Evolution of Human - Computer Interaction: From UNIVAC to Brain - Computer Interfaces

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Abstract: *The evolution of human-computer interaction (HCI) has witnessed remarkable advancements since the introduction of the UNIVAC, the first commercial computer in 1951. Initially controlled via modified typewriters and oscilloscopes, modern computers now integrate diverse interfaces such as haptics, voice, and gaze control. Among these, Brain-Computer Interfaces (BCIs) stand out as revolutionary systems enabling direct communication between the brain and external devices through electroencephalographic (EEG) signals. BCIs hold promise particularly for individuals with severe motor disabilities, offering them newfound independence and quality of life. This review explores the technological foundations, applications, and challenges of BCIs, highlighting their transformative potential in biomedical and non-biomedical domains.*

Keywords: *Human-Computer Interaction, Brain-Computer Interfaces, EEG, Biomedical Applications, Non-Biomedical Applications.*

I. INTRODUCTION

The interaction way between humans and computers has greatly evolved since the appearance of when the first commercial computer, the UNIVAC, in the year of 1951. The only way to control that complicated piece of machinery was a modified IBM electric typewriter, and feedback to the user was given trough a Tektronix oscilloscope. Modern computers are completely mobile and even though they are mainly controlled by a mouse and a keyboard, several alternative human-computer interfaces have been developed during the last two decades using haptics, voice and gaze. Brain computer interface (BCI), also known as brain machine interface (BMI), is a system that enables humans to interact with their surroundings via employing control signals generated from electroencephalographic (EEG) activity, without the intervention of peripheral nerves and muscles. BCI presents a muscular-free channel for conveying individuals' purposes of certain actions to external devices such as computers, speech synthesizers, assistive appliances, and neural prostheses. BCI systems are of particular attraction for individuals with severe motor disabilities as such systems would improve their quality of life and would, at the same time, reduce the cost of intensive care. A brain computer interface (BCI) systems permit encephalic activity to solely control computers or external devices. Hence, the basic goal of BCI systems is to provide communications capabilities to severely disabled people who are totally paralyzed or 'locked in' by neurological neuromuscular disorders, such as amyotrophic lateral sclerosis, brain stem stroke, or spinal cord injury [1].

Unlike traditional neuromuscular output channels, BCIs facilitate communication solely through brain signals, offering real-time interaction between the user and external devices. Users receive feedback based on the BCI's operation, influencing subsequent intentions and their expression in brain signals. Effective BCI paradigms begin by identifying suitable control signals from EEG, characterized by precise individual characterization, mod lability for expressing intentions, and consistent, reliable detection and tracking. EEG signals from eye blinks possess all these attributes and are thus viable as control signals.

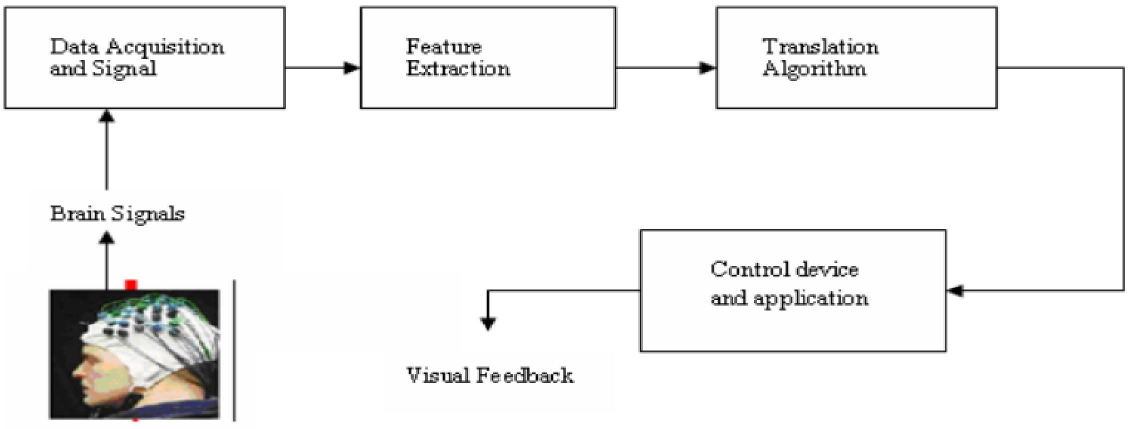

Fig 1: Representation of a BCI

II. APPLICATIONS OF BCI

BCIs may be used for various purposes and the application determines the design of a BCI. According to Nijholt [17], applications based on BCI have two methods of usability. One can command whether the other one can be observed or monitored. The majority of command applications concentrate on manipulating brain impulses using electrodes to control an external device. On the other hand, applications that involve observation focus on recognizing a subject's mental and emotional state to behave appropriately depending on their surroundings. Some applications of BCI [18] based on usability are described below:

A. Biomedical Applications

The majority of BCI integrations and research have been focused on medical applications, with many BCIs aiming to replace or restore Central Nervous System (CNS) functioning lost with sickness or by accident. Other BCIs are more narrowly targeted. In diagnostic applications, on treatment and motor rehabilitation following CNS disease or trauma, BCIs for biological purposes are also employed in affective application domains. Biomedical technologies and applications can minimize extended periods of sickness, can provide supervision and protection by empowering persons with mobility difficulties, and can support their rehabilitation. The necessity to build accurate technology that can cope with potentially abnormal brain responses that might occur due to diseases such as brain stroke is a significant challenge in developing such platforms [19]. The following subsections go through each of these applications in further detail.

Substitute to CNS: Brain-Computer Interfaces (BCIs) serve as a potential substitute for the Central Nervous System (CNS) in individuals with severe motor disabilities. By translating neural signals into actionable commands for external devices, BCIs restore communication and control abilities, enabling users to interact with their environment independently.

Assessment and Diagnosis: BCIs play a crucial role in the assessment and diagnosis of neurological conditions by monitoring brain activity and interpreting neural signals. Electroencephalography (EEG)-based BCIs, for instance, provide real-time data on brain function, enabling healthcare professionals to diagnose conditions such as epilepsy, sleep disorders, and cognitive impairments more accurately. These systems facilitate the identification of abnormal brain patterns and help in understanding how the brain responds to various stimuli. By offering objective measurements of brain activity, BCIs enhance the diagnostic process, inform treatment strategies, and contribute to advancements in neurology and psychiatry.

Therapy or Rehabilitation: In therapeutic and rehabilitation settings, BCIs are instrumental in facilitating neurorehabilitation and enhancing recovery outcomes for individuals recovering from neurological injuries or diseases. BCIs enable neurofeedback training, a technique that allows patients to learn to control their brain activity through real-time feedback. This process promotes neuroplasticity—the brain's ability to reorganize and form new connections—and supports motor and cognitive rehabilitation efforts. By providing personalized and adaptive therapy interventions, BCIs help patients regain lost functions, improve motor skills, and achieve greater independence in daily activities, thereby promoting overall well-being and quality of life.

Affective Computing: BCIs are increasingly employed in affective computing to assess and interpret emotional states and cognitive processes based on EEG signals. These applications utilize machine learning algorithms to analyse brain activity patterns associated with different emotions, cognitive loads, or levels of engagement. Affective BCIs find applications in diverse fields, including market research, user experience design, and mental health monitoring. By providing insights into users' emotional responses and cognitive states in real-time, these systems enable more personalized and responsive interactions between humans and technology. They contribute to the development of empathetic and intuitive interfaces that adapt to users' emotional needs and enhance overall user experience.

B. Non-Biomedical Applications

BCI technologies have shown economic promise in recent years, notably in the field of non-biomedical applications. Most of these applications consist of entertaining applications, games, and emotional computation. In comparison, researchers focus on robustness and high efficiency in medical and military applications, and innovations targeted at leisure or lifestyle demand a greater emphasis on enjoyment and social elements. The most challenging aspect of this entertainment application is that it must be a user favourite to be commercially successful. As an example, some of the most popular forms of amusement are as follows

Gaming: BCIs are revolutionizing the gaming industry by offering novel interfaces that allow players to interact with games using their brain activity. These interfaces detect and interpret neural signals to control game elements, such as character movements or actions, without the need for traditional input devices like keyboards or controllers. By providing immersive and hands-free gaming experiences, BCIs enhance gameplay dynamics and engage players on a deeper level. This technology opens up new possibilities for game design, virtual reality (VR) applications, and adaptive gaming experiences that cater to individual cognitive abilities and preferences.

Industry: In industrial applications, BCIs contribute to improving efficiency, safety, and productivity in various sectors. BCIs enable workers to control machinery, robots, or industrial processes using their brain signals, eliminating the need for manual input and reducing human error. This technology enhances operational precision and facilitates remote operation of complex systems in hazardous or challenging environments. By integrating cognitive state monitoring and adaptive control mechanisms, BCIs optimize workflow management, enhance task performance, and ensure safer working conditions for personnel in manufacturing, logistics, and other industrial settings.

Artistic Application: BCIs are increasingly utilized in artistic and creative domains to explore the intersection of neuroscience, technology, and artistic expression. Artists and performers use BCIs to create interactive artworks, performances, and installations that respond to neural activity in real-time. These applications enable the visualization and sonification of brain signals, turning cognitive processes into creative outputs. BCIs empower artists to experiment with new forms of expression, engage audiences in multisensory experiences, and challenge traditional boundaries between art, science, and technology. This technology fosters innovation and collaboration across disciplines, promoting the integration of neuroscience insights into cultural and creative practices.

Transport: In the transport sector, BCIs contribute to advancements in vehicle control systems and driver assistance technologies. BCIs enable brain-controlled interfaces for navigation, vehicle operation, and control of in-vehicle systems. This technology enhances driver/operator interface design by integrating cognitive state monitoring, predictive analytics, and adaptive control mechanisms. BCIs improve driver safety, reduce human error, and optimize vehicle performance by enabling real-time monitoring of driver attention, fatigue, and cognitive workload. These applications support the development of autonomous vehicles, intelligent transportation systems, and personalized driving experiences that prioritize safety, efficiency, and user comfort in modern transportation infrastructures.

III. LITERATURE REVIEW

Nicolas-Alonso, L.F. et al. (2012) [4]: This review focuses on the various components of a BCI model, including signal acquisition, signal processing, feature extraction, classification, and applications in controlling diverse devices. It discusses the advancements, risks, and benefits associated with each step.

Peksa, J.; Mamchur, D. (2023) [5]: This article provides an overview of BCIs, detailing their operational principles, hardware components (such as EEG electrodes and amplifiers), and software infrastructure for real-time signal processing. It explores current research trends and applications in medical and educational domains.

Hossain, K.M. et al. (2020) [6]: This study highlights recent advances in EEG-based BCIs, particularly focusing on the use of deep learning for signal processing and classification. It discusses the evolution from traditional methods to deep learning models and their applications in various domains.

Luo, S., Rabbani, Q., & Crone, N.E. (2023) [7]: This review examines BCI applications for speech synthesis, particularly in conditions like locked-in syndrome, where traditional communication methods are limited. It discusses advancements in neuroanatomy and neurophysiology supporting speech-related BCIs.

Sonko, S., et al. (2024) [8]: This study explores the advancements, ethical issues, and potential societal impacts of BCIs in the United States. It emphasizes the technological progress, ethical considerations, and regulatory frameworks necessary for the future development of neural interfaces.

Kawala-Sterniuk, A. et al. (2021) [9]: This review traces the historical and technological advancements in BCIs over several decades. It highlights the transformative impact of BCIs in enhancing the quality of life for individuals with disabilities and their potential future applications.

W. Tao et al., (2024) [10]: This article introduces a novel attention-based two-temporal fusion convolutional neural network (ADFCNN) for BCI applications, focusing on improving classification accuracy using EEG data. It discusses advancements in machine learning techniques for BCIs.

J. Zhao et al. (2023) [11]: This review presents the ADFR-DS method for asynchronous BCI control, emphasizing improvements in accuracy and information transfer rate using EEG data from multiple locations. It compares its performance with existing algorithms.

Cervantes, J.-A et al. (2023) [12]: This systematic review evaluates technologies like social robots and BCI-based video games for managing ADHD. It discusses their effectiveness, ethical implications, and technological challenges in integrating these technologies into healthcare settings.

IV. STRUCTURE OF BCI

The BCI system operates with a closed-loop system. Every action taken by the user is met with some feedback. For example, an imagined hand movement might result in a command that causes a robotic arm to move. This simple movement of this arm needs a lot of processes inside it. It starts from the brain, which is one of our body's most extensive and most complicated organs. It is made up of billions of nerves that link billions of synapses to communicate. The processes from taking signals from the human brain to transforming into a workable command are shown in Figure 2 and described below:

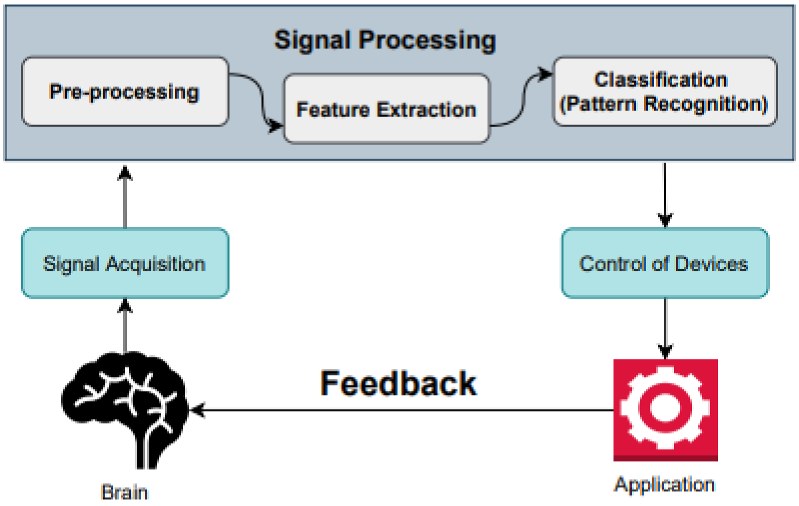

Fig 2: Basic architecture of a BCI system [13].

- Signal acquisition: In the case of BCI, it is a process of taking samples of signals that measure the brain activity and turning them into commands that can control a virtual or real-world application. The various techniques of BCI for signal acquisition are described later.
- Pre-processing: After the signal acquisition, the pre-processing of signals is needed. In most cases, the collected signals from the brain are noisy and impaired with artifacts. This step helps to clean this noise and artifacts with different methods and filtering. That is why it is named signal enhancement.
- Feature extraction: The next stage is feature extraction, which involves analyzing the signal and extracting data. As the brain activity signal is complicated, it is hard to extract useful information just by analyzing it. It is thus necessary to employ processing algorithms that enable the extraction of features of a brain, such as a person's purpose.
- Classification: The next step is to apply classification techniques to the signal, free of artifacts. The classification aids in determining the type of mental task the person is performing or the person's command.
- Control of devices: The classification step sends a command to the feedback device or application. It may be a computer, for example, where the signal is used to move a cursor, or a robotic arm, where the signal is utilized to move the arm.
- The basic architecture of the BCI system was explained in the preceding section. It prompts us to investigate the classification of BCI system. Based upon various techniques, BCI system is classified. The BCI techniques are discussed in following parts.

V. CONCLUSION

The development of BCIs marks a significant milestone in HCI, providing a direct neural pathway for communication and control. While biomedical applications focus on restoring CNS functions and aiding neurorehabilitation, non-biomedical uses span gaming, industrial automation, artistic expression, and transport. Challenges remain in signal acquisition, preprocessing, and classification, crucial for improving BCI accuracy and reliability. Future advancements hinge on enhancing signal processing techniques and integrating AI for more adaptive and intuitive interfaces. With continued research and innovation, BCIs are poised to redefine the boundaries of human-computer interaction, offering unprecedented possibilities for individuals with disabilities and beyond.

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