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Research on EEG Channel Selection Method for Emotion Recognition

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***Abstract* - In this paper, based on the DEAP dataset, we studied the effects of different EEG channel selection methods on the accuracy of emotion recognition for different frequency bands. First, the discrete wavelet transform method is used to divide the EEG signals into four bands of gamma, beta, alpha and theta, and extract the entropy and energy of each band as classification features. Then, the following three channel selection methods are compared to select the best EEG channel combination for the four emotions classification susing, the channel selection method based on experience, the indirect channel selection method based on the mRMR feature selection algorithm, and the direct channel selection method based on the mRMR feature selection algorithm. Finally, the extreme learning machine with kernel is used to verify the effectiveness of the channel selection method. The results show that based on the mRMR feature selection algorithm, the channel selection method taking each channel as a whole is more powerful in balancing the number of channels and classification accuracy. In the beta band, the number of channels is reduced from 32 to 22, which is only 1.37% (from 80.83% to 79.37%) lower than the best classification accuracy, and the emotion recognition performance remains at a high level. Compared with the results of others, this paper can use less channels to achieve similar or higher emotional recognition performance than others, which further proves the effectiveness of the method. In addition, we also found that high frequencies (gamma and beta bands) are better for emotional recognition. This study provides a reference for channel and band selection in EEG-based emotion recognition.**

Index Terms -Channel selection, emotion recognition, mRMR.

I. INTRODUCTION

Human emotion is a comprehensive psychological and physiological experience, often accompanied by physiological awakening and certain external performance. Studies show that 80% of human communication information is emotional information. With the development of human-computer interaction technologies, emotion recognition is becoming more and more important at professional, personal and social level. It is an important part of achieving complete interaction between people and machines. Emotion recognition can be applied in different fields. For example, emotional states can be used to monitor and predict fatigue status[1]. In the medical field, identifying a patient's emotional state can provide an indication for the healthcare professional of the patient's mental, physical state, and progression of the healing process.

At present, the signals used for emotion recognition are mainly behavioral signals and physiological signals, wherein the behavior signals include facial expressions[2], speech[3], body postures[4], etc. These signals are external manifestations caused by human emotions. Although they have achieved certain results in emotion recognition, these signals are indirect manifestations of emotional information, easy to disguise and hide. Physiological signals such as EEG[5], nuclear magnetic, ECG[6], myoelectric[7], and skin resistance[8] are intrinsic expressions that are subject to subjective control and can more realistically reflect human emotions. Neuropsychology studies have found that EEG signals are rich in brain activity information compared to other physiological signals, and proper signal processing allows us to obtain more information about neural activity and emotional state[9-11]. In addition, EEG signals features non-invasive, low cost, portability and high time resolution. Therefore, EEG signals have become one of the main researching objects in the field of emotion recognition.

In order to improve the accuracy of emotion recognition, researchers used multi-channel EEG signals (usually 32-channel or 62-channel EEG signals of the whole brain) for emotion recognition. However, in practical applications, many EEG channels contain noise or redundancy, which is not helpful to emotion recognition. In addition, a large number of EEG channels is a challenge for data acquisition, and also increases the computational complexity of data processing. Therefore, the selection of EEG channels is crucial.

At present, most of the choice of EEG channels is based on experience. Some studies suggest that the neural activity of the frontal lobe is associated with emotional processing. For example, Dawson et al. analyzed the EEG of the prefrontal and parietal lobe in adults and infants and found that the prefrontal cortex is a brain region in charge of the treatment of emotions[12]. Therefore, the EEG channel in the frontal lobe is the first choice for many studies. Mohammadi et al. used discrete wavelet transform to decompose the 10-channel EEG signals in the frontal lobe and its surrounding area into corresponding frequency bands, and performed emotion recognition on the valence and wake-up dimensions for each frequency band[13]. Atkinson et al. selected 14 channels related to emotion in the frontal region, and combined the feature selection method based on mutual information with the kernel function to complete the emotion classification task[14]. Recent studies have shown that the frontal, prefrontal, temporal, parietal and occipital regions of the brain are involved in emotional responses[15]. Ahmet et al. selected 18-channel EEG signals in the frontal and temporal regions, and performed empirical mode decomposition (EMD), and

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then extracted temporal and frequency domain features to identify emotions in the valence and arousal dimensions[16]. However, the latest findings in neuroscience suggest studying the corresponding relationship between emotional states and the entire brain region [13]. Xu et al. studied the effects of 10-channel EEG signals and 32-channel EEG signals throughout the brain on the accuracy of emotion recognition. The results show that the 10 channel EEG signals characterized by power have higher classification accuracy[17]. Therefore, the automatic finding of the optimal subset of EEG channels from the whole system has attracted more and more attention. There are also some studies based on feature selection that indirectly select channels based on the channels involved in the selected features. Zhang et al. used the reliefF feature selection algorithm to reduce the number of EEG channels from 21 (30 features) to 15 (20 features), and the accuracy of emotion recognition decreased slightly[18]. Wang et al. used the min-Redundancy Max-Relevance (mRMR) feature selection algorithm to select the top 30 best features for emotion recognition. The results showed that the average number of channels involved was 25 for 5 participants [19]. The above-mentioned EEG channel selection methods have achieved certain effects, but the channel selection using just one method may not be able to select a relatively better EEG channel.

Based on the DEAP dataset, this study systematically studied the influence on emotion recognition accuracy of EEG channel selection methods based on experience to select EEG channels (10 channels, 14 channels, 18 channels and 22 channels), indirect selection of EEG channels based on mRMR feature selection and direct selection of EEG channels based on mRMR. The discrete wavelet transform is used to transform the EEG signals into different frequency bands, and the entropy and energy of each frequency band are extracted as features. After that, the above three different channel selection methods are applied, and KELM is used to identify four types of emotions to verify the performance of different channel selection methods. The emotion recognition performance of different frequency bands is also compared.

II. PRELIMINARIES

In this section, we introduce the emotional model, the classification method, and the selection of the time window.

A. *Emotional model*

Human beings have a variety of researches on emotions. People's emotions change with changes of external stimuli. Many researchers made different definitions of emotions. There is no unified conclusion for the dispute that emotions are independent or continuous.

Usually the emotional state is divided into two models: one is a discrete emotional model, which consists of several basic emotions, but different researchers have different views on the selection of basic emotions, as shown in TABLE I Nevertheless researchers agree that complex emotions are formed by the superposition of basic emotions. The other is a dimensional-based emotional model that evolves from a valence-arousal two-dimensional model to a valence-arousal-like three-dimensional model. Then there was higher valence-arousal-like-dominate four-dimensional model.

TABLE I
DIFFERENT RESEARCHERS SELECTED BASIC EMOTIONS[25]

Researcher	Basic emotion
James	anger，fear，sad，love
Ekman	anger, fear, sadness, enjoyment, disgust, surprise
Clynes	anger, hatred, sadness, happiness, love, romantic love, reverence
Izard	anger, fear, guilt, pain, joy, shame, surprise, interest, disgust
Frijda	anger, fear, pain, pride, happiness, accidental disgust, contempt

B. *Time window*

Time is an important factor for emotion recognition. Time windows that are too long or too short may cause different emotions to be covered. The acquisition time of EEG signals is generally longer than the accurate recognition time of emotional state. In order to accurately identify the emotional state, the EEG signal is usually processed by adding windows, but the length of the windows is a controversial topic. Thammasan et al. analyzed the emotional recognition accuracy of the EEG window for 1-8 seconds, and the results showed that the smaller window (1-4 seconds) had higher emotion recognition accuracy than the larger window (5-8 seconds)[13]. Mohammadi et al. tested the 2s and 4s windows, and the results showed that the 4s window got better emotional classification results. Zhang et al. also used the 4s window to classify four types of emotions[21].

C. *KELM Classifier*

The Extreme Learning Machine (ELM) was proposed by Professor Huang Guangbin of Nanyang Technological University in 2004. It is a single hidden layer feedforward neural network learning algorithm. The algorithm does not have the process of iterative tuning parameters in the operation, the training process is fast, and the unique optimal solution is generated, so the learning speed is fast and the generalization performance is good.

For any N different samples (x_i, t_i), the standard ELM mathematical model with L hidden layer nodes and the activation function $g(x)$ is

$$\sum_{i=1}^{L} \beta_i g_i(x_j) = \sum_{i=1}^{L} \beta_i g(\omega_i \cdot x_i + b_i) = o_j, \quad j = 1, \ldots, N \tag{1}$$

where w_i is the weight vector connecting the i-th hidden layer node and the input node, β_i is the weight vector connecting the i-th hidden layer node and the output node, and b_i is the offset of the i-th hidden layer node.

If N> L, ie the number of training data is greater than the number of hidden layers nodes, β has the following solution:

$$\beta^* = \left(H^T H + \frac{I}{C}\right)^{-1} H^T T \tag{2}$$

If N< L, ie the number of training data is less than the number of hidden layer nodes, β has the following solution:

$$\beta^* = H^T \alpha^* = H^T \left(HH^T + \frac{I}{C} \right)^{-1} T \quad (3)$$

$H^T H$ and HH^T are referred to as "ELM kernel matrices", where $h(x_i) \cdot h(x_j)$ is the kernel of the ELM.

Usually in order to enable features to be mapped to higher dimensions, a kernel function is often used instead of a kernel matrix, and the ELM with kernel is called KELM.

III. MATERIALS AND METHODS

A. Data Acquisition

In this paper, we use the MATLAB preprocessed data in the DEAP dataset, which is an open source multimodal physiological signal database for emotion analysis. During data collection, 32 participants watched 40 clip videos that could trigger different emotions, and recorded 60 seconds of data for each video. Each participant will score the four dimensions of valence-arousal-dominant-like, ranging from 1-9 points, representing the degree of emotion from small to large. The emotional state of the four dimensions is shown in Fig. 2. The emotional state changes from left to right as the individual score increases. For example, Fig. 2a shows the change in valence (pleasure) from small to large (from negative to positive), and Fig. 2b shows the change in arousal (degree of stimulation) from small to large (from calm to excitement). The dataset records seven types of physiological modalities for each video, including 32 channels of EEG data and 8 channels of other peripheral physiological signals. The preprocessing stage removes the EOG interference from the original signal and performs bandpass filtering, and reduces the sampling frequency of the original signal from 512 Hz to 128 Hz[22, 23].

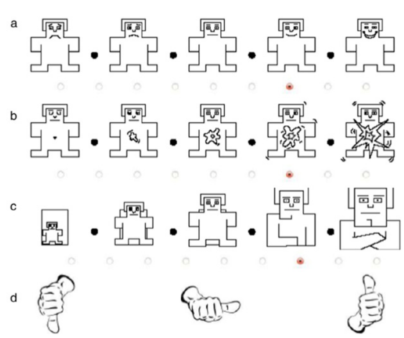

Fig. 2 Emotional state a Valence b Arousal c Dominance and d Liking[22,23].

This paper analyzes the emotions of the titer-wake dimension. If the individual score is >5, then we think the level of valence/arousal is high. If the individual score is ≤5, then the valence/arousal level is low. To eliminate individual differences and channel differences, we normalized each channel EEG signal to [0,1] using the min-max normalization method. A 4s window is used for each 60s of EEG data, for a total of 15 windows, so the total sample size is 19200 (32 people * 40 videos * 15 windows).

B. Feature Extraction

We use the discrete wavelet transform (DWT) to process EEG signals. The wavelet transform uses a mother wavelet function to stretch and translate the signal to obtain a series of wavelet coefficients. It has the ability to perform both time and frequency analysis and can be applied to transient, non-stationary or time-varying signals. In our study, the db4 discrete wavelet 4th order decomposition is performed on the EEG data of each channel, and all the high frequency components are extracted. They are four bands of gamma, beta, alpha and theta. Finally, the entropy and energy of each frequency band are extracted as features.

1) Entropy

Entropy represents the degree of disorder of the signal. The larger the entropy is, the higher the disorder degree of the signal is. The entropy of each band is calculated as follows:

$$ENT_j = -\sum_{k=1}^{N} \left(D_j(k)^2 \right) \log\left(D_j(k)^2 \right), \; k = 1, \ldots N \quad (4)$$

2) Energy

The energy of each band is calculated as follows:

$$ENG_j = \sum_{k=1}^{N} \left(D_j(k)^2 \right) \quad (5)$$

where j is the level of wavelet decomposition and k is the number of wavelet coefficients.

C. Channel Selection Method

(1) ES method

In the selection of emotion-based EEG channels, many researchers have studied the relationship between emotional state and brain regions. This study refers to the method of selecting channels based on experience as the ES method. Emotional recognition studies were performed using commonly used 10 channels[23]and 14 channels[24] of frontal and adjacent; 18 channels of frontal and temporal[16] and 22 channels of frontal, parietal, temporal and occipital of EEG signals. The 10 channels are FP1–FP2, F3–F4, F7–F8, FC5–FC6 and FC1–FC2, as shown in Fig. 3a; 14 channels add AF3-AF4, C3-C4 four EEG channels on the basis of 10 channels, as shown in Fig. 3b; 18 channels add T7-T8, Fz and Cz four EEG channels on the basis of 14 channels, as shown in Fig. 3c; 22 channels add P3-P4 and O1-O2 four channels on the basis of 18 channels, as shown in Fig. 3d.

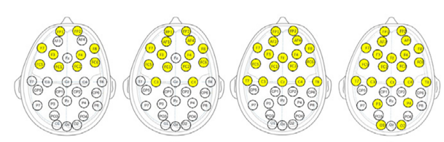

Fig. 3 EEG channel based on experience selection.

(2) mRMR-FS method

This study will use the min-Redundancy Max-Relevance[25] algorithm for feature selection and indirect channel selection, this method is called mRMR-FS method.

mRMR is widely used for feature selection in classification tasks due to its effectiveness and computational simplicity. Its core idea is to maximize the correlation between features and categories while minimizing the redundancy between features and features. The calculation method is as follows.

Max-Relevance:

$$\max D(S, c) = \frac{1}{|S|} \sum_{x_i \in S} I(x_i; c) \tag{6}$$

x_i is the i-th feature, c is the categorical variable, $I(x_i; c)$ is the mutual information of the feature x_i and the category c, and S is the feature subset.

min-Redundancy:

$$\min R(S), R = \frac{1}{|S|^2} \sum_{x_i, x_j \in S} I(x_i; x_j) \tag{7}$$

$I(x_i; x_j)$ is the mutual information between the feature x_i and the feature x_j.

mRMR algorithm:

$$\max \phi(D, R), \phi = D / R \tag{8}$$

For a feature set with M features, the feature evaluation will last for M rounds. After these evaluations, according to the weights from large to small, we will get a feature set F through the mRMR algorithm.

$$F = \{x_1', x_2', \ldots, x_h', \ldots x_M'\} \tag{9}$$

This study uses 64 features to identify four types of emotions. Firstly, the mRMR algorithm is used to rank 64 features by weight. The features with larger weights contribute more to distinguishing samples, while the features with smaller weights contribute relatively smaller. In channel selection, feature selection is first performed, the first n features are selected, and then the channels containing these features are selected.

(3) mRMR-CS method

Although in the mRMR-FS method, the reduction of features usually leads to a reduction in the channel, the actual effect is not obvious, so we expect to evaluate the channel as a whole directly. Based on the mRMR algorithm, we use all the feature weights belonging to a channel to evaluate the emotion recognition capabilities of the channel. We take the average of all the feature weights from one channel as the weight of the channel, and calculate the weight of the EEG channel C as follows

$$W(C) = \frac{1}{N} \sum_{i=1}^{N} w(x_i) \tag{10}$$

where $W(x_i)$ is the weight of the i-th feature of channel C, and N is the number of features in channel C.

According to the weight of the channel, the channels are sorted descendingly. According to the sorting, the features of the channel are added into the feature subset to verify the emotion recognition ability. We define the method based on the mMRM algorithm to directly select the channel as the mRMR-CS method. A total of 32 EEG channels were included in the study. Each channel contained 2 features. The mRMR-CS method was used to evaluate the emotional recognition performance of 32 EEG channels. It is expected to select the least channels to achieve better emotion recognition performance.

D. *Classification*

We use KELM with RBF as the kernel for classification. The RBF parameter is 10 and the regularization coefficient is C=1000. KELM is used to identify high valence high arousal (valence >5, arousal >5), high valence low arousal (valence >5, arousal ≤5), low valence low arousal (valence <5, arousal ≤5) Low valence high arousal (valence ≤ 5, arousal > 5) four types of emotions, the division of the four types of emotions is shown in Fig. 4 For 19,200 samples, we used a 10-fold cross-validation method to classify and take the average of 10 tests as the final classification result.

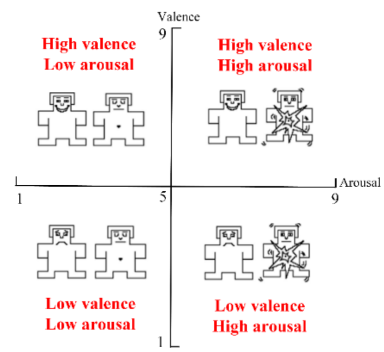

Fig. 4 Four categories of emotion.

IV. Results and Discussion

In this section, we used KELM to classify emotions based on the DEAP dataset, compared and analyzed the results of three channel selection methods.

A. *Results Analysis of ES Method*

Based on DEAP, the classification accuracy of the four types of emotions in the gamma, beta, alpha, and theta bands is shown in Fig. 5 We can see from the figure that with the number of channels increasing, the recognition accuracy in each frequency band is accordingly improved. For each channel combination, the gamma and beta frequency bands have higher classification accuracy than the alpha and theta frequency bands, indicating that high frequency are more helpful for emotional recognition. In the 10-channel EEG signal, the classification accuracy of the gamma frequency band was 59.63%, which was significantly higher than the classification accuracy of the beta frequency band ($p<0.05$). Based on the classification of 14-channel EEG signals, the beta frequency band had the highest classification accuracy

(65.81%), but there was no significant difference compared with the gamma frequency band classification results ($p>0.05$). In the emotional recognition based on 18-channel EEG signals, the classification accuracy of the beta frequency band was 73.51%, which was significantly higher than that of the gamma frequency band ($p>0.05$). In the emotion recognition based on 22-channel EEG signals, the classification accuracy of the beta frequency band was 77.85%, which was significantly higher than that of the gamma frequency band ($p>0.05$).

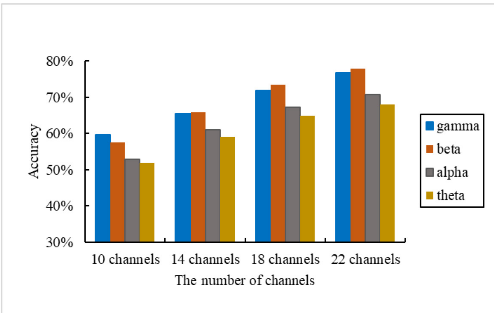

Fig. 5 Emotional classification results for each channel selected based on experience.

B. *Results Analysis of the mRMR-FS Method*

First, the mRMR algorithm was used to sort the 64 features according to the importance of emotion classification, and then the features were added one by one to evaluate the emotion classification. It can be seen from Fig. 6 that in each frequency band, the features in the initial stage are relatively smaller, and the accuracy of emotion recognition increases rapidly. As the features increase gradually, the increase of the accuracy of emotion recognition becomes smaller and smaller, indicating that the features of large weights are more related to emotional changes, which proves the effectiveness of the mRMR feature selection algorithm. As the feature continues to increase, the classification accuracy of the gamma and beta frequency bands begins to decline, indicating that redundant features appear in these two frequency bands, affecting the accuracy of emotion recognition. In addition, we found that the gamma and beta frequency bands have similar recognition accuracy and are generally higher than the alpha and theta frequency bands, so we analyzed the gamma and beta frequency bands separately.

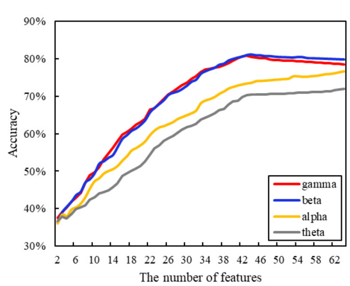

Fig. 6 Classification accuracy of different frequency bands over varying number of features based on the mRMR-FS method.

Fig. 7 is a graph showing the variation of the emotion recognition accuracy of the gamma band as the number of features changes. Point A in the figure is the best classification performance point, using the top-43 features, which are distributed in 28 channels, and the emotion recognition accuracy reaches 80.80%. From the point of B (35 features, involving 24 channels), the performance of emotion recognition began to stabilize. Although the number of channels at point B decreased relative to point A, the accuracy of emotion recognition also decreased to 77.29%.

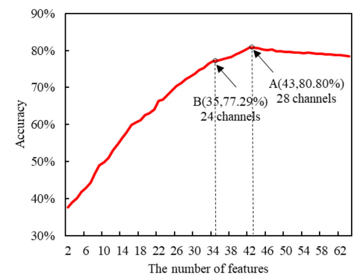

Fig. 7 Classification accuracy of gamma frequency bands over varying number of features based on the mRMR-FS method.

Fig. 8 is a graph showing the variation of the beta band emotion recognition accuracy as the number of features changes. Emotion recognition accuracy reduced from the highest point A (44 features, involving 28 channels, recognition accuracy81.14%) to B (36 features, involving 22 channels, recognition accuracy 77.61%), reduced 6 channels, and reduced recognition accuracy 3.53%.

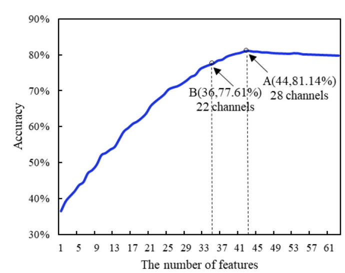

Fig. 8 Classification accuracy of beta frequency bands over varying number of features based on the mRMR-FS method.

Comparison with A and B points in Fig. 7 and in Fig. 8 shows that the accuracy of emotion recognition using 22 channels in the beta band and 24 channels in the gamma band is similar when the accuracy reduction is acceptable, indicating that the channel reduction performance of the beta band is better.

In order to evaluate the channel reduction performance of the two bands as a whole, this study compares TABLE II and TABLE III. The results show that the channel reduction performance of the gamma band is slightly higher than the beta band when the channel involved is less than 18 channels. At 18 channels or more, the channel reduction performance of the beta band is higher than that of the gamma band.In practical applications, too few channels will lose too much precision. Therefore, this study balances the number of channels and the accuracy of recognition for channel reduction. With the acceptable accuracy of the loss, the least channel is chosen, so we believe that the performance of the beta band is slightly higher than the gamma band.

TABLE II
CLASSIFICATION ACCURACY OF THE TOP N FEATURES IN THE GAMMA BAND

Top-N Features	Number of Channels Involved	Accuracy
4	4	40.14%
8	7	46.82%
12	9	53.05%
16	10	59.83%
20	11	63.06%
24	14	68.10%
28	18	72.17%
32	22	75.33%
36	25	77.63%
40	27	79.43%
50	30	79.67%
64	32	78.46%

TABLE III
CLASSIFICATION ACCURACY OF THE TOP N FEATURES IN THE BETA BAND

Top-N Features	Number of Channels Involved	Accuracy
4	4	40.58%
8	8	47.02%
12	10	52.66%
16	12	58.61%
20	13	62.42%
24	14	67.92%
28	16	71.29%
32	18	74.45%
36	22	77.61%
40	27	79.98%
50	28	80.48%
64	32	79.83%

C. Results Analysis of the mRMR-CS Method

Based on the weight of the above features, according to the mRMR-CS method, each channel is used as a whole, and the weight of each channel is calculated, and the weight values are sorted according to the weight value, that is, the contribution of each channel to the emotion classification. Figure 9 is a graph showing the emotion recognition performance of each frequency band. As the number of channels increases, the accuracy of emotion recognition in each frequency band increases, and the growth rate decreases with the increase of the number of channels, indicating that the channel with greater weight contributes more to emotion recognition. The effectiveness of the channel selection method is demonstrated. At the same time, we also find that high frequency has better performance in emotion recognition than low frequency. Among them, gamma frequency band performs better when the number of channels is small, but the loss precision is more when the number of channels is small. The beta band performs better when the number of channels is large. Therefore, based on the acceptable accuracy of the loss, the number of channels is reduced. We choose the beta band for analysis.

Figure 10 shows the change in the accuracy of the emotion recognition in the beta frequency band. The highest accuracy of emotion recognition is 80.83%, which occurs at point A and involves 28 channels. After B, the accuracy of emotion recognition began to stabilize, the number of channels involved at this point was 22, and the recognition accuracy was 79.46%. Compared with all 32 channels, this point reduces 10 channels. Compared with the highest recognition accuracy, the precision loss of this point is 1.37%. Under the premise of reducing a large number of channels, the loss accuracy is less. Therefore, we believe that point B is the best point for balance accuracy and number of channels. This method is superior to the mRMR-FS method overall.

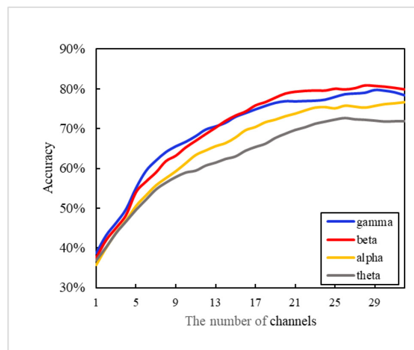

Fig. 9 Classification accuracy of different frequency bands over varying number of channels based on the mRMR-CS method.

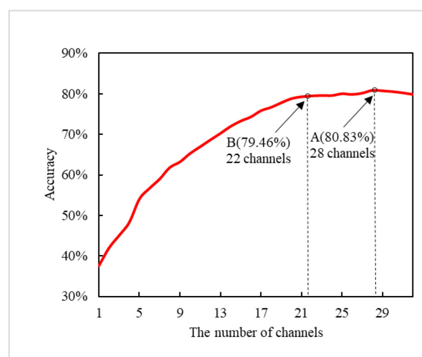

Fig. 10 Classification accuracy of beta frequency bands over varying number of channels based on the mRMR-CS method.

D. Comparison of Results

In the EEG based on experience selection (ES), we used 10 channels, 14 channels, 18 channels and 22 channels of EEG signals for emotion recognition. To demonstrate the effectiveness of our method, we also selected the 10, 14, 18 and 22 channel EEG signals optimized by the mRMR-FS and mRMR-CS methods for comparison. In the ES we selected the optimal value in each channel combination (gamma frequency band in 10 channels, beta frequency band in 14, 18 and 22 channels) for comparison. In the mRMR-FS and mRMR-CS methods, we selected the results of the beta frequency band for comparison. As we can see from the Fig. 11, the mRMR-CS method shows the best classification performance in each channel combination, indicating that this channel selection method selects channels that contributes a lot to emotion recognition, and can use fewer channels to achieve better classification results. According to the results in 4.3, the mRMR-CS method can achieve the highest recognition accuracy of 80.83% using 28 EEG channels. When the number of channels is 22, the accuracy of emotion recognition can reach 79.46%, and 10 channels are reduced and the accuracy loss is acceptable, which can better balance the number of channels and the recognition accuracy. The selected 22 channels ranking is shown in Table 5.

TABLE IV

THE TOP 22 COMMON CHANNELS

Channel Rank	Electrode	Channel Rank	Electrode
1	CP2	12	PO3
2	FC1	13	P8
3	Fz	14	T7
4	FC5	15	C4
5	AF3	16	Cz
6	Oz	17	CP1
7	F8	18	Pz
8	C3	19	CP5
9	O1	20	P7
10	P4	21	AF4
11	P3	22	P3

Our results were compared with other four-class studies on the valence and arousal dimensions on the DEAP dataset. In TABLE V, the results of this comparison are illustrated. This study can verify the effectiveness of our method by using fewer channels to achieve similar or higher results than others.

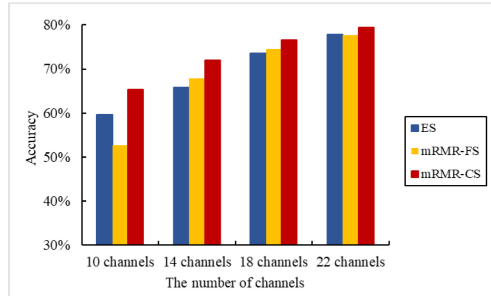

Fig. 11 Emotion recognition accuracy of three channel selection methods on 10, 14, 18 and 22 channels.

V. CONCLUSION

This study explores the emotion recognition performance of the three types of channel selection methods. First, the DEAP data is normalized using the min-max normalization method, then the EEG signal is transformed into the gamma, beta, alpha, and theta bands using discrete wavelet transform techniques, and the entropy and energy of each band are extracted as features. The method of selecting the EEG channel based on experience (ES), the method of indirectly selecting the EEG channel based on the mRMR feature selection (mRMR-FS), and the method of directly selecting the EEG channel based on the mRMR feature selection method (mRMR-CS) are used to analyze EEG channels. The results show that mRMR-CS has the best channel reduction performance among the three methods, using 22-channel EEG signals, the emotion recognition accuracy reaches 79.46% with 10 channels reduced. Compared to the other two methods, the method can achieve higher emotional recognition accuracy using fewer EEG channels. The effect of the method is further verified in comparison with others methods. In addition, the study also found that the high frequency band is more conducive to emotion recognition. Our research provides channel and band selection references for EEG-based emotion recognition.

TABLE V

COMPARISON OF THE ACCURACY OF EMOTION RECOGNITION IN DIFFERENT STUDIES

Reference	Feature	Classifier	No. channels	Accuracy (%)
Zhang et al.(2016) [18]	Power features	SVM	19	59.13
Chen et al.(2017) [26]	time, frequency	KNN RF	32	70.04
Chen et al.(2017) [27]	time and frequency-domain, hemispheric	KNN, C4.5, RF, SVM	32	77.57
Rami et al.(2018)[28]	quadratic time-frequency distribution	SVM	22	79.3
Nakisa et al.(2018) [29]	time, frequency and time frequency	PNN	32	67.47
Li et al.(2018) [30]	linear and non-linear	SVM	32	59.06
Our research(2019)	Entropy and Energy	KELM	22	79.46
			28	80.83

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