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Review

Challenges and Future Development of Neural Signal Decoding and Brain-Computer Interface Technology

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Abstract: Brain-computer interface technology can decode neural signals and realize two-way information exchange between brain and computer. The development of brain-computer interface technology is gradually becoming the mainstream direction of neuro-engineering and intelligent control research. In this paper, the structural characteristics and decoding methods of BCI system are described in detail, and the key challenges of neural signal stability and individual model design, real-time performance and security are discussed, as well as the technological development of low invasive acquisition, multi-modal fusion, adaptive algorithms and brain-computer interactive intelligence, comprehensive simulation and comparative analysis. It is expected to provide theoretical reference for the practical application and intelligent research of BCI system.

Keywords: brain-computer interface; neural signal decoding; deep learning; system structure

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1. Introduction

With the vigorous development of neuroscience, artificial intelligence and human-computer interaction technology, brain-computer interface has gradually become a major breakthrough technology in the integration innovation of neural engineering, rehabilitation therapy and intelligent management. However, for the BCI system, neural signal recognition is the key element, which has a decisive influence on the interpretation effect of human brain consciousness and the communication ability of the system. Although the signal sampling analysis technology has been greatly developed in recent years, there are still many problems and challenges such as system stability, individual bias adaptability, real-time and security. In this paper, the characteristics, core technical problems and future development of neural signal decoding and BCI system are systematically discussed and analyzed, aiming at providing theoretical reference and research direction for the development of BCI system.

2. Characteristics of Neural Signal Decoding and Brain-Computer Interface Technology

2.1. Structural Characteristics and Signal Pathway Model of Brain-Computer Interface System

A brain-computer interface is a device that reads neural information from the brain and converts it into control signals for external devices. The basic workflow of BCI is a closed-loop system of "perception-processing-execution-feedback", including modules such as neural signal acquisition, preprocessing, feature extraction, intention decoding and output feedback (see Figure 1). The brain-computer interface can bypass the conventional neuromuscular pathway under the somatosensory motor cortex and realize a non-muscular transmission and interaction between the brain and the external environment [1]. The brain generates certain electrical activity when it gives off certain thoughts or actions. The signals obtained by the electrode array (such as EEG or ECOG) are filtered and artifacts eliminated to improve the signal-to-noise ratio, and the features are extracted and the decoding algorithm is used to recognize the user's intention, then the peripheral equipment such as the robot arm or the computer cursor is controlled to perform the task, and the feedback information is returned to the user to realize the human-machine interaction.

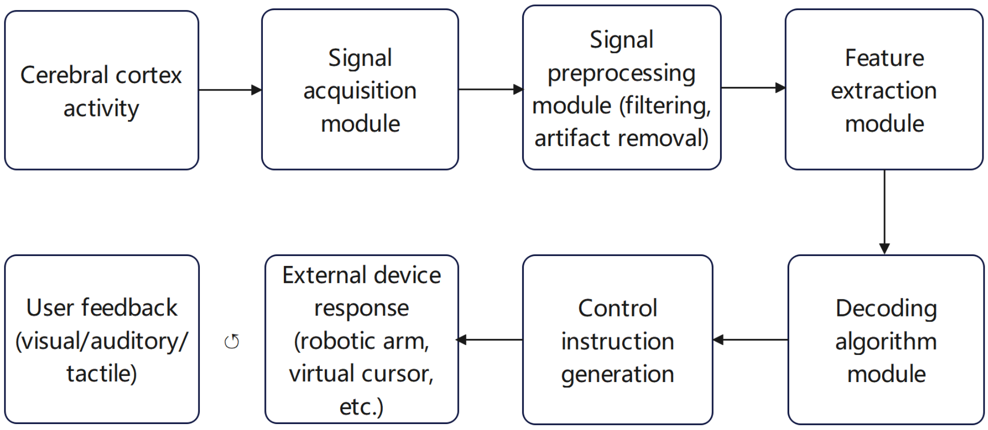

Figure 1. Structure and Signal Transduction Path of Brain-Computer Interface System.

2.2. Information Characteristics and Modeling Methods in the Process of Decoding Neural Signals

It is very difficult to decode neural signals because of their multi-dimensionality, low signal-to-noise ratio, nonlinearity and high personalization. The common methods, such as power spectral density, common spatial pattern and event-related potential, can reveal the cortical neural activity patterns related to specific tasks to some extent.

Classical algorithms such as LDA and SVM are widely used in real-time BCI systems because of their computational efficiency and interpretability [2]. In terms of processing time series data, HMM in statistics shows a very stable effect. In recent years, CNNs and RNNs of deep learning have become mainstream tools to improve decoding accuracy because they can automatically extract features, but at the same time, deep learning models' demand for large data and high hardware resource requirements may affect their popularization to light BCI devices. Table 1 below compares the characteristics of common decoding algorithms.

Table 1. Comparison of Common Decoding Algorithms.

Model type	Example algorithm	Feature dependence	Sequential modeling	Decoding accuracy	real-time	adaptability
Linear model	LDA, SVM	high	weak	medium	strong	high
Probabilistic model	HMM	medium	strong	medium	medium	medium
Deep model	CNN, RNN	low	strong	high	medium	medium

Table 1 is a comparative analysis of three common decoding models. The linear model has high computational efficiency and strong adaptability, which is very suitable for the application scenarios that require high real-time performance. Probabilistic model can process time sequence information and is especially suitable for event-related tasks. The decoding performance of deep model is higher, but the resource consumption is large, and the adaptability to real-time and deployment is poor.

3. Challenges of Neural Signal Decoding and Brain-Computer Interface Technology

3.1. Stability and Adaptability Obstacles in Signal Acquisition

The quality of neural signal acquisition is the source quality of decoding performance of BCI system. The problem with the existing scheme is its poor stability during frequent use (Table 2). On the one hand, EEG is a safe and convenient non-invasive acquisition method, but it is subject to myoelectric interference, electrode movement, environmental noise, etc., resulting in poor sequential consistency and low repeatability. On the other hand, invasive acquisition methods of ECOG or deep electrodes have attracted much attention due to their high spatial resolution and high signal-to-noise ratio, but they also encounter problems such as biological immune reaction, electrode aging and poor implantation stability. Moreover, the interface between the electrodes and the brain is subject to long-term electrochemical instability, and even small shifts can lead to disruption of the signaling pathway, which over time can significantly affect the stability of the system and the user experience [3]. Table 2 below shows the key characteristics of common nerve signal types:

Table 2. Comparison of Neural Signal Acquisition Methods.

Signal type	Invasiveness	Spatial resolution	Time resolution	Signal-to-noise ratio	Application scenario
EEG	no	low	high	low	Experiment and rehabilitation
ECOG	micro-intrusion	medium	high	medium	Clinical monitoring
LFP	high	high	medium	high	Animal experiment
Spike	high	extremely high	high	extremely high	Fine control

Table 2 provides a comparison of the characteristics and important attributes of the common neural signal types. Because EEG is non-invasive and non-harmful, it is suitable for rehabilitation or laboratory research. As a microinvasive technology, ECOG has the advantage of high temporal and spatial resolution, and is generally used in clinical monitoring. LFP and Spike are highly invasive signals with high signal-to-noise ratio and high precision, etc. They are mainly used in applications requiring high precision such as animal experiments and fine motor control.

3.2. Lack of Cross-Subject Modeling and Decoding Generalization Ability

One of the most challenging is the problem of individual variability in neural signal modeling. Even when performing the same task, different individuals have great differences in spatial distribution and frequency characteristics of neural responses. Moving from one user's model to another typically results in a significant degradation in decoding performance across different users, which is a serious impediment to the large-scale use of BCI systems. The generalized estimation formula of cross-individual error is as follows:

$$\varepsilon_{gen} = E_{x \sim P_{target}}[L(f(x), y)] - E_{x \sim P_{source}}[L(f(x), y)] \quad (1)$$

Where P_{source} and P_{target} represent the data distribution of different individuals respectively, and L is the loss function. At present, there have been some attempts to solve the above problems from the perspectives of transfer learning, domain adaptation and self-correcting mechanisms, but there are still some problems such as high training data demand, unstable model convergence and difficult abstract of personality characteristics.

3.3. Computation Delay and Energy Consumption Constraint in Real-Time Decoding

In recent years, neural network models based on deep learning, such as CNN, RNN and Transformer, have been widely used to improve the decoding accuracy of EEG signals [4]. However, due to their large parameters and high computational load, these models have obvious inference delay problems, and it is difficult to apply them in real-time interactive environments (such as real-time robot control). On wearable or embedded terminals, the implementation of deep learning is difficult to achieve due to the constraints of computing resources and energy consumption. In addition, model compression is often accompanied by its performance loss, not only the decoder quality assurance, but also the resource consumption and execution time requirements must be taken into account. Table 3 below compares the performance of various common BCI decoding models in response speed, resource adaptation, and deployment environments:

Table 3. Comparison of Computing Resource Requirements of Different Decoding Models.

Model type	Number of parameters (M)	Mean inference time (MS)	Real-time adaptability	Embedded deployable	Decoding accuracy level	Energy consumption demand
Linear model	<0.01	<10	extremely high	extremely strong	intermediate	extremely low
Shallow CNN	0.2-1.5	50-100	higher	good	higher	moderation
RNN/LSTM	3-10	150-300	normal	poor	higher	on the high side
Transformer class	>20	>500	extremely low	range	extremely high	high

Table 3 compares the differences of different decoding models in terms of computing resources and system adaptability. Linear models are very suitable for embedded real-time applications because they have very few parameters and very little delay. Shallow CNN model can strike a balance between high accuracy and high efficiency. Although the accuracy of the RNN model is high, the delay is also high. Transformer is the most accurate, but takes up the most resources, is the most difficult to deploy, and is more suitable for high-end devices.

3.4. Lack of System Safety and Ethical Risk Prevention and Control

"Consciousness-like data" refers to the general characteristics of neural signals, which contain the user's emotional, cognitive and decision-making information. Improper use will face considerable personal privacy disclosure and moral hazard. For example, unauthorized interpretation of "brain data" may be used for emotional control, bias recognition, or even "thought monitoring" and "behavior prediction", which can directly harm the user's free will.

At present, the moral regulation system specifically applicable to BCI has not yet been formed. Existing data protection principles are for regular behavior data and do not cover highly personalized, irregular, and predictive hierarchical complex data such as brain activity, nor do they provide guidance on the scope of device use, data ownership, informed and consent processes, and sound ideological judgments. As BCI technology becomes more widespread and commercialized, this regulatory gap is likely to lead to more legal and social ethical crises.

4. Future Development of Neural Signal Decoding and Brain-Computer Interface Technology

4.1. Innovation of High-Resolution and Low-Intrusion Acquisition Technology

In order to achieve a more realistic and comfortable brain-computer communication experience, the evolution of acquisition methods will move towards the direction of "high performance + low intrusion". Whereas conventional EEG is limited by skull coverage and spatial resolution, the researchers set out to experiment with soft electronic materials and nanoscale sensor grids as new acquisition methods. These electrodes can better adhere to various curvatures on the brain surface, reducing friction and enhancing the signal-to-noise ratio of electrode-skin contact. In addition, some non-electrical signal acquisition technologies have also been widely used, including near infrared spectroscopy, functional ultrasound imaging and so on. FNIRS technology can indirectly represent the neural activity of the cerebral cortex through the changes of blood oxygen level imaging. The temporal resolution is not as good as EEG, but it can be used to decode cognitive load and emotion. FUS imaging, which records fluctuations in brain blood flow as a tool to assess the depth of activity, can be combined with electrophysiological signals to form a "multi-channel, multi-dimensional" infographic [5]. Table 4 below compares the key performance dimensions of different types of new low-intrusion neural signal acquisition technologies:

Table 4. Comparison of New Low-Intrusion Acquisition Equipment.

Technology type	Spatial resolution	Time resolution	Intrusion or not	Flexibility/portability	Whether suitable for long-term use	Current technology maturity
EEG	low	high	no	high	Yes	mature
FNIRS	intermediate	intermediate	no	high	partial adaptation	intermediate
Micro needle electrode array	high	high	Micro-intrusion	Can be designed to be flexible	yes (still need to verify)	R&D stage
Flexible ECOG	high	high	Low intrusion	high	yes (preclinical validation)	experimental stage

Table 4 compares the main characteristics of various new low interference data acquisition methods. EEG is considered the best choice due to its stability and long-term wearability. FNIRS has a moderate resolution and can be used to monitor thought activity. The microneedle electrode array, as well as the bendable ECOG with optimal resolution and bonding capabilities, show promise for long-cycle applications and are being developed and tested.

4.2. Further Application of Multi-Modal Neural Information Fusion Strategy

Multi-mode fusion is not only the cooperative processing of different types of physiological signals, but also the improvement and perfection of multi-mode cooperation construction strategies. From the perspective of technology implementation, in recent years, the commonly used methods are through feature level fusion, decision level fusion and deep collaborative learning. Feature level fusion is to map the feature vectors from different modes to a common space through matrix joining, principal component analysis or canonical correlation analysis to enhance the representation of the model. Decision level fusion usually adopts independent model training for each mode, weighted voting, confidence average, etc., to form the final decision, which is mostly suitable for asynchronous control systems. Some recent studies have adopted cross-modal self-attention mechanisms and designed joint deep networks that can dynamically update the weights and importance of each modality over time, so as to realize multiple signal decoding in the "demand management" mode. Cross-modal attention mechanism expression:

$$z = soft\,max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

Among them, Q, K and V are the query, key and value vectors of EEG mode and auxiliary mode respectively, and the attention weight adaptively changes in task dynamics. On the basis of practical application, it has been proved that the combination of multiple modes can effectively improve the robustness of the system. EEG + EMG fusion model has been successfully applied in fine motor control, and it has a good application prospect in prosthetic feedback control system.

4.3. Development Trend of Adaptive Intelligent Decoding Algorithm

Personalized modeling is one of the important directions of BCI system development in the future, especially in the reality of population heterogeneity and high sample labeling cost, the traditional static model is difficult to maintain a long decoding ability. For this reason, the researchers propose a variety of adaptive structures for online updating, which can complete the automatic correction of the system without interrupting the operation of the system. In recent years, self-supervised learning is regarded as the most promising method, which can use the structure inside the data as the assumed annotation information, so as to achieve "label free training" and reduce the need for manual annotation. The commonly used methods include comparison learning representation optimization and auto-encoder reconstruction loss minimization, which are widely used in the feature learning of unlabeled data. In addition, researchers are also trying to incorporate federated learning in BCI applications. This pattern applied to BCI uses local model learning and centralized parameter aggregation to make data "usable but invisible", respecting user privacy and enabling collaborative modeling among multiple agents. The federal BCI system can extract data from different users to establish a common neural signal pattern to enhance universality and adaptability, especially for practical applications such as mobile BCI and medical remote monitoring. The second is "meta-learning", which is the method of "learning how to learn". With the help of meta-learning models, the system can quickly adapt to new users based on a small amount of data, which can greatly shorten the online time of the system, and can bring a possible technical solution for the "plug and play" of the brain computer interface. Table 5 below shows the comparison of different learning styles:

Table 5. Comparison of Adaptive Learning Strategies.

Learning style	Whether labels are required	Whether online updates are supported	Privacy protection	Adaptive speed	Technology maturity
Self-supervised learning	no	yes	intermediate	fast	intermediate
Federated learning	selectable	yes	strong	intermediate	intermediate
Meta-learning	yes	yes	intermediate	fast	early exploration

Table 5 compares three adaptive learning methods. Self-supervised learning does not need manual labeling, and has the advantage of fast adaptation, which can adapt to the unlabeled environment. Federated learning ensures privacy and model collaboration well, and can adapt to multi-user distributed training. Meta-learning has the advantage of rapid adaptation, but it is still in the early stage of research.

4.4. Foresight of Brain-Computer Collaborative Intelligence and Consciousness Interface

From the technical point of view, the development of BCI is not only a channel to realize the transmission of ideas, but also may become an "auxiliary cognitive system", that is, the future BCI will gradually have the ability to predict the state, judge the action and even operate autonomously, which means that the interaction between humans and machines is not only an artificial manipulation mode. It becomes a fusion system with exchange intelligence at its core. In addition, using circulatory neural stimulation (such as TMS and TDCS), the system can recognize specific neural patterns and then slightly adjust the state of brain activity to reverse regulation. In addition, BCIs in the future may grow into an infrastructure for digital consciousness simulation that can track the evolution of an individual's brain condition over time to assist in diagnosing and managing cognitive disorders. However, the ethical concerns of advanced communication are not small, and questions such as "who controls consciousness", "the limits of controlling neural stimulation" and "whether the participation of machines is ethical" are undoubtedly important issues that will require multidisciplinary management in the future.

5. Conclusion

The research in the field of neural signal decoding and brain-computer interface technology continues to move out of the laboratory to the application stage. Based on the system architecture and data analysis technology, this paper summarizes the essential characteristics and decoding methods of BCI, and analyzes the key issues such as signal reliability, individual universality, real-time and ethical safety in detail. Finally, based on the research hotspots in recent years, the future development ideas such as low-intrusion high-resolution acquisition technology, multi-modal integration method, intelligent automatic analysis platform and brain-computer collaborative intelligence are proposed. With the maturity of relevant basic scientific theoretical research and the improvement of practical operation, BCI is expected to play a greater role in other aspects in the future, such as rehabilitation treatment, auxiliary communication, intelligent interaction and so on.

References

1. M. Ren, R. Xu, and T. Zhu, "Double Deep Q-Network Decoder Based on EEG Brain-Computer Interface," *ZTE Commun.*, vol. 21, no. 3, p. 3, 2023, doi: 10.12142/ZTECOM.202303002.
2. M. H. Mahrooz, F. Fattahzadeh, and S. Gharibzadeh, "Decoding the Debate: A Comparative Study of Brain-Computer Interface and Neurofeedback," *Appl. Psychophysiol. Biofeedback*, vol. 49, pp. 47–53, 2024, doi: 10.1007/s10484-023-09601-6.
3. Y. Ji, F. Li, B. Fu, Y. Zhou, H. Wu, Y. Li, et al., "A novel hybrid decoding neural network for EEG signal representation," *Pattern Recognition*, vol. 155, p. 110726, 2024, doi: 10.1016/j.patcog.2024.110726.
4. E. C. Djamal and D. A. Sury, "Multi-channel of electroencephalogram signal in multivariable brain-computer interface," *IAES International Journal of Artificial Intelligence*, vol. 12, no. 2, pp. 618–626, 2023, doi: 10.11591/ijai.v12.i2.pp618-626.
5. D. Jaipriya and K. C. Sriharipriya, "Brain Computer Interface-Based Signal Processing Techniques for Feature Extraction and Classification of Motor Imagery Using EEG: A Literature Review," *Biomedical Materials & Devices*, vol. 2, pp. 601–613, 2024, doi: 10.1007/s44174-023-00082-z.