International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

AI-Driven Eeg Signal Processing for Brain-Computer Interfaces

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Submitted: 10/05/2023 **Revised:** 12/07/2023 **Accepted:**03/08/2023

Abstract: Intracortical brain-computer interfaces (iBCIs), shown as Neuralink, have considerable promise for facilitating direct communication between the human brain and external equipment. The intricacy and elevated dimensionality of neural data provide obstacles in deciphering and converting brain activity into significant orders. This study offers a thorough examination of the existing status of iBCIs, including sophisticated signal collecting and decoding methodologies, while also addressing the constraints of conventional methods in facilitating seamless brain-machine interface. We suggest an innovative method that utilizes sophisticated AI agents, endowed with capacities such as reflection, hierarchical planning, and decision-making, as an interface between the brain and invasive brain-computer interfaces (iBCIs). By integrating these sophisticated AI methodologies, we want to augment the analysis of brain signals, optimize task execution efficiency, and provide a more intuitive and flexible user experience to get goal-oriented results from cognitive processes. The suggested methodology is examined comprehensively, emphasizing its prospective advantages and the obstacles that must be confronted. We conclude by delineating prospective research avenues and the potential for combining sophisticated AI agents with invasive Brain-Computer Interfaces (iBCIs) for diverse applications, including neurorehabilitation, assistive technologies, and human enhancement.

Keywords: *Intracortical Brain-Computer Interfaces (iBCIs), Advanced AI Agents, Neural Signal Interpretation, Hierarchical Planning, Reflective AI, Adaptive Learning, Multimodal Integration, Neurorehabilitation, Assistive Technologies, Signal Acquisition Techniques, Deep Learning, Reinforcement Learning, Prosthetic Limb Control, Brain-Machine Interaction*

INTRODUCTION

Intracortical brain-computer interfaces (iBCIs) have surfaced as a potential technique for facilitating direct communication between the human brain and external equipment. These interfaces include the implantation of electrodes directly into the brain to monitor and stimulate cerebral activity, facilitating the control of prosthetic limbs, communication devices, and other assistive technology [2]. The elevated dimensionality and intricacy of neural data provide considerable obstacles in precisely understanding and converting brain activity into relevant directives [3]. Conventional methods of iBCI control often depend on basic decoding algorithms that correlate brain activity with designated actions, which may be constrained in flexibility, adaptability, and capacity to manage complex tasks [4]. To address these constraints, we suggest the incorporation of sophisticated AI agents as an intermediary between the brain and iBCIs, as seen in Figure 1. AI bots have shown exceptional proficiency across several areas, including natural language comprehension, decision-making, and adaptive control [5]. By using these sophisticated AI methodologies, we want to augment the interpretation of brain signals, optimize task execution efficiency, and provide a more intuitive and flexible user experience.

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Survey of Intracortical Brain-Computer Interfaces Intracortical brain-computer connections have seen substantial progress in recent years. These interfaces include the implantation of microelectrode arrays into the brain to capture neural activity from designated cortical areas [6]. The captured signals are then analyzed and decoded to ascertain the user's intents and regulate external devices appropriately. Numerous research have shown the potential of iBCIs across many applications. Hochberg et al. demonstrated that patients with tetraplegia could use a robotic arm using an iBCI to execute reach and grip actions [7]. Carmena et al. established the viability of using iBCIs for the real-time continuous control of a prosthetic device [8]. These investigations underscore the potential of iBCIs in rehabilitating motor functions and facilitating direct brain-machine interaction. Traditional methods of iBCI control often depend on basic decoding algorithms, such linear regression or Kalman filters, that correlate brain activity with designated actions

[9]. These methods may be constrained in their capacity to manage the enormous complexity and unpredictability of brain data, as well as their flexibility to changing user intents and settings [10].

Methods for Signal Acquisition and Decoding Advanced signal gathering and decoding methodologies are crucial for enhancing the efficacy and dependability of iBCIs. Signal acquisition include the capture of brain activity with many techniques, including intracortical microelectrode arrays, electroencephalography (EEG), and electrocorticography (ECoG).

Intracortical microelectrode arrays provide high-resolution recordings but are invasive, while EEG and ECoG are less invasive alternatives with diminished spatial resolution [11].

Recent improvements in signal collection methods include the enhancement of electrode materials and designs to improve biocompatibility and signal quality. Flexible and biocompatible electrode arrays have been engineered to mitigate immune reactions and guarantee the long-term stability of brain recordings [11].

Signal decoding entails converting brain activity into significant directives. Conventional decoding techniques include linear regression, Kalman filters, and support vector machines (SVMs).

Nonetheless, these techniques often encounter difficulties because to the enormous complexity and unpredictability of brain signals. To tackle these issues, sophisticated machine learning methodologies, including deep learning and recurrent neural networks (RNNs), have been used [11].

Deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown efficacy in identifying intricate spatiotemporal patterns in brain data. These algorithms can autonomously extract pertinent information from unprocessed brain signals, enhancing decoding precision and resilience [11]. Furthermore, transfer learning and domain adaption methodologies have been investigated to improve the generalization of decoding models across various users and recording sessions.

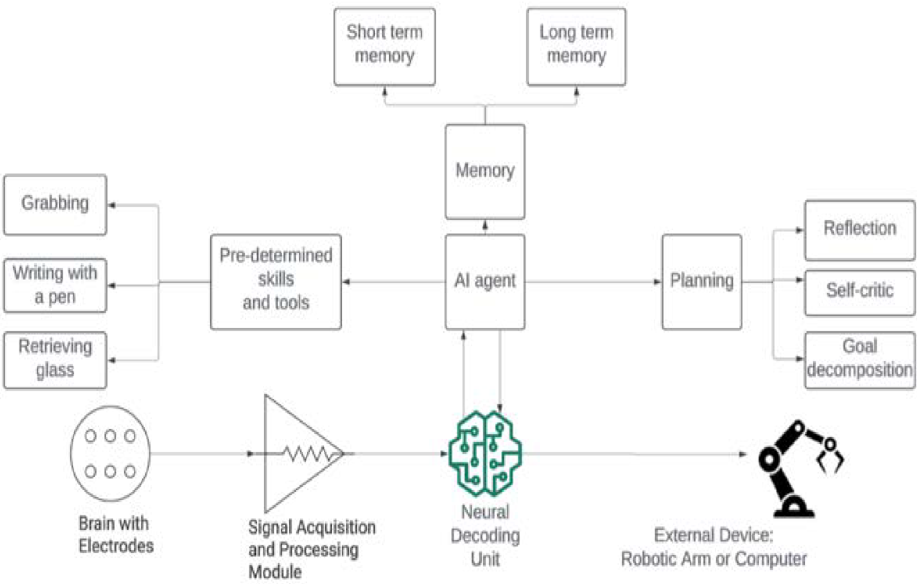

Figure 1: Comprehensive Architecture of an Intracortical Brain-Computer Interface (iBCI) Enhanced with AI Agents

Methods

High-quality brain signal data is necessary for the development of the suggested generative AI model for brain-computer interface (BCI) applications. We concentrated on using electroencephalogram (EEG) data, which captures electrical activity on the scalp produced by neuronal firing in the brain. We used data from OpenNeuro, a reputable and esteemed open-source platform for neuroimaging datasets. OpenNeuro offers EEG data that has had minimum

preprocessing, therefore preserving the raw signals for further study.
The data was gathered from subjects situated in a controlled setting, with electrodes arranged according to the International 10-20 system, a standard for EEG electrode placement. This technique guarantees uniformity in the acquisition of signals from various brain areas. Despite its limitations, such as noise and artifacts, EEG data offers significant insights on the cognitive, emotional, and behavioral states of people.

The data preparation of EEG signals entails the use of several approaches to improve signal quality. Independent Component Analysis (ICA) is a technique used to deconstruct multivariate EEG data, facilitating the isolation of brain activity from physiological aberrations such as ocular movements or muscular activity (Gong et al., 2023; Subasi & Gursoy, 2010). This approach enhances data dependability by revealing concealed patterns. The Common Average Reference (CAR) approach enhances the signal-to-noise ratio by deducting the average activity from all electrodes from each individual channel (Hochberg et al., 2006; Bell et al., 2008). This technique mitigates pervasive noise but may impair the differentiation between clean and noisy channels (Shaw & Routray, 2016).
Independent Component Analysis (ICA) has been validated as successful for EEG signal categorization in several research (Subasi & Gursoy, 2010; Fahimi et al., 2020), while Common Average Reference (CAR) has been established as an efficacious spatial filtering method for improving signal quality (Johnson et al., 2007). Moreover, dimensionality reduction methods like Principal Component Analysis (PCA) are used for feature extraction and noise attenuation in EEG data, hence enhancing signal refinement (Jannat et al., 2020; Zhang et al., 2020). The integration of these techniques facilitates enhanced accuracy in EEG signal processing and motor activity identification (Lahane et al., 2019).

Adaptive filters modify filter coefficients in real time according to variations in signal properties, enabling systems to reduce mistakes and enhance AI model efficacy (Gong et al., 2023; Patel et al., 2009; Johnson, Yuan, & Ren, 2007). This technique has shown efficacy in improving signal characteristics (Islam et al., 2018).
Principal Component Analysis (PCA) decreases the dimensionality of EEG data, retaining essential characteristics while eliminating duplication, hence streamlining input for generative AI models and enhancing computing efficiency (Subasi & Gursoy, 2010; Shaw & Routray, 2016; Zhang et al., 2020).

The Surface Laplacian (SL) method is often used to augment spatial resolution by calculating scalp current densities, hence improving the localization of cerebral activity (Deng et al., 2011). This method enhances the precision of signal interpretation without necessitating more neuroanatomical assumptions (Hochberg et al., 2006; Zhang et al., 2020).

Signal de-noising is essential in EEG data processing, with methods such as wavelet de-noising and empirical mode decomposition (EMD) proving to be very successful. Wavelet de-noising attenuates coefficients of trivial signal components to mitigate high-frequency noise (Johnson et al., 2007; Shaw & Routray, 2016), whereas EMD disaggregates non-linear and non-stationary signals into intrinsic mode functions (IMFs), preserving significant variations (Islam et al., 2018; Gong et al., 2023). These strategies enhance EEG signal refinement for improved analysis (Fahimi et al., 2020; Bitbrain Team, 2020).

Extensive Linguistic Models (ELMs): These models used self-supervised learning methods and were trained on large datasets to comprehend the intricate patterns present in brain signals (Siebers, Janiesch, & Zschech, 2022). Their deep learning architectures, including attention mechanisms and embedding layers, facilitated the identification of relationships within the input data (Kingma & Welling, 2013; Rombach, Blattmann, Lorenz, Esser, & Ommer, 2022).

Generative Adversarial Networks (GANs) include a generator and a discriminator functioning collaboratively. The generator was assigned the role of producing synthetic brain signals from noise, whilst the discriminator differentiated between authentic and produced data (Goodfellow et al., 2014). The model underwent iterative training using a minimax game framework, enabling the generator to enhance the quality of its synthetic signals progressively (Fahimi, Dosen, Ang, Mrachacz-Kersting, & Guan, 2020; Hu, Shen, Wang, & Lei, 2020).

Variational Autoencoders produced novel, realistic EEG-like signals from the latent representations (Kingma & Welling, 2013; Zhao, Adeli, Honnorat, Leng, & Pohl, 2019).

Electroencephalogram (EEG)

An EEG is a diagnostic procedure that identifies brain wave activity, assisting your physician in comprehending the current state of your brain. For instance, several physicians only monitor for epileptic seizures throughout their occurrence. Other physicians do normal or emergency EEGs and may detect seizures throughout the process. Understanding your electrical brain activity patterns prior to therapy enables a more comprehensive insight into your brain's functionality. These anomalies may be linked to a diverse array of diseases. If your EEG is abnormal, your physician will use the information to diagnose and elucidate potential explanations. This information may assist in diagnosing epilepsy, detecting brain injury, or identifying other illnesses or disorders. An EEG that reveals no abnormalities does not imply that you are devoid of any disorders or illnesses. Nonetheless, it suggests that you possess a typical brain. Your abnormal EEG may be due to an ear infection or another medical condition. In an EEG, it is typical to see various aberrant brain waves, as well as other anomalies such as spikes, zig-zags, or other irregular formations without an identifiable cause. Nonetheless, the absence of these forms or abnormalities may signify a genuine brain damage or illness [5].

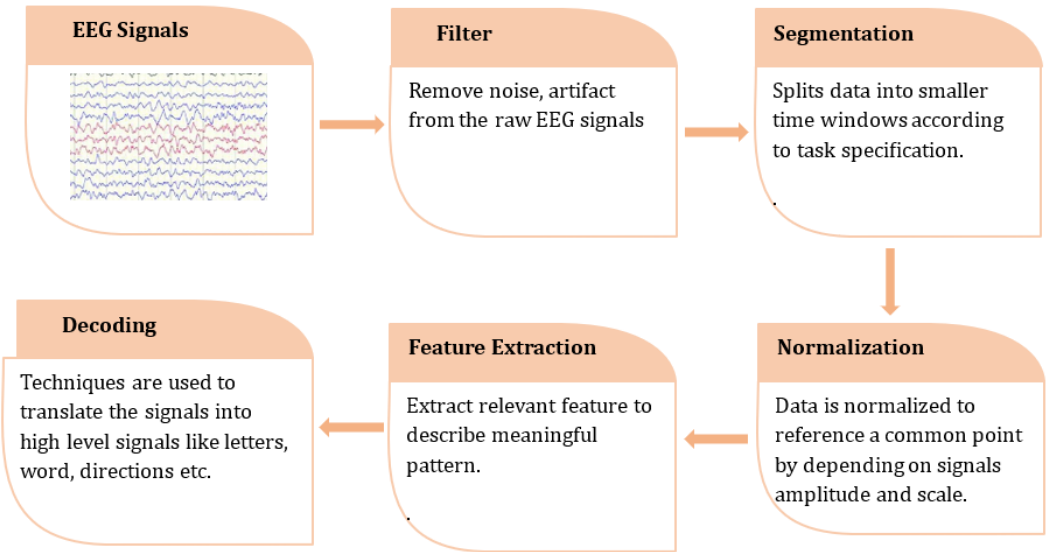

Figure 2. The most common pipeline when processing EEG signals[6]

Brain-computer interface technology

The computer may be a mobile device such as a smartphone, gaming console, wheelchair, laptop, desktop, or a standalone machine. Numerous instances of BCI systems exist, ranging from those implanted in the brain for research and rehabilitation purposes to wearable systems such as helmets, gloves, or spectacles that facilitate the operation of objects like robotic arms or computer cursors. BCI systems may provide diagnostic and control functionalities. Robotic arms may replace conventional hand-eye systems in future applications. A hand-eye system necessitates that an individual visually engage with a screen and maneuver a computer cursor accordingly, while the BCI system utilizes the individual's cognitive processes to control the cursor's movement. Present technology has not yet developed a BCI system with the requisite signal-to-noise ratio or information transmission rate (bandwidth) to provide real-time human-computer interaction [2].

The primary objective of using a BCI is to interpret and translate brain signals to ascertain the user's intentions. The system can capture many forms of brain activity from one or more individuals as they engage in different activities, and translate these neural signals into instructions for the users' equipment. An appropriate quantity of electrodes can record activity from hundreds or even thousands of neurons. These neural signals may consist of a continuous pattern of activity or an erratic pattern of activity. Numerous BCI techniques need comprehensive calibration to provide dependable results from multiple participants. This calibration may be laborious and time-intensive. Consequently, there is a need to develop an enhanced, automated system capable of recording brain activity to generate instructions from many participants. Numerous significant elements may influence the outcomes of brain-computer interface (BCI) research. The factors include the dimensions of the target region in the brain, the extent of the brain area that may be stimulated in reaction to the target region, and the quantity of electrodes.

Deep learning

Deep learning is an algorithm that use a sequence of mathematical formulae to learn classification or categorization of patterns. Deep learning has gained significant prominence in computer vision, particularly in picture recognition. There is no distinct separation between deep and traditional neural networks; nonetheless, deep learning often involves layers including hundreds of nodes. Recent advancements have emerged from the use of deep learning in neural networks. Deep learning has been used for image identification, object detection, voice recognition, and text recognition, among other applications. The neural network serves as an effective model for real-world issues because to the many factors that cannot be accurately anticipated. A neural network has many layers of neurons, each processing input and using that information to generate output values. The three-layer neural network is the most basic kind of neural network capable of doing simple tasks [3]. Deep learning encompasses both unsupervised and supervised learning methodologies. Deep learning is now the most prevalent application in computer vision. Additional essential applications include voice recognition, speech synthesis, handwriting recognition, machine translation, and natural language processing. Implementing neural networks in deep learning requires substantial data sets for training. The accessibility of internet resources has significantly contributed to the advancement of neural networks and deep learning. The primary benefit of deep learning is its ability to address intricate issues via nonlinear mapping. It enables computers to comprehend spoken language and identify pictures or sounds. Artificial neural networks are often extensive and consist of several layers. Each layer corresponds to a certain learning function. These neurons may be organized into clusters or layers. The architecture and the quantity of neurons in each layer characterize a deep learning method. A neural network serves as a mathematical model for information processing via the use of layers composed of basic nonlinear mathematical operators [5].

Machine Learning

Machine learning may be used in many facets of medical diagnosis and therapy, including image analysis, computer-assisted diagnosis, voice recognition, and clinical decision support. Artificial intelligence has shown potential in three domains: decreasing false-negative diagnoses, enhancing diagnostic rates, and improving treatment results. Machine learning can forecast the likelihood of sickness and bad events prior to their manifestation. Machine learning has significant promise in healthcare. It can evaluate extensive datasets and, over time, instruct us on their interpretation as a computational model. Data may consist of unprocessed formats such as audio files, video files, text, or photos, or it may be generated from these by automated processing methods. Data-driven artificial intelligence acquires the ability to draw conclusions and make predictions via data analysis. Machine learning seeks to develop a model capable of forecasting future occurrences. The beginnings of machine learning go back to antiquity, when primitive statistical and mathematical analyses were used for divination and the prediction of astronomical occurrences based on prior observations. It has achieved success in several domains, including but not limited to natural language processing, voice recognition, robotics, computer vision, financial analytics, online searching, and machine translation.

Artificial intelligence (AI) is a discipline within computer science, mathematics, and philosophy that develops systems demonstrating intelligent behavior. Artificial intelligence refers to the cognitive capabilities of robots, in contrast to the intelligence shown by humans and other animals. For instance, it may refer to a robot capable of doing tasks linked to human intelligence, including problem-solving, planning, learning, and reasoning. Conversely, the robot lacks any capabilities linked to consciousness or animal-like intellect. Additional pertinent phrases include human-level AI and strong AI. A machine or system with high AI capabilities is referred to as a brain-computer interface. AI may also be used to elucidate the internal processes of a machine's brain, rather than its exterior behavior, particularly in relation to the modeling of the brain in computer simulations. There are at least three distinct methods to artificial intelligence: machine learning, reinforcement learning, and Bayesian modeling. These vary in their methodologies regarding intelligence, the foundational algorithms used, and the philosophical underpinnings of the approach. Artificial intelligence is a technology that use computers to develop intelligent devices capable of functioning and reasoning like humans. The primary objectives of artificial intelligence have been to reproduce, elucidate, or augment human intellect, rather than to emulate humanity. This study will delineate the characteristics that render a model human in artificial intelligence and how the methodology of artificial intelligence might be used to attain this objective. Artificial intelligence in healthcare seeks to facilitate medical decision-making. Contemporary models are predicated on human cognitive capabilities to diagnose diseases, forecast disease outcomes, and anticipate therapeutic responses. The foremost aspirations of Artificial Intelligence include the creation of computers capable of human-like cognition and autonomous learning. This may lead to many applications, including computing, robotics, healthcare, manufacturing, transportation, telecommunications, and legal sectors. The applications would resemble those of other computer types, such as current applications, in contrast to those used in telephone switching centers.

Adaptive Learning: To address the unpredictability in brain inputs and accommodate the user's evolving requirements, we suggest the integration of adaptive learning processes into the AI agent [19]. Through the ongoing analysis of the user's cerebral activity and the results of its activities, the agent may enhance its comprehension of the user's goals and preferences progressively. Methods such as online learning, transfer learning, and reinforcement learning may be used to allow the agent to modify its behavior in response to user input and evolving environmental circumstances.

Multimodal Integration: We suggest the incorporation of other sensing modalities, including eye tracking, gesture recognition, and natural language interfaces, alongside brain inputs, to get a more thorough comprehension of user intents [20]. By integrating data from several modalities, the AI agent may acquire a comprehensive understanding of the user's condition and situation, resulting in enhanced precision and dependability in iBCI control. Multimodal integration may augment the naturalness and intuitiveness of interactions, enabling users to convey their intents across many channels.

Techniques for System Calibration and Adaptation

The suggested method integrates many methods to guarantee precise calibration and adaptation to the user's distinct brain patterns:

The AI agent utilizes adaptive learning techniques to perpetually enhance its comprehension of the user's neurological signals. This continuous learning process guarantees that the system stays aligned with the user's distinct brain patterns and adjusts to any temporal variations. By constantly adapting to the user's changing brain attributes, the AI agent sustains a high degree of precision and dependability in discerning the user's goals.

• Enhanced Intention Interpretation by Multimodal Integration: To improve the calibration process's robustness and diminish the risk of misinterpreting brain signals, the proposed method amalgamates data from many modalities, including eye tracking and gesture recognition [16]. By cross-referencing the user's intents via these supplementary input channels, the system may more precisely ascertain the user's intended actions [17]. This multimodal integration enhances the interpretation of brain signals, yielding a more thorough comprehension of the user's goals.

• Real-Time Performance Monitoring and Adjustment: The AI agent's reflecting features allow it to introspect and evaluate its performance in real-time [18]. Through the ongoing assessment of its understanding of user intents and juxtaposing them with actual results, the AI agent may detect any disparities or inaccuracies in its calibration. This self-monitoring feature allows real-time modifications and precise calibration of settings, ensuring the AI agent consistently aligns with the user's desired activities.

Conclusion

Brain-computer interfaces (BCIs) facilitate human-computer interaction via electrical brain impulses. Numerous research domains now depend on brain-computer interfaces for human-computer interaction. We present our study using Brain-Computer Interfaces (BCIs) as a new and potent instrument for external access to the human brain, particularly focusing on their use in the educational sector. The primary emphasis is on brain-computer interfaces (BCIs) using electroencephalography (EEG). Additionally, we delineate research conducted via functional magnetic resonance imaging (fMRI), since it is an alternative method for visualizing cerebral activity. This article examines the concepts of EEG-BCI, explores present applications in BCI, and emphasizes future trajectories of BCI technology. This review is not comprehensive; references were confined to peer-reviewed papers and presentations. The author has diligently sought to discover relevant and high-quality sources. The motor rehabilitation of the human brain represents an innovative approach. This study regards the signals captured from the scalp's surface as a series of samples representing a signal source. The findings indicate a strong performance of this technology in the motor rehabilitation of patients. Brain-computer interfaces (BCI) are extensively used in clinical settings and are anticipated to enhance communication between patients and healthcare professionals. This study assesses the implementation of BCI approaches for human-machine communication, focusing on signal capture, feature extraction, and classification. The authors provide an overview of categorization algorithms used in brain-computer interfaces for real-time pattern identification. A overview of the predominant classification techniques for pattern recognition in contemporary literature is presented, along with a discussion of the characteristics used for categorization.

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