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Four-Classes Human Emotion Recognition Via Entropy Characteristic and Random Forest

Yimin Hou, Jian Zhang*

School of Automation Engineering, Northeast Electric Power University, China

***Corresponding author:** zhangjianohlala@163.com, phone: +185 6042 2443

Human Emotion Recognition is of vital importance to realize human-computer interaction (HCI), while multichannel electroencephalogram (EEG) signals gradually replace other physiological signals and become the main basis of emotional recognition research with the development of brain-computer interface (BCI). However, the accuracy of emotional classification based on EEG signals under video stimulation is not stable, which may be related to the characteristics of EEG signals before receiving stimulation. In this study, we extract the change of Differential Entropy (DE) before and after stimulation based on wavelet packet transform (WPT) to identify individual emotional state. Using the EEG emotion database DEAP, we divide the experimental EEG data in the database equally into 15 sets and extract their differential entropy on the basis of WPT. Then we calculate the value of DE change of each separated EEG signal set. Finally, we divide the emotion into four categories in the two-dimensional valence-arousal emotional space by combining it with the integrated algorithm, Random Forest (RF). The simulation results show that the WPT-RF model established by this method greatly improves the recognition rate of EEG signal, with an average classification accuracy of 87.3%. In addition, we use WPT-RF model to train individual subjects, and the classification accuracy reached 97.7%.

KEYWORDS: Emotion recognition, EEG, Wavelet packet transform, RF.

1. Introduction

In recent years, intelligent computing technology has brought forth new ideas in the field of biomedicine, and many scientific research problems have been solved in the cross-collision of the two fields such as the image analysis and EEG calculation in biomedicine. Image analysis is an effectiveness method for assistant diagnosis. In document [36], researchers used intelligent computer technology to recognize fluorescent signals and successfully solved the problem of poor human perception of fluorescent signals under the influence of environment. Richhariya et al. [29] proposed an assistant recognition method based on computational intelligen, and realized automatic classification of X-ray images for disease diagnosis. EEG is also wildly used in the biomedicine field. It is an important method for HCI systems and diagnosis of some diseases such as Depression, Hyperactivity, Schizophrenia and so on. For example, Wozniak et al. [36] proposed a novel machine learning approach based on universum support vector machine (USVM) for classification， and achieved highest classification accuracy of 99% for the healthy and seizure EEG signals. Acharya et al. [1] developed a computer-aided detection (cad) system to assist EEG signal detection, and successfully applied it to epilepsy localization.

It is noteworthy that HCI technology has been widely studied in recent years. EEG signal is a non-stationary time series. It can be analyzed in time domain by extracting features such as standard deviation, skewness, peak mean absolute value of the signal or by using event-related potential (ERP) [19]. Frequency domain features also should be paid attention to. In frequency domain, the signal could be divided into five frequencies, also known as the rhythm. They are delta rhythm, theta rhythm, alpha rhythm, beta rhythm and gamma rhythm. Some researchers focused on the EEG analysis algorithm. By using the long-term and short-term memory (lstm) network for causal filtering, Chen et al. [12] reduced the filtering delay of EEG signals and improved the performance of neurofeedback devices. Butkeviciute et al. [8] used baseline estimation and sparse filtering algorithm to remove the motion artifacts in EEG signals, and achieved good results. Chen et al. [12] proposed a generalized correlation entropy based on generalized Gauss density (ggd) function and applied it to adaptive filtering. Damaševičius et al. [14] used electroencephalogr-am (EEG) data to evaluate biometric cryptosy-stems. It is concluded that the biometric user authentication system described in this paper is effective with a bit error rate of 0.024. Lin et al. [22] reviewed emotional recognition based on physiological signals, compared and sumarized recent research work.

The key area to fill this capacity is affective computing (AC) [5] that is to establish a model to recognize human emotional state through the biological emotional response cues generated in human-computer interaction. Emotion recognition is not only an important task for computer to understand human state in BCI, but also has a wide range of applications in many other fields. In the field of medicine, affective computing model can help medical researchers to understand the human emotional mechanism, and be used for patients' physical health monitoring and psychological treatment [32], [28]. In the business field, it can also be used for consumer psychoanalysis, market regulation and so on. Emotion recognition is a subject in the fields of pattern recognition, human-computer interaction, emotion computing, intelligent control, etc. Its research will greatly promote the development of artificial intelligence. Lots of studies were done bu the researchers in emotion recognition using EEG. Atkinson et al. [5] took EEG standard data set as experimental object, and combined (mRMR) based feature selection method based on mutual information with nuclear classifier to improve the accuracy of emotional classification task. Mert et al. [25] proposed a memd-based feature extraction method for multi-channel EEG signals, and analyzed the value of multi-channel IMF extracted by MEMD as participants and the characteristics of wake-up scale. Alarcao et al. [2] presented a survey of the neurophysiological research performed from 2009 to 2016, providing a comprehensive overview of the existing works in emotion recognition using EEG signals. Ullah et al. [33] proposed an ensemble learning algorithm for automatically computing the most discriminative subset of EEG channels for internal emotion recognition, the algorithm is improved useful in reducing the amount of data while improving computational efficiency and classification accuracy at the same time. Balaubramanian et al. [7] used the multi-resolution analysis algorithm of wavelet packet decomposition (wpd), established the frequency localization model of given stimulus relative to time in different EEG bands, and analyzed the participants' emotional responses induced by music.

Feature extraction is one of the key steps of emotion recognition through EEG signals. Due to the low complexity of time-frequency calculation, it is more likely to extract features in the frequency domain or the time-frequency domain in the actual research process [9]. In recent years, many entropy estimators have been used to quantify the complexity of EEG signals according to the instability of EEG signals [3], [20], among them, the estimation of differential entropy is equivalent to the logarithmic energy spectrum of a certain frequency band [4]. Wavelet transform can be used to analyze the characteristic, but there are some disadvantages on high frequency and low frequency resolution. In contrast, the wavelet packet transform (WPT) can not only be decomposited in multi-scale, but can also select frequency bands adaptively according to the characteristics, which greatly improves the processing ability of non-stationary signals such as EEG sequences. Many feature extraction methods of EEG signals based on WPT have achieved good results. For example, Avila et al. [6] calculated the autoregressive coefficient on the basis of wavelet packet transform, and used SVM classifier as the feature of EEG signal to obtain good recognition effect. Yong et al. [39] used local wavelet packet coefficient to extract EEG signal feature, then BP Neural Network as classifier, and achieved 94% classification rate in EEG motion imagination classification.

On the basis of feature extraction, researchers have built a large number of emotion computing models. Yong et al. [39] used BP Neural Network, SVM and Mahalanobis Discriminant to respectively establish classification models and compare the classification results. autoregressive model was introduced by Di et al. [16] to classify positive and negative emotions according to the frequency domain characteristics of EEG signals. However, EEG signal was instability and with low signal-to-noise ratio, which easily lead to a decline in accuracy and posing great challenges to classification [35]. At the same time, with the improvement of ensemble learning model, Random Forest model with decision tree as the basic classifier gradually occupies a higher position in the field. It contains multiple decision trees trained by bagging integrated learning technology, and the output results are determined by voting. RF overcomes the over-fitting problem of decision tree and becomes a popular classification model by virtue of its good tolerance to noise and outliers. Its application in a lot of fields has achieved excellent results. For instance, Lu et al. [24] used RF to train ship classification models with coded information of mixed context-aware features, and achieved good classification results. Zhang et al. [40] proposed a vascular segmentation method based on RF classifier. Değer et al. [15] proposed a classification algorithm based on RF, which solved the problem of poor robustness in face emotion recognition. Xiao et al. [38] greatly improved the success rate of acoustic event monitoring system by using RF classifier. Fabris et al. [17] used RF to predict gene expression as the brain ages. Especially, RF has superior scalability and parallelis for multi-dimensional data classification, and has obvious advantages for EEG signal classification based on feature extraction in multiple frequency bands. Ranran et al. [27] used RF to classify the EEG of moving images, and obtained 89% of the median classification accuracy. Silveira et al. [30] improved sleep stage classification performance by using single channel EEG based on RF. Vijayakumar et al. [34] trained a Random Forest model to predict pain score by using time-frequency wavelet representation of independent components in EEG data, and finally achieved an average classification accuracy of 89.45%. However, there are few researches on the application of RF in emotion recognition based on EEG signals.

Based on the above research status, this paper proposes an emotional classification model based on wavelet packet transform and Random Forest classifier, which divides human emotions into four categories in two-dimensional space. In addition, a new method is used to extract the changes of EEG entropy characteristics before and after stimulation, eliminating the influence of baseline data on classification results. The simulation results show that this method greatly improves the accuracy of WPT-RF model for human emotion classification. The average classification accuracy is 87.3%. In addition, we conduct model training for individual subjects, with the highest classification accuracy of 97.7%.

The rest of this paper is organized as follows. The first section of method briefly introduces the two-dimensional emotional model, the second section gives the differential entropy feature extraction technology based on WTP, and the third section introduces the construction of classifier and parameter selection in detail. In the first three sections of the experiments and results analysis, two different methods of extracting the change of features are compared, and the results are analyzed. In addition, the results of single-person training model are given. In the fourth section, different emotion classification models are compared. Next comes the conclusion.

2. Method

In this section, we first set up an emotion classification label based on two-dimensional space. Afterwards, the DE feature were extracted based on wavelet packet transform algorithm, and the baseline data DE feature of 3s were subtracted from the eigenvalues, then we get the value of DE change for each experimental data. Finally, the RF classifier was used to classify the two-dimensional emotional space into four classes.

Figure 1 shows the BCI simulation system of the affective computing model we proposed. Subjects received video stimuli and recorded their EEG signals. Each group contained 3s blank and 60s video stimuli. After signal pretreatment, the experimental data of 60s were divided into 15 copies with the same length of time.

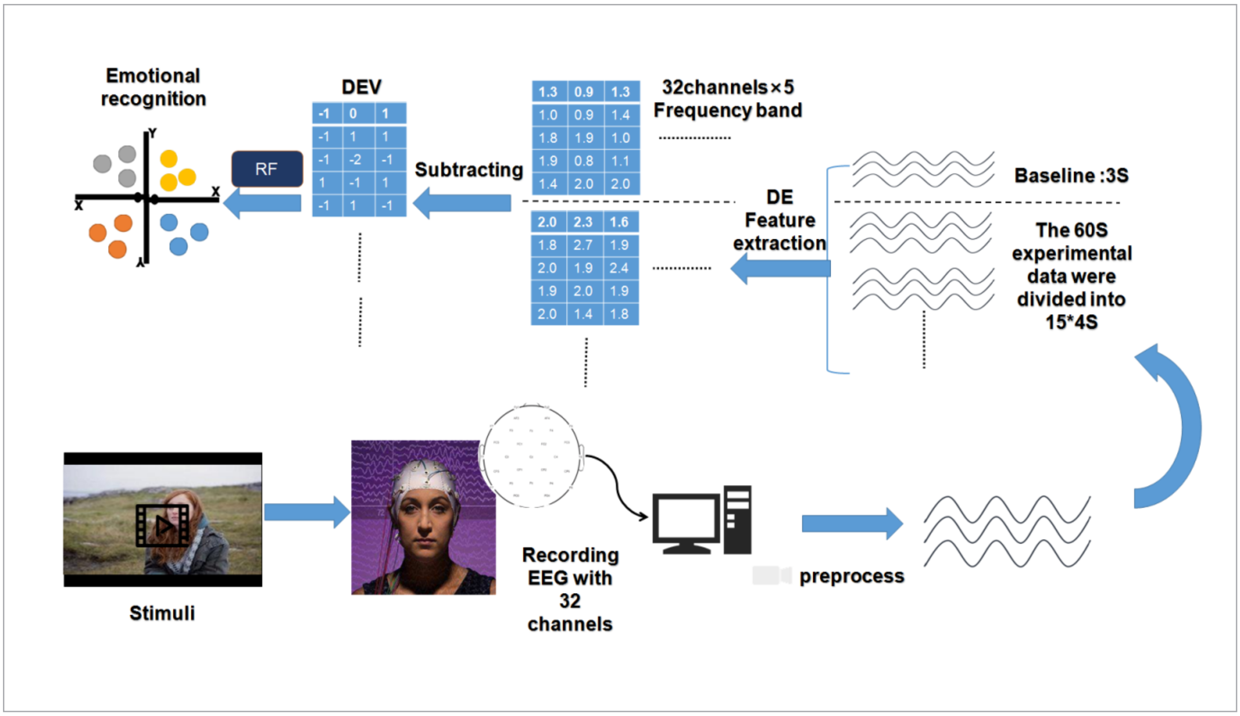
2.1. Feature Extraction

2.1.1. Wavelet Packet Transform and Differential Entropy

For time series signals $s(t) \in L^2(R)$, the wavelet packet transform can be defined as the projection coefficient of s(t) on the orthogonal wavelet packet basis.

Figure 1

BCI simulation system based on EEG signal, the ultimate task is emotional recognition



That is，

$$p_s(n,j,k)=\left\langle s(t),w_{n,j,k}(t)\right\rangle=\int_{-\infty}^{+\infty}s(t)\left[2^{-\frac{j}{2}}\cdot\overline{w_n}(2^{-j}t-k)\right]d_t \quad (1)$$

Among them, $w_{n,j,k}(t)$ is the wavelet packet basis function. On orthogonal wavelet packet space U_n^j which is expressed by Formula (2), the sequence of wavelet packet transform coefficients can be expressed as $\{p_s(n,j,k)\}_{k\in Z}$, where j represents the decomposition level and n represents the n-th node.

$$U_n^j=Span\{w_{n,j,k}(t)\}=Span\{2^{-\frac{j}{2}}\cdot\overline{w_n}(2^{-j}t-k)\\ j,n\in Z\}. \quad (2)$$

In the decomposition process of the wavelet packet, each layer is divided into high-frequency sub-bands and low-frequency sub-bands as the number of layers progresses. Thus, the recursive formulas of $p_s(n, j, k)$ can be expressed by Equations (3) and (4), where $\{h_k\}_{k\in Z}$ and $\{g_k\}_{k\in Z}$ represent the coefficients of low-pass and high-pass conjugate orthogonal filters, respectively.

$$p_s(n,j,k)=\sum\nolimits_{l\in Z}h_{l-2k}\cdot p_s(n,j-1,l). \quad (3)$$

$$p_s(2n+1,j,k)=\sum\nolimits_{l\in Z}g_{l-2k}\cdot p_s(n,j-1,l). \quad (4)$$

The node coefficients of each frequency band after wavelet packet decomposition are reconstructed, and the sum of squares is used as the sign of energy. Therefore, the energy distribution of continuous-time signal s(t) in the time-frequency localization space is defined as follows:

$$E(j,n)=\sum[p_s(n,j,k)]^2. \quad (5)$$

DE is a measure of the complexity of continuous random variables and the entropy of continuous random variables. That is to know the size of all the information needed for a random variable. As a non-linear dynamic characteristic, DE is very effective in the study of non-stationary signals. In practical applications, when the time series obeys the Gauss distribution N(u, o_2), the value of DE can be approximately regarded as the logarithm of the band energy spectrum. Therefore, DE can be approximately expressed as follows:

$$DE_i=\log_{10}E_i, \quad (6)$$

where E_i denotes the energy spectrum of a certain frequency band.

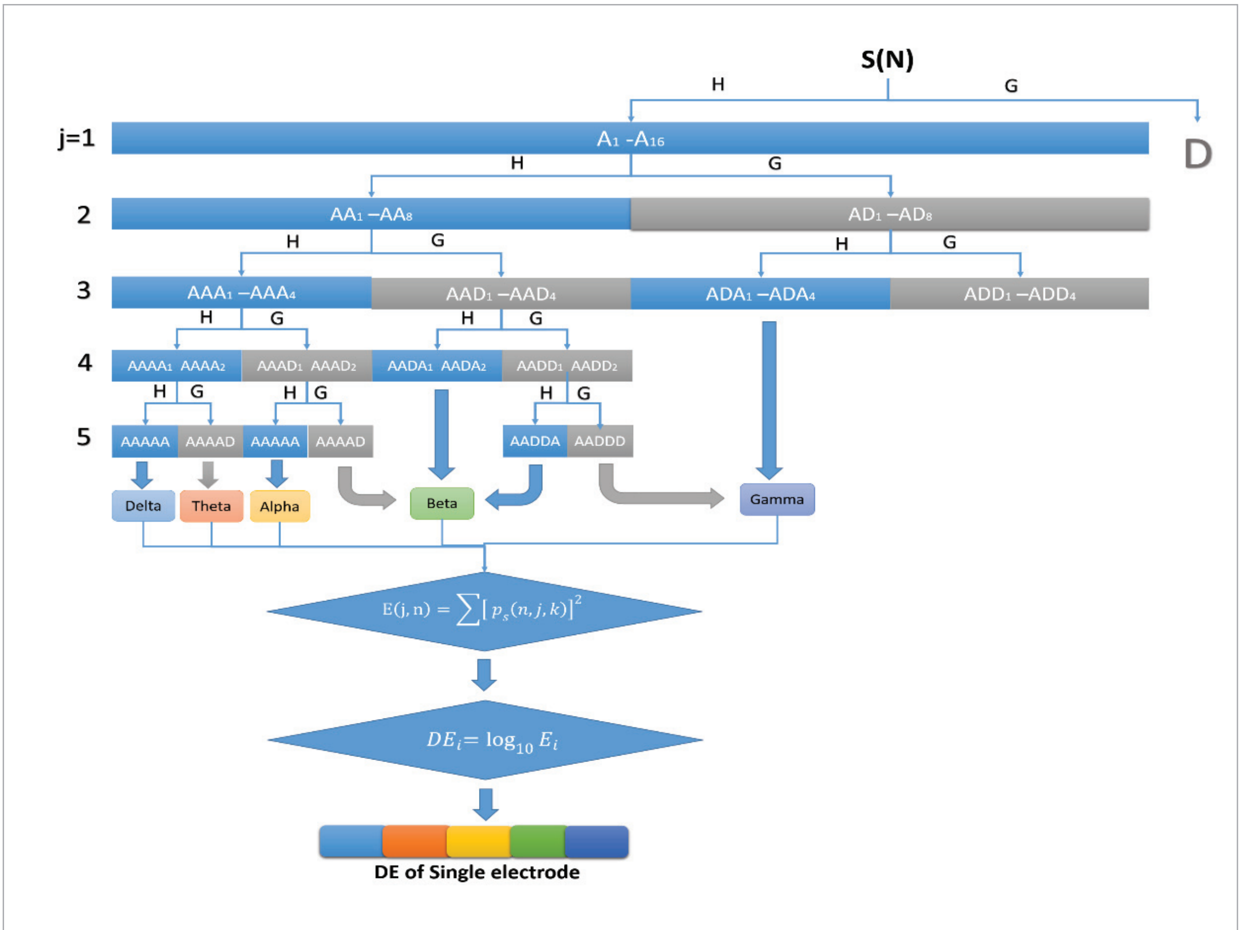
The typical algorithm used to analyze the frequency structure of time domain signal is wavelet transform. However, orthogonal wavelet transform only decomposes the low-frequency part of the signal further, while the high-frequency part(the detail part) of the signal, is no longer decomposed. Therefore, wavelet transform can not well represent signals containing a large number of details (small edges or textures), such as non-stationary vibration signals, remote sensing images, seismic signals and biomedical signals [34]. In contrast, the wavelet packet transform can provide more precise decomposition for the high frequency part, and this decomposition has neither redundancy nor omission, can effectively overcome the problem that wavelet decomposition has poor frequency resolution in high frequency band and poor time resolution in low frequency band. For the reasons above, wavelet packet transform is considered to be more effective for extracting local features of non-stationary signals such as EEG signals.

In this paper, WPT-based feature extraction for emotion recognization was proposed, and algorithm flow is given in Figure 2. In the figure, j represents the number of decomposition layers, A_i and D_i represent the approximate and detailed values of EEG signals obtained by high pass filter (G) and low pass filter (H), respectively.

As can be seen from the Figure 2, the fourth-order Daubechies wavelet packet basis was selected to decompose the high frequency and low frequency of each layer, and the original EEG signal with a sampling frequency of 128 Hz was decomposed into five layers. In practical application, the strategy of further decomposition will be determined according to the problems to be solved and the energy distribution of signals. The wavelet packet sub-bands are superimposed according to the rhythm of EEG signals. Finally, five sub-bands signals are approximately obtained, which are delta frequency band: 0.1-4 Hz, theta frequency band, 5-8 Hz, alpha frequency band: 8-13 Hz, beta frequency band: 14-30 Hz, gamma frequency band: 31-48 Hz. In practical research, most

Figure 2

Proposed WPT-based entropy feature extraction



EEG signals above 48HZ are high-frequency noise, which has no contribution to the emotional research of EEG signals, so this part of the signal was removed by us [10]. As a nonlinear dynamic characteristic, DE is very effective in the study of non-stationary signals. Therefore, we used DE for emotional classification. The value of DE on the five rhythms were calculated according to the above formulas. For each EEG set, the characteristics dimension is 32×5 according to the number and frequency band of EEG channels.

2.1.2. Extracting the Difference of Eigenvalues

In order to correct the time-dependent change of the entropy features(DE) independent of stimulus, we need to subtract the baseline data features from the experimental data features and use the difference of eigenvalues as the input of the classifier. Choosing the 3s EEG record before video as baseline data, we can adopt two measures of equal segmentation and non-segmentation for experimental data. In the experimental part, we discuss the effect of these two methods to remove the effect of baseline data, and the results show that the first scheme of equal segmentation of experimental data achieves higher accuracy.

We selected some feature examples for every emotion statures of every volunteers as shown in Figure 3. We can find some obvious differences between the four emotions.

Figure 3

The feature examples for every emotion statures of volunteers

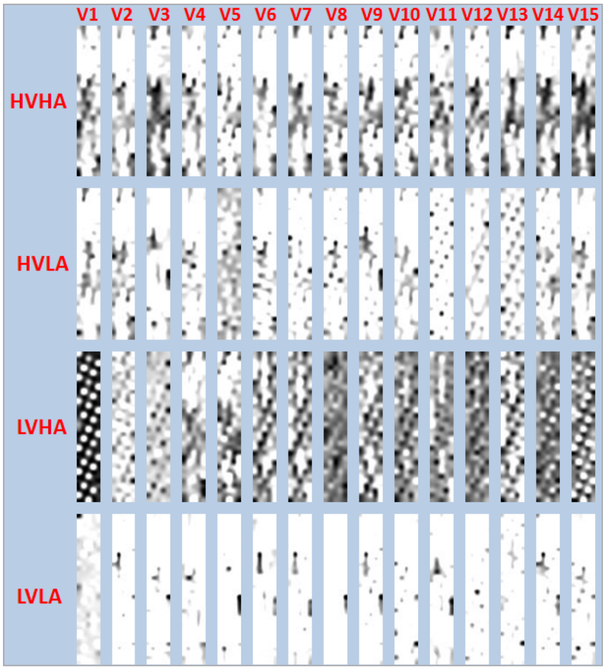
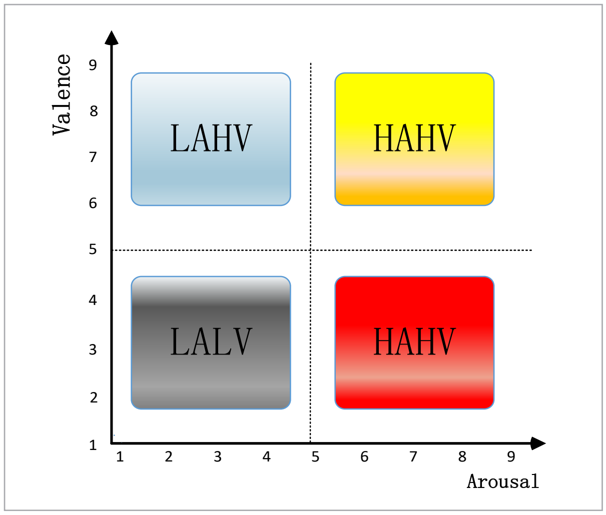


Figure 4

Two-dimensional Emotional Space



2.2. Classification Label

For the same stimulus material, the subjective emotion experience of different subjects is different, which is a major problem of emotion recognition. Therefore, disputes can easily arise in discrete emotional models that define only a few limited emotional states. Meanwhile, the dimension model of dividing emotional space can manipulate emotions quantitatively and determine emotional types according to spatial location, thus effectively accommodating individual differences. The self-evaluation value of video material watched by volunteers was used to establish a dimensional model and construct a 2-d label of valence-arousal degree. Four emotional states were divided according to the score value of 1-9: High arousal and high valence (HAHV); High arousal, low valence (HALV); Low arousal, low valence (LALV); Low arousal and high valence (LAHV). Among them, the valence indicates the degree of individual pleasure, that is, the positive and negative emotions, and the arousal degree indicates the intensity of individual subjective emotions. As shown in the Figure 4, considering the ambiguity of boundary emotions, the data with a score of 5 in the two-dimensional label is removed.

2.3. Classifier

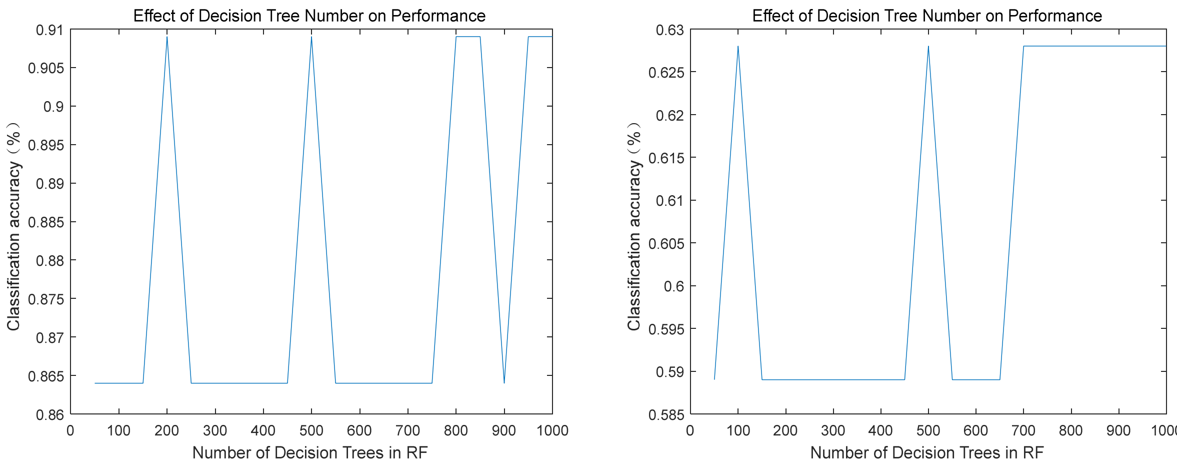
RF is an unsupervised machine learning method with multiple decision trees,which was proposed by Breiman in 2001, and its output category is determined by the mode of individual tree output categories. RF can quickly process data with a large number of inputs, maintain classification accuracy when missing some feature features, and balance the errors caused by the unbalanced number of classification samples. Informer, it has the advantages of high fault tolerance and fast learning speed. In addition, the model error is estimated by Obb-error in RF. Different bootstrap samples are used in the training set when constructing each tree. Therefore, about 1/4 of the training instances have never participated in the K-th tree generation of each tree (assuming that for the K-th tree). They are called the OOB samples of the K-th tree. The classification error rate of the OOB samples calculated is the unbiased estimation of the generalization error of the RF, which is similar to the result of the K-fold cross-test, so it proves needless to cross-validate the reserved data [31].

2.3.1. Construction Process of Random Forest

First of all, we implement self-sampling of data. In the input sample, A sample is randomly extracted from N sample data by playback (randomly selecting one sample at a time, then returning to continue selection) and

Figure 5

Effect of decision tree on performance in RF, (a) is of Scheme 1 and the (b) is of Scheme 2



(a) (b)

repeated n times. In this way, a data set of the same size as the original data set is created. Next, using each newly created data set to construct a decision tree.

For a single decision tree, the algorithm randomly chooses a subset feature at each node, that is, assuming that each sample has m features, when each node of the decision tree needs to be split, it randomly chooses a subset of features whose size is m from the M features, and satisfies the condition of $m \ll M$. Then, some strategies (such as information n gain) are adopted to select a feature in the subset of the feature as the decomposition attributes of the nodes. When the number of feature selection m is reduced, the correlation and classification ability of the tree will decrease correspondingly, and when m is increased, both will increase accordingly.

According to the above steps, stop splitting when reaching the leaf node and build a large number of trees to form the decision tree forest.

2.3.2. RF Parameter Selection

Based on the above process, bootstrap sampling method was used to train each tree, and 3/4 of all samples were randomly selected as training set. Setting the number of attributes $m=\sqrt{M}$ when a node splits. Because the number of decision trees will directly affect the generalization performance of RF classifiers, in order to construct a reasonable decision tree forest, we took the number of decision trees from 50 to 1000 at intervals of 50. For each tree, we established 100 RF models, and used the average value of classification accuracy as the evaluation criterion to select the optimal number of decision trees. Figure 4 shows the effect of the number of decision trees on the performance of the models under the two schemes. According to the left-hand graph of Figure 5, for the first time, the classification accuracy reaches its peak when the number of decision trees for scheme one is 200. Considering that the number of decision trees is proportional to the complexity of classification, which affects the modeling speed, we chose to construct an RF classifier containing 200 trees. For Scheme 2, the number of decision trees was set to 100.

3. Experiments and Results Analysis

In order to verify the effectiveness of the methods proposed in Section 2 for removing the effect of baseline data, comparative experiments was carried out in this section. Three schemes for extracting features of EEG signals were established and the experimental results were analyzed. All the experiments used the standard DEAP described separately below.

3.1. DEAP Dataset Description

The data used in this paper are the DEAP dataset [21], which records more than 32 particle libraries aged between 19 and 37. The experimental contents include: (1) Based on arousal, valence and liking, 120 one-minute videos were scored by online self-assessment, and the top 40 videos with higher scores were selected as stimulus materials; (2) Subjects watched the 40 video clips separately and scored each video in the above way after watching. The experimental data included 32-channel EEG data, self-assessment scores of 32 subjects and 8 peripheral physiological signals, including electromyography (EMG), electrocardiogram (EOG), blood volume pulse (BVP), skin temperature and GSR. In addition, some subjects' facial information was recorded.

The original data were down-sampling into 128 Hz, and the bandpass filter with 4.0-45.0 Hz was used to remove noise. Each participant has 8064 sampling points, including baseline data of the first 3s and experimental data of the last 60s.

3.2. Experiment Settings

15 repeated tests were carried out for all three cases. The specific settings of the scheme are as follows. The experimental design process is shown in Figure 5.

Scheme 1: Segmentating the experimental data in 4s unit of time, we processed 60 seconds of experimental data under the stimulation of video playback into 15 non-overlapping EEG sequences. Next, the differential entropy of each EEG sequence was extracted by wavelet packet transform, and the baseline data features of 3s were extracted, then we subtracted baseline data feature from each experimental data feature. Finally, the change of the entropy feature relative to the pre-stimulus feature was obtained. Because each participant watched 40 emotional videos, the experiment recorded the participants' EEG data each time they watched the video,the number of samples for a single participant is 40×15.

Scheme 2: Using the method of undivided experimental data, we extracted the differential entropy of the whole EEG sequence of each sample, and subtracted the baseline data eigenvalues from the experimental eigenvalue.

Scheme 3: Set Scheme 3 as the control group. Without removing the baseline data features, we directly calculated the eigenvalues of the experimental data. According to the simple sampling method, 8 subjects' databases from DEAP database were used as experimental data. RF classifier was used to process the data.

3.3. Results Analysis

Three measurement indexs are used to evaluate the above experimental results, That is:

1. Accuracy. The correct number of classified samples divided by the total number of samples. For the above scheme, the average classification accuracy of 15 repeated tests and the peak classification accuracy are given respectively. The comparison of classification indexes of three schemes is illustrated in Table1.

Table 1
The classification accuracy of BCI simulation implemented according to the three schemes

Project	Accuracy		The number of samples
	Peak	Average	
1	90.90%	87.30%	4800
2	62.84%	56.98%	320
3	56.60%	52.08%	320

2. Significance level. In hypothesis testing, a small probability criterion that can be allowed as the judgment limit is determined in advance, which is expressed as P. When the degrees of freedom set to (n-2), the results of repeated experiments of four categories in Scheme 1 are analyzed, which can be seen in Figure 6.
3. Precision and the percentage of the number of correct classifications in the number of classifications. In the proposed method, the Precision of 15 repeated experiments for all categories is calculated, as shown in Table 2.

Figure 5
EEG signal processing scheme for the classification

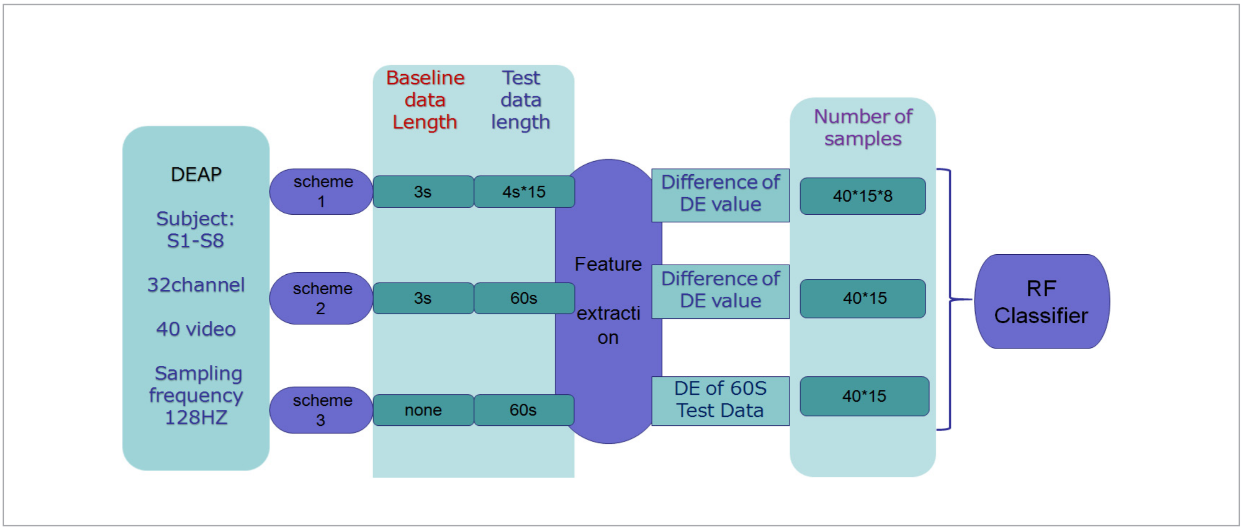
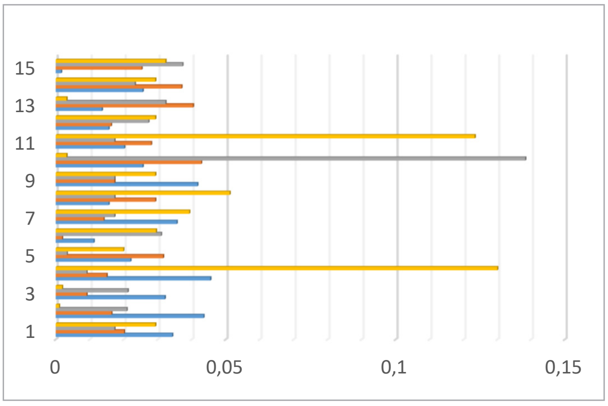


Table 2
The classification precision of BCI simulation implemented according to the first scheme

Category	The number of samples	Precision
HAHV	960	0.921
HALV	1164	0.890
LAHV	960	0.901
LALV	1716	0.888

Figure 6
The significance level of repeated experiments of four categories in Scheme 1

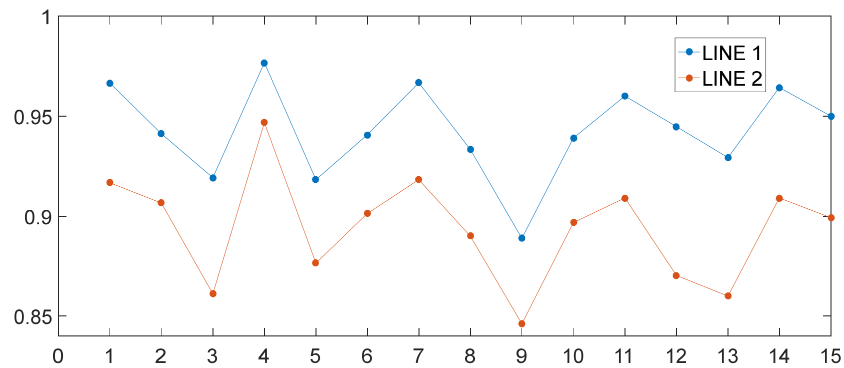


As can be seen from Table 1, the average classification accuracy of the model training results of Scheme 1 is 87.3%. Compared with the control group, the classification effect of Scheme 3 has been greatly improved. Our results have shown that the removal of baseline data features can significantly improve the accuracy of emotional classification. In contrast, the average classification accuracy of Scheme 2 is only 57.1%. The difference between the classification accuracy of the Scheme 2 and the control group without baseline features is between 0.08 and 0.02, which is of little significance. For the average classification accuracy, Scheme 1 is about 1.5 times that of Scheme 2. As can be seen from Figure 6, except for a few pulses, the significance level of the four categories in Scheme 1 is $p > 0.05$ (the smaller the p value, the lower the probability of error). It can be seen from Table 2 that the number of samples of each category is obtained according to the label, and the accuracy of the four categories is calculated, respectively, implying that the classification according to Scheme 1 is effective.

Therefore, we divided the experimental data of emotional video stimulation into equal parts, and removed the influence of baseline features on segmentation data from each segment. The method we proposed has significant advantages over the non-segmented experimental data in removing baseline features.

Based on the above conclusions, in order to verify the

Figure 6
Classification index of Scheme 1



validity of Scheme 1, we selected 15 subjects' databases to test the model training of individual subject. Figure 6 shows the classification index of 1-15 subjects, broken line 1 represents the peak classification accuracy, broken line 2 represents the median classification accuracy.

It can be seen that in the individual training results, we get higher classification accuracy. Except for P9, the accuracy of peak classification obtained by using Scheme 1 is higher than 90%, while the accuracy of median classification is above 85%, and the accuracy of peak classification of P4 is as high as 97.7%. Therefore, our research method is not only effective in general sense, but also adapts to individual participant.

3.4. Comparison of Classification Models

The emotion calculation model of WPT-RF is compared with other researches using DEAP data set, and the results are shown in Table 3. The performance of

Table 3
The comparison of the emotion recognition with previous studies

Study	Recognition		Accuracy (%)	Methods
Koelstra et al. (DEAP) [21]	Two categories of labels	High/low arousal	62.00	SP, SPA, BC, LOO
		High/low valence	57.60	
Jiang et al. [42]		High/low arousal	66.90	WT -based features, SVM
		High/low valence	65.30	
Mert and Akan [25]		High/low arousal	75.00±7.48	MEMD-based features, ICA, k-NN
		High/low valence	72.87±4.68	
Zhang et al.[40]	Four categories of labels	HAHV	80.00	WT-based features, CNN
		HALV	78.90	
		LAHV	82.30	
		LALV	85.30	
This Method		HAHV	92.10	WPT-based features, RF
		HALV	89.02	
		LAHV	90.13	
		LALV	88.80	

various classification models was compared by classification accuracy. In Table 3, it can be seen that the first three research schemes are classified in two dimensions, while the latter two are classified in four dimensions. The WPT-RF model implemented according to Scheme 1 was compared with several other classification models based on SVM [42] and Convolutional Neural Network [40]. The Method poposed by this paper is more competitive.

4. Conclusion

An emotional classification model based on wavelet packet transform and RF was proposed in the paper, and a DE-baseline feature method was used in order to improve the model classification ability based on EEG signal. The results were shown to be significantly better than other emotion classification models based on video induction. The main work and innovation are as follows.

1 Three experimental methods to research the influence of entropy characteristics of baseline data were set up, and two groups of the experiments were used to compare the classification effects of experimental data cutting and non-cutting, while the other group was the control group without baseline removal. The experimental investigations revealed that the classification accuracy of EEG signals can be effectively improved by equally removing the entropy features from baseline EEG data with combination of WPT-RF model.
2 In addition, the EEG data of single person to the above method was also applied. Through training the WTP-RF model of 15 subjects. The accuracy of single-person training model was higher, this result suggests that the method is effective for other subjects, even in single-person experiments.

The research method proposed in this paper broadens the application scope of radio frequency classifier in the field of neurology and provides a new idea for correcting the changes of EEG characteristics before and after stimulation.

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