Proceedings of the 2023 International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/31/20230117

Brain-computer interface technology for rehabilitation exoskeleton applications

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Abstract. In recent years, the development of brain-computer interface (BCI) and exoskeleton technology has received more and more attention. Brain-computer interface, a technology that allows the human brain to communicate with electronic devices or computer programs, has potential applications in sports rehabilitation for the disabled and smart home control. Exoskeleton technology, on the other hand, provides humans with enhanced movement and strength, offering new possibilities for improving the quality of life for people with mobility disorders. Several applications of brain-computer interface and exoskeleton technology are discussed. Applications of brain-computer interfaces range from motor rehabilitation, allowing patients to regain control of paralyzed limbs, to controlling virtual environments and assistive devices. Exoskeletons, on the other hand, enable people with reduced mobility to walk again, providing them with more independence and function. This paper introduces the latest research progress of BCI and exoskeleton technology, including the latest breakthroughs in machine learning and artificial intelligence algorithms, which greatly improve the accuracy and speed of BCI control. Challenges such as developing lightweight and user-friendly exoskeletons and addressing safety and ethical issues in BCI applications are also discussed. The purpose of this paper is to provide a comprehensive and up-to-date reference for researchers and science enthusiasts interested in brain-computer interface and exoskeleton technology.

Keywords: Brain-computer interface, exoskeleton, signal acquisition, signal processing, rehabilitation exoskeleton.

1. Introduction

1.1. Research background

Brain-computer interface technology aims to establish direct contact between man and machine and provide more convenient living and working conditions for special people. By recording human brain activity signals through EEG or MRI, they can be converted into command signals to achieve remote control of machines. For example, researchers used non-invasive EEG measurements to record human brain signals and convert these signals into commands to remotely control a moving robot [1]. They have achieved high accuracy handwriting recognition by recording human brain signals and converting them into handwritten characters, which has high practical value [2].

Exoskeleton technology is a technology that can help disabled people regain physical function, and currently mainly uses nerve reconstruction technology to rebuild the function of amputated muscles. In the study of Kuiken et al. (2009), neural reconstruction technology was used to achieve real-time

DOI: 10.54254/2755-2721/31/20230117

multifunctional motion control of prosthetics, allowing transplanted muscle nerves to be redirected to muscles, restoring nerve function and providing a more natural signal source. Exoskeleton technology can also play a major role in medical, military, industrial and other fields, such as assisting soldiers to complete high-intensity tasks or improving the productivity of mining workers [3].

1.2. Research status

Brain-computer interface (BCI) technology connects the human brain with external devices such as computers, providing external information or controlling computers by detecting and interpreting human brain activity. Since it was proposed, it has played an increasingly important role in neuroscience, computer science, medicine and other fields, and has been widely used in many fields such as health care, health monitoring, human-computer interaction, and game control. BCI technology advances rapidly with the development of brain science and artificial intelligence technology, benefiting from the development of new application scenarios and algorithm technology. For example, at present, more and more researches have adopted deep learning, machine learning and other algorithms in the implementation of BCI technology to achieve more refined and efficient command control. These algorithms produce better results based on electroencephalogram (EEG) signal analysis and training of individuals, achieving more amazing effects of human-machine symbiosis [4]. At the same time, the widely used magnetoencephalography (MEG) and functional magnetic resonance (fMRI) technologies have also promoted the rapid development of BCI technology, and the application of these technologies can obtain higher levels of neural activity and functional area information through non-invasive means, thus achieving more accurate control [5]. In addition, the development of wearable brain-computer interface devices has also received attention. These devices can enable BCI technology to be applied to different experimental scenarios, such as sports and game control, physical health monitoring, etc., by focusing on the intelligence, miniaturization and portability of hardware devices, Minimal interference to the user is achieved [6]. Although BCI technology faces many challenges and difficulties in the implementation process, such as signal quality, training time, real-time and accuracy issues, with the emergence of these new development technologies, the future development of BCI technology is bound to be unlimited [7].

Research focus on the application of brain-computer interface technology and exoskeleton technology. It converts brain activity into electrical signals and interacts with external devices via a computer. Researchers have developed some exoskeleton systems that can realize man-machine cooperative control and improve the walking freedom of the exoskeleton. The application of invasive and non-invasive BCI in exoskeleton is explored, which is helpful to promote the development of BCI technology in practical applications. The objective of this work were: 1) Develop new rehabilitation technologies to provide better treatment for paraplegia and other patients. 2) Realize man-machine collaborative control, improve the walking freedom of the exoskeleton, and become people's life and work helpers; 3) Explore the application of different brain-computer interface technologies in exoskeletons, so as to achieve the best use effect.

2. Brain-computer interface and exoskeleton technology

Brain-computer interface and exoskeleton are two advanced technologies, and their combination brings more possibilities for humans. As the old saying goes, "opportunities often favor those who are ready", in this era, with the help of modern technology, making our life more convenient has become our only way. In real life, there are many people who cannot walk normally because of some physical problems, resulting in difficulties in life, and even can not take care of themselves. The combination of brain-computer interfaces and exoskeleton technology can help these people walk with ease.

2.1. Invasive brain-computer interface and exoskeleton technology

The combination of brain-computer interfaces and exoskeleton technology offers a broader range of possibilities for people with disabilities. In recent years, this technology has become a hot research field at home and abroad [8, 9]. Studies have shown that the combination of brain-computer interface and exoskeleton technology can significantly improve the quality of life and rehabilitation of patients with paralysis [10].

The development of brain-computer interface technology provides an effective means for exoskeleton control. In recent years, researchers at home and abroad have validated the effectiveness of invasive and non-invasive brain-computer interfaces and exoskeleton technologies through clinical trials. For example, a research team at the University of Southern California has successfully developed a new transfer walking system composed of an exoskeleton and a brain-computer interface, which can help paralyzed patients with mobility difficulties carry out walking training and improve their quality of life.

However, current invasive brain-computer interface technologies still have some limitations and risks compared to non-invasive technologies. Therefore, experts and researchers are constantly exploring safer and more efficient brain-computer interfaces and exoskeleton technologies.

2.1.1. Information collection. Signal acquisition is the first critical step in invasive brain-computer interface technology, which collects neural signals in the cerebral cortex by implanting tiny electrodes. The signal collection uses the technology of microelectronics, using tiny electrodes on the surface of the brain to collect EEG electrical signals, cerebrospinal fluid electrical signals, neuron signals and so on. These signals are then transmitted to an external system for further processing.

In order to ensure the quality and effectiveness of the collected signal, it is necessary to carry out filtering and denoising in the process of signal acquisition. De-noising the signal with low SNR can reduce the error in subsequent signal processing and improve the accuracy of signal processing. In addition, attention should be paid to avoid or reduce mechanical collisions or other factors that affect signal quality during the acquisition process.

In the process of signal acquisition, it is necessary to establish a stable and durable connection between the implanted electrode and the cerebral cortex, and ensure the safety of the implant and the human body. To address this problem, some new microelectronics technologies are being investigated, such as reconfigurable implantable electrodes, which can reduce the physiological impact on the human body and improve the reliability of the electrode. In addition, a number of technologies are being developed around micromanipulation and micromanipulation, and these devices can make the implantation and fixation of the implant more precise, while reducing the size of the implant and the wound.

Signal acquisition is the first important step in invasive brain-computer interface technology. The collected neural signals need to go through a series of filtering and denoising processing to ensure the quality and effectiveness of the signals. Only when a good signal is obtained, the subsequent signal processing and generating control command steps can be carried out. With the emergence and development of new technologies, the importance and breadth of signal acquisition for the application of invasive brain computer interface technology will be further enhanced.

2.1.2. Information processing. Signal processing refers to the processing, processing and analysis of the signal to extract the information contained in the signal. Signal processing is a crucial step in controlling and identifying exoskeletons. In the process of signal acquisition, the EEG signal of the human body can be recorded, and the signal is analyzed and processed by pattern recognition and machine learning algorithms. This process maps EEG signals to specific command or control sequences to achieve control of the exoskeleton. In the process of signal processing, various methods can be used, including filtering, feature extraction, spectrum analysis and pattern classification. These methods can help us identify and classify EEG signals more accurately, and extract useful signal features to achieve precise control of the exoskeleton.

In the process of controlling the exoskeleton, signal processing technology is very critical, because it can help us achieve high precision control. Figure 1 shows the recording and processing of electrical EEG signals by implanting electrodes into the brain and converting them into control signals for the manipulation of exoskeleton devices. Schematics of the technology include invasive brain-computer interfaces, signal processing units, feature extraction algorithms and recognizers, and exoskeleton devices. It provides rehabilitation training and movement recovery support for people with movement disorders or limb paralysis.

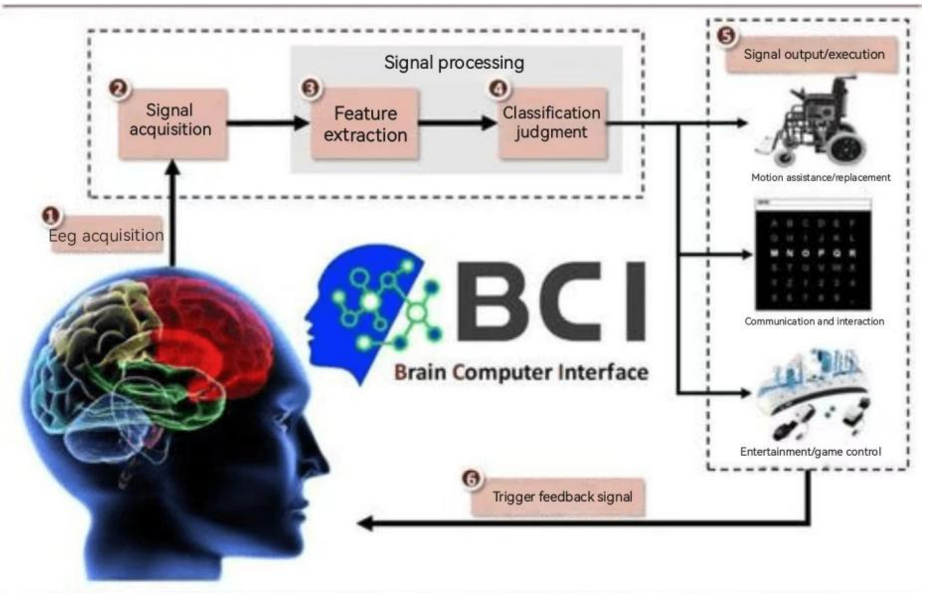

Figure 1. Schematic diagram of an invasive brain computer interface [11].

2.1.3. Rehabilitation exoskeleton based on invasive brain computer interface. The application of invasive brain-computer interface (BCI) technology in rehabilitation exoskeleton is a research topic of great concern. The invasive brain-computer interface can control the rehabilitation exoskeleton by directly recording the activity of brain neurons, which can avoid the influence of traditional EMG signal by muscle fatigue and movement noise, thereby improving the control accuracy. Here are some relevant research results:

1) Researchers have made some achievements in the study of rehabilitation exoskeleton control for paralyzed patients by using invasive brain-computer interface technology. Among them, researchers implanted invasive electrodes into the brains of paralyzed patients to achieve control of rehabilitative exoskeletons by training deep convolutional neural networks [12]. The results show that this method can achieve high precision single joint and multi-joint control.
2) Another study indicates that the use of invasive brain-computer interface technology for lower limb rehabilitation exoskeleton control is also feasible. They collected brain signals by implanting electrodes and used pyramid algorithm to classify signals, and finally realized the control of lower limb rehabilitation exoskeleton [13].
3) While invasive brain-computer interfaces are being used in the field of rehabilitation exoskeletons, there is also some research driving the development of industrial production. For example, researchers have developed a reusable, invasive brain-computer interface device that can be embedded in the brain of a paralyzed patient in a low-cost and efficient manner to enable control of a rehabilitative exoskeleton [14].

2.2. Non-invasive brain-computer interface and exoskeleton technology

The combination of non-invasive brain-computer interface technology and exoskeleton technology also provides a broader possibility for the disabled, and has become a hot research field at home and abroad. Research has shown that the combination of non-invasive brain-computer interfaces and exoskeleton technology can significantly improve the quality of life and rehabilitation outcomes of patients with paralysis [15, 16].

The development of non-invasive brain-computer interface technology provides an effective means for exoskeleton control [17]. In recent years, researchers at home and abroad have experimentally verified the effectiveness of non-invasive brain-computer interfaces and exoskeleton technologies. For example, a research team at Shanghai Jiao Tong University used non-invasive brain-computer interface technology to develop a wearable lower limb exoskeleton system that converts electrical signals into control commands, achieving gait restoration in patients with paralysis [18]. Figure 2 shows what a non-invasive brain-computer interface converts electrical signals into control commands.

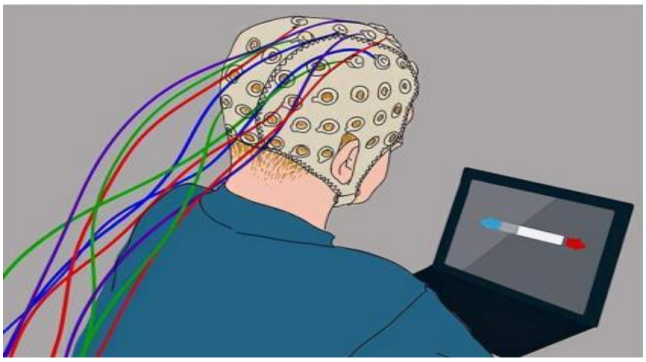

Figure 2. Non-invasive brain computer interface diagram [18].

2.2.1. Information collection. Non-invasive brain-computer interface means that it does not need to open the skull and other ways to enter the brain, but uses sensors to collect brain electrical signals on the surface of the human scalp, so as to achieve interaction with the computer. The advantage of this method is that it is safe, does not require surgery, and does not cause any trauma and harm to the human body. But at the same time, compared with the invasive BCI, the signal acquisition difficulty of non-invasive BCI is much higher.

In the non-invasive BCI signal acquisition, it is necessary to use highly sensitive electrodes and amplifiers to collect and amplify EEG signals. Electrodes usually need to be attached tightly to the scalp surface, and the number and arrangement of electrodes are closely related to the quality of the collected signal. In order to prevent the impact of environmental interference on signal quality, it is necessary to isolate the laboratory's power cord and other objects that may cause environmental noise. In addition, the person's mood swings, the influence of hair, blinking and chewing can also cause artifacts of signals. In order to reduce the effect of these motion artifacts on signal quality, subjects need to be as quiet, still, and eyes closed as possible under ideal conditions. Pre-processing and signal quality assessment are required to ensure the accuracy and stability of the signal. The pre-processing includes removing the faulty electrode and filtering the signal.

The signal quality of non-invasive BCI is affected by many factors, so it is necessary to obtain accurate and reliable EEG signal through reasonable acquisition equipment, strict testing and data processing methods, so as to promote the development and application of BCI technology. Figure 3 shows the content of the Non-invasive EEG Brain-Computer Interface Technology Roadmap

DOI: 10.54254/2755-2721/31/20230117

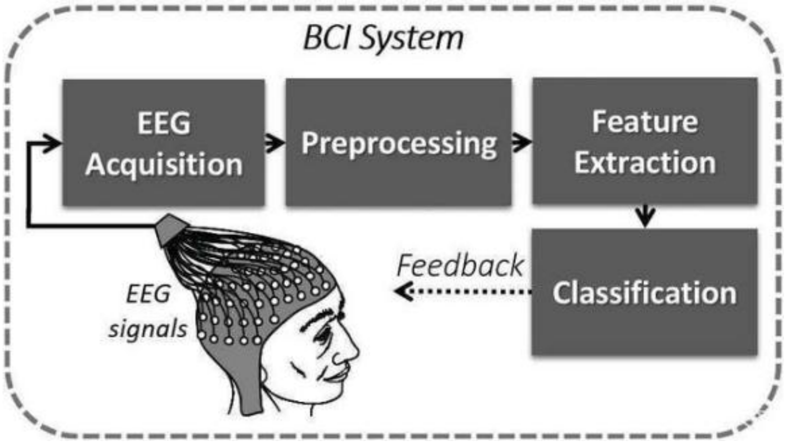

Figure 3. Schematic diagram of non-invasive brain-computer interface technology [17].

2.2.2. Information processing. The signal processing process of non-invasive brain computer interface includes four stages: signal acquisition, signal processing, feature extraction and pattern recognition. The signal acquisition stage is to collect the EEG signal on the human scalp surface to the computer or other equipment through the amplifier and filter circuit, and the signal processing is to filter and de-noising the collected EEG signal and time frequency analysis and other operations to improve the quality and accuracy of the signal. Non-invasive BCI requires a large amount of computing power of the computer for signal processing, so the computational complexity of signal processing is high, and a variety of algorithms and techniques need to be flexibly used to optimize processing speed and accuracy.

Feature extraction refers to extracting characteristic information representing specific brain activity from EEG signal, which is usually realized by using time-frequency analysis, pedigree decomposition and high order statistics. Once the feature information is obtained, a classification model can be built using machine learning or other pattern recognition techniques. Common pattern recognition algorithms include support vector machine, K-nearest neighbor, neural network and decision tree. These algorithms all require some training and optimization to adapt to different tasks and data sets, and predict the action intent of the brain-computer interface.

It should be noted that the signal quality of non-invasive BCI is relatively poor due to the impact of background noise and interference, so effective measures need to be taken to reduce errors and improve accuracy. For example, adaptive filters can be used to weaken interference signals, multi-channel simultaneous EEG acquisition can be used to quickly and accurately extract features in EEG signals, or other perceptual technologies can be combined to improve classification accuracy, so as to achieve efficient brain-computer interface interaction.

2.2.3. Rehabilitation exoskeleton based on non-invasive brain computer interface. In recent years, the combination of non-invasive brain-computer interfaces and exoskeleton technology has been widely used in the field of rehabilitation robotics to help paralyzed patients regain gait and balance function. Some studies have shown that non-invasive brain-computer interfaces can be used as a control mode for rehabilitative exoskeletons, allowing paralyzed patients to complete actions such as walking and posture adjustment through EEG signals. For example, a research team at the Institute of Automation of the Chinese Academy of Sciences has developed a lower limb exoskeleton rehabilitation system based on a non-invasive brain-computer interface, which can achieve the movement control of the exoskeleton and enhance the patient's movement ability by extracting specific EEG signals [19]. A study by Nanjing University of Science and Technology showed that the combination of non-invasive brain-computer interface and exoskeleton technology can significantly improve the walking ability and balance ability of paralyzed patients, and improve the rehabilitation effect [20].

However, current rehabilitation exoskeleton technologies based on non-invasive brain computer interfaces still face many challenges and limitations. Researchers need to further improve the signal quality and accuracy of non-invasive brain-computer interface systems, as well as optimize brain-computer interaction algorithms and control strategies to improve the stability and reliability of rehabilitation robot systems. In addition, the design of rehabilitation exoskeleton needs to be more humane and comfortable to improve patients' wear experience and rehabilitation effect [21].

The combination of non-invasive brain-computer interface technology and exoskeleton technology has broad application prospects in the field of rehabilitation robots. With the continuous development and improvement of technology, non-invasive brain-computer interface and exoskeleton technology are expected to be widely used in rehabilitation robot systems to provide better rehabilitation services and life support for people with disabilities.

2.3. Applications of brain-computer interfaces

Since the advent of brain-computer interface technology, its application field has been expanding. At present, it has been widely used in the field of health care, such as the control of prosthetics, the treatment of mental disorders and strokes. It also extends to entertainment and consumer products, such as controlling games and creating virtual reality experiences [22] (Table 1).

Table 1. Table of application examples of brain-computer interface technology.

Application type	Research object	Type of brain computer interface	Exoskeleton site	Implemented function
Invasive	Patient A	Brain-computer invasive interface	Lower limbs	Control exoskeleton walking [23]
Invasive	Patient B	Brain-computer invasive interface	Lower limbs	Controls the exoskeleton to walk, stop and turn [24]
Non-invasive	Patient C	Brain-computer non-invasive interface	Lower limbs	Control exoskeleton forward, backward, left and right turn and other control methods [25]
Non-invasive	Patient D	Brain-computer non-invasive interface	Upper limb	Control the grasp and release of the exoskeleton and other actions [26]

3. Discussion

With the continuous development of Internet of Things technology, brain-computer interface technology is becoming one of the more promising research and application fields. In healthcare, applications of brain-computer interface technology are helping people with disabilities regain mobility and psychotherapy. In the Internet of Things, the application of brain-computer interface technology can also bring more intelligent, humanized and convenient experiences and services. For example, when people are at home or in the car, they can directly control the opening and closing of smart home appliances through brain waves, saving time and effort. In addition, intelligent vehicles can also be controlled through brain-computer interface, such as automatic driving, remote control and other operations, which also has great potential and prospects for future transportation.

However, brain-computer interface technology also faces many challenges and problems in iot applications. The instability and error of signal quality is one of the main challenges. For example, different people's body movements and behaviors are very different, which requires targeted analysis and research. In addition, the use of brain-computer interface technology also needs to face privacy risks and data protection issues, and measures need to be taken to protect user privacy (Table 2).

Table 2. The development trend table is discussed from many aspects.

Development	Discussion content

trend	
Healthcare applications	Brain-computer interface technology is becoming a cutting-edge research direction in the field of healthcare, which can help disabled people regain mobility and psychological therapy.
Internet of Things application	The application of brain-computer interface technology in the Internet of Things brings intelligent and convenient experiences and services, such as controlling appliances in smart homes through brain waves, controlling intelligent vehicles, etc.
Challenge	The application of brain-computer interface technology still faces challenges such as unstable signal quality, error problems, privacy risks and data protection issues, which require targeted research and measures.

3.1. Comparative analysis of invasive and non-invasive techniques
Invasive brain computer interface (BCI) and non-invasive brain computer interface (NBI) are both methods used to acquire brain signals, but they differ greatly in the ways of obtaining signals, advantages and disadvantages, and application range. Invasive BCI uses surgically implanted electrodes to capture brain signals. Non-invasive brain-computer interfaces, on the other hand, attach electrodes to the scalp surface and collect electrical signals from the scalp through sensors. Because invasive BCI requires surgery, it is difficult and risky to operate, while non-invasive BCI is safer and more convenient.

3.2. Comparison of advantages and disadvantages
Invasive brain computer interface technology can directly collect electrical signals of brain neurons, and the signal quality is high, so more accurate brain signal information can be obtained. However, surgery is required, and the risk is greater, and the signal cannot be obtained again after the brain area is damaged. In addition, due to the implantation of electrodes in the brain, it will lead to inflammation of the brain tissue and electrode displacement, affecting the stability of signal quality. Although the signal quality of non-invasive BCI is relatively low, it does not require surgery, is convenient to operate, and can collect brain signals from a large number of subjects. At the same time, non-invasive BCI can be affected by problems such as environmental interference, hair and motion interference, and the signal quality is unstable.

For non-invasive BCI, the most significant advantage is that it does not invade the human body, so it is safer and easier to use, and also easier to test and verify. However, the defect of non-invasive BCI is that its accuracy will be interfered with by scalp, hair and other factors, but also affected by brain structure, thickness and other factors, and the detected signal accuracy is low.

For the invasive brain computer interface, its biggest advantage is that it can directly receive the cross-connection signal of the neuron unit, and the signal accuracy is very high, but the implanted electrode causes certain damage to the human body, so it is more difficult to promote and use.

4. Conclusion
Invasive brain-computer interface technology has a narrow range of applications, mainly used in clinical research and treatment, such as locked-in syndrome, pain management and other fields. Non-invasive brain computer interface technology is more widely used in clinical and scientific research fields, including brain computer interface, cognitive neuroscience, neural rehabilitation, neural intervention, etc. Although invasive brain-computer interface technology has the advantages of high precision and high stability, its popularity and application scope are limited due to surgical risks and costs. Although the signal quality of non-invasive BCI is relatively low, it has been widely studied and applied in BCI, cognitive neuroscience, neural rehabilitation and neural intervention due to its convenient operation, convenient participation of a large number of subjects and wide range of applications. With the continuous development of technology, it is believed that the application prospect of invasive and non-invasive brain computer interface technology will be more broad. 1) To develop more efficient and safe invasive brain-computer interfaces, such as minimally invasive technologies or implantable brain-

DOI: 10.54254/2755-2721/31/20230117

computer interference technologies; 2) Develop more flexible and high-precision non-invasive brain-computer interface technologies, such as new sensor technologies based on optical and electromagnetic wave principles; 3) Combine the two technologies and take advantage of their advantages, such as the combination of implantable electrodes and non-invasive EEG.

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