Correlation Study of Emotional Brain Areas Induced by Video

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Abstract. Emotions are physiological phenomena caused by complex cognitive activities. With the in-depth study of artificial intelligence and brain mechanism of emotion, affective computing has become a hot topic in computer science. In this paper, we used the existed emotional classification model based on electroencephalograph (EEG) to calculate the accuracy of emotion classification in 4 brain areas roughly sorted into frontal, parietal, occipital, and temporal lobes in terms of brain functional division, to infer the correlation between the emotion and 4 brain areas based on the accuracy rate of the emotion recognition. The result shows that the brain areas most related to emotions are located in the frontal and temporal lobes, which is consistent with the brain mechanism of emotional processing. This research work will provide a good guideline for selecting the most relevant electrodes with emotions to enhance the accuracy of emotion recognition based on EEG.

Keywords: Brain areas · EEG · Correlation · Emotion

1 Introduction

Emotional state affects human cognition and behaviour to a great extent. In the past few decades, most of the relative research works existed in the fields of psychology and cognitive science. With the development of information technology and artificial intelligence, emotional computing has been proposed by Professor Picard [1], who defined it as "the calculation of factors related to emotion, triggered by emotion or able to affect emotion." Emotion recognition using computer technology is the crucial factor to realize advanced human-computer interaction, which will be of considerable significance to the study of Brain-like Intelligence.

Facial expressions, phonetic intonation, body posture, and physiological signals are commonly used in affective computing. Electroencephalograph (EEG), one of the physiological signals, are extensively studied in the research field of affective computing because of its distinguished characteristics of non-expensive, time resolution,

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bearable space resolution, and higher recognition rate than other physiological signals [2], and many research methods based on the EEG, such as stimulus selection, categories of induced emotions, acquisition equipment, feature extraction methods, different dimensionality reduction, classification algorithms, and so on, has been proposed, along with a mass of achievements of significant research results.

Although a mass of significant research results based on the EEG has been achieved, brain research is still in the exploratory stage, the mechanism by which emotions are generated is somewhat unclear. All of these have become the bottleneck in selecting most relevant electrodes with emotions to enhance the accuracy of emotion recognition based on EEG.

Therefore, first of all, this paper will explore the recognition accuracy of the universal emotional recognition system based on EEG, and then seek the correlation between emotions and brain areas with the higher accuracy of emotion recognition based on EEG, to provide the guideline for selecting most relevant electrodes with emotions to enhance the accuracy of emotion recognition based on EEG.

2 Related Works

2.1 Research on Affective Computing

EEG signals contain sufficient emotional information and can directly reflect the electrical activity of the brain. There are many methods to extract EEG features, such as time-frequency distribution, fast Fourier transform, eigenvector method, wavelet transform, and autoregressive method, and so on [3, 4]. Feature extraction means minimizing the most critical loss in the original signal, so the feature extraction method should minimize the complexity of application to reduce the consumption of information processing.

Duan et al. [5] performed a short-time Fourier transform on the EEG signals to obtain the Fourier transform coefficients for each electrode in each frequency band, and then train and classify them with support vector machine. The average accuracy of emotional classification using differential entropy as an emotional feature is 84.22%. Nie et al. [6] decomposed the original EEG signal into five bands: delta, theta, alpha, beta, and gamma. The five groups of the original EEG signal were transformed by Short-time Fourier Transform (STFT) with a one-second open window. The power spectrum of each electrode in five frequency bands was obtained, which will be trained and classified using SVM, and the average accuracy of the five groups is 87.53%. Murugappan et al. [7] carried out a 5-layer discrete wavelet transform on the original EEG signal, calculated the energy of each frequency band through the wavelet coefficients of each frequency band, and then selected three modified emotional characteristics, which are the ratio of power to total energy in each frequency band, logarithm of energy ratio and the absolute value of logarithm of energy ratio, and then KNN and linear discriminant analysis are used to classify the above three emotional features. The results show that the KNN classification method with the absolute value of the logarithm of energy ratio is the highest accuracy.

Zheng et al. [8] performed short-time Fourier transform (STFT) on the original EEG signal using 1 s uncovered Hamming window, and took the differential entropy of each electrode at five frequency bands as EEG characteristics, that were classified by a classifier combined with depth trusted network and hidden Markov model. The average accuracy was 87.62%.

The classification of EEG emotion is essentially a pattern recognition problem. At present, the commonly used classification methods are linear discriminant analysis (LDA), support vector machine (SVM), BP neural network and deep learning model [8, 9]. The concept of deep learning originates from an artificial neural network, which is a general term for such learning algorithms as a deep neural network and is a research hotspot in the field of machine learning. At present, the commonly used deep learning models include deep belief network (DBN), self-coding model (AE), convolutional neural network (CNN) and recurrent neural network (RNN) [10–12]. Deep belief network is a multi-layer neural network model formed by stacking multiple restricted Boltzmann machines (RBM), which effectively overcomes the problem of inadequate training effect of the multi-layer neural network. Still, it has not been widely used in EEG. Zheng Weilong et al. used the DBN model to classify positive and negative emotions in EEG signals, and the average classification accuracy is 87.62% [13]. Because EEG signals are composed of multi-channel signals and contain a large amount of time-frequency information, if deep learning can make full use of this feature, it may achieve better results.

2.2 Study on Emotional Brain Areas

As early as the 18th century, scientists in the field of psychology and physiology proposed many emotional theories to explain how emotion originated and produced, such as Darwin's Three Principles Theory of 1872 [14] and James-Lange theory of 1884 [15]. Izard [16] proposes that emotions are caused by neural circuits, reflective systems, and cognitive behaviours through the investigation of existing literature.

Current brain nerve research suggests that the process of emotion is mainly related to the amygdala. The amygdala is divided into deep cortical pathways for deep processing and subcortical pathways for shallow processing [17]. When studying the mechanism of emotional development in patients with cognitive impairment, it was found that temporal lobe plays a vital role in effective signal detection and depression [18]. Also, it was found that there exists a strong correlation between forehead and emotion. The left prefrontal lobe produces intense EEG activity for positive music, and the right prefrontal lobe produces intense EEG activity for negative music [19].

Studies on the mechanism of emotional production in the brain are mainly focused on the functions of brain areas based on the functional division of the brain. But the research on the external physiological signals corresponding to the particular brain area is not much.

Researchers on emotion recognition based on EEG are interested in extracting features from the external physiological signals corresponding to the particular brain area, and feature classification, but pay little attention to the mechanism of emotional production in the brain. Because we are still not fully aware of the mechanism of the emotional output in the brain and the degree of association between different brain areas, we naturally think that it is necessary to use all electrodes (64 leads/128 leads, etc.) to obtain more emotional information to improve the recognition rate of emotions, besides studying new recognition algorithms. This may not be true. When all electrodes are used, it is possible that some redundant (or even useless) information will be mixed with the useful information, which will increase the complexity of the algorithm and occupy more computational resources and time.

Therefore, making use of what we have done previously [20, 21], this paper explores the correlation between emotional information and different brain areas based on the existing rough functional division of brain areas and the results of emotional recognition with high accuracy and obtains the optimized location of electrodes corresponding to a certain emotion, which provides credible, stable and streamlined information data for emotional recognition based on EEG source.

3 Research Methodology on Correlation Between Emotions and Brain Areas

3.1 Brain Areas

As usual, the brain can be divided into four areas: the frontal lobe, the parietal lobe, the occipital lobe, and the temporal lobe. But there is no strict division among the four brain areas. The electrode name on the 64-channel electrode cap is composed of letters plus numbers. The endless amount of notes is 1 to 2, which represents the coronal line of the skull, that is, the initials of the English word in the brain areas to which the electrode belongs. The numbers represent the sagittal lines, and the electrodes containing the same number represent the electrodes in the same sagittal line. The electrodes included in the four brain areas selected in this experiment are shown in Fig. 1-a, -b, -c, and -d.

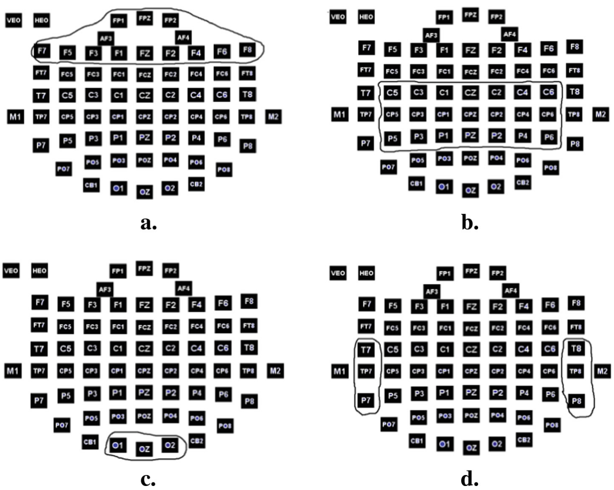

Fig. 1 a. Frontal electrodes, b. Parietal electrodes, c. Occipital electrodes, d. Temporal electrodes

The partition electrodes of the four brain areas were utilized to obtain the emotion information data on which feature extraction and classification are performed to get emotion recognition result.

3.2 Feature Extraction

To get a reasonable emotion recognition rate, it is very crucial to extract emotional EEG features. As usual, EEG features can be time-domain features, frequency domain features, and time-frequency features. Because of the most significant correlation between frequency domain features and emotion, the EEG features selected in this paper are frequency domain features. The frequency-domain signals of EEG transformed from time-domain signals are classified into ones with 5 bands, named as δ, θ, α, β, and γ. Therefore, the EEG features selected in this paper include frequency band energy, frequency band energy ratio, frequency band energy ratio logarithmic and differential entropy.

A 5-layer wavelet transforms with the selected wavelet basis is performed on the EEG signals in each brain area. The approximate coefficient (AC) and the detail coefficient (DC) of each frequency band are obtained, shown in Table 1.

Table 1. Wavelet decomposition result

Wavelet coefficient	Five bands + Noise	Frequency range (Hz)
CD1	Noise	64–125
CD2	Gamma	32–64
CD3	Beta	16–32
CD4	Alpha	8–16
CD5	Theta	4–8
CA5	Delta	0–4

Frequency band energy feature: the frequency band energy $c\boldsymbol{E_{ik}}$ is the sum of the squares of the wavelet coefficients of *the* i-th band in the k-th brain area, expressed as Eq. (1):

$$E_{ik} = \sum\nolimits_{j=1}^{n_i} \left(d_{ij}^k\right)^2 \tag{1}$$

Where d_{ij}^k is the j-th wavelet coefficient of the i-th frequency band in k-th brain area, $i = 1, 2, 3, 4, or\, 5$, n_i is the number of wavelet coefficients of the i-th frequency band, and $k = 1, 2, 3, or\, 4$.

a. Frequency band energy ratio feature: the frequency band energy ratio REE_{ik} is the ratio of $\boldsymbol{E_{ik}}$ to the total energy of 5 bands in the k-th brain area, expressed as Eq. (2):

$$REE_{ik} = \frac{E_{ik}}{\sum\nolimits_{j=1}^{5} E_{ik}} \tag{2}$$

b. Frequency band energy ratio logarithmic feature: the frequency band energy ratio logarithmic $LREE_{ik}$ is the logarithm of the REE_{ik} expressed as Eq. (3):

$$LREE_{ik} = log_{10}^{REE_{ik}} \tag{3}$$

c. Differential entropy feature: the differential entropy DE_{ik} is the logarithm of the $LREE_{ik}$, expressed as Eq. (4):

$$DE_{ik} = log_{10}^{E_{ik}} \tag{4}$$

3.3 Emotional Classification

Currently, there are many classifiers in the field of machine learning, and each classifier has a suitable application field. Support vector machine (SVM) performs better performance when dealing with a small sample and high-dimensional classification problems. Therefore, this study will use SVM as emotional classifier because of the small sample size of the EEG signal and the high dimension of the signal feature.

Selecting kernel functions is the key to successful use of SVM. Standard kernel functions include polynomial kernel functions, linear kernel functions, Gaussian radial basis kernel functions, and sigmoid kernel functions. Compared with polynomial kernel function, Gaussian radial basis kernel function has fewer parameters (only two parameters: penalty factor, gamma function parameters) and can perform the same as linear kernel functions with one parameter (penalty parameter). The parameter selection of the sigmoid kernel function is too complicated. Thus the kernel function selected in this experiment is a Gaussian radial basis kernel function. And the trained SVM was used to analyze the training set, and to predict the sample type of the test set: shown as Eq. (5).

$$f\left(X^T\right) = \sum\nolimits_{i=1}^{l} y_i a_i x_i X^T + b_0 \tag{5}$$

Where y_i is the class label of the support vector x_i, X^T is the test sample, l is the number of support vectors, and $a_i b_0$ are parameters.

3.4 Correlation Between Emotion and Brain Areas

Accuracy Rate. In this paper, the accuracy rate $\mathbf{R_a}$ is defined as the ratio of the number of correct emotion classification $\mathbf{N_c}$ to the total number of the test samples $\mathbf{N_{ts}}$, expressed as Eq. (6):

$$\boldsymbol{R_a} = \frac{\boldsymbol{N_c}}{\boldsymbol{N_{ts}}} \tag{6}$$

Correlation Method. In this pape. The correlation method is divided into several steps, explained as follows:

Step1: Pick up EEG features from each brain area to construct a vector $\boldsymbol{V_i}(\boldsymbol{i} = \mathbf{1}, \mathbf{2}, \mathbf{3}, \mathbf{4})$ respectively;
Step 2: Cascade two vectors from selected two brain areas with higher $\mathbf{R_a}$ in the four brain areas to build a vector $\boldsymbol{V_{22}}$;
Step 3: Cascade three vectors from selected three brain areas with more senior $\mathbf{R_a}$ in the four brain areas to construct a vector $\boldsymbol{V_{33}}$;
Step 4: Cascade 4 vectors from the four brain areas to build a vector $\boldsymbol{V_{44}}$;
Step 5: Perform the emotion recognition on $\boldsymbol{V_i}$, $\boldsymbol{V_{22}}$, $\boldsymbol{V_{33}}$, and $\boldsymbol{V_{44}}$, respectively, and calculate the maximum of recognition rate, which corresponds to the most relevant correlation between emotion and brain areas.

All of this processing is shown in Fig. 2.

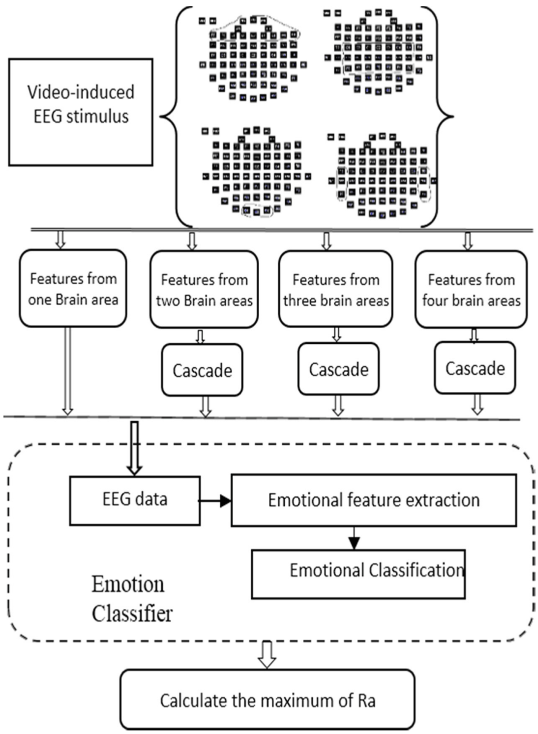

Fig. 2 Schematic diagram of the correlation method

4 Experiments and Discuss

4.1 Stimuli Materials

Emotional induction is a vital issue in affective computing, and the choice of emotional stimuli affects the effectiveness of emotions evoked. In the existing research, the relevant stimulus materials commonly used include visual, auditory, and olfactory stimuli. Because the video stimuli material combines the characteristics of vision and hearing, it can better induce the emotions of the subjects. Therefore, this paper plans to use video clips to influence emotions to ensure the effectiveness of emotion-induced.

As stimuli, we selected a total of 30 video clips to induce the emotions of the subjects, including joy, sadness, and neutral video material. The length of each video clip is 1 min.

Fifty-three undergraduates were selected to watch 30 target videos in the emotional database, and a questionnaire survey was conducted on the pleasure, arousal, and dominance of each video using the 9-point scale to complete the quantitative evaluation [24].

Six clips were selected as positive emotion video from high to low, six clips were selected as negative emotion video from low to high, and the average arousal degree of the 12 clips was about 8, indicating that the 12 clips can effectively evoke the emotions of the subjects. The 12 movie clips selected were shown in Tables 2 and 3.

Table 2. Video stimulating material 1

Movie clips	Name	Start and end time
	Lost on Journey	0:44:07–0:45:07
	Shaolin Soccer	0:22:56–0:23:56
	Flirting Scholar	0:31:13–0:32:13
	Dad's lies	0:00:10–0:01:10
	Packing articles of "Going Home"	0:00:16–0:01:16
	A Dog's Tale	1:22:05–1:23:05

Table 3. Video stimulating material 2

Movie clips	Name	Start and end time
	A Chinese Odyssey	0:41:33–0:42:33
	Crazy Stone	0:46:56–0:47:56
	Shaolin Soccer clip 2	0:31:13–0:32:13
	Beijing Love Story Movie	0:44:43–0:45:43
	Dearest	0:17:29–0:18:29
	Titanic	2:47:44–2:48:44

4.2 Subjects

EEG data in this study were recorded from three women and three men aged around 22. They are physically and mentally healthy, right-handed, and clearly understood the experimental content. All of the subjects were undergraduate students from the Minzu University of China and were informed about the purpose of this experiment. Ample sleep and mental concentration were ensured before the trial. And this study protocol was approved by the institutional review boards (ECMUC2019008CO) at Minzu University of China. All participants provided IRB-approved written informed consent after they were explained the experimental procedure.

4.3 Data Collection

Let a subject view a piece of movie clip lasting no more than 1 min, and collect the EEG signals by SynAmps2 and Scan4.5 developed by Neuroscan company. The sampling rates are $f = 500\,\text{Hz}$ for EEG. The experimental procedure includes a training phase and a formal testing phase. The recorded EEG data is divided into training data group and testing data group in term of the ratio of 4:1.

4.4 Feature Extraction

A 5-layer wavelet transforms with the selected wavelet basis is performed on the EEG signals in each brain area. The selection of wavelet basis in the wavelet transform is a crucial issue, and each wavelet base has its characteristics. In this experiment, four standard wavelet basis of db4, db8, sym8, and coif5 are selected to calculate EEG features with the Eqs. (1)–(4). The emotional classification results (subject cyf) are shown in Table 4.

Table 4. CYF's emotional classification accuracy

Subject	Feature	Wavelet	Accuracy
cyf	Energy	db4	76.39%
		db8	80.56%
		sym8	73.61%
		coif5	75%
	REE	db4	75%
		db8	77.78%
		sym8	75%
		coif5	65.28%
	LREE	db4	79.17%
		db8	77.78%
		sym8	73.61%
		coif5	69.44%
	DE	db4	83.33%
		db8	79.17%
		sym8	84.72%
		coif5	80.56%

The results show that the differential entropy feature, along with the wavelet function sym8 has the highest emotion recognition rate. Thus the differential entropy feature along with the wavelet function sym8 is selected to perform the emotional recognition in this paper.

4.5 Brain Areas and EEG Correlation

In this experiment, the differential entropy is taken as the EEG feature, and sym8 is selected as the wavelet function. According to the method presented in Sect. 3, correlations between brain areas and emotions are performed on EEG feature vectors of $\mathbf{V_i}(\mathbf{i} = \mathbf{1}, \mathbf{2}, \mathbf{3}, \mathbf{4})$ and calculate recognition rate $\mathbf{R_a}$ respectively. The classification results are shown in Fig. 3-(a, b, c, d, e, f).

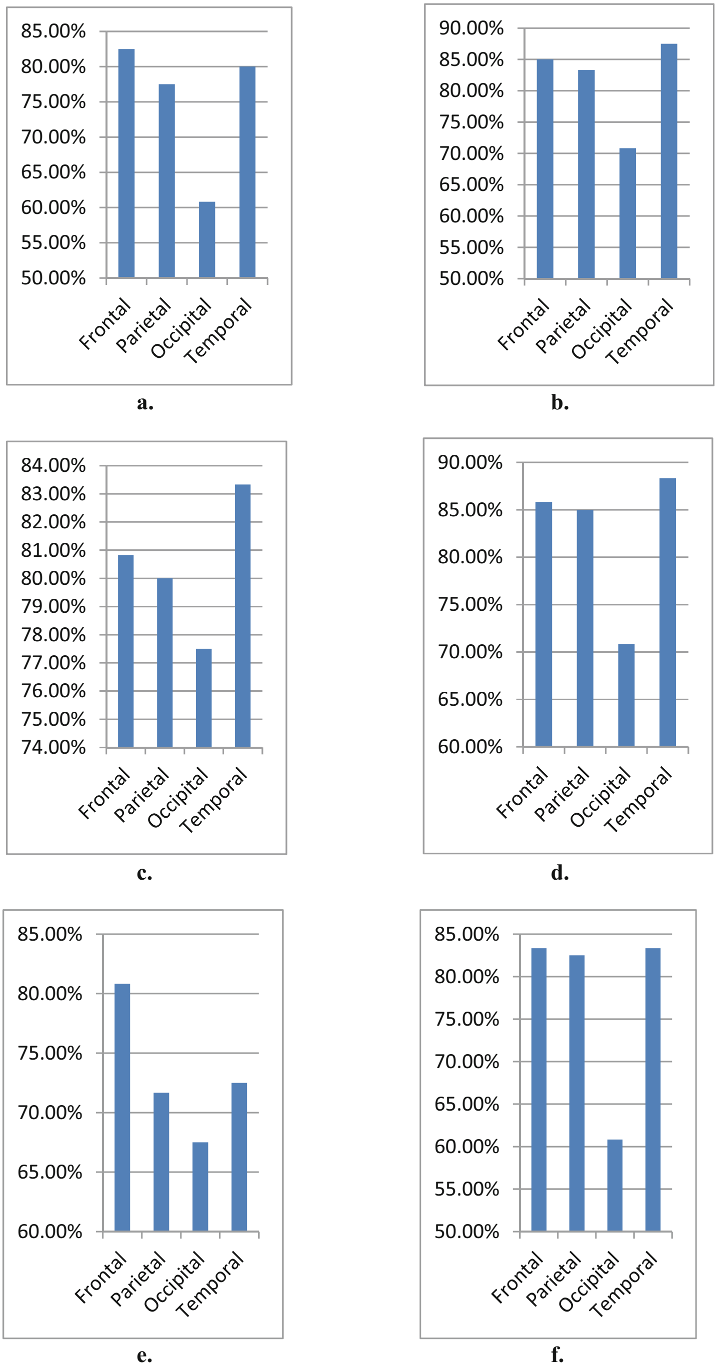

Fig. 3 a. Accuracy of four brain areas of cyf, b. Accuracy of four brain areas of fxs, c. Accuracy of four brain areas of fyh, d. Accuracy of four brain areas of lzs, e. Accuracy of four brain areas of sxl, f. Accuracy of four brain areas of zq

The above results indicate that the accuracy of emotional classification of the six subjects in the four brain areas is different. However, it can be seen that the emotion classification on the frontal and temporal lobes is the highest, followed by the parietal lobe, and the occipital lobe is the lowest.

To find the brain areas most associated with emotion. The emotion classification accuracy was calculated by stacking brain areas in the order of high to low precision. That is to calculate the emotional classification accuracy of the three groups of brain areas: frontal and temporal lobes; frontal, temporal and parietal lobes; frontal, temporal, parietal, and occipital lobes. The experimental results of the six subjects are shown in Fig. 4.

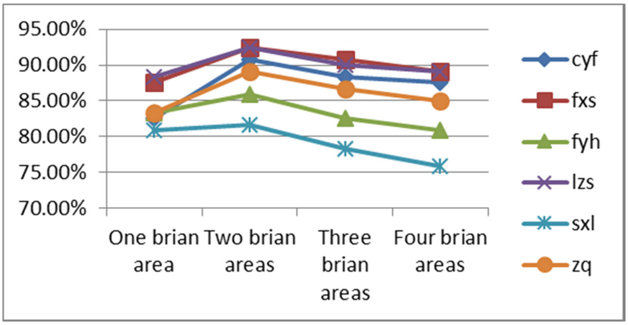

Fig. 4 Accuracy of the four brain areas of the six subjects

Figure 4 shows that the accuracy of emotional classification when joining data from frontal and temporal lobes is the highest; the accuracy of emotional classification when joining data from frontal, temporal and parietal lobes is higher; the accuracy of emotional classification when joining data from frontal, temporal, parietal, and occipital lobes is lower; the accuracy of emotional classification with only one brain area is the most economical.

5 Conclusion

In this work, we have explored the recognition accuracy of the standard emotional recognition method based on EEG, and then sought the correlation between emotions and brain areas with the higher accuracy of emotion recognition based on EEG, to provide the guideline for selecting most relevant electrodes with emotions to enhance the accuracy of emotion recognition based on EEG. Both the theoretical analysis and experiment have demonstrated that the brain areas most related to emotions are located in the frontal and temporal lobes. This conclusion can be further developed by correlating emotions with electrodes in the most relevant brain area.

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