Real-Time Monitoring Technology for Physiological States in Brain Computer Interface Systems

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Abstract: Since the early 2000s, Brain-Computer Interface (BCI) systems have emerged as a transforma-tive technology in neuroscience, enabling direct communication between the brain and exter-nal devices. Originally developed to restore motor functions and control external systems, BCIs now extends to real-time physiological state monitoring. This paper explores the evolu-tion and methodologies of BCIs, focusing on signal detection techniques. Non-invasive meth-ods, such as Electroencephalography (EEG) and Functional Near-Infrared Spectroscopy (fNIRS), provide safe and accessible options, while invasive techniques like Electrocorticogra-phy (ECoG) offer superior precision. Hybrid BCIs, integrating modalities such as EEG-fNIRS, enhance performance by combining the strengths of individual technologies. The applications of BCIs span clinical and non-clinical domains, including stroke rehabilitation, communica-tion for individuals with severe impairments, brain-controlled gaming, and artistic creation. Recent advancements in signal acquisition, processing, and integration, such as improved electrode designs and real-time signal processing algorithms, have established BCIs as a criti-cal tool for neurotechnological innovation, with immense potential to transform healthcare and human-computer interaction.

1 INTRODUCTION

Brain-Computer Interface (BCI) systems have become a key focus of research, offering direct communication pathways between the brain and external devices. Early BCI studies focused on restoring motor functions and controlling external systems, and this research has expanded to include real-time monitoring of physiological states. The foundation of BCI research was laid in the early 20th century with Hans Berger's discovery of electroencephalography (EEG). This breakthrough demonstrated that neural activity could be measured and analysed, forming the basis for the modern exploration of direct brain-to-machine communication. From this foundational work, the field of BCIs has advanced significantly, with a particular focus on the development of technologies capable of accurately detecting and interpreting neural signals. These signals serve as the fundamental medium through which brain activity is translated into actionable commands for controlling external devices. The brief history of BCIs evolution is shown in Figure 1.

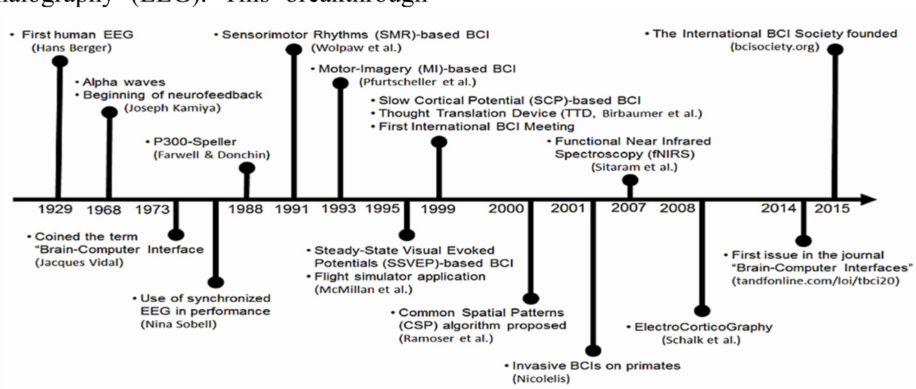

Figure 1. This diagram shown a span of evolution of BCIs range from 1929 to 2015 (Fabien et. al. 2018).

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Alt Text for the figure: the timeline labelled with various important events of BCI evolution from 1929 to 2015. The brackets conclude the names of scientists who discovered or invented this specific event. For example, Hans Berger recorded the first human EEG in the 1920s.

Following the historical development, it is essential to understand how BCIs function. The methodology of BCI involves several steps that enable direct communication between the brain and external devices. Figure 2 shows the basic processing of BCI system.

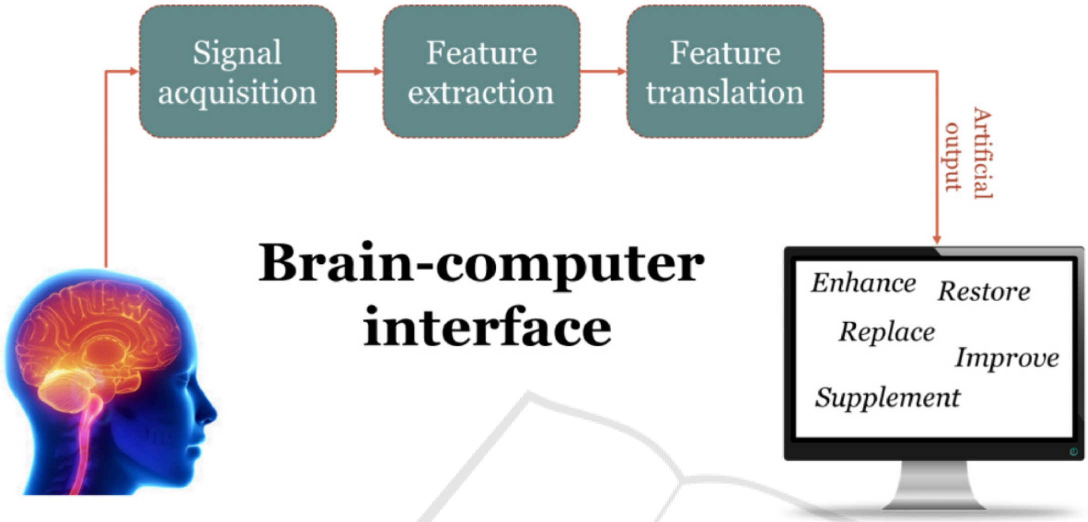

Figure 2. A schematic representation of the basic processing of BCI systems (Aricò et. al. 2018).
Alt Text for the figure: the Brain-computer interface starts at brain to signal acquisition, then feature extraction, and feature translation. The artificial output from the translation will then enhance the brain instruction to the computer device.

The first step in any Brain-Computer Interface (BCI) system is signal acquisition, where brain signals is captured using various techniques. While all these detection methods aim to capture brain signals accurately, they can be broadly categorized into non-invasive and inva-sive approaches based on their implementation. Non-invasive techniques, such as Electroen-cephalography (EEG) and functional near-infrared spectroscopy (fNIRS), are widely used due to their safety, ease of use, and accessibility. These methods measure neural activity indirectly through the skull and scalp, making them particularly well-suited for real-world applications due to their non-invasive nature and minimal risk to users. In contrast, invasive methods like Electrocorticography (ECoG) directly record electrical activity from the cortical surface, offer-ing superior spatial and temporal resolution, which is ideal for specific applications requiring high precision. Recently, hybrid systems that integrate multiple modalities have emerged, combining the strengths of each technology to overcome individual limitations and enhance overall performance. However, raw brain signals are often noisy and require preprocessing to remove artifacts. One of the most common artifacts, especially in EEG signals, is eye move-ment. To address this, specific preprocessing techniques are employed, such as digital filtering for noise removal and Independent Component Analysis (ICA) for artifact correction.

Next, the feature extraction phase begins, where relevant features are extracted from the pre-processed signals to identify specific patterns in brain activity. Common techniques in-clude time-domain features (such as signal amplitude, variance, and peak values) and frequen-cy-domain features (such as power spectral density and wavelet transforms), which together provide a comprehensive description of signal characteristics. Effective feature extraction is critical for improving the accuracy and robustness of BCI systems, as it directly influences the performance of the subsequent classification algorithms. There are three main types of classi-fication algorithms used in the BCI field: Machine Learning (ML), Deep Learning (DL), and Transformer-based models. These algorithms translate brain activity into actionable outputs, which can then be used to control external devices such as robotic arms, prosthetics, or speech synthesis systems. This paper primarily focuses on the signal detection aspect of BCI systems, exploring various techniques and their role in enhancing the quality and reliability of brain signal acquisition.

2 TECHNOLOGY OF SIGNAL DETECTION

Neural signals are essential in brain-computer interfaces (BCIs) for translating brain activity into device control commands. These signals reflect the electrical and physiological activity of the brain, enabling direct interaction between neural functions and external systems. BCIs primarily rely on accurately capturing these signals, thereby enabling applications such as prosthetic control and communication aids. To achieve this, various techniques are employed to measure brain activity, with non-invasive methods being the most widely used due to their safety, ease of application, and accessibility.

2.1 Non-Invasive Signal Detection

Currently, among the non-invasive approaches, Electroencephalography (EEG) and Functional Near-Infrared Spectroscopy (fNIRS) are two prominent technologies for recording brain activity.

2.1.1 Electroencephalography (EEG)

Electroencephalography (EEG) is a widely adopted non-invasive technique for monitoring electrical activity in the brain. By placing electrodes on the scalp, EEG captures voltage fluc-tuations arising from current flows within neuronal networks (Finnis et. al. 2024). Since its introduction nearly a century ago, EEG has been a foundational tool in both clinical diagnos-tics and neuroscience research. Rather than detecting action potential, EEG measures postsynaptic potentials generated by neurotransmitter activity. These signals originate from cortical pyramidal neurons, which are aligned in a way that makes their synchronized activity more detectable. However, the signal is often modulated by factors such as cerebrospinal fluid and the skull, which can distort or attenuate its propagation (Andrea et. al. 2019).

EEG plays a pivotal role in diagnosing neurological disorders, including epilepsy, sleep dys-functions, and other conditions (Andrea et. al. 2019). In recent years, its integration with brain-computer interface (BCI) systems has expanded its applications, enabling innovations such as mind-controlled prosthetics and rehabilitation devices (Lee et. al. 2017). A major ad-vantage of EEG lies in its exceptional temporal resolution, which allows it to track rapid neu-ral changes in real-time (Mathewson et. al. 2017). Modern EEG systems, which can support over 128 recording channels and achieve sampling rates exceeding 10 kHz, are lightweight, portable, and cost-efficient (Andrea et. al. 2019). These features make EEG suitable for both controlled laboratory environments and real-world applications, such as classrooms and athlet-ic training.

However, EEG systems are not without limitations. They are highly sensitive to noise, in-cluding electrical interference and movement artifacts, such as eye blinks or head motion (Mathewson et. al. 2017). Moreover, variations in signal preprocessing methods and referenc-ing techniques between different research studies can reduce result reproducibility and limit their broader application. Despite these challenges, continued advancements in signal pro-cessing and computational analysis ensure that EEG remains a critical tool for exploring brain function and developing neurotechnological innovations (Pfeffer et. al. 2024).

2.1.2 Functional Near-Infrared Spectroscopy (fNIRS)

Functional Near-Infrared Spectroscopy (fNIRS) is an emerging non-invasive imaging technol-ogy that monitors brain activity by measuring changes in blood oxygenation (Finnis et. al. 2024). Compared to EEG which directly records electrical activity, fNIRS indirectly tracks neural processes by capturing fluctuations in oxyhaemoglobin (HbO2) and deoxyhaemoglobin (HbR) levels. These changes are indicative of hemodynamic responses to brain activation. Employing near-infrared light, fNIRS detects these variations with greater spatial resolution (approximately 1 cm) than EEG (roughly 3 cm) (Borgheai et. al. 2020). Furthermore, fNIRS is less susceptible to artifacts caused by muscle activity or motion, making it an advantageous choice in many scenarios (Finnis et. al. 2024). Unlike EEG, one of fNIRS's most notable ben-efits is its immunity to electromagnetic interference, which is particularly valuable in envi-ronments where electrical noise poses a challenge. This characteristic has made fNIRS a pre-ferred tool in applications such as controlling prosthetic devices and studying brain activity under real-world conditions. In the context of BCIs, fNIRS has shown great promise for assist-ing individuals with severe motor impairments, such as late-stage amyotrophic lateral sclerosis (ALS) patients (Borgheai et. al. 2020). It can translate haemodynamic changes into actionable control signals during cognitive tasks, such as mental arithmetic or imagery.

Recent innovations include the development of hybrid EEG-fNIRS systems, which combine the temporal resolution of EEG with the spatial precision of fNIRS (Liu et. al. 2021). Fur-thermore, advanced paradigms such as the Visuo-Mental (VM) task combine visual stimuli and mental calculations to generate distinctive hemodynamic patterns in single trials (Bor-gheai et. al. 2020). These advances reduce response times and enhance usability, particularly in spelling systems for communication. Unlike traditional methods requiring multiple trials, fNIRS-based systems can identify target responses rapidly, often achieving classification accu-racies above 80% (Liu et. al. 2021). The robustness of fNIRS against motion artifacts and its compatibility with bedside setups highlight its transformative potential for neurotechnological applications (Cutini et. al. 2012). As research continues, refinements in algorithms, real-time processing, and system integration are expected to further enhance its effectiveness, particu-larly in personalized and clinical settings (Yücel et. al. 2017).

2.2 Invasive Signal Detection

ECoG is a neurophysiological method used to record electrical activity directly from the sur-face of the brain. It involves placing electrode grids on the exposed cerebral cortex, typically during a surgical procedure. It is considered a minimally invasive technique compared to fully invasive methods like intracortical recordings, as the electrodes rest on the brain surface rather than penetrating it (Wilson et. al. 2006).

ECoG based BCIs leverage several key advantages over non-invasive alternatives. The signal quality is enhanced in ECoG as the electrodes are closer to the neural sources, yielding signals with higher amplitude compared with EEG (Wilson et. al. 2006). This reduces signal noise and allows for better artifact rejection. It also has higher spatial and temporal resolution. The millimetre-scale spatial resolution achievable with ECoG enables discrimination of fine neural patterns. This contrasts with the centimetre-scale resolution of EEG, which often leads to sig-nal overlap. The applications of ECoG have proven effective for both motor and sensory im-agery-based control tasks, particularly in tasks like imagining limb movements which activate distinct sensorimotor rhythms. ECoG's precision allows mapping these activities across adja-cent cortical areas. Despite its advantages, ECoG-based systems face challenges including sur-gical risks, chronic viability, and signal interpretation. The implantation of ECoG grids re-quires craniotomy, carrying inherent risks such as infection and inflammation. In the long-term, it raises concerns about electro stability and biocompatibility.

2.3 Hybrid BCI (hBCI)

To enhance BCI performance, BCI systems are increasingly being incorporated with other physiological signals. The EEG-fNIRS mentioned in the fNIRS technology part is one of the most promising hybrid BCI systems. It combines the high temporal resolution of EEG and the spatial resolution of fNIRS, which provides a complementary insight into brain dynamics.

Electrocardiography (ECG) and heart rate variability (HRV) are also gaining attention in BCIs for detecting emotional and autonomic responses. The study in states that the fusion of ECG and EEG features for hBCI enhances the average imagery classification accuracy in training and evaluation stages (Shahid et. al. 2011). However, more recent studies have pre-dominantly focused on combining EEG with other modalities such as electromyography (EMG) and functional near-infrared spectroscopy (fNIRS). For example, a 2024 study intro-duced a motor imagery classification model based on a hybrid BCI that integrates EEG and EMG signals, demonstrating improved classification accuracy. Another study in 2020 eval-uated the performance of a compact hybrid BCI combining EEG and fNIRS, achieving high classification accuracy with a reduced number of channels (Choi et. al. 2017). These develop-ments suggest that while the fusion of ECG and EEG in hybrid BCIs has been explored, re-cent research trends have shifted towards other combinations of physiological signals to en-hance BCI performance and practicality.

3 APPLICATIONS OF BCI

The BCI has significant potential in both clinical and non-clinical fields, with different applications tailored to distinct purposes.

3.1 Clinical Applications

Brain-Computer Interfaces (BCIs) have revolutionized clinical rehabilitation and assistive technologies. These systems offer transformative solutions for patients with severe motor or communication impairments. In stroke rehabilitation, BCIs leverage motor imagery and real-time feedback to activate neural pathways, promoting neuroplasticity and aiding motor recovery, especially when combined with robotic devices or functional electrical stimulation (Ang et. al. 2015). For individuals with amyotrophic lateral sclerosis (ALS), BCIs provide an essential communication channel by detecting brain signals like P300 or steady-state visual evoked potentials (SSVEP), enabling word spelling or device control even in advanced disease stages (Vansteensel et. al. 2016). Furthermore, BCIs enable intuitive control of prosthetic limbs and wheelchairs by translating electroencephalography (EEG) signals into commands, empowering individuals with severe motor impairments to regain mobility and independence. Additionally, combining BCI with machine learning has led to significant advancements in natural language processing (NLP), allowing real-time text generation or speech synthesis through neural decoding, which is especially beneficial for patients with locked-in syndrome (Moses 2021). These clinical applications highlight the profound impact of BCIs on improving patient quality of life and enabling greater independence.

3.2 Non-Clinical Applications

In non-clinical fields, Brain-Computer Interfaces (BCIs) have demonstrated transformative potential across diverse fields such as gaming and creative arts. In gaming, BCIs enable brain-controlled experiences that allow players to interact with games through their thoughts, which enhance engagement and creates innovative design possibilities. This advancement highlights the potential of BCIs to revolutionize entertainment and education by driving the development of more intuitive human-computer interfaces (Nijholt et. al. 2015). Similarly, in the creative arts, BCIs allow users to create music, paintings, or digital art through neural activity, providing a unique platform for self-expression and creativity. This is particularly impactful for individuals with physical disabilities, as it broadens access to artistic creation while pushing the boundaries of traditional art production and experience (Miranda et. al. 2011). These applications underscore the versatility of BCIs in shaping interactions with technology beyond clinical use.

4 CONCLUSIONS

Brain-Computer Interface (BCI) systems have emerged as one of the most transformative technologies in modern science, bridging the gap between neural activity and external device control. BCIs have come a long way since their foundational discovery with EEG in the early 20th century. Today's advanced hybrid systems have demonstrated remarkable potential in both clinical and non-clinical domains. Central to the effectiveness of these systems is the methodology of signal detection, which encompasses non-invasive techniques like EEG and fNIRS, invasive methods such as ECoG, and hybrid BCIs that combine multiple modalities for enhanced performance. Each of these approaches offers unique advantages: EEG provides ex-ceptional temporal resolution, fNIRS delivers superior spatial resolution, and ECoG achieves unmatched precision through direct cortical contact.

The clinical applications of BCIs are diverse, including stroke rehabilitation, assistive tech-nologies for individuals with ALS, and communication solutions for locked-in syndrome. These applications demonstrate BCIs' capacity to significantly improve quality of life. These systems leverage advanced signal processing and machine learning to translate neural activity into actionable outputs, facilitating motor recovery, communication, and mobility. Non-clinical applications, such as brain-controlled gaming and artistic creation, demonstrate the versatility of BCIs beyond healthcare, offering new platforms for self-expression, creativity, and intuitive interaction with technology. Despite these advancements, several challenges need to be addressed through ongoing research, including signal noise reduction, movement artifact compensation, and minimizing risks associated with invasive methods. Variability in preprocessing techniques and the complexity of integrating multimodal systems also present obstacles to widespread adoption. However, ongoing research in computational algorithms, re-al-time signal processing, and system miniaturization continues to address these limitations, paving the way for broader usability in both laboratory and real-world settings.

Looking ahead, BCIs are positioned to revolutionize human-computer interaction, enabling seamless integration between neural processes and external systems. Emerging hybrid sys-tems, such as EEG-fNIRS combinations, highlight the potential to enhance classification ac-curacy and usability, particularly for personalized and clinical applications. The fusion of BCIs with fields like artificial intelligence, natural language processing, and robotics is creating synergistic effects. These combinations are accelerating innovation by enabling more sophisti-cated interpretation of neural signals, thus opening doors to new possibilities in communica-tion, rehabilitation, and entertainment. In conclusion, BCIs have the potential to redefine the relationship between humans and technology, transforming how humans interact with ma-chines and the environment. While significant challenges remain, continued advancements in signal acquisition, processing techniques, and system integration ensure that BCIs will play an increasingly vital role in addressing societal needs, improving accessibility, and enhancing the overall quality of life for individuals across the globe.

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