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Exoskeleton Robot Based on Brain-Computer Interface

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Abstract. Brain-computer interface (BCI) technology represents a means of facilitating human-computer interaction. One of the most widely accepted paradigms of brain-computer interface is motor imagery, which enables the recognition of electroencephalogram (EEG) signals generated in a specific brain region by imagining the movement of a limb. Following the acquisition, preprocessing, feature processing, and signal classification of the EEG signals, the complex signals are accurately recognized. Therefore, by creating a control system that translates the recognized EEG signals into movement commands for the robot and transmits them to the robot, it is possible to control the robot's movements by motor imagery. The convolutional neural network is the most popular signal processing algorithm due to its high EEG recognition accuracy, excellent performance in feature extraction, and superior performance in end-to-end learning. The convolutional neural network is an optimal method for signal processing in robot control. This makes CNN an optimal choice for processing EEG signals in robot control, enhancing both the effectiveness and user experience of BCI systems by enabling more intuitive and responsive interactions with robotic devices.

Keywords: BCI, exoskeleton robot, CNN.

1. Introduction

A brain-computer interface (BCI) is a human-computer interaction system that transmits information between an external device and the human brain [1]. The BCI system recognizes electroencephalogram (EEG) signals generated by measuring brain activity and converts them into detectable signals through a control system. Brain-computer interface technology builds a bridge between the human brain and machines by using communication means, and its use can be involved in medicine, virtual reality, machinery, entertainment, and other aspects. In the field of medicine, the potential benefits of a brain-computer interface that can control the operation of exoskeleton robots are significant [2]. Such a technology could greatly improve the quality of life for individuals with disabilities or mobility issues. However, for this to become a reality, the control system must be able to accurately recognize and transmit EEG signals to the exoskeleton robots [3]. Presently, motion imagery and associated algorithms are predominantly employed to extract EEG signals. This paper seeks to elucidate the methodology of a convolutional neural network based on motion imagery for the processing and precise identification of signals, as well as the issuance of robot behavioral action commands through the control system [4].

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2. Extraction of MI-EEG signals

An Electroencephalogram (EEG) signal is a type of low-frequency, high-randomness bioelectric signal that requires amplification prior to display and processing. In order to correctly recognize EEG signals, the processing and transmission of these signals must be carried out in a specific manner. This entails the following steps: signal acquisition, pre-processing, feature extraction, signal classification, and signal transmission. The primary distinction between signal acquisition techniques is between those that are extracutaneous and those that are subcutaneous. Each of these techniques has its own set of advantages and disadvantages. The objective of signal pre-processing is to eliminate the interference of identical frequency noise affecting the EEG signal. This may be achieved through the utilisation of spatial filters, which serve to filter out low-frequency noise, such as myoelectricity. Feature extraction is primarily employed to reduce the dimensionality of the EEG signal [5]. Signal classification is utilized to categorize the pertinent features extracted from the signal, thereby facilitating enhanced signal recognition. Signal transmission is the process of aligning the recognized EEG signals with the corresponding human body movements, enabling the transformation of recognized signals into commands that are input to the robot.

2.1. Classification of types of EEG signals

The signal acquisition of BCI systems can be categorized into invasive and non-invasive. Implantable BCI requires micro-electrodes to be surgically invasive into the neural cortex of the body to collect the potential information of individual neurons or localized neural cortex; in general, signals acquired by implantation have the advantages of high signal-to-noise ratio and high spatial resolution, but surgical implantation carries a variable degree of risk, as well as the test subject is often unacceptable; whereas, non-invasive BCI is a way of acquiring information on neural activity, which is easy to operate, has little risk, and is often accepted by the test subjects.The non-invasive brain-computer interface is easier to operate in order to make it easier for the operator to control external devices through the brain-computer interface, and it can also exclude the influence of uncertainties such as surgery, however, the signal collection is also affected by other external noises, which increases the complexity of the signals.

2.2. Characteristics of EEG signals

Currently, the features of EEG data are mainly classified into three categories: time-domain features, frequency-domain features and air-domain features. For different features, different extraction methods are used. For example, air-domain features are usually extracted by common spatial pattern (CSP) filters; frequency-domain features can be obtained by Fourier transform, wavelet transform or autoregressive (AR) model. Time-domain features, on the other hand, are extracted at different time points or time periods, such as statistics like mean, variance and skewness.

2.3. Preprocessing

EEG has a low signal-to-noise ratio (SNR) because there is a variety of noise that intermixes with the EEG during the acquisition process. These noises are physiological noises from power lines, external noises from the environment in which the electronic devices are located, EMG signals from muscle contractions, and ECG signals. Therefore, pre-processing of the acquired EEG signals is required to reduce the interference of noise and to improve the low signal-to-noise ratio [6]. According to the previous research report, the classification of MI task is generally taken in the frequency band of 8 to 30 Hz, and band-pass filter can pass the frequency components in a certain frequency range and attenuate the frequency components in other ranges to a very low level of the filter, so the researchers usually use temporal band-pass filter to reduce the noise of the signal, so as to complete the pre-processing of EEG signals [7].

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2.4. Convolutional neural network based feature extraction

The method of feature extraction of MI-based EEG signals is generally to transform the signals into the form of vectors, and then input the feature vectors into a pre-trained algorithmic model, and then use the model to classify the data transformed by these features. According to previous research, the general mainstream algorithm is csp, which can utilize the spatial correlation of eeg signals and can extract the spatial characteristics of each class of data from multi-channel brain-computer interface data. However, the csp algorithm can only take into account the information in the spatial domain, but not in the temporal domain, and because of the need to analyze multi-channel signals, more electrical signals from other brain regions that are not correlated with the i-eeg signals are collected, which reduces the accuracy of feature extraction. So far, several researchers, in order to solve the shortcomings of the traditional CSP algorithm, have made updates on the basis of the CSP algorithm, thus removing the more advanced CSSP algorithm, CSSSP algorithm and FBCSP algorithm. This paper deals with a convolutional neural network algorithm with excellent performance for image recognition and feature extraction.

Convolutional Neural Network (CNN) is an effective deep learning model specifically designed for image processing and recognition tasks such as image classification, target detection and image segmentation. Its architecture is inspired by the cortex of the human brain and relies on large-scale training datasets to learn features through backpropagation and gradient descent algorithms [8]. The convolutional layer of a CNN consists of multiple feature maps, each of which extracts features from the input image by means of different weight vectors. Each convolutional layer is followed by a pooling layer to reduce the resolution of the feature maps and to reduce the sensitivity to bias and distortion in order to preserve the maximum activated features [9]. In addition, CNNs contain fully connected layers that connect each neuron and feature vector of the input layer to ensure comprehensive information transfer. In the convolutional layer, multiple convolutional kernels of the same size scan the input data in set steps and patterns to perform feature extraction.

CNN work incredibly well at extracting features from images and spaces. By expanding the CNN's layer count, complicated signals like EEG signals may be identified as input signals. However, a high number of parameters in indeterminate layers must be trained on a huge dataset in order to increase the number of layers in a CNN. Due to the limited number of subjects and trials in the current dataset, it is difficult to train the parameters efficiently. It is difficult to increase the number of convolutional layers in a CNN because of the limitations of the current dataset. Usually there are one or two CNN layers. This problem has been solved by using a migration learning approach in a study by Zahra et al. Migration learning is one of the most effective methods to bridge this gap [10]. A type of migration learning uses a convolutional neural network that has been pre-trained with a large number of datasets to perform feature extraction on EEG signals. In order to obtain a CNN network with more accurate recognition capability, multiple convolutional layers need to be stacked. However, architectures with too many layers are prone to overfitting, and the computation of stacking a large number of convolutions can take a long time, which can also lead to gradient vanishing problems. In this regard, Zahra et al. used a hybrid neural network consisting of CNN and LSTM networks to learn the temporal and spatial features of EEG signals [10].

CNN Networks Can Extract Robust Spatial Features from Images Effective Deep Learning Models In order to enhance the robustness of convolutional neural networks under spatial transformations (e.g., displacements, scaling, and distortions), it contains three key architectural features: a local receptive field, a convolutional layer, and a pooling (subsampling) layer. The convolutional filter extracts basic visual features from a small region of the input image through the local receptive field. These features are then combined in subsequent layers to recognize higher-order features. That is, the filters in the convolutional layers work in a hierarchical fashion, with patterns in earlier layers combined to form complex patterns in subsequent layers. A pooling layer is often included after each convolutional layer to subsample the output of the convolutional layer. This lowers the breadth and height of the input space and, in turn, lowers the likelihood of overfitting. In this way, the CNN is able to maintain a strong feature extraction capability at different scales and deformations [11].

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The training process of CNN algorithm mainly adopts the back-propagation algorithm, inputting training data, previously calculating the activation value of each neuron, and then calculating the error in the reverse direction, and finding the gradient of each weight and bias for the error, and adjusting each weight and bias accordingly, so as to obtain more accurate EEG signals. The CNN algorithm can extract effective spatio-temporal features, and performs excellently in the process of image and time series processing. Excellent performance. The CSP (Common Spatial Patterns) algorithm is a spatial filter for two-classification tasks and is commonly used for data feature extraction in brain-computer interfaces (BCI). By maximizing the variance difference between different categories of signals, CSP can extract highly discriminative feature vectors to enhance classification. Translating the experimenter's action imagery into behavioral control of the robot, due to the multivariate nature of the brain's imagery of limb movements, the CSP algorithm will be less accurate than the cnn algorithm's accuracy for imagining EEG signals of multiple limb movements.

Table 1. The current commonly used classifiers

Classifier category	Presentations
Linear Discriminant Analysis(LDA)	An effective tool for classification of motion image signals.The core principle of LDA is to maximize the ratio of interclass distance to intraclass distance to identify the best distinguishing features.
Support Vector Machines(SVM)	Classification is performed by finding the maximum bounding hyperplane between different classes of data points.One of the advantages of SVMs is the ability to use kernel functions to reduce computational requirements while efficiently handling high-dimensional data.
The K Nearest Neighbor Classifier(KNN)	Classification is performed by determining the category of a set of samples closest to the data point to be classified, with K representing a set number of neighboring points. When classifying, the category with the highest frequency of occurrence among the K neighboring samples is the category of the samples to be classified. The intuition and fast training of the KNN model are its advantages, but it is prone to overfitting, which affects the classification performance.
The decision tree approach	Consists of a series of flowchart-like decision nodes. In contrast to a series of nested if statements, the decision tree algorithm develops parameters at the decision points. The advantages of this approach are high visualization, easy interpretation, and fast prediction. However, the performance of decision trees usually cannot compete with more complex advanced algorithms.

2.5. Feature classification

In this stage, the extracted features are mainly classified using classification algorithms, and the process is divided into two steps: first, the model is trained using the features of the training samples to obtain the classification parameters. Then, the features of the test samples are classified using the trained classifiers. The current commonly used classifiers are shown in Table 1.

The categorization process involved four distinct methods, as outlined in Table 1. Among these, the KNN classifier emerged as the most effective combination of features and classifiers for classifying

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motion imagery signals within that dataset. Interestingly, adding more high-performing features resulted in decreased classification accuracy, suggesting that additional features may introduce redundant information. In summary, the findings indicate that using the median number of samples in conjunction with the KNN classifier is a promising approach for classifying subject-independent motion imagery systems [12].

3. Control of exoskeleton robots

The angle sensor at the joints of the exoskeleton nylon can feed back the angle signal in real time, which can be inputted to the feedback bar on the screen to simulate the movement of the exoskeleton; at the same time, it can be used as the output value of the classification model, and combined with the expectation value to evaluate the classification performance. It can be seen that the motion information of the exoskeleton robot can be utilized to feed the CNN algorithm model to train the algorithm to accurately process the EEG signals.

S.Y. et al. simulated subjects controlling an exoskeleton equipped with a multimodal human-machine interaction (HMI) system under realistic conditions. A multimodal HMI control system is proposed which can utilize foot motion images (MI) or actual foot movements. The use of electroencephalography (EEG) or electromyography (EMG) signals to control assistive devices offers great potential for rehabilitation. For example, reliable detection of movement-related EEG signals is critical for individuals who are totally disabled or in the early stages of rehabilitation with minimal muscle activity. In contrast, EMG-based detection is more appropriate for those who still have some muscle activity or are in the later stages of treatment. The results demonstrate that an HMI system combining EEG and EMG can achieve high accuracy for effective control of lower extremity exoskeletal [13].

Aljalal et al. explored robotic navigation in unknown environments using two mental tasks: left- and right-handed motor imagery. The researchers employed Common Spatial Patterns (CSP) with log-band power, as opposed to variance, to create feature vectors, and utilized Linear Discriminant Analysis (LDA) for classification. A pose-dependent control architecture was developed, incorporating four motion commands forward, turn left, turn right, and stop to translate the identified categories of right-handed and left-handed imagery into corresponding robot motion commands [14].

4. Conclusion

Through the brain-computer interface to the experimenter's action imagination into the behavioral control of the robot, due to the brain's imagination of the body movement has variability, CNN algorithm model. Although it can have a very accurate collection of EEG signals, but its large number of operations and the need to go to a large number of training data so that the application of the robot needs a huge cost. In the future, optimization on the training volume accordingly is a feasible way, so as to have better performance in recognizing more complicated EEG signals in the future.

For the exoskeleton robot, due to its more degrees of freedom, wanting to flexibly control the robot for example in the movement control of the arm, in the future, slam technology can be added to make it in the path planning and map construction, which is directly calculated by the software in the robot, and at the same time, using the left and right hand imagined movements, combined with the CNN algorithm of the EEG signals of the continuous training and processing, to accurately identify the EEG signals, and to transmit its corresponding instructions to the robot, at the same time, using the robot to identify the markers in the space, project the target position, and finally move to the target point to stop all instructions, thus realizing the movement of the exoskeleton robot in line with the results of the movement imagination.

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