ReliefF Matching Feature Selection for Emotion Recognition based on EEG Signal

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Abstract ReliefF Matching Feature Selection (RMFS) is proposed in the paper, which can solve the problem of individual specificity and global threshold mismatch of emotion recognition. Firstly, EEG was decomposed into six emotion-related bands by wavelet packet, then EMD was employed for extracting the 10 categories of features of wavelet coefficient and IMF component of the reconstructed signal; Secondly, the optimization formula of the feature group weight was proposed based on feature sets selected by ReliefF, and it can get the weights of different test features, which were the global optimal matching feature group and the corresponding matching channel, so it can eliminate the redundant information and solve the problem of individual specificity. Finally, SVM was employed to identify the test feature group data to obtain emotional recognition results. The experimental results show that the average correct rates of RMFS for two-category of the valence and the arousal are 93.28\% and 93.32\%, and the four-categories are higher than 83\%. The efficiency of the single subject using RMFS is improved by 42.65\%, which is better than the traditional ReliefF algorithm.

Key words emotion recognition; RMFS; wavelet packet decomposition; empirical mode decomposition; support vector match

1 Introduction

The 21st century is known as the century of artificial intelligence and brain science [1]. Emotion recognition is to automatically identify human emotional states by acquiring human physiological and unphysiologic signals, and to realize human-computer interaction more friendly and naturally [2]. According to the 10-20 international system of 16, 32, 64 or 128 channels distributed on the entire scalp to obtain multi-channel EEG sensor signals, the increase in the number of electrodes will cause the feature dimension to rise sharply, resulting in excessive calculations. At the same time, some scholars have proved that the data of a few electrodes does not affect the accuracy of emotion recognition [3-4]. This may be achieved by 16 subjects’ universal optimal channels for using Relief algorithm to channel selection. The same features cannot accurately reflect the information of some subjects, because of the individual differences between subjects [6]. In Ref.[7], Lin used the F-score algorithm to select subject-independent features, and the corresponding accuracy of emotion recognition remains basically unchanged by using a half of the features.

Jenke et al. [8], in the study, based on the unique model of different emotion recognition accuracy evaluation method, imply to dimensionality reduction by using ReliefF algorithm. In addition, Bos [9], Schmidt, Traitor [10], Zhang, Lee [11] et al. According to the famous "emotional valence hypothesis" (Asymmetry of the forehead (F3, F4) when the brain is dealing with negative and positive emotions,) and they selected to perform two types of emotion recognition in the valence dimension. Mommennezhad and A [12] used wavelet transform for feature extraction, and the accuracy rates of the two-class recognition of valence and arousal degree were 0.73 and 0.77, respectively; Lin Jingxin [13-16] extracted time-domain and frequency-domain features, and used KNN for the two classifications of valence and arousal potency have an average recognition accuracy rate of 69.9\% and 71.2\%. In the above
research progress, the same problem is individual specificity and global threshold mismatch of emotion recognition, and lead to a low emotional recognition rate.

In order to solve the above problems, this paper proposes RMFS algorithm [17-19]. This may be achieved by reducing the feature dimension, eliminating the redundant, prioritizing weighting channels and improving the accuracy of emotional recognition for being weighted formula is optimized for the characteristics of the different subjects set of weights, thus optimizing the matching characteristics of the subjects groups.

2 Method

2.1 ReliefF algorithm

The ReliefF algorithm [20-22] is a feature selection algorithm, which is, assigning weights to feature vectors based on the correlation between signal features and classification labels, and deleting feature subsets that have a small impact on the classification effect based on the weights.

Specific method: randomly select a sample X in a certain signal characteris α, and find its corresponding type label C; find K nearest neighbor samples H in other samples similar to sample X, and then find the K samples M closest to sample X in samples different from X. If the distance d₁ (α, X, H) of sample X from H on the EEG signal α is smaller than (or greater than) the distance d₂ (α, X, M from M), and it will indicate that the feature is beneficial to the classification of the signal (or caused a negative effect), then increase (or decrease) the weight of the feature W.

Owing that the signal samples initially drawn are random and unrepresentative, the ReliefF algorithm needs to be repeated M times to obtain the average value of the weight of each attribute (the degree of effect of the attribute on the classification effect).

2.2 ReliefF Matching Feature Selection

The RMFS algorithm [23] conducts the research on subject-related and subject-independent channel selection, which consists of RMFS feature type selection and RMFS channel selection.

First, the RMFS feature type selection[24] is used to achieve the weights of all kinds of features of subjects. What’s more, effectively reducing the number of channels and improving the emotion recognition rate by selecting a feature group with a high recognition rate, and then selecting RMFS channels based on the weight of these features.

2.2.1 RMFS Matching Feature Type Selection

We adopted ReliefF matching feature selection algorithm for each type of feature weight calculation, determined the contribution of each type of characteristics of classification (the accuracy of recognition rate), and a variety of feature combinations are treated as the basis.

Among them, the weight coefficients of various types of features need to be calculated. The change of weight coefficient is shown in formula (1).

\[
W(f_l) = W(f_l) - \frac{1}{mk} \sum_{i=1}^{k} \text{diff}(f_l, R_i, H_l) + \frac{\sum_{C=class(R_i)} \frac{P(C)}{1-P(class(R_i))} \sum_{j=1}^{k} \text{diff}(f_l, R_j, M(C))}{mk}
\]

(1)

Formula (1) is the total sample for m sample concentration of the \(i^{th}\) a calculation formula of the sample weight, among them, \(W(f_l)\) is a set weights, the value of \(f_l\) feature for the first \(l, H_i\) and R the spacing of the same sample, \(M(C)\) is the spacing between R and different sample, \(P(C)\) is a \(C\) in the sample concentration proportion, the \(\text{diff}(f_l, R_j, R_2)\) represents the distance between sample \(R_1\) and \(R_2\) on the characteristics of \(f_l\), when \(f_l\) continuous:

\[
\text{diff}(f_l, R_1, R_2) = \frac{R_1[f_l] - R_2[f_l]}{\max(f_l) - \min(f_l)}
\]

(2)

All feature weights in the feature subset by ReliefF algorithm are added to obtain the weight of each type of feature and learn the contribution of “per subject” to as a basis for the classification [25].

However, when performing emotion recognition, it is necessary to use the combination of multiple types of features as classification. Based on this, and the ReliefF algorithm does not well in eliminating simplified special effects, this paper imply the ReliefF Matching Feature Selection Method (RMFS).
This paper reveals that ReliefF is not only computing the weight of feature types and channels, and acquiring the classification by employing cross validation to adjust the weights, but also eliminating irrelevant and redundant information to obtain matching feature groups for identification, so as to improve the identification accuracy and reduce the running time.

The RMFS matching feature selection steps are as follows:

RMFS matching feature selection

Enter: EEG Data.
Output: Matching feature set.
Step1: Calculating class $n$ features weights by traditional ReliefF. ($n \leq 10$)
Step2: If the weights are all positive, the features will be sorted in descending order of weights and go to Step4.
Step3: If the weight value is negative, the corresponding feature will be removed, and the process returns to Step 1 to recalculate the weights of the remaining features with positive weights. Repeating this step until the weights of all features are positive, and go to Step 2.
Step4: Gaussian kernel SVM classifier and 20times 5-Fold cross-validation were used to gain the first $n$ and $n+1$ types of feature recognition accuracy rates $p(n+1)$ and $p(n)$.
Step5: Set the threshold $\delta_i = 0.01$ and judge: $|p(n+1) - p(n)| < \delta_i$.

1. If $|p(n+1) - p(n)| < \delta_i$, it will output matching feature group.
2. If $|p(n+1) - p(n)| > \delta_i$, it will judge the size relationship $p(n+1)$ between $p(n)$.

A. When only $p(n+1) > p(n)$, we calculate the first $n$ features weights on the basis of formula (3) to obtain a larger gain.

\[ W_i(f_n) = W(f_n)[1 + \frac{p(n+1) - p(n)}{p(n)} \frac{\sum_{i=1}^{n} W(f_i)}{W(f_n)}] \tag{3} \]

B. When $p(n+1) < p(n)$, the $n+1$ feature is moved to the end of the column, and the rest is moved as before. The weight of the $n$ features is calculated on the basis of formula (4):

\[ W_i(f_{n+1}) = W(f_{n+1})[1 - \frac{p(n) - p(n+1)}{p(n)} \frac{\sum_{i=1}^{n} W(f_i)}{W(f_{n+1})}] \tag{4} \]

Step6: Go to step 4, repeat the above steps, and finally meet 5(3) to complete the feature selection.

In Ref. [26] and Feature weights said the $n^{th}$ terms, the proportion of its use value in the proportion of matching feature set of cumulative values [26]. It may be achieved by making contribution to the classification of higher features in groups plays a more important role for make the right value characteristics of greater rights worth to more incremental, and the weights of the characteristics of the small get smaller increment. RMFS matching feature selection is judged each feature, and adjusted the proportion of each adjustment weight in the matching feature group.

As a consequence, the features with larger weights get more gain, and features with smaller weights get smaller. In this way, the features with higher classification contribution play a greater role in the feature group, which screen the preferred matching feature group, and improve the recognition accuracy rate, and reduce the running time.

### 2.2.2 RMFS channel selection

The RMFS algorithm is used to treat the channel as a whole. After calculating the channel weights, the cross-validation method is appropriate for acquiring the contribution of different channels to the classification. The weight is adjusted on the basis of
the contribution to removing. RMFS channel selection

Enter: Feature groups corresponding to 32 channels

Output: Matching feature set of optimal channels

Step1: Calculation with the weight of 32 channels
Step2: If the weight is negative, we will remove the corresponding channel, return to Step1, recalculate the weights of the remaining channels with positive weights and arrange them in descending order. Repeat this step until all channels have positive weights, and go to Step3
Step3: We set a variable threshold δ2 (δ2 = 0.05, 0.1 ... 0.9), take weights and the first n channels less than δ2, and use different thresholds to form different of the combinations of channel.
Step4: Performing 20 times 5-fold cross-validation through the SVM classifier to obtain the recognition accuracy and running time of different channel combinations
Step5: Outputting the matching feature set of the optimal channel

After the weights of the features and channels by the RMFS channel selection are calculated. The cross-validation method is used to acquire the contribution of different features and channels to the classification. The weights are adjusted on the basis of the contributions to obtain the matching feature group and the optimal channel.

3 Experiments and Results

3.1 Single participant feature selection

The DEAP dataset contains EEG and peripheral physiological signals recorded from 32 subjects. In the data collection process, 560 samples were randomly divided into two groups: one part is valence labels, and another part is arousal labels, and each was taken 1/2 sample as training set and the rest as test set. All randomized trials were repeated 10 times to eliminate randomness. The result after taking the mean value was the final classification accuracy.

Table 1 shows the result of selecting the feature category of the 25th participant using the DEAP dataset, and we discovered an increase in accuracy of classification and weights especially in feature types. When there are more than 4 features, the recognition accuracy does not change significantly, but program run-time has been significantly improved. In valence recognition, based on the first four features, and the accuracy rate is 95.35%. Although the accuracy rate and weight sum of the awakening based on the top 6 features are "." in Table 1, it shows that the weight of 5 features is greater than 0 and the rest are negative, but the running time can be measured.

| The first n features | Valence | Arousal | The running time (%) |
|---------------------|---------|---------|-----------------------|
|                     | Accuracy (%) | The sum of weighs | Accuracy (%) | The sum of weighs |                  |
| 1                   | 83.43   | 0.3772  | 84.25     | 0.3896   | 685.31          |
| 2                   | 91.03   | 0.6136  | 90.37     | 0.6257   | 710.10          |
| 3                   | 93.33   | 0.8066  | 93.48     | 0.7644   | 786.46          |
| 4                   | 95.35   | 0.9370  | 93.96     | 0.9033   | 836.29          |
| 5                   | 95.55   | 0.9603  | 93.40     | 0.9356   | 870.11          |
| 6                   | 95.42   | 0.9724  | —         | —        | 956.86          |
Using to the poor spatial resolution of the EEG signal, and the feature types are used to select directly while ensuring the same rate of emotional recognition. On the one hand, it will increase the use of channels to result in excessive calculation. On the other hand, it will affect the real-time of emotional recognition. The channel selection method is to take the channel as a whole and delete them on the basis of the corresponding recognition accuracy of the channel to obtain the optimal subset of channels. Therefore, Fig. 1 presents the advanced RMFS combined the advantages of both is not only improving the recognition accuracy, but also reducing run time.

Figure 1 The flow chart of RMFS
Compared with the first three features, the accuracy rate is increased by 0.0202, which is greater than the set threshold $\delta$. As the increasing of number of features, the absolute value of the increment of accuracy is less than $\delta$. Based on the first 4 features, the accuracy rate of the two-category classification is 93.96%, with the accuracy rate of the first 3 feature groups is 93.48%, and the difference between them is 0.048 and less than the threshold. The first 3 features of the feature set are preferred.

Due to individual differences between subjects, different groups of matching feature groups are different, as well as different features directly affect the size of the corresponding channel weights and affect the recognition results. Additionally, selecting the characteristic group that matches the subject is an important prerequisite for correctly identifying emotions. The classification accuracy above the valence and arousal from our dataset are respectively shown in Fig.2 and Fig.3. The three curves in the figure are the selection features using the RMFS algorithm. The three curves in the figure respectively with using RMFS algorithm, Characteristics of Wavelet Coefficient (COE) and IMF reflect the law of the change of accuracy of different methods in the process of channel selection. Table 2 shows the running times of the identification programs of the first $n$ channels when different thresholds $p (p = 0.05, 0.1...0.9)$ are selected for the channels used.

**Figure 2** potency two classification channel selection result

**Figure 3** wake-up two classification channel selection results
It can be seen from Figures 2 and 3 that the recognition accuracy rate of feature selection used the RMFS algorithm increases with the increase of the sum of the weights of the selected channels. When the sum of the weights of the channels is 0.6, the classification results of the two groups have reached a maximum value: 95.46% and 93.63%, respectively. The number of 12 channels’ running time of the recognition program is 586.28s, which is 42.64% shorter than the 836.29s time with no channel selection is performed; When the channel weight sum is 0.9, the accuracy rate of identification does not increase significantly with the increase of the channel weight sum. The numbers of channels with valence and arousal degree are 27 and 25, respectively, and the time taken increases to 799.61s. The channel corresponding to the weight sum of 0.6 is selected in the two categories of potency and arousal degree with time complexity.

**Table 2** Program running time with different p-values for channel selection

| Order number | Item | Sum of channel weights | Running time (s) | Number of channel (V, A) |
|--------------|------|------------------------|------------------|--------------------------|
| 1            | 0.5  | 524.59                 | 9, 9             |
| 2            | 0.6  | 586.28                 | 2, 12            |
| 3            | 0.7  | 634.25                 | 16, 14           |
| 4            | 0.8  | 726.51                 | 19, 18           |
| 5            | 0.9  | 799.61                 | 27, 25           |

**3.2 Impact of RMFS on feature selection**

The 32-bit subjects in DEAP were allowed to selected as the experimental objects, in order to increasing the sample size, a 4-second overlapping time window was used to divide the 60s sample into 14 segments, each segment was corresponded to 1024 data points, divided into two groups, and 100 random experiments were performed.

Fig. 4-5 show that there are significant differences in the matching feature group composition among different individuals’ the matching feature group composition and weight of the dichotomy of valence and arousal degree of all subjects respectively, which are composed of COE Mean, COE Std, IMF Std and Eng. However, the matching feature set of 32.81% of the samples contained 4 types of features, 59.38% of the samples contained 3 types of features, and only 7.81% of the subjects' classification results were significantly affected by the 2 characteristics. The matching feature group is composed of Eng and IMF Diff, and the weight of IMF Diff without RMFS feature selection is negative, and indicating that it has a negative impact on the classification of the majority of samples, and only starts in the second degree of arousal of this subject. To strong positive effects, as shown in the red dotted box in Fig. 5. We demonstrate that these four types of matching features and their weights can be applied to most subjects, but not match all the subjects. At the same time, if the sample proportion increases, the specific proportion of matching features will further increase.

![Figure 4](image-url) Composition of 32-bit subject titer two-category matching feature group and its weight
3.3 The results of comparison between RMFS algorithm and ReliefF algorithm

In order that verifying the effectiveness of the RMFS, we analyze the results of the dual classification of emotions on valence and arousal on 32 subjects, and two different characteristics are used for classification experiments as a reference. The two sets of characteristics are: wavelet coefficients class features and COES, IM and wavelet energy (IMFS).

Two sets of experiments are selected through the ReliefF channel, and then used SVM classifier for recognition. Table 3 subjects for each emotional recognition result and comparative experiment results: RMFS represents experiments by using RMFS, ReliefF-COES represents experiments by using COES, and ReliefF-IMFS represents experiments by using the IMFS.

Table 3 Results of 32 - bit subjects 'affective dichotomy of valence and arousal

|     | Valence            | Arousal            |     |     |     |
|-----|--------------------|--------------------|-----|-----|-----|
|     | RMFS (%)           | ReliefF- COES (%)  | RMFS (%) | ReliefF- COES (%) | RMFS (%) | ReliefF- IMFS (%) |
| 1   | 96.08              | 89.56              | 98.04 | 91.32 | 89.10 |
| 2   | 89.38              | 83.39              | 88.86 | 81.11 | 74.86 |
| 3   | 91.94              | 88.54              | 74.85 | 97.18 | 91.47 | 89.33 |
| 4   | 83.11              | 78.37              | 70.71 | 76.67 | 67.13 |
| 5   | 91.52              | 82.31              | 67.24 | 78.73 | 68.17 |
| 6   | 95.58              | 90.10              | 93.55 | 88.25 | 74.55 |
| 7   | 96.68              | 91.10              | 96.66 | 89.14 | 75.03 |
| 8   | 98.63              | 89.37              | 93.66 | 86.14 | 76.27 |
| 9   | 88.26              | 82.58              | 73.14 | 82.91 | 72.93 |
| 10  | 96.30              | 87.59              | 76.86 | 86.79 | 78.80 |
| 11  | 90.07              | 84.14              | 69.49 | 89.01 | 82.87 |
| 12  | 95.10              | 87.79              | 69.53 | 95.65 | 89.81 |
| 13  | 91.80              | 87.15              | 76.03 | 92.28 | 90.69 |
| 14  | 90.77              | 83.80              | 76.40 | 91.06 | 84.60 |
| 15  | 95.98              | 88.34              | 77.20 | 97.35 | 89.58 |
| 16  | 93.36              | 90.18              | 79.35 | 95.02 | 88.14 |

Figure 5 Composition of 32-bit subjects' arousal degree binary classification matching feature group and its weight
From the above experimental results, the accuracy of the experimental recognition is better than the results of the comparison experiment after the feature selection of the RMFS:

1. The highest and lowest recognition rates of valence based on the RMFS are 98.63% and 83.11%, respectively, and the average recognition rate is 93.28%; the highest and lowest accuracy rates of arousal are 98.04% and 80.88%, and the average recognition rate is 93.32%;

2. The average recognition rate of the two classifications of valence and arousal of COES features are 88.42% and 87.46%, respectively, the classification results are improved by 5.5% and 6.7%, respectively.

3. The experimental results by using IMFS features are 76.59% and 77.51%, and the classification results of the RMFS algorithm are improved by 21.8% and 20.4%.

In the two comparative experiments, the recognition accuracy of the latter is lower than that of the former, which also corresponds to the proportion of the two types of features in the matching feature group.

The statistical results of emotional two-category and four-category classification of 32-bit participants based on RMFS algorithm are statistically analyzed, and divided into different intervals according to the accuracy of the sample, as used in Figure 6-7. Figure 6 is the statistical results of classification in the recognition of valence and arousal.

From Figure 6, it can be seen that the 84.375% of subjects have a recognition accuracy rate higher than 90% in the two categories of valence and arousal degree, of which 34% have a higher accuracy rate than 95%, and merely 3.125% in the awakening degree two classifications. The accuracy rate of the subjects' recognition is lower than 85%.

Experimental results presented that the RMFS algorithm is significantly better than the traditional Relief algorithm.

The emotions of 32 subjects are classified: happiness, anger, sadness and relaxation, as well as obtained their respective classification accuracy rates. The average accuracy rates of the four types of emotions are weighted by the respective accuracy rates.
The effectiveness of the RMFS algorithm is proved through the same comparative test of the two categories of emotions. The experimental results are listed in Table 4.

### Table 4  The accuracy of the four categories of emotions of 32 subjects

| Order number | Happiness (%) | Anger (%) | Sad (%) | Relax (%) | RMFS (%) | Relief-COES (%) | Relief-IMFS (%) |
|--------------|---------------|-----------|---------|-----------|-----------|----------------|----------------|
| 1            | 97.79         | 96.80     | 92.70   | 96.25     | 95.04     | 87.62          | 73.51          |
| 2            | 87.55         | 86.71     | 75.65   | 88.94     | 82.34     | 74.80          | 52.80          |
| 3            | 91.76         | 91.78     | 90.43   | 78.96     | 89.08     | 86.96          | 66.42          |
| 4            | 79.52         | 73.58     | 79.44   | 93.23     | 77.66     | 68.53          | 50.57          |
| 5            | 80.00         | 86.33     | 80.56   | 91.55     | 82.92     | 72.30          | 45.66          |
| 6            | 91.00         | 95.60     | 89.18   | 76.71     | 89.49     | 84.57          | 63.64          |
| 7            | 98.48         | 96.63     | 93.97   | 96.14     | 95.70     | 87.18          | 64.76          |
| 8            | 97.00         | 97.11     | 86.00   | 84.76     | 89.68     | 82.29          | 62.55          |
| 9            | 81.20         | 80.12     | 76.04   | 71.62     | 76.81     | 72.54          | 55.02          |
| 10           | 95.40         | 88.02     | 89.66   | 93.92     | 91.47     | 81.36          | 61.26          |
| 11           | 76.96         | 81.99     | 74.50   | 98.44     | 80.89     | 71.69          | 49.82          |
| 12           | 95.93         | 95.40     | 88.80   | 95.22     | 91.66     | 83.81          | 56.75          |
| 13           | 82.83         | 81.98     | 81.28   | 99.64     | 90.17     | 80.78          | 51.86          |
| 14           | 90.77         | 88.31     | 77.93   | 85.65     | 84.33     | 77.34          | 56.39          |
| 15           | 93.01         | 90.93     | 95.78   | 93.99     | 93.02     | 84.52          | 59.33          |
| 16           | 93.12         | 88.98     | 93.73   | 88.45     | 90.53     | 85.91          | 64.60          |
| 17           | 90.03         | 87.23     | 74.61   | 99.93     | 85.49     | 67.37          | 46.86          |
| 18           | 92.73         | 92.57     | 88.09   | 76.88     | 88.12     | 82.85          | 55.24          |
| 19           | 93.31         | 92.89     | 88.66   | 80.71     | 88.30     | 84.36          | 58.68          |
| 20           | 92.62         | 92.71     | 86.71   | 91.83     | 89.63     | 84.82          | 67.73          |
| 21           | 92.93         | 92.05     | 89.28   | 97.43     | 92.34     | 84.59          | 58.33          |
It should be noted that since the experiment of the 23rd participant without including samples of relaxation emotions, the classification accuracy of relaxation is 0, and its average accuracy is weighted by the accuracy of the first three types of emotions.

The highest recognition rates of the four types of emotions of 32 subjects are 98.71%, 98.84%, 95.78%, and 100%, which are all greater than 95%. The average recognition rate of the four types of emotions based on the RMFS algorithm is 88.32%, which is 9.1% higher than the experimental results of the COES feature.

In particular, the reason is that the two matching feature sets of valence and arousal are used in the four categories, which adds the advantage of one feature. When emotions divided by more dimensions are classified, the emotion recognition rate based on the RMFS algorithm will be higher. The statistical results of four types of emotions used in Figure 7.

**Figure 7** Statistical results of emotion classification

Figure 7 shows that more than 75% of the subjects have an accuracy rate of greater than 85% for the three types of emotions: happiness, anger, and relaxation. 37.5% of the subjects had a recognition accuracy rate higher than 90% in the average accuracy rate, and 75% of the subjects had a recognition accuracy rate higher than 85%. Furthermore, the overall recognition result of the four emotion categories is better.
4 Conclusion

These studies presented RMFS algorithms are significantly better than classifying by the traditional ReliefF algorithm using the 32-bit EEG data from the DEAP dataset to perform emotion recognition. Revealing the emotional recognition of EEG signal:

(1) The weight formula is optimized to acquire the classification contribution of the feature group and the matching feature group of the subject, as well as its proportion in the matching feature group. In particular, the feature groups with few contributions are eliminated to improve the recognition rate and efficiency of the algorithm;

(2) In addition, in order to obtaining a higher accuracy of recognition rate, effectively identifying the channels on the basis of subjects’ specific features; specific feature groups of different subjects and select channels on the basis of subjects’ specific features

(3) Compared with the traditional ReliefF algorithm, it can achieve higher recognition accuracy in the second and fourth types of emotion recognition.

In summary, RMFS proposed in the paper can obtain the global matching feature groups and matching feature groups of different subjects, thereby improving the recognition accuracy and algorithm efficiency, and verifying the effectiveness and feasibility of the RMFS algorithm.

Abbreviations
RMFS: ReliefF Matching Feature Selection; EEG: Electroencephalogram; EMD: Empirical Mode Decomposition; IMF: Intrinscs Mdoe Functionin; SVM: Support Vector Machine; COE: Wavelet Coefficient; DEAP: Dataset for Emotion Analysis using eeg, Physiological and Video signals

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Availability of data and material
All authors can provide the data and material. We would like to share all of our data in the paper.

Competing interests
The authors declare that they have no competing interests.

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Authors’ contributions
All authors take part in the discussion of the work described in this paper. The author ZHANG xiao-dan wrote the first version of the paper, the author SHE yi-chong, LI tao, DU jin-xiang and ZHAI ya-wen did part experiments of the paper, ZHAO rui did another part experiments of the paper, KE xi-zheng revised the paper in different version of the paper.

The contributions of the proposed work are mainly in two aspects:

(1) To our best knowledge, our work is the first one to apply the ReliefF for the feature selection and the channel selection. It can achieve the global matching feature groups and matching feature groups of different subjects.

(2) The novelty of our method attributes to the use of RMFS to improve the average recognition accuracy while improving the integrated computing efficiency.

Ethics approval
The dataset is from DEAP which is open and provides download service. It has already get the ethics appraisal in 2012, and it is free for scholars to research. The website is as follows:
http://www.eecs.qmul.ac.uk/mmv/datasets/deap/

References
[1] LAN Zinui, SOURINA O, WANG Linpo et al. Real-time EEG-based emotion monitoring using stable features [J]. The Visual Computer, 2016, 32(3): 347-358.
[2] SUN Yao, WEN Cheng-lin, WEI Wei Research on EEG and EOG based multistage reorganizations method of motor imagery [J]. Acta Electronica Sinica, 2018, 3(29):714-720.
[3] ANUCHIN C, WONGKW, LANCE. A comparison study on the relationship between the selection of EEG electrode channel and frequency bands used in classification for emotion recognition [A]. International Conference on Machine Learning and Cybernetics[C].
Chen, S. Research on emotional judgment model based on EEG [J]. Journal of Xi'an Polytechnic University, 2017, 27(7): 37-50.

ZHANG Jianhai, CHEN Ming, ZHAO Shaokai, et al. ReliefF based EEG sensor selection methods for emotion recognition [J]. Sensors, 2016, 16(10): 1558-1573.

LAN Zirui, SOURINA O, WANG Linpo, et al. Real-time EEG-based emotion monitoring using stable features [J]. The Visual Computer, 2016, 32(3): 347-358.

Lin C. H, Jung T. P. WU, et al. EEG-based emotion recognition in music listening [J]. IEEE Transactions on Biomedical Engineering, 2010;57(7): 1798-1806.

HE P, WILSON G, RUSSEL C. Removal of ocular artifacts from electroencephalogram by adaptive filtering [J]. Medical & Biological Engineering & Computing, 2014, 42(3):407-412.

Allowably T, El-Sammie F E A, Alshebeili S A, et al. Reviews of channel selection algorithms for EEG signal processing [J]. EURASIP Journal on Advances in Signal Processing, 2015, 10(1): 1-21.

Schmidt L A, Trainer L J. Frontal brain electrical activities (EEG) distinguish valence and intensity of musical emotion [J]. Neurocomputing, 2009, 72(6): 1302-1306.

XU BG, SONG AG, FEI SM. Feature extraction and classification of EEG in online brain-computer interface [J]. Acta Electronicsonica, 2011, 39(5):1025-1035.

MOMENNEZHAD, et al. An EEG-based emotion recognition utilizing wavelet coefficients [J]. 2018, 77(20): 27089-27106.

Yan L, Yoshua B, Geoffrey Hinton. Deep learning [J]. Nature, 2015, 521(7553): 436-444.

Robniksikonja M, Kononenko I. et al. Theoretical and Empirical Analysis of Relief and Relief [J]. Machine Learning, 2003, 53(1): 23-69.

FLANAGAN JR JOHANSSON RS. Action plans used in action observation [J]. Nature, 2003, 424(6950): 769-774.

LI Xin. Application of Wavelet Transform Combined with Empirical Mode Decomposition in Music Intervention EEG Analysis [J]. Journal of Biomedical Engineering, 2016, 33(4): 762-769.

Jianhai Zhang, Ming Chen, Shaokai zhao, et al. ReliefF based EEG sensor selection methods for emotion recognition [J]. Sensors, 2016, 16(10): 1558-1573.

N. Thammasan, K. Fukui, M. Numao, K. Moriyama, et al. Familiarity effects in EEG-based emotion recognition[J]. Sensors, 2017, 16(10): 50-57.

I. Guyon, J. Weston, S. Barbi, and V. Vapnik et al. Gene selection for cancer classification using support vector machines [J]. Machine Learning, 2002, 1(3): 389-422.

B. Schlogl, A. Smola, et al. Learning with Kernels (J]. MIT Press, 2002, 34-35.

T. N. Lap, M. Schroder, T. Hinter Berger, et al. Support vector channel selection in BCI [J]. IEEE Trans Biomed. Engineering, 2004, 51(6): 1003-1010.

E. E. Sutter, The brain response interface: communication through visually-induced electrical brain responses [J]. Journal of Microcomputer Application, 1992, 31-45.

S. Lem, Summa Technological, Wydawnictwo et al. Literackie, Krakow, Poland, 2nd edition[J]. 1996, 2-4.

G. Pfurtscheller, C. Neuter, C. Gorger, et al. Current trends in Graz brain-computer interface (BIC) research [J]. IEEE Trans, 2000: 164-173.

Y. Ben and D. Yeku, The control of the false discovery rate in multiple testing under dependency [J]. ANN, Statist: 2010, 49(3): 507-510.

S. G. Mallat and Z. Zhang, Matching pursuits with time frequency dictionaries [J]. IEEE Trans. Signal Processing: