Brain-computer interfaces

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Abstract—**Brain–computer interfaces (BCIs) enable direct communication between neural activity and external computational systems by translating brain signals into actionable outputs without relying on peripheral nerves or muscles. These technologies typically record neuronal dynamics using invasive or non-invasive sensors, extract informative patterns through advanced signal processing and machine-learning algorithms, and map these features onto commands that control external devices. BCIs are now increasingly applied to domains such as motor rehabilitation, assistive communication, neuroprosthetics, neuromodulation, and experimental cognitive augmentation.**

I. INTRODUCTION

Efforts to establish direct communication between the human brain and artificial systems have shaped decades of interdisciplinary research. Brain–computer interfaces (BCIs) constitute a class of neurotechnologies that decode neural activity to infer user intent and translate it into meaningful actions performed by external devices. By bypassing traditional neuromuscular pathways, BCIs offer unprecedented access to brain internal states and allow the control of computers, robotic prostheses, communication systems, and other digital or mechanical platforms [1]. The term "brain–computer interface" was introduced in the early 1970s by Jacques Vidal, whose foundational work demonstrated that electroencephalographic signals could serve as a practical communication channel [2]. Since then, the field has evolved into a rich intersection of neuroscience, biomedical engineering, artificial intelligence, neurosurgery, and rehabilitation medicine.

Over the past two decades, BCI research has accelerated dramatically due to advances in electrophysiological recording methods, computational modeling, and machine learning. These developments have led to systems capable of decoding high-dimensional motor representations, interpreting speech-related neural dynamics, and allowing individuals with profound disabilities to regain meaningful interaction with their environment [3], [4]. Modern BCIs now span a continuum of applications, from non-invasive communication aids to fully implantable neuroprosthetic platforms capable of restoring movement in tetraplegic patients or translating attempted handwriting into text at high speed.

To understand how BCIs function, it is important to note that neurons communicate through action potentials (APs), rapid electrical impulses generated by the influx of voltage-gated sodium ions, creating a depolarization of the membrane, followed by the efflux of potassium ions, which return the membrane potential to its resting level near $-70\ \mathrm{mV}$. Although the AP shape and amplitude are constant, information is encoded in firing rates and temporal patterns of activity in neuronal populations [5].

At the population level, coordinated neuronal activity produces local field potentials (LFPs) and macroscopic oscillations detectable at the scalp or cortical surface. These oscillatory rhythms are commonly categorized into delta (0.1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and gamma ($>$ 30 Hz) frequency bands, each associated with distinct cognitive or behavioral states. Their spatiotemporal characteristics offer valuable information for decoding motor intentions, attentional dynamics or pathological activity [6]. Moreover, the location of neural recordings determines the type of information accessible to a BCI: motor and premotor cortices are central targets for prosthetic control, whereas speech decoding interfaces typically rely on activity from perisylvian language networks. Together, these biological principles underpin the design, implementation, and interpretation of modern BCIs.

II. DEVELOPMENT

A. Overview

1) BCI Definition: A brain–computer interface (BCI) is commonly defined as a system that acquires and interprets neural activity and translates it into commands capable of replacing, restoring, enhancing, or supplementing natural neural outputs [7]. In contrast to conventional assistive technologies, BCIs do not depend on residual muscle activity or peripheral nerve function; instead, they derive information directly from the brain.

Modern definitions include bidirectionality as a defining property, as BCIs can both decode neural activity and encode information back into the brain via electrical or sensory feedback with closed-loop neuromodulatory devices capable of altering neural states in real time [8].

2) General Architecture: Despite their diversity in form and purpose, most BCIs are built upon a common architectural framework (Fig. 1) that involves several sequential and interdependent stages [3]. The process typically begins with the acquisition of neural activity, which can arise from numerous recording modalities that differ in invasiveness, spatial resolution, signal quality, and long-term stability. Once captured, the raw signals must undergo preprocessing to remove noise and artifacts generated by environmental interference or the recording hardware itself. This step often includes band-pass filtering, notch filtering to eliminate line noise, and spatial filtering methods (e.g., Common Average Referencing, Laplacian transformations) [10].

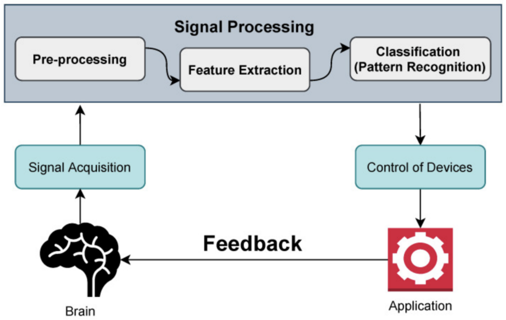

Fig. 1. General architecture of a BCI system [9].

Following preprocessing, the system extracts features that reflect neural states or intentions. These may include oscillatory power modulations, event-related potentials, high-frequency broadband activity, or patterns of neuronal spiking. Additionally, the rise of deep learning has increasingly enabled data-driven feature discovery [11]. The extracted features are then passed to decoding algorithms designed to infer the user's intended action or cognitive state. Classical methods such as support vector machines or more complex techniques such as Kalman filters, recurrent neural networks, and convolutional neural networks are used for intracortical motor decoding and end-to-end classification [12].

Once neural intentions are decoded, they are translated into control signals that actuate an output device or trigger an internal system. Importantly, BCIs can operate in a closed-loop or open-loop fashion. In the open architecture, the user doesn't recieve any feedback while in the closed-loop form, visual, auditory or even tactile feedback is delivered following neural activity which enables adaptive learning through a dynamic, interactive system where patients refine their neural strategies as the interface adjusts [13].

3) Signal Acquisition Modalities: Acquisition of neural activity can be grouped into three categories: non-invasive techniques (e.g., EEG), partially invasive (e.g., ECoG), and fully invasive (e.g., intracortical approaches) (Fig. 2). These techniques represent a trade-off between safety, spatial and temporal resolution, signal fidelity, and stability over time [3].

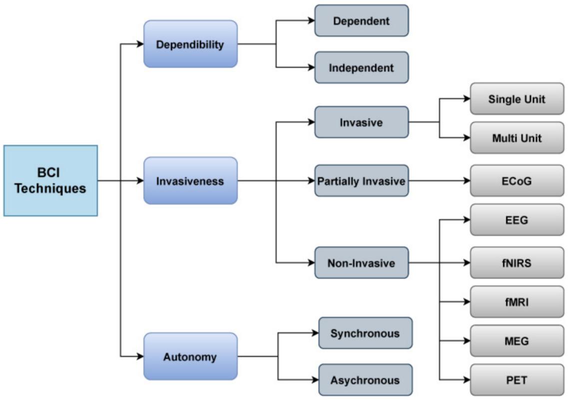

Fig. 2. Existing BCI techniques classification [9]

Most non-invasive BCIs rely on EEG, which measures voltage fluctuations resulting from postsynaptic activity in cortical neurons. EEG offers millisecond temporal resolution but relatively poor spatial precision due to signal attenuation and distortion with current shunting on the skull and scalp [14]. Nevertheless, EEG enables several robust BCI paradigms and is safe, inexpensive and deployable outside clinical settings, making it the cornerstone of consumer and research-oriented BCIs. Other non-invasive methods offer complementary advantages such as higher spatial fidelity in magnetoencephalography (MEG) or sensitivity to hemodynamic changes in functional near-infrared spectroscopy (fNIRS), but are less frequently used in real-time BCIs due to practical or temporal limitations [15].

ECoG is a partially invasive technique in which an array of electrodes is placed directly on the exposed cortical surface, typically during neurosurgical procedures. Because ECoG bypasses the skull, it provides an improved spatial resolution and signal quality compared to EEG while maintaining excellent temporal precision. Importantly, ECoG captures high-gamma activity, which correlates closely with the dynamics of the local neuronal system and offers rich information to decode motor and speech processes [16], [4]. Although ECoG has proven to be a powerful tool for high-performance BCIs, it requires a craniotomy, which is a relatively heavy surgery where a part of the skull is removed.

Finally, intracortical BCIs are the most invasive yet highest-resolution category. By inserting microelectrode arrays directly into cortical tissue, these systems record action potentials from individual neurons and local field potentials from surrounding neural populations. Intracortical arrays provide unparalleled temporal and spatial resolution, enabling accurate decoding of complex motor intentions and supporting multidimensional control in individuals with paralysis [17] [18]. However, their clinical viability remains constrained by challenges such as long-term biocompatibility, glial tissue encapsulation, and risks associated with neurosurgical implantation that could lead to hemorrhages, infections, etc.

4) Control Signals and Paradigms: The effectiveness of a BCI depends on the identification of neural patterns that can serve as reliable control signals. These signals may arise from externally evoked responses, spontaneous oscillatory activity, voluntary modulation of sensorimotor areas, or cognitive and affective processes. The choice of paradigm influences not only decoding accuracy but also user comfort, training duration, and long-term usability [1].

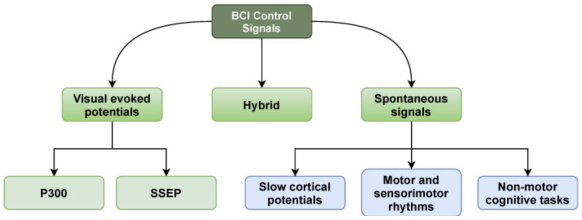

Fig. 3. BCI Control Signals [9]

Evoked potential paradigms are based on the brain's stereotyped responses to external stimuli. Among them, the P300 response has become a foundational method for BCI-based communication due to its robustness across users and minimal training requirements [19], [20]. Similarly, SSVEP-based BCIs exploit the steady-state oscillatory responses generated when users focus on visual stimuli, providing high signal-to-noise ratios and strong performance in multi-choice interfaces 3. However, these paradigms require continuous sensory stimulation thus, they are less suitable for long-term or mobile use.

A second major class of control signals involves sensorimotor rhythms (SMRs), which arise from oscillatory activity in the μ and β bands over the motor cortex. Users learn to modulate these rhythms voluntarily through motor imagery or attempted movement, enabling self-paced and stimulus-independent control [21]. Although SMR-based BCIs generally require longer training than evoked paradigms and may yield lower information transfer rates, they offer greater autonomy and are widely used in motor rehabilitation and assistive technologies.

At the invasive end of the spectrum, intracortical motor signals derived from neuronal spiking activity provide the most precise form of control. Action potential firing rates and local field potentials encode fine-grained information which enables high-dimensional prosthetic control even in individuals with complete paralysis [18], [22]. These systems represent the current pinnacle of BCI performance although they are more risky due to their high invasiveness and diminished long-term unit stability.

Finally, cognitive and affective signals have emerged as a growing domain within BCI research. Neural signatures associated with attention, mental workload, error monitoring, or recognition provide avenues for passive BCIs that adapt interfaces to the user's internal state, as well as for neurofeedback-based interventions targeting learning, emotional regulation, and clinical therapy [9].

B. BCI Applications

1) Speech and thoughts decoding: One of the most transformative applications of BCIs is the restoration of communication in individuals who have lost the ability to speak due to neurological injury or neurodegenerative disease. Conditions such as stroke, traumatic brain injury, or amyotrophic lateral sclerosis (ALS) can lead to aphasia or complete loss of speech production. BCIs for speech decoding aim to translate cortical activity associated with attempted or imagined speech into synthetic spoken output or written text, providing a means for patients to regain communicative ability.

Recent breakthroughs have demonstrated the feasibility of continuous, naturalistic speech restoration. [23] presented a streaming brain-to-voice neuroprosthesis using a high-density Utah array implanted in the speech motor cortex. Neural signals were captured from populations of neurons encoding articulatory and phonetic information. These signals were routed through a real-time recurrent neural network decoder trained to map neural activity to acoustic speech features, enabling the production of intelligible synthesized speech in near real time. Their system integrated low-latency neural recording hardware, spike-sorting algorithms, and a speech vocoder optimized for naturalistic output.

Parallel advancements in low-power, implantable hardware have further increased the feasibility of speech BCIs. [24] introduced a 2.46-mm² miniaturized brain–machine interface (MiBMI) system-on-chip capable of on-device neural signal acquisition, feature extraction, and classification. Their BCI achieved 31-class brain-to-text decoding with 91.3% accuracy, significantly exceeding prior hardware-constrained decoding systems. By allowing subjects to imagine handwriting individual characters, the MiBMI extracted motor-imagery signatures of graphemic movements and decoded them directly into text. Importantly, the chip's low power consumption and real-time processing pipeline suggest a path toward fully implantable communication neuroprostheses.

Despite rapid progress, several challenges remain. Ethically, the possibility of decoding unintended internal thoughts raises questions about cognitive privacy and consent. Although current technologies lack the spatiotemporal resolution required to decode unconstrained inner speech [23], future improvements may complicate boundaries between voluntary and involuntary cognitive states. Technical limitations include signal instability due to gliosis around implanted electrodes, limited vocabulary generalization, and the need for frequent decoder recalibration. Improvements in long-term biocompatibility, adaptive machine learning, and multimodal decoding strategies may help overcome these technical obstacles.

2) Motor / Prosthetic control: Motor BCIs constitute the most mature and clinically validated category of neural interfaces. These systems aim to restore motor function by translating neural activity into control signals for robotic or prosthetic devices. In individuals with paralysis, spinal cord injury, or limb loss, BCIs can provide a direct means to control a robotic arm or prosthetic limb through motor intention alone.

The fundamental principle relies on decoding neural signals from motor cortex regions representing limb position, force, or movement trajectories. [18] demonstrated that invasive BCIs using intracortical microelectrodes allow high-degree-of-freedom control of robotic limbs, enabling tasks such as reaching, grasping, and object manipulation [25]. These systems capture spike trains or local field potentials, which are processed using decoding algorithms to infer intended movement kinematics.

Recent research has expanded the robustness and usability of motor BCIs. For instance, [26] developed a prosthetic hand control method integrating augmented reality, steady-state visual evoked potentials (SSVEP), asynchronous state transitions, and machine vision. This hybrid architecture enabled users to switch between intention states and interact with objects in real environments with improved precision and reduced cognitive load. EEG-based shared-control frameworks have also emerged, such as the assistive architecture developed by [27], which combined motor imagery with autonomous robot behaviors to enhance user performance and decrease effort.

BCIs are also increasingly applied in rehabilitation. [28] showed that non-invasive motor-imagery BCIs could be used as training tools to restore voluntary motor control after stroke, leveraging neuroplasticity and sensorimotor reorganization. Similarly, [29] reviewed emerging trends in BCI-robotics for motor rehabilitation, emphasizing the integration of exoskeletons, adaptive decoders, and personalized training paradigms.

The main challenges include limited long-term stability of intracortical electrodes, bandwidth constraints in non-invasive systems, user fatigue, and the difficulty of achieving naturalistic proprioceptive feedback. Ethical concerns involve autonomy, dependence on implanted devices, and issues of equitable access. Improvements may arise from bidirectional BCIs with somatosensory stimulation, fully implantable wireless systems, and self-calibrating models.

3) Cognitive control: BCIs can also be used to monitor and modulate cognitive states, enabling applications in neurorehabilitation, psychiatric treatment, and cognitive enhancement. Cognitive control BCIs typically rely on decoding oscillatory neural activity associated with attention, working memory, executive function, or mental effort.

[30] demonstrated that cognitive signals such as selective attention could be harnessed for BCI control, showing that patients can voluntarily modulate slow cortical potentials or event-related potentials to operate external devices. Neurofeedback applications have also gained traction: [31] used motor-imagery-based BCIs to evaluate neurofeedback training for cognitive rehabilitation, showing improvements in brain activation patterns associated with cognitive control.

In psychiatric and neurodevelopmental disorders, cognitive BCIs are increasingly explored as therapeutic tools. [32] developed a BCI-based gaming application for enhancing cognitive control in individuals with psychiatric disorders, demonstrating feasibility and user engagement. [33] argued that BCIs may augment neuroplasticity during neurological rehabilitation, particularly when paired with task-specific training or closed-loop feedback.

Technical implementations vary from scalp EEG systems to intracranial BCIs and the encountered limitations are mostly due to the cognitive variability across patients, susceptibility to noise and artifacts, and questions regarding long-term training effects.

4) Augmented Human Capabilities: Beyond clinical rehabilitation, BCIs are increasingly investigated as tools for enhancing cognitive or behavioral performance in healthy individuals. Although still nascent and ethically controversial, these applications aim to improve learning, gaming performance, memory encoding, or even interaction speed with digital environments.

[34] developed a real-time SSVEP-based gaming interface, demonstrating rapid and accurate control in interactive tasks. P300-based gaming BCIs have also been explored extensively to improve responsiveness and user engagement [35], [36].

Beyond entertainment, BCIs hold potential for adaptive learning systems. [37] presented an EEG-based passive BCI that adjusts the learning pace in real time according to cognitive load, improving engagement and knowledge retention. Moreover, on the memory enhancement aspect, [38] demonstrated that intracranial stimulation timed to specific phases of hippocampal activity could improve episodic memory performance in humans.

The ethical implications of human augmentation are substantial: unequal access to cognitive-enhancing BCIs may exacerbate social inequalities, and in the future, they could redefine notions of effort, achievement, or flaws in the quest to the augmented human. Furthermore, invasive augmentation raises safety concerns related to long-term implantation, data privacy, and dependence on neurotechnological systems in healthy humans.

III. CONCLUSION

To conclude, brain–computer interfaces provide substantial benefits that continue to motivate clinical and scientific research efforts, enabling communication and motor capacities restoration in individuals with severe neurological injury or disease. Beyond assistive applications, BCIs provide tools for high-resolution investigation of neural population dynamics, contributing to fundamental discoveries on motor control, perception, and cognitive processing [3], [39].

These benefits, however, coexist with persistent challenges that constrain the usability and scalability of current systems and the crucial need of personnalization. Brain signals, whether captured non-invasively or invasively, are inherently noisy and sensitive to numerous physiological and environmental sources of interference [40], and machine-learning approaches require extensive calibration or continuous adaptation to sustain high performance [10], [41]. Furthermore, user-related factors introduce additional complexity and endogenous BCIs demand significant training [42], while a lot of open research questions remain about hardware longevity issues. The critical trade-off between invasiveness and decoding accuracy lead to innovations such as soft biocompatible electrodes, fully implantable wireless interfaces, adaptive deep-learning decoders, and closed-loop neuroprosthetic architectures who might be able to redefine completely our definition of rehabilitation.

Beyond technical considerations, BCIs raise important societal and ethical concerns as neural recordings represent sensitive personal data [43]. Equity and access also pose challenges: the most advanced BCIs—particularly implantable systems—remain costly and accessible to only a small subset of patients [44]. Finally, as BCIs evolve toward augmentation or hybrid neuro-AI systems, questions regarding autonomy, enhancement, fairness, and the boundaries of human agency become increasingly salient [45]. These challenges highlight the need for responsible innovation that balances technological progress with ethical rigor. BCIs hold the potential not only to restore lost functions but to reshape medicine, erasing the frontier between humans and machines.

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