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Trends, Challenges, and Threats in Brain-Computer Interfaces

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ABSTRACT - *Brain–computer interface (BCI) is an emerging technology that enables direct communication between the brain and computers, gaining significant research attention in recent years. Studies have shown that BCI can restore abilities for individuals with physical disabilities, enhancing their quality of life. It has also revolutionized industries such as entertainment, automation, education, neuromarketing, and neuroergonomics. Despite its wide-ranging applications, discussions on global BCI trends remain limited in the literature. Understanding these trends can help researchers and practitioners identify key areas for further exploration. To address this, we analyzed 25,336 BCI-related publications from Scopus, revealing exponential growth in China's BCI research since 2019, surpassing the United States, where publications have declined. This shift, along with its implications, is explored in detail. Additionally, we examine challenges and threats hindering BCI adoption, particularly privacy and security concerns, and propose a BCI architecture to mitigate these risks, making the technology more commercially viable.*

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I. INTRODUCTION

Humans naturally rely on their peripheral nerves and muscles to interact with their external environment and perform desired actions. However, for individuals with severe neurological disorders such as amyotrophic lateral sclerosis and brainstem stroke, this ability is significantly impaired. As a result, they often require assistance from others, which may not always be available. To address this limitation, scientists and researchers have developed brain–computer interface (BCI) technology, enabling brain signals to be translated into actions without the need for peripheral nerves or muscles.

Also referred to as a brain–machine interface, BCI establishes direct communication between the brain and external devices like computers or robotic limbs. By bypassing traditional communication pathways used for functions such as vision, movement, and speech, BCI connects the brain's electrical activity with the external world, enhancing human interaction with the physical environment. This technology provides a non-muscular communication channel, facilitating the acquisition, processing, analysis, and translation of brain signals to control various devices and applications.

Despite the promising applications of BCI, there remains a lack of studies exploring the future of this technology and the potential threats it poses when applied to humans. This study examines key BCI-related risks, including medical safety, privacy, ethics, and security. We aim to encourage discussions within the scholarly community on the preparedness to adopt BCI technology while addressing its challenges and possible threats. Moreover, given that the brain's natural working principles are not yet fully understood, we provide recommendations for researchers to focus on both the short- and long-term impacts of BCI on human well-being. Additionally, our study highlights several research opportunities within the field of brain–computer interfaces, allowing researchers and practitioners to leverage these possibilities in developing safe and effective BCI products that enhance human life.

Furthermore, we analyzed 25,336 metadata entries from Scopus to investigate research patterns and trends in BCI. The findings indicate exponential growth in BCI publications, with China emerging as the leading contributor since 2019, surpassing the United States within the same period. While this trend underscores the growing importance of BCI to the global community, it also raises critical concerns regarding the potential threats this technology may pose to humanity.

II. FUNDAMENTAL COMPONENTS OF BCI SYATEM

The BCI system consists of three essential components, each serving a distinct role: signal acquisition, signal processing, and application (Fig. 1). These components are interconnected, enabling the seamless flow of brain signals to the intended BCI application, such as a robotic arm. In certain cases, control signals from the BCI application can be transmitted back to the brain to stimulate fundamental human functions, including vision and hearing.

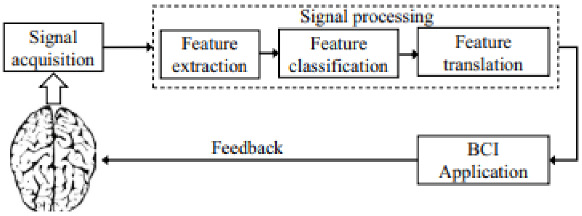

Figure 1: Main components of BCI System

Phase I: Signal acquisition

This component consists of an electronic device equipped with electrodes designed to acquire brain signals—oscillating electrical voltages generated by the brain's biological activities that define its neurophysiological states. Signal acquisition involves capturing electrophysiological signals that correspond to specific brain functions, such as movement, speech, hearing, and vision. Most BCI systems, including commercial ones, process the following electrophysiological signals: electroencephalography (EEG), which records the brain's electrical activity using electrodes placed on the scalp [1-3]; electrocorticography (ECoG), which measures electroencephalographic signals directly from electrodes placed on the surgically exposed cerebral cortex [4–5]; local field potential (LFP), which detects electric potential fluctuations in the neuron's extracellular space [6]; and neuronal action potential, which represents rapid and temporary changes in a neuron's membrane potential [7-8]. Before being transmitted to the next BCI component, the captured brain signals undergo filtering, amplification, and digitization [9]. The overall performance of a BCI system heavily depends on the quality of acquired brain signals, particularly the signal-to-noise ratio.

Based on the signal acquisition method, BCI systems can be broadly classified into two categories: invasive and non-invasive. Invasive BCI involves implanting electrodes beneath the scalp to record signals directly from the brain, providing more precise readings but requiring surgical procedures. Non-invasive BCI, on the other hand, utilizes electrodes placed on the scalp without the need for surgery. However, non-invasive systems suffer from weaker brain signals (low signal-to-noise ratio), necessitating expensive amplification hardware and advanced signal processing techniques to improve accuracy.

Phase II: Signal Processing

At this stage, the BCI system identifies and extracts key electrophysiological features from the acquired signals to interpret brain activity and encode the user's intent [10]. Just like in the previous phase, the accuracy of feature extraction is crucial, as the extracted features must strongly correlate with the user's intent to optimize the system's overall performance. BCI systems typically utilize features derived from either the time domain or frequency domain [11–13], each representing distinct characteristics such as the amplitude or latency of event-related potentials (e.g., P300), frequency power spectra (e.g., sensorimotor rhythms), or neuronal firing rates [14]. Consequently, before developing a BCI system, it is essential to determine the appropriate domain transformation and feature characteristics. Additionally, any artifacts within the extracted features that could interfere with later processing stages should be effectively removed to ensure reliable system functionality.

Phase III: Feature Classification and Translation

Once the features are extracted, they serve as representations of brain activity associated with specific intended actions. The classification process then identifies patterns within these features, linking them to corresponding actions. For instance, it can detect patterns that signify an instruction to move a robotic arm. This classification stage is typically achieved using machine learning techniques and various classification algorithms [15–17], which enhance the accuracy and reliability of interpreting brain signals.

Following classification, the processed features are converted into actionable commands that control an external device, forming the core function of a BCI application. These outputs can include commands for moving a cursor on a screen, adjusting audio volume, or generating text. A crucial characteristic of a feature translation algorithm is adaptability [55, 56], meaning it must dynamically adjust to fluctuations in brain signals and continuously refine the output to ensure accurate execution of user intentions.

III. BRAIN–COMPUTER INTERFACE: APPLICATIONS AND FUTURE PROSPECTS

In this contemporary society, scientists and engineers have been striving to apply advanced technologies in improving quality of human life [18]. 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. Te BCI technology allows physically challenged people to control machines using their thoughts. Tis advantage gives such people a revealing experience to interact with the external environment and accomplish diferent activities without dependence from healthy people. Te BCI feld is moving fast with a number of promising outcomes that can signifcantly 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 [19-20]. 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.

The brain, as a highly complex organ, governs a wide range of human functions, including thoughts, emotions, sensory perception, motor skills, memory, and physiological processes like breathing and temperature regulation. While certain responses, such as anger or changes in breathing rate, can be outwardly expressed through physical actions, many cognitive processes remain internal and undetectable to others. Current technology lacks the capability to accurately interpret an individual’s thoughts with high precision. Although this privacy of human cognition—represented by brain signals in a BCI system—offers certain advantages, there are scenarios where decoding thoughts with accuracy could be valuable.

For instance, in criminology, law enforcement agencies often seek methods to determine whether a suspect is being truthful. Researchers have recently explored how BCI technology can enhance polygraph tests, which assess the credibility of a person's statements [2, 21–24]. By integrating BCI with artificial intelligence, it may be possible to develop more reliable methods for detecting deception, ultimately improving investigative techniques.

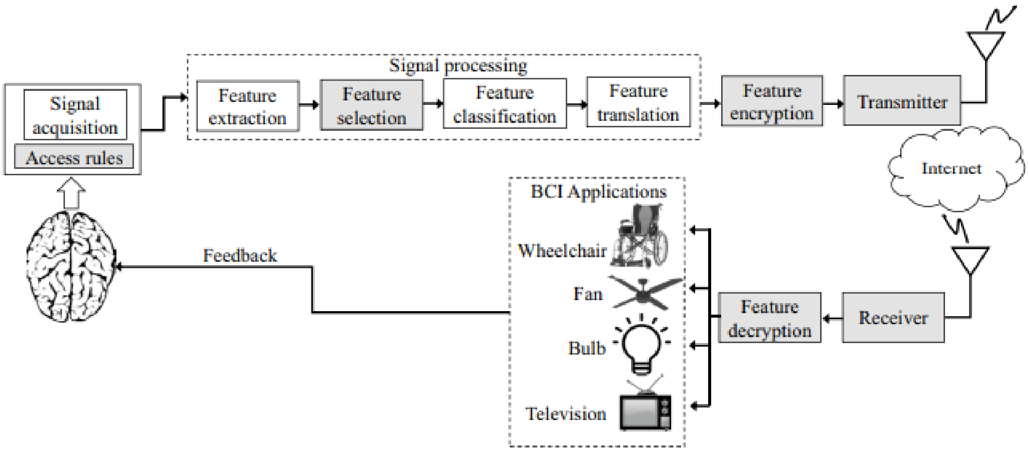

Figure 2: BCI system with encryption and decryption components for enhancing privacy

In this study, we have proposed a functional BCI system model designed to address privacy and security concerns (Fig. 2). Expanding on the work of Mason and Birch [25], this model incorporates key components aimed at preventing unauthorized access to sensitive personal data without the user's consent.

As illustrated in Fig. 2, the system enforces predefined access rules before acquiring brain signals, ensuring the integrity and confidentiality of user information. Within the signal processing stage, a dedicated "Feature Selection" component filters and retains only high-quality features for classification and translation. Furthermore, for BCI applications that operate over networked devices via the Internet, we suggest encrypting the translated features (control commands) prior to transmission. This encryption mechanism safeguards the system from potential cyber threats, preventing attackers from altering control commands and compromising user safety.

IV. CHALLENGES AND POTENTIAL THREAT OF BCI

Although BCI technology offers a wide range of applications, it also presents potential risks that must be carefully addressed. To ensure that BCI remains both beneficial and user-friendly, researchers should focus on developing applications that align with fundamental human values. An ideal technology should not only improve daily life but also prioritize key human considerations such as usability, convenience, privacy, security, and safety [106–108]. Before integrating BCI technology into mainstream use, researchers and industry professionals must actively engage with users to assess their needs and concerns. Additionally, it is essential to ensure that BCI systems undergo rigorous testing and meet predefined quality standards before being widely adopted by society. Safety concerns are most prevalent in invasive BCI systems, as they require implantation directly into brain tissue. This procedure poses risks such as potential damage to nerve cells and blood vessels, increasing the likelihood of infections. Additionally, the body's immune system may perceive the implant as a foreign object, leading to rejection—a key issue related to biocompatibility. Another significant risk is the formation of scar tissue post-surgery, which can progressively deteriorate the quality of acquired brain signals.

Effectively addressing these challenges requires a deep understanding of human physiology and its response to foreign materials. This knowledge is essential for BCI researchers and engineers to design safer, high-quality BCI applications. Moreover, it can provide neurosurgeons with more precise guidance on optimal brain regions for electrode implantation, minimizing risks and improving overall system performance.

Many BCI applications rely on calibration data to counteract unwanted variations caused by neural plasticity or slight shifts in electrode arrays [26]. This requirement necessitates frequent retraining of the decoder, a process that is both time-consuming and inconvenient for users.

[27] underscored this challenge in their ground breaking research on brain-to-text communication via handwriting. Although their model demonstrated impressive performance, it still required daily decoder retraining. Future research should explore more efficient training methods that eliminate the need for direct user involvement, improving both usability and system adaptability.

The field of BCI is inherently multidisciplinary, requiring collaboration across various domains to develop more advanced and effective applications. Our analysis of Scopus data revealed that certain crucial disciplines remain underrepresented in BCI research as shown in Fig. 2. Notably, psychology—central to understanding human cognition and behaviour—accounts for only 1% of BCI-related publications. Integrating psychology with other fields could significantly enhance the development of practical and transformative BCI systems. While forming multidisciplinary research teams may necessitate strategic planning and funding, such collaborations are essential for fully unlocking the potential of BCI technology and its positive impact on society. The brain stores vast amounts of information and continuously generates electrical signals that regulate human activities. This creates a significant big data challenge in BCI, requiring advanced techniques for effective processing and analysis. However, due to limited understanding of the brain’s underlying mechanisms, researchers may not have fully captured or utilized all relevant brain signals. To advance BCI technology, it is crucial to identify key neurological features, such as neuroplasticity, which enables the brain to reorganize neurons during learning or recovery from injury [28]. Additionally, in non-invasive BCI, optimizing the resolution of electrode networks on the scalp is essential for improving the accuracy and efficiency of brain signal collection.

As an emerging technology, BCI presents significant opportunities, particularly for disadvantaged groups. However, awareness of its benefits and drawbacks remains low, especially in developing countries, as reflected in the limited number of BCI-related publications from these regions. This lack of awareness poses challenges in recruiting a sufficient number of participants for testing BCI medical applications. Ethical considerations dictate that individuals must provide informed consent before adopting and using BCI technology[29-30]. Notably, our analysis revealed limited efforts to initiate clinical trials for BCI devices, highlighting the need for further exploration and implementation in real-world medical settings.

V. DISCUSSION AND CONCLUSION

This study provides insights into the perspective of brain–computer interface (BCI). Inspired by its benefits, society should seize the opportunities this technology presents. To maximize its advantages and enhance usability across various sectors, researchers and scientists must address the potential threats highlighted in our work. Fully exploiting BCI's potential requires a multidisciplinary effort to overcome the limitations of current systems.

Considering the key components of BCI, five possible research directions emerge: cognitive psychology, medicine, biomedical electronics, signal processing, and engineering. These fields necessitate collaborative research, where experts work together to tackle BCI sub-challenges. Psychologists and medical professionals should establish the fundamental principles of brain function, scientists should develop advanced signal acquisition devices and algorithms for brain signal processing (including extraction, classification, and translation), and engineers should create physical BCI applications while evaluating their performance against predefined standards.

The BCI field presents numerous unexplored research opportunities. A review of the existing literature reveals that many challenges in BCI have received minimal attention. The research community is encouraged to address these challenges and extend BCI's capabilities, including the development of BCI-Internet and BCI-CBI communication devices. Additionally, researchers may investigate how mind–body intervention techniques, such as hypnotherapy, could enhance BCI systems.

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