IOP Conf. Series: Journal of Physics: Conf. Series **1487** (2020) 012002 doi:10.1088/1742-6596/1487/1/012002

An Emotion Classification Method Based on Energy Entropy of Principal Component

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Abstract. Emotional recognition based on electroencephalogram (EEG) has attracted more and more attention, and various methods emerge in an endless stream. An emotion classification method based on energy entropy of principal component (PCEE) is proposed in this paper. EEG data are divided into five rhythms (δ, θ, α, β and γ) by wavelet decomposition and reconstruction (WDR). Each rhythm signal uses principal component analysis (PCA) to perform dimensionality reduction on the channels (electrodes). The energy entropies of the principal components that meet the requirements are used as the classification feature. Results show that the classification accuracy can reach 87.61% by using the support vector machine (SVM) classifier.

1. Introduction

The EEG signal is a kind of non-stationary nonlinear random signal. The basic methods for analyzing such signals are time domain, frequency domain, time-frequency analysis and non-linear analysis. As an effective time- frequency analysis method, wavelet transform (WT) can effectively extract the detailed features of signals for multi-resolution analysis. Since studies found that different emotions of human lead to different activities of rhythmic waves in EEG signals, the changes of music emotional EEG signals will be analyzed by dividing EEG signals into basic rhythm waves by WDR, and then extracting features from those rhythm waves for emotion classification. The WT was used to classify the physiological signals, and good results were achieved [1-4]. Chen et al. performed WDR on emotional EEG signals with wavelet packet, and used β rhythm for emotional state recognition [5]. Murugappan achieved a great classification accuracy of 82.87% with WT and K-nearest-neighbor (KNN) classifier [6]. Ang et al. extracted features by using time- frequency analysis and WT from EEG signals, and achieved a great classification accuracy of 81.8% [7]. Bajaj et al. achieved a great accuracy of 86.1% with flexible analytic wavelet transform (FAWT) and weighted-KNN classifier [8]. Mohammadi et al. decomposed EEG signals with discrete wavelet transform (DWT) and extracted

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features [9].

EEG shows different dominant frequencies in different situations, i.e. rhythms. Studies show that different rhythms have different relationships with emotion. Kabuto et al. found that in the happy mood state, the energy of the EEG signal increased, while the energy of α rhythm decreased significantly [10]. Wang found that θ rhythm in frontotemporal region was proportional to inhibitory emotion, while β rhythm was proportional to incentive emotion [11]. Lai et al. found that the power of α rhythm of the positive emotion in the frontal area is relatively greater than the negative emotion [12]. There was a negative correlation between α rhythm and positive music mood, and a positive correlation between β rhythm and positive music mood [13]. After studying the relationship between happy and sad music and brain activity, Sammler et al. found that happy music is associated with the increase in the power of θ rhythm [14]. Wang et al. used empirical mode decomposition (EMD) and energy moments to extract the features from all the rhythms, and classified them by SVM [15].

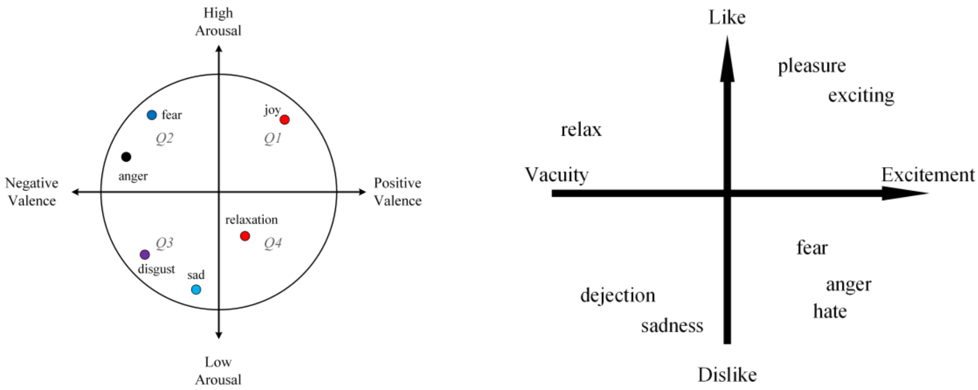
Entropy is a feature used to express signal complexity. Approximate entropy, sample entropy, wavelet entropy, and energy entropy are often used as features for emotion classification. Li et al. used Kolmogorov-Complexity, wavelet entropy and approximate entropy as features and SVM for classification [16]. Li et al. used sample entropy as features and classified with weighted SVM [17]. Li et al. used improved multi-scale entropy for feature extraction and classified emotions with SVM [18]. Lu et al. used the combination of EMD and energy entropy as features [19]. Zhang et al. used auto-regressive (AR) model and approximate entropy as features [20]. Hosseini et al. used approximate entropy and wavelet entropy as features and SVM as classifier [21]. Xiang et al. classified emotions with the feature of sample entropy and SVM [22]. Tian et al. used EMD and sample entropy as features, then selected the sample entropies and formed a feature vector [23]. Li et al. used sample entropy and approximate entropy as features for classification [24].

In this study, EEG signals were divided into five rhythms by the WT, and the energy entropies were extracted as the features of emotional states after PCA, and the SVM classifier was used for classification.

2. Materials

2.1 Models of emotions

The study of emotional classification has been controversial. Emotions have been divided into seven categories (i.e., joy, anger, worry, overthinking, sadness, fear and surprise) since ancient times in China. Modern scholars believe that all human emotions are derived from the basic emotion set, and they have put forward different basic emotion sets. For example, James's basic emotion set included anger, fear, sadness, and love, while Ekman's set included anger, fear, sadness, happiness, disgust, and surprise [25]. With the advance of researches, it is found that there are certain correlations between some emotions. For example, anger and disgust sometimes occur simultaneously. Therefore, some scholars described emotions in different dimensions according to these correlations. Davidson and Lang presented their own two-dimensional emotional models [26-27], which are shown in figure 1. Then a three-dimensional emotional model was proposed, in which the three dimensions are pleasure, arousal and dominance (PAD) [28-29]. Lang's emotion model was used to evaluate stimulus materials in the experiment.



(a) Davidson's model [26]. (b) Lang's model [27].

Figure 1. 2D emotional models.

2.2 Statement of Ethics and human rights

All subjects signed informed consent before the experiments, which was approved by the Beihang University ethical review committee (IRB). All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

2.3 Audio stimuli

The stimulus induction method was used to induce different emotions in the subjects through external stimuli. To effectively induce the emotional state of the subjects, it is necessary to objectively evaluate the stimulus materials. Therefore, the audio stimuli were evaluated via Lang's 2D emotion model. All audio files were downloaded from the Internet and evaluated. Then, six audio clips ranging from 30 to 45 seconds were chosen as stimuli, half of which were positive and the other half were negative. All audio clips are in wav format and are dual tracks with a sampling rate of 44.1 kHz. Table 1 illustrates that the audio stimuli that were used in the experiment had better emotion discrimination and excitation effects.

Table 1. Evaluation of audio stimuli.

Audio stimuli number	Emotion type	Valence	Arousal
1	Positive	7.5	7
2	Positive	7	7.67
3	Positive	7.33	7.17
4	Negative	3.17	6.67
5	Negative	2.33	7.67
6	Negative	2.83	7.17

2.4 Participants

A total of 14 volunteers participated in this study were divided into two groups: the evaluation group and the acquisition group. Each volunteer joined only one group. The evaluation group consisted of 4 males and 4 females, and did not participant in EEG data acquisition. The acquisition group consisted of 6 males, and all the EEG data used in this study were from them.

All participants were healthy, right-handed postgraduate students. The age ranged from 22 to 26 years in the evaluation group and from 22 to 36 years in the acquisition group. All participants had no personal history of neurological or psychiatric illnesses, and did not receive professional music training. The emotional evocation and EEG data acquisition were completed in a closed and quiet room to reduce the interference.

2.5 EEG data

EEG data were recorded with a 64-channel (electrodes) electrical signal imaging system (Neuro Scan Labs), and the SCAN 4.5 software, and a 64-channel Quick Cap with Ag/AgCl electrodes. Those electrodes were arranged according to the extended International 10–20 system. The resistance between the scalp and the electrode is less than 5 kΩ. The EEG data were recorded at the sampling rate of 1000 Hz. Parts of the experimental devices and scenarios are shown in figure 2. Part (a) shows the electrodes and cap. Part (b) shows the EEG signal amplifier used in the experiment. Part (c) shows the corresponding resistances between the scalp and each electrode when injecting the conductive gel.

(a) the electrodes and cap. (b) EEG signal amplifier. (c) Resistances when injecting the gel.

Figure 2. Parts of the experimental devices and scenarios.

3. Methodology

In this paper, an emotion classification method based on PCEE is proposed. The EEG data acquired from experiments were analyzed through several procedures, including filtering, segmenting, WDR, PCA, energy entropy calculation and classification, as shown in figure 3. All five rhythms (δ, θ, α, β and γ) were reconstructed by wavelet transform decomposition. PCA was used for dimensional reduction of channels (electrodes) in time domain waveforms of all five rhythms. When the cumulative variance contribution rate reached 90%, the corresponding principal components were stored, while the other principal components were ignored. The energy entropies were calculated as the classification features according to the stored principal components. Finally, emotional states were classified with SVM.

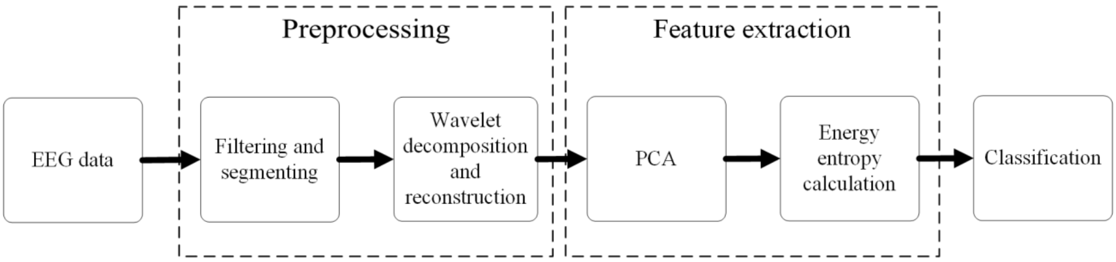


Figure 3. The flowchart of this study.

3.1 Filtering and segmenting

Since the frequency range of effective EEG components is usually 0.5-45 Hz, a low-pass filter with a cut-off frequency of 50 Hz was being used when EEG data were acquired. But in order to cooperate with the wavelet transform, the upper limit of the frequency of EEG data must be increased to 64Hz. Therefore, the acquired EEG data first needed to pass through an ideal low-pass filter with a cut-off frequency of 64 Hz in this study. And then the time domain waveform of the EEG data were segmented into segments of 500 ms. The last segment of the EEG data that is less than 500 ms was complemented by ‘0’s.

3.2 WDR

Db2 wavelet was used to perform a five-layer decomposition on the segments of EEG data in this work, as shown in figure 4.

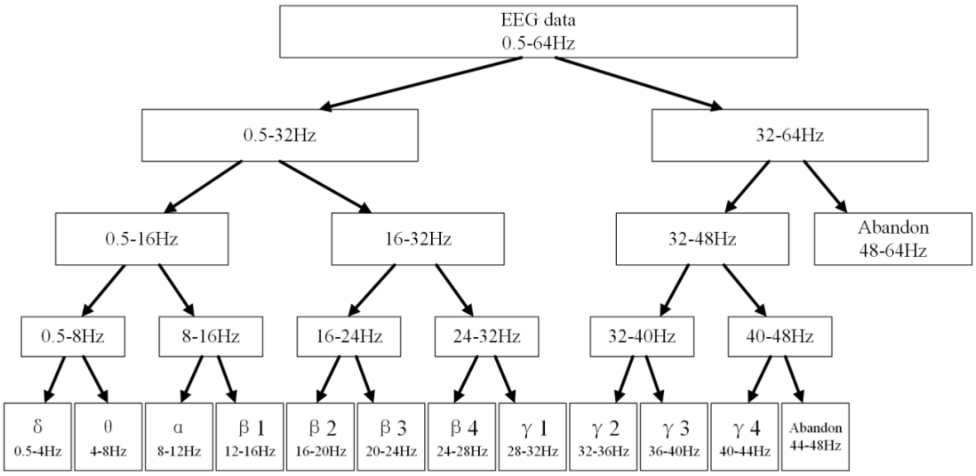
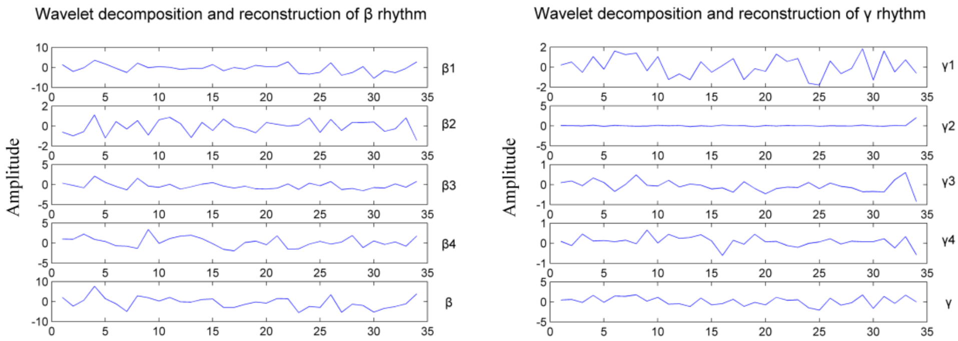


Figure 4. Frequency space corresponding to five-layer decomposition via db2 wavelet.

The reason for choosing dbN wavelet was that dbN wavelet can achieve a good effect of two divided-frequency. The higher the vanishing moment N, the smaller the high frequency coefficient. However, in the process of decomposition, both the high frequency coefficient and the low frequency coefficient of the signal were important, so N was set to 2.The results of the five-layer wavelet decomposition corresponded to the five rhythms of the EEG signal, namely δ (0.5-4Hz), θ (4-8Hz), α (8-12Hz), β (12-28Hz), and γ (28-44Hz). Since the β and γ rhythms were divided into four sub-bands respectively, each sub-band needed to be reconstructed separately and then superimposed to restore the complete β and γ rhythms, as shown in figure 5.



(a) WDR of β rhythm. (b) WDR of γ rhythm.

Figure 5. WDR of β and γ rhythms.

3.3 PCA

PCA is a multivariate data processing technology that transforms multiple related indicators into a small number of uncorrelated comprehensive indicators (i.e., principal components) through dimensionality reduction. Studies have shown that when the human brain was stimulated to produce emotions, there was a certain correlation between emotional state and stimulating material and active areas of the brain[30-33]. As a result, it was reasonable to believe that the principal components will better reflect the relationships between emotional states and active brain regions. In this study, PCA was performed on the channels (electrodes) of EEG data. The cumulative variance contribution rate η is usually used to select the appropriate principal component. The parameter η was set to 90% in the experiment. In other words, the cumulative contribution rate of the first n principal components was calculated until reached 90%, and then the first n principal components were recorded.

3.4 PCEE

Assuming that $\{pc_1, pc_2, \ldots, pc_n\}$ were the first n principal components obtained by PCA, and $\{E_1, E_2, \ldots, E_n\}$ were defined as the energies of the corresponding principal components, and then PCEE can be expressed as:

$$\begin{cases} p_i = E_i\left(\sum_i E_i\right)^{-1} \\ PCEE = -\sum_i \left(p_i \log p_i\right) \end{cases} \quad i = 1, 2, \cdots, n \tag{1}$$

where p_i was the ratio of the energy of the ith principal component to the sum of the energies of all principal components.

4. Experimental results

There were 3366 segments of EEG data in all in this study, of which 2278 segments were from positive excitations and 1088 segments were from negative excitations. A maximum of 4 principal components could be achieved when η was set to 90%. The SVM classifier and the leave-one-out method were used for the emotion classification after the PCEE of all the segments were extracted. In order to sufficiently understand the roles of different rhythms in emotion recognition, all combinations of the five rhythms were classified.

The classification results of all combinations of the five rhythms are shown in Table 2. The results show that the proposed method achieves the best classification accuracy of 87.61% in four cases, including one of three rhythms, two of four rhythms and one of five rhythms. The results also show that the more the number of rhythms participating in the classification, the better the average accuracy. This means that all rhythms contribute to emotion recognition under the conditions of this study. When only a single rhythm is used, the classification accuracy of θ rhythm (72.81%) is the highest, while those of α and γ rhythms (67.98%) are the lowest. When multiple rhythms are used at the same time, the classification accuracy is the highest when δ and β rhythms are used simultaneously, while that is the lowest when α and γ rhythms are used simultaneously. In addition, the result obtained by only using the δ+β rhythms is very close to the highest classification accuracy.

Table 2. The classification results of all combinations of the five rhythms.

The number of rhythms used	Only one rhythm	Two rhythms	Three rhythms	Four rhythms	All five rhythms
The highest classification accuracy	72.81%	85.5%	87.61%	87.61%	/
The rhythm(s) corresponding to the highest accuracy	θ	δ+β	δ+α+β	δ+θ+α+β δ+α+β+γ	/
The lowest classification accuracy	67.98%	67.98%	70.69%	72.81%	/
The rhythm(s) corresponding to the lowest accuracy	α γ	α+γ	α+β+γ	δ+θ+α+γ θ+α+β+γ	/
The average accuracy	69.31%	72.45%	76.47%	81.27%	87.61%

Table 3 compares the classification accuracy of the proposed method with that of some existing methods. These existing methods are based on EEG data for auditory stimuli. All methods are compared in terms of used stimuli for evoking the emotions, proposed features extraction approaches, used classifiers and the classification accuracy. The proposed method also used auditory stimulation, and the classification accuracy rate was 87.61%. The classification performance of the proposed method shows its advantages in emotional classification and has practical value.

Table 3. Comparison emotion classification methods.

Methods	Stimuli	Features	Classifiers	Accuracy
Wang et al. [15]	Audio-Video	Energy moment of IMF [a]	SVM	68.59%
Bhatti et al. [4]	Music	Statistical features, PSD[b], FFT[c], and WT	MLP [d]	78.11%
Bajaj et al. [34]	Audio-Video	Multi wavelet	MC-LS-SVM [e]	84.79%
Bajaj et al. [8]	Audio-Video	FAWT	Weighted-KNN	86.1%
Mohanmadi et al. [9]	Audio-Video	Entropy and energy	KNN and SVM	86.75%
Proposed method	***Audio***	***PCEE***	***SVM***	***87.61%***

[a] IMF: Intrinsic Mode Function.

[b] PSD: Power Spectrum Density.

[c] FFT: Fast Fourier Transform.

[d] MLP: Multi-Layer Perceptron.

[e] MC-LS-SVM: Multi-Class Least Squares Support Vector Machine.

5. Conclusion

In this work, an emotion classification method based on energy entropy of principal components is proposed. The EEG data acquired from experiments are analyzed through several procedures, including filtering, segmenting, WDR, PCA, energy entropy and classification. EEG data are divided into five rhythms (δ, θ, α, β and γ) by WDR. PCA is used for dimensional reduction of channels (electrodes) in time domain waveforms of all five rhythms. When the cumulative variance contribution rate reaches 90%, the corresponding principal components are stored, while the remaining principal components are ignored. The energy entropies are calculated as the classification features according to the stored principal components. The proposed method reaches a great classification accuracy of 87.61% with SVM.

Acknowledgments

This work was supported in part by Specialized Research Fund for the Doctoral Program of Higher Education (SRFDP) under grant 20121102130001, the National Science Foundation for Young Scientists of China under grant 61603013, and the Fundamental Research Funds for the Central Universities (No. YWF-19-BJ-J-197).

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