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Implementation of Artificial Intelligence on Brain-Computer Interface: Review

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Abstract:

Brain-computer interface technology (BCIs) has established a potential pathway for direct two-way communication between humans and computers. In recent years, with the help of Artificial Intelligence (AI) in advancing the analysis of neural activity and the decoding of brain signals, the combination of AI and BCI applications is becoming a hot direction. The objective of this paper is to offer a comprehensive overview of the implementations of the combination integrating AI and BCIs. In recent years, AI has garnered significant attention across five key application areas, including communication, psychological state estimation, motor imagery (MI), calibration, and interference suppression. Therefore, this paper will review the current state of BCI technology, analyze the hot fields of AI and BCI combined applications, and finally make a forecast for future trends. Despite the current shortcomings, the combination of AI and BCIs remains promising, foretelling a broad future in the decoding and analysis of brain signals.

Keywords: Artificial intelligence; brain-computer interfaces; language decoding.

1. Introduction

BCIs are advanced technologies that connect the brain with computers, allowing for directly two-way communication between them [1,2]. By measuring brain activity signals and transmitting them to computers for analysis, this technology enables monitoring, communication, or control of the user's state [1]. In the medical field, BCIs have brought revolutionary changes to severely disabled patients, offering a new means of communication, especially for those who have lost muscle function due to neurodegenerative diseases or brain injuries.

Research on BCIs not only aids in disease diagnosis, such as identifying sleep disorders or predicting epileptic seizures by detecting brain abnormalities [3], but also plays a significant role in rehabilitation therapy, helping patients recover mobility, reduce the impact of injuries, or assist them in daily activities. Beyond medical applications, BCIs also show great potential in non-medical fields, including neuroergonomics [4], smart environments, neuromarketing, advertising, and the fields of gaming and entertainment. Despite these advances, the development of BCIs still faces many challenges. How to improve the efficiency of information transmission [5] and how to accurately identify personal intentions from the brain's background electrical activity [6] are just a few of the tough questions. But the latest advancements in AI offer hope for solving these problems. AI has surpassed humans in decoding and encoding neural signals, making it an ideal assistant for processing brain signals. They simulate intelligent behavior through computer simulations, and their performance in specific tasks can even surpass that of humans [7]. In BCIs, AI algorithms continuously receive internal parameters, recognize useful information in data, and produce the desired functional outcomes. Although most of these studies are still in the preclinical stage, continued progress may make the clinical application of BCIs more feasible.

In the new era of technological transformation, the combination of BCIs and AI has attracted widespread attention. This paper will review the current applications of BCIs, focusing on the status of BCIs, the role of AI in BCIs, and the future direction of AI-based BCIs. The paper conducted a thorough review of research on multimodal brain language decoding. This included studies that involved texts, speeches, images, and videos. The analysis was from the viewpoint of AI methods.

2. The Development and Current Status of Brain-Computer Interfaces

Looking back at the history of BCIs, their development can be roughly divided into three stages, which can be seen in figure 1: interface, interaction, and intelligence [8]. During the first stage, BCI systems primarily assisted individuals with disabilities in communication and control, converting intentions into actions such as characters on a screen or cursor movement through a direct brain-computer interface. These systems were categorized into active and passive types [9]. Active BCIs required conscious user participation, while passive BCIs monitored the user's cognitive state. Brain signal acquisition was achieved through electrophysiological signals (such as EEG and MEG) and metabolic signals (such as fMRI), which were decoded through preprocessing, feature extraction, and pattern classification. In recent years, AI techniques have been widely applied in this field[10,11].

The second stage introduced closed-loop BCI systems that not only controlled devices but also facilitated the restoration of human functions, creating a closed-loop feedback control circuit that includes the brain [12]. In the control of neural prosthetics, these systems could convert brain activity into control signals and provide sensory feedback to the brain through electrical stimulation. The closed-loop design allowed for two-way interaction between the neural prosthetic and the brain, enabling the exchange of movement and sensation. The core of the system lies in neuromodulation techniques, the construction of closed-loop systems, and the mutual adaptation between the brain and the system[8].

The third stage, which is where BCI technology currently stands, has seen the rapid development of AI technology promoting the integration of biological intelligence and AI, resulting in brain-computer intelligent systems These systems are used in the medical field for rehabilitation therapy [13] and in non-medical fields to enhance human cognition, information processing, and decision-making capabilities[14-17]. BCI technology utilizes high-order cognitive brain signals to achieve a synergistic effect between human intelligence and AI by extracting human cognitive information and integrating it into AI systems to improve AI performance. This hybrid intelligent system combines human cognitive abilities with the operational speed and storage capacity of computers to jointly accomplish complex tasks. The mutual adaptation between the brain and the computer is key to BCI technology, involving mutual learning and behavioral adjustments between humans and AI systems.

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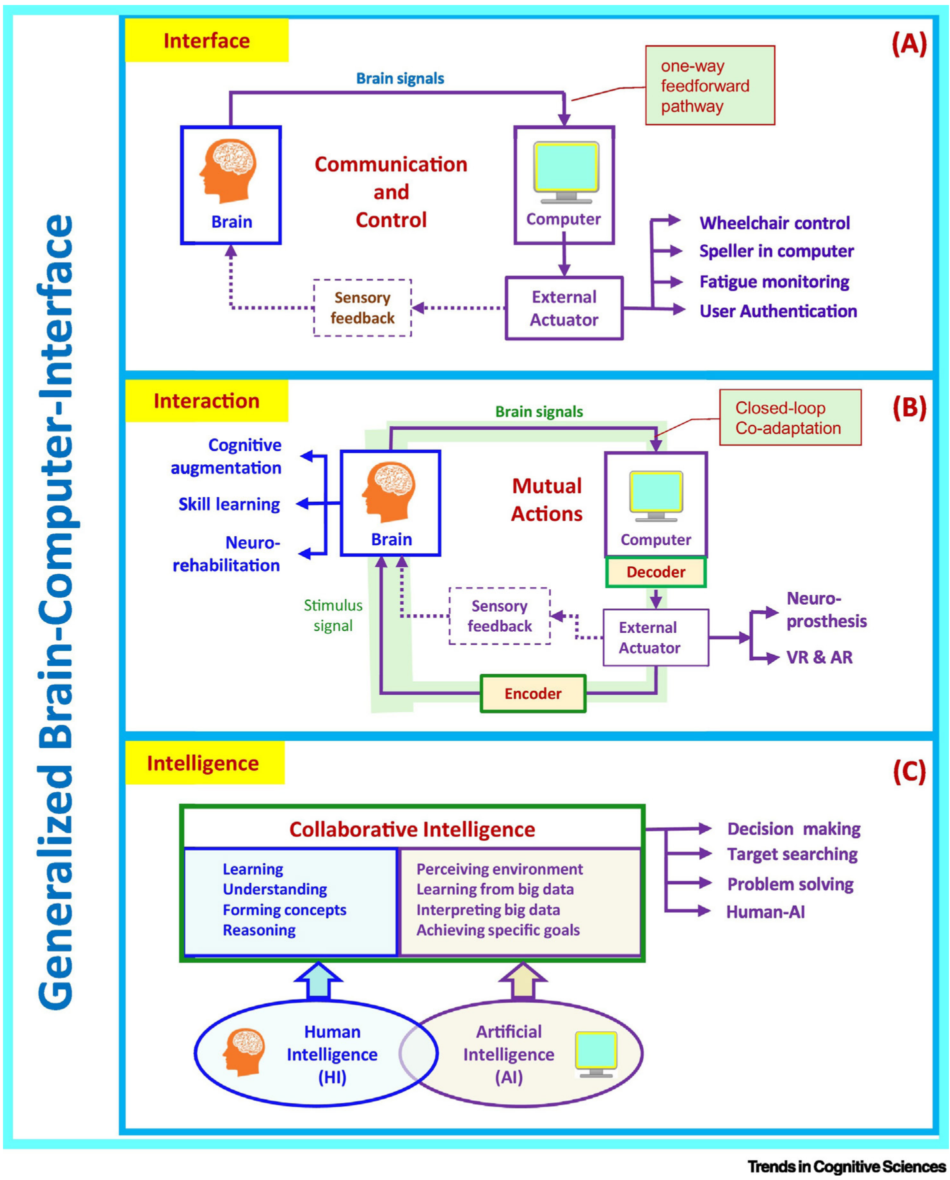

Figure 1 An evolutionary model for generalized BCI technology [8]

3. The Application of AI in the Field of BCIs

3.1 The Application of AI-Based Multimodal Brain Language Decoding

Brain language decoding techniques have the capability to convert neurological reactions to external prompts into written text or spoken language. This technology is of great significance for the development of brain-computer interfaces and for assisting patients with communication disabilities [18].

The process generally involves three steps: first, extracting semantic or acoustic features from text, speech, images, or video; second, training a decoder to understand the relationship between brain signals and these features; and finally, using this decoder to predict the semantic information of brain activity. Although the decoding process varies in different contexts, there are differences in the level of detail of decoding, the AI techniques applied, the way semantic features are extracted, and the potential for decoding accuracy.

3.1.1 Text Modality

In the text modality, brain language decoding involves transforming the brain's activity generated when viewing text into semantic categories or textual descriptions. This process consists of several steps: initially, recording the brain's response to textual stimuli, followed by classifying these stimuli or extracting their semantic features, and finally, training a decoder to predict new brain activities.

Semantic classification is the primary focus of research, which includes the decoding of words and sentences. In their 2012 research, Buchweitz and colleagues observed that bilingual individuals exhibited similar brain activity patterns when processing both their native and second languages, a finding that was linked to the degree of language proficiency. Utilizing a Gaussian Naive Bayes decoder, they trained a model that accurately foresaw brain activity in bilinguals as they read words in English and Portuguese, thereby highlighting the feasibility of cross-linguistic decoding [19].

Subsequently, in 2019, Sheikh and colleagues investigated the neural mechanisms underlying the processing of noun semantics across varying levels of consciousness. Their analysis employed a supervised Support Vector Machine (SVM) model. The findings indicated that specific brain regions demonstrated an unexpectedly high level of accuracy in decoding the native language even during semi-conscious or unconscious states. Nevertheless, the accuracy of cross-language decoding was not significantly above chance levels, implying that proficient semantic decoding across languages necessitates conscious awareness in addition to an in-depth understanding of semantics [20].

The first attempt at sentence-level decoding was made in the research by Yang et al. (2017), who tried to decode sentences in English, Portuguese, and Mandarin. They discovered that decoders trained with data from two languages were more effective than those trained with data from a single language [21]. After them, Pereira et al. (2018) proposed a universal decoder based on fMRI data, capable of decoding words and sentences across a broad semantic space, marking the first extension of decoders from the word level to the sentence level [22].

3.1.2 Speech Modality

Individuals afflicted with speech motor disorders could potentially reap benefits from an innovative technology capable of translating neural signals into audible speech. This cutting-edge technology is predicated on the principles of brain language decoding, necessitating the scrutiny of the brain's reactions to auditory prompts. The objective is to cultivate a decoder that can discern the link between neural activity and the semantic or acoustic attributes. Studies have been conducted across various linguistic tiers, encompassing words, sentences, and phonemes.

In the realm of word-level analysis, Correia and associates in their 2014 investigation discovered that an SVM-model-based decoder was competent in semantic decoding. Remarkably, this capability extended to facilitating translations across distinct languages. Subsequent research in 2015 by the same team confirmed that this decoder could interpret EEG signals evoked by specific words with a precision that surpassed random probabilities [23].

Advancing to the phrase level, studies like those conducted by Dash et al. in 2020 have illustrated the practicality of deconstructing phrases using ECoG signals and neural network models. Notably, the highest levels of accuracy in decoding were observed during the phrase production phase [24]. Shifting focus to sentence-level decoding, Makin et al. in 2020 deployed an RNN framework to translate ECoG signals into English sentences, achieving a commendably low margin of error [25].

Lastly, at the phoneme level, Ramsey et al. in 2018 conducted a study that underscored the importance of temporal information in decoding phonemes through ECoG signals [26]. This finding underscores the intricate relationship between timing and the decoding of linguistic sounds.

3.1.3 Image Modality

Typically, people primarily gather information from the external environment through their sense of sight. With the continuous advancement of machine vision and natural language processing technologies, an increasing number of researchers are attempting to decode brain activity induced by visual images into textual descriptions. Image modality language decoding refers to the process of transforming brain signals when viewing natural images into text descriptions. This includes training a decoder to map image features to brain activity features and generate sentences from brain activity. In 2016, Matsuo and colleagues made the first attempt to convert brain activity into natural language. Although the initial accuracy was not high, it was a breakthrough in the field. They used VGGNet and LSTM to build an encoder-decoder network and generated movie subtitles under the Chainer framework [27]. Subsequent studies found that a ridge regression model without an attention mechanism performed better in decoding, and a three-layer neural network was superior in generating high-quality sentences.

By 2020, Takada et al. proposed an innovative approach, arguing that directly generating image features and text features from fMRI data might result in information loss. So they used the fMRI dataset from Horikawa and Kamitani, constructing a model that directly mapped fMRI data to text features [28], using unmarked images to improve decoding accuracy.

In 2021, Huang et al. proposed the PT-LDM model, which decodes the brain's response to images through three parts: an image encoder, an fMRI encoder, and a language decoder. They trained the model using a progressive

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transfer strategy to enhance decoding accuracy. In the same year, they also proposed the DC-LDM model, which introduced the multi-head attention mechanism of the Transformer architecture to improve performance [29].

Furthermore, studies by Branco et al. and Wang et al. showed that the brain's response to sign language and handwritten digits could also be decoded [30], indicating that brain language decoding in the image modality is not limited to natural images.

3.1.4 Video Modality

The field of BCIs has seen significant advancements with the development of video modality brain language decoding technology. This technology aims to translate the brain's response to video content into written text, thereby describing the video's narrative. The process typically involves analyzing the video, breaking it down into distinct scenes, and identifying objects within those scenes. These objects are then labeled with semantic tags or converted into word vectors. Researchers train decoders to find correlations between brain signals and this semantic information.

In 2015, Hu and colleagues recorded fMRI signals from participants while they watched videos and used the SMLR algorithm to train a decoder, establishing a correlation between brain activity and semantic tags [31]. In 2016, Huth et al. adopted a more nuanced approach, using WordNet to tag objects and actions in movie scenes and an HLR model to train the decoder, successfully decoding categories of various objects and actions [32].

By 2018, Nishida and Nishimoto employed a more detailed word vector representation to decode brain activity [33]. They recorded fMRI signals from participants watching commercials and used a large Japanese corpus to train the word vector model. A regularized regression model allowed them to learn how to link brain signals with scene vectors.

3.2 The Application of AI in BCI Systems

3.2.1 BCI Calibration

Calibrating a BCI is crucial for ensuring that the device operates effectively for a specific user. During training, users must perform tasks to generate data that will be used for predictions during testing. However, calibration is not only time-consuming but also involves storing a large amount of information for each user [34]. For patients with ALS or brainstem stroke, this lengthy calibration process can be quite challenging. Consequently, researchers are exploring the use of AI to expedite the calibration process and seek to eliminate the need for personalized calibration. The subsequent list outlines various effective strategies and efforts implemented by researchers:

Convolutional neural networks (CNNs) are adept at automatically identifying and extracting features from brain signals.

Transfer learning (TL) reduces the time and resource consumption required for training new models by leveraging pre-trained models.

Linear discriminant analysis (LDA), a classifier used in supervised learning, excels in situations where features can distinctly separate classes.

Gaussian process regression (GPR) is a powerful technique that provides effective solutions even with a limited amount of data.

Hierarchical clustering analysis (HCA) is an unsupervised learning technique that groups data by assessing similarities between data points.

3.2.2 Noise Suppression

Obtaining valuable data from brain signals requires high-quality signals free from interference. EEG signals, due to their low amplitude, are frequently disturbed by noise, and their low signal-to-noise ratio makes noise reduction a challenge [35]. To address this issue, researchers have employed a variety of AI algorithms.

Artificial neural networks (ANNs) can recognize and adapt to changes in brain signals, aiding in the automatic removal of interferences not related to EEG. In 2017, Radüntz et al. introduced an automated algorithm that combines Artificial Neural Networks (ANNs) with Independent Component Analysis (ICA) to remove artifacts from EEG recordings [36]. The algorithm first uses ICA to generate topographic maps and power spectra, then proceeds to remove the artifacts and reconstruct the EEG signals. Upon testing, it achieved an accuracy rate of 95.84%. This method is not restricted to specific types of EEG artifacts, but it requires a large amount of data for training, optimal network parameter selection, and is relatively time-intensive.

The K-nearest neighbors (KNN) is also a supervised learning technique used for classifying EEG signal interferences. The K-means clustering technique reduces EOG interference by assigning signals to the nearest centroid.

3.2.3 Communication Assistance in BCI Systems

BCI systems play a crucial role in assisting individuals with disabilities to communicate, particularly those who have lost muscle function due to ALS, stroke, or spinal cord injuries. These systems interpret brain signals for communication without the need for muscle movements [37]. In BCI communication applications, AI is primarily used for character recognition, which typically involves two main approaches: Event-Related Potentials (ERPs) and Steady-State Visually Evoked Potentials (SSVEPs). Researchers employ various techniques to enhance the effectiveness of BCI systems, including CNNs, Long Short-Term Memory networks (LSTMs), Support Vector Machines (SVMs), Random Forests (RFs), and fuzzy logic [35]. These technologies help improve the accuracy of text recognition, refine cursor control, and optimize the user experience for error correction during communication.

3.2.4 Assessment of Psychological States in BCI Systems

Passive BCI systems apply to the field of psychological state estimation by sensing spontaneous brain activity of participants without any special stimulation. They are used to optimize work environments and performance, such as classifying mental workload, detecting stress levels, and estimating memory load. These systems are also employed for the early detection of driver fatigue to prevent accidents and for estimating emotions and levels of consciousness in patients with disorders of consciousness (DOC) [35]. BCI systems are further utilized to assess cognitive states, such as wakefulness and sleep [38].

In the realm of psychological state estimation, AI algorithms play a pivotal role, analyzing brain signals to identify and predict an individual's psychological conditions. For instance, ANNs, with their five hidden layers and backpropagation algorithm, improve work environments with an accuracy rate of 72.57% [39]. However, accuracy may decline if there is a long interval between training and testing phases.

Multilayer perceptrons (MLPs), a type of ANN, use their multi-layered structure to assess emotional states. An MLP with three hidden layers performs optimally in these tasks, achieving an accuracy rate of up to 85.00%, although this requires a substantial amount of data for training. CNNs have also shown effectiveness in evaluating emotions and workload. Nevertheless, they necessitate extensive training and perform better after personalized calibration. Principal Component Analysis (PCA), when combined with Autoencoders (AEs), is utilized for inferring emotions derived from EEG signals, but with an accuracy rate of only 52.74%. As the number of nodes in the hidden layers of AEs increases, so does the computational time. SVMs are used to identify emotions in DOC patients, with an accuracy rate of 91.50% for healthy subjects and 58.50% for DOC patients. Logistic regression (LR), a fundamental supervised learning algorithm, is employed to differentiate between wakeful and sleep states in epilepsy patients, particularly effective when analyzing high gamma band signals [35].

3.2.5 BCI Systems Based on Motor Imagery

BCI systems leverage motor imagery to classify brain signals, marking a significant application area for AI. Users generate brain signals by imagining physical movements without any external stimuli, thus achieving motion control. These systems can identify various limb movements or types of motion, such as hand flexion, extension, or grasping, demonstrating potential applications in controlling robotic arms, lower limbs or exoskeletons for hands, wheelchairs, and vehicles.

To enhance the classification accuracy and efficiency of BCI systems, researchers have employed a variety of algorithms. Artificial neural networks (ANNs) perform well in distinguishing between imagined movements of the left and right hands [40], optimizing feature selection through genetic algorithms, simplifying the system, and improving classification accuracy. Deep belief networks (DBNs) enhance training efficiency by combining multiple unsupervised ANNs.

Multilayer perceptrons (MLPs) have also shown effectiveness in classifying functional MRI (fMRI) signals for robotic arm control, although further improvements are needed for real-time operation [41].

CNNs have proven effective in classifying motor imagery of hands, feet, or the tongue. Capsule networks (CapsNets) further enhance the performance of CNNs by establishing hierarchical relationships [42].

Fuzzy logic through the neural fuzzy classifier of the self-organizing map theory (ART) effectively handles the non-stationarity of EEG signals and classifies multiple types of motor imagery tasks [43]. Although this method requires appropriate parameter adjustment to optimize performance, it provides a solid foundation for the practical application of BCI systems. The development of these algorithms and technologies supports the practical efficacy and usability of BCI systems in real-world applications.

4. Conclusion

The integration of AI with BCIs holds substantial promise for the decoding and analysis of brain signals. As AI continues to advance, its application in the realm of BCIs has shown tremendous potential, particularly in decoding and processing brain signals. In recent years, AI has garnered significant attention across five key application areas: communication, psychological state estimation, motor imagery (MI), calibration, and interference suppression.

In the field of calibration, researchers are striving to develop BCI systems that are either quick to calibrate or calibration-free, aiming to reduce the time required for this process. When it comes to interference suppression, especially with EEG signals, the focus of research is on how to minimize interference caused by broad-spectrum

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artifacts that typically have low amplitudes. Furthermore, the continued development of deep learning models is expected to enhance the accuracy of brain language decoding, and the paradigm of combining audio-visual stimuli may represent a new direction for future research.

Despite the current challenges associated with the integration of AI and BCIs—such as limited sample sizes and insufficient generalization capabilities leading to suboptimal decoding outcomes, and a notable decrease in algorithmic accuracy in disabled patients compared to healthy subjects—further improvements are necessary. However, these challenges also signal opportunities for future development. To improve classification accuracy, it is possible to select the optimal channels through AI-based algorithms or to design hybrid BCI systems that integrate two measurement techniques. Additionally, exploring the potential for parallel processing to reduce computational costs and enable real-time application of these technologies is an important direction for future research.

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