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The Mechanism of Brain-Computer Interfaces: Converting Motor Cortex Neural Signals into Robotic Arm Control Commands

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Abstract. Brain-computer interfaces (BCIs) can provide patients with severe motor disorders with a new way to bypass damaged nerve pathways and control external devices by decoding the nerve activity of the motor cortex. Current research has made progress in continuous movement, multi-degree-of-freedom control and sensory feedback, but long-term stability, control accuracy and clinical safety are still limited. This paper analyses the signal acquisition characteristics of invasive, non-invasive and intravascular BCIs, sorts out the signal preprocessing, feature extraction and neural decoding processes, and summarizes the generation methods of continuous, discrete and multi-degree-of-freedom robotic arm instructions. Analysis shows that the collaborative optimization of signal quality, decoding algorithm and shared control strategy is the key to improving the naturalness and reliability of robotic arm operation. This article provides a systematic reference for the design and research of the BCI robotic arm system. Future research should focus on developing stable neural interfaces, adaptive individual decoding, computer vision assistance and two-way sensory feedback to promote their long-term clinical and daily applications.

Keywords: Brain-computer interface, robotic arm control, neural decoding

1. Introduction

With the development of neuro-engineering, artificial intelligence and robotics, brain-computer interface (BCI) has gradually become an important research direction for restoring motor function. For patients with spinal cord injury, amyotrophic lateral sclerosis or post-stroke paralysis, although the limb movement pathway is destroyed, the motor cortex of the brain may still retain neural activity related to motor intent. The BCI takes advantage of this feature to convert human movement intentions into control instructions of robotic arms, prosthetic hands or other external devices by collecting, processing and decoding motor cortex signals. Compared with traditional rehabilitation methods, the BCI provides a technical path to bypass the damaged neural pathway, making it possible for patients to re-complete actions such as grabbing, moving, clicking and interacting.

The BCI converts motor cortex nerve signals into robotic arm control instructions, which is an important research direction in the field of neuro-engineering and rehabilitation robots. For patients with spinal cord injury, amyotrophic lateral sclerosis (ALS) or severe paralysis, peripheral nerve and

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muscle pathways may have been damaged, but the motor cortex can still produce nerve activity related to "wanting to move arms, wrists or fingers". Therefore, the BCI can bypass the damaged pathway, directly collect these neural signals, and convert them into movement commands of the robotic arm or prosthesis hand through decoding algorithms. Existing studies show that invasive BCI has obvious advantages in high-precision control. For example, some laboratories have built a two-way BCI system, which not only decodes robotic arm movement instructions from the motor cortex, but also generates tactile feedback by stimulating the body sensory cortex, thus significantly improving the grasping efficiency of the robotic arm. At the same time, the decoding algorithm is also a key factor affecting the control effect. Some experimenters found that the shallow feedforward neural network can better realize high-speed and naturalized prosthetic finger movement than the Recalibrated Feedback Intention-Trained (ReFIT) Kalman filter, indicating that the conversion of neural signals to control instructions not only depends on electrodes, It also depends on algorithm performance. In addition, the intravascular BCI study of another experimental team shows that brain signals can also be recorded for a long time through intravascular electrodes and used for digital device control, providing a new technical path for lower-traumatic robotic arm control in the future.

Therefore, studying how BCI completes the whole process of "signal acquisition - feature extraction - nerve decoding - robotic arm control - sensory feedback" is of great significance to promote the functional recovery of paralyzed patients and the development of intelligent neural prosthesis. This article will review how the BCI converts the neural signals of the motor cortex into robotic arm control instructions. First, introduce the basic working principle of BCI. Secondly, compare the three signal acquisition methods of invasive, non-invasive and intravascular BCI. Then analyse the neural signal processing and decoding algorithms. Then discuss the generation of robotic arm control instructions and sensory feedback. Finally, summarize clinical challenges, ethical issues and future development.

2. The basic working principle of BCI

BCI is through direct communication between the brain and external devices, collecting and decoding brain nerve signals, and directly converting them into control instructions. Its core values cover two dimensions: first, to help patients with severe movement disorders regain communication and control ability; second, to expand the boundaries of human ability and create a new paradigm of human-computer interaction.

The technology is divided into three categories according to the degree of intrusion: invasive BCI requires surgical implantation of electrodes, non-invasive BCI collects signals through the scalp without surgery, and intravascular BCI is implanted along the blood vessel electrodes, and the degree of invasion is between the two.

The conversion from "nerve signal" to "robotic arm control instruction" usually includes five stages: signal acquisition, feature extraction, motion decoding, equipment control and feedback correction. First, the microelectrode array implanted in the hand or upper limb representative area of the motor cortex records the discharge activity of neurons, and the system then extracts characteristics such as peak count, discharge rate or 300~1000 Hz spike band power from the original cortex electrical signal. Subsequently, the decoding algorithm analyses the correspondence between different neural channels and the direction of movement, speed and finger state, and converts the movement intention into continuous control variables. There are studies using Kalman and ReFIT Kalman filters to convert the motor cortical signal into the independent flexion and extension speed of two groups of fingers in real time. The standard Kalman control success rate

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reaches 95% and 96%; ReFIT improves the path efficiency of a monkey from 61% to 68%, The target time is reduced from 0.99 s to 0.73 s, indicating that the linear model can effectively separate multiple degrees of freedom of motion [1]. Willsey et al., for the purpose of improving the decoding performance of real-time continuous finger movement, input the latest 150 ms of neural signals into the shallow feedforward neural network, and outputs two sets of finger speeds through the time characteristic layer and the nonlinear hidden layer [2]. The speed instructions obtained by decoding will continuously update the position of the end of the robotic arm, wrist or mechanical finger to form real-time closed-loop control. At the same time, the pressure or moment sensor on the robot can detect the contact and grip of objects and transform it into micro-stimulation of the somatic sensory cortex, so that the user can obtain artificial touch. Therefore, the complete conversion logic can be summarized as: the movement intention is converted into cortical neural signals, then into feature extraction, then into algorithm decoding, then into speed or position instructions, then into robotic arm movement, then into sensory feedback, and finally into action correction.

3. Methods for acquiring motor cortex neural signals

3.1. Invasive BCI

The invasive BCI places the electrode directly on the surface of the brain or inside the brain tissue. Its main advantage is that the signal quality is high, because the electrode is very close to the active neurons. Therefore, such systems can usually achieve more accurate signal decoding and control multiple motion dimensions at the same time. At present, some studies have shown that the invasive BCI has made important breakthroughs in motion control and voice decoding. In terms of motion control, the study has achieved continuous control of 3 groups of fingers with a total of 4 degrees of freedom, and the goal completion rate after proficiency has reached 100%, reflecting the potential of complex multi-degree-of-freedom control. In terms of voice decoding, BCI has achieved 125,000 words of vocabulary decoding at a speed of 62 words/minute and further improved the decoding accuracy to about 97.5% in subsequent studies, which significantly improved the possibility of paralysed patients returning to natural communication. These breakthroughs prove that invasive BCI can not only restore basic capabilities but also support complex interactions and meet the social participation needs of users [3-5]. However, invasive BCI requires surgery, so it may bring risks such as infection, bleeding and brain tissue damage. Over time, scar tissue may also form around the electrode, resulting in a gradual decline in signal quality. Therefore, the long-term maintenance, equipment replacement and clinical monitoring of this kind of equipment are relatively complicated. Although the invasive BCI can provide the clearest neural signals, most systems are still only tested in smaller-scale clinical studies.

3.2. Non-invasive BCI

Non-invasive BCIs usually use electroencephalography electrodes placed on the scalp, that is, Electroencephalography (EEG) electrodes. Its main advantages include high security, low cost, easy to carry, and reusable. Because it does not require surgery, it is very suitable for rehabilitation training and home environment applications. However, the electrical signals generated by the brain must pass through the brain tissue, skull and scalp before they can be recorded by electrodes. Therefore, these signals are usually weak and more susceptible to noise interference. Physical movement, blinking, muscle activity and poor electrode contact may reduce the recognition accuracy of the system. In recent years, researchers have made progress in robot interaction and

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even using electroencephalograms to decode single finger movements in real time. However, non-invasive systems still rely heavily on signal processing, machine learning algorithms and repeated user calibration [6-8].

3.3. Intravascular BCI

The intravascular BCI uses a catheter to place the electrode device inside the blood vessels close to the brain. This method does not require craniotomy, so it may reduce some risks posed by traditional invasive BCIs. At the same time, compared with scalp electroencephalography, intravascular Electrocorticography (ECoG) can record neural activity closer to the motor cortex, which can reduce the attenuation of signals and external noise interference in the skull, so it has the potential to obtain higher resolution and more stable signals. Relevant studies show that the signal quality recorded by Stentrode is roughly equivalent to that of subdural and epidural ECoG, and the neural signal frequency range of the four subjects remained generally stable during the 12-month follow-up, indicating that it has good long-term recording stability. However, this method still requires medical intervention, so a more accurate description should be "low-invasive" rather than completely "non-invasive". Its actual effect also depends on whether the relevant brain area can still produce neural signals that can be decoded. Current research shows that intravascular BCIs may help severely paralyzed patients control digital devices. However, before large-scale application, larger patient samples, longer follow-up visits, and clearer clinical effect verification are still required [9-11].

4. From neural signals to robotic arm control

4.1. Neural signal processing and feature extraction

In the BCI, primitive neural signals are usually weak and easily disturbed by physiological activities, movement false marks and environmental noise, so signal preprocessing is required before feature extraction. The collected neural signals can first undergo low-noise amplification, analogue-to-digital conversion and filtering to improve the signal-to-noise ratio and obtain digital signals suitable for computer analysis; for high-dimensional neural data, Principal Component Analysis (PCA) or Ind can also be used. Dependent Component Analysis (ICA) reduces redundant information, thus reducing the complexity of follow-up processing [12]. For EEG signals, preprocessing can also include steps such as false trace removal, signal segmentation, filtering and normalization to reduce the impact of noise and retain information related to brain activity and provide a more stable data basis for the subsequent extraction of time, frequency, time-frequency and spatial characteristics [13].

After signal preprocessing, it is necessary to extract typical features that can effectively represent brain activity from neural signals. For EEG signals, common features include statistical characteristics of the time domain and the coefficient of the autoregressive model, the power spectrum density (PSD) and frequency band power of the frequency domain, as well as the time-frequency characteristics obtained by using wavelet transform or short-time Fourier transform; for multi-channel EEG, it can also be used through the common space mode (CSP), etc. Method to extract spatial features with discrimination [13]. For intrusive BCIs, neuronal discharge activity and group neural activity can be used as important features, such as using neuronal discharge rate and its group activity mode to express movement-related information, and further input decoding algorithms to estimate movement intentions and control variables [12].

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4.2. Neural decoding algorithms: from motor intent to control variables

The core of the neural decoding algorithm is to convert the neural activity in the motor cortex into continuous control variables that can drive external devices, such as position and speed. The calculation of the traditional linear decoder is simple and has strong real-time performance. Nason and others use the Kalman filter to convert the neural signals in the cortical layer into the independent movement speed of two groups of fingers in real time, and recalibrate the model based on the user's expected movement direction through ReFIT, which improves the control efficiency in some experiments, which shows Linear models can realize continuous multi-degree-of-freedom decoding [1]. Neural network decoders can learn more complex nonlinear and time relationships. Willsey et al. input the last 150 ms of neural activity into the shallow feedforward neural network and output two sets of finger speeds; in the 7-day experiment of two animals, the overall throughput of the neural network decoder was 36% higher than that of the ReFIT Kalman filter, showing higher continuous motion decoding [2]. In terms of adaptive and individualized calibration, ReFIT can retrain the model according to the user's movement intention, while Flesher and others also use daily re-trained five-degree-of-freedom speed decoders to adapt to the individual's neural activity on that day, and combine tactile feedback to form closed-loop control for individualized BCI control. It provides further evidence [14].

4.3. Generation of robotic arm control commands

The generation of robotic arm control instructions usually requires the user movement intention obtained by BCI decoding to be further converted into continuous, discrete and multi-degree-of-freedom control variables. In terms of continuous control, Forenzo and others use the individualized deep learning model based on the Electroencephalography Network, (EEGNet) to return the EEG motion imagination signal to two continuous speed variables horizontal and vertical in real time, and the independent binary "Click" signal triggers grabs or releases, allowing users to continuously complete the tasks of arrival, grabbing and handling. High-performance participants can move about 7 cups in 5 minutes on average, indicating that continuous movement variables and discrete action instructions can work together to control the robotic arm [15]. In terms of discrete control, Zhou et al. built BCI through Steady-State Visual Evoked Potential (SSVEP) and Electrooculography (EOG) and recognized from 15 preset commands. Other user intentions, and map them to robot actions such as direction, stop, return and drinking water, and the accuracy of online command recognition reaches 92.4±5.5% [16]. In terms of multi-degree-of-freedom control, the research further combines vertical and horizontal commands into 3D motion instructions through three-dimensional vector synthesis and controls the seven-degree-of-freedom robotic arm to complete the space arrival task; after combining computer vision, the system can also automatically complete accurate grabbing and drinking water, thus reducing the simple reliance on brain-computer connection. The number of commands and operational burden required to directly control the multi-degree-of-freedom robotic arm [16].

5. Current challenges and future development directions

At present, the BCI still faces many challenges in converting motor cortex nerve signals into robotic arm control instructions. First, neural signals have obvious individual differences and time changes. Electrode position changes, neural activity fluctuations and tissue responses after long-term implantation may reduce signal stability, make the decoder need frequent calibration, and affect the

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reliability of long-term continuous control of the robotic arm. Research in recent years has therefore begun to explore decoding algorithms that can automatically adapt to changes in neural signals to improve the stability of long-term use. Secondly, high-degree-of-freedom robotic arm control requires accurate decoding of multiple control variables such as direction, speed, grip and finger movement at the same time, which puts forward higher requirements for signal quality, real-time computing power and algorithm accuracy. Intrusive systems also have safety problems such as surgical risks, infection, tissue damage, long-term electrode stability and equipment failure. Therefore, implanted equipment must undergo strict biocompatibility, electrical safety and long-term reliability assessment. In terms of ethics, the BCI can acquire highly sensitive neural data, so it is necessary to focus on protecting neural privacy, data security, informed consent and user autonomy, while avoiding problems such as unauthorized data use, behavioral manipulation and unequal distribution of technical resources. Future development will mainly focus on more flexible and stable high-density neural interfaces, adaptive and individual decoding algorithms, and closed-loop control systems combining computer vision and sensory feedback, so that robotic arms can gradually develop from short-term control in the experimental environment to become more natural, stable, safe and suitable for long-term daily use the auxiliary technology.

6. Conclusion

This article reviews how the BCI converts motor cortex nerve signals into robotic arm control instructions. It mainly analyses the three neural signal acquisition methods of invasive, non-invasive and intravascular BCI, and further discusses neural signal preprocessing and feature extraction, neural decoding algorithm and continuous and discrete and the generation process of multi-degree-of-freedom robotic arm control instructions, and at the same time, the role of sensory feedback and closed-loop control in improving the operation performance of the robotic arm are introduced. Comprehensive analysis shows that the BCI can bypass the damaged nerve and muscle pathways and directly transform the user's movement intention into the control variables of external devices, providing an important technical path for patients with severe motor disorders to restore the ability to grasp, move and daily interaction. This article believes that the collaborative optimization between signal acquisition quality, decoding algorithm performance and robotic arm control strategy is the key to improving the practical application ability of BCI and can also provide reference for the construction of a more natural and stable neural prosthesis system in the future. However, at present, this field is still limited by factors such as long-term stability of neural signals, high degree of freedom control accuracy and clinical safety. Future research should further develop high-stability neural interface, adaptive and individual decoding algorithms, and build a more perfect closed-loop control system in combination with computer vision and sensory feedback, to promote BCI robotic arms from experimental research to long-term, reliable clinical and daily applications.

References

[1] Nason, S. R., Mender, M. J., Vaskov, A. K., Willsey, M. S., Ganesh Kumar, N., Kung, T. A., Patil, P. G., & Chestek, C. A. (2021). Real-time linear prediction of simultaneous and independent movements of two finger groups using an intracortical brain-machine interface. *Neuron, 109*(19), 3164–3177.e8. https://doi.org/10.1016/j.neuron.2021.08.009

[2] Willsey, M. S., Nason-Tomaszewski, S. R., Ensel, S. R., Temmar, H., Mender, M. J., Costello, J. T., Patil, P. G., & Chestek, C. A. (2022). Real-time brain-machine interface in non-human primates achieves high-velocity prosthetic finger movements using a shallow feedforward neural network decoder. *Nature Communications, 13*(1). https://doi.org/10.1038/s41467-022-34452-w

DOI: 10.54254/2753-8818/2026.HZ36492

[3] Willett, F. R., Kunz, E. M., Fan, C., Avansino, D. T., Wilson, G. H., Choi, E. Y., Kamdar, F., Glasser, M. F., Hochberg, L. R., Druckmann, S., Shenoy, K. V., & Henderson, J. M. (2023). A high-performance speech neuroprosthesis. *Nature, 620*(7976), 1031–1036. https://doi.org/10.1038/s41586-023-06377-x

[4] Card, N. S., Wairagkar, M., Iacobacci, C., Hou, X., Singer-Clark, T., Willett, F. R., Kunz, E. M., Fan, C., Vahdati Nia, M., Deo, D. R., Srinivasan, A., Choi, E. Y., Glasser, M. F., Hochberg, L. R., Henderson, J. M., Shahlaie, K., Stavisky, S. D., & Brandman, D. M. (2024). An accurate and rapidly calibrating speech neuroprosthesis. *New England Journal of Medicine, 391*(7), 609–618. https://doi.org/10.1056/nejmoa2314132

[5] Willsey, M. S., Shah, N. P., Avansino, D. T., Hahn, N. V., Jamiolkowski, R. M., Kamdar, F. B., Hochberg, L. R., Willett, F. R., & Henderson, J. M. (2025). A high-performance brain–computer interface for finger decoding and quadcopter game control in an individual with paralysis. *Nature Medicine, 31*(1), 96–104. https://doi.org/10.1038/s41591-024-03341-8

[6] Ding, Y., Udompanyawit, C., Zhang, Y., & He, B. (2025). EEG-based brain-computer interface enables real-time robotic hand control at individual finger level. *Nature Communications, 16*(1). https://doi.org/10.1038/s41467-025-61064-x

[7] Edelman, B. J., Zhang, S., Schalk, G., Brunner, P., Müller-Putz, G., Guan, C., & He, B. (2025). Non-invasive brain-computer interfaces: State of the art and trends. *IEEE Reviews in Biomedical Engineering, 18*, 26–49. https://doi.org/10.1109/rbme.2024.3449790

[8] Saibene, A., Caglioni, M., Corchs, S., & Gasparini, F. (2023). EEG-based BCIs on motor imagery paradigm using wearable technologies: A systematic review. *Sensors, 23*(5), 2798. https://doi.org/10.3390/s23052798

[9] Mitchell, P., Lee, S. C. M., Yoo, P. E., Morokoff, A., Sharma, R. P., Williams, D. L., MacIsaac, C., Howard, M. E., Irving, L., Vrljic, I., Williams, C., Bush, S., Balabanski, A. H., Drummond, K. J., Desmond, P., Weber, D., Denison, T., Mathers, S., O'Brien, T. J., … Campbell, B. C. V. (2023). Assessment of safety of a fully implanted endovascular brain-computer interface for severe paralysis in 4 patients. *JAMA Neurology, 80*(3), 270. https://doi.org/10.1001/jamaneurol.2022.4847

[10] Brannigan, J. F. M., Fry, A., Opie, N. L., Campbell, B. C. V., Mitchell, P. J., & Oxley, T. J. (2024). Endovascular brain-computer interfaces in poststroke paralysis. *Stroke, 55*(2), 474–483. https://doi.org/10.1161/strokeaha.123.037719

[11] Oxley, T. J. (2025). A 10-year journey towards clinical translation of an implantable endovascular BCI a keynote lecture given at the BCI society meeting in Brussels. *Journal of Neural Engineering, 22*(1), 013001. https://doi.org/10.1088/1741-2552/ad9633

[12] Salahuddin, U., & Gao, P.-X. (2021). Signal generation, acquisition, and processing in brain machine interfaces: A unified review. *Frontiers in Neuroscience, 15*, 728178. https://doi.org/10.3389/fnins.2021.728178

[13] Singh, A. K., & Krishnan, S. (2023). Trends in EEG signal feature extraction applications. *Frontiers in Artificial Intelligence, 5*. https://doi.org/10.3389/frai.2022.1072801

[14] Flesher, S. N., Downey, J. E., Weiss, J. M., Hughes, C. L., Herrera, A. J., Tyler-Kabara, E. C., Boninger, M. L., Collinger, J. L., & Gaunt, R. A. (2021a). A brain-computer interface that evokes tactile sensations improves robotic arm control. *Science, 372*(6544), 831–836. https://doi.org/10.1126/science.abd0380

[15] Forenzo, D., Zhang, Y., Wittenberg, G. F., & He, B. (2025). Continuous reaching and grasping with a BCI controlled robotic arm in healthy and stroke-affected individuals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 33*, 3888–3899. https://doi.org/10.1109/tnsre.2025.3611821

[16] Zhou, Y., Yu, T., Gao, W., Huang, W., Lu, Z., Huang, Q., & Li, Y. (2023). Shared three-dimensional robotic arm control based on asynchronous BCI and computer vision. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 31*, 3163–3175. https://doi.org/10.1109/tnsre.2023.3299350