From Limitations to Future: ML/AI in Advancing BCI

Yunhan Liang *

School of Nanjing University of Aeronautics and Astronautics

* Corresponding Author Email: lyh_0112@foxmail.com

Abstract. Brain-computer interface (BCI) technology enables direct communication between the human brain and external devices and has broad applications in rehabilitation, assistive communication, and human-computer interaction. However, traditional EEG-based BCI methods, including spatial filtering and time-frequency analysis, are limited by low signal-to-noise ratio, non-stationary signals, artifact interference, manual feature extraction, and weak adaptability across individuals. This paper analyzes these limitations and discusses how machine learning and artificial intelligence can improve BCI systems. Convolutional neural networks can automatically extract spatial-temporal EEG features, attention mechanisms can strengthen task-relevant channels and frequency bands, lightweight convolutional models can support real-time decoding, and transfer learning with data augmentation can improve individual adaptation. These methods help enhance the accuracy, robustness, and practicality of BCI systems. With further development, ML/AI-based BCI technologies are expected to play an increasingly important role in medical rehabilitation, daily assistance, and intelligent human-computer interaction.

Keywords: Brain-Computer Interface; EEG; Machine Learning; Artificial Intelligence; Signal Processing; Deep Learning.

1. Introduction:

In recent years, Brain-Computer Interface has rapidly developed and gradually become one of the most promising technologies. Brain-Computer Interface is a vital technique that establishes a direct signal transmission channel between the human brain and external computers, without the participation of peripheral nerves and muscles.[1] Today, this technology has been widely used in scenarios such as medical rehabilitation and adjuvant therapy, especially in assisting patients who cannot speak or move to express their damands and improve their life quality. However traditional methods of BCI like spatial filtering methods have lots of limitations on their accuracy, efficiency, signal acquisition and processing [3]. These drawbacks limit BCI 's clinical translational capability, also make it difficult to put this technology into real-life situation and may lead to misjudgment of actual circumstances. Meanwhile, the development of machine learning and artificial intelligence provides new opportunities for the acquisition and decoding of complex brain signal [5] [6].

2. Traditional Methods of BCI

2.1. Method Description

2.1.1. Spatial Filtering Method

This is a key method in processing BCI signals. Mainly, it is used to extract task-related spatial features from multi-channel Electroencephalogram (EEG) signals. The core of the method involves the weighted combination of signals from different electrode channels through mathematical algorithms. This method projects the high-dimensional multi-channel EEG data into a low-dimensional feature space by linear transformation to highlight the spatial features of the signal. Thus, can not only suppress noise and irrelevant interference (such as ophthalmic interference) but also enhance neural activity signals in specific brain regions. Its mathematical essence is to solve the generalized eigenvalue problem [2]. The algorithm is highly dependent on the covariance matrix of EEG signals. By identifying the optimal spatial projection direction, the signal differences between different task states. Common Space Pattern (CSP) is a typical representative.[3]

Take Left and right hand imaginary motor task as an example. When users try to imagine a movement from their left hands, the primary motor cortex of the right hemisphere act a higher performance. But when they imagine another on right hands, the primary motor cortex of the left hemisphere becomes active. According to this kind of difference, researchers create amachine called Combined Diagonalization Spatial Filter. This can make the above difference more obvious.

2.1.2. Time-Frequency Analysis Methods

Joint Time-Frequency Analysis is a method that can describe the change of signal frequency as time changes. The core of this is to create a joint function on time and frequency. This can reveal the instantaneous frequency of a signal.[8]

Conventional Fourier transform has the ability to show the frequency but cannot tell the relationship with time. This limitation cannot be overlooked which can have a negative effect, especially for analyzing EEG signals, because EEG signals change over time. Here time-frequency analysis can solve this problem.

Short-time Fourier transform is a typical one. It’s principle is to observe signals through a fix-size tool like a time magnifying glass. This method performs Fourier transform in each time window by slipping each window to process signals. This process can be view as analyzing movie frames frame by frame. The advantage of this method is the principle is easy to understand, and the calculation is relatively stable. Also, it can fit in the situation with non-stationary signals, like EEG signals.[4]

But this method cannot performe its best in both time and frequency at the same time.

2.2. Deficiencies of traditional methods

Although traditional BCI methods have certain effects in recognizing and classifying EEG signals, they exhibit significant inherent. First, their mathematical models usually assume that EEG signals are in a stationary state and some linear methods assume that the noise component follows a Gaussian distribution. But in real situation the signals are unstable in most of the time. What’s more, they are easily affected by individual differences and environmental changes. These make it difficult to meet the ideal distribution [4] assumption. Another drawback is that these methods are sensitive to noise interference. When users have eye movement or facial muscles activity, it is hard to ensure the signals that computers collect are pure EEG signal. This can seriously impact BCI task’s accuracy and make some misleading result. Moreover, most traditional methods are linear methods which have limited capacity to handle nonlinear relationships and cannot effectively capture complex spatiotemporal coupling patterns in EEG signals. In terms of data processing, the aforementioned traditional methods rely heavily on manual feature extraction. This can significantly compromise the recognition accuracy of BCI systems.[5]

3. New ML/AI Based Methods

Brain signals usually have low signal-to-noise ratio and are easily affected by external interference, such as eye movements, muscle activities, and changes in personal state. Also, EEG signals show strong feature that the change of it is unstable and has little regular pattern. This feature brings great challenges to signal processing and recognition. To solve the limitations above, we can introduce machine learning and artificial intelligence related methods, especially neural networks to make up the shortcomings. Here are three feasible methods based on machine learning or artificial intelligence.[6]

3.1. Convolutional Neural Networks (CNN): Adaptive Feature Extraction

In BCI system, CNN can be view as a strong model of deep learning. Through its special convolutional layer, CNN can constantly and automatically scan EEG signals. Also it can extract the meaningful feature directly from original data and get rid of the dependence on artificially designed features.[6]This data-driven approach significantly rise the ability of the model in catching subtle but complex neural activities, especially in the field of motor imagery tasks.[11][12][13]In these tasks ,brain signals often contain different kind of change in both time and space dimensions. To better use this information, the researchers designed a multi-branch three-dimensional CNN architecture, which can process signal in different channels, time and frequency at the same time [6]. Through these computers can find out each tiny movement of the brain signals and can rise the accuracy of classification.

And the pooling layer is also important. It employs down-sampling technology, which help the model keep key features required for classification while decreasing the complexity in calculation. In some extent, it can suppress overfitting risks and enhance model generalization capability.[5]

3.2. Attention Mechanism and Lightweight Convolution: Focus and Real-Time Decoding

The introduction of attention mechanism gives model the ability to focus on the important point.[6]

By building channel attention and frequency domain attention modules, models can adaptive recalibration of feature weights. In one aspect it can precisely focus on the channels which are highly related to the task, such as the sensorimotor cortex region in motor imagery tasks. In another aspect, it can make the characteristic expression of specific vital frequency part like μ-rhythm or β-rhythm.[8] In the meantime, surpress interference from noise and other body signals.

What’s more, Given the stringent real-time requirements of brain-computer interface systems, researchers adopted lightweight convolutional architectures, such as depth separable convolution. This decreases the hardware deployment threshold and ensures the system meets millisecond-level real-time decoding requirements. This effectively prevents the users from having terrible experiences caused by high latency.[7]

In multimodal brain-computer interface application scenarios, this optimized CNN architecture demonstrates enhanced fusion advantages. The system is no longer limited to single electroencephalogram (EEG) signals but simultaneously extracts features from multiple physiological signals such as eye movement trajectories and electromyogram (EMG)[15][16].This method effectively address the problem that the single-modality systems may get failure under special interference, and keep a high stability and continues control performance.

3.3. Data Augmentation and Transfer Learning: Adaptation to Individuals

In practical applications of brain-computer interface systems, differences between individuals and the high cost are two bottle neck. To address this, data augmentation and transfer learning techniques have become vital approaches for enhancing model generalization capabilities and can help the model to achieve effective adaptation to different individual characteristics.[9][10]

Data augmentation techniques simulate various changes that may occur in real-world environments by giving diversity to the model during the training phase. This can enlarge the scale of the training set and decrease the dependence of artificial data.

Transfer learning focus on narrow the gap between resource and target. In cross-subject brain-computer interfadecreaseons, the model is first tested on source participant data which contain abundant samples. After that, when facing new individuals the model only needs subtle adjustment to fit in new situation. Through this method, models can quickly meet the requirement of new users, cutting the time to adjust the system, anmethod, modelse BCI system can keep great and stable performance in real life situations.

In general, the introduction of machine learning and artificial intelligence makes up for many defects of traditional BCI systems. These technologies do not need complex manual feature design, can automatically learn effective features from signals, have stronger adaptability to noise and non-stationarity, and also improve the speed and accuracy of decoding. With the help of lightweight structure, multimodal fusion and transfer learning, the BCI system is more practical and stable, and can be better used in rehabilitation training, human-computer interaction and daily equipment control.[17]

4. Future of BCI

Today, brain-computer interfaces (BCIs) are technology primarily utilized in medical applications, and is undergoing continuous development with improvements in precision, accuracy, and efficiency. By integrating artificial intelligence-related technologies, the adaptability of BCI systems to diverse individuals and environments will progressively enhanceFurthermore, brain-computer interface (BCI) technology is advancing toward greater personalization to achieve precise individual adaptation.[20] While ensuring safety, improvements in device comfort enable users to have better integration into social life.[21] Beyond medical applications, BCI has significant potential in other fields. For instance, it can enhance gaming experiences by allowing players to control characters through conscious awareness. Also it can be utilized in smart home systems to enable precise control of family divices and improving quality of life.[21]It is evident that brain-computer interface (BCI) technology will not merely serve as a medical tool, but will permeate various aspects of human life, becoming a pivotal component in the field of human-computer interaction.

References

[1] WOLPAW J R, WOLPAW E W. Brain–computer interfaces: principles and practice[M]. Oxford: Oxford University Press, 2012.

[2] HEERMANN D W. Analysis of covariance matrices in brain–computer interfaces[M]. Berlin: Springer-Verlag, 1990.

[3] ANG K K, CHUA K S, CHUA M L, et al. Filter bank common spatial pattern algorithm for EEG-based brain-computer interfaces[J]. IEEE Transactions on Biomedical Engineering, 2008.

[4] LOTTE F, BONNET S, LAROCHE G, et al. A review of classification algorithms for EEG-based brain-computer interfaces: a 10-year update[J]. Journal of Neural Engineering, 2018.

[5] HOSSAIN K M, ALAM S, SULTANA S, et al. Deep learning-based EEG signal processing for brain-computer interfaces: a comprehensive review[J]. Computers in Biology and Medicine, 2023.

[6] LAWHERN V J, SOLON A J, WAYTOWICH N, et al. EEGNet: a compact convolutional neural network for EEG-based brain-computer interfaces[J]. Journal of Neural Engineering, 2018.

[7] GUGER C, SCHEWEGGER A, KRAZENBAUER M, et al. Real-time brain-computer interfaces: from lab to real-world applications[J]. Frontiers in Human Neuroscience, 2021.

[8] ABIRI R, BORHAN S, REYNOLDS K J, et al. A comprehensive review of EEG-based brain-computer interface paradigms[J]. Journal of Neural Engineering, 2019.

[9] PAN S J, YANG Q. A survey on transfer learning[J]. IEEE Transactions on Knowledge and Data Engineering, 2009.

[10] DU Y, LIU Y, ZHANG H, et al. Hybrid transfer learning for motor imagery-based BCI[J]. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2023.

[11] EL OUAHIDI Y, EL ABBASSI N, EL ACHHAB A, et al. Unsupervised deep learning for EEG-based motor imagery decoding[J]. Sensors, 2023.

[12] MA P, LIU X, ZHANG Y, et al. Improved multivariate synchronization index classification for motor imagery-based BCI[J]. IEEE Sensors Journal, 2024.

[13] WANG W, ZHANG L, LIU S, et al. Lower-limb motor imagery recognition for BCI using deep learning[J]. Biomedical Signal Processing and Control, 2024.

[14] YANG R, SONG L. Machine learning applications in motor imagery-based brain-computer interfaces: a review[J]. Chinese Journal of Biomedical Engineering, 2023.

[15] ZHANG L, WANG W, ZHAO Y, et al. Multimodal fusion of EEG and fNIRS for brain-computer interfaces[J]. Optics and Lasers in Engineering, 2023.

[16] ZHOU J, YAN L. Multimodal emotion recognition for BCI using deep learning[J]. Applied Intelligence, 2024.

[17] WU S, ZHANG H, LIU Y, et al. Machine learning-based stroke rehabilitation using BCI[J]. Journal of Medical Systems, 2023

[18] WANG K, ZHANG Y, LIU X, et al. EEG-based BCI for depression diagnosis and treatment[J]. Journal of Affective Disorders.

[19] XIAO F. Current status and prospects of brain-computer interface technology in China[J]. Chinese Science Bulletin, 2023.

[20] SELLERS E W, KRANE N, ZHANG Y, et al. Future directions for brain-computer interface research[J]. IEEE Transactions on Biomedical Engineering, 2024.

[21] WANG G, DENG C. Development trends of brain-computer interface technology in daily life[J]. Chinese Journal of Electronics, 2023.