Proceedings of CONF-SEML 2026 Symposium: Multimodal Data Acquisition: Applications in Physiological and Behavioral Research
DOI: 10.54254/2755-2721/2026.AD33461

Research on the Application of Communication Technology in the Field of Neurology

Yutong Li

School of Electronic Engineering, Xidian University, Xi'an, China
23022100079@stu.xidian.edu.cn

Abstract. With the in-depth integration of communication technology and neurology, the application of communication technology in neural signal acquisition, transmission, analysis, diagnosis and treatment has become increasingly widespread. This paper mainly adopts the literature analysis method to sort out the research status of communication technology in the field of neurology. First, it outlines the basic characteristics of neural signals and related communication support technologies, focuses on analyzing three major application scenarios: brain-computer interface (BCI), neurological disease monitoring and implantable neural devices, then summarizes the main challenges faced by current technologies, and looks forward to the future development trends. The research finds that core communication technologies such as wireless transmission, signal processing and decoding have been initially applied in scenarios such as neural rehabilitation, disease monitoring and implantable devices, effectively solving key problems such as high-fidelity transmission and remote regulation of neural signals. However, there are still prominent bottlenecks in biocompatibility, technical standardization and ethical norms. In the future, it is necessary to rely on technologies such as 6G and artificial intelligence to break through existing limitations and promote the in-depth integration and clinical transformation of communication technology and neurology.

Keywords: Communication Technology, Brain-Computer Interface (BCI), Neurological Disease Monitoring, Implantable Neural Devices

1. Introduction

Neural engineering is an emerging interdisciplinary research field that uses engineering and technological means to detect, regulate, repair and enhance the functions and behaviors of the central and peripheral nervous systems [1,2]. This field integrates knowledge from different disciplines. As an important branch of biomedical engineering, neural engineering is developing rapidly, and the founding of the Journal of Neural Engineering in 2004 is one of the symbols of the maturity of this field. The application scenarios of neural engineering have covered the management of chronic pain, movement disorders, epilepsy, hearing and visual impairments, as well as brain-computer interfaces for speech and paralysis function recovery [2]. On this basis, its application scope has been further expanded to the treatment of depression, cognitive disorders, stroke rehabilitation, and inflammatory diseases such as diabetes, rheumatoid arthritis , and inflammatory

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/2026.AD33461

bowel disease. This field has also proposed a series of intervention strategies such as brain-computer interfaces, neural prostheses, neural robots and neural tissue engineering, which realize precise interaction with the nervous system through electrical, mechanical, chemical and biomedical engineering principles [3].

Neural signals are characterized by weakness, high noise and complex environment, making it difficult for traditional medical methods to achieve real-time and accurate monitoring and intervention. The intervention of communication technology has effectively solved the problems of high-fidelity transmission and remote control of neural signals, a development that is of great engineering significance and social value for promoting the clinical application of brain-computer interfaces, precise diagnosis and treatment of neurological diseases, and the intelligent development of rehabilitation medicine.

This paper reviews the application of communication technology in the field of neurology. This study offers predictions for the future application and evolution of communication technology in neurology.

2. Characteristics of neural signals and key communication technologies

2.1. Characteristics of neural signals

Neural signals are the core carrier reflecting brain activity. Common types include electroencephalography (EEG), electrocorticography (ECoG) and neuron discharge signals. Their frequency, amplitude and noise characteristics directly determine the design of communication and decoding schemes.

EEG covers multiple frequency bands, including delta waves (1-4Hz), theta waves (4-8Hz), alpha waves (8-13Hz), beta waves (15-25Hz), gamma waves (25-70Hz) and high gamma waves (70-170Hz). Different frequency bands are related to physiological states such as pain perception and movement intention [4]. The amplitude of its scalp signals is weak, usually at the microvolt level (μV), with the amplitude of alpha waves and beta waves at about 10-50 μV, and the amplitude of gamma waves even lower (<10 μV) [5]. It is easily affected by volume conduction effect, electromyographic interference and power frequency noise (60Hz and its harmonics), resulting in a low signal-to-noise ratio (SNR). Therefore, noise suppression is required through technologies such as filtering and reference reconstruction [4,5].

ECoG overlaps with EEG in frequency bands, but is more sensitive to high-frequency signals (gamma and above), and can accurately record neural activities in the 25-170Hz frequency band. It can directly record electrical activities on the cortical surface with an amplitude at the millivolt level (mV), which is 10-100 times that of EEG, and the signal strength is more stable [6]. As an invasive recording method, it can directly contact neural tissue, reducing signal attenuation caused by scalp, skull and other tissues. Its noise mainly comes from electrode contact interference and local irrelevant neuron activities. Compared with non-invasive EEG, it not only has a significantly higher SNR but also offers a spatial resolution of up to millimeters [5,6] .

In neuron discharge signals, the discharge frequency of a single neuron is 1-200Hz, and the synchronous discharge of group neurons can form specific frequency band oscillations (such as theta and gamma waves). Its action potential is a spike signal with an amplitude of about 50-100μV (intracellular recording) or 10-20μV (extracellular recording), a duration of 1-2ms, and a biphasic or multiphasic waveform. In addition, extracellular recording is easily interfered with by the activities of surrounding neurons, so it is necessary to extract pure discharge signals through methods such as waveform clustering and threshold screening [6] .

DOI: 10.54254/2755-2721/2026.AD33461

2.2. Core communication support technologies

Wireless transmission technology focuses on the wireless transmission needs of neural signals, focusing on wireless body area network (WBAN), low-power design and high-fidelity signal transmission. It adopts short-range wireless communication protocols to support parallel transmission of multi-channel neural signals. For example, when 128-channel EEG signals are transmitted at a sampling rate of 1024Hz, it is necessary to balance high bandwidth and low latency (latency <1s) to adapt to scalp and in vivo implantation scenarios [5]. For implantable devices such as ECoG electrodes and neural stimulators, it adopts a low-power modulation and demodulation scheme, combined with analog in-memory computing (AIMC) technology, to complete signal preprocessing during transmission, thereby reducing device energy consumption and supporting long-term continuous monitorin At the same time, it resists channel fading through technologies such as orthogonal frequency division multiplexing (OFDM) and quadrature amplitude modulation (QAM), and uses low-density parity-check code (LDPC) for error correction coding to control the bit error rate (BER) below 0.045%, ensuring the integrity of neural signals [7].

Neural signal processing and decoding focuses on signal purification, feature extraction and accurate decoding, integrating traditional signal processing and artificial intelligence technologies. It uses notch filtering to suppress power frequency noise, and reduces far-field interference through laplacian re-referencing. It eliminates artifacts such as electromyography and electrooculography with wavelet denoising and adaptive Kalman filtering to improve signal SNR, and performs band-pass filtering (mainly 4-40Hz) and downsampling (100Hz) on signals to reduce data volume while retaining key features [6]. Its BCI signal decoding methods include traditional methods and deep learning methods. Traditional methods are based on spectral spatial features (such as power changes of EEG rhythms), and use Elastic-Net and support vector machine (SVM) to achieve binary classification (such as high and low pain states, finger movement intention) with an accuracy of 66%-81%. Deep learning methods use models such as EEGNet, ResNet-18 , and LSTM to enable automatic spatiotemporal joint feature extraction of neural signals, which can capture key information of signal spatial channel distribution and time series changes without manual intervention, supporting multi-classification movement intention decoding tasks. Through model fine-tuning, it adapts to the individual differences and non-stationary characteristics of EEG signals, effectively improving the robustness and generalization ability of the decoding system. In terms of AI-driven analysis and optimization, it adopts k-fold cross-validation (k-fold CV) to avoid model overfitting, locates key neural circuits (such as sensorimotor cortex and limbic system) through feature importance analysis, and combines transfer learning and data augmentation technologies to reduce the amount of individual training data, realizing rapid adaptation and supporting real-time decoding (such as the latency of robot finger control <1.5s) [5,7].

3. Specific applications of communication technology in neurology

3.1. Brain-computer interface (BCI) and neural rehabilitation

The core is to restore the movement and communication abilities of patients with motor or language dysfunction (stroke, spinal cord injury, ALS) through a closed-loop link of high-resolution neural signal acquisition - wireless transmission - intelligent decoding, combined with adaptive regulation technology, taking into account rehabilitation training and functional compensation.

In terms of motor rehabilitation, a 32-channel wireless EEG or a 65,536-electrode high-density subdural ECoG array is adopted, and the movement intention is accurately decoded through 2.4

DOI: 10.54254/2755-2721/2026.AD33461

GHz frequency band or ultra-wideband (UWB) low-latency transmission (end-to-end latency <1.5s), combined with 8-30 Hz frequency band neural features and adaptive speech recognition (ASR) denoising technology [8,9]. A CNN-KF hybrid adaptive decoder is introduced to extract nonlinear features through convolutional neural network, combined with Kalman filtering to real-time adapt to the non-stationary characteristics of EEG signals, improving decoding stability. An AI copilot is integrated to infer user goals based on reinforcement learning and computer vision (CV), assisting in optimizing the movement trajectory of cursors or manipulators [10]. Portable devices transmit EEG data via Bluetooth, combined with closed-loop continuous theta burst stimulation (cTBS), triggering targeted neural regulation with the threshold of 5 consecutive activations of event-related desynchronization/synchronization (ERD/ERS) <0, and balancing interhemispheric neural activity by accurately adjusting the neural excitability of the bilateral hemispheres of the brain [11].

Technological advancements enable control of exoskeletons and prostheses for fine movements, increasing target hit rate for paralyzed patients by 3.9 times with AI assistance. A 4-week systematic VR-BCI training enhances neural remodeling in stroke patients. Home rehabilitation utilizes the Magnetic NeuroRing device to adjust cortical excitability via EEG-triggered cTBS. Furthermore, personalized speech synthesis aids ALS patients by enhancing word emphasis and intonation [10-12]. The core values include breaking through the limitations posed by neural pathway damage and signal noise, and improving task completion efficiency through AI assistance and closed-loop stimulation technology.

3.2. Remote monitoring of neurological diseases

Relying on low-power wireless sensor networks and 5G ultra-reliable low-latency communication (uRLLC) technology, it enables long-term non-invasive monitoring and accurate early warning of epilepsy, Parkinson's disease, etc., thereby improving transmission reliability and diagnostic timeliness. The core of this technology is to use wearable EEG or implantable ECoG sensors to continuously collect signals, extract local time-frequency features through quantum wavelet transform (QWT) and global spectral features through quantum Fourier transform (QFT), and fuse them to form compact feature vectors; realize low-jitter (within 1ms) and high-reliability transmission through 5G uRLLC link with message queuing telemetry transport (MQTT) protocol, and accurately identify epileptic spikes and tremor-related neural rhythms combined with AI models, with an accuracy of over 90% [13]. It can conduct long-term home monitoring of EEG signals in epilepsy patients and send remote early warnings before seizures; continuously track tremor data of Parkinson's disease patients to provide a basis for remote medication adjustment. It can also capture epileptiform waveforms through high-density ECoG arrays to improve the accuracy of remote diagnosis [9].

The core value is to get rid of the limitations of hospital monitoring and realize all-weather non-invasive monitoring; the low-power and high-fidelity transmission design reduces medical costs, breaks geographical barriers, and provides objective data support for personalized treatment.

3.3. Implantable neural medical devices (deep brain stimulation)

Through two-way wireless communication, biocompatible materials and integrated circuits, it realizes non-invasive programming and long-term safe implantation of devices such as deep brain stimulation (DBS), and accurately treats refractory neurological diseases.

The core of the technology is that the implantable DBS device is compatible with 3.0T magnetic resonance imaging (3-T MRI), adopts a low-power wireless module to realize in vitro remote

DOI: 10.54254/2755-2721/2026.AD33461

parameter adjustment (60-130 Hz frequency, pulse width, amplitude), and synchronously transmits back the electrical activity data of brain nuclei. The device adopts biocompatible elastic organic transistors (DPPT-TT:BIIR blend material) and Ag-Au double-layer anti-corrosion electrodes, which can maintain stable electrical performance even when the tensile strain reaches 50%, with no obvious inflammation and tissue damage after long-term implantation; it integrates inverters, NOR or NAND logic circuits to support dynamic optimization of closed-loop stimulation parameters. It can treat Parkinson's disease (high-frequency stimulation improves tremor, low-frequency stimulation relieves gait disorders) and refractory epilepsy [14]. It can also form a "monitoring-programming-feedback" closed loop through wireless data transmission to track treatment effects and device safety over the long term. Besides, its elastic structure adapts to the dynamic deformation of the brain, reducing complications caused by mechanical mismatch [14,15] .

The core value is to replace invasive operations for craniotomy adjustment, realize non-invasive and personalized programming; the biocompatible and integrated design improves the safety of long-term implantation, and precise targeted treatment improves the quality of life of patients with refractory neurological diseases.

4. Current technical challenges

The core problem lies in the long-term adaptation and safe retention of implantable devices and biological tissues. The mechanical mismatch between traditional rigid materials and soft biological tissues is likely to lead to chronic inflammation, tissue damage and fibrosis, while some flexible materials have shortcomings in biocompatibility. Electrodes are prone to corrosion and performance degradation after long-term implantation, affecting signal acquisition and stimulation accuracy, and the extraction surgery may cause irreversible neural damage [16,17].

In addition, the mechanism of immune response induced by implants is not yet clear, and long-term retention may lead to tissue encapsulation or functional degradation, further limiting the service life and treatment effect of the device. Secondly, insufficient accuracy of signal processing and component standardization are the main bottlenecks. The individual differences, non-stationary characteristics of neural signals and complex environmental interference lead to easy deviations in the clinical transformation of AI algorithms, affecting functional reliability. There is a lack of unified technical standards for core components of devices, and the compatibility of products from different manufacturers is poor, so patients are prone to the risk of "neuroabandonment" where devices cannot be repaired and parameters cannot be calibrated. At the same time, the long-term stability of implantable devices is insufficient, the electrode life of AI-VNI (visual neural implants) is unknown, and performance degradation may occur after long-term implantation [17].

The lack of long-term post-operative support and ethical disputes are relatively prominent. After the device is deactivated, patients not only lose the therapeutic function, but also may face risks such as infection and failure due to the device remaining in the body, and suffer from psychological trauma and impaired identity recognition. Concerns regarding post-operative support systems for AI-integrated implantable devices include imperfect maintenance and legal barriers limiting third-party repairs. These issues, combined with long-term software updates that pose security vulnerabilities, threaten patient safety and autonomy. Additionally, neural signals carry sensitive personal information, risking theft or misuse during data handling, while some brain-computer interfaces might unintentionally disclose users' internal thoughts, infringing on psychological privacy. At the same time, the material preparation, precision manufacturing and clinical verification of neural implants are costly. The limited target patient group leads to high pricing, and incomplete medical insurance coverage further limits technical accessibility. Remote areas lack professional

DOI: 10.54254/2755-2721/2026.AD33461

implantation surgery, post-operative debugging and maintenance capabilities, making it difficult to support the long-term application of devices and exacerbating the uneven distribution of medical resources [16,17].

5. Conclusion

The development of the neural engineering field will be deeply integrated with 6G smart medical care. The microsecond-level low latency, ultra-high reliability , and ultra-high-speed transmission characteristics of 6G can support the deployment of technologies such as holographic communication, tactile Internet , and wireless brain-computer interfaces, providing key communication assurances for remote surgery and global rehabilitation. Artificial intelligence and deep learning technologies help the efficient analysis of medical big data. Combined with digital twin and blockchain technologies, they can realize the safe sharing of medical data and personalized intervention design. Federated learning technology can also effectively solve the practical contradiction between data privacy protection and cross-domain sharing. Neural regulation technology will be gradually integrated into the rehabilitation medical system, cooperating with wearable devices, robot-assisted training and other technologies to improve the functional recovery effect of neurological diseases such as stroke and spinal cord injury by enhancing neural plasticity.

However, this paper still needs to be improved. First, it relies solely on the literature analysis method to summarize existing research results and does not combine experimental data to analyze the actual effectiveness of communication technology in neurological applications. Thus, the practicality and persuasiveness of the research conclusions require further strengthening. Second, it does not conduct in-depth analysis on the regional differences and economic costs of the actual application of the technology, and fails to provide more targeted references for the large-scale application of communication technology. Future research could focus on regional heterogeneity analysis and full-cycle economic cost assessment to enhance the accuracy and feasibility of the application and promotion of communication technologies in the field of neurology.

References

[1] Krames, E. S., Hunter Peckham, P., Rezai, A., & Aboelsaad, F. (2009). What Is Neuromodulation? In Neuromodulation (Vol. 1, pp. 3-8). Elsevier. https: //doi.org/10.1016/B978-0-12-374248-3.00002-1
[2] Krames, E. S., Peckham, P. H., & Rezai, A. R. (2018). Neuromodulation: comprehensive textbook of principles, technologies, and therapies. (Second edition). Academic Press is an imprint of Elsevier.
[3] Willerth, S. (2025). Introduction to neural engineering. In Handbook of neural engineering (pp. 1–14).
[4] Huang Y, Gopal J, Kakusa B, et al. (2025). Naturalistic acute pain states decoded from neural and facial dynamics. Nature Communications, 16, 4371.
[5] Ding Y, Udompanyawit C, Zhang Y, et al. (2025). EEG-based brain-computer interface enables real-time robotic hand control at individual finger level. Nature Communications, 16, 5401.
[6] Xu T, Zhang X, Jiang Y, et al. (2026). A machine learning-driven electrophysiological platform for real-time tumor-neural interaction analysis and modulation. Nature Communications, 17, 49.
[7] Yang Z Z, Wang C, Zhao Y, et al. (2026). Communication-aware in-memory wireless neural networks. Nature Electronics.
[8] Valente M, Branco D, Bermúdez i Badia S, et al. (2026). EEG-based predictors of motor recovery during immersive VR-BCI rehabilitation. Scientific Reports, 16, 7870.
[9] Jung T, Zeng N, Fagg J D, et al. (2025). A wireless subdural-contained brain–computer interface with 65, 536 electrodes and 1, 024 channels. Nature Electronics, 8, 1272-1288.
[10] Lee J Y, Lee S, Mishra A, et al. (2025). Brain–computer interface control with artificial intelligence copilots. Nature Machine Intelligence, 7, 1510-1523.

DOI: 10.54254/2755-2721/2026.AD33461

[11] Tang Y, Wang Y, Zhang W, et al. (2026). Magnetic NeuroRing: a portable adaptive brain-computer interface for real-time transcranial magnetic stimulation in poststroke motor rehabilitation. npj Biomedical Innovations, 3, 4.
[12] Wairagkar M, Card N S, Singer-Clark T, et al. (2025). An instantaneous voice-synthesis neuroprosthesis. Nature, 644, 145-152.
[13] Jayanthi V, Sivakumar S. (2026). Quantum inspired wavelet and Fourier feature fusion for EEG based epilepsy and seizure detection. Scientific Reports, 16, 1988.
[14] Ren J, Jiang C, Zhang W, et al. (2026).Circuit response to neuromodulation characterized with simultaneous deep brain stimulation and precision neuroimaging in humans. Nature Neuroscience.
[15] Jung K H, Hyun J, Jeong M W, et al. (2025). A biocompatible elastomeric organic transistor for implantable electronics. Nature Electronics, 8, 831-843.
[16] Kouvas G, Coenen C, Hommrich D, et al. (2025). Building resilience when neural implants are abandoned. Nature Medicine, 31, 2850-2853.
[17] van Stuijvenberg O C, Broekman M L D, Wolff S E C, et al. (2024). Developer perspectives on the ethics of AI-driven neural implants: a qualitative study. Scientific Reports, 14, 7880.