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Design of a Non-Invasive Brain Computer Interface System for Handwritten Text Based on L2 Regularization and Attention Supervision Paradigm, and Optimization of EEG Signal Decoding

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Abstract: This article focuses on the design of a non-invasive brain computer interface (BCI) system for handwritten text based on L2 regularization and attention supervision paradigm, and the optimization of EEG signal decoding. In response to the challenges of non-invasive BCI in terms of signal acquisition accuracy and classification accuracy, this paper innovatively proposes a segmentation recombination preprocessing method, and designs an MLSTM algorithm combining a mapping module and LSTM to achieve accurate output from EEG signals to text. In terms of system implementation, attention supervision paradigm was introduced, combined with L2 regularization technology to optimize the model, significantly improving the quality of signal acquisition and decoding accuracy. The research results not only promote the further development of BCI technology, but also provide a new self-control method for patients with physical disabilities. The research in this article has important theoretical and practical value, and is of great significance for the widespread application of BCI technology in the future

1. Introduction

Stroke, as a serious disease that affects the quality of life of patients, leads to a large number of new cases every year, causing patients to be unable to effectively communicate with the outside world and greatly reducing their quality of life. With the deepening development of neuroscience, people gradually realize that the recovery process after stroke depends on the reshaping of neural mechanisms, which provides a theoretical basis for the birth of brain computer interface (BCI) technology. BCI technology, as an innovative means of neural regulation, has opened up new avenues for patients to communicate with the outside world. It not only shows great potential in the field of medical rehabilitation, but also has broad application prospects in various fields such as military and entertainment. In the field of medical rehabilitation, BCI technology can achieve accurate diagnosis, scientific evaluation, and effective prognosis judgment of consciousness disorders by collecting and analyzing patients' EEG signals, and even establish a direct communication bridge with patients. In terms of military applications, BCI technology can significantly improve communication speed, enhance environmental situational awareness, and provide strong support for soldiers' military technology. In the field of leisure and entertainment, combining BCI technology and virtual reality technology can create more interesting gaming experiences while improving the friendliness of games for people with physical disabilities. BCI technology can be divided into various types based on different triggering methods, such as motor imagery BCI, stimulus induced BCI, and event-related potential BCI. The BCI of motor imagery has a wider range of applications due to its spontaneous and non-dependent nature on external stimuli. The BCI system for motor imagery typically includes key components such as EEG signal acquisition, EEG data preprocessing, feature extraction, classification algorithms, and instruction output. The motor imagery BCI system includes EEG acquisition, preprocessing, feature extraction, classification, and output. In medicine, it offers a new self-control method for physically disabled patients, especially text-oriented BCI for communication. BCI technology is divided into invasive (high accuracy but high risk and cost) and non-invasive (low cost and risk but lower accuracy) based on EEG acquisition. Improving non-invasive accuracy is a research focus. Both methods have limitations, and long-term concentration is challenging.

2. Correlation theory

Recently, significant progress has been made in the fields of neuroscience, signal processing, and machine learning through extensive research. These studies cover multiple aspects such as data augmentation, regularization techniques, differential privacy assessment, photoacoustic imaging reconstruction, motion recognition, attention mechanisms and applications, BCI technology, handwriting task cognitive impairment detection, motor imagery EEG signal decoding, multimodal information decoding, and EEG brain signal decoding into text. There are studies evaluating the effectiveness of data augmentation, dropout using L2 regularization, and differential privacy against member inference attacks; There are studies exploring the application of L1~L2 regularization in sparse view photoacoustic imaging reconstruction; A study has successfully identified displacement forces from combined response measurements by combining L1 and weighted L2 regularization methods[8]; There are studies focusing on new paradigms of attention and attention training, exploring their mechanisms and applications; In terms of brain computer interface technology, research has classified EEG handwritten characters through continuous motion decoding, and cognitive impairment detection in handwriting tasks has been achieved based on frontal camera scenes; A large number of studies have enhanced the decoding ability of motor imagery EEG signals through machine learning, and a systematic review has been conducted; A study has proposed the CognitioCapturer system, which uses multimodal information to decode visual stimuli in human EEG signals; There is also a review of the progress in decoding EEG brain signals into text[14], and a novel hybrid decoding neural network for EEG signal representation is proposed. These studies not only drive the development of related fields, but also provide new ideas and methods for future research and applications.

3. Method

3.1. Motion imagination BCI model for handwritten text

The motion imagination BCI model for handwritten text aims to solve the problems of poor signal acquisition quality and complex decoding process in existing non-invasive motion imagination brain computer interfaces. This model includes four parts: EEG signal acquisition, data preprocessing, classification algorithm model, and result output. The subjects engaged in continuous writing and imaginative movements, and their mental state was monitored using a concentration monitoring device. EEG signals were collected when the concentration level exceeded 60. The collected EEG signals are preprocessed to eliminate power frequency noise and significant signal artifacts, and interference such as electrocardiography and electrooculography is filtered out using a 50Hz low-pass filter. On this basis, the text is segmented using the complexity of time and reassembled into a new dataset based on the similarity between segments to improve data utilization. The model is shown in Figure 1.

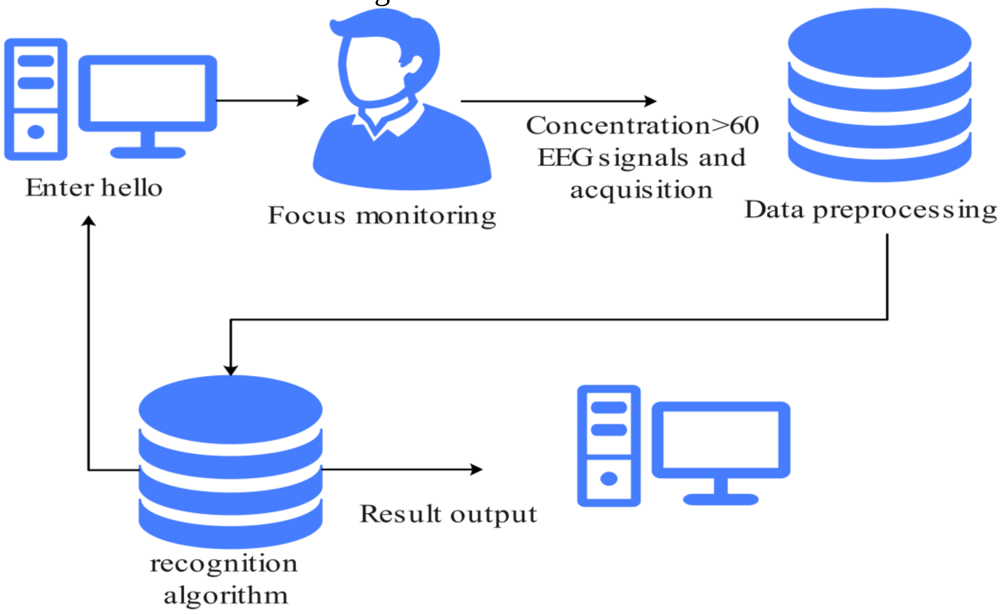

Figure 1. Process of Attention Monitoring and EEG Signal Recognition

In terms of recognition algorithm models, in response to the problems of slow convergence speed and large curve fluctuations that conventional classification and recognition algorithms such as RNN and LSTM are prone to during model training, this study adds a matching module to LSTM and proposes the MLSTM algorithm to improve the classification accuracy of the algorithm. This algorithm obtains the correspondence between EEG and handwritten text through direct mapping of model input and output, thus achieving the process of directly converting EEG into text. In order to ensure the accuracy of experimental data, this study designed a set of handwritten character templates and collected the stroke order of 200 individuals when writing 31 characters, in order to select the writing method with the highest proportion as the reference for designing handwritten character templates. At the same time, in order to avoid the problem of insufficient data caused by short writing time of individual characters, the sampling frequency of EEG signals on EEG devices has been adjusted, and a random character order has been set. In the process of EEG signal acquisition, this study developed an experimental device based on TGAM chip to monitor the concentration of subjects, ensuring that they always maintain their attention and concentration, thereby improving the quality of EEG signal acquisition. We also designed an experimental supervision paradigm for imagining the movement of handwritten characters to collect high-quality EEG signals. The preprocessed EEG signal data is converted into a multidimensional data matrix to construct a dataset of imagined handwritten text in the state of brain focus.

3.2. Data preprocessing and restructuring

This chapter mainly introduces the data preprocessing and reassembly methods in the non-invasive motion imagination BCI model for handwritten text. Aiming at the problems of low signal strength, weak anti-interference ability, and poor signal acquisition quality in non-invasive BCI technology, a segmentation recombination data preprocessing method is proposed based on traditional data preprocessing. Perform preprocessing operations such as filtering, denoising, and normalization on the collected EEG data to improve the signal-to-noise ratio of the signal. According to the time difference of each character during imagined movement, the corresponding EEG data of the character is divided into n segments in chronological order, and the starting position of each segment's pen tip is set as the label for that segment. In order to fully utilize existing data and improve data utilization, this chapter is inspired by the music staff and reassembles similar paragraphs of different characters together to form a new dataset. By calculating the Spearman correlation coefficient between the numerical matrices of each segment, determine which segments of data have similarities and set them with the same labels. This method transforms the 31-class classification problem into an n-classification problem, effectively expanding the dataset and increasing the amount of data. The experimental results show that after segmentation recombination data preprocessing, the utilization rate of the data has been significantly improved, providing a reliable data foundation for subsequent classification algorithm training and result output. This chapter also introduces the application of attention detection devices in the model to ensure that subjects remain focused during the experiment and further improve the quality of EEG signal acquisition

3.3. Construction and optimization of MLSTM network model

This chapter successfully designed a non-invasive brain computer interface system for handwritten text based on L2 regularization and attention supervision paradigm, and optimized the decoding process of EEG signals. By introducing LSTM neural network as a variant of RNN and utilizing gating mechanism, the common problems of gradient explosion and vanishing in RNN processing time series have been effectively solved. On this basis, we propose a new MLSTM classification and recognition model that combines segmentation reassembly data preprocessing method and penalty term added to the loss function, effectively avoiding overfitting problems. The MLSTM network model consists of an improved LSTM network. By elaborating on the working principles of the forget gate, input gate, and output gate in the LSTM network, we have achieved the updating of cell states and the control of long-term memory over the current output. In terms of network parameter settings, we determined the optimal network parameter setting (Units=128) by adjusting the size of the hidden units inside the LSTM. At this point, the model achieved the highest recognition accuracy of 96.87% and the lowest loss function value of 0.0635. This research achievement not only verifies the effectiveness and stability of the MLSTM network model, but also provides new ideas and methods for the development of brain computer interface technology, especially in the application prospects of motion imagination brain computer interface systems for handwritten text

4. Results and discussion

4.1. BCI system design and optimization of EEG signal processing

The acquisition and processing of EEG signals play a crucial role in the motor imagery brain computer interface system, and their quality directly affects the accuracy of the algorithm network and the feasibility of the entire brain computer interface system. Therefore, when designing experimental paradigms and methods for processing EEG signals, it is necessary to ensure their rationality. We have successfully built the corresponding system. In response to the weak intensity, low frequency, and susceptibility to interference of non-invasive motor imagery EEG signals, we have designed an experimental supervision paradigm to improve the quality of EEG signal acquisition. To address potential mental fatigue issues among participants during the experiment, we employed a "multiple person, multiple times" experimental method. On this basis, we combined the segmentation recombination data preprocessing method proposed earlier with the MLSTM algorithm model to construct a motion imagination brain computer interface system for handwritten text. The system has added a matching module, which collects the brainwave signals of subjects imagining handwriting, and after data preprocessing, segmentation recombination, classification algorithm model and matching module, finally completes text output. The segmentation reassembly data preprocessing method has been improved in terms of training data volume and classification category number. Similar segments of different characters are recombined, reducing the number of categories from 31 to 5. This not only increases the amount of data contained in each category, but also increases the number of extractable features, significantly improving the recognition accuracy of the algorithm model.

4.2. Experimental design and implementation of BCI system

This chapter mainly introduces the implementation process of a motion imagination brain computer interface system for handwritten text. We have designed a corresponding system and built a hardware platform to address the issues of non-invasive motion imagination BCI. The platform uses 24 conductive electrode caps for EEG signal acquisition, and uses the electroencephalogram and evoked potential instrument NCERP produced by Shanghai Nuocheng Electric Co., Ltd. for data acquisition and amplification. The data is then transmitted to a computer through fiber optic and USB interfaces for subsequent processing. In order to improve the quality of signal acquisition, we have added an attention monitoring device that uses NeuroSky's TGAM chip to monitor the subject's concentration in real time, ensuring that EEG signals are only recorded when the subject's attention is focused. In terms of experimental design, we propose an experimental supervision paradigm to address the issue of subject fatigue caused by poor signal quality and long experimental time in traditional motor imagery experimental paradigms. This paradigm effectively reduces the fatigue level of subjects and improves the accuracy of EEG signal acquisition through the experimental method of "multiple people multiple times" combined with eSense parameter monitoring of TGAM chip. At the same time, we have planned the experimental process in detail, including character experiments and short sentence experiments, to collect as many EEG samples as possible. In the character experiment, we selected 26 lowercase letters and 5 special characters as experimental subjects, requiring participants to imagine handwriting and collect corresponding EEG signals. In the short sentence experiment, we selected eight simple sentences with no more than four words and asked participants to imagine handwriting while also collecting EEG signals. During the experiment, we strictly followed the experimental precautions to ensure a quiet and comfortable environment. We reminded the subjects to adjust their posture to a comfortable state and relax, avoiding any physical movements. We regularly check whether the head electrode is loose or detached to ensure the accuracy and reliability of experimental data. In summary, this chapter has successfully implemented a motion imagination brain computer interface system for handwritten text, and designed a reasonable experimental paradigm and process, providing a solid foundation for subsequent data preprocessing, classification algorithm model training, and matching module design.

4.3. Comparative analysis of evaluation effects

This article proposes a new preprocessing method and MLSTM model for handwritten text recognition via BCI. Experiments show their stability and reliability. Using t-SNE and time warping, we found n=5 optimal for classification, with MLSTM achieving 96.87% accuracy. Tests on short sentences with spelling errors further validated MLSTM's effectiveness. The experimental results show that although there are spelling errors and character confusion, the system can still maintain a high character accuracy. For example, when "how>are>you?" is mistakenly written as "how>ave>you?", the character accuracy still reaches 91.67%. The experiment selected 50 participants with an age range of 15 to 40 years old and divided them into five age groups. The results showed that the accuracy rate was highest among subjects aged 20-25, followed by those aged 25-30. Specifically, in terms of gender differences, the average accuracy of males is generally higher than females in all age groups. The experimental data also indicates that the proposed data preprocessing method and MLSTM algorithm are equally applicable to male and female subjects. In order to comprehensively evaluate the performance of MLSTM algorithm, we also conducted ablation comparison experiments and comparison experiments with other commonly used deep learning classification algorithms. The comparative experiments with other algorithms clearly demonstrate the significant advantages of MLSTM algorithm in classification performance as shown in Table 1.

Table 1. Comparison of Classification Accuracy Among Algorithms

Classification Algorithm	Classification Accuracy
MLSTM	ⅨⅥ. ⅧⅦ%
LSTM	ⅨⅠ. ⅤⅦ%
RNN	ⅨⅩ. ⅩⅧ%
GRU	ⅧⅧ. ⅢⅥ%
CNN	ⅧⅣ. ⅧⅨ%
SVM	ⅦⅧ. ⅤⅧ%

The classification accuracy of MLSTM algorithm is as high as 96.87%, significantly better than LSTM's 91.57%, RNN's 90.08%, GRU's 88.36%, CNN's 84.89%, and SVM's 78.58%. The MLSTM algorithm's accuracy improved with iterations, stabilizing at 96.87% after 1250 iterations. It's effective for different ages and genders, and further tests on short sentences confirmed its general effectiveness.

5. Conclusion

As a spontaneous brain computer interface technology, exercise imagination BCI is of great significance for patients who have lost their language or activity abilities due to diseases, such as stroke patients, spinal cord injury patients, and amyotrophic lateral sclerosis patients. Given the high risk of intracranial infection, complex experiments, and poor practicality of invasive brain computer interfaces, non-invasive brain computer interface technology has become a hot research topic due to its high safety. This article conducts in-depth research on non-invasive brain computer interface systems, aiming to overcome their technical challenges and meet the needs of international cutting-edge fields and social markets. In terms of model building, this article successfully constructed a non-invasive brain computer interface model, which consists of four core parts: EEG signal acquisition, data preprocessing, recognition algorithm, and result output. This model has laid a solid foundation for subsequent research. In response to the problem of reduced data volume caused by a small number of electrodes during non-invasive brain computer interface data acquisition, this article draws inspiration from music staff and innovatively proposes a segmented recombination data preprocessing method. This algorithm achieves accurate output from EEG signals to text, and its effectiveness has been verified through experiments. In terms of system implementation, in response to the problems of long experimental time and poor signal quality caused by reduced focus in existing experimental paradigms, this paper designs an experimental supervision paradigm for handwritten text and builds a non-invasive motion image brain computer interface system for handwritten text based on it. The system has added an attention detection device to the traditional paradigm, which can detect the real-time focus state of the subjects, simplify imaginative actions, shorten the experimental duration, and set up a "multiple person multiple time" experimental method, significantly improving the quality of signal acquisition. In terms of future prospects, this article summarizes and analyzes the research work and experimental results, and proposes further research directions. In future research, eye electrical activity can be considered as an auxiliary feature, and multi feature fusion methods can be used to fully utilize the collected data, further achieving the conversion of EEG to text. This will open new paths for the development and application of motion imagination BCI technology.

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