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Selection of Optimal EEG Electrodes for Human Emotion Recognition

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Abstract: In recent years, emotion recognition has attracted increasing interest from researchers from diverse fields. Because of their intrinsic correlation with emotions, physiological signals based emotion recognition method is not susceptible to the so-called social masking and thus more objective than traditional visual, audio or text data based methods. In particular, EEG signals are more responsive to emotion fluctuations than other peripheral physiological signals. In this paper, a 4-class EEG-based emotion classification problem is considered. Firstly the subjective data clustering is performed to identify the optimal number of emotional states. Then wavelet and nonlinear dynamics analyses are used to extract EEG features of emotions. Finally, we consider the brain areas for emotion generation and show that the use of only a small number of EEG electrodes placed on the frontal area of scalp can achieve a 4-class emotion classification accuracy of higher than 90%.

Keywords: Emotion recognition; Electroencephalogram (EEG) signals; Wavelet; Nonlinear dynamics; Feature dimensionality reduction.

1. INTRODUCTION

Emotion recognition is a key component of affective computing. It is an interdisciplinary field that integrates computer science, psychology, neuroscience and cognitive science. Human emotions can be identified by facial expression, speech, behavior, or physiological signals (Petrushin, 1999; Anderson and McOwan, 2006; Pantic and Rothkrantz, 2000; Yin, Zhao and Wang et al., 2017). However, the first three methods of emotion recognition are somehow subjective. For instance, the subjects under study may deliberately conceal their true feelings, which may be inconsistent with their performance. In contrast, the emotion recognition by means of physiological signals is more reliable and objective (Wang, Nie and Lu, 2014). EEG signals are generated by the central nervous system (CNS) and respond more rapidly to emotional changes than other peripheral neural signals. Moreover, EEG signals have been shown to provide important features for emotional recognition (Petrantonakis and Hadjileontiadis, 2011; Li et al., 2009).

Picard and her associates from the MIT collected four types of physiological signals (electromyography, pulse rate, galvanic skin response, and respiration) to recognize eight emotional states (Picard, Vyzas and Healey, 2001). They extracted the time- and frequency-domain features from those physiological signals respectively. The feature selection was performed by forward floating search method, Fisher projection method and the hybrid algorithm of the two. Finally, the KNN algorithm is used to perform classification. The results showed that the 3-class (anger, sadness, and happiness) classification accuracy achieved 88.3%, demonstrating the feasibility of using the physiological signals for emotional state recognition. Brady, Gwon, and Khorrami *et al.* (2016) used visual and auditory cues to induce emotion, collected four types of physiological signals, namely temperature, galvanic skin response, blood volume fluctuation, and electrocardiogram (ECG), and achieved an average classification accuracy of 61.8%. Chanel, Kronegg, and Grandjean *et al*. (2006) used the international emotional picture system to induce emotions in the subjects, and performed 100 high arousal and low arousal emotion induction on the four subjects, and recorded the EEG, blood pressure, and skin conductance response of the subjects. Heart rate, skin temperature and respiratory signals were extracted, and linear discriminant analysis and naive Bayes were used for emotion recognition. A classification accuracy of about 55% was reported. Koelstra, Mühl and Soleymani *et al*. (2012) used music video clips as stimulating material, instructing each of the 32 subjects to watch 40 pieces of music video material, and recorded the self-report (subjective ratings), facial expression, EEG and peripheral physiological signals. A classification accuracy of 0.67.7% was achieved. Schmidt and Trainor (2001) used music to induce four emotions and found that when using positive musical materials, the EEG activity in the frontal areas of left hemisphere was enhanced, while the EEG activity in the frontal areas of right hemisphere is enhanced when using the negative music materials. They concluded that there is a strong correlation between the frontal areas of human brain and the emotion. Wagner, Kim and Andre (2005) collected four types of physiological signals (ECG, galvanic skin response, EOG, and respiration). Three feature selection methods were compared, namely variance analysis, Fisher projection method, and sequence forward drifting selection algorithm. Three classifiers, namely K-nearest neighbor, linear discriminant analysis, and multi-layer perceptron, were used to identify the four emotions of joy, happiness, anger

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and sadness, and encouraging classification results were achieved.

In this paper, we study the emotion recognition problem using EEG signals with an aim to analyze the complex correlation between EEG signals and emotional states in humans. Firstly, the subjective-rating data were clustered to determine the target emotion classes. Then we perform feature extraction based on wavelet and nonlinear dynamics analyses of the EEG signals. Finally, in order to find the brain areas that are most relevant to emotions and to select the optimal number of EEG electrodes, we use the mRMR and Relieff algorithms to rank the importance of electrodes on brain topography.

2. DATASET AND EEG SIGNAL PROCESSING

2.1 Emotion Elicitation Experiment and Signal Acquisition

In this section, the DEAP database is described. Based on the 2D model of emotions, Koelstra, Mühl and Soleymani *et al*. (2012) used 40 music videos to elicit emotions of 32 subjects (half male, half female; aged between 19 and 37 with mean of 26.9 y/o) and recorded their physiological signals and facial expressions. There were 40-channel physiological signals, including 32-channel EEG and 8-channel peripheral physiological signals (such as galvanic skin response, respiration, skin temperature, ECG, blood volume, EMG, and EOG). The experimental procedure is shown in Fig. 1.

There were 40 trials of emotional stimulation experiment for each subject (each trial corresponding to watching one of the 40 music video clips). Each trial consists of four steps:

Step 1: Before each video starts, display the video number for 2 s.

Step 2: Record the 5s baseline EEG data.

Step 3: Play the 1-min music video.

Step 4: Collect subjective ratings on four rating scales: arousal, valence, liking, and dominance.

The flowchart of EEG-based emotion recognition algorithms is shown in Fig. 2.

2.2 Data Preprocessing

EEG signals respond to the change of emotional state more rapidly than other peripheral physiological signals, therefore in this paper we focus on using EEG signals for emotion classification. In the data acquisition experiment, the original EEG signals were collected at a sampling rate of 512 Hz and then down-sampled to 128 Hz. The EOG artifact is removed from the EEG recordings by using a 4 - 45 Hz band-pass filter. The pre-processed EEG data includes the 60s emotion-related EEG data (during music video watching) and 3s baseline data (prior to watching the music video). Subjects were asked to take 2min break after watching two videos.

The pre-processed EEG data includes emotion-related and baseline (emotionless) EEG data. In order to minimize the influence of the previous stimulus material on the current emotional state and the effect of cross-subject variability of physiological signals, the pre-stimulus baseline EEG features (prior to the emotional stimulation) are subtracted from the post-stimulus EEG features and the resultant differences are normalized within the unit interval [0, 1].

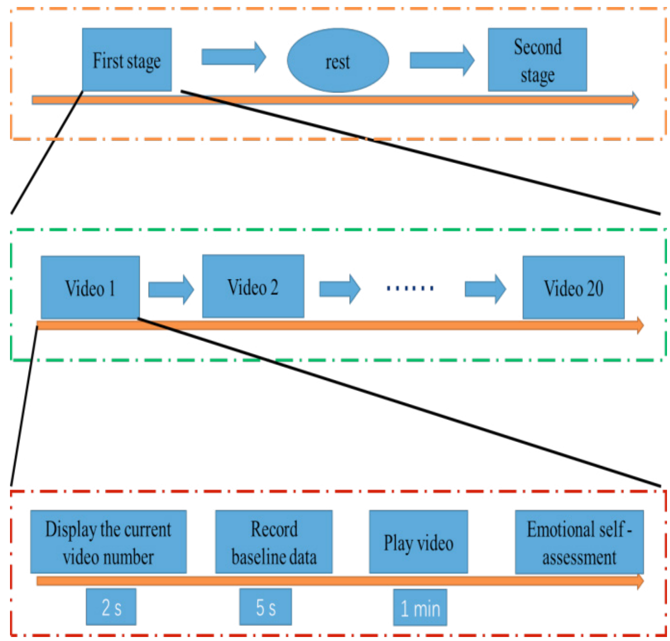

Fig. 1. The procedure of emotion induction experiment.

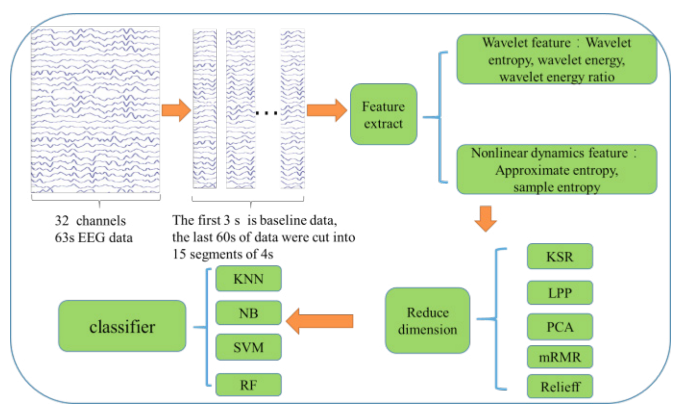

Fig. 2. Flowchart of EEG-based emotion recognition system.

The 60s EEG signal is segmented into 15 equal, non-overlapping segments. Here, 4s is taken as the length of the time window. After such processing, the number of samples is 40*15=600 per subject. For 32 subjects, 32*600=19200 samples are available.

In most previous studies, the number of emotion classes is usually small. For example, in the DEAP-based emotion recognition, many studies focused on the binary (positive vs. negative valence or high vs. low arousal) classification problem and obtained the target emotion labels by hard threshold of subjective data (Yin, Zhao and Wang et al., 2017; Petrantonakis and Hadjileontiadis, 2011; Daimi and Saha, 2014; Yoon and Chung, 2013). In order to determine reliably the target emotional classes, we use the following method. By performing *k*-means clustering of subjective ratings on the arousal and valence rating scales, we can determine the target emotion class for each data point on the 2D (arousal and valence) emotion plane. The clustering results are shown in Fig. 3. Fig. 4 shows the 2D emotion plane, where LV represents low valence (negative emotion), HV represents high valence (positive emotion), LA represents low arousal, and HA represents high arousal. The cluster centers when k=4 are given in Table 1.

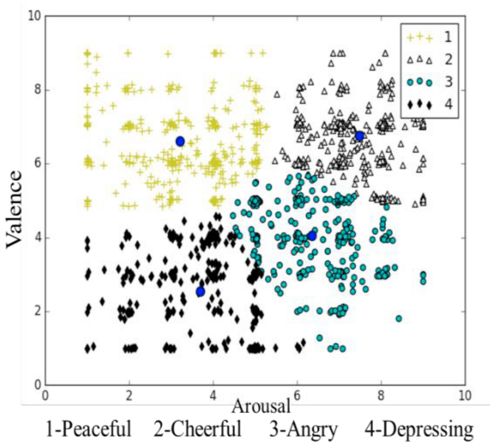

Fig. 3. The k-means clustering result.

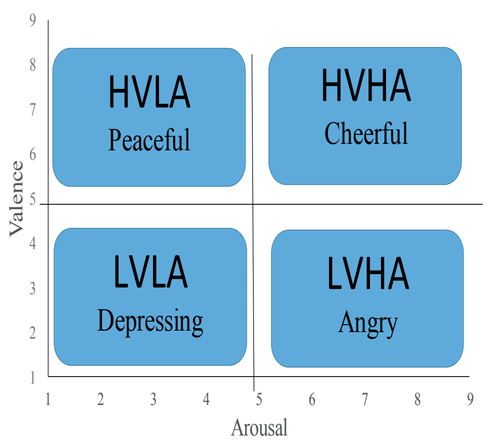

Fig. 4. A two-dimensional model of emotions.

When k-means algorithm is used for clustering, it is necessary to set the initial clusters. The setting of the initial cluster centers is mainly based on two considerations: 1) whether the target classes obtained by data clustering can be reasonably explained by the two-dimensional emotion model, i.e., the clusters obtained can be found on the 2D emotion plane; 2) the Silhouette coefficient (Rousseeuw, 1987) is used to evaluate the clustering performance since the true labels of clusters are unknown.

The Silhouette coefficient is defined by:

$$S = \frac{b-a}{\max(a,b)} \tag{1}$$

Where a represents the average distance of the sample from other samples in the same cluster, b represents the average distance of the sample from all samples in the closest (different) cluster, S denotes a measure of the clustering quality. Generally, the larger the S, the higher the clustering quality.

Fig. 5 depicts the Silhouette coefficient and the corresponding sum of squared errors (SSE) when the value of k is varied from 2 to 8. It can be seen that the largest Silhouette coefficient (0.42) is reached when k=3 and the second largest Silhouette coefficient is 0.40 when k=4. On the other hand, the two-dimensional emotion plane can be divided into four types of emotions by the threshold method. Therefore, the number of clusters is set as 4.

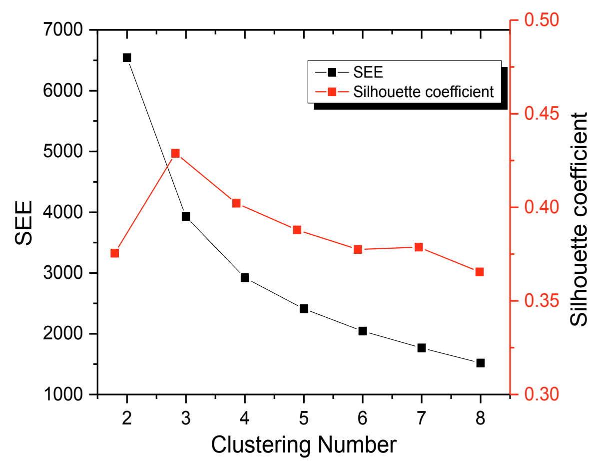

Fig. 5. The Silhouette coefficient.

3. EEG FEATURE EXTRACTION

In this work, we use two methods for EEG feature extraction: one is wavelet transform (time-frequency analysis) and another is nonlinear dynamics analysis (approximate entropy and sample entropy).

3.1 Wavelet Transform

Wavelet decomposition is a typical and practicable time-frequency analysis method. It is a localized analysis method based on time window and frequency window. The EEG signal is non-stationary and is characterized by slow change of the lower-frequency components and fast variability of the higher-frequency components, so wavelet transform is ideally suited to its signal analysis. The multi-scale analysis of EEG signals using wavelet transform allows for the EEG signal to exhibit both details and approximations at different wavelet scales. By wavelet decomposition of EEG signals, a series of wavelet coefficients can be obtained at different scales. These coefficients can completely describe the characteristics of the signal and thus can be used as a feature set of the signal.

For EEG signal from each channel, three features are derived from the wavelet coefficients of each sub-band, including wavelet energy (the sum of squared wavelet coefficients of each order), wavelet energy ratio (the ratio of each sub-band energy in the total energy of all sub-bands), and wavelet entropy which are defined as follows:

- wavelet energy:

$$E(i) = \sum_{j=1}^{n_i} D_{i,j}^2 \qquad (2)$$

- wavelet energy ratio:

$$R(i) = E(i) / \sum_{j=1}^{n} E(j) \qquad (3)$$

- wavelet entropy:

$$W_e = \sum_{i=1}^{n} R_i \ln R_i \qquad (4)$$

3.2 Nonlinear Dynamics Analysis

EEG signals are highly complex and nonlinear. In recent years, nonlinear dynamics analysis (e.g., entropy and other complexity measures) has been widely used in the analysis of EEG signals (Zhang, Wang and Fu, 2014; Vijith, Jacob and Iype et al., 2016; Guido, 2018). Among them, two nonlinear dynamics methods, approximate entropy and sample entropy, are important tools for quantifying the complexity of time series (Zhang, Chen and Wang, 2019).

3.3 EEG Feature Reduction/Selection

Dimensionality reduction of EEG features is an important step in EEG-based emotion recognition. Selecting an effective feature reduction and selection algorithm can improve not only the efficiency of model training, but also the accuracy of model prediction. Feature reduction and selection is usually required to: 1) help with data visualization and understanding; 2) reduce the training time of the model; 3) overcome the curse of dimensionality, thereby improving the model prediction performance (or generalizability).

The EEG signals has 32 channels, the signal from each channel is decomposed into five levels, and the wavelet coefficients corresponding to the five frequency bands are obtained. Then three features are derived using wavelet coefficients: wavelet energy, wavelet energy ratio, and wavelet entropy. If the features of all frequency bands are considered simultaneously, the dimensionality of the wavelet-based feature vector is 32*5*3=480, whereas the feature dimensionality of each frequency band is 32*3=96. Similarly, if the ApEn and SampEn are used simultaneously in the feature set, the nonlinear dynamics feature dimensionality is 32*2=64. Based on our recent work (Zhang, Chen, Nichele and Yazidi, 2019; Zhang, Chen and Wang, 2019), we will compare three dimensionality reduction algorithms (KSR, LPP, and PCA) and two feature selection algorithms (mRMR, Relieff) on EEG features. Here PCA is used as a reference for comparison of other algorithms. The kernel spectral regression (KSR) *discriminant analysis* algorithm is very effective when dealing with big massive data (Cai, He and Han, 2011).

3.4 Random Forest (RF) Classifiers

In order to obtain accurate recognition, we adopt the ML classifier, random forest (RF). RF is a classifier formed by combining decision trees. It is an ensemble learning algorithm based on the idea of bagging. The output of RF is determined by voting of all decision trees (Breiman, 2001).

4. EMOTION RECOGNITION USING SELECTED EEG ELECTRODES

This section discusses the brain regions that are most correlated to emotions, with an aim to use fewer EEG electrodes to achieve satisfactory emotion classification. In Sect. 4.1, the EEG measurement electrodes were grouped according to different brain regions where they fall in. EEG features were extracted from each group of electrodes (placed on a distinct brain region) and then emotion classification were performed. In Sect. 4.2, all the 32 electrodes are ranked according to their relative importance quantified by the feature selection algorithms. The visualization of the relative importance of the electrodes on brain topography allows for identification of the brain areas that are mainly responsible for generating emotions.

4.1 Emotion-relevant Brain Areas

Physiological studies showed that the cerebral cortex is primarily responsible for the high-level emotional function in humans. The cerebral cortex can be roughly divided into frontal lobe, parietal lobe, occipital lobe and temporal lobe. The task here is to find the brain areas that are closely relevant to emotions through EEG-based emotion recognition. The 32 EEG electrodes are grouped according to the respective cerebral cortex where they are distributed. The placement of the electrodes is shown in Fig. 6, where red ones are distributed on the frontal cortex, green ones on the parietal cortex, blue ones on the occipital cortex, yellow ones on the temporal cortex, and squares on the central area. The specific electrode groups are shown in Table 1.

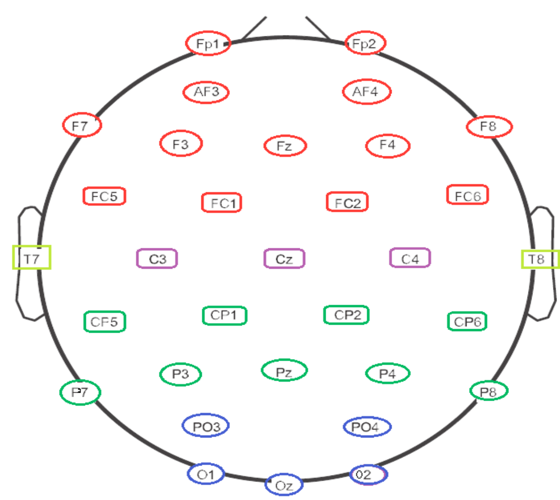

Fig. 6. The groups of EEG electrodes.

From Fig. 7, we can see that despite the use of partial channels of EEG, the emotion classification accuracy is acceptable. If only comparing the five brain regions of Frontal, Parietal, Occipital, Temporal, and Central, we can find that the classification accuracy of the frontal cortex group is the highest. Nonetheless, as there are different number of electrodes placed on different brain regions, it is hard to determine the brain regions that are most relevant to emotions only by comparing the emotion classification accuracy. We will select the most dominant EEG electrodes by an importance ranking procedure in next section.

Table 1. Brain areas and the groups of EEG electrodes.

Area	No.	(sub)groups of electr.
Frontal	13	Fp1,Fp2,AF3,AF4,F7,F8,F3,Fz,F4,FC5,FC1,FC2,FC6
Frontal_1	2	Fp1, Fp2
Frontal_2	2	AF3, AF4
Frontal_3	5	F7, F3, Fz, F4, F8
Frontal_4	4	FC5, FC1, FC2, FC6
Parietal	9	CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8
Parietal_1	4	CP5, CP1, CP2, CP6
Parietal_2	5	P7, P3, Pz, P4, P8
Occipital	5	PO3, PO4, O1, Oz, O2
Occi._1	2	PO3, PO4
Occi._2	3	O1, Oz, O2
Temporal	2	T7, T8
Central	11	FC5,FC1,FC2, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6

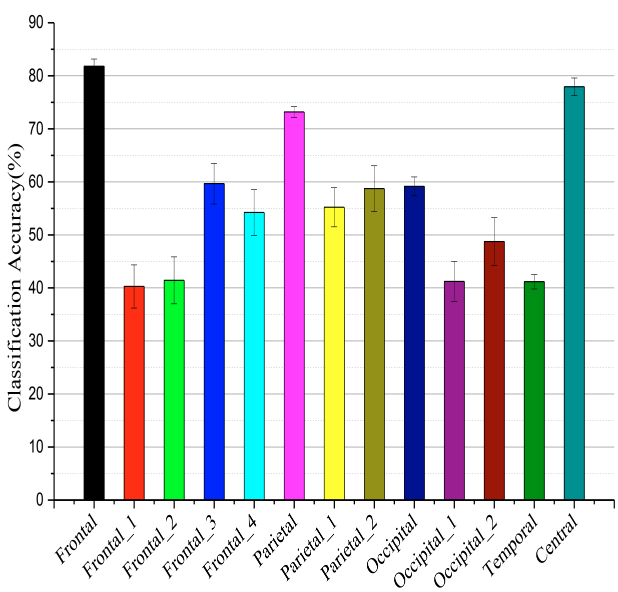

Fig. 7. The emotion recognition accuracy using different groups of EEG electrodes.

4.2 *Selection of Emotion-relevant EEG Electrodes*

In order to further study the relationship between brain regions and emotional states, using the two feature selection algorithms mRMR and Relieff, we can sort out the EEG electrodes according to the importance of the features in decreasing order (from extremely important to unimportant). We gradually increase the number of electrodes and use KSR for feature dimensionality reduction and RF classifier. The order of importance of the electrodes sorted out was not exactly the same across subjects, but it was similar in general. The results for subject 1 is shown in Fig. 8. It can be found that when the number of EEG electrodes is increased beyond a certain threshold, the increase trend of classification accuracy tends to reach a plateau. In Fig. 8(a), when the number of electrodes is 12, the classification accuracy reaches 90%, and when the number of electrodes is 27, the classification accuracy reaches a maximum of 97.33%. In Fig. 8(b), when the number of electrodes is 13, the classification accuracy reaches 90.67%, and when the number of electrodes is 26, the classification accuracy reaches a maximum of 98%. In Fig. 8(c), when the number of electrodes is 23, the classification accuracy reaches 80%, and when the number of electrodes is 32, the classification accuracy reaches a maximum of 85.33%. In Fig. 8(d), when the number of electrodes is 21, the classification accuracy reaches 81.83%; When the number of electrodes is 32, the classification accuracy reaches the maximum 86.17%. The above results indicate that emotion classification can be performed by using the EEG features from only a part of the brain. In particular, when using nonlinear dynamics features (i.e., sample entropy and approximate entropy), by using only 12-channel EEG signals which are mainly measured from the frontal area of brain, we could achieve a 4-class emotion classification accuracy of 90%.

Since the order of importance of the electrodes is different across subjects, the results for all the 32 subjects are analyzed. Firstly, the mRMR and Relieff algorithm were used separately to obtain the order of importance of the 32 EEG electrodes. The electrodes are then assigned different weights. For example, if the electrode ranked highest in the first test is F7, then it is assigned a weight of 32; if the lowest ranked electrode is Pz, then it is assigned a weight of 1. In this way, we can also obtain the subject-average weight of each EEG electrode. The electrodes ranking obtained by the mRMR and Relieff algorithm is shown in Table 2.

In order to intuitively show the importance of each electrode, the brain topography is shown in Fig. 9, where the average importance of the 32 electrodes is marked.

In this section, mRMR and Relieff algorithms are used to sort out the electrodes based on the importance of the features selected. It can be found that for the same subject, the electrode ranking obtained by using two different feature extraction algorithms is slightly different. However, in general some electrodes on the frontal cortex (such as F7, F3, Fp1, and F8) are always highly ranked regardless of which feature selection algorithm is used. Other highly ranked electrodes include Po3, P8, P3, and O2. These results are in good agreement with the general finding in physiological literature that the prefrontal cortex plays an important role in emotion generation.

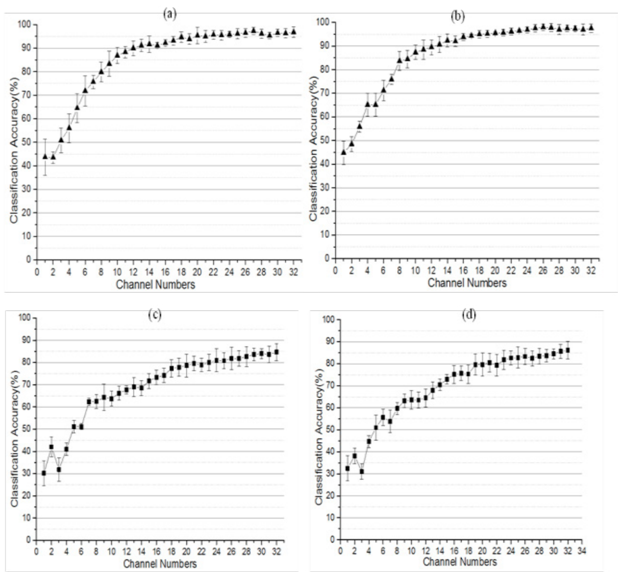

Fig. 8. The 4-class emotion classification accuracy vs. the number of EEG electrodes (subject 1): (a) entropy features + mRMR; (b) entropy features + Relieff; (c) wavelet features + mRMR; (d) wavelet features + Relieff.

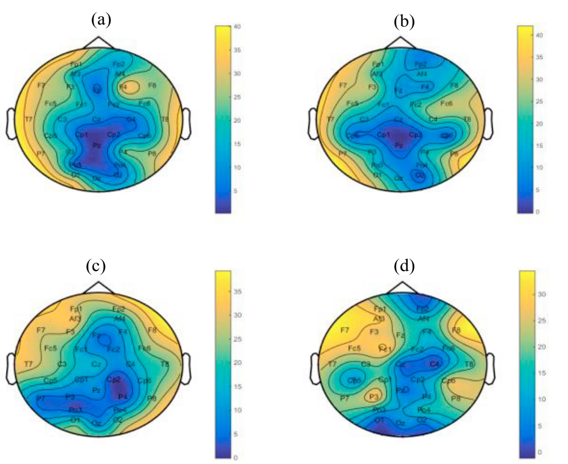

Fig. 9. The brain topography with EEG electrodes importance ranking (subject 1): (a) entropy features + mRMR; (b) entropy features + Relieff; (c) wavelet features + mRMR; (d) wavelet features + Relieff.

Table 2. The EEG electrodes ranking obtained by mRMR and Relieff.

Rank	mRMR	Relieff	Rank	mRMR	Relieff
1	F7	Po3	17	P7	Af4
2	P8	F8	18	Af4	Af3
3	O1	Fp1	19	Cp2	C3
4	F8	P3	20	Pz	P7
5	C4	Fp2	21	Fc5	Cp5
6	T7	F3	22	Af3	P4
7	Po3	O2	23	Fc6	C4
8	Fp1	P8	24	C3	Cp6
9	Fp2	Oz	25	Po4	F4
10	O2	F7	26	Cp5	Po4
11	P3	T8	27	Fc1	Cp1
12	Fz	Cz	28	Oz	Fc1
13	T8	Fc5	29	Cp6	Fz
14	Cz	Fc6	30	Cp1	O1
15	F3	T7	31	P4	Fc2
16	F4	Pz	32	Fc2	Cp2

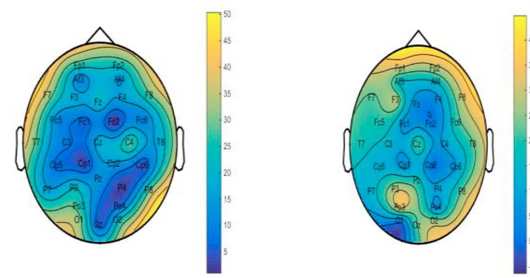

Fig. 10. The EEG electrode importance ranking obtained by: (left) mRMR and (right) Relieff.

4.3 Discussions

In order to explore the brain regions most relevant to emotions, the importance of the electrodes is ranked by using the mRMR and Relieff algorithms, as shown in Fig. 10. It is found that we can achieve comparable classification accuracy by using fewer important EEG electrodes. Brain topography was drawn, on the basis of the importance of the electrodes, to find out the brain regions where more important electrodes are placed. Through the study of the relationship between brain areas and emotion, it is found that the EEG features from the frontal cortex lead to higher emotion classification accuracy than those from other brain regions. After ranking the EEG electrodes based on the mRMR algorithm, we can use only 12 EEG electrodes mainly from frontal cortex (out of 32) to achieve an emotion classification accuracy of 90%.

5. CONCLUSIONS

In this paper, we study the EEG-based emotion recognition problem using the DEAP dataset. We consider feature extraction, feature reduction/selection, ML classifiers, as well as the brain areas that are most related to emotions. The novel contributions of this work are as follows:

(1) In most literature on DEAP-based emotion recognition, labeling the emotion data is based on the threshold method. Moreover, in many literatures only binary classification (of each dimension of emotion, like arousal and valence) problem is considered. In this paper, we use k-means clustering algorithm to determine the target/actual emotion classes on 2D plane of emotion (arousal and valence dimensions).

(2) In many previous studies on emotion recognition, researchers only use the EEG data in emotional state while ignoring the baseline (emotionless) EEG data. In this paper, the EEG features were extracted as the difference between the baseline EEG feature and the emotionally aroused EEG feature. The results show that when using the relative change

(difference) as the features, rather than the absolute values of the EEG features under emotional stimuli, the emotion classification accuracy can be effectively improved.

(3) The emotion classification accuracy of using only a part of the EEG electrodes (not all 32 electrodes) is analyzed. We found that using only 12 EEG electrodes placed on frontal cortex can achieve emotion classification accuracy of 90%. This work may provide basis for real-time application of the EEG emotion recognition techniques developed.

The future work along this line of research may include:

(i) The 3D or even higher-dimensional emotion model can be considered to perform classification of more types (i.e., more than 4) of emotions.

(ii) It may be possible to determine the target classes by incorporating the content of the emotion-stimulus material.

(iii) We need to combine heterogeneous physiological signals by certain data/information fusion method to realize multi-modal emotion recognition.

(iv) In real-world applications, a subject-independent (or called generic) emotional recognition model would be of paramount importance. However, the subject-independent emotion classifier must incorporate transfer learning technique in order to obtain stable emotion recognition accuracy across subjects.

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