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Brain Machine Interface for Robotic Application: A Review

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Abstract. Over the past few decades, the brain-machine interfaces (BMI) application has rapidly developed, particularly BMI robotic devices, with the aim of restoring independence and autonomy to patients with movement disorders. This paper is based on 20 research papers published over the past 17 years, summarizing the current status of non-invasive BMI systems and focusing on the interaction between patients, robots, and BMI systems. We found that BMI is now applied to machine-driven devices, and BMI systems are mainly based on external information stimuli, while the vast majority of BMI robots use discrete control systems. The key is that only a few research and development teams have investigated the evaluation of BMI robots by disabled users. The review highlights urgent challenges in this field, from the integration of robots and BMI systems to user-centered design concepts, which enhance BMI conversion.

Keywords: brain-machine interface, robot, system, component

1. Introduction

Brain-machine interface (BMI) is a technology that helps people with movement disorders communicate their neural signals through the normal nervous system, providing them with another way of interaction [1]. The main key to BMI is to recognize the neural signals emitted by the brain in response to external stimuli and issue control commands to mechanical devices. The basic operating principle of BMI is that the device can correspond to the patient's neural signals according to the specific requirements of different situations [2]. In the early stages of BMI research, the main focus was on the computational challenge of identifying patients' specific intentions. Later, with breakthroughs in multiple interdisciplinary technologies, it was proven that the brain could control a virtual keyboard, which gave patients with movement disorders the hope to communicate and interact with family and friends again [3].

Recently, there have been new advances in BMI research, particularly in the field of connecting BMI systems with robotic devices. In today's robotic devices, once the true purpose of the patient is decoded and proven, it will not only be displayed on a virtual keyboard for patients to choose from but also enrich the database for different machine devices and provide solutions. At present, researchers have invented various robots to assist patients in their daily lives. For example, electric wheelchairs, robotic arms, and other mechanical devices help patients move or rehabilitate [4].

However, integrating robots with BMI systems is not a simple task, nor should it be simply classified as an engineering project, which involves the integration of multiple interdisciplinary

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technologies [5]. In fact, BMI interacting with complex mechanical devices in a complex and irregularly changing environment may alter users' neural signals, leading to a series of serious consequences such as misinterpreting instructions. At the same time, various other factors should be taken into account, such as the most stable way to generate control instructions and the fast familiarization method for BMI to interact with new users.

Currently, there are some challenges when combining BMI with robotic devices. For instance, the integration between BMI system and robots is in the basic stage. In fact, in the area of brain-machine interfaces, robots are seen as tools for executing user quality. Most studies have not considered human-computer interaction, and most research has focused on the components of BMI systems. This biased research overlooks the key to the BMI cycle: artificial intelligence, robots themselves, and user interaction strategies [6]. As mentioned earlier, many studies focus on robot control and underestimate (or even ignore) the intelligence of robots. In addition, even if the concept of human-machine communication is included in the design and the collaborative effect of robots is achieved, it also dilutes user participation and influence

The papers review the academic area of BMI robotic devices. Emphasize will be placed on BMI, the interaction between robotic devices and users. Section 2 introduces the closed-loop learning of the BMI system and describes its system framework and common methods. In section 3, we will explain how users' neural signals are converted into control signals for robotic devices [7]. In section 4, we will explain common control methods and interactions between devices, as well as common strategies for applying mechanical intelligence to BMI application systems. Finally, in section 5, based on BMI research and market conditions, we will discuss current challenges and identify potential areas for the future development of BMI robotic devices.

2. Core principles of Brain-Machine Interface (BMI)

2.1. Data acquisition

The BMI system traditionally consists of multiple different units responsible for collecting neural information, filtering useful information, classifying information, and producing instructions for external mechanical equipment [8]. Figure 1 shows the BMI cycle working diagram. However, the common workflow of BMI systems may result in errors. BMI is not only used as a tool to read patients' inner thoughts. In fact, the interaction between users and machines in the BMI system has achieved good control over external machines. On the one hand, patients learn how to adjust brain neural signals based on the real-time feedback provided by sensors. On the other hand, the BMI system updates and upgrades based on data accumulation, establishing exclusive data models for users to better serve them. The interaction between users and the BMI system is called interactive learning, which is an important component of the successful application of BMI [9].

Nowadays, the vast majority of BMI systems adopt a cyclic structure, but there are subtle differences in information collection, processing, classification, and other aspects. There are significant differences in issuing instructions to mechanical equipment. Can robots respond quickly to users when designing BMI circulation systems? The interaction between robots and BMI systems supports users in completing complex behaviours. These two concepts are very important.

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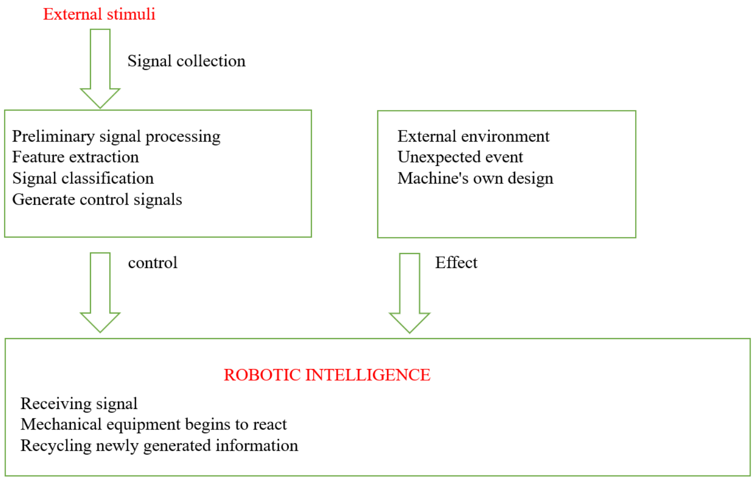

Figure 1. BMI system cyclic control mode

2.1.1. Invasive and non-invasive acquisition techniques

According to neuroscience research, the information collection of the BMI system could be divided into Invasive and Non-invasive methods. Invasive BMI refers to the direct interception of local electronic signals from neurons by implanting micro electrons below the cerebral cortex. Although invasive acquisition technology has fast acquisition speed and high space utilization efficiency. However, signal transmission is still affected by brain tissue [10].

The non-invasive BMI system utilizes the electrical activities of the brain, for example brain magnetic resonance image, electroencephalography, etc [11]. The non-invasive BMI system has a high resolution, which ensures rapid response of the robot and enhances communication between the user and the mechanical equipment. Non-invasive BMI has become a common BMI collection technique due to its low cost and portability.

2.1.2. Processing of neural signals and extraction of information

The BMI system processes neural signals and extracts specific information from data. The operation of these programs is related to the users' psychological state, aims to the better summarize the users' intentions.

The Non-invasive BMI system, common information processing method aims to improve which the quality of recorded data. For example, using tools such as filters to eliminate potential interference in signals and enhance the signal response of brain tissue [12]. Other methods aim to place data on virtual platforms in order to better address differences in signals. At the same time, technologies such as public space models use useful information to create new characteristic spaces for classification.

2.1.3. Selection of information features

There is a lot of information that needs to be classified during the information extraction process in the above paper. Due to the limited available data in the study of BMI system, the difficulty of classification deduction is high, and the model construction may have significant deviations. Based on the above reasons, BMI systems are usually equipped with feature selection techniques, similar to traditional robot learning applications.

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The selection of information features in the BMI system depends on the supervision and statistics of each different type of feature in order to quickly identify and separate features [13]. This automatic selection program is usually modified and upgraded by professionals based on the psychological and neural information of relevant users. Therefore, neurophysiological signals will be prioritized for transmission through information channels.

2.2. Interaction modalities in Brain–Machine Interfaces

The BMI systems decode neural signals to a certain extent and convert them into commands for controlling robots. In the past, based on the tasks performed by users and their associated neural channels, the interaction process between BMI systems and robots has been successfully discovered. To some extent, users are required to engage in different psychological activities to obtain information controlled by robots.

2.2.1. Changes based on external stimuli

Previous studies have shown the connection between external stimuli and EEG signals, which can also be used simultaneously to control the movements of devices. In this approach, the BMI system is the most explored [14]. The BMI system under stable voltage can decode neural signals from multiple groups of visual nerves, as visual responses are strictly related to the frequency of external stimuli. When users fix their perceived visual perception, their visual response can accurately select targets from multiple relatively stationary visual stimuli and generate visual signals for transmission. In this type of system, each stimulus-generating target is associated with a specific action of that robot. Users can issue low-level commands (such as forward, left turn, etc.) or select from multiple location targets (such as a bathroom, bedroom, living room, etc.) to achieve the purpose of driving the robot [15].

2.2.2. Self-paced, endogenous paradigms

Sports imagery has always been the most explored method for the BMI self-paced system. The BMI system based on motion imageries mainly relies on which autonomous regulation of decoding rhythm, and users achieve this by imagining the movement of a certain part of their body. In the field of neurophysiology, the characteristic of this activity is the fluctuation of brain electrical activity, which is called event-related synchronization and reflects the aggregation and dispersion of neural tissue during the execution of the activity [16]. The neural signals associated with motor imagery often occur on waves of different frequencies, and the exact location and frequency depend on the user.

2.3. Driving device and control modes

Discrete control strategy is a strategy that converts the information decoded from BMI into signals suitable for controlling robot equipment. When users issue discrete commands to the outside with intervals of a few seconds, we adopt a discrete control strategy. In fact, the combination of BMI based on external stimuli with this strategy is relatively smooth. However, this strategy can only generate discrete instructions, and robots can only use these instructions to trigger semi-automatic actions.

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2.3.1. Continuous control strategy

Compared with discrete control strategies, continuous control strategies are based on brain-autonomous decoding, and this BMI system is independent of external discrete events. This strategy can improve the accuracy and related to performances for the brain-controlled device. Whale, considering the complexity of neural signals, generating continuous signals still poses certain challenges. The known solutions now include directly projecting activity-related neural signals into the robot or using advanced technology to control the BMI system and improve the output stability of the decoder.

2.4. BMI for robotic application

The BMI system mentioned above has been widely applied in various robotic devices. So far, remote-controlled brain-computer interface robots are a common type, accounting for 38.4% of the research sample [17]. The data in the study shows that more than half of BMI systems use non-invasive methods to collect data. As shown in the picture (Figure 2), 81.7% of which studies reported experiments on healthy users, while only 18.3% of patients with movement disorders were evaluated in extensive research. The future fields of BMI systems will include medical rehabilitation, virtual interaction, industrial and daily life assistance, robot creation, etc. [18]. BMI will have a wide range of fields in the future, with broad prospects for industry development, and will further provide employment opportunities.

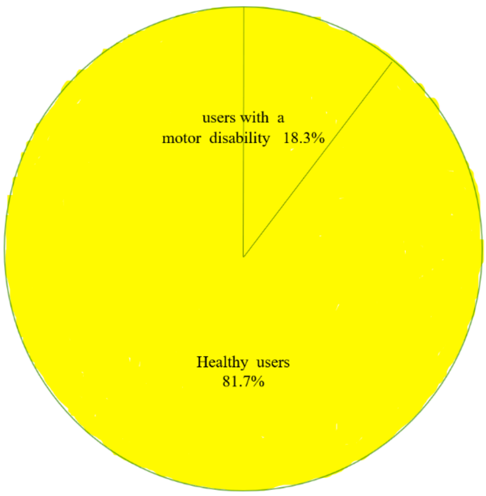

Figure 2. Percentage of healthy users and users with movement disorders in BMI devices

3. Conclusion

Despite various achievements in the research of brain-computer interfaces, there are still many challenges in the field of BMI. The BMI system is closely related to external stimuli, although non-invasive acquisition techniques ensure rapid iteration of calibration cycles [19]. But this BMI system cannot fully control the response of the machine equipment, but restricts users from making choices from a limited selection list, thereby reducing the coupling between the robot and the user. On the other hand, the effectiveness and user acceptance of self-paced BMI systems are low, and highly focused attention is required during human-computer interaction. The way to overcome the limitations of these two BMI systems is to design a BMI system that relies on multiple patterns.

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So far, which of the most pressed challenges are related to domain transformation of brain-computer interface design goals? As mentioned earlier, only 18.3% of applications are evaluated by individuals with motion impairments, and even fewer are specifically designed for device control.

This trend has its drawbacks. Firstly, the effectiveness of training strategies for some BMI systems is not optimal. Whether it is collection technology or interaction technology, specific corrections should be made to the corresponding BMI technology module to simulate the user's neural signals separately. However, a long training period can reduce user interest and which lower quality of the data decoded by BMI decoders [20]. Secondly, currently, most programs are used for booting, and there is no evidence to suggest that this is a daily priority for users. We only speculate that widespread user participation in device evaluation will promote the research and upgrading of the new generation of BMI machine devices.

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