Brain-Computer Interfaces in Human-Computer Interaction

Chengyu Li *

High School affiliated to Shanghai Jiao Tong University, Shanghai, 200123, China

* Corresponding Author Email: li.chengyu.23@jdfzib.org

Abstract. Brain–computer interfaces (BCIs) enable direct communication between neural activity and external devices, offering novel input channels that expand and redefine human–computer interaction (HCI). Originally developed from early electroencephalography (EEG), BCIs have evolved to include both invasive and implantable systems, with applications extending beyond clinical settings into rehabilitation, assistive communication, and interactive entertainment. This paper provides a concise survey of BCIs within HCI. The review begins by introducing neuroscience and signal-processing foundations, including signal acquisition—such as EEG, electrocorticography (ECoG) and intracortical recordings—as well as preprocessing, feature extraction, and decoding methods. Subsequently, representative application domains are explored, including: (1) assistive technologies, exemplified by brain-controlled wheelchairs, prosthetics, neurorehabilitation systems; (2) communication systems, such as P300 spellers, intracortical spelling interfaces, and emerging speech neuroprostheses; and (3) entertainment and gaming applications, including neurogaming and VR/AR integration. The discussion then turns to emerging trends—AI-enhanced decoding, wearable and wireless form factors, and multimodal integration—along with cross-cutting challenges such as neural data privacy, user autonomy and consent, usability, and regulation. The paper concludes with design implications for HCI and proposes a research agenda for safe, reliable, and equitable BCI deployment.

Keywords: BCIs, HCI, EEG.

1. Introduction

A brain-computer interface (BCI) is a system that creates a direct communication pathway between the human brain and external devices. By detecting and decoding neural activity, BCIs enable users to control computers or machines without using peripheral nerves or muscles. The concept origins of BCIs can be traced back to the early electroencephalography (EEG) studies of the 1920s–30s (Hans Berger's first human EEG recordings) and was formally introduced by Jacques Vidal in the 1970s. Subsequent milestones include the first implanted human BCI by Kennedy in 1998 and the formation of Brain Gate (a U.S. university consortium) in 2006, which achieved early successes in neural cursor control.

Today, BCIs have expanded into medical, research, and consumer domains. They are being explored as assistive technologies for paralysis and communication, as well as for gaming, virtual reality, and enhancement of human cognition. For example, BCIs have been proposed for rehabilitation and disease diagnosis, for entertainment, including video games, and even for "neurogaming" where thoughts control game actions.

This paper reviews the principles, applications, and future of BCIs in human-computer interaction (HCI). First, the neuroscience and signal--processing foundations of BCIs, as well as their classification into invasive, semi-invasive, and non-invasive types are described. Then, this paper examines current BCI applications in HCI, focusing on three representative use cases: assistive technologies such as wheelchair and prosthetic control, gaming/entertainment, and communication tools including spellers and speech prostheses. Each use case is illustrated with real-world examples and studies. Besides, emerging trends like the integration with artificial intelligence and wearable BCI devices, and ongoing challenges related to ethical, legal, and usability issues will be discussed. Finally, the paper concludes with a summary of key points. [1,2].

2. Principles and Types of BCIs

BCIs translate neural activity into device commands through a multi-step signal-processing pipeline. First, brain signals are acquired via electrodes or sensors, such as EEG electrodes on the scalp, ECoG grids on the cortical surface, or intracortical microelectrodes within brain tissue. Next, the raw data are preprocessed, including filtering and artifact-removal. Then, features are extracted, such as power in specific frequency bands or evoked-response amplitudes, and a classifier or decoder maps the features to control signals. Machine learning and adaptive algorithms are often used to improve accuracy. In effect, the BCI "reads" brain activity associated with intentions—such as imagined movement or attention to a flashing stimulus—and outputs corresponding device commands.

BCIs are commonly classified based on their invasiveness, with three primary types. Non-invasive BCIs record neural signals without surgery. The most widely used non-invasive modality is EEG, which measures voltage fluctuations from the scalp. Other non-invasive methods include fMRI and functional near-infrared spectroscopy (fNIRS). EEG-based BCIs have high temporal resolution and excellent safety, but suffer lower signal quality due to skull attenuation. EEG signals used for control typically include evoked potentials and rhythms. For example, a classic paradigm is the P300 speller, which relies on the P300 event-related potential (a positive EEG deflection ~300 ms after an attended oddball stimulus). Other non-invasive signals include steady-state visually evoked potentials (SSVEPs) and sensorimotor rhythms (μ and β bands) generated by motor imagery. Semi-invasive, or partially invasive, BCIs typically involve sensors placed on or just below the dura mater (for example, ECoG). ECoG provides better spatial fidelity than EEG, with electrodes on the cortical surface, but avoids penetrating brain tissue. In contrast, invasive BCIs involve surgical implants of microelectrode arrays into brain tissue, enabling direct recording of action potentials or local field potentials. Invasive BCIs achieve the highest signal quality and bandwidth, enabling fine-grained control (e.g. of robotic limbs). However, they require surgery and face challenges such as immune response over time. Thus, invasive BCI systems are mainly used in research and clinical trials for severe paralysis.

Each BCI approach involves inherent trade-offs between safety, ease of use, and control fidelity. EEG and other non-invasive BCIs are most practical for consumer and wearable applications, such as neurofeedback headsets, whereas invasive BCIs are promising for restoring function in paralysis but entail significant risk. Regardless of modality, all BCIs share the goal of detecting interpretable neural signals and converting them to computer-executable commands [3].

3. Current Applications of BCIs in HCI

BCIs have demonstrated remarkable potential in several human-computer interaction domains. The following typical use cases illustrate how BCIs enable novel interaction for users with and without disabilities.

Firstly, in the field of assistive technologies, particularly for disability assistance, BCIs are perhaps most mature in medical assistive roles. For example, brain-controlled wheelchairs (BCWs) allow paralyzed users to navigate by thought. Research systems combine EEG-based commands with navigation planning, such as computer vision for obstacle avoidance, to safely drive a wheelchair. Similarly, implanted BCIs have enabled people with severe tetraplegia to control robotic limbs or cursors. In one landmark study, three participants with paralysis used an intracortical array to control a tablet computer in real time, performing tasks including web browsing, music playback, and even mutual text message exchanges. Other implant studies have enabled users to move a robotic arm to drink water, eat, or write. These examples show that BCIs can restore mobility and autonomy. Importantly, BCIs are also used for neurorehabilitation, such as driving electrical stimulation of muscles, as well as in diagnostics for monitoring seizure activity.

Secondly, BCIs are increasingly explored for interactive gaming and immersive experiences. BCI-integrated video games allow players to control game events with their brain activity. For instance, Moreno-Calderón et al. implemented a two-player "Connect 4" game where each move is made via a steady-state visual evoked potential (c-VEP) BCI. Healthy participants achieved a high accuracy of approximately 94% and reported that the BCI-driven gameplay was intuitive and engaging [4]. Similarly, lightweight wearable EEG devices with dry electrodes have been demonstrated to control simple video games such as moving a cursor or character, as proof-of-concept [5]. Major companies are also invested heavily in this space: for example, Neuralink (2024) showcased a human patient playing video games via an implanted BCI, and consumer EEG headsets (e.g. Muse, Emotiv) are marketed for neurofeedback games. Thus, BCIs offer a new interaction channel for entertainment and “neurogaming,” especially benefiting users with limited motor ability.

Furthermore, in the realm of communication tools, BCIs have also found extensive application value with a classic application being enabling communication for people with severe disabilities, such as locked-in syndrome. The P300 speller is a well-known non-invasive BCI: it displays a matrix of letters and detects the P300 response when the user focuses on a desired character. Medina-Juliá et al. evaluated P300 spellers of different sizes with amyotrophic lateral aclerosis (ALS) patients and showed that such systems let motor-disabled individuals spell words without any muscle movement [6]. Advances in this area include intracortical spelling BCIs: Chaudhary et al. implanted microelectrode arrays in a completely locked-in ALS patient and enabled the patient to spell words via an auditory feedback speller. More recently, speech BCIs are emerging: Willett et al. (2023) decoded attempted speech from motor cortex signals of an ALS patient, achieving fluent 62 words-per-minute text output--approaching conversational rates. These communication BCIs highlight how neural interfaces can translate intention into language or text.

In summary, assistive BCIs have empowered disabled users to interact with their environment through applications in mobility, prosthetics, communication, while BCI-enhanced HCI is also expanding into mainstream domains like gaming.

4. Future Trends and Challenges

BCIs are advancing rapidly thanks to emerging technologies, but important challenges remain. Key development trends include the application of modern machine learning, especially deep learning, is being applied to improve BCI signal processing. AI can learn complex neural patterns from signals such as electrocorticography or EEG more accurately, increasing information throughput and reducing calibration time. For example, hybrid systems combining neural-network decoders with high-density electrode data promise higher speed and accuracy. Recent reviews note that neural decoding algorithms and adaptive AI are among the fastest-growing areas in BCI research [7].

Concurrently, there is a growing emphasis on wearable and wireless devices aimed at improving the practicality and usability of BCIs for everyday use. Examples include EEG headsets with dry electrodes and wireless links, enabling operation beyond laboratory settings. Novel sensors, such as ear-EEG and flexible scalp electrodes, offer improved comfort and user experience. Furthermore, miniaturized implantable chips (like Neuralink’s) aim for whole-brain coverage. Augmented reality (AR) and virtual reality (VR) interfaces are also integrating BCI technology for more immersive control, as in the AR-enhanced wheelchair system. Overall, future BCIs are expected to be more wearable, multi-modal, and integrated with consumer devices.

Despite this progress, BCIs raise significant ethical, legal, and usability concerns. One major issue is privacy and security, as neural data can be highly sensitive. Unlike typed or spoken inputs, brain signals may inadvertently reveal private information, such as emotions, intentions, or health state. Current data protection regulations, including the general data protection regulation (GDPR), do not explicitly cover neural data, resulting in ambiguous governance. Research has shown that even simple BCI games can expose user-specific patterns. Ensuring secure handling of neural data and protecting user privacy is critical.

Questions of autonomy and consent also arise due to the blurred boundary between user intention and device action, raising issues regarding user agency and informed consent, especially for populations with limited communication. Scholars caution that BCIs capable of modulating neural activity could affect an individual’s sense of self or decision-making. Legal questions arise over responsibility: for example, determining liability when a BCI-controlled device causes harm. Early surveys suggest considerable public uncertainty regarding responsibility frameworks. Clear ethical guidelines and regulations are needed to address identity, responsibility, and fairness.

Usability and accessibility present additional challenges. Many BCIs still require lengthy training, calibration, and setup. Non-ideal signal quality caused by noise and artifacts limits reliability and accuracy. To become practical, BCIs must be user-friendly and robust under real-world conditions. Issues include fatigue, cognitive load, and ease of use must be addressed by optimizing interface design and stimulation paradigms. Additionally, equitable access is a concern – currently most BCI research is in wealthy countries, and cost can be prohibitive.

Regulatory and societal aspects are increasingly coming to the fore. Governments and standards bodies are beginning to address BCI technology. For instance, Chinese authorities have set goals for BCI breakthroughs by 2027, and international discussions are ongoing about neurotechnology oversight. Public acceptance varies: a recent survey in China found that factors like health and technical literacy predict willingness to adopt BCIs. It is essential for developers to engage stakeholders to ensure BCIs are developed in a socially responsible manner.

In summary, while advances in AI, materials, and clinical research promise to make BCIs faster, smaller, and more ubiquitous. However, careful attention to ethical design, legal frameworks, and human factors will be essential as BCIs enter everyday HCI.

5. Conclusion

BCIs represent a transformative technology at the intersection of neuroscience and HCI. This paper reviewed their definition, history, and structure, and surveyed current applications in assistive technology, gaming, and communication. Real-world examples show BCIs enabling disabled users to regain autonomy like wheelchair control and communication spellers, and opening new interaction modalities such as BCI-driven games. Underlying these systems are neural signal acquisition and processing methods, which vary from non-invasive EEG to implanted electrodes. Looking ahead, BCIs are evolving through AI-enabled decoding and wearable designs. Simultaneously, ethical, legal, and usability challenges must be addressed – including privacy of neural data and ensuring user agency. In conclusion, while BCIs are still emerging, they hold great promise to augment human-computer interaction. With continued research and responsible development, BCIs may soon move from laboratory demonstrations to everyday use, fundamentally broadening how humans interact with technology.

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