A novel mothed for EEG motor imagery classification with graph convolutional network

Zongfu Qu[1], Zhigang Yin[2] and Luo Yang[1]
[1]School of Artificial Intelligence, University of Chinese Academy of Sciences
[2]Institute of Automation, Chinese Academy of Sciences
quzongfu2020@ia.ac.cn
zhigang.yin@ia.ac.cn
yangluo2020@ia.ac.cn

Abstract

A motor imagery brain-computer interface system with practical application value should be able to show stable performance when facing new users. The distribution of electrodes on the cerebral cortex is the same for any user. Therefore, in order to solve the subject-independent problem, we propose a novel Graph Convolutional Convolution Transformer Net (GCCTN), which uses a graph convolutional neural network to calculate the relationship between an electrode and other electrodes, uses a convolutional neural network to extract temporal and spatial information and uses a Transformer Encoder for further extraction of time-domain information. Finally, the classification accuracy of our model is optimal.

1. Introduction

Brain-computer interface (BCI) based on motor imagery (MI) which can acquire, pre-process and classify electroencephalogram (EEG) signals offers new approaches to neurorehabilitation for physically disabled (e.g. paralyzed and amputee) and brain-injured (e.g. stroke patients). When the MI task is executed, the relevant EEG signals are generated in the sensorimotor cortex of the brain, whose frequency spectrum produces the event-related desynchronization (ERD) phenomenon. When the MI task is over, the EEG signals exhibit event-related synchronization ERS phenomenon [1]. This is the basis on which we can do signal classification.

Traditional EEG signal classification tasks usually select artificial features from the original signals and then classify them using machine learning algorithms. One of the most commonly used features is the power spectral density (PSD). Differential entropy (DE) is also a widely used feature in the classification of emotional EEG signals [2]. Commonly used machine learning algorithms include linear discriminant analysis (LDA) and support vector machines (SVM) [3]. The process of feature selection largely depends on the experience of the analyst, so it is difficult to avoid the loss of potential key information in the process of feature calculation. The development of deep learning technology has realized end-to-end data processing, training neural networks to automatically extract features related to the classification task in the original signal, and retain key information, thereby improving the classification accuracy. Many methods using deep learning have achieved outstanding results in EEG signal classification tasks. For example, a convolutional neural network (CNN) is used to treat the multi-channel EEG signal as a picture to extract its spatial domain features, and a recurrent neural network (RNN) or long short-term memory (LSTM) cells are used to extract the temporal domain features of the EEG signal. In addition, some hidden layers in deep neural networks can also be input into corresponding classifiers as features for classification.

At present, most studies on motor imagery EEG classification are subject-dependent, using part of the data of one subject as the training set and another part as the test set. In this way, the classifier obtained by training can only be applied to the user who provides training data. Although the accuracy is relatively high, it is not universal. A brain-computer interface system with practical application value should still show sufficiently robust performance when facing new users. In order to solve the subject-independent problem while improving the robustness of brain-computer interface

systems, this work proposes a novel Graph Convolutional Convolution Transformer Net (GCCTN). The main contributions of this work are as follows.

- Using a graph neural network to automatically extract electrode position information features makes the brain-computer interface system more robust when facing different subjects. As far as we know, the proposed network is state-of-the-art.

- This work uses a Transformer to extract temporal domain features of EEG signals. Compared with recurrent neural networks and long short-term memory networks, the unique network structure of the Transformer can improve the calculation speed and can also better extract time-domain features.

The remaining parts of this paper are organized as follows: In section 2, some classification algorithms of MI EEG signals are introduced. Section 3 describes the specific structure of the proposed network. Section 4 gives the organization of the experiments and the results. Meanwhile, future work is also described. Finally, in Section 5, the conclusion of the study is presented.

2. Related works

2.1 Classification methods

Multi-channel EEG signals are naturally two-dimensional. Therefore, the channels can be convolved to extract the features in the spatial domain, and the sampling points in different time periods can also be convolved to extract the features in the time domain. Robin et al. first proposed that convolutional neural networks (ConvNets) trained end-to-end within subjects can achieve at least the same range of accuracy as filter bank common spatial patterns (FBCSP) in decoding task-relevant information from EEG [4]. At the same time, they found batch normalization and exponential linear units from the field of deep learning are crucial for reaching high decoding accuracies. Vernon J et al. used depthwise and separable convolutions to build an EEG classification model where spatial optimal filtering and filter bank construction were constructed and the number of trainable parameters was reduced [5]. Siavash et al. used a new temporal representation of the data and a CNN to build a system classifying EEG signals [6]. Different CNNs having different depths and kernel sizes were merged to form features. And these features were robust for MI EEG classification [7]. Xu et al. introduced a deep transfer CNN framework consisting of a pre-trained CNN based on VGG-16 and a target CNN model. In the training phase, they fixed the front layer's parameters while fine-tuning the parameters in later layers [8]. Slightly different from previous studies, the data here used time-frequency spectrum images of EEG signals. Lun et al. proposed a simplified CNN classification architecture including five layers, where one layer is convoluted along the timeline and others are convoluted along the space axis [9]. In addition to being used alone, CNNs are often used in combination with other neural networks as part of feature extraction. Raghu et al. used different hidden layers of CNN as input of the SVM [10].

Similar to a piece of text, EEG signals are time-series signals, and there is a specific relationship between voltages at different times. Therefore, some methods of natural language processing, such as RNN, LSTM, and Transformer, also can be found in EEG signal classification tasks. Khademi et al. proposed a hybrid deep learning model employing pre-trained CNNs in combination with the trainable LSTM and fully connected neural networks in MI BCI [11]. The Transformer was first proposed by Ashish et al. to solve machine translation problems bringing the attention mechanism and the self-attention mechanism to us [12]. Song et al. calculated the correlation between different channels through the attention mechanism. At the same time, the encoder in Transformer is used to extract temporal domain features and then classify them [13].

Although deep learning methods are very popular, traditional machine learning methods can also be found in many studies of EEG signal classification tasks. Venkatachalam et al. introduced a Hybrid Kernel Extreme Learning Machine (Hybrid-KELM) which is based on Principal Component Analysis (PCA) and Fisher's Linear Discriminant (FLD) for MI EEG signals classification [14]. Luo et al. proposed an Ensemble Support Vector Learning (ESVL) for motor imagery EEG classification [15].

2.2 Graph representation

The distribution of electrodes across the brain was an obvious commonality for different subjects, and it did not change over time. Therefore, rational use of this point is conducive to the realization of a subject-independent brain-computer

interface. Zhang et al. proposed three methods to build a two-dimensional matrix describing electrodes' position. Multiplying this matrix with the original EEG signal will get the EEG signal containing the electrode position information. The resulting signals are then classified through deep learning methods [16].

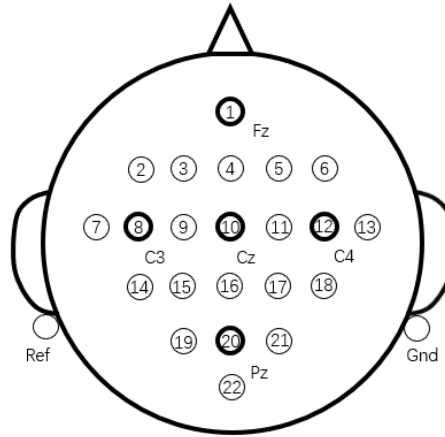## 3. Dataset and method

3.1 Dataset

Figure 1. Distribution of electrodes

BCIC IV dataset 2a is used in this work which recorded EEG signals from twenty-two positions on the cerebral cortex by Ag/AgCl electrodes. The montage is shown in figure 1. The dataset collects EEG signals from 9 subjects performing four motor imagery sessions, including the left hand, right hand, feet, and tongue. Every subject did two experiments on two different days. Each experiment consists of 6 runs including 48 trials (Each motor imagery was performed 12 times) [17]. The detailed process of one trial can be found in figure 2. There will be a beep at first, and a cross cursor will be displayed on the screen to remind the subject that the time is about to start. In the second, the subject is told what movement to imagine. The subject then began performing motor imagery for three seconds. Finally, there is rest. This process will be looped until the end of all trials. The Sampling frequency is 250Hz.
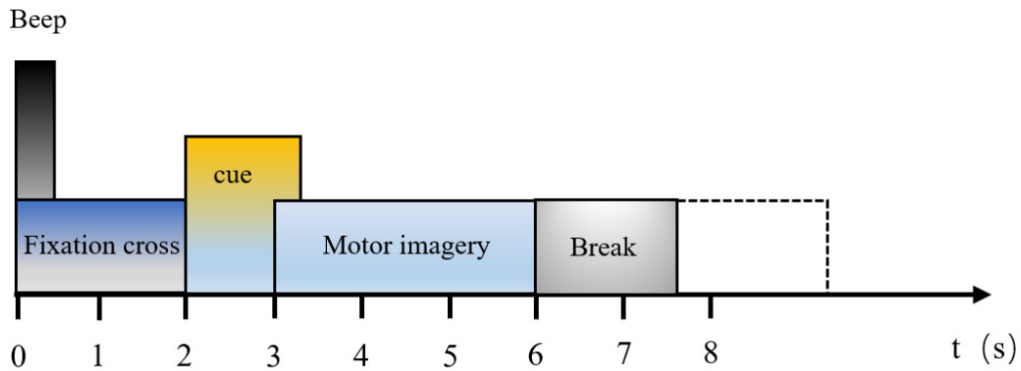

Figure 2. Process of one trial
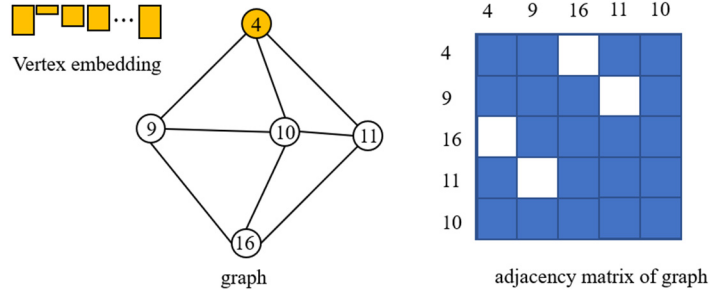
3.2 Method

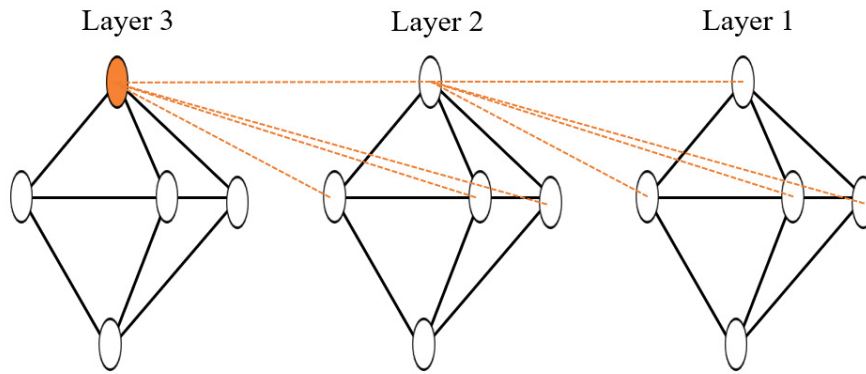Figure 3. Graphical representation of electrodes

Figure 4. Graph Neural Network

The location of the electrodes on the brain is the same for each subject, which can be used as an important common feature for the classification of EEG signals from different subjects and can be seen as an undirected graph. Taking electrodes 4, 9, 16, 11, and 10 in figure 1 as an example, a graph can be obtained as shown in figure 3 [18]. Each electrode is represented by a vertex. If two electrodes are adjacent, the two vertices are connected by a straight line. An adjacency matrix is a simple and
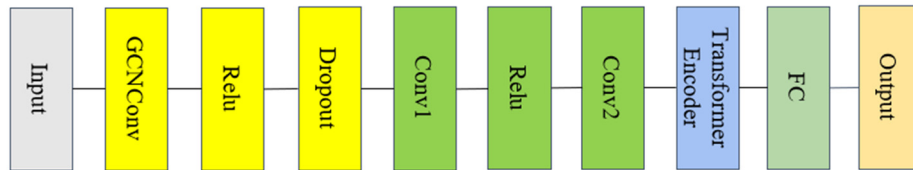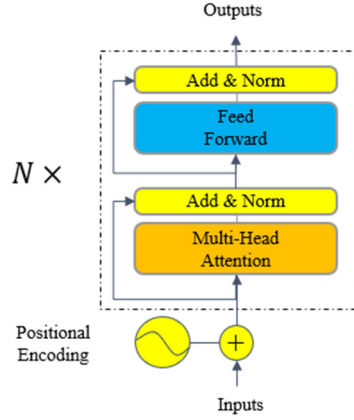

Figure 5. Network structure

Figure 6. Brief structure of Transformer Encoder

efficient representation of a graph where the blue color block indicates that the two vertices are connected. Each vertex has an embedding, which we define as the sequence of EEG signals collected by the corresponding electrode. As we all know, the EEG signal itself is a signal with high temporal resolution but low spatial resolution. For the signal collected by a certain electrode, a simple weighted summation with the signal collected by the surrounding electrodes can reduce the influence of the noise signal on the signal. Therefore, exploring the relationship between different electrodes is very important to improve the robustness of the final classification result.

The principle of the graph neural network is shown in figure 4. The value of the vertex of each layer is related to the value of the vertex of the previous layer. In an iterative calculation, the value of a vertex in Layer2 is defined as $node_{new}$, the value of this vertex in Layer1 is defined as $node_{old}$ and the values of the adjacent nodes of this node are defined as a set $nodes_{adj}$. The calculation process is shown as in equation (1).

$$node_{new} = f(node_{old}, nodes_{adj}) \qquad (1)$$

$f()$ is a learnable function with parameters. After several layers of calculations, the value of a vertex in the last layer may be affected by the values of all vertices in the first layer. Therefore, potential relationships between different electrodes can be sought through such calculations.

In order to illustrate the above calculation process more vividly, the following definitions are made. $X \in \mathbb{R}^{N \times F}$ is the input EEG signal having N nodes and F samples in every node. $A \in \mathbb{R}^{N \times N}$ is an adjacency matrix of the graph. $\Theta \in \mathbb{R}^{C \times F}$ is a matrix of filter parameters. $Z \in \mathbb{R}^{N \times F}$ is the output having N nodes and F samples in every node. The detailed calculation process of equation (1) is shown as in equation (2) (3) (4) [19].

$$\tilde{A} = A + I_N \qquad (2)$$

$$\tilde{D}_{ii} = \sum_j \tilde{A}_{ij} \qquad (3)$$

$$Z = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} X \Theta \qquad (4)$$

Based on the above ideas, we propose the model shown in figure 5 to classify EEG signals. Apart from the input and output, the model consists of 4 parts marked with different colors. The first part mainly consists of a graph convolutional network to obtain the relationship between different electrodes. The second part consists of two layers of convolutional neural networks to extract features in the temporal and spatial domains, respectively. The third part uses the Encoder part

of the Transformer to further extract the time domain features of the input signal, and its brief structure is shown in figure 6 [12]. The Transformer Encoder firstly performs position encoding on the input time series to ensure that the calculated results retain time information. Then, the self-attention mechanism is used to calculate the relationship between the current moment and the rest of the time to extract the features of the time domain. Compared with RNN, the calculation process of the Transformer Encoder is parallel, so its calculation process is relatively fast. The last part is the fully connected layer, which is used for the final classification.

4. Experiments and results

Table 1. Comparison of experimental results

Methods	Accuracy
EEGNet [20]	0.5130 ± 0.0518
CTCNN [21]	0.4767 ± 0.1506
EEG Image [22]	0.3270 ± 0.0430
Cascade Model [23]	0.3183 ± 0.0399
Parallel Model [23]	0.3267 ± 0.4499
FBCSP [24]	0.3569 ± 0.0853
PSD-SVM [25]	0.3611 ± 0.0817
NG-CRAM [16]	0.6011 ± 0.0996
Ours	0.6570 ± 0.0182

Table 2. Classification accuracy of different subjects

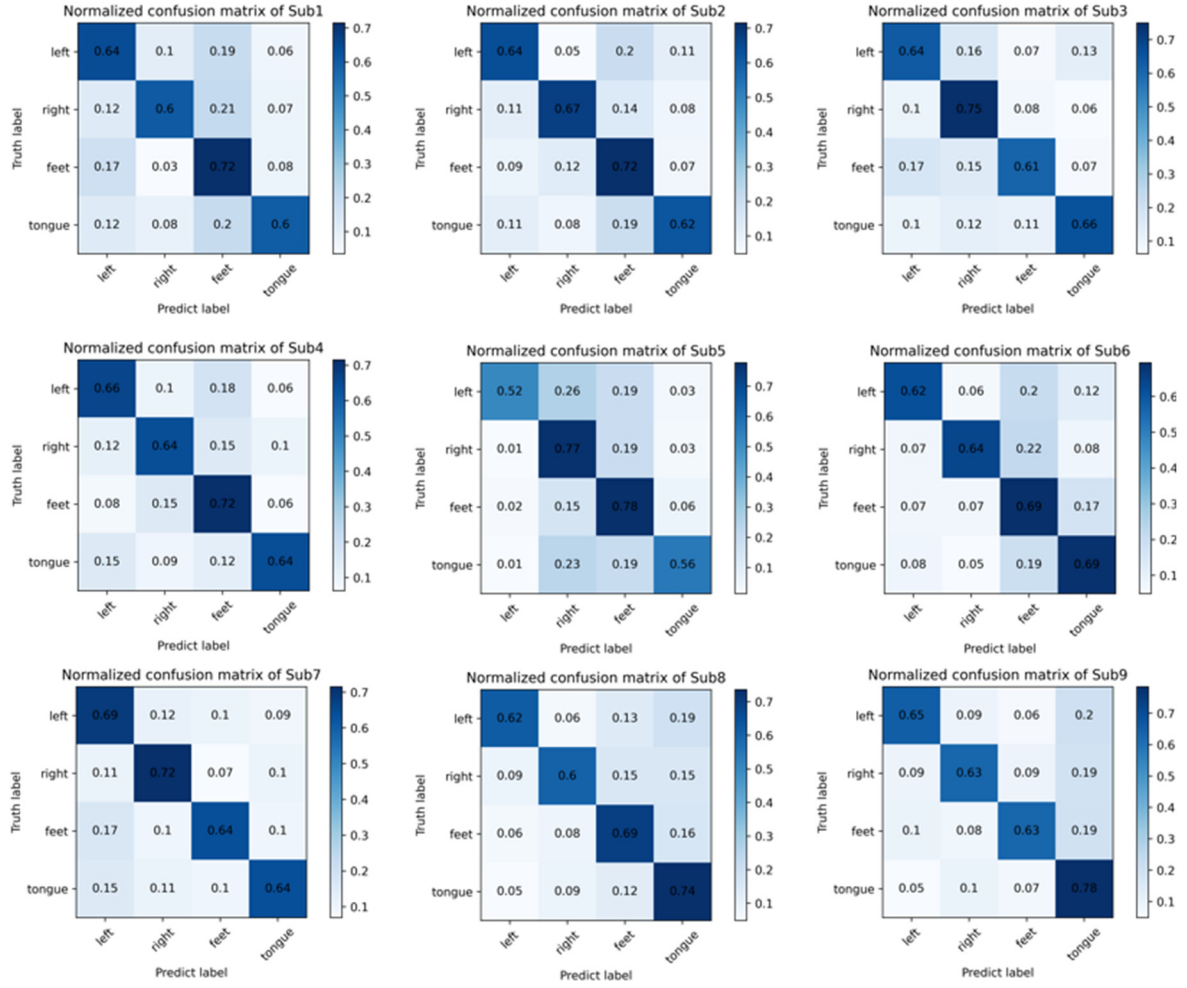| Subject	Accuracy
Sub1	0.6388
Sub2	0.6614
Sub3	0.6649
Sub4	0.6631
Sub5	0.6579
Sub6	0.6597
Sub7	0.6701
Sub8	0.6631
Sub9	0.6753

Figure 7. Confusion matrix of classification results for 9 subjects

The dataset consisted of 9 subjects in total, with the data of one subject as the test set and the remaining 8 subjects as the training set. In this way, 9 experiments were carried out. The loss function is CrossEntropyLoss function and optimizer is Adam optimizer. The experiment environment is Ubuntu 18 which having two 2080Ti graphics cards.

The comparison results of the classification accuracy of the proposed method and some previous methods are shown in table 1. And in different methods, the way of data partitioning is consistent. Our method achieves the highest accuracy. The classification accuracy of different subject data as the test set is shown in table 2. The confusion matrix of the classification results for each subject is shown in figure 7. From figure 7, we can see that the classification accuracy for different categories of EEG signals is roughly the same, but there are large differences for some subjects. For example, Sub5, the classification accuracy of the right hand and the foot is 0.77 and 0.78, but the classification accuracy of the left hand and the tongue is only 0.52 and 0.56. Therefore, in the future work, we can pay more attention to the classes with large differences to improve the classification accuracy. Furthermore, an actual BCI system is usually calibrated first when it is in use. Therefore, taking a small fraction of the data from the test set as data for calibrating the system will also be considered in future work.

5. Conclusion

A brain-computer interface system with practical value should be subject-independent. It can still have stable performance when facing new subjects. In this paper, we propose a model to solve the subject-independent four-class motor imagery EEG classification problem. The location distribution of electrodes on the brain is an obvious commonality between different subjects. Considering the distribution of electrodes can be represented using a graph, a

graph convolutional neural network was used in this work to extract the relationship between different electrodes. Compared with other methods, our method achieves the highest accuracy.

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