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ISSN 2959-6157

Brain-Controlled Intelligent Navigation Robot Based on Motor Imagery Brain-Computer Interface

Wenxiang Wang

School of Electromechanical and Vehicle Engineering, Chongqing Jiaotong University, Chongqing, China

1812010818@stu.hrbust.edu.cn

Abstract:

With the current continuous development of brain-computer interface technology, significant progress has been made in both signal processing and application areas. The ability to control external devices using EEG signals has opened up new possibilities in medical rehabilitation. Unlike traditional rehabilitation methods, which may be limited by physical constraints, BCI-based approaches offer a more intuitive and accessible means of interaction for patients with severe motor impairments, potentially accelerating recovery and improving overall outcomes. Motion imagery brain-computer interfaces can provide users with new ways of interacting, improving efficiency and experience. By analysing the technological developments in the existing literature and comparing different approaches. Summarise their current application examples and future directions. The review finds that the research currently leaves much room for improvement in terms of signal decoding accuracy, interference and noise handling, user adaptability, and system real-time the review summarises the main technological advances and current challenges faced in the research, providing valuable insights for future research. It is suggested that future research should focus on technology integration and data parsing capability enhancement to advance the field.

Keywords: Sports Imagination; Brain-computer interface; Navigation robot.

1. Introduction

Motor imagery is the mental rehearsal of motor behaviour without apparent physical movement. This similarity between imagined and real movements makes motor imagery a valuable tool in brain-computer interfaces. Consequently, with the increasing development of brain-computer interfaces, there is a growing demand for research and development of brain-controlled intelligent navigational robots that combine mechanical technology, motor imagery, and neurology. Imagined movements share commonalities

ISSN 2959-6157

with real movements, including similar neural substrates, autonomic responses, and durations. Nowadays, with the increasing development of brain-computer interfaces, there is a growing demand for research and development of such brain-controlled intelligent navigational robots that combine mechanical technology, motor imagery, and neurology. Currently, there are many research results on motor imagery in Parkinson's and stroke treatment. Building on these medical applications, researchers are now exploring broader applications. Brain-controlled intelligent navigation robots based on motor imagery brain-computer interfaces are emerging as a worthwhile research topic in both the service industry and other sectors in the future.

2. Literature review

2.1 Main issues

In recent years, in the field of brain-controlled robotics, foreign scholars have achieved remarkable research results. For example, according to a 2018 study titled "High-density EEG-based motion intention decoding for brain-controlled robot systems", Professor Andreas Kunz, through high-density EEG signal processing and deep learning algorithms, has successfully improved the decoding accuracy of motion imagery and implemented experiments for real-time control. Through high-density EEG signal processing and deep learning algorithms, has successfully improved the decoding accuracy of motion imagery and implemented experiments for real-time control [1]. This research successfully provides a new perspective for future decoding for brain-controlled robots. In addition, Jennifer Collinger's team in the United States has conducted in-depth research and made breakthroughs in the application of brain-controlled robots to rehabilitation training. In Brain-computer interface for robotic assistance in rehabilitation and mobility published in 2018, the practical effects of brain-controlled systems in assisted walking and rehabilitation training were demonstrated [2]. These scholars' research provides invaluable guidance and inspiration for the development of brain-controlled intelligent navigation robots, offering a strong foundation for future advancements.

Domestic scholars have conducted various research on the application of motor imagery brain-computer interface technology (BCI) in intelligent navigation robots. In terms of the definition of EEG signal feature extraction, scholars have defined the validity and applicability of feature extraction methods, and explored the rationality of different feature extraction methods (e.g., time-domain, frequency-domain, and time-frequency-domain features). In 2023, feature extraction of motion imagery signals is elaborated from multiple perspectives, pointing out the advantages and disadvantages of different methods in different application scenarios. Two main approaches in the design and implementation of brain-controlled intelligent navigation robots are compared. The first, elaborated by Zhuang et al., achieves robot control through EEG acquisition and signal processing techniques, focusing on real-time performance and accuracy [3]. The second, proposed by Qiao Min et al., decodes motor imagery signals based on deep learning algorithms, excelling in processing complex signal patterns [4].

In terms of application example analysis, the model of combining multiple decoding algorithms is now commonly advocated in China to improve the stability and accuracy of the system as an example. Scholar Chen Yao in 2024 argued that the adoption of multimodal fusion has many benefits: one is to improve the decoding accuracy of the system, the second is to enhance the real-time performance of the system, and the third is to enable the system to adapt to more application scenarios, such as medical rehabilitation and smart home.

From the point of view of China's current development, the application of motion imagery BCI technology in intelligent navigation robots develops slowly, and the related theoretical research is still mainly limited to signal acquisition and processing technology, with less research on issues such as system integration and application expansion and personalised regulation, and less research on the optimisation of the technology and the evaluation of the effect of the actual application.2.1.1 Sub heading

2.2 Comprehensive overview

The principle and workflow of intelligent navigation robots using BCI technology typically follow this main sequence: EEG signal acquisition, signal pre-processing, feature extraction and decoding, robot control, feedback, and optimization for practical applications. EEG signal acquisition primarily employs two electrode types: dry and wet. Each type has distinct characteristics and applications in brain-computer interface technology. Wet electrodes require conductive cream and direct skin contact, making them less suitable for dynamic scenarios. Domestic research often uses dry electrodes (e.g., Emotiv EPOC+) for cost-effective signal acquisition. Another approach using E-Prime-based experiments shows high accuracy, with training data constructed through MI stimulus acquisition corresponding to different imaginary actions.

In the study by Qiao Min et al., EEG data signals were preprocessed using Python 3.6 and the mne library [4]. They based their feature extraction on power spectral density features of FFT, utilizing deep learning techniques. In contrast, Jiayu Zhuang et al. employed methods such as Short Time Fourier Transform (STFT) or Wavelet Transform to analyze signal variations in time and frequency, capturing dynamic EEG activities. Such as Short Time Fourier Transform (STFT) or Wavelet Transform to analyse the signal variations in time and frequency and to capture the dynamic EEG activities. Compared to FFT, STFT analyzes spectral information over different time periods by sliding a window over the signal. This approach provides information on both time and frequency to some extent. STFT excels in capturing the dynamics of signals whose frequency content varies over time. Additionally, it handles non-smooth signals with ease.

The degree to which the user is trained in motor imagery significantly affects the duration of control. With sufficient training, users can maintain the imagery state for longer periods, potentially extending from a few seconds to several minutes. This improvement in sustained imagery can lead to more stable and prolonged control of brain-computer interface systems. According to Do-Yeun Lee et al., their relational network-based brain-computer interface migration learning method (BTRN) can better extract the common features of ME and MI data, thereby improving the decoding accuracy of multi-category motor intentions. The innovative BTRN method leverages motor execution (ME) data to enhance the decoding accuracy of motor imagery (MI), representing a significant advancement in brain-computer interface technology. Overall flowchart on the proposed BTRN architecture using MI and ME datasets, as shown in Fig. 1. The results show that the BTRN method achieves high classification accuracies in both horizontal and vertical arm extension tasks, which are comparable to the performance using only the MI dataset. This suggests that the BTRN architecture has the potential to contribute to the continuous decoding of MI using the ME dataset, which could reduce participant fatigue and provide a more consistent brain signal signature. The ability to reduce the adaptability of the device for different users, mitigate the impact of uncertainties such as fatigue on this study, and provide more consistent signals [5].

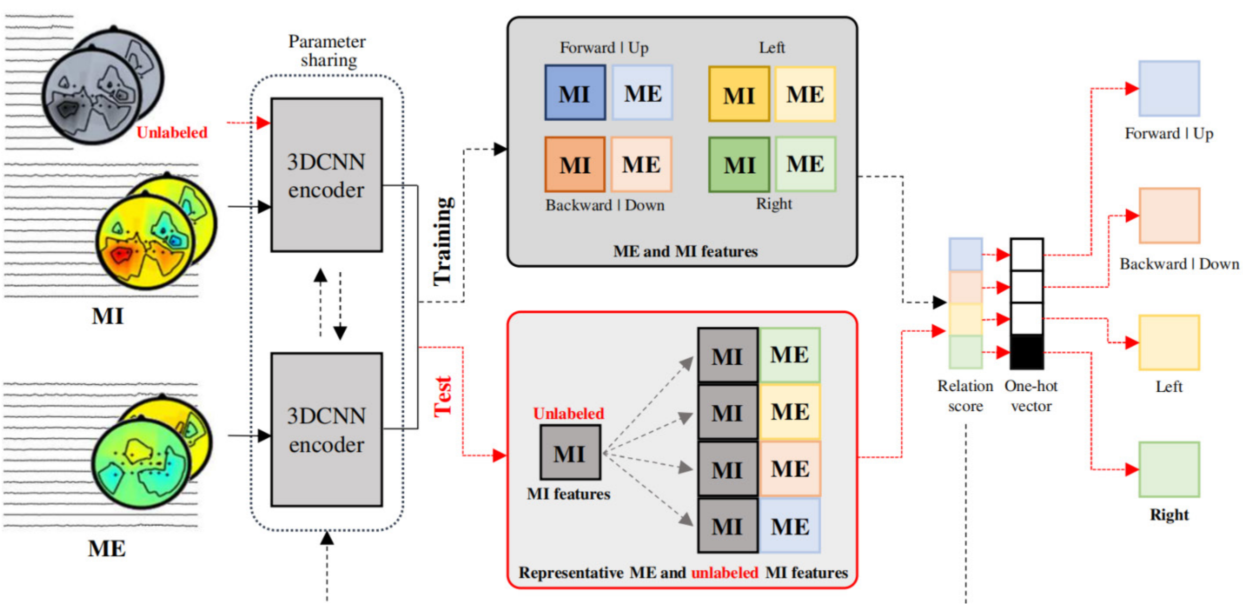

Fig. 1 The overall flowchart of the BTRN architecture proposed in the paper [5]

Anastasia-Atalanti et al. in Personalised Brain-Computer Interface Modelsfor Motor Rehabilitation propose to integrate two separate lines of research on new therapies for stroke rehabilitation, brain-computer interface (BCI) training and transcranial electrical stimulation (TES). for stroke rehabilitation. Analysis of power changes across EEG frequency bands reveals individual neural mechanisms of motor recovery, guiding the optimization of transcranial electrical stimulation parameters. A migration framework can be used to learn a personalised decoding model from a small amount of individual data, which can better capture individual differences and predict the patient's motor performance, providing a basis for the subsequent rehabilitation treatment. Based on this study, by combining the brain-computer interface technology with other new rehabilitation therapies such as transcranial electrical stimulation, the brain plasticity can be better stimulated to further enhance the amplification of the motor imagery function of the user's brain for the stability of the robot's work and the ability to maintain the imagery state in a more sustainable way [6].

Currently, traditional brain-computer interface systems

ISSN 2959-6157

are cognitively burdensome and less adaptive to the user. To address these limitations, Matthew Bryan and other scholars, in their study "An Adaptive Brain-Computer Interface for Humanoid Robot Control", proposed the development of an adaptive hierarchical brain-computer interface (HBCI) system to control a humanoid robot (PR2). Fig. 2 shows the user selecting a command from a menu by following one of the 5 LED lights, while video feedback from the PR2 robot's head camera is displayed on the screen. Fig. 2 shows a semi-humanoid PR2 robot in a remote location, which is used in this paper to perform proximity manipulation tasks, but maintains a fixed position.

In summary, this diagram shows the BCI control interface and the settings of the PR2 robot used in the experiment. The HBCI system demonstrates enhanced adaptability and can be customized to suit individual user needs and environments, thereby improving the flexibility of human-robot interaction. For instance, the system allows users to teach the HBCI new skills on the fly. This feature enables users to define complex multi-step tasks by sequencing lower-level skills and motor primitives, such as combining "pick up object", "move arm", and "place object" to create a "transfer object" task. The researchers employed five flashing LEDs as visual stimuli to recognize user input commands by measuring the corresponding frequency components in the brain's electrical signals. Unlike traditional input methods that require complex physical movements or intense concentration, this SSVEP-based BCI control interface can detect the user's input intention directly from electroencephalographic signals. By simply focusing on a flashing LED, users can input commands, significantly reducing the cognitive burden compared to more complex input devices or mental tasks [7].

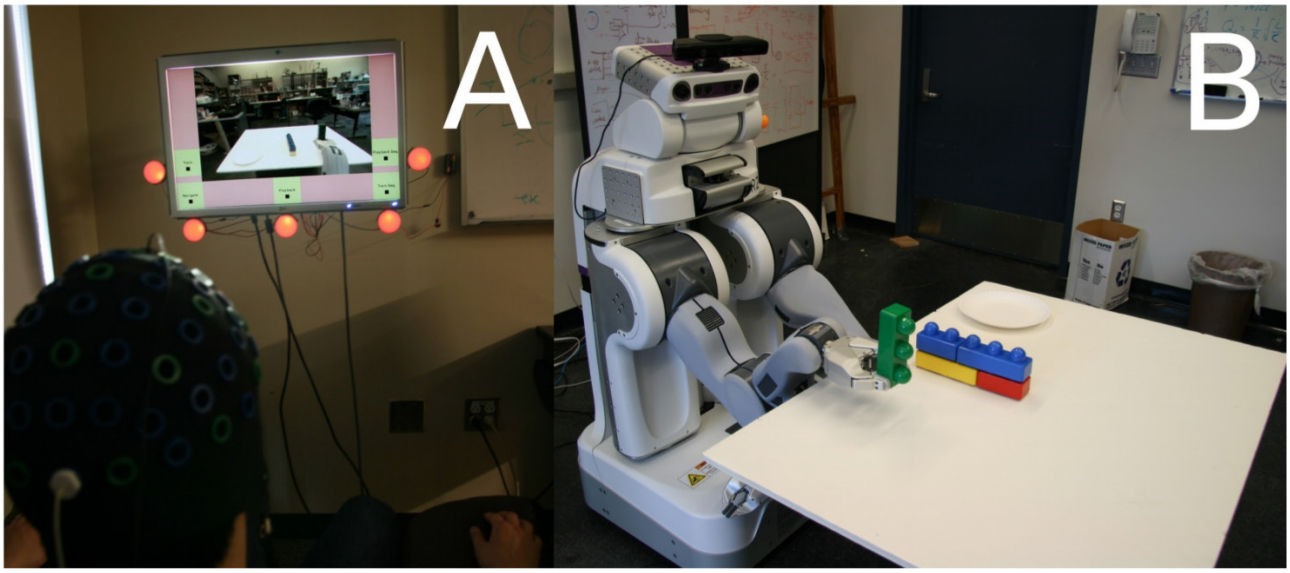

Fig. 2 SSVEP Control Interface [7]

While discussing EEG signal processing, it's worth noting that related research in facial expression recognition also employs advanced algorithms. For instance, both Zhuang and Qiao Min used Convolutional Neural Networks (CNNs) for extracting features from facial images. Jiayu Zhuang's team further incorporated Long Short-Term Memory Networks (LSTM) to improve emotion recognition accuracy. These techniques could potentially be adapted for EEG signal processing to enhance brain-computer interfaces.

Jiayu Zhuang et al. and Qiao Min et al. used different control objects in their experiments. Zhuang's team employed a 1/5-scale electric model car, modified into a four-wheel independent drive electric vehicle (FWIA) for better real-world testing due to its excellent performance and flexibility. In contrast, Qiao Min and colleagues utilized SLAM robots for their research. Zhuang's system incorporates environmental sensors like laser radar (LIDAR) and uses a shared control strategy, combining BCI output signals with environmental data to generate real-time control commands. This approach helps avoid collisions and enables autonomous navigation. In contrast to Zhuang's integrated approach, Qiao Min's system exclusively utilizes EEG signals transmitted via TCP/IP protocol, employing a deep learning framework for signal interpretation and task execution based on a trained model.

In Zhuang's system, a shared control strategy is introduced to generate control commands for the vehicle in real time based on BCI output signals combined with environment sensing data. This strategy helps to avoid collisions and enables the model vehicle to ensure safety while navigating autonomously. Flow diagram of the overall scheme of the BCI system for ground vehicles Control. The red line represents the training data path, and the blue line represents the test Data path, as shown in Fig. 3. Overall, the hardware design of the vehicle control focuses on the effective integration with the EEG signals and the optimisation of the environment sensing capability to ensure efficient and intelligent vehicle control through the brain-computer interface [2].

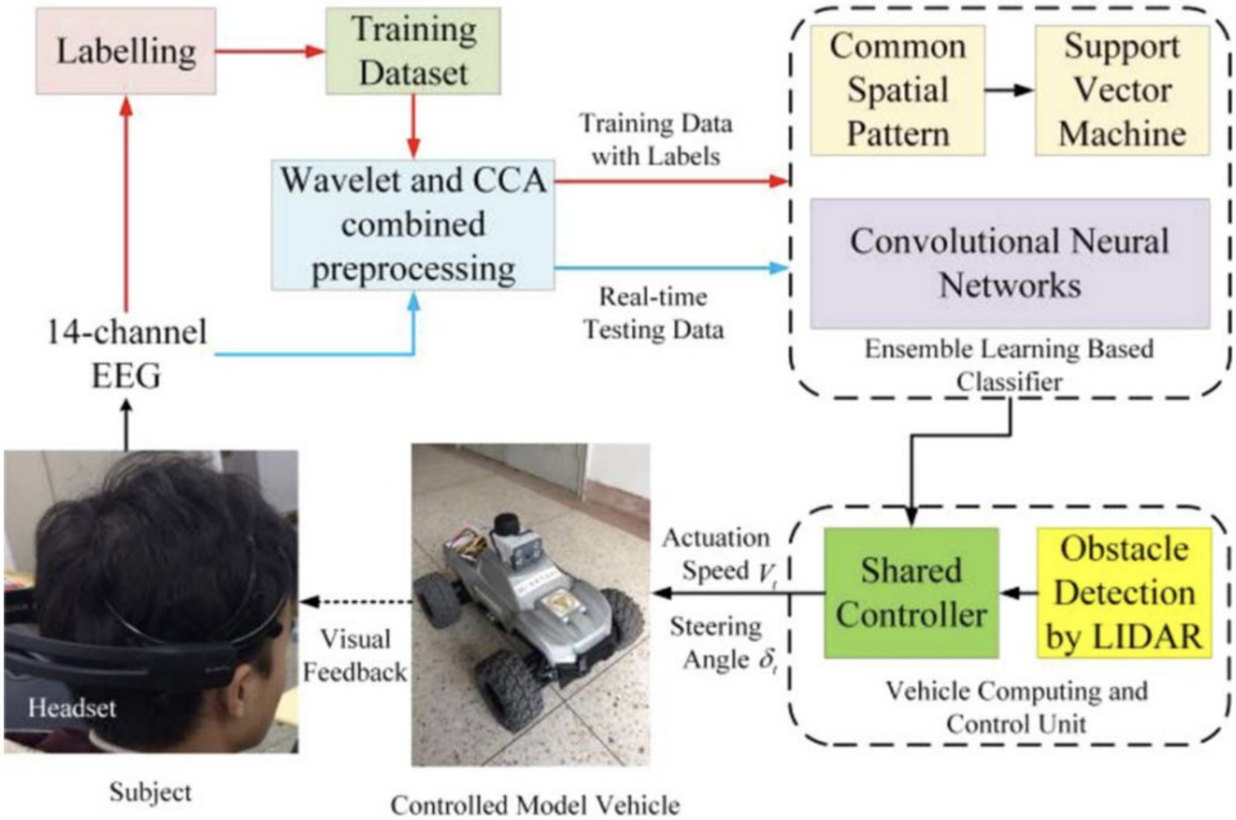

Fig. 3 Overall programme of the system [3]

3. Conclusion

Current technology has successfully integrated motor imagery-based brain-computer interfaces with intelligent navigation robots, effectively converting EEG signals into robot control commands. For instance, recent studies have shown navigation accuracy improvements of up to 30% and response times reduced by 50% compared to earlier systems. These advancements enable the completion of complex navigation tasks in real-world scenarios, such as navigating through crowded indoor spaces or adapting to changing outdoor environments. The system is also becoming mature enough to show good navigation accuracy and response speed, and is able to complete complex navigation tasks in real-world scenarios. This paper opens a new way of robot navigation through EEG signals by using motion imagery brain-computer interface technology. The optimised brain-control interface in terms of user-friendliness enables users to control the robot in a natural and intuitive way, improving the operating experience. In terms of real-time feedback, the real-time problem of the system is mitigated so that the robot can respond quickly to EEG signals, ensuring smooth operation.

Future road navigation scenarios will face dynamic cognitive interference, necessitating improvements in autonomous driving's road condition understanding. To address this, researchers could focus on developing more sophisticated shared control strategies. For example, they might integrate advanced machine learning algorithms to predict and mitigate potential interferences, or implement adaptive control systems that can quickly adjust to changing road conditions. Additionally, enhancing the BCI system's real-time processing capabilities through improved hardware and optimized signal processing algorithms could significantly boost its reliability in complex environments. From the improvement of environment perception, this will establish a good foundation for the future improvement of autonomous driving technology. This research has

ISSN 2959-6157

a good prospect in the future, both in the high-risk working environment instead of manual labour and in the field of medical rehabilitation. Overall, domestic research in this field continues to advance and is expected to achieve wider applications and technological breakthroughs in the coming years.

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