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ОБЗОР: ТЕНДЕНЦИИ В ОБЛАСТИ ТЕХНОЛОГИЙ ИНТЕРФЕЙСА МОЗГ-КОМПЬЮТЕР (ИМК)

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Аннотация: В этом обзоре рассматриваются новые тенденции в технологии интерфейса мозг-компьютер (ИМК), подчеркивая достижения, приложения и проблемы по состоянию на 2024 год. BCI создают прямой путь связи между мозгом и внешними устройствами, позволяя осуществлять управление посредством нейронных сигналов. Заметный рост исследований ИМК с 2019 года был обусловлен государственным финансированием и институциональной поддержкой. В обзоре освещаются приложения ИМК в здравоохранении, особенно в реабилитации лиц с неврологическими нарушениями, а также их потенциал в робототехнике, образовании и безопасности. Несмотря на такие проблемы, как качество сигнала и этические соображения, текущие междисциплинарные исследования обещают светлое будущее для технологии ИМК.

Ключевые слова: технологии интерфейса мозг-компьютер (ИМК), нейронные сигналы, получение сигнала, нейрообратная связь, тенденции в области ИМК, проблемы.

REVIEW: BRAIN COMPUTER INTERFACE TECHNOLOGY (BCI) TRENDS

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Abstract: This review examines emerging trends in Brain-Computer Interface (BCI) technology, emphasizing advancements, applications, and challenges as of 2024. BCIs create a direct communication pathway between the brain and external devices, enabling control through neural signals. Notable growth in BCI research since 2019, has been fueled by government funding and institutional support. The review highlights BCI applications in healthcare, especially in rehabilitation for individuals with neurological disabilities, as well as their potential in robotics, education, and security. Despite challenges such as signal quality and ethical considerations, ongoing interdisciplinary research promises a bright future for BCI technology.

Keywords: Brain-Computer Interface technologies (BCIs), neural signals, signal acquisition, neurofeedback, BCI trends, challenges.

1. Introduction to Brain Computer Interface technology

This comprehensive review explores the emerging trends in Brain Computer Interface (BCI) technology, emphasizing advancements, applications, and challenges faced by the field as of 2024. BCIs have significant implications across various sectors, notably healthcare, industry, and communication. The review discusses the rapid research growth, technological innovations, ethical considerations, and future directions for BCI technology, aiming to offer an insightful overview of this transformative field.

Brain-Computer Interfaces (BCIs) are systems that establish a direct communication channel between the brain and computers, enabling control of external devices through neural signals [1] [2]. BCIs can be invasive or non-invasive, utilizing various recording methods to capture brain activity [3]. The field has evolved significantly since its inception in the 1970s, with applications ranging from assistive technologies for disabled individuals to potential enhancements of human capabilities [2] [4]. Medical applications, such as cochlear implants and deep brain stimulation, are becoming more common, while emerging areas include security, gaming, and human augmentation [2]. BCI research also contributes to advancements in artificial intelligence and computational intelligence [1]. As the field continues to grow, researchers are exploring new paradigms, methods, and applications, addressing challenges in signal processing, machine learning, and ethical considerations [2] [3] [4].

2. Research Growth in BCI Technologies

2.1 Exponential Increase in Publications

Brain-Computer Interface (BCI) research has seen remarkable growth, particularly since 2019, with over 25,000 publications highlighting China's surge in output, surpassing the United States (Picture 1). This shift is driven by increased government funding, research initiatives, and institutional support, establishing China as a global leader in BCI research.

Recent advancements in wireless EEG devices, computational intelligence, and machine learning [5] have fueled this growth [6]. Initially focused on medical applications, BCI research has broadened into fields like education, gaming, marketing, and security [7]. By 2020-2022, China dominated BCI authorship globally.

Looking ahead, research is increasingly focused on artificial intelligence and ethical considerations as BCI technologies evolve [7].

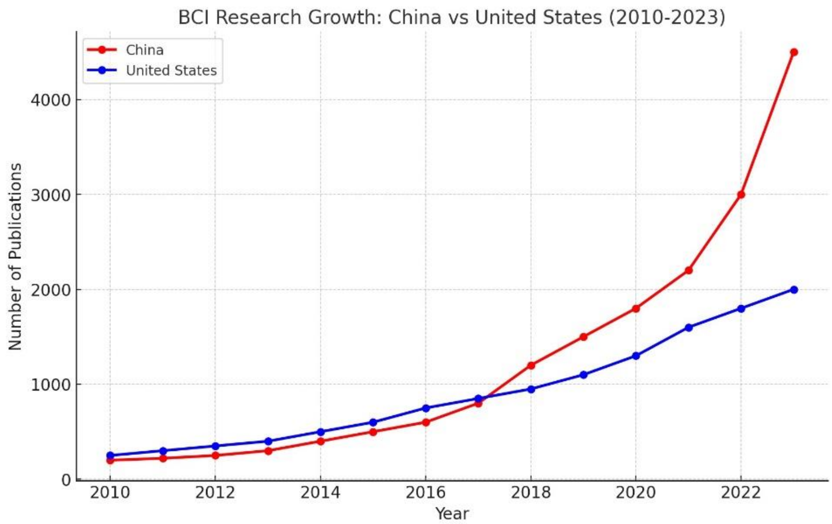

Fig.1. The growth of Brain-Computer Interface (BCI) research publications in China and the United States from 2010 to 2023.

2.2 Global Collaborative Efforts

Brain-Computer Interface (BCI) research has seen significant global collaborative efforts in recent years. International collaborations are particularly strong between Germany, USA, Austria, and Italy [8]. These collaborations have led to advancements in various BCI applications, including rehabilitation and collaborative work. Studies have shown differences in performance and brain activity when users perform tasks jointly versus individually using BCIs. Despite progress, challenges remain in tackling complex brain dynamics, feature extraction, and classification. Time-variant psycho-neurophysiological fluctuations also pose difficulties in transitioning BCI technology from laboratory settings to daily life applications [9]. Ongoing research efforts focus on technology standardization and addressing these challenges to expand BCI applications in fields such as rehabilitation, affective computing, robotics, and gaming. Regular updates on collaborative efforts and research quality are crucial for improving the visibility of the BCI research community [8].

3. Technological Innovations in BCIs

3.1 Components of BCI Systems

BCI systems typically consist of three fundamental components: signal acquisition, signal processing, and application execution. Each component plays a crucial role in converting brain activity into actionable commands, enabling control over external devices. Recent advancements have greatly improved the efficiency and accuracy of these components, enhancing user experience and the effectiveness of BCI applications.

These systems create direct connections between the brain and external devices by using neuroimaging techniques such as EEG, MEG, fMRI, and fNIRS [10]. BCI hardware captures brain signals, while specialized software processes and decodes them into commands [11]. BCIs have been applied in motor control, sensory augmentation, and rehabilitation, benefiting individuals with spinal cord injuries, motor neuron diseases, amputations, and stroke [12]. Recent innovations include hybrid systems that integrate multimodal sensory inputs, AI-driven algorithms for improved signal classification, and neurofeedback mechanisms to boost user control [13]. However, challenges remain in achieving widespread BCI adoption [11].

Table 1. Summary table of Neuroimaging techniques

Technique	Temporal Resolution	Spatial Resolution	Advantages	Limitations
EEG	Excellent (ms)	Poor (cm)	Non-invasive, real-time, inexpensive	Noisy, limited localization
MEG	Excellent (ms)	Better (cm)	Non-invasive, good spatial/temporal resolution	Expensive, requires specialized setup
fMRI	Good (s)	Excellent (mm)	High spatial resolution, deep structures	Poor temporal resolution, expensive
fNIRS	Good (s)	Moderate (cm)	Portable, relatively inexpensive	Limited depth, lower spatial resolution

3.2 Signal Acquisition Methods

Recent research on brain-computer interface (BCI) signal acquisition methods highlights the interdisciplinary nature of the field and the importance of balancing signal quality, invasiveness, and biocompatibility [14] [15]. Signal acquisition technologies can be broadly categorized into invasive and non-invasive methods, with electroencephalogram (EEG) being a prominent non-invasive technique [16]. Various signal processing approaches, including time-frequency methods and spatiotemporal techniques, are employed to enhance signal quality and extract relevant features [16]. The field faces ongoing challenges in integrating diverse perspectives and achieving a balance between signal fidelity and other critical factors [15]. Future developments in BCI signal acquisition should prioritize interdisciplinary collaboration to advance the technology's efficiency, safety, and reliability [14].

4. Applications of BCIs

4.1 Healthcare and Rehabilitation

Brain-computer interfaces (BCIs) have emerged as promising tools in healthcare and rehabilitation, particularly for individuals with neurological disabilities. BCIs enable direct communication between the brain and external devices, facilitating motor control, sensory augmentation, and environmental interaction [12]. Applications include motor and speech rehabilitation, virtual reality control, and assistive technologies for paralyzed patients [17] [18]. In stroke rehabilitation, BCIs contribute to gait and balance improvement, communication assistance, and cognitive rehabilitation through neurofeedback and task-oriented training [19]. Integration with other technologies like functional electrical stimulation, virtual reality, and robotics enhances their effectiveness in mobility assistance and personalized rehabilitation [19]. While BCIs show great potential in improving quality of life for people with disabilities, challenges remain in signal quality, long-term usability, and cost-effectiveness [19]. Ongoing research aims to refine BCI technology and explore novel applications in neurorehabilitation.

4.2 Enhancing Quality of Life

For individuals with severe disabilities, BCIs offer unprecedented opportunities for independence. Reports indicate that BCIs can facilitate control over essential daily activities, such as communication, mobility, and environmental interaction, transmitting brain signals to operate computers, wheelchairs, and smart home devices. The implications of increasing the autonomy of individuals with disabilities are profound, as they can lead to improved quality of life and reintegration into society.

BCIs can augment communication, environmental control, and self-care for tetraplegic patient [20]. These systems rely on the brain's plasticity, allowing users to learn to modify neural activity through practice and feedback. Future applications may extend to rehabilitation of motor and cognitive impairments in hemiplegic or paraplegic patients [20]. As BCI technology advances, it is expected to impact a broad range of applications, including communications and prosthetic control [21]. Recent developments in deep learning have further improved BCI performance, with CNN models achieving 98.3% accuracy in classifying EEG signals [22]. This progress enables the creation of smart, data-driven systems that can assist elderly individuals in interacting with their environment, potentially enhancing their quality of life [22].

4.3 Expanding into Other Industries

Brain-computer interfaces (BCIs) are expanding beyond clinical applications into various industries. In Industry 4.0, BCIs show potential for optimizing cognitive load, facilitating human-robot interactions, and enhancing safety in critical conditions [23]. BCI technology can be used to assess operators' cognitive states in industrial settings, potentially leading to assistive technologies that prevent accidents [24]. Beyond industry, BCIs are being explored in diverse fields such as robotics, education, and security (Patel et al., 2023). Therapeutic applications of BCIs are also emerging, with potential uses in motor rehabilitation for stroke patients, Parkinson's disease treatment, and psychiatric disorders [26]. While these advancements are promising, challenges remain in developing operational solutions outside laboratory conditions [23]. The integration of deep learning and machine learning approaches in interpreting brain signals is crucial for advancing BCI technology (Patel et al., 2023).

5. Challenges Facing BCI Technologies

5.1 Ethical and Privacy Concerns

Brain-Computer Interfaces (BCIs) raise significant ethical, privacy, and security concerns as they create unprecedented direct connections between human brains and computers [27]. Key issues include personhood, autonomy, privacy, research ethics, and justice [27]. The collection and use of brain data, as well as inferences about users' mental states, pose privacy risks [28]. Security vulnerabilities in BCI applications could allow malicious actors to extract private information [29]. These concerns span various usage scenarios, including neuromedical applications, user authentication, gaming, and smartphone-based applications [29]. While these issues have been extensively discussed, there is a lack of concrete recommendations and practical solutions [27]. Addressing these challenges requires a coordinated response from engineers, neuroscientists, ethicists, legal experts, government, and industry to develop appropriate devices, algorithms, standards, and regulations (Bonaci et al., 2015).

5.2 Technical Limitations

Brain-computer interfaces (BCIs) have shown promise in various applications, but face significant technical challenges. Non-invasive and invasive recording methods each have limitations, including potential neuronal damage and usability issues [31]. The complex, non-linear nature of brain dynamics complicates feature extraction and classification [9]. Time-variant psycho-neurophysiological fluctuations further hinder the transition from laboratory to real-world use [9]. While visual and auditory BCIs offer advantages like high communication speeds and minimal user training, developing robust systems remains challenging [32]. Researchers are working to address these issues through improved signal processing, classification algorithms, and standardization efforts [9] [33]. Despite progress, BCIs are still in early stages of development and require significant further research to achieve seamless integration with biological systems and support widespread adoption [33].

6. Future Directions in BCI Research

6.1 Interdisciplinary Research Approaches

Brain-computer interfaces (BCIs) have shown significant progress in recent years, enabling communication and motor control for paralyzed individuals [34]. However, the field faces challenges such as fragmentation among researchers and inconsistent terminology [35]. Future directions in BCI research emphasize interdisciplinary collaboration, involving neuroscientists, engineers, psychologists, and rehabilitation specialists [36]. Emerging applications span medical domains, robotics, education, and security [25]. Key areas for improvement include signal acquisition and processing, translation algorithms, and user training [36]. Non-invasive BCIs based on EEG are ready for large clinical studies and commercial production [34]. Integration of deep learning and machine learning approaches in interpreting brain signals presents a critical challenge [25]. Future research may also explore brain metabolism regulation and brain stimulation techniques [34].

6.2 Enhanced AI Integration

Recent advancements in artificial intelligence (AI) have significantly enhanced brain-computer interface (BCI) research and applications. Machine learning and deep learning techniques have improved the analysis and decoding of neural activity, particularly in EEG-based BCIs [37] [38]. Generative AI has emerged as a promising approach to address challenges in BCI development, such as limited data availability, inter-subject variability, and spatiotemporal resolution enhancement of brain signals [39]. AI-assisted BCIs have shown notable clinical success in motor and sensory applications, improving the lives of paralyzed patients and expanding human capabilities [38]. Various BCI paradigms, including motor imagery, event-related potentials, and visually evoked state potentials, have been explored using different signal collection techniques like EEG, ECoG, and MRI [25]. Despite these advancements, challenges remain in real-time feedback, long training periods, and monitoring of BCIs [38].

7. Conclusion

In conclusion, Brain-Computer Interface technology presents a revolutionary approach to bridging the gap between human cognition and external technology. With rapid advancements in research, diverse applications across various sectors, and a clear trajectory for future development, BCIs have the potential to transform lives, particularly for those with physical disabilities. However, the field must address critical challenges, including ethical considerations and technical limitations, to progress effectively. Continuous interdisciplinary efforts and adherence to ethical standards will be essential for realizing the full potential of BCIs in enhancing human capabilities and quality of life.

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