# Recognizing the level of organizational commitment based on deep learning methods and EEG

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**Abstract.** In recent years, the application scenarios for Electroencephalogram (EEG) research have become increasingly extensive. Compared to other tasks, using EEG to recognize the difference in the levels of subjects' personality traits is a greater challenge to some extent. In this paper, we propose a new task of recognizing the level of people's Organizational Commitment based on EEG signals and Deep Learning methods. Aiming at this goal, we constructed a graph convolutional neural network structure (EEG-GCN) based on the topological graph of EEG features, and compared it with other deep learning model frameworks such as one-dimensional convolutional neural network (1D-CNN), two-dimensional convolutional neural network (2D-CNN), and LSTM. Meanwhile, we have studied the construction of the adjacency matrix of the EEG feature topology map, and finally found that the combination of Pairwise Phase Consistency (PPC) and geodetic distance is the best choice. The model we constructed can achieve an average accuracy of 79.1%. Furthermore, after expanding the size of our dataset, our model is able to achieve an overall average accuracy of 81.9%. Therefore, it can be seen that the combination of resting-state EEG and deep learning method is effective in recognizing organizational commitment personality traits.

**Keywords:** Deep learning, EEG, Organizational commitment, Graph convolutional neural network.

## 1 Introduction

With the continuous development of EEG analysis and pattern recognition technology, many researchers have been devoted to the automatic recognition or prediction task of EEG signals. In this paper, we aim to distinguish people with different levels of Organizational Commitment through resting-state EEG signals. Organizational commitment is a kind of personality trait, first proposed by the American sociologist Becker [1]. This concept can be described as a psychological phenomenon that individuals insist on staying in a specific organization with the increase of "unilateral investment" into the organization. Before the

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work in this paper, some researchers have used EEG signals to analyze other types of personality traits [2-5], such as the Big Five. However, there is still relatively little literature on the correlation between personality traits and EEG, so the in-depth exploration of this direction is still a big challenge.

With the rapid development of Deep Learning algorithms [6] in different field, many different deep learning models have been gradually applied to research on EEG, which can avoid complicated feature engineering and may achieve better performance. Ma et al.[7] used a 5-layer convolution neural network (CNN) to identify subjects based on resting-state EEG with eyes open and eyes closed, and finally achieved an accuracy of 88%. In actual research, the structures of the convolution neural network also have various changes rather than simply stacking several layers. For instance, Wen et al.[8] designed a multi-view convolution neural network (MVCNN) model based on Inception V1[9] to improve the classification performance. Zhao [10] studied the performance of different CNN structures, including shallow CNN, CNN based on feature map and deep residual CNN. However, deep learning models may overfit if the size of our dataset is not large enough. Therefore, some researchers have found some solutions. Luo et al. [11] converted the EEG into spectrogram and expanded the dataset with reference to the data augmentation method in image classification when studying the classification task for patients with schizophrenia and depression.

In addition to convolution neural network, recurrent neural network (RNN) such as LSTM are also used in some research on EEG. Alhagry et al. [12] achieve emotion recognition based on EEG using LSTM recurrent neural network. Zhang et al. [13] used an encoder-decoder recurrent neural network based on attention mechanism to achieve identifying subjects by EEG.

Furthermore, graph convolutional neural network [14] has also gradually emerged in various fields, including EEG analysis. For instance, Yin et al.[15] combined graph convolutional networks and LSTM for EEG emotion recognition; Tang et al.[16] achieved automated seizure detection and seizure type classification from EEG with a graph neural network and self pre-training; Lun et al.[17] proposed a graph convolutional neural network approach for decoding time-resolved EEG motor imagery signals.

To sum up, there is currently no relevant literature that combines EEG with deep learning methods to recognize the level of organizational commitment. Therefore, our purpose is to make up for the lack of research in this area. Our main contributions are as follows:

We construct a set of deep learning models for organizational commitment recognition and achieve good accuracy on experimental data.

We construct a graph convolutional neural network based on EEG topological graphs and EEG features (EEG-GCN), which further improves the overall accuracy and other metrics in the classification task of organizational commitment level.

We further compare the different metrics of the adjacency matrix of EEG graph, and finally select the best method.

## 2 Data recording

### 2.1 Label based organizational commitment

Before conducting the EEG recording experiment, the recruited subjects were required to fill out a psychological scale of organizational commitment (the psychological scale was developed with the assistance of cooperators from the Institute of Psychology, Chinese Academy of Sciences). Then, we assigned labels to the subjects according to their scores—

subjects with scores above a set threshold are labelled as positive class (label=1), the others are labelled as negative class (label=0). In this paper, we focus on the Behavioural Organization Commitment scale with a full score of 40 and a threshold of 21.

### 2.2 EEG Recording

After these subjects completed the questionnaire, their EEG signals were recorded by a Neuroscan EEG system with 64-channel wet electrodes. During the recording process, the electrode M1 was regarded as the reference electrode and the sampling rate was set to 1000 Hz. It should be emphasized that the entire experiment was conducted in a special laboratory that was isolated from external disturbances such as noise. In addition, all subjects were asked to avoid blinking, muscle movements and other behaviours as much as possible so as to reduce interference and guarantee the quality of EEG signals. The whole experiment process needs to record 2-min resting-state EEG of each recruited subject. The reason why we collected resting state EEG instead of evoked EEG is that personality traits are theoretically defined as relatively stable cognitive processes and resting EEG has similar properties[18]. In this paper, we used data from 10 subjects for this research.

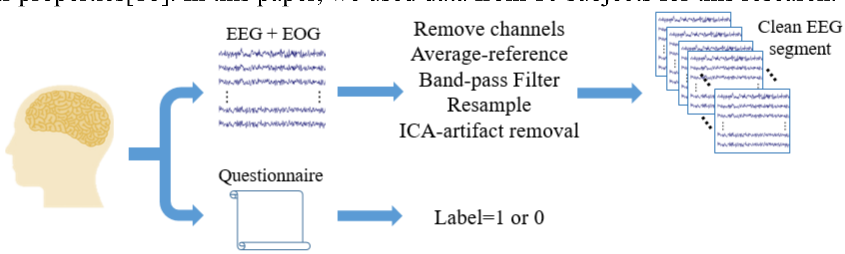



**Fig. 1.** The process of recording data and data preprocessing in our experiments.

## 3 Methodology

### 3.1 Graph convolution

For a graph G = (V, E) (V represents the nodes in the graph and E represents the edges in the graph), graph convolution is equivalent to a mapping function. The input of this function is the feature matrix $F^{N\times d}$ of the nodes, where N is the number of nodes and d is the dimension of the initial EEG feature. The output of this function is a new feature matrix $F'^{N\times d'}$, where d' is the dimension of the new feature. To some extent, graph convolution is similar to the traditional convolution operation, and its core idea is weight sharing and local calculation. Therefore, the graph convolution operation depends on the adjacency matrix $A^{N\times N}$ and the weight matrix $W^{d\times d'}$ of the graph. Its formula is briefly expressed as follows:

$$F' = f(D^{-\frac{1}{2}}\hat{A}D^{-\frac{1}{2}}FW) \tag{1}$$

where $\hat{A} = A + I$ (I is identity matrix), D is the degree matrix of $\hat{A}$, W is the weight matrix and *f* is a nonlinear activation function. Similar to the convolutional neural network, a multi-layer graph convolutional neural network can be obtained by stacking multiple graph convolutional mapping functions. The mapping function of each layer can be expressed as follows:

$$H^{(l+1)} = f(D^{-\frac{1}{2}}\hat{A}D^{-\frac{1}{2}}H^{(l)}W^{(l)}) \tag{2}$$

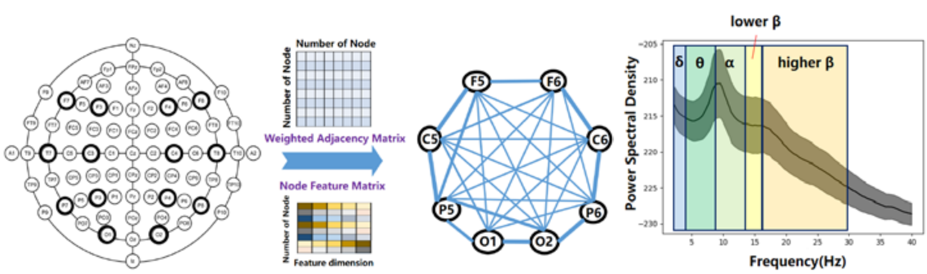
where $H^{(l)}$ is the feature matrix of lth layer. When l=0, $H^{(l)}$ is the input initial feature matrix $F^{N\times d}$. In general, the effect of graph convolution operation can be regarded as the transformation of the feature representation according to the interconnection between nodes. Therefore, the classification of graphs can be achieved by transforming the feature matrices of the last graph convolutional layer into 1-D tensors and regarding it as the input of the classifier.

### 3.2 Constructing the graph of EEG

Considering that the spatial distribution of EEG electrodes has certain graph structure characteristics, we use EEG multi-channel node features and the topology between channels to construct a graph convolutional neural network in this paper. Firstly, we select some typical channels located in various brain regions as nodes of the graph. Here we consider the fluctuation of the local EEG signal, so we choose the difference between the two-channel signals in the neighborhood as the final signal: F7-F3, F8-F4, T7-C3, T8-C4, P7-P3, P8-P4, O1-P3, O2-P4. Then, we compute the weighted adjacency matrix $A^{N\times N}$ and the node feature matrix $F^{N\times d}$ of the graph. This is shown in Figure 2(a).

To compute the weighted adjacency matrix of the graph, we use "geodetic distance" to define the weight $A_{ij}$ of the edge between *ith* node and *jth* node:

$$A_{ij} = r \cdot \arccos(\frac{x_i x_j + y_i y_j + z_i z_j}{r^2}) \tag{3}$$




(a) (b)

**Fig. 2.** (a) Schematic diagram of the process of constructing the topological graph of EEG features by multi-channel resting state EEG; (b) Feature extraction based on power spectral densit.

Where $(x_i, y_i, z_i)$ and $(x_j, y_j, z_j)$ represent the spatial coordinates of *ith* node and *jth* node respectively, and r is the radius of the brain sphere (which defaults to the unit circle, i.e. r=1).

In addition, connectivity metrics [19] of multi-channel EEG signals can also be used to construct a weighted adjacency matrix for graphs. These metrics include: Phase-Locking Value(PLV), Phase Lag Index (PLI), Weight Phase Lag Index (WPLI), Corrected Imaginary PLV (CIPLV), Imaginary Coherence (IMCOH), Pairwise Phase Consistency (PPC) and Coherence (COH). We compare these metrics in section IV of this paper.

Finally, we choose to use the power spectral density (PSD) [20] of different frequency bands of the EEG signal to construct the feature matrix of the graph. The formula for calculating the power spectrum is:

$$P(f)=\frac{1}{NF_s}\left|\sum_{n=1}^{N}X[n]w[n]e^{-j2\pi fn/Fs}\right|^2 \tag{4}$$

where X[n] represents preprocessed discrete EEG signals, w[n] represents a window function (e.g. rectangular window function), *Fs* is the sampling rate of EEG signals. Then, the corresponding features can be obtained by summing the powers in a specific frequency band. In this paper, the selected frequency bands include δ (1-4Hz), θ (4-8Hz), α (8-13Hz), lower β (13-16Hz), and higher β (16-30Hz). This is shown in Figure 2(b).

### 3.3 Architecture of graph convolutional neural networks: EEG-GCN

The architecture of this graph convolutional neural network (EEG-GCN) based on the topological map of EEG features consists of the following parts (Figure 3):

**Input**: The topological graphs of EEG.

**Graph Convolution Module**: This module contains 2 parallel submodules. Each submodule consists of 3 graph convolution operations that are all followed by Batch Normalization operation, Leaky ReLU activation function and Dropout operation in sequence. Then, these Graph Convolution Modules output different node embeddings in parallel.

**Concatenation**: This operation concatenates all the matrices of node embeddings and the matrix of initial input node features, which can integrate different features to facilitate classification.

**Global mean pooling**: This operation can transform the matrix of node embeddings to a one-dimension tensor for classification.

**Fully connected layers**: This module containing 3 layers finally outputs the respective probability of two classes (i.e. high/low level of Organizational Commitment).

In these modules, Batch Normalization operation and Dropout operation can regularize the model for avoid overfitting to a certain degree. And the Leaky ReLU function is better than ReLU because the former can avoid the dying ReLU problem.

### 3.4 Construction of other deep learning frameworks

We also construct other deep learning models for comparison which are as follows:

**Time-domian EEG-1DCNN**: Referring to the idea of TextCNN[21], we constructed a one-dimensional CNN model for the time-domain EEG sample $X^{N\times T}$. This model contains 2 convolution layers, where the size of the convolution kernels in the first layer is $N\times 1$ and the size of the kernels in the second layer is $1\times M$ (M is a hyperparameter). The first-layer convolution can integrate the spatial information of multi-channel EEG; and the second-layer convolution is similar to filtering in the time domain so as to extract the time-domain features.

**Time-domain EEG-LSTM**: Since EEG signals are time series, LSTM[22] module can be used for end-to-end model construction. We take the multi-channel data of each timestep as the feature vector which is similar to word vector in NLP (Natural Language Processing).

**2D-CNN based on EEG Spectrogram Image(ESI-2DCNN)**: We transform the time-domain EEG signals into spectrogram images. Therefore, the classification task in this paper is equivalent to 2-D image classification and 2-D convolution neural network[23] is suitable for this task. Then, we normalize the size of input images to $1 \times 60 \times 60$ .The architecture is shown in Figure 4.

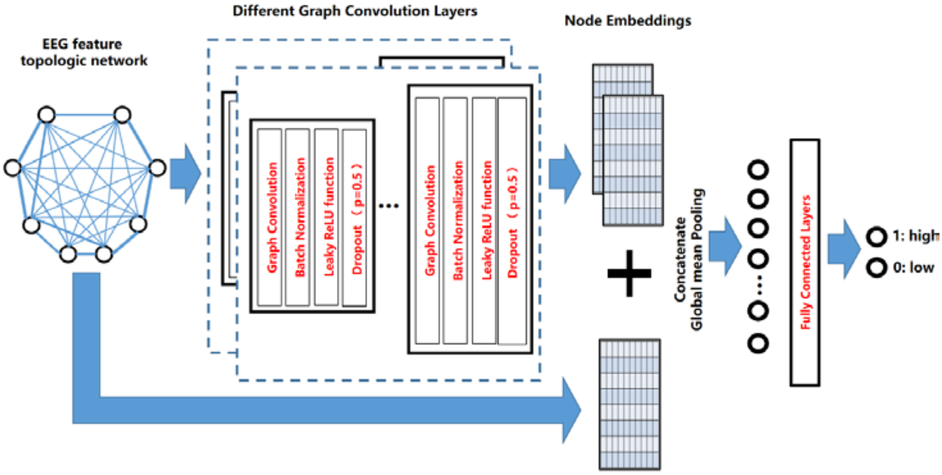



**Fig. 3.** The structure of EEG-GCN: Graph convolutional neural network based on topological graph of EEG features.

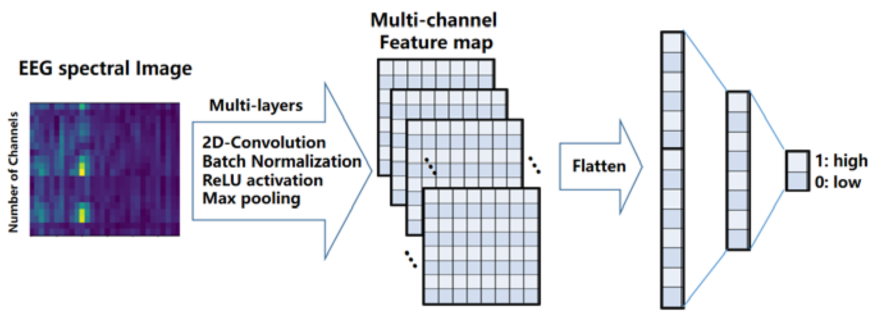



**Fig. 4.** Structure of the 2D-CNN model based on EEG spectrogram images.

## 4 Experimental results and analysis

### 4.1 Preprocessing and parameters

We need to carry out a series of preprocessing on the recorded EEG data before training models.

**Channel rejection:** We rejected 4 channels (M1, M2, CB1, CB2) and remained the other 60 channels.

**Band-pass filtering (1-30Hz)**: It can remove high frequency noise, low frequency noise and power line noise.

**Downsampling**: We downsampled the EEG from 1000Hz to 250Hz for avoiding computational redundancy.

**Independent Component Analysis (ICA)** [18]: It is used to remove the artifacts in EEG.

**Segmenting**: We segmented EEG signals into samples with short time-length (0.5 s), and each sample corresponds to a label (1 or 0).

**Normalization**: Finally, we used the z-score method to normalize all EEG samples.

Then, EEG samples are input into each network for model training. The parameters of network structure are as follows:

**Time-domian EEG-1DCNN**: The first convolution layer contains 2 kernels with a size of 60×1. The second convolution layer contains 2 kernels with a size of 1×40; The hidden state dimensions in fully connected layers are set as 16, 8, 2.

**Time-domain EEG-LSTM**: This model contains 3 LSTM layers whose output dimensions are set as 8, 8, 16. Then the hidden state dimensions in fully connected layers are set as 8, 2.

**2D-CNN based on EEG Spectrogram Image (ESI-2DCNN)**: This model contains 3 convolutional modules and there are 4 kernels in every layer. All convolution kernels have a size of 5×5. The hidden state dimensions in fully connected layers are set as 8, 2.

**EEG-GCN**: The 2 parallel graph convolution modules contain 3 graph convolution layers respectively. The output feature dimensions of the first submodule are set as 8, 8, 16 and the output feature dimensions of the second submodule are set as 8, 8, 8. Then, the dimension of the concatenated feature is 29. The hidden state dimensions in fully connected layers are set as 16, 8, 2.

In the experiment, the loss functions of the above models are cross-entropy functions, the probability of Dropout is set as 0.5, the optimizer is Adam, and the learning rate is set as 0.001. Finally, we used Pytorch[24] to build the above models, the batch size is 64.

### 4.2 Cross validation and evaluation metrics

We used cross validation to evaluate the performance of different models for two reasons. On the one hand, there may be randomness in a single validation. On the other hand, due to the individual differences of different subjects, we did not shuffle all EEG samples and directly divide them into the training set and the validation set. Instead, we randomly selected the EEG samples of a negative subject (label=0) and a positive subject (label=1) to constitute the validation set, and the other samples to constitute the training set. In general, repeating the above operations for cross-validation can avoid errors caused by subject specificity. Finally, we show the overall average of the cross-validation results in this paper.

The evaluation metrics in this paper include Accuracy, Precision, Recall and F1-score. The calculation of these metrics requires the following statistics:

**TP (True Positive)**: Number of samples that are correctly predicted as positive class.

**TN (True Negative)**: Number of samples that are correctly predicted as negative class.

**FN (False Negative)**: Number of samples that are incorrectly predicted as negative class.

**FP (False Positive)**: Number of samples that are incorrectly predicted as negative class.

Then, the formulas of four evaluation metrics are as follows:

$$
\begin{aligned}
&Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \\
&Precision = \frac{TP}{TP+FP}, \\
&Recall = \frac{TP}{TP+FN}, \\
&F1\text{-}score = \frac{2 \cdot recall \cdot precision}{(recall + precision)}
\end{aligned}
\tag{5}
$$

### 4.3 Performance comparsion

We compared the cross-validation results of different deep learning models, which are shown in Table 1. It can be seen that the overall average accuracy of these methods can be over 70% with above 0.7 F1-scores. Besides, Both EEG-LSTM and EEG-1DCNN have relatively larger recall, which indicates that both of them prefer to recognize samples as positive samples (i.e. high level of Organizational Commitment). In contrast, the classification performance of EEG-GCN is not the best when we only use geodetic distance to construct topological graphs of EEG features.

**Table 1.** Performance of different Deep Learning model.

| Model | Acc | Precision | Recall | F1-score |
|---|---|---|---|---|
| ESI-2DCNN | 0.712 | 0.717 | 0.698 | 0.708 |
| EEG-LSTM | 0.739 | 0.709 | 0.813 | 0.758 |
| EEG-1DCNN | 0.749 | 0.722 | 0.810 | 0.763 |
| EEG-GCN | 0.739 | 0.723 | 0.776 | 0.748 |

In order to further improve the performance of our EEG-GCN, we combine geodetic distance with other connectivity metrics we mentioned above to construct new adjacency matrices of graph. Then, the new experimental results (Table 2) show that our model obviously obtains different levels of improvement. EEG-GCN based on geodetic distance and PPC can achieve an overall accuracy of 79.1% and EEG-GCN (geodetic distance + COH) can achieve an accuracy of 78.8%. In contrast, the former has relatively lower recall and higher accuracy, indicating that it can recognize as many subjects with a low level of Organizational Commitment as possible while maintaining a relatively high overall accuracy. Therefore, this method can timely recognize individuals with a low level of Organizational Commitment in some special application scenarios.

**Table 2.** Comparison of different method for constructing adjacency matrix of graphs.

| metrics | Acc | Precision | Recall | F1-score |
|---|---|---|---|---|
| Geodetic distance | 0.739 | 0.723 | 0.776 | 0.748 |
| Geodetic distance + PLV | 0.776 | 0.785 | 0.762 | 0.773 |
| Geodetic distance + PLI | 0.776 | 0.783 | 0.766 | 0.774 |
| Geodetic distance + WPLI | 0.776 | 0.783 | 0.766 | 0.774 |
| Geodetic distance + CIPLV | 0.786 | 0.800 | 0.762 | 0.781 |
| Geodetic distance +IMCOH | 0.781 | 0.789 | 0.768 | 0.778 |
| **Geodetic distance +PPC** | **0.791** | **0.800** | **0.776** | **0.788** |
| **Geodetic distance + COH** | **0.788** | **0.787** | **0.791** | **0.789** |

The above experimental results show that our model can integrate EEG features well with the topological structure of EEG and achieve relatively good classification for different levels of Organizational Commitment. Besides, we find that every evaluation metric of our model in cross validation improves after the number of samples (the size of dataset) increases, which may illustrate the potential of this framework for future research. The comparison results are shown in Table 3.

**Table 3.** Comparison of results when choosing different size of dataset.

| The size of dataset | Acc | Precision | Recall | F1-score |
|---|---|---|---|---|
| 2400 | 0.791 | 0.800 | 0.776 | 0.788 |
| 2880 | 0.819 | 0.837 | 0.792 | 0.814 |

## 5 Conclusion

In this paper, we use deep learning methods to recognize the level of subjects' organizational commitment and prove its effectiveness based on the cross-validation method. Before that, we haven't found other literature using similar methods to carry out relevant research on personality traits. Besides, we construct a deep learning structure (EEG-GCN) based graph convolution neural network for this task. Then we validate this model's performance better than other deep learning models such as 1D-CNN, 2D-CNN and LSTM when the adjacency matrix of EEG topological graph is defined using geodetic distance and Pairwise Phase Consistency (PPC). Finally, our model can achieve an average accuracy of 80% in the face of this new challenging task and obtain higher accuracy when expanding the dataset. In the future, we will use more effective modules and better EEG features to improve the performance of our models. Besides, we will further conduct new experiments to expand the dataset.

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