Motor imagery EEG signals classification based on attention mechanism and EEGNet

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ABSTRACT

Brain-computer interface technology (BCI) enables users to directly control external devices by establishing an information transmission path between the brain and external devices. Brain-computer interfaces based on the motor imagination paradigm have also begun to enter various fields. Therefore, the research on the brain-computer interface encoding and decoding algorithm of the motor imagination paradigm is particularly important. This paper proposes a model based on attention mechanism CBAM and EEGNet to classify motor imagination electroencephalogram signals (MI-EEG), and verified it on a public data set. Compared with a single EEGNet model, it improved by 3.7%, which is 8.1% higher than the traditional FBCSP model. The experimental results show the effectiveness of the new CBAM-EEGNet model on the four classification tasks of motor imagery.

Keywords: MI-EEG, CBAM, EEGNet

1. INTRODUCTION

Brain-computer interface (BCI) serves as a bridge, allowing the brain to directly exchange information and transmit instructions with external devices[1]. Among them, motor imagery (MI) refers to the phenomenon in which people spontaneously imagine body movements and produce changes in brain waves[2]. By decoding and analyzing the motor imagination electroencephalogram (MI-EEG), it is possible to determine what body movements the subject is imagining. Motor imagination has thus been applied to brain-controlled wheelchairs, robotic arms and other external equipment for disabled people[3], thus improving MI-EEG classification accuracy of EEG is extremely important.

The traditional MI classification task is mainly divided into three stages: preprocessing, feature extraction and feature classification. Among them, feature extraction is the most critical step, including signal analysis in the time domain, frequency domain and spatial domain[4][5]. Commonly used time domain analysis methods include autoregressive (AR) models and Hjorth parameter feature extraction methods; time domain analysis usually uses Fast Fourier Transform (FFT) and Power Spectral Density (PSD)[6]; spatial domain analysis mainly uses the Filter Bank Common Spatial Pattern(FBCSP)[7] analysis method. However, these feature extraction algorithms rely on artificial knowledge and experience, which greatly limits the decoding performance. Lawn et al.[8]proposed a lightweight convolutional neural network model EEGNet suitable for electroencephalography. It performs well in four brain-computer interface (BCI) paradigms, but this model considers the information between channels to be independent and ignores the characteristics of the non-Euclidean space of the brain[9], resulting in insufficient spatial feature extraction of EEG signals.

Therefore, this experiment introduces the convolutional attention mechanism CBAM[10] based on EEGNET to optimize it. As an emerging hot spot in deep learning, attention mechanism has attracted a large number of researchers' attention and investment in recent years. Its goal is to allow the evaluation model to focus on more critical features, thereby improving the performance of the model.

2. DATA

2.1 Dataset description

This study was carried out on the public data set BCI Competition IV-2a, which was provided by 9 different subjects. Each subject used 25 brain electrodes to record EEG signals. In the data preprocessing stage, the 50Hz power frequency interference is removed, and a band-pass filter from 0.5Hz to 100Hz is applied, with a sampling rate of 250Hz. During the experiment, subjects were asked to perform four different motor imagery tasks, including motor imagery of the left hand

International Conference on Future of Medicine and Biological Information Engineering (MBIE 2024), edited by Yudong Yao, Xiaoou Li, Xia Yu, Proc. of SPIE Vol. 13270, 132700J · doi: 10.1117/12.3039780

(Category 1), right hand (Category 2), feet (Category 3), and tongue (Category 4)[11]. Although the 25-lead EEG signal contains a three-lead electrooculogram channel (EOG), which is used to monitor eye movement information, in the classification task of this study, the data of the three EOG channels were not included in the analysis. The dataset comprises two sessions recorded for each subject on different days, utilizing data from one session for model training and the other session's data for evaluating the model's performance. Each session contains 288 experiments, each experiment lasts 7.5 seconds, and the experimental flow is recorded following the timing scheme shown in Figure 1.

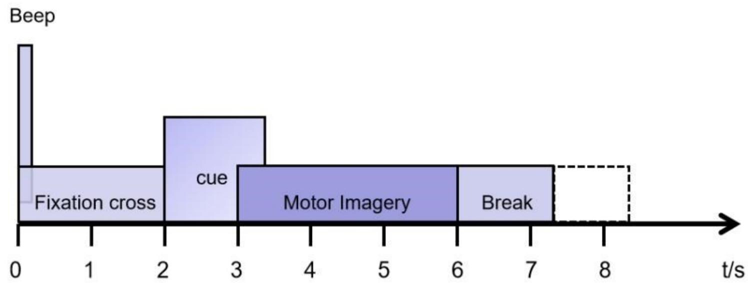

Figure 1. EEG experiment timing arrangement

2.2 Data preprocessing

In order to extract neuroelectric signals associated with motor imagination, this study implemented a 7-35 Hz bandpass filter to isolate theta, alpha, and beta waves related to motor imagery[12]. Subsequently, the three-channel EEG data was filtered and cleaned, leaving only the 22-channel EEG data relevant to motor imagery classification. The data was then segmented, with a duration of 2 to 6 seconds chosen considering the subjects' reaction time and data validity. EEG signals during this time frame were analyzed.

3. METHODOLOGY

3.1 Overall framework

This article uses the innovative CBAM-EEGNet model to classify and train IV-2a data. The overall structure of the model is shown in Figure 2.

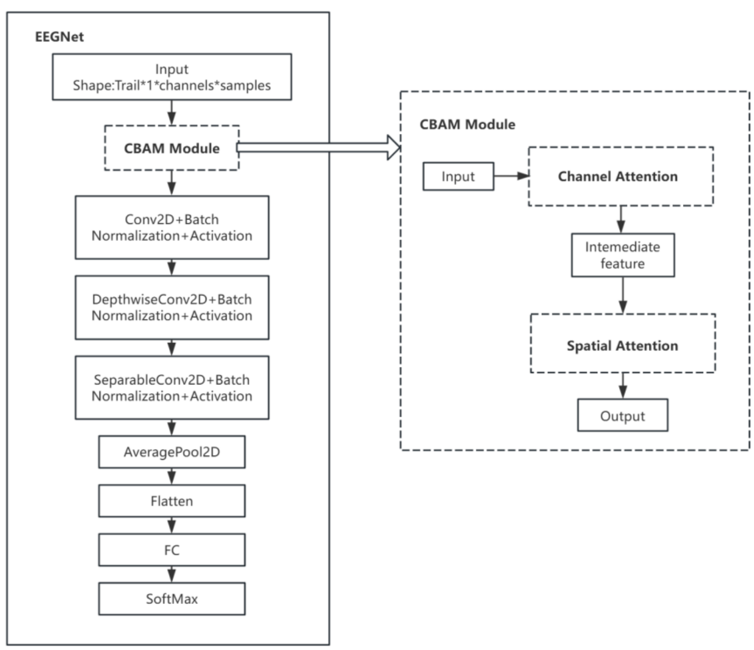

Figure 2. Overall structure of the model

The shape of the original data is (288 × 22000), where 288 is the sample size and 22000 is the number of sampling points in an experiment. The input layer first performs dimensionality enhancement processing on the original EEG signal and converts it into a form of (288×1×22×1000), and then inputs it into the CBAM module to extract channel and spatial features[13]. The extracted CBAM features are further input into the EEGNet network structure for deeper feature extraction. The EEGNet network structure mainly consists of three layers of networks: the first layer is a convolutional layer, whose purpose is to divide and filter the input signal; the second layer is a deep convolutional layer, whose purpose is to filter each multi-channel signal after spatial filtering and noise reduction, it is converted into a single-channel signal; the third layer is a separate convolution layer, whose purpose is to extract features of each filtered signal separately; after the original signal is processed by the network, the extracted Features are passed to the fully connected layer for classification.

3.2 CBAM module

In the CBAM module, as shown in Figure 3. The input feature F with dimensions Z×H×W is first multiplied with the same elements of the channel attention weight M_C to obtain the output F´; F´ is then multiplied with the same elements of the spatial attention weight M_S to obtain the final output F´´ of the CBAM [14]. Where Z, H and W represent the number of channels, height and width of the feature map respectively. In this experiment, Z is 1, H is 22 and W is 1000.

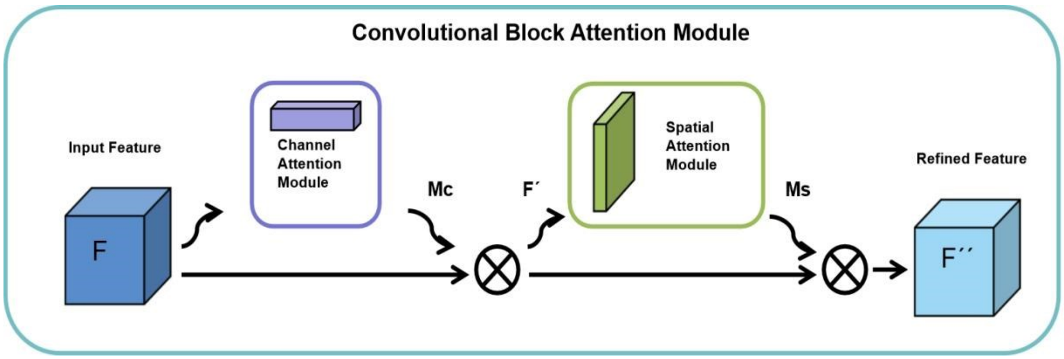

Figure 3. Overall structure of CBAM module

CAM module is shown in Figure 4. The input is recorded as F. F undergoes global maximum pooling and global average pooling at the same time. Extract two different pooled features, and then go through a shared MLP to fuse the two pooled features in the MLP. The output features of the MLP concatenate each other element by element, and then generate channel attention weight M_C with dimension (Z × 1 × 1) through Sigmoid activation. The output of the CAM can be calculated by the following formula:

$$M_C(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \quad (1)$$

In the formula, F is the input feature, $AvgPool$ and $MaxPool$ represents the global average pooling and maximum pooling operations respectively, MLP refers the multi-layer perceptron, and σ refers the Sigmoid activation function.

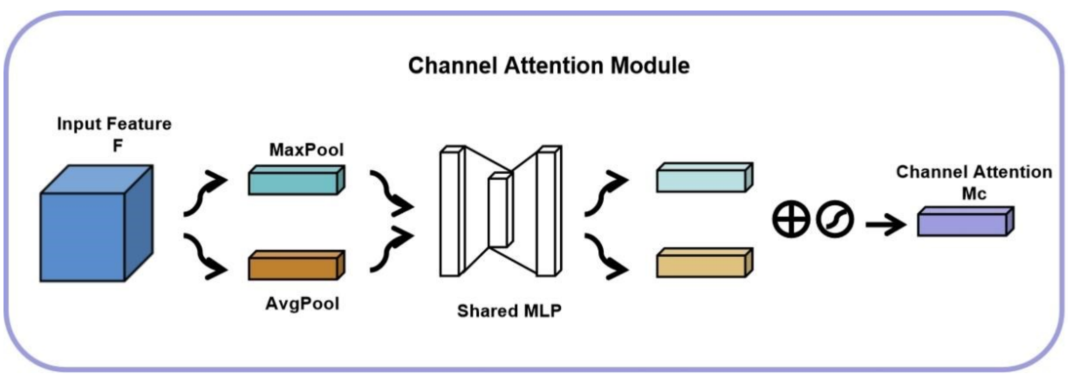

Figure 4. CAM module

SAM module is shown in Figure 5. This module performs global average pooling and global maximum pooling operations[15] on the input feature map F´ from the channel dimension to obtain two (1 × H × W) feature maps. Then the two feature maps are spliced through the concatenate operation, and finally a layer of (7 × 7) two-dimensional convolution is used to obtain the spatial attention weight M_S with the dimension of (1 × H × W), the output of the SAM can be calculated by the following formula:

$$M_s(F) = \sigma(f^{7\times7}(AvgPool(F))(MaxPool(F))) \tag{2}$$

In the formula, $f^{7\times7}$ refers a（7 × 7）convolution operation.

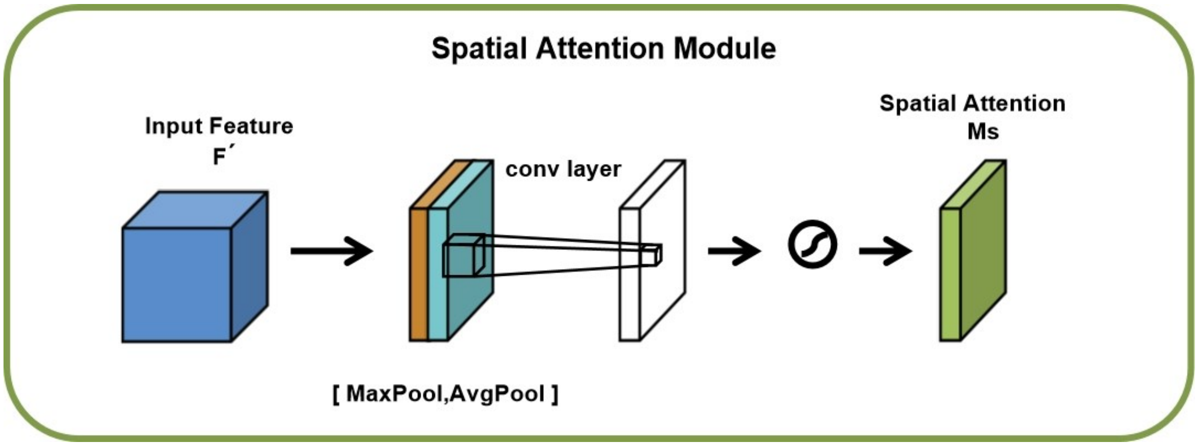

Figure 5. SAM module

4. RESULTS AND DISCUSSION

In order to evaluate the effectiveness of the CBAM-EEGNet, we selected the Adam optimization algorithm to train the network model, and compare and analyze the EEGNet combined with the CBAM module and the unoptimized traditional EEGNet model on the public data set. The loss rate and accuracy curves of the training process are shown in Figures 6 and 7 Show.

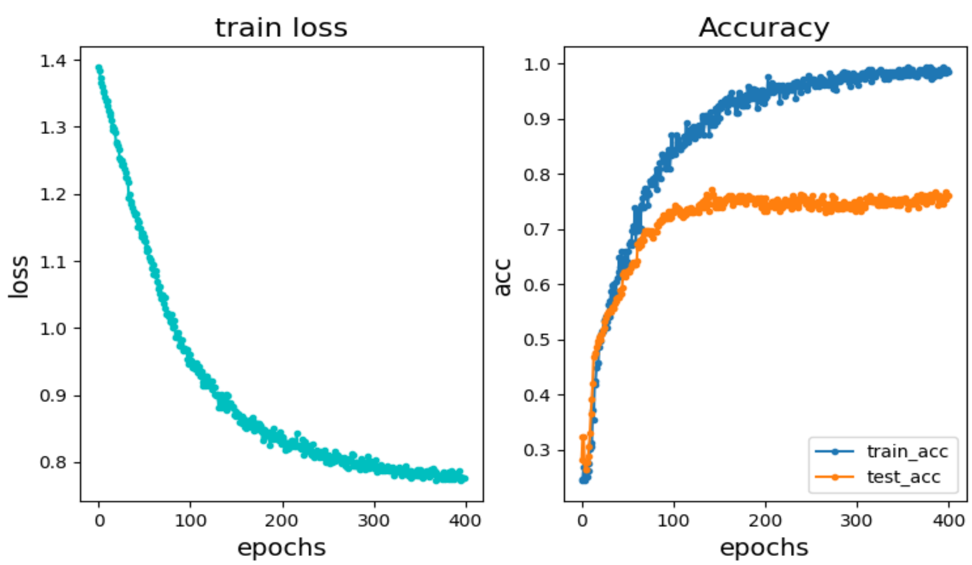

Figure 6. The train loss diagram and accuracy fitting curve diagram of the ninth subject during the training process under the EEGNet model

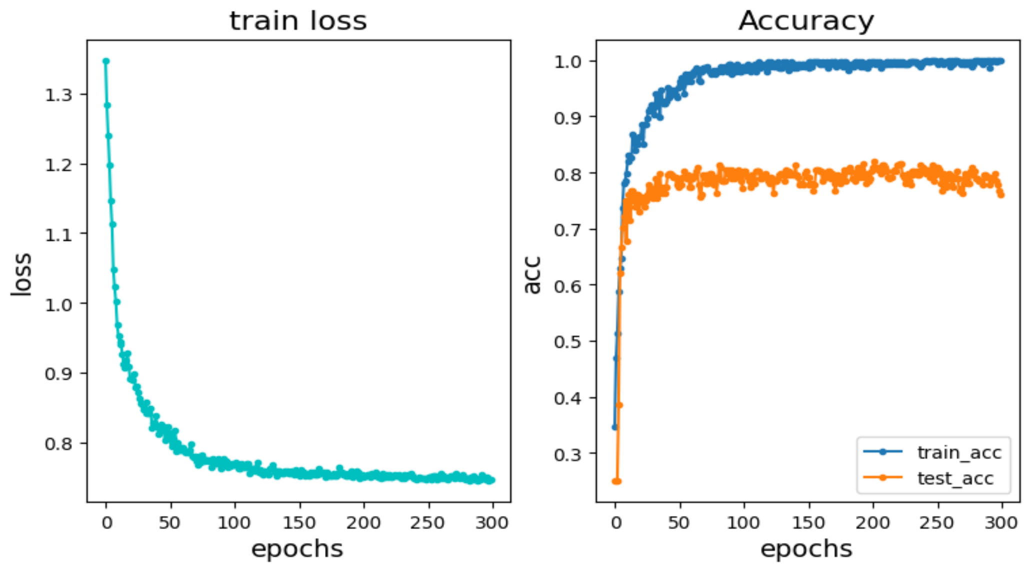

Figure 7. The train loss diagram and accuracy fitting curve diagram of the ninth subject during the training process under the CBAM-EEGNet model

As can be seen from Figures 6 and 7, under the single EEGNet model, subject 9 began to stabilize after training for 300 epochs. After the introduction of the CBAM module, the train loss curve dropped rapidly between 50 epochs and basically stabilized after 100 epochs the accuracy fitting curve graph can reach a relatively high level and remain stable within 100 epochs, which further proves that after the introduction of the CBAM module, the model fitting speed is faster and the model's prediction performance is good.

Table 1. Statistics the classification accuracy of 9 subjects under the same environment and different classification methods

Subjects	FBCSP[16]	EEGNet	CBAM-EEGNet
1	0.676	0.715	0.768
2	0.417	0.470	0.546
3	0.745	0.882	0.842
4	0.481	0.471	0.463
5	0.398	0.396	0.478
6	0.273	0.451	0.421
7	0.773	0.620	0.782
8	0.755	0.701	0.743
9	0.606	0.771	0.809
AVG	**0.569**	**0.613**	**0.650**

By comparing the classification results based on EEGNet, CBAM-EEGNet and traditional FBCSP, as shown in Table 1, it is found that the overall performance of the improved combination model proposed in this article is better than other classification models that also use this data set. The average accuracy of the traditional FBCSP model is 56.9%, the EEGNet model is 61.3%, and the CBAM-EEGNet model can reach 65%. Compared with a single EEGNet model, the accuracy of the model proposed in this article is improved by 3.7%, and is 8.1% higher than the traditional FBCSP model. This proves that CBAM-EEGNet improves the classification performance of MI-EEG signals to a certain extent and provides an effective solution for efficient interaction of brain-computer interface (BCI) technology.

ACKNOWLEDGEMENTS

This work is supported by the Research Initiation Project of Tianjin University of Technology and Education (Grant Nos.KYQD202358) and the fund of Scientific Research Project of Tianjin Education Commission (Grant No.2022KJ114).

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