Combining Robotic Vision with Non-Invasive Brain-Computer Interfaces Development and Future Directions

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Abstract. The profound growth in brain-computer interface (BCI) technology has brought forth novel interdisciplinary applications, particularly in the realm of robotics. This review delves into the challenges of using non-invasive BCIs for precise robotic arm operations, with an emphasis on the transformative potential of integrating BCI with machine vision. Based on some problems in BCI applications, this paper emphasizes the use of machine vision combined with BCI signals to help non-invasive brain-computer interfaces improve the correctness and efficiency. Through detailed analysis, it is demonstrated how computer vision complements BCI, ameliorating issues like inherent noise and decoding inefficiencies associated with non-invasive BCIs. Moreover, the discussion touches upon the enhanced user experience offered by this integrated approach, and the potential it holds for addressing the compatibility challenges in BCIs. Although the combination of the two technologies can solve mutual problems, there are also certain limitations. For example, two different data may be more complex, so there are higher requirements for algorithms and processing methods. In addition, the development of a combination of two devices The system will have higher overhead, making it impossible for the average person to afford the cost of using it at the same time。As BCI technology continues its upward trajectory, this synthesis with robotic vision heralds a new era of harmonized human-machine interactions.

Keywords: Brain-computer interface (BCI), robotic vison, robotic arm.

1. Introduction

As the development of brain-computer interface (BCI) technology, it is constantly applied in new fields, and it is also associated with more disciplines and technologies to produce more comprehensive and diversified designs [1-4]. Recently, research into BCI-controlled robots has become part of the field of neuroscience and robotics[5, 6]. Invasive BCI-operated robotic arms show good promise in helping many patients with disabilities or limited mobility due to the disease. BCI enable external software or applications to directly receive human brain instructions or enable communication between humans and machines. BCI can typically categorized into three types, Invasive BCI, semi-invasive BCI and non-invasive BCI [7-9].

Although great progress has been made in existing BCI research to help people with diseases and people with disabilities, this method is generally controlled by EEG signals, but this work is still challenging due to the low decoding efficiency of BCI, and the problem is more serious in non-invasive BCI [10, 11]. In addition, controlling the robotic arm through the BCI may result in some redundant commands, which may cause an uncomfortable experience for the user when using the robotic arm. Regarding the above problems, Kwon [12-14] and his team have proposed an effective solution, that is, using BCI to identify user ideas while combining visual information to make comprehensive judgments, so as to make a breakthrough in the limitations of the aforementioned use of BCI alone, reduce the possibility of meaningless actions by the robotic arm, and achieve the effect of accurately identifying user intentions [15, 16]. In addition, the use of vision for intelligent assistance is also a proven and feasible method, the user only needs to output a simple BCI based on motion imagination combined with vision to complete the function of controlling the movement of the robotic arm and target selection [17-19]. These solutions have higher accuracy for BCI that would otherwise be used alone, especially for non-intrusive BCIs that are themselves subject to a variety of signal interferences, which also means much higher efficiency[20-23].

In this article,This article will present the challenges of using non-invasive brain-computer interfaces to operate robotic arms with precision and discuss current efforts to address these challenges. This paper explains the important role of BCI in helping patients interact with robotic arms and discusses compared with using BCI signals alone as instructions the advantages that after combining machine vision and BCI.

2. Related Works

As shown in Figure 1, the workflow of using robotic vision and BCI to control the robotic arm. By transmitting the collected visual information and EEG information to the robotic arm at the same time for comparison and verification, if the EEG signal can correspond to the visual information, The arm will execute the corresponding grasp or release command. If there is no response, the robot arm will not take any action [1]. And visual information precedes EEG information, so when some visual information is transmitted, no EEG information will be transmitted to the robotic arm. In terms of hardware, the sensor on the robotic arm will display the current force situation of the robotic arm. When the pressure reaches a certain level, it will stop moving. This design also allows the robotic arm to adjust the strength according to objects of different sizes and shapes, and the visual information is provided by A pair of glasses equipped with a camera for image collection [4, 5].

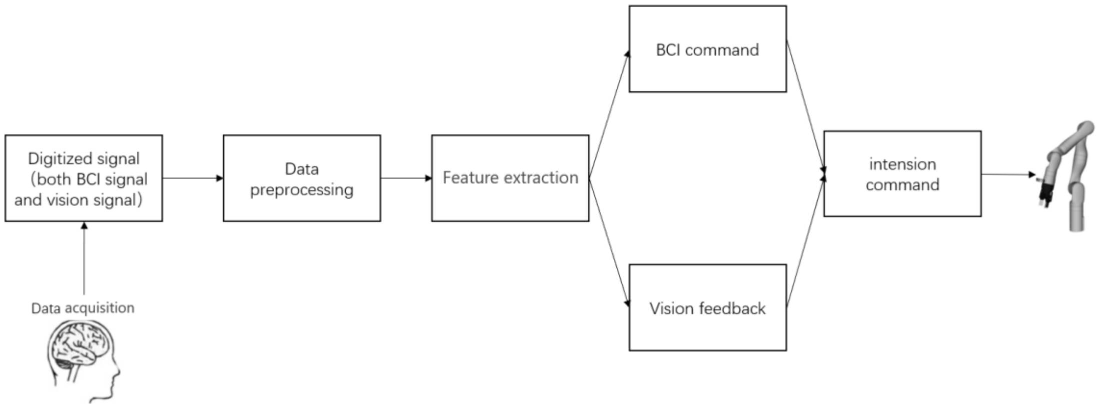

Fig. 1 workflow of use robotic vision and BCI to control the robotic arm [3]

In principle, machine vision can provide real-time feedback of the current environment. For example, if the user wants to grab an object, then machine vision can provide information such as the position, shape, size, etc. of the object. The collected image information is compared with the BCI extracted image information. The signals are combined to issue instructions to guide the robot arm to make movements. It is precisely because BCI signals have similar processing steps to visual signals, including signal preprocessing, feature extraction, data analysis, etc. This also means that the two can be better compatible with each other. Non-invasive BCIs primarily leverage EEG signals, which often come with inherent noise. External factors like muscle movements, ambient electrical noises, or even the user's state of alertness can influence these signals. Consequently, this affects the clarity of commands being sent to robotic arms, potentially leading to unintended movements or actions. One significant challenge of BCIs, especially the non-invasive type, is the potential for redundant or superfluous commands. These might stem from involuntary brain signals or distractions in the user's environment, which the BCI might interpret as valid commands. When translated to a robotic arm's movement, this can result in erratic or uncoordinated actions [7]. Decoding brain signals into meaningful commands for robotic arms in real-time is computationally demanding [16]. Low decoding efficiency can lead to lags or imprecise movements, potentially frustrating users or leading to operational errors [17].

While non-invasive BCIs offer numerous advantages, especially in terms of safety and accessibility, they come with challenges that researchers and developers must address[19]. By understanding these challenges and employing the aforementioned principles and methods, the field can move closer to creating more effective and user-friendly interfaces between the human brain and robotic systems [21].

In summary, integrating robotic vision and non-invasive BCI presents a promising avenue for controlling robotic arms through a harmonious blend of visual and neural information. The setup, However, the non-invasive nature of BCIs, while beneficial in terms of safety and accessibility, introduces complexities due to inherent noise and potential for unintended signals. As these challenges surface, it becomes imperative for researchers and developers to delve deeper, seeking solutions that enhance the efficiency, precision, and user experience of this integrated system. By holistically addressing these hurdles and harnessing the power of machine vision and BCI, and it will bring users a better user experience and a simpler use process.

3. Discussion

Compared with the previous method of solely relying on BCI to receive instructions to control the robotic arm, the accuracy of combining BCI with computer vision has been significantly improved. Data is read through computer vision, and then the visual data is processed, so that the system can identify and identify objects. Positioning allows the robotic arm to more accurately locate the specific location of the object to be grasped, as well as the size and shape of the object, etc. [13]. In addition, imitating human vision can better help the robot arm interact with objects. In Y's experiment [15], the grasping instructions were only executed through the BCI signal, so the robot arm may be due to the force generated during grasping. Too small causes the object to slip, or too much force causes the soft object to deform, etc. Problems caused by the inaccuracy of the BCI signal [18].

Secondly, computer vision is very effective in improving user experience [10]. After using an external BCI to receive the signal, it takes a lot of time to process the signal and extract features, and then convert it into instructions and send them to the robotic arm. As a result, the user cannot control the robotic arm in real time, which also greatly reduces the user experience [2, 3]. Integrating computer vision will greatly improve this problem. Possible errors can be corrected through the recognition of new environments without the need for secondary user intervention to save time

In research on brain-computer interfaces, compatibility seems to have become a new challenge. Different systems may only receive and process specific EEG signals, so it is difficult to have a brain-computer interface that can adapt to different systems, and in real life one Brain-computer interfaces may need to transmit signals to multiple systems, which places new requirements on the compatibility of brain-computer interfaces [4, 9]. Compared with configuring different types of brain-computer interfaces according to different systems, using robotic vision can potentially alleviate this challenge. By integrating computer vision, it can provide real-time visual data feedback for the system so that the system can adjust and improve the output instructions instead of Control the robotic arm directly based on the BCI signal [14].

This chapter mainly discusses the dilemmas and challenges currently faced by BCI technology. The BCI system after integrating computer vision will be improved in three aspects. The precise positioning of objects through computer vision improves the accuracy of robotic arm movement. Through visual signals and The signals received by the BCI are combined to analyze the environment and fine-tune possible erroneous operations to improve the user experience and enable users to control the robotic arm in real time. Finally, regarding the compatibility issues between BCI and other systems, computer vision can correct instructions based on feedback from visual data so that the system can be backward compatible with other devices.

4. Conclusion

In light of the profound evolution in brain-computer interface (BCI) technology, the integration of BCI with robotic vision has emerged as a pioneering solution for enhancing robotic arm control. The amalgamation of these two technologies substantially improves precision, mitigates the limitations inherent in non-invasive BCIs, and offers a holistic approach to addressing redundancy in commands. The augmentation of computer vision notably streamlines real-time command processing, thereby enhancing the user's experience, and offers a potential solution to the compatibility challenge across diverse systems. The combination of the two technologies also brings new challenges, such as the high cost of visual acquisition devices and non-invasive brain-computer interface devices, and the burden on the system caused by the simultaneous processing of multiple data, etc., it is recommended to use glasses to connect the camera combined with the EEG cap to reduce the additional overhead caused by machine vision equipment. At the same time, prioritizing visual data as a guide will enable the robotic arm to react faster. As the dynamics of these two technologies coalesce, it's pivotal for research and innovation to remain centered on maximizing efficiency, enhancing user experience, and ensuring adaptability across platforms, With the development of future technology, more potential application scenarios will be gradually discovered, and many of the current limitations will be solved in sequence.

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