Brain Functional Connectivity Analysis and Crucial Channel Selection Using Channel-Wise CNN

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Abstract. Brain functional connectivity analysis and crucial channel selection, play an important role in brain working principle exploration and EEG-based emotion recognition. Towards this purpose, a novel channel-wise convolution neural network (CWCNN) is proposed, where every group convolution operator is imposed only on a separate channel. The inputs and weights of the full connection layer are visualized by using the brain topographic maps to analyze brain functional connectivity and select the crucial channels. Experiments are carried out on the SJTU emotion EEG database (SEED). The results demonstrate that positive and neutral emotions evoke greater brain activities than negative emotions in the left frontal region, which is consistent with the result from the power spectrum analysis in the literature. Meanwhile, 16 crucial channels, which are mainly distributed in the frontal and temporal regions, are selected based on the proposed method to improve emotion recognition performance. The classification accuracy by using the selected crucial channels is similar to that without channel selection. But the model with the 16 selected channels is more memory-efficient and the computation time can be reduced substantially.

Keywords: Channel-wise convolution neural network · Brain topographic maps · Full connection layer · Weights · Crucial channels

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1 Introduction

Correct recognition of emotions can make artificial intelligence better serve human beings in many aspects, such as human-machine interaction [1], emotional disorder diagnose and therapy [2,3], and lie detection [4]. In the earlier research on emotion recognition, physical signals were mainly used, which include facial expressions, gestures, voice information, etc. [5,6]. However, these external features are easy to be disguised and unstable, which will lead to inaccurate recognition results. On the contrary, physiological indicators [7], including galvanic skin response, electrocardiogram, and especially electroencephalogram (EEG), can directly reflect emotional changes with a high temporal resolution. Therefore, EEG-based emotion recognition has become an important research direction.

Many features (differential entropy, power spectral density, common spatial pattern, etc.) and classifiers (SVM, fuzzy logic, neural network, etc.) have been proposed for EEG-based emotion recognition [8–10]. However, basic research on brain functional connectivity under different emotions is still in the phase of infancy. Tandle et al. found that positive emotions could induce a higher theta power in the left hemisphere, while negative emotions could induce a higher theta power in the right [11]. Zheng et al. found that features from beta and gamma rhythms were more closely related to emotion recognition [12]. Zheng and Lu proposed a deep belief network based method to investigate crucial frequency bands and channels for emotion recognition, and the best classification accuracy with the selected channels was 86.65% on the SEED database [13]. However, there still exist several related problems, two of which concerned in this paper are given as follows:

- Firstly, the relationship between brain functional connectivity and emotions of different valence is still not well understood. Studying the influence of different emotions on the brain functional connectivity, and exploring topological properties of brain network, can provide a new evidence and perspective for brain functional network research.
- Secondly, in the process of multi-channel EEG data collection, signals from different channels are usually redundant, which has a negative effect on computation efficiency. Therefore, it is necessary to find crucial EEG channels for emotion recognition. Channel selection can make data processing more efficiently, while ensuring recognition rate with minimal loss.

To address the issues mentioned above, we propose a channel-wise convolution neural network (CWCNN), where every group convolution operator is only imposed on a separate input channel. Specifically, we divide the signals into 62 groups, of which the number is same to that of the original EEG channels. For each channel, different convolution kernels are allocated to extract characteristics of each channel, which ensures that the information from each channel is independent. The main contributions of this paper can be summarized as follows:

1. A novel channel-wise CNN is proposed, which can be used to analyze brain functional connectivity and select crucial channels.

2. The brain functional connectivity is analyzed based on the full connection layer's inputs, which are visualized by using the brain topographic maps.
3. The channel importance to emotion recognition is determined by analyzing inputs and weights of the full connection layer. 16 channels are selected as the crucial channels for emotion recognition. It is found that crucial channels are mainly concentrated in the frontal and both sides of temporal regions.
4. The emotion recognition performance before and after channel selection are compared. From the comparison, it can be seen that after channel selection the classification accuracy can be maintained while the computational efficiency can be improved substantially.

The remainder of this paper is organized as follows: Descriptions of short time Fourier transformation (STFT) and CWCNN model structure are presented in Sect. 2. Experiment setups and result analysis are given in Sect. 3. Finally, this paper is concluded in Sect. 4.

2 Methods

2.1 Short Time Fourier Transformation

Temporal-frequency spectra, which are obtained by STFT of the EEG signals, are used as the inputs of the emotion recognition model of this paper. The principle of the STFT is to extract the local signal by a sliding time window first, and then the Fourier transform is applied to the extracted signal to get the time-varying frequency spectrum. The sliding time window ensures that the Fourier transform only applies in a small range of the signal, which avoids the deficiency of the FFT's local analysis capability and makes Fourier transform have the ability to local orientation.

2.2 Design of the CWCNN Model

CNN has been developed in recent years and is widely applied in the field of pattern recognition. Compared with the fully connected network, CNN has two characteristics, namely weight sharing and local perception. Weight sharing refers to sharing of weights between certain neurons in the same layer. Local perception refers to the fact that the neurons are not fully connected, but local. Because of these two features, the number of parameters can be reduced greatly, thus reducing the complexity of the model.

The convolution operation is the most important operation in CNN, which is used to extract characteristics. In the convolution layer, different convolution kernels are set to operate on the input data to obtain different characteristics. Different characteristic expressions can be obtained by different convolution kernels, and the effective features will be strengthened in the continuous iterative training process. In this way, the feature extraction can be implemented.

In order to ensure information independence among channels, the collected data are grouped by different channels and convolution operation is carried out for each group in this paper, which means each kernel is imposed on one channel only.

Let the size of input data be N×M×T (channel numbers × frequency nodes × time nodes), and the class number of output data be 3, then the specific structure of the CWCNN model can be described by Fig. 1.

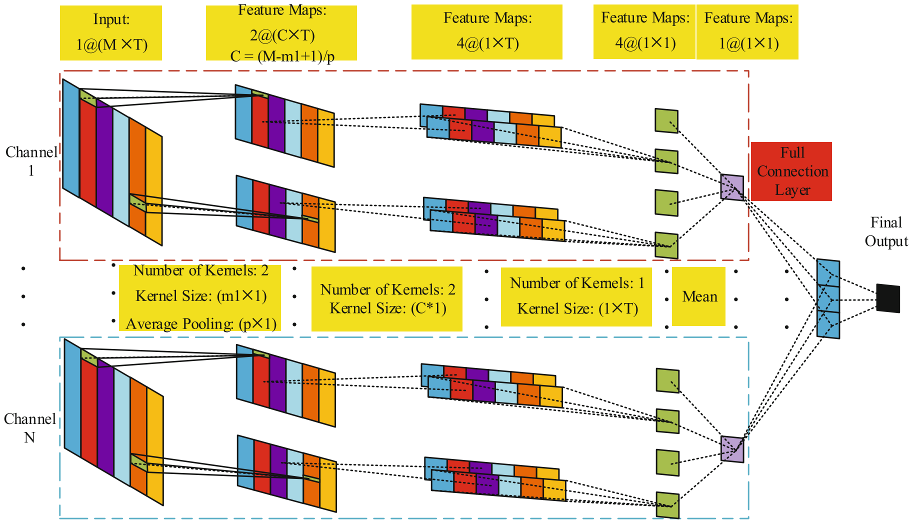


Fig. 1. The structure of the CWCNN model. The descriptions in yellow rectangles are parameter settings for each channel. The final mauve neurons, whose size are 1×1, are taken as the full connection layer's inputs.

From Fig. 1, it can be seen that all operations prior to the full connection layer are imposed on one channel. The average inter-class inputs of the full connection layer ($\mathbf{I}$) and contributions of different channels to recognition results ($\mathbf{P}$) can be calculated by:

$$\boldsymbol{i_c} = \frac{1}{\mathrm{D_c}} \sum_{d=1}^{\mathrm{D_c}} (\boldsymbol{i}(d)) \tag{1}$$

$$\mathbf{W_c} = diag(w_1, w_2, ..., w_N) \tag{2}$$

$$\boldsymbol{p_c} = \mathbf{W_c} \cdot \boldsymbol{i_c} \tag{3}$$

$$\mathbf{I} = [\boldsymbol{i_1}, \boldsymbol{i_2}, \boldsymbol{i_3}] \tag{4}$$

$$\mathbf{P} = [\boldsymbol{p_1},\ \boldsymbol{p_2},\ \boldsymbol{p_3}] \tag{5}$$

where $\mathrm{D_c}$ means the number of samples with the label of c, and $c \in \{1,\ 2,\ 3\}$, representing positive, neutral and negative emotions, respectively; $\boldsymbol{i} \in R^{N\times 1}$ represents the inputs of the full connection layer; $\boldsymbol{i_c} \in R^{N\times 1}$ means the average inter-class inputs of the full connection layer obtained by the samples whose original label is c. $\mathbf{W_c} \in R^{n \times n}$ is a diagonal matrix and represents the full connection layer's weights, which are related to the class c.

From the equations above we can see that, $\mathbf{I} \in R^{N \times 3}$ represents the average inter-class inputs of the full connection layer for positive, neutral and negative emotions. It can reflect the activities of different brain regions under different emotions, and therefore, the activation degrees of brain can be got roughly by analysis of the brain topographic maps based on $\mathbf{I}$. The analysis result about brain activation degrees is consistent with the previous study [11], which verifies the validity of the data. Moreover, $\mathbf{P} \in R^{N \times 3}$, represents channel contributions to recognition results of different emotions. The crucial channel selection can be realized based on the $\mathbf{P}$ matrix.

The detailed implementation process is given in Fig. 2. It can be seen that the experiment is divided into two modules. The first module is the training process of the CWCNN model. The second module is for analysis. On one hand, the average inter-class inputs of the full connection layer is calculated and visualized by brain topographic maps to analysis brain activation degrees and functional connectivity. On the other hand, channel contributions to emotion recognition results, which are calculated according to the weights and average inter-class inputs of the full connection layer, are analyzed to select crucial channels.

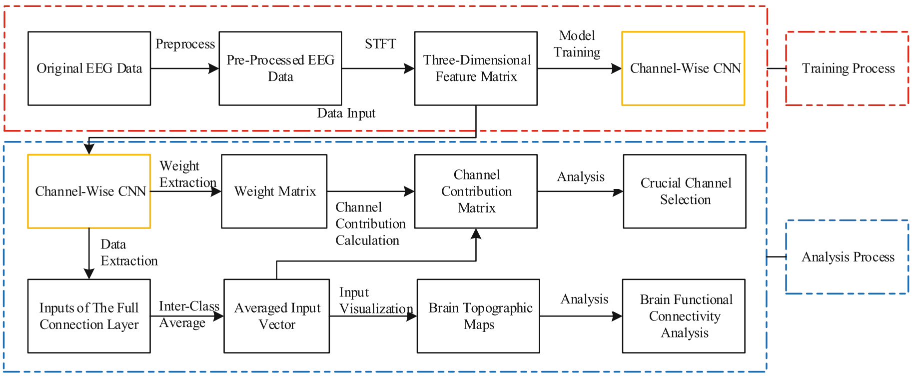


Fig. 2. The system block diagram for brain connectivity analysis and crucial channel selection.

3 Experiments and Results

3.1 Emotional Dataset

The dataset used in the experiments is the SJTU emotion database (SEED) [13], which contains 15 subjects' EEG data (7 males and 8 females). 15 Chinese film clips with three types of emotions, including positive, neutral and negative, were selected to arouse the subjects' inner feelings. All these films were simple, easy to understand, emotional, and the duration of each film was around 4 minutes.

The EEG data were collected by a 62-channel Neuroscan system at a sampling rate of 1000 Hz when they were watching each film clip. After each experiment, the subjects were asked to report their feelings by filling in a questionnaire to ensure that they had produced the same emotions as the film conveyed. To improve the reliability of the EEG signals, each subject was required to perform the experiment three sessions. The time interval between two sessions was at least one week. Therefore, there were 15 trials for each subject and each session, and 675 trials totally.

3.2 Data Processing and Model Training

The raw EEG signals were downsampled at 200 Hz, and band-pass filtered with a frequency band between 1 Hz and 100 Hz, which can cover all the important EEG rhythms. The preprocessed EEG signals were decomposed by the STFT with a 3-s sliding window (hamming window) and 1.5-s overlap. The resulting spectra were divided into 60 fragments without overlapping to increase training samples, and each sample inherited its parent's label with size of $62 \times 295 \times 2$ (channel numbers $\times$ frequency nodes $\times$ time nodes). Therefore, 40500 samples were obtained (675×60), and one fifth data chosen in random were used as the validation set, and others as the training set.

The CWCNN model was composed by three convolution layers and one full connection layer, which was same to that of Fig. 1. The first two convolution layers were used to extract the frequency domain information of each channel at each time node, and the first convolution layer was followed by an average pooling layer with size 2×1. The temporal domain characteristics were obtained by the last convolution layer. The group number was set equal to that of EEG channels. Kernel sizes for the convolution layers were 50×1, 123×1 and 1×2, respectively.

All experiments were established in Pytorch framework with the batch size of 32 [14]. The SGD method with 0.01 learning rate was used as the optimizer. Categorical cross entropy and Relu were used as the loss function and activation function, respectively.

3.3 Experiment Results

Once the final CWCNN model is determined, the weights of the full connection layer will be fixed, and the inputs of the full connection layer will be changed with the input data. The average inter-class inputs of the full connection layer can be calculated by (1) and (4). In order to analyze brain functional connectivity and select crucial channels, brain topographic maps associated with the average inter-class inputs and weights are shown in Figs. 3 and 4.

From Fig. 3, it can be seen that the overall connectivities of the brain are similar to each other for different emotional states. The areas with high activation are mainly distributed in the left side of prefrontal and bilateral frontal regions, while a small part of the parietal region is also highly activated. This means that the emotional processing unit of the brain is mainly distributed in the frontal

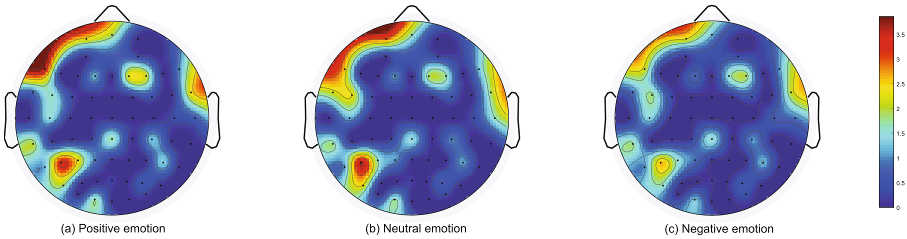


Fig. 3. Brain topographic maps of the inputs of the full connection layer under three emotions of different valence.

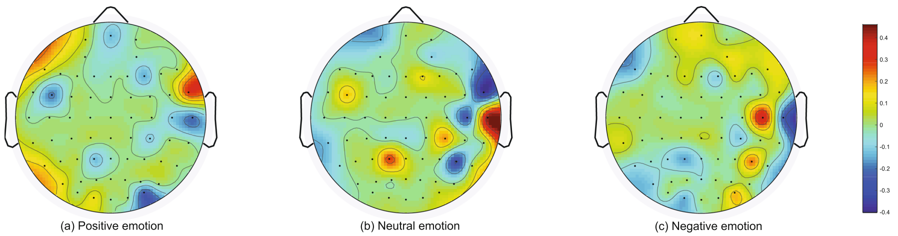


Fig. 4. Brain topographic maps of the weights of the full connection layer under three emotions of different valence.

region. In detail, compared with positive or neutral emotions, negative emotions evoke a lower activation in the left side of the brain, which is consistent with the results of previous study [11].

As shown in Fig. 4, for positive emotions, the channels with high weights are mainly distributed in both the left sides of the frontal and parietal regions. For neutral emotions, the channels with high weights are mainly distributed in right side of the temporal region. For negative emotions, channels with high weights are mainly distributed in the right frontal and temporal regions.

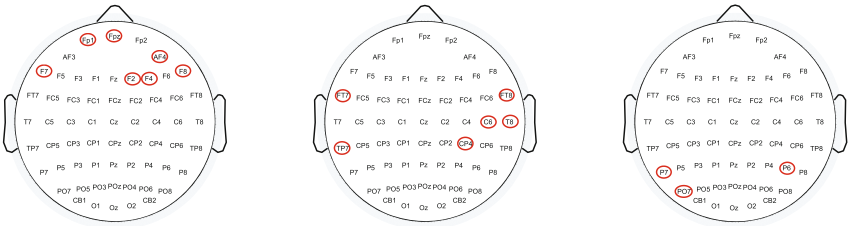
By comparing the high peak distributions in the above two figures, it can be seen that, the channels with high activation degrees are not necessarily of high importance to emotion recognition; on the contrary, the channels which are important to emotion recognition, are not necessarily high activated. The averaged channel contributions to emotion recognition results, which are calculated according to (2) and (3), are given in Table 1.

According to Table 1 and the channel distributions in brain (asymmetric properties in brain emotion processing), we selected 16 channels having relatively big contributions, as the crucial channels. The specific channel distributions in three different brain regions are given in Fig. 5.

In order to determine whether the selected channels have the ability to improve emotion recognition performance, an emotional classification neural network based on the general CNN, which consists of two convolution layers and two full connection layers, were designed. The first convolution layer aimed to

Table 1. Crucial channels and channel contributions to emotion recognition

Emotional valence	Channel ranking (Channel name/Contribution [%])						
Positive	FT8 5.0	F7 3.9	PO7 2.7	FT7 2.6	P7 2.4	FP1 2.2	TP7 2.0
Neutral	T8 3.2	FC5 2.5	P1 2.3	CP4 2.1	F2 2.1	P5 1.9	F4 1.8
Negative	P6 3.2	C6 3.0	FP1 2.6	F4 2.5	FT8 2.5	TP7 2.4	FPZ 2.4



(a) Selected channels in frontal region (b) Selected channels in temporal region (b) Selected channels in parietal region

Fig. 5. The final selected channels which are distributed in frontal, temporal and parietal regions, respectively.

extract the characteristics in the frequency domain (kernel size: 50×1), and the second convolution layer was mainly used to extract the characteristics in the temporal and frequency domains (kernel size: 2×2). It should be noted that, owing that the coupling relationships among different channels are difficult to be reflected by the CWCNN, it is needed to design this emotion recognition model.

Performances of the classifiers including classification accuracy, model size, parameter number, and run-time performance are given in Table 2.

Table 2. Emotion recognition performance

Model name \ PARM	Accuracy [%]	Mode Size [M]	Parameter Number	Run-Time Performance [ms]
CNN-16	91.14±0.26	23.03	5,895,891	40.49
CNN-62	92.89±0.41	80.50	20,607,783	90.25

Note: "CNN-16" and "CNN-62" mean classifiers that input EEG data with the selected channels (16), and all the EEG channels (62), respectively. "Run-Time Performance" means that the time required for processing one sample.

From Table 2 we can see that, in terms of classification accuracy, there is basically no difference between the models of CNN-16 and CNN-62. But in terms of model size, number of parameters, and run-time performance, CNN-16 is much better than CNN-62, which verifies that the channel selection method of this paper can reduce the amount of memory and computational cost substantially.

4 Conclusion

In this paper, a channel-wise CNN is proposed, based on which the brain functional connectivity analysis and the crucial channel selection are implemented. The results show that connectivity for different emotions are similar to each other. The areas with high activation are mainly distributed in the left side of prefrontal and bilateral frontal regions, meanwhile, a small part of the parietal region is also highly activated. Compared with the positive or neutral emotions, the negative emotions evoke a lower activation in the left side of the brain. According to the channel contributions to the emotion recognition results, 16 channels are selected as the crucial channels. The comparison experiment between the two classifiers, the inputs of which were obtained respectively from the 16 selected channels and all of the channels, were carried out. The results show that similar classification accuracy can be obtained by the two classifiers. But in terms of model size and run-time performance, the classifier by using the selected channels is much better, which means the model with the selected channels are more memory-efficient and less time-consuming.

References

1. Guo, S., Zhao, X., Wei, W., Guo, J., Zhao, F., Hu, Y.: Feasibility study of a novel rehabilitation training system for upper limb based on emotional control. In: 2015 IEEE International Conference on Mechatronics and Automation (ICMA), pp. 1507–1512 (2015)
2. Sourina, O., Liu, Y., Nguyen, M.K.: Real-time EEG-based emotion recognition for music therapy. J. Multimodal User Interfaces **5**(1–2), 27–35 (2012)
3. Datko, M., Pineda, J.A., Müller, R.A.: Positive effects of neurofeedback on autism symptoms correlate with brain activation during imitation and observation. Eur. J. Neurosci. **47**(6), 579–591 (2017)
4. Hartwig, M., Bond, C.F.: Lie detection from multiple cues: a meta-analysis. Appl. Cogn. Psychol. **28**(5), 661–676 (2014)
5. Jiang, M., Rahmani, A.M., Westerlund, T., Liljeberg, P., Tenhunen, H.: Facial expression recognition with sEMG method. In: 2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing, pp. 981–988 (2015)
6. Renjith, S., Manju, K.G.: Speech based emotion recognition in Tamil and Telugu using LPCC and hurst parameters #x2014; a comparitive study using KNN and ANN classifiers. In: 2017 International Conference on Circuit, Power and Computing Technologies (ICCPCT), pp. 1–6 (2017)

7. Wen, W., Liu, G., Cheng, N., Wei, J., Shangguan, P., Huang, W.: Emotion recognition based on multi-variant correlation of physiological signals. IEEE Trans. Affect. Comput. **5**(2), 126–140 (2014)
8. Li, H., Qing, C., Xu, X., Zhang, T.: A novel DE-PCCM feature for EEG-based emotion recognition. In: 2017 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC), pp. 389–393 (2017)
9. Matiko, J.W., Beeby, S.P., Tudor, J.: Fuzzy logic based emotion classification. In: 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 4389–4393 (2014)
10. Leslie, G., Ojeda, A., Makeig, S.: Towards an affective brain-computer interface monitoring musical engagement. In: 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, pp. 871–875 (2013)
11. Tandle, A., Jog, N., Dharmadhikari, A., Jaiswal, S.: Estimation of valence of emotion from musically stimulated EEG using frontal theta asymmetry. In: 2016 12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), pp. 63–68 (2016)
12. Zheng, W.L., Zhu, J.Y., Peng, Y., Lu, B.L.: EEG-based emotion classification using deep belief networks. In: 2014 IEEE International Conference on Multimedia and Expo (ICME), pp. 1–6 (2014)
13. Zheng, W.L., Lu, B.L.: Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. IEEE Trans. Auton. Ment. Dev. **7**(3), 162–175 (2015)
14. PyTorch deep learning framework. http://pytorch.org. Accessed 22 Aug 2018