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A review of recent developments and challenges in the brain-machine interface

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Abstract. With the advancement of technology and materials, brain-machine interface technology is also developing rapidly and has achieved a lot in recent years. However, BMI still needs to overcome many challenges due to the short development time. This paper reviews the development of BCI in recent years, mainly focusing on electrode materials, BMI signals (EEG and ECoG), BMI applications, and the challenges of BMI. In terms of electrode materials, nanomaterials have made significant progress and shown good biocompatibility. Regarding BMI signals, EEG is often associated with mood research and machine learning, while ECoG is widely used to treat diseases. BMI is mainly used in medicine (recovery of movement and brain sensation) and the life entertainment field. The challenges facing BMI today are mainly animal experiments in neuroethics and the imperfection of BMI in electrode materials.

Keywords: BMI, electrode, EEG, ECoG.

1. Introduction

As technology advances, BMI—a technique building direct operative interfaces between the brain and manufactured devices—is also developing fast. Since 1999, when the first experimental proved that cortical neurons were able to directly control the robotic manipulator [1], loads of fundamental research on Brain Machine Interfaces have been conducted, primarily because of BMI's potential for restoring the motor movement of disabled people. Moreover, BMI can be applied to other fields like the military, education, entertainment, and daily life, bringing convenience to people, which also arouses great interest in this technology.

Although BMI holds considerable promise for curing patients and facilitating people's lives, there are still a lot of technical bottlenecks and challenges, like ethical issues, to overcome. Many invasive BMI experiences have been done on animals and face many moral problems. There is still much effort to make.

Here, by reviewing the recent findings and research on BMI, the work summarizes the recent development of BMI and discusses its challenges.

2. The development of BMI

2.1. Breif introduction of BMI

A brain-machine interface is a "system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, informs, or improves

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natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment "[2]. Its primary processes are signal acquisition, information decoding, encoding processing, and giving feedback to users. The signal acquisition mainly involves the tool (electrode material) and the collected signal (EEG in the case of non-invasive BMI; In invasive BMI, it is mostly ECoG). Signal decoding and encoding also involve the above two kinds of signals. On the whole, interpreting the application of BMI is also an essential aspect of understanding the direction of BMI development. Therefore, in this part, the author will introduce the development and recent research on BMI from three aspects: electrode material, signals, and BMI applications.

2.2. The development of Electrode materials

The choice of electrode material is critical in the application of BMI. Electrodes with ideal mechanical properties can effectively avoid inflammatory responses and have high-quality signals. The basic requirements of BMI electrodes are (a) a high signal-to-noise ratio, (b) biologically transparent and biocompatible, (c) long-term stability, (d)high density of neural probes, (e) neuronal cell loss and minimal inflammation [3,4]

Materials science has recently provided many advanced electrodes for studying BMI. From metal microfilaments and MEMs-based silicon electrodes in the early years, the mainstream electrode materials will be nanomaterials (including conductive polymers, carbon materials, nanowires, and hybrid nanomaterials) around 2020.

Although metal microfilaments are easy to manufacture, they perform poorly in signal-to-noise ratio because they are challenging to break through the limitation of high resistance. The recording point density of MEMS-based silicon electrodes is high, but due to the hardness of the silicon electrode, it has a low fit with soft tissue.

Nanomaterials can exhibit better electrical properties because they are more similar in size to brain tissue and because of the combination of ions and electrical conductivity. Compared with metal materials, conductive polymers have good biocompatibility, excellent electrical conductivity, and flexibility, making them popular. Carbon materials have low electrical impedance, stability, and excellent thermal conductivity, such as graphene and CNTs, but the potential biotoxicity of graphene and CNTs is still controversial [3]. Nanowires have a high surface-to-volume ratio, which can effectively improve sensitivity. Hybrid nanomaterials can learn from each other and integrate the advantages of various materials, which can effectively improve the various properties of materials, especially the stable system and biocompatibility.

In recent years, several neural probes and electrode materials have developed around better bionic properties [5-10], which generally have a more similar size and better flexibility to brain nerves so that neuron loss and neuroinflammation can be alleviated. For better biocompatibility, some groups have created rough electrode surfaces from laser patterns and then electroplated them with conductive polymers to create a form close to brain cells. [7,8] Another approach to enhancing biocompatibility is using mixed-material strategies, such as appropriate contact of bioactive molecules with brain tissue and anti-inflammatory probe coatings to alleviate inflammation [9,10].

There are also some detector studies for electrical signal enhancement [11], paying more attention to increasing the electrode signal-to-noise ratio to obtain higher sensitivity and better signal quality.

2.3. The development of BMI signals

BMI is divided into invasive BMI and non-invasive BMI. EEG and ECoG are used more, respectively. Therefore, in this section, the work will discuss the development of EEG and ECoG separately.

2.3.1. EEG. The main way BMI applies non-invasively is by detecting mental activity and studying it with the help of external devices and machine learning. EEG is the most commonly used imaging method in this way. EEG has developed rapidly because of its non-invisibility and simplicity.

Recent research has focused on EEG and emotion and EEG-based machine learning.

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EEG and emotion: Emotion recognition based on electroencephalogram (EEG) has recently been one of the hotspots of BMI research. It can identify basic emotions by recognizing brain wave signals and establishing information channels for people with disabilities. Multiple groups have studied EEG emotional signatures and classification methods [12-14]. Both groups [12,14] mention that selected characters are best when used with classical classifiers like random forests. The most accurate single classifier, the Deep mental network, can achieve 94.89% accuracy [14].

Combination of EEG and machine learning: Machine learning in BMI refers to using labeled data to learn brain signals from users, which requires classification and regression of data features involving classifiers and data modeling. Based on this, some groups evaluated diverse kinds of primary combinatorial classifiers [15] and then developed classifiers that performed well in stability and accuracy. In the latest study, convolutional neural networks (CNNS) and deep neural networks proved effective and were used by multiple groups in BMI based on P300 and MI (two EEG brain electrical paradigms). [16,17]

2.3.2. Electrocorticography (ECoG). Compared with non-invasive EEG, invasive ECoG has stronger electrical signals and is more suitable for recording large-scale nerve signals, which has great potential in neuroscience. Because of its invasive nature, ECoG was less developed than EEG in its early years. However, as researchers progress on nanomaterial electrodes that optimize biocompatibility, shape size, and signal-to-noise ratio, ECoG will play a more critical role in BMI.

Recent research on ECoG has focused on its application in the medical field. ECoG is primarily used to treat those with amyotrophic lateral sclerosis (ALS) [18] and with quadriplegia [19], the mechanism of which will be explained in detail in the next section, "the application of BMI."

2.4. The application of BMI

BMI is mainly applied in the medical field, and the development of this field is relatively perfect. BMI is often used to restore movement and brain sensation and has achieved considerable success. In addition, the application of BMI in life and entertainment is also gradually developing and will be slowly put into commercial use to facilitate people's lives.

2.4.1. Medical field (restoring movement). In the medical field, brain-computer interfaces are mainly used to restore motor function and treat diseases such as stroke, epilepsy, and Parkinson's disease

There are two main methods of BMI-based treatment: driving neuroprostheses and orthotics. The former primarily involves invasive and interventional BMI, while the latter involves non-invasive BMI. In addition to the above two treatment methods, the author will also describe the development of clinical technology in medicine and the research and development of assistive devices, which have contributed to restoring patient mobility and facilitating patient life.

Drive neuroprostheses: This method is primarily used to help quadriplegic patients regain mobility. By applying a continuously online ECoG to decode the patient's brain activity and send commands to the effector, the approach helps the patient activate the exoskeleton to drive the neuroprosthesis to complete action commands such as walking. The method can last up to seven weeks without recalibration [19].

Orthotic combination: This method is mainly used to help stroke patients with rehabilitation training. Tailoring rehabilitation exercises by measuring and decoding brain activity with an EEG headset and transmitting that information to a computer, thus facilitating patient recovery [20,21].

Clinical technology development: Although BMI promises to restore patients’ motor function and sensation, its clinical use has yet to been widely developed, partly because the quantity of channels has been limited. For clinical applications of brain-machine interfaces, some groups are now developing neurosurgical robots that efficiently insert electrodes and use implantable devices to detect and record test data [22].

2.4.2. Medical field (restoring brain sensation). When it comes to restoring brain sensation, cochlear implants are the most mature application in this area. A cochlear implant uses electrical impulses to stimulate the cochlear nerve, thus conveying audio info to the brain. Meanwhile, cochlear implants stimulate various parts of the cochlea according to sound frequencies, which helps people distinguish sounds.

Other implants, such as the vestibular apparatus and artificial retinas, are examples of how BMI can help patients regain perception.

2.4.3. Life and entertainment. In life and entertainment, applications of brain-computer interfaces are also growing steadily. However, they are in the early stages of research for robot control, brain control, spellers, and wheelchairs, among others.

Robot control: Several studies have shown that using BMI to drive mobile robots has reliability and continuity [23,24]. Researchers can control the robot to reach a certain location to obtain a certain item.

Brain Control: Let users learn to make themselves relax by controlling their Alpha waves [24].

Spellers: Researchers use EEG to decode brain activity, thus helping people with ALS or paralysis communicate with the outside world, complete activities such as spelling, and get out of a "locked" state [25].

Wheelchairs: Several studies have suggested that wheelchairs can be driven by P300-based BMI [26,27]. One of them [26] collected data from a non-invasive EEG headset, trained a classifier with user-based P300 features, decoded the user's brain activity, and transmitted the command to the wheelchair, completing real-time control of the wheelchair with an accuracy of about 84%.

3. The challenges of BMI

As a newly developed technology, BMI is still in the early stages of immaturity and faces multiple challenges. Unreasonable use of BMI may lead to hidden dangers in user safety, psychology, privacy, and so on. Among these pitfalls, neuroethics and technical inadequacies are of the most concern.

3.1. Neuroethics

Neuroethics mainly confronts the ethical issue of animal experiments.

The controversy over animal testing began as early as 2018. At the 2018 American Brain Project, the neuroethics group and researchers clashed over whether to conduct research on non-human animals, with deontological and utilitarian influences on both sides. Between 2018 and 2022, brain-computer interface technology company Neuralink Inc., to rapidly expand, killed about 1,500 experimental animals used for brain-machine interfaces, facing federal department review in the US. Due to the need for rapid development, brain-machine interface-related experiments emerge one after another, but this conflicts with animal welfare protection, causing controversy and becoming a socialization problem [28].

3.2. Technique imperfections

Currently, the main technical difficulties lie in the electrode material of ECoG.

The ideal electrode material has the following three main characteristics: (a) improved electrical properties, significantly reducing the impedance of the electrode; (b) flexibility; and (c) mechanical properties with biocompatibility.

In terms of improving electrical performance, the biggest challenge is to reduce electrode impedance. Since the BMI electrode generally has a smaller surface area, it usually has a higher electrode impedance, which leads to a weakening of the electrical signal and a decrease in the quality of the electrode signal.

The softness and mechanical properties of electrode materials are also challenges worth considering. If the mechanical properties of the electrode are incompatible with the brain tissue, when the electrode moves, the tissue will be injured, and an inflammatory response will occur.

4. Conclusion

This paper reviews the recent research progress of BMI, including electrode materials, BMI signals (EEG and ECoG), applications of BCI, and challenges faced by BCI. The paper reviews various electrode materials, including metal microfilaments, silicon materials, carbon materials, and nanomaterials. Among them, nanomaterials have an excellent performance in biocompatibility and have made significant progress recently. Regarding BMI signals, EEG is often associated with mood research and machine learning, while ECoG is widely used to treat diseases. In terms of the application of BMI, BMI is mainly used in the medical field and life entertainment. The current challenges facing BMI are animal testing in neuroethics and the imperfection of BMI in electrode materials.

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