. The choice of method depends on the task and the balance between signal quality, how invasive it is, and safety.

*"The ultimate goal of **brain-computer interface** technology is to seamlessly translate our thoughts and intentions into actions, allowing us to control external devices with the power of our minds."*

Invasive and Non-Invasive BCI Technologies

Brain-Computer Interfaces (BCIs) are of two types: invasive and non-invasive. Invasive BCIs need surgery to put electrodes in the brain, usually in the motor cortex. These implants give precise control but are risky and complex. Non-invasive BCIs use *Electroencephalography (EEG)* or *Electrocorticography (ECOG)* and sit on the scalp to catch brain signals. They are safer but don't work as well as invasive ones.

Choosing between invasive and non-invasive BCIs means picking between precision, control, and risk. Researchers are improving non-invasive BCIs for paralyzed people and those with movement issues. Despite the signal quality issues, the field of *neural interfaces* is growing. The choice between invasive and non-invasive BCIs will be key in making assistive tech effective and easy to get.

CHARACTERISTIC	INVASIVE BCI	NON-INVASIVE BCI
Signal Quality	High	Low
Precision and Control	High	Low

Surgical Procedure	Complex	Simple
Risk	High	Low
Applications	Specialized, medical	Consumer, assistive

The development of *brain-computer interfaces* is ongoing. The choice between invasive and non-invasive BCIs will be important. It will help make assistive tech effective and easy to get for those who need it.

Applications of Brain-Computer Interfaces

Brain-computer interfaces (BCIs) have many uses, from helping people with disabilities to making games more fun. In neuroprosthetics, BCIs help control robotic limbs or bring back senses like vision or hearing for those with disabilities.

Neuroprosthetics and Assistive Technologies

BCIs let people control brain-controlled prosthetic limbs for everyday tasks. They also make wheelchairs that move with just your thoughts, helping people with mobility issues.

Gaming and Entertainment

BCIs aren't just for helping people; they're also for fun. Gamers can control games with their minds. With ongoing work in *neuroprosthetics*, *assistive technologies*, and more, the possibilities with BCIs keep growing.

"In 2019, researchers at the University of California, San Francisco, developed a brain implant that enabled a paralyzed woman to type at a rate of eight words per minute using only her thoughts, showcasing the effectiveness of BCIs in enhancing the quality of life for individuals with severe disabilities."

Ethical Considerations and Challenges

Brain-computer interfaces (BCIs) bring new possibilities but also raise big ethical questions. As these technologies grow, we face issues like **privacy**, **security**, and personal freedom.

One big worry is **privacy**. BCIs can tap into our brain data, which is very private. This data could be at risk of being shared without our okay, leading to big **privacy** problems.

Also, making sure people understand and agree to use BCIs is crucial. In medical settings, where BCIs help people, we must make sure patients know the risks and benefits before they agree.

- The case of Matthew Nagel, who uses BrainGate technology, shows how BCIs need time to learn from us.
- Stories of success, like helping a man with locked-in syndrome talk, show how BCIs can change lives.
- Yet, Kevin Warwick's early experiment, where he put a chip in his body, makes us wonder about the long-term effects on our brains.

Cyborgology, the study of humans and technology, is becoming more important. BCIs could lead to new drugs that change how we think and feel, making ethics even trickier.
We need more research and talks to tackle these issues. By focusing on privacy, **security**, and our freedom, we can make the most of BCIs. This way, we keep our values of justice and fairness as we move forward.

Animal Research and BCI Development

Animal research has been key to improving **brain-computer interface** (BCI) technology. Scientists have recorded neural signals from monkeys and rats. This lets them control computers and robots with just their thoughts.

This research has shown how the brain can control devices. It's helping create better BCIs.

Monkey and Rat Studies

At the Korea Advanced Institute of Science and Technology (KAIST), they've gone further. They've made a system to control turtles with human thoughts. This setup includes a special headpiece for humans and a "cyborg system" for the turtle.

The system turns brain waves into commands. This helps the turtle move around. It shows how versatile this technology can be.

Elon Musk's Neuralink and BCI in Animals

Elon Musk's **Neuralink** is also making big steps in **neural implants** and BCI tech. They've put their device in a pig and shown a monkey playing games with it. This work is crucial for improving BCI technology.

"Animal research has been crucial in unlocking the potential of brain-computer interfaces, providing the necessary insights and breakthroughs that will shape the future of this transformative technology."

Animal research is key to advancing BCI technology. It drives innovation and expands what we can do with mind-controlled devices.

BCI in Medicine and Neuroscience

Brain-Computer Interfaces (BCIs) are changing the game in medicine and neuroscience. They connect the human brain with devices outside it. This opens up new ways to bring back lost functions and senses.

Restoring Function and Sensory Abilities

BCIs are key in making neuroprosthetics. They use brain signals to control robots and prosthetics. This helps people with paralysis or missing limbs move again and be more independent.
BCIs are also being tested to bring back senses like sight and hearing. They send sensory info straight to the brain. This could change lives for those with disabilities.

BCIs have huge potential to improve life for people with disabilities. They could change how we care for patients and help them recover. This makes BCIs a key focus in research and development.

KEY BCI APPLICATIONS IN MEDICINE AND NEUROSCIENCE	ADVANTAGES	CHALLENGES
Neuroprosthetics and **Assistive Technologies**	– Restoring mobility and independence for individuals with paralysis or limb loss – Enabling non-verbal communication for those with neurological disorders	– Improving signal quality and reliability – Addressing ethical concerns and privacy issues
Sensory Restoration	– Restoring vision, hearing, and other sensory functions through direct brain-computer interfacing	– Overcoming technical challenges in neural signal decoding and sensory information transmission
Cognitive Function Treatments	– Potential applications in treating neurological disorders, depression, and other mental health conditions	– Ensuring safety, efficacy, and ethical considerations in clinical applications

The BCI field is growing fast, with new tech like AI and **machine learning** playing a big part. These advancements will make BCIs better and more useful. With more research and teamwork, BCIs could greatly improve life for many people with disabilities.

Future Directions and Advancements

The field of brain-computer interfaces (BCIs) is growing fast, bringing new possibilities for our daily lives. Soon, we might control devices and interact with our world just by thinking. This is thanks to the work of researchers and entrepreneurs.

New **neural decoding** algorithms and **machine learning** are making BCIs better. For example, **Neuralink** has made a chip that can talk to over 1,000 brain cells directly. This chip is part of their work on brain-machine interfaces.

Non-invasive BCIs could soon make mind-control tech common. This could change how we use devices, play games, and even control our homes. Companies like Bitbrain and NextMind are already working on wearable devices that read brain signals.

Even with challenges, BCI research is moving forward. This means the idea of *brain-machine convergence* is getting closer to reality. Scientists have shown one person can control another's hand with brain signals, showing the huge potential.

Most articles on BCIs have been published in the last decade, showing the field's growth. Studies on EEG-based BCIs have also increased. With new tech like EEG signal isolation and brain-to-brain interfaces, the future of **mind-machine integration** looks bright.

Prominent Researchers and Pioneers

The growth of brain-computer interfaces (BCIs) has been led by key researchers and scientists. Jacques Vidal, a UCLA researcher, is known as the BCI inventor. In 1973, he introduced the term "brain-computer interface" and proposed using EEG signals for device control. His early work set the stage for **BCI development**.

Miguel Nicolelis and Multi-Electrode BCIs

Miguel Nicolelis, a Duke University professor, is also a big name in BCI research. He suggested using many electrodes to capture detailed brain signals. His studies with monkeys, controlling robotic limbs, have pushed the field forward. This work has opened new doors in mind-machine interfaces.

"Neuralink is seeking individuals with quadriplegia for a clinical trial on its brain-computer interface technology."

Researchers like *Jacques Vidal* and *Miguel Nicolelis* have greatly advanced **brain-computer interface research**. Their work has led to the creation of *multi-electrode BCIs*. This has opened up new possibilities for connecting our minds with machines.

Conclusion

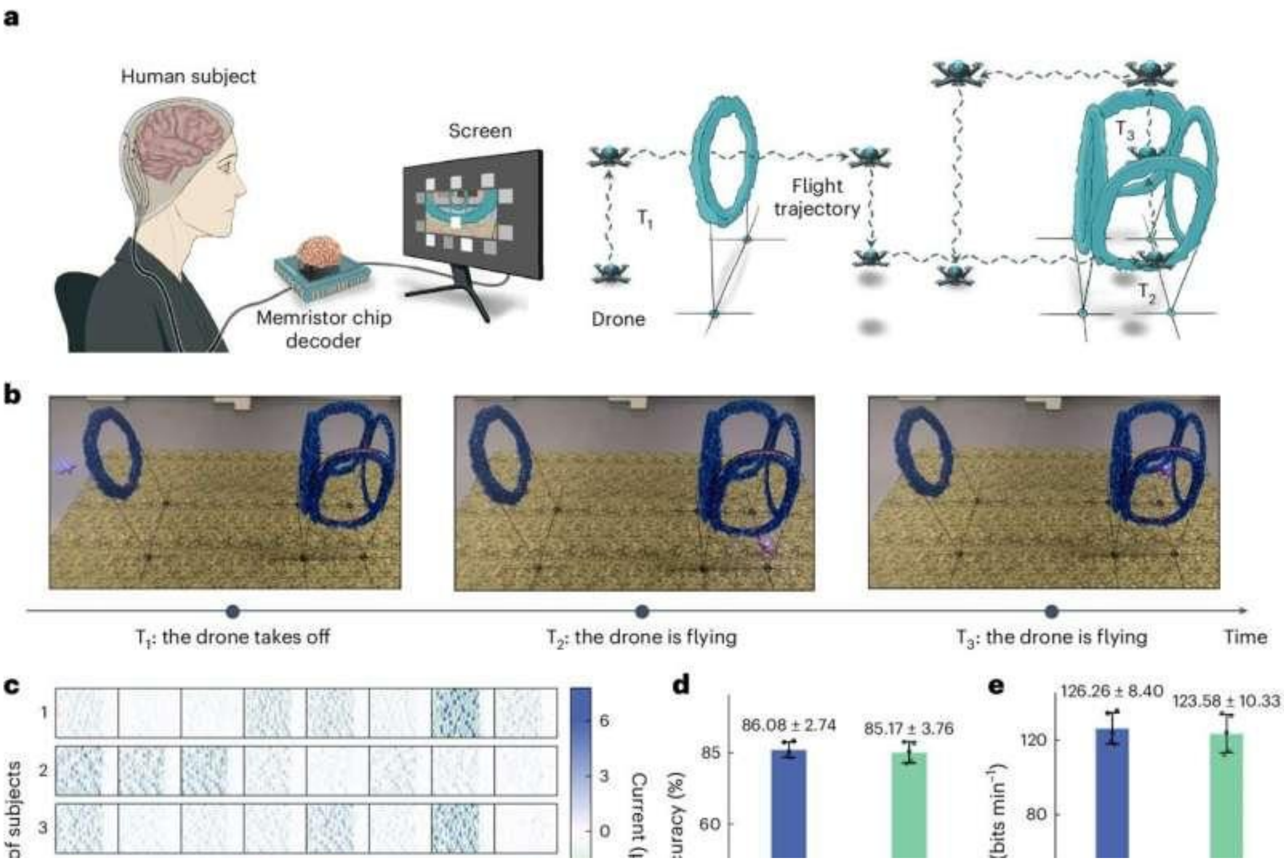
Brain-computer interfaces, or "mind control technology," are changing fast and changing how we see human and machine interactions. They link the brain's electrical signals to devices, opening new ways to improve human abilities and connect with our world. These interfaces are used in many areas, from helping people with disabilities to making games more fun.

As the tech gets better, thanks to the hard work of researchers and the study of brain signals, we're looking at a future where humans and machines work together more smoothly. But, we also need to think about the right way to use this tech. We must make sure it's used in a way that's good for everyone. We're expecting big things from brain-computer interfaces in the future, changing many areas like medicine and entertainment. But, we still face challenges like making the tech more accurate and keeping user data safe. Despite these hurdles, the potential to improve lives is huge. As we explore new possibilities, we must keep an eye on ethics. We want to make sure this "mind control technology" helps everyone, not just a few.

FEBRUARY 20, 2025 **REPORT**

First two-way adaptive brain-computer interface enhances communication efficiency

by Bob Yirka , Tech Xplore



Real-time brain-controlled drone flight with a memristor-chip-based decoder. Credit: *Nature Electronics* (2025). DOI: 10.1038/s41928-025-01340-2

A team of bioengineers at Tsinghua University, working with medical research colleagues from Tianjin University, both in China, have developed what they describe as the world's first two-way adaptive brain–computer interface (BCI). In their study published in the journal *Nature Electronics*, the group used a memristor-based adaptive neuromorphic decoder to build their BCI.

Over the past several decades, bioengineers have developed a variety of BCI devices; some that attach to the scalp, others that work via embedded brain electrodes. What they all have in common is that they listen for brain waves, learning to recognize patterns that can be associated with known thoughts and then listening for those same patterns to carry out a desired behavior—moving a cursor on a screen to a button and pushing it, for example.

In this new study, the team in China brought a whole new dimension to BCI devices by adding technology that allows for feedback directly to the brain, making it a two-way communications device. The whole point of making BCI devices two-way, the team notes, is to improve efficiency and to allow for their use in a wider array of applications. They claim their new device boosts efficiency 100-fold and reduces energy demand by approximately 1,000 times compared to conventional BCI devices.

The new system came about as the research team discovered that brain signal changes are due to interactions with a traditional device. That gave them the idea to create a dual-loop feedback device using a memristor chip—this was chosen due to its neural network architecture and energy efficiency.

Real-time brain-controlled drone flight with the memristor-enabled neuromorphic BCI. Credit: *Nature Electronics* (2025). DOI: 10.1038/s41928-025-01340-2

The first loop is based on machine learning. It updates the brain wave decoder, allowing it to adapt to changes in signals. The second loop helps the user refine their thoughts to improve control via feedback.

Adding feedback, the researchers note, allows the device to recognize more brain wave patterns, which gives the user the ability to perform more complex tasks. For example, when used with hands-free drone control, the BCI allows additional degrees of freedom, such as rotation and forward-backward motion—all governed exclusively by brain signals.

The researchers suggest their device marks the next step toward the development of a BCI that could eventually allow people with brain damage to regain lost abilities.

More information: Zhengwu Liu et al, A memristor-based adaptive neuromorphic decoder for brain–computer interfaces, *Nature Electronics* (2025). DOI: 10.1038/s41928-025-01340-2
Journal information: Nature Electronics

DARPA's Mind-Control Project Is More Real Than You Think

In recent years, the concept of mind control has moved from the realm of science fiction into tangible reality, largely due to advancements spearheaded by the Defense Advanced Research Projects Agency (DARPA). Known for pushing the boundaries of technology, DARPA's work in mind-controlled interfaces promises groundbreaking advancements, though it also raises ethical and privacy concerns.

Understanding DARPA's Mission and Mind-Control Initiatives

DARPA, established in 1958 in response to the Soviet Union's Sputnik launch, has always aimed to prevent strategic surprise by fostering innovative research and technology. Over the decades, it has been instrumental in developing technologies that have reshaped military and civilian life, from the internet to GPS. DARPA's commitment to cutting-edge military technology is evident in its long history of breakthroughs.

The evolution of mind-control research at DARPA is a testament to its forward-thinking approach. What began as theoretical concepts has gradually morphed into practical applications.

Key milestones include the development of mind-controlled prosthetics, which provide amputees with unprecedented levels of control and feedback.

The Science Behind Mind-Control Technology

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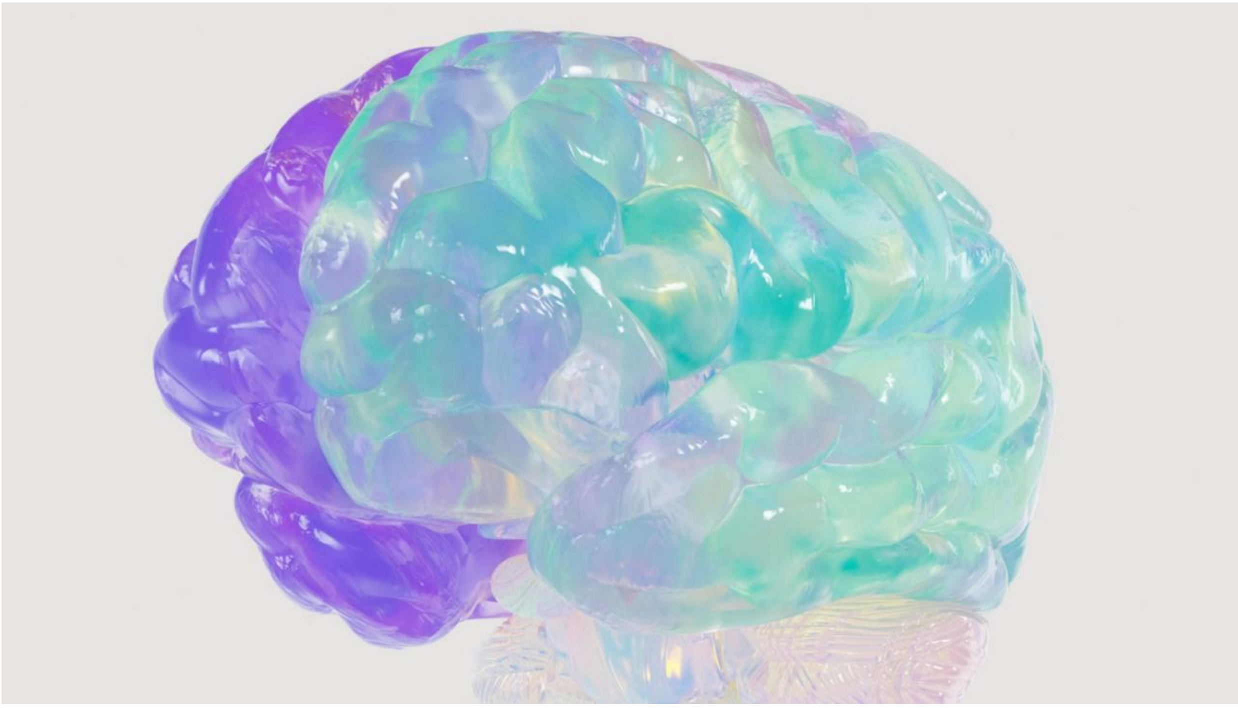
The core of mind-control technology lies in Brain-Computer Interfaces (BCIs), which translate neural activity into commands. BCIs are designed to bypass traditional communication pathways, enabling direct interaction between the brain and external devices. Recent advancements, driven by DARPA's efforts, have significantly enhanced the accuracy and efficiency of BCI technology.

Neural engineering is another critical component of mind-control technology. It holds the potential to expand applications beyond military use, offering solutions in fields like healthcare and communication. DARPA has partnered with academic institutions to refine these technologies, exploring new ways to integrate them into everyday life and discussing their broader implications.



In the military and defense sectors, mind-control technologies could revolutionize operations. DARPA’s mind-controlled robotic arm project exemplifies this potential, allowing soldiers to operate machinery remotely in high-risk environments.
The implications of such advancements could redefine battlefield strategies and safety protocols.

Beyond defense, these technologies offer promising applications in healthcare. For instance, BCIs can aid individuals with disabilities by restoring communication capabilities or controlling prosthetic limbs. However, as these technologies move into civilian use, ethical concerns arise regarding privacy and the potential for misuse. It is crucial to consider these implications as mind-control technology becomes more integrated into society.

Ethical Considerations and Public Concerns

©Image by Freepik

With the advent of mind-control technology, privacy and security risks have become significant concerns. The potential for unauthorized mind control or data breaches underscores the need for stringent safeguards and regulations. Addressing these challenges is paramount to ensuring that individuals’ rights are protected in the evolving technological landscape.

The ethical debate surrounding mind-control technology also touches on philosophical questions about free will and autonomy. As these technologies become more prevalent, it is vital to consider diverse perspectives, including expert opinions and public sentiment, to navigate the complex issues they present. Understanding the broader societal impact is essential for developing responsible policies and practices.

The Future of Mind-Control Technology

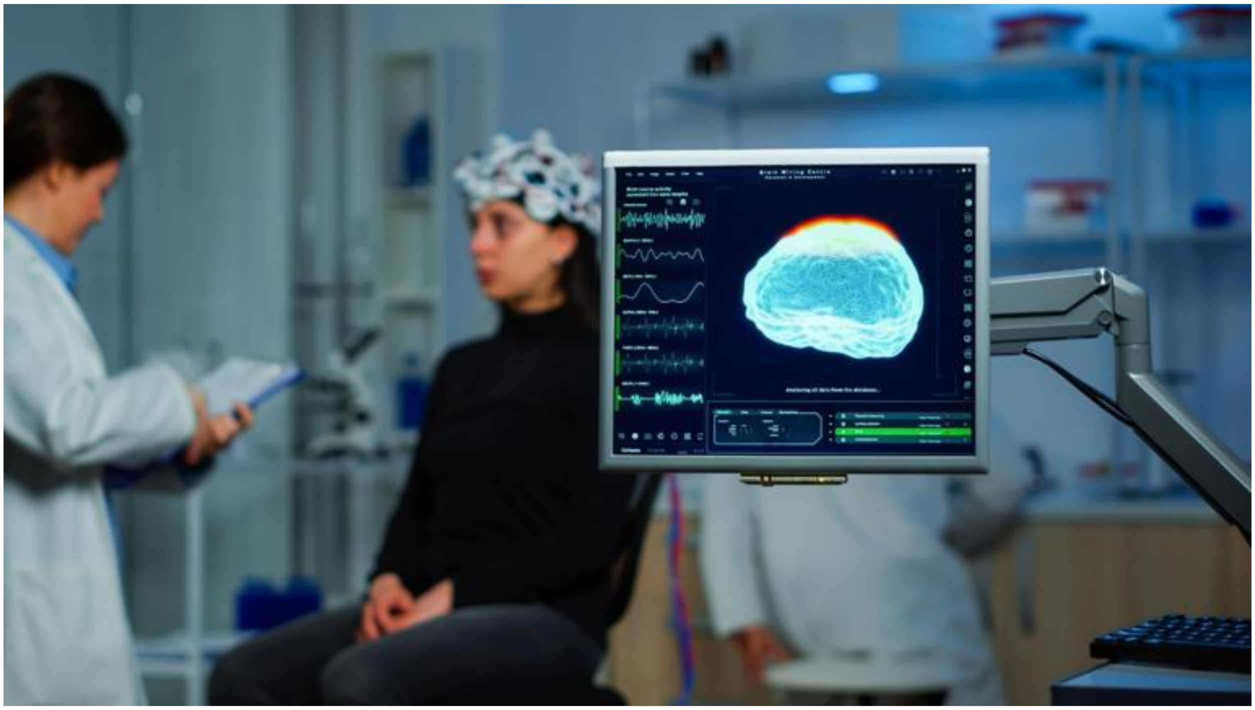
Looking ahead, DARPA continues to explore new frontiers in mind-control technology. Ongoing projects aim to push the boundaries of what is possible, with potential advancements on the horizon. However, the timeline for technology readiness remains uncertain, as researchers must balance innovation with ethical considerations.

International cooperation and regulation will play a crucial role in managing these technologies responsibly. By fostering collaboration and dialogue, society can harness mind-control advancements to benefit humanity while mitigating risks. The challenge lies in embracing innovation while ensuring that ethical responsibility guides technological progress.

World's first brain-powered biocomputer debuts with human cells

In a groundbreaking leap forward for technology, Cortical Labs has unveiled the CL1, the world's first commercial biological computer powered by living human brain cells. This revolutionary development merges the fields of neuroscience and computing, offering unprecedented processing power and efficiency. The CL1 sets a new benchmark in computational capabilities, heralding a new era in how we approach complex problem-solving and artificial intelligence.

The Science Behind Biological Computing



The CL1 harnesses the intrinsic processing power of biological neurons, which are the fundamental building blocks of the human brain. These neurons possess natural capabilities for processing and transmitting information, enabling the CL1 to perform complex computations in a manner similar to the human brain. Unlike traditional computers that rely on binary code, the CL1 can process information in parallel, allowing for more efficient and adaptable processing.

Integrating these biological components with silicon technology presents unique challenges and opportunities. Cortical Labs has developed innovative methods to seamlessly combine these two distinct systems. By embedding human neurons within a silicon framework, the CL1 leverages the speed and reliability of traditional computing while enhancing it with the adaptability and learning potential of biological systems. This hybrid approach not only boosts computational power but also opens new avenues for developing more intuitive and intelligent technologies.

The advantages of biological computing over traditional systems are significant. Biological computers like the CL1 are inherently more efficient, as they can dynamically rewire themselves in response to new information, much like the human brain. This adaptability enables them to learn and improve over time, presenting immense potential for self-optimizing systems. Additionally, the energy efficiency of biological neurons offers a sustainable alternative to the power-hungry processes of conventional computing, reducing the environmental impact of large-scale data processing.

Development and Testing of the CL1

Image Credit: Anders Sandberg from Oxford, UK – CC BY 2.0/Wiki Commons

The journey of the CL1 from concept to commercial product has been a remarkable one. The project began with a visionary idea to combine the unparalleled capabilities of the human brain with modern computing technology. Over the years, a dedicated team of neuroscientists, computer engineers, and researchers worked tirelessly to bring this vision to fruition. Through numerous experiments and trials, the team refined their approach, overcoming significant technical challenges to achieve a viable product.

During the development phase, the team encountered various experimental successes and challenges. One key breakthrough was the ability to maintain and control living neurons outside the human body for extended periods. This was essential for creating a stable and reliable computing platform. However, the team also faced obstacles, such as ensuring the compatibility of biological and silicon components and optimizing communication between the two.

The success of the CL1 project would not have been possible without collaborative efforts across multiple disciplines. By bringing together experts from neuroscience, computing, and engineering, Cortical Labs was able to leverage a diverse range of skills and knowledge. These collaborations were instrumental in overcoming technical hurdles and pushing the boundaries of what is possible in biological computing. The result is a groundbreaking product that stands at the forefront of a new technological era.

Potential Applications and Implications

The CL1 is poised to revolutionize artificial intelligence by enabling machines to process information more like the human brain. This development could lead to significant advancements in AI, allowing for the creation of more intelligent and intuitive systems. With the ability to learn and adapt in real-time, the CL1 offers a promising platform for developing AI applications that can better understand and respond to complex environments.

Beyond AI, the implications of biological computing extend to various fields of scientific research. The CL1's unique processing capabilities have the potential to advance research in genomics, environmental modeling, and pharmaceuticals. For instance, its ability to handle vast amounts of data efficiently makes it ideal for analyzing genetic information, leading to breakthroughs in personalized medicine and disease treatment. Similarly, its adaptability can enhance environmental models, providing more accurate predictions for climate change and resource management.

However, the use of human brain cells in technology raises important ethical and societal considerations. As with any emerging technology, there are concerns about privacy, consent, and the potential for misuse. The integration of biological components into computing systems also prompts questions about the nature of consciousness and the boundaries between humans and machines. Addressing these ethical issues is crucial to ensuring the responsible development and deployment of biological computing technologies.

Market Availability and Future Prospects

The commercial release of the CL1 marks a significant milestone in the field of computing. Industries such as healthcare, finance, and robotics are poised to benefit from this groundbreaking technology. The CL1's ability to process complex data efficiently makes it an attractive option for businesses seeking innovative solutions to enhance their operations. As more companies recognize the potential of biological computing, the demand for the CL1 is expected to grow rapidly.

Looking ahead, Cortical Labs is already exploring future innovations and upgrades for the CL1 platform. Potential developments include enhancing the scalability of the technology to accommodate larger and more complex datasets. Additionally, the company is investigating ways to improve the integration of biological and silicon components, further boosting the performance and capabilities of the CL1. These advancements will not only solidify the CL1's position in the market but also pave the way for new applications and opportunities.

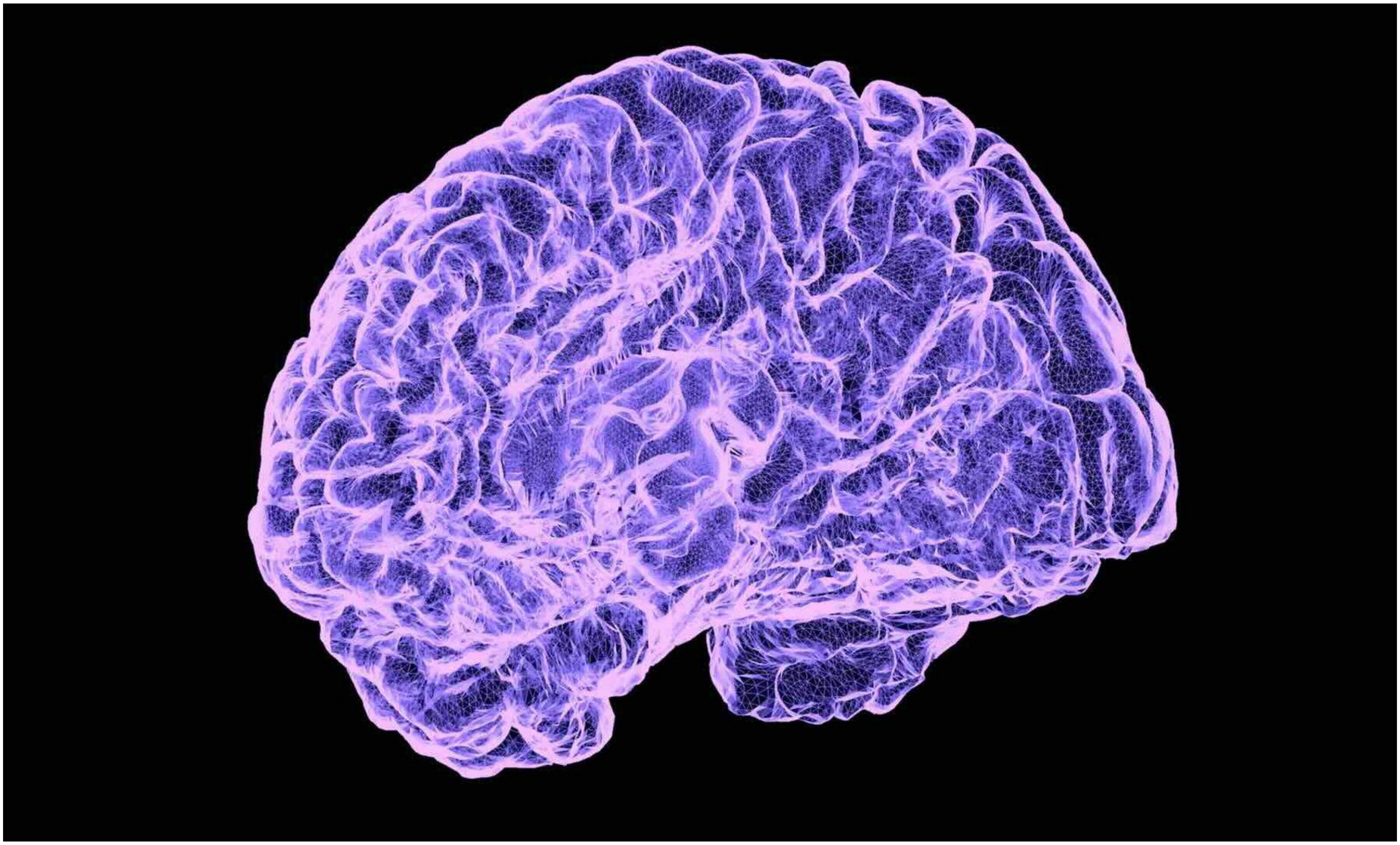
Scaling and accessibility are key challenges for the widespread adoption of biological computing. Cortical Labs is actively working on strategies to make the CL1 more accessible to a broader audience. This includes developing cost-effective production methods and expanding distribution channels to reach more customers. By addressing these challenges, the company aims to make biological computing a viable option for a wide range of industries, driving innovation and growth in the tech sector.

Expert Opinions and Industry Reactions

The introduction of the CL1 has garnered significant attention from experts in neuroscience and computing. Leading figures in these fields have praised the groundbreaking nature of the CL1, highlighting its potential to transform the landscape of technology. As more insights from thought leaders emerge, the significance of this development becomes increasingly clear. Their perspectives underscore the importance of continued research and innovation in biological computing.

The industry response to the CL1 has been marked by both excitement and anticipation. Competitors in the tech sector are closely monitoring this innovation, recognizing its potential to disrupt existing market dynamics. Some companies are already exploring similar technologies, seeking to capitalize on the opportunities presented by biological computing. This competitive landscape is likely to spur further advancements and drive the evolution of computing technologies.

Public perception of biological computing is also evolving, with growing interest and curiosity about the possibilities it offers. Factors such as cost, accessibility, and ethical considerations will play a significant role in determining the adoption of this technology across different sectors. As awareness and understanding of biological computing increase, it is expected that more industries will embrace the CL1, leading to a broader impact on society and the economy.



BRAIN-COMPUTER INTERFACE BREAKTHROUGH SUCCESSFULLY DECODES SILENT "INNER SPEECH," STUDY SAYS

AUGUST 18, 2025

In a breakthrough for brain-computer interface technology, researchers at Stanford University and Emory BrainGate have decoded a person's "inner speech," offering new hope for restoring communication to individuals with severe paralysis.

The achievement, detailed in a recent study, reports that researchers have successfully decoded the silent monologue in a person's mind with up to 74 percent accuracy. A team jointly based at Emory BrainGate and Stanford University led the research, which opens up new possibilities for individuals who are unable to speak due to severe paralysis or other neurological conditions.

"This is the first time we've managed to understand what brain activity looks like when you just think about speaking," said lead author Erin Kunz of Stanford University. "For people with severe speech and motor impairments, BCIs capable of decoding inner speech could help them communicate much more easily and more naturally."

Companies such as Neuralink, Synchron, INBRAIN Neuroelectronics, and Cognixion are among those pushing innovation in the BCI field, applying the technology to various applications, including video games, robotic limb movement, music composition, and communication without speaking.

Now, thanks to these advancements, BCIs can also detect the brain signals used when a person tries to speak, even if no words are spoken clearly, by reading the neural patterns that control speech muscles.

For people with limited muscle control due to various disabilities, this research could provide a way to bypass the physical act of speaking altogether. The team hypothesized that directly decoding inner speech could not only be possible, but also would likely be more efficient than attempting to speak aloud.

"If you just have to think about speech instead of actually trying to speak, it's potentially easier and faster for people," explained co-first author Benyamin Meschede-Krasa of Stanford University.

The study examined four patients with severe paralysis caused by either amyotrophic lateral sclerosis (ALS) or a brainstem stroke. Microelectrodes were implanted in their motor cortex, the part of the brain responsible for controlling speech. Participants were then asked to either attempt to speak or imagine speaking a series of words.

The results showed that both attempted and imagined speech activated overlapping brain regions and produced similar neural patterns, though inner speech generated weaker signals. With the help of trained AI models, the system decoded imagined sentences with notable success, reaching an accuracy of up to 74 percent across a 125,000-word dataset.

One surprising result was that BCIs sometimes picked up inner speech that participants had not been instructed to produce, such as silently counting objects on a screen. This demonstrated the system's sensitivity. The researchers also found that the system could distinguish between participants trying to vocalize words and those merely thinking them, filtering out unintended thoughts.

Privacy and control were built into the study design through a password mechanism: decoding began only when participants silently thought of the phrase "Chitty Chitty Bang Bang," which the system recognized with over 98 percent accuracy.

"The future of BCIs is bright," said senior author Frank Willett. "This work gives real hope that speech BCIs can one day restore communication that is as fluent, natural, and comfortable as conversational speech."

The research was published in the *Cell Press journal* on August 14, 2025.