Emotion recognition using empirical mode decomposition and approximation entropy☆

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ABSTRACT

Automatic human emotion recognition is a key technology for human-machine interaction. In this paper, we propose an electroencephalogram (EEG) feature extraction method that leverages empirical mode decomposition and Approximation Entropy. In our proposed method, Empirical Mode Decomposition (EMD) is used to process EEG signals after data processing and obtains several intrinsic eigenmode functions. The Approximation Entropy (ApEn) of the first four Intrinsic Mode Functions (IMFs) is computed, which is used as the features from EEG signals for learning and recognition. An integration of Deep Belief Network and Support Vector Machine is devised for classification, which takes the eigenvectors from the extracted feature to identify four principal human emotions, namely happy, calm, sad, and fear. Experiments are conducted with EEG data acquired with a 16-lead device. Our experimental results demonstrate that the proposed method achieves an improved accuracy that is highly competitive to the state-of-the-art methods. The average accuracy is 83.34%, and the best accuracy reaches 87.32%.

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1. Introduction

Automatic human emotion recognition is a key technology for human-machine interaction [1,2]. Many research on emotion recognition relies on data from images, audio, and videos [3–5]. Discrete models [6] and dimensional models [7] are proposed to describe emotional states. Among a variety of data, physiological signals such as electroencephalogram (EEG), electrocardiogram (ECG), and electromyography (EMG) signals have been employed for emotion recognition [8]. EEG signal is closely correlated with brain activities and is more promising for recognizing emotional states [9–11].

Most recently, Hu et al. [12] proposed a classification method that combines Correlation-based Feature Selection (CFS) and a k-nearest-neighbor (KNN) algorithm for attention recognition. Lin et al. [4] used Support Vector Machine (SVM) to classify the emotional states based on EEG into four categories and found that the frontal and temporal lobes of the brain are the main areas of emotion generation, and the average classification accuracy of emotion achieves 82.29%. Goyal
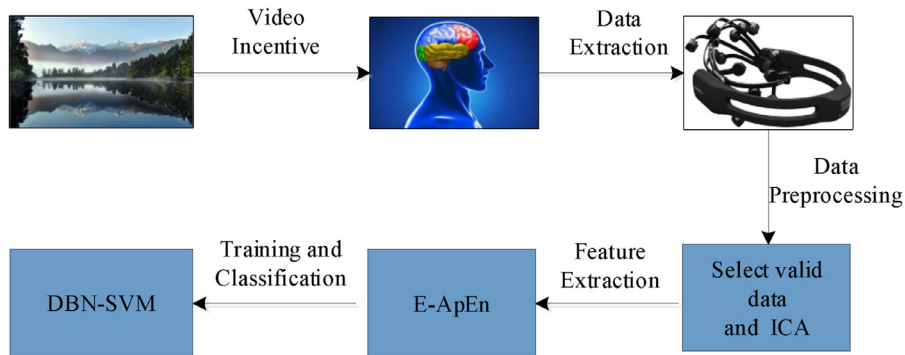

Fig. 1. The flow chart of the proposed emotion recognition method.

et al. [13] described the acquisition of EEG signals on frontal electrodes from five subjects for the classification of emotions. Gonuguntla et al. [14] analyzed the network mechanisms related to human emotion based on synchronization measure phase-locking value in EEG to formulate the emotion-specific brain functional network.

In addition to the development of classification methods, signal processing techniques have been studied. Empirical mode decomposition methods based on the Hilbert-Huang Transform (HHT) have been explored in the field of signal processing to improve the recognition performance [15,16]. HHT includes empirical mode decomposition (EMD) and Hilbert transformation. It decomposes a signal into several approximate cosine waves and looks into their periods and amplitudes, which effectively suppresses noise and obtain the time-frequency characteristics of the signal. Such methods achieved greater results when dealing with non-stationary signals.

Despite the advancements in emotion recognition using EEG signals, there is much room to improve. This paper integrates EMD and Approximation Entropy (ApEn) and proposes an EEG feature extraction method (namely EMD-Approximation Entropy, in short E-ApEn) for feature extraction. This combined feature extraction method reduces the complexity of feature extraction. Using the emotion recognition model and integrating Deep Belief Network (DBN) and Support Vector Machine to get the feature vectors for training and classification, It is expected that a higher rate of emotion recognition can be achieved.

The rest of this paper is organized as follows: Section 2 presents our proposed method for emotion recognition using EEG signals. The section starts with an overview of the framework followed by the feature extraction method that integrates EMD and ApEn. A DBN-SVM is discussed, which makes multi-class decisions for emotion recognition. Section 3 discusses our experimental results and the section includes a description of data acquisition and preprocessing, as well as a comparison study with the state-of-the-art methods. Section 4 concludes this paper with a summary of our work and a highlight.

2. Emotion recognition model

2.1. Framework of the proposed method

The framework of our proposed method is shown in Fig. 1. The process of establishing the emotion recognition model using EMD decomposition and approximate entropy consists of the following four steps:

1. The signal is preprocessed to get signal clips of a fixed size and an independent component analysis (ICA) is used to suppress noise.
2. For each attribute of a signal clip, EMD is used for decomposition, and the approximate entropy of the first 4 IMFs of the decomposed signal is calculated.
3. Select the appropriate combination of attributes and feed the entropy of the selected attributes to the DBN network to feature extraction.
4. The features extracted by DBN network are classified with SVM classifiers for emotion recognition.

In this paper, videos are used to stimulate emotions of the subjects, and the EEG data is recorded and different channel combinations are extracted for emotion recognition.

2.2. Feature extraction

Approximate entropy is a method to measure the complexity and regularity of time series [17], which relies on a less amount of data to calculate and is robust to noise. Li et al. [18] used approximate entropy to characterize brain electrical signals and uses these characteristics to study the phenomena of the brain. This paper proposes a method that applies EMD to decompose EEG signal and calculates the ApEn of the decomposition, which is named E-ApEn. EMD is a time-frequency analysis method for nonlinear and unsteady signals [15]. It decomposes nonlinear and non-stationary signals into
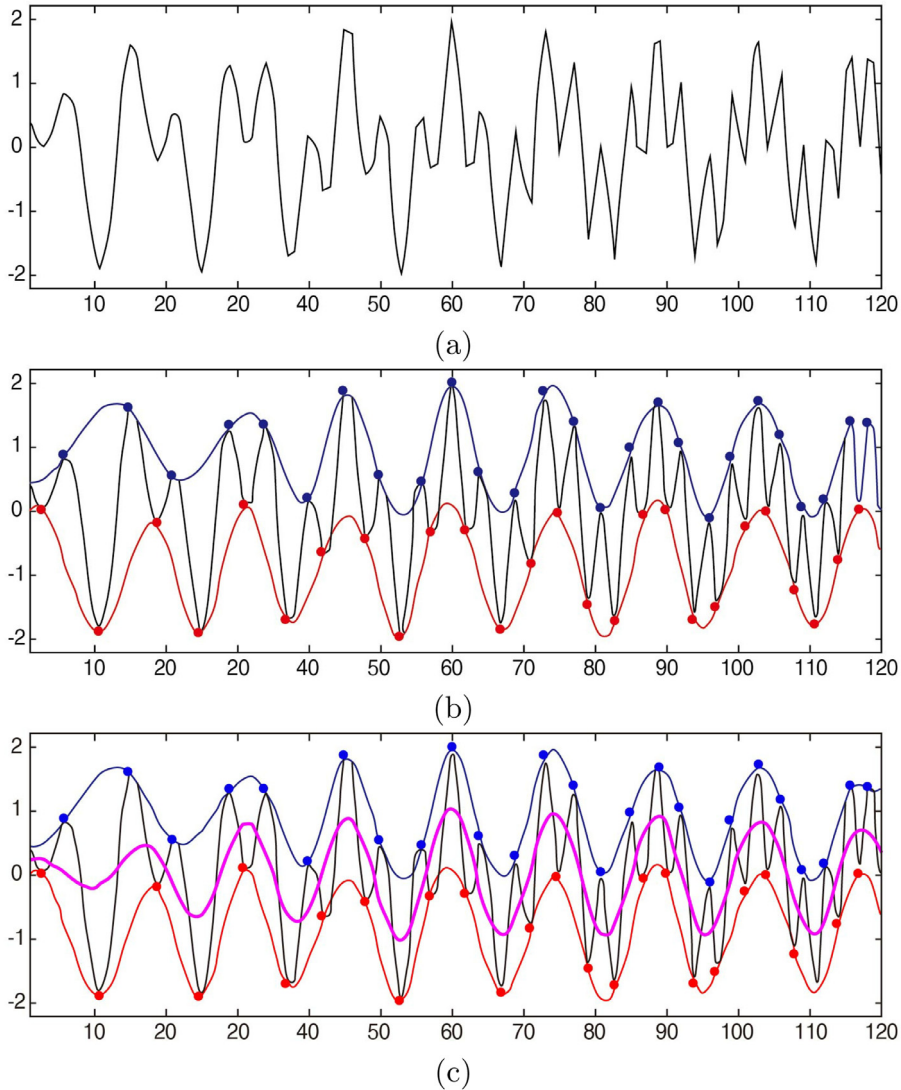
Fig. 2. Examples of the intermediate results of the EMD solution IMF signal.

oscillations at various frequencies. The oscillation extracted by the EMD is the intrinsic eigenmode function (IMF), which is obtained by finding the minimum and maximum points of the original signal, such as the one depicted in Fig. 2(a). And then obtaining the upper envelope and lower envelope of the signal using the cubic spline interpolation. An example is depicted in Fig. 2(b). We calculate the average of the upper and lower envelopes and subtract the average of the upper and lower envelopes obtained from the original signal, as shown in Fig. 2(c). If the obtained difference satisfies the following two conditions:

1. During the entire data period, the extreme points the number of zeroes and the number of zero crossings must differ no more than one;
2. At any moment, the average of the local upper and lower envelopes is 0

the resulted difference is the IMF. Hence, the original signal can be expressed as:

$$x(t) = \sum_{i=1}^{n} c_i + r_n \tag{1}$$

where c_i is the IMF, r_n is a signal that cannot be decomposed again.

In our experiments, each EEG signal is decomposed into 10 to 12 IMFs. However, not all IMFs are valid for emotion recognition. The variance contribution rate is used to evaluate the importance of each IMF. To determine the number of
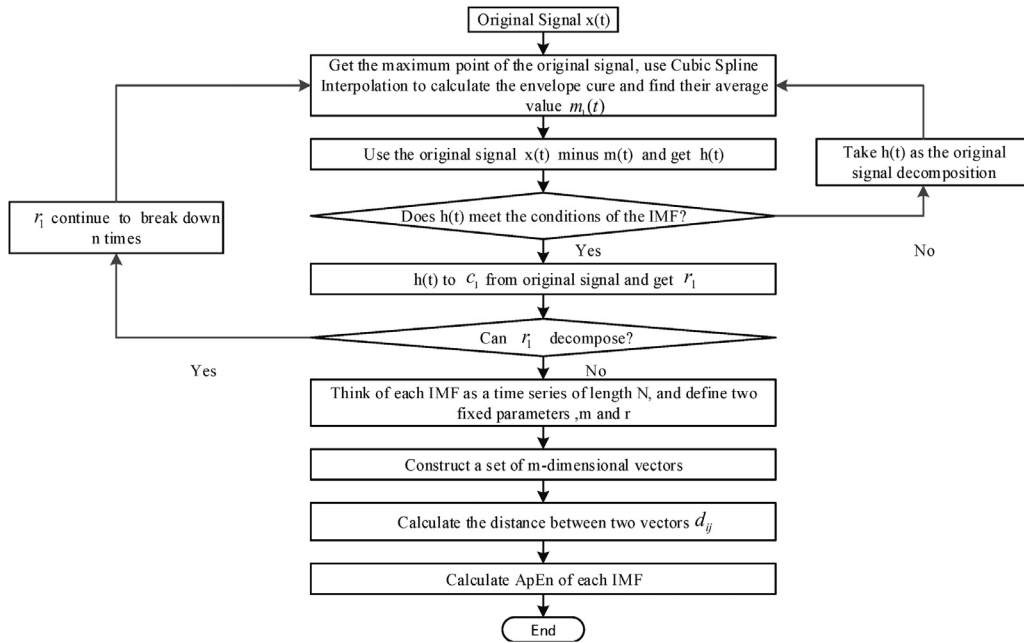
Fig. 3. The flow chart of the feature extraction method.

effective IMFs. We calculate the cumulative variance contribution of the IMF. The results show that the variance contribution rate of the first four IMFs is over 94%. Therefore, the first four IMFs are used to compute the approximate entropy.

The IMFs are extracted by the EMD method and are used to approximate the entropy calculation. Fig. 3 shows the flowchart of our proposed feature extraction method. The steps for obtaining E-ApEn are as follows:

Step 1: find the maximum and minimum points of the original signal $x(t)$ and calculate the average of the upper and lower envelopes $m_1(t)$ from the cubic spline difference.

Step 2: get $h(t)$ from the original signal $x(t)$ minus $m_1(t)$ and decide whether $h(t)$ is to meet the two conditions of the IMF. If it is unsatisfied, put $h(t)$ above process repeated as an original signal to perform decomposition until the two conditions of the IMF are met, and the first IMF obtained is recorded as c_1.

Step 3: Separate c_1 from the original signal $x(t)$ and get r_1. If r_1 is a monotonic function, the decomposition is over, otherwise, put r_1 as the original signal continues to decompose.

Step 4: Treat each IMF as a time sequence of length N, $\{u(1), u(2)\ldots u(N)\}$, and define two fixed parameters m and r, among them, m is the length of the comparison sequence, also the length of the window, r is a threshold in the range of $\{0.2, 0.3\}$.

Step 5: For each IMF, a set of m-dimensional vectors ($\{u(1), u(2), \ldots, u(N)\}$) are constructed according to the sequence.

$$x_i = \{u(i), u(i+1), \ldots, u(i+m-1)\} \tag{2}$$

where $i \in \{1, N-m+1\}$.

Step 6: Given x_i, x_j, the distance between them is d_{ij}

$$d_{ij} = d[x_i, x_j] = \max_{x \in (0, m-1)} |u(i+k) - u(j-k)| \tag{3}$$

The distance between x_i and x_j is the maximum distance between $u(i+k)$ and $u(j+k)$ for various k.

Step 7: Compute ApEn.

$$ApEn(m, r, N) = \varphi^m(t) - \varphi^{m+1}(t) \tag{4}$$

Among them:

$$\varphi^m(t) - \varphi^{m+1}(t) = [N-m+1]^{-1} \sum_{i=1}^{N-m+1} ln(c_i^m(r)) \tag{5}$$

$$c_i^m(r) = \frac{1}{N-m+1}\{The\,number\,of\,d_{ij} \leq r\} \tag{6}$$

Approximate entropy is obtained by this method, which alleviates the redundancy problem of the original approximate entropy algorithm and has a high computational efficiency and good robustness. For each alternative channel of the brainwave instrument, the preprocessed signal is decomposed into four bands, namely Theta, Alpha, Beta, and Gamma bands.
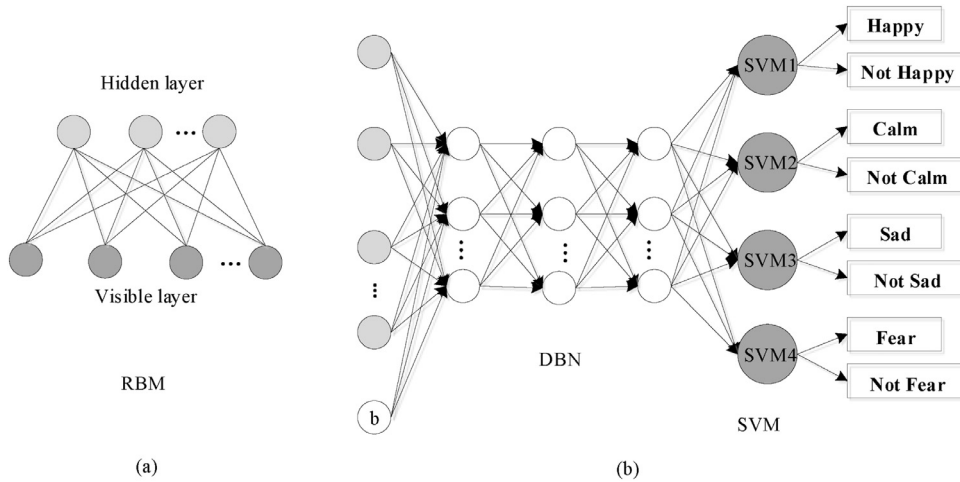
Fig. 4. (a) Restricted Boltzmann Machine; (b) DBN-SVM Emotion Recognition Model.

After each frequency band is decomposed by the EMD method and the first four IMFs are selected, and we compute the ApEn of each IMF. Overall, each channel produces sixteen features.

2.3. Deep belief network and support vector machine

We integrate DBN and SVM for classifying emotions from the obtained features. DBN is a method that extracts the deep features of data and a probabilistic generation model with a deep structure, which solves the problem that traditional multilayer neural networks are difficult to train. The DBN is composed of layers of Restricted Boltzmann Machines (RBM) superimposed as shown in Fig. 4(a). The output of the lower RBM is the input of the high-level RBM, which is characterized by the use of hidden variable input data distribution [19]. SVM is a widely used classifier. Based on statistical learning theory, SVM constructs an optimal hyperplane in the high-dimensional space [20]. Although DBN has strong nonlinear fitting ability and fault tolerance and maps arbitrarily complex nonlinear relations with a strong robustness, it converges much slower in contrast to SVM. To get a better effect of emotion recognition, a combination of DBN and SVM is used to construct an emotion recognition model.

For the eigenvalues of the selected channels in the same frequency band, unsupervised learning is performed through DBN, which is followed by SVM as a classifier. The structural model is shown in Fig. 4(b). In a DBN-SVM emotion recognition model, DBN employs three hidden layers. For each EEG frequency band, the number of input layer nodes is 4 times the number of selected channels, which is to handle four approximate entropies. The number of nodes in the hidden layers is decided by the empirical formula $y = \sqrt{z + y} + a$, where z is the number of nodes in the previous layer, y is the number nodes in the output layers, which is four in our experiments. In this formula, *a* is a constant in the range of [0, 10] and we set it to 5 in our experiments. Each node of the DBN output layer is connected to an SVM for the final decision. The SVM layer includes four SVM nodes, each of which has one emotion as a class I and the remaining three as a class II class.

The features obtained using E-ApEn are trained and tested as follows:

Step 1: Use the DBN network to perform unsupervised training on the input eigenvalues to obtain related parameters of weights;

Step 2: The top-level output of the DBN is connected to the SVM layer for supervised classification training. The SVM1 takes the vector corresponding to the happy as class I, and the other three types as class II, which is the unhappy emotional state. It can identify whether the emotional state is happy or not. The SVM2 takes the vector corresponding to the calm as class I, and the other three categories as class II, namely the non-quiet emotional state, which can identify whether the emotional state is calm or not. The SVM3 and the SVM4 are similar. Among them, when using the SVM classifier to determine that the first class is, the output is 1; when using the SVM classifier to determine that the second class is, the output is 0. For the identification of a happy emotional state, the first SVM should judge it as class I. Other SVMs should judge it as class II. Calm, sadness and fear are similar to the recognition of the happy state. Therefore, the output of identifying the four emotions of happy, sad, calm and fear as 1000, 0100, 0010 and 0001, respectively;

Step 3: From the expected output of the training and the actual output of the SVM, the error is fed back to the top layer of the DBN using the Backpropagation (BP) algorithm, and the correlation weight between the SVM layer and the top layer of the DBN is adjusted;

Step 4: The RBM below the top-level of the DBN is fine-tuned by the DBN tuning process.

Fig. 5. Example of emotionally inducing videos.

3. Experiments

3.1. Data acquisition

3.1.1. Human subjects and acquisition device

Ten healthy subjects participated in the experiment (5 men, 5 women, and ages range 20–25). All participants had normal hearing and vision and no mental disorders. We use a 16-lead Emotiv brainwave instrument (14 of which are EEG acquisition channels and 2 of which are reference electrodes) at a frequency of 128 Hz.

3.1.2. Emotional induction

To induce the emotional states of human subjects, we used movie clips as experimental materials following the strategy in [21]. We select 20 videos from 200 videos prepared for the experiment and each emotion state is induced by five video clips. The duration of each clip is approximately 3–5 min.

The experiment was conducted in a quiet room that allows the subjects to sit at 60 cm from the computer in a comfortable manner to reduce the interference to the subject from the external environment. When watching a video, there is a five-second countdown before the start of each movie clip as a reminder of the start of the video clip. At the end of each video clip, the subject is asked to assess the degree of emotional induction from watching the video clip. The subject's assessment serves as the ground truth for emotional recognition. At the end of each video clip, there is a resting period of 30 seconds to allow the subject to recover from the influence of the previous video. To ensure the effectiveness of the experiments, we set the sequence of different emotional movie clips in the order of sadness, calmness, happiness, and fear. Fig. 5 shows an example of videos we used to introduce emotions.

3.1.3. Data preprocessing

To select the data for the most effective period of emotion induction, we intercepted the EEG data with a duration of 30 seconds according to the evaluation of the subjects. To verify the characteristics of different frequency bands of the EEG, EEG signals are divided into different frequency bands: (4 Hz-8 Hz), (9 Hz-13 Hz), (14 Hz-30 Hz), (> 3 1Hz). Since the electro-oculogram signal generated by blinking has a greater impact on the brain electricity, we adopt ICA to remove the noise interference.
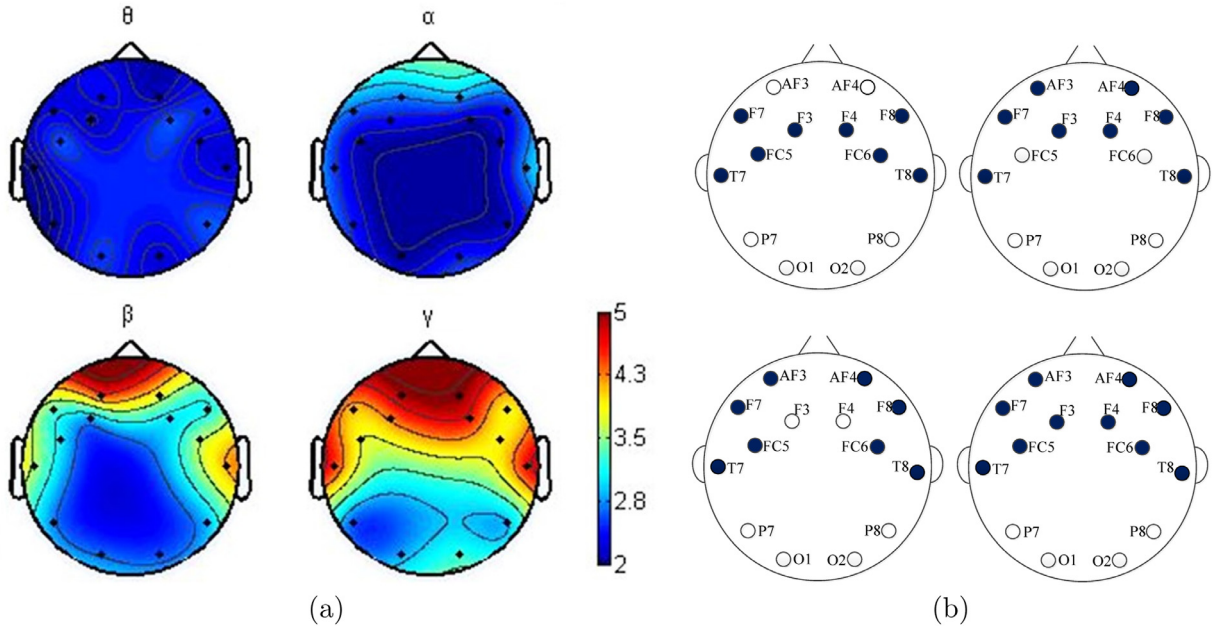
Fig. 6. (a) Energy map of EEG channels. (b) Channel positions on the subject.

Table 1
EEG characteristics E-ApEn, PSD, ApEn optimal recognition rate under different classifiers (%).

Feature	Classifier	Theta	Alpha	Beta	Gamma
ApEn	DBN-SVM	57.16	67.85	78.86	**87.32**
	SVM	55.20	62.12	76.25	80.68
	kNN	50.63	58.22	68.68	72.35
PSD	DBN-SVM	58.03	68.42	77.25	**82.95**
	SVM	60.25	63.21	76.38	79.99
	kNN	55.34	57.36	65.25	70.84
ApEn	DBN-SVM	58.58	66.73	76.32	**79.82**
	SVM	57.32	66.57	74.45	78.17
	kNN	53.26	56.28	60.96	68.65

3.2. Results and discussion

Since not all EEG frequency ranges and electrode positions carry important information, we select effective frequency bands and electrode positions to suppress errors. In our work, we systematically compare the performance of different frequency bands and different electrode positions. Fig. 6(a) shows that the emotional activities are mainly concentrated in the β-band and γ-band, and α-band are mainly distributed in the frontal and temporal lobes. To determine the effective positions of electrodes, we select different positions for testing and an example is shown in Fig. 6(b).

Fig. 7 shows the average recognition rate for each frequency band under different characteristics of power spectral density (PSD), ApEn, and E-ApEn. By comparing the results obtained using different characteristics for emotion recognition, it is clear that the results shown in Fig. 7(a) is better than those shown in Figs. 7(b), (c), and (d), and E-ApEn is used as the EEG feature in the average of the gamma band. The accuracy rate reaches 83.34% for the case shown in Fig. 7(a), whereas the accuracy for the cases in Fig. 7(b), (c), and (d) are 82.28%, 81.23%, and 82.13%, respectively. When all channels were selected for the experiment, the average recognition rate under the three characteristics was worse than the above four conditions, the accuracy was 76.92%. It is evident that not all electrode positions are suitable for emotional classification. Selecting a brain region and good positions of electrodes improves the recognition accuracy.

Table 1 shows the performance of different signal characteristics and different classifiers. It can be observed that the use of beta and gamma bands can achieve better recognition results in emotion recognition. This also proves that the beta and gamma bands of brain activity and emotional processing are more accurate. Related. The best recognition rates of E-ApEn in DBN-SVM, SVM, and k-Nearest Neighbor (kNN) are 87.32%, 80.68%, and 72.35%, respectively. The best recognition rates of PSD and ApEn under the three classifiers are respectively. It is 82.95%, 79.99%, 70.84% and 79.82%, 78.17%, 68.65%. This shows that the performance of E-ApEn is better than that of PSD and ApEn, and the DBN-SVM emotion recognition model
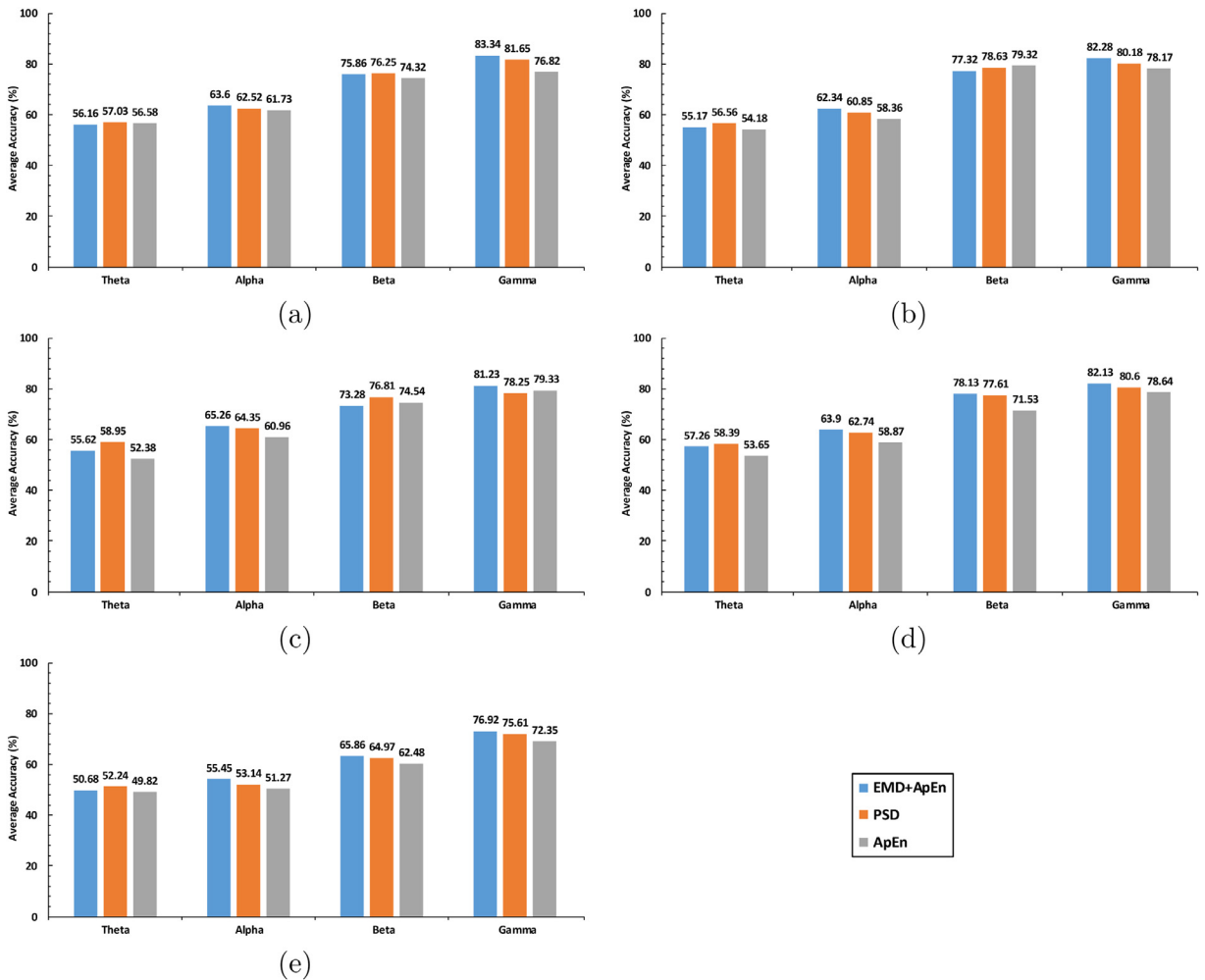
Fig. 7. Comparison of the average recognition rate of different electrode positions under different characteristics. (a) F7, F8, F3, F4, FC5, FC6, T7, T8; (b) AF3, AF4, F7, F8, F3, F4, T7, T8; (c) AF3, AF4, F7, F8, FC5, FC6, T7, T8; (d) is AF3, AF4, F7, F8, F3, F4, FC5, FC6, T7, T8; (e) represents all channel positions.

Table 2

Comparison of Average Accuracy (%) and Best Accuracy (%) of the Project's Project and Other Projects.

	Hu et al. [12]	Goya et al. [13]	Lin et al. [4]	Gonuguntla et al. [14]	E-ApEn
Classifier	CFS+KNN	LIBSVM	MLP/SVM	ANFC	DBN-SVM
Ave. Accuracy	80.84	79.16	82.29	66.7	83.34
Best Accuracy	83.84	76.14	85.35	61.5	87.32

is better than SVM and kNN under the same characteristics. At the same time, the experiment also proved the effectiveness of E-ApEn as an eigenvalue for EEG emotion recognition.

Table 2 is the comparison of the classification accuracy of the proposed method and four state-of-the-art methods. The classification performance was measured by repeating the training 10 times and each time with a 3-fold cross-validation. The data was derived from 10 subjects while they are exposed to the movie clips. The average recognition rate and the best recognition rate was 80.84% and 83.84%, respectively for the method proposed by Hu et al. [12]. Goyal et al. [13] evaluated their method by performing classification using LIBSVM classifier that employs radial basis function (RBF) kernel and 3-fold cross-validation. And the average recognition rate and the best recognition rate obtained under LIBSVM are 79.16% and 76.14%, respectively. Using power spectral density (PSD) as the EEG feature, Lin et al. [4] achieved an average recognition rate and the best recognition rate using SVM classifier at 82.29% and 85.35%, respectively. Gonu et al. [14] achieved an average recognition rate and the optimal recognition rate at 66.7% and 61.5%, respectively. The average accuracy rate and the best accuracy rate achieved by the method proposed in this paper are better than other schemes with 83.34% and 87.32%, respectively.

The experiments demonstrate that E-ApEn is an effective feature extraction method, and the DBN-SVM emotion recognition model identifies the emotional states of the brain. In addition, choosing the right frequency band and electrodes' position improves the recognition accuracy.

4. Conclusion

In order to find out the correlation between emotional states and EEG signals and improve the recognition rate of emotion, an emotion recognition model using empirical mode decomposition and approximation entropy is proposed. In this method, empirical mode decomposition is performed to the EEG signals after intercepting valid duration data segments and noise suppression by ICA. Subsequently, the approximate entropy of the EEG signals is calculated. An integration of DBN and SVM is devised for learning and classification.

Experiments are conducted with EEG signals acquired by a 16-lead Emotiv brainwave instrument. It is observed that human emotions are mainly distributed in the frontal and temporal lobes, and the Gamma band is most suitable for emotion recognition. The results of our experiments are consistent with neuroscience. It is evident that not all positions of the electrode are advantageous for emotion recognition. Different electrode positions are investigated for emotion recognition, and the best positions are used in the comparison study. It can be seen from the comparison results that the emotion recognition model proposed in this paper demonstrate an improvement in terms of accuracy of emotion recognition. Our proposed method achieves an improved accuracy; the average accuracy is at 83.34% and the best accuracy is at 87.32%.

In our future work, we plan to explore ways to automate the choice of selecting the optimal placements of the EEG electrodes to improve the quality and minimize the confusion from muscle signals. In addition, questions such as how to choose more effective EEG emotion characteristics and reduce the interference from the external environment need to be further studied.

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