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Research article

An approach to EEG-based emotion recognition using combined feature extraction method

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HIGHLIGHTS

- Propose an EEG-based emotion recognition method using empirical mode decomposition (EMD) and sample entropy.
- Only select two channels to calculate IMFs through EMD and use the first 4 IMFs to calculate sample entropies.
- Analyze the effect of parameters on the results in detail.
- Experimental results indicate the proposed method is more suitable for emotion recognition than other methods of comparison.

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ABSTRACT

EEG signal has been widely used in emotion recognition. However, too many channels and extracted features are used in the current EEG-based emotion recognition methods, which lead to the complexity of these methods This paper studies on feature extraction on EEG-based emotion recognition model to overcome those disadvantages, and proposes an emotion recognition method based on empirical mode decomposition (EMD) and sample entropy. The proposed method first employs EMD strategy to decompose EEG signals only containing two channels into a series of intrinsic mode functions (IMFs). The first 4 IMFs are selected to calculate corresponding sample entropies and then to form feature vectors. These vectors are fed into support vector machine classifier for training and testing. The average accuracy of the proposed method is 94.98% for binary-class tasks and the best accuracy achieves 93.20% for the multi-class task on DEAP database, respectively. The results indicate that the proposed method is more suitable for emotion recognition than several methods of comparison.

1. Introduction

Human emotion plays an important and significant role in communication activities. Understanding and further recognizing emotions have become a key issue to construct Human-Computer Interaction (HCI) system [1,2]. Researchers have done many work on emotion recognition. Among them, how to describe human's emotional states is a prime issue of emotion recognition. Discrete model and dimensional model have been presented to describe emotional states. Discrete model is generally expressed by the six basic emotional states, such as *anger*, *disgust*, *fear*, *happiness*, *sadness*, and *surprise* [3], while the dimensional model can be represented by the valence-arousal space [4]. The valence-arousal space uses valence and arousal scales to represent all emotional states. Presently many studies based on DEAP database [5] are on the basis of the dimensional model.

Facial expression and speech analysis are often used to perform emotion recognition [5]. Another approach to emotion recognition is to analyze physiological signals, such as electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), and blood volume pressure (BVP) [5]. Among these signals, EEG plays an important role on detecting an emotion directly from the brain activity [2]. EEG-based emotion recognition has attracted many researchers' attention [6,7].

In recent years, empirical mode decomposition (EMD) method based on Hilbert-Huang transformation is widely used in the field of signal processing [8,9]. EMD is a time-frequency analysis method to deal with non-linear and non-stationary signal. In this paper we use a combination of EMD and sample entropy (SampEn) to construct

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feature vectors from EEG signals, and then use these features to recognize emotions by a support vector machine (SVM) classifier.

2. Materials and methods

To recognize emotional states, the proposed method applies EMD to decompose emotion data into several intrinsic mode functions (IMFs). Then, SampEn values are calculated for each time window of IMFs to form a feature vector. Obtained feature vectors are used as the input of SVM classifier.

2.1. Data acquisition

This paper uses DEAP database, which is a multimodal database created for the analysis of human affect by participants watching music videos [5]. EEG and peripheral physiological signals of 32 participants were recorded in DEAP database, in which each participant watched 40 one-minute music videos.

After watching each video, the participant performed a self-assessment to quantify emotional response to the video. Emotional response includes 5 dimensions, namely, valence, arousal, dominance, liking and familiarity. This paper only considers a valence-arousal model. Valence measures the pleasantness of the stimulus and varies from unhappy or sad to happy or joyful. Arousal depicts the intensity of emotion provoked by the stimulus and varies from bored to excited. Valence and arousal dimensions are main components of emotions and their ratings range from 1 (low) to 9 (high) on DEAP database.

Verma and Tiwary [10] compared the classification results of 40-channel (32 EEG and 8 peripheral) features and only 32 EEG-channel features. It is interesting to note that there is not much improvement in terms of the classification accuracy when using 40-channel features compared to only EEG channel features. Therefore, we only extract features from EEG-channel to classify emotional states in our experiments.

2.2. Data division and channel selection

According to values in arousal and valence dimensions on DEAP database, we can divide each video into 4 types of emotions, i.e., high arousal high valence (HAHV), low arousal high valence (LAHV), high arousal low valence (HALV), and low arousal low valence (LALV). In this partition, the value ranging from 1 to 5 is low and the value ranging from 5 to 9 is high.

Related research shows that the β band of EEG signal is significant when the cerebral cortex presents the excited state, which is suitable for the emotional recognition [11,12]. β activity is obvious in the frontal, temporal and central regions, such as F3, F4, C3, C4, T3, T4 channels. Through the reconstruction of the β band and the calculation of the average power spectral density (PSD) estimate of the different channels, the average PSD of different emotions is more obvious on the F3 and C4 channels. Therefore, we select F3 and C4 channels to conduct our studies.

Each video lasts for 1 min. Each trial collected 63 s signal including the first 3 s baseline signal. Obviously, each trial contains 8064 data points for the sampling rate of 128 Hz. However, too long data may affect the running speed and classification performance. We only need to select a piece of data which makes each participant settled down to certain emotions. We think the EEG signals collected from the middle segment of a video can express a stable emotional state. Therefore, we removed the 3 s pre-trial baseline signal and the first half of a trial signal. Then we take a 9 s signal from 34 s to 42 s. The last 21 s signal is also removed. Namely, a 9 s signal including 1152 data points for each EEG signal is applied to feature extraction and performance evaluation.

2.3. Feature extraction based on EMD and sample entropy

The main objective of feature extraction is to obtain reliable data for emotion recognition. EMD is first applied in feature extraction to decompose EEG signals into a series of IMFs. And then sample entropies of IMFs are calculated to construct feature vectors. These feature vectors are fed into a SVM classifier to recognize emotional states.

2.3.1. Empirical mode decomposition

EMD is a data-driven signal processing analysis technique [8]. The main idea of EMD is to decompose the non-linear and non-stationary signal into many oscillations on various frequency scales. The decomposition process is intuitive and adaptive. The oscillations extracted by EMD are called IMFs. In general, each IMF satisfies the following two conditions: (1) the number of extrema and the number of zero-crossings must either be equal or differ at most by one; (2) the mean value between the upper envelope and the lower envelope must be zero at every point.

Typically, these IMFs depict local characteristics of the original signal. The difference between the original signal and the IMFs is expressed as the residual. A non-stationary signal $x(t)$ can be expressed as:

$$x(t) = \sum_{m=1}^{M} imf_m(t) + r_M(t) \tag{1}$$

where $imf_m(t)$ is the mth extracted IMF and M is the number of IMFs, $r_M(t)$ denotes the final residue.

Each EEG signal can be decomposed into 8 or 9 IMFs by EMD in our experiments. However, not all of the IMFs are useful for emotion recognition. The variance contribution rate is usually used to characterize the relative importance of each IMF. In order to get the useful IMFs, the cumulative variance contribution rate of IMFs is calculated. The calculation results show that the cumulative variance contribution rate of the first 4 IMFs reaches above 95%. Therefore, this paper chooses the first 4 IMFs to calculate SampEn.

2.3.2. Sample entropy

We then calculate SampEn values of the first 4 IMFs. SampEn was developed to reduce the bias caused by the self-matching of approximate entropy, which has been applied successfully to feature extraction of EEG signals [7,13].

The SampEn algorithm for a time-series $\{u(i), 1 \leq i \leq N\}$ of N data points is described as follows.

Step 1. Form a sequence of m-length vectors $x(1)$, $x(2)$, ..., $x(N-m+1)$ using the time-series $\{u(i)\}$, where $x(i) = [u(i), u(i+1), \ldots, u(i+m-1)]$, $i = 1, \ldots, N-m+1$, and m is the embedding dimension.

Step 2. Define the distance between two vectors $x(i)$ and $x(j)$ as

$$d[x(i), x(j)] = \max_{k=0,1,\ldots,m-1} (|u(i+k) - u(j+k)|), \tag{2}$$

where $d[x(i), x(j)]$ represents the maximum difference between their scalar components.

Step 3. For a given $x(i)$, define $(N-m-1)^{-1}$ times the number of $x(j)$ within r of $x(i)$ as

$$C_i^m(r) = \frac{\sum_j \{1 | d[x(i), x(j)] < r\}}{N-m-1}, \tag{3}$$

where r is the threshold value, j ranges from 1 to $N-m$ and $j \neq i$ to exclude self-matches. $\sum_j \{1 | d[x(i), x(j)] < r\}$ denotes number of j such that the distance between $x(i)$ and $x(j)$ is less than r.

Step 4. Define $B^m(r)$ as

$$B^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} C_i^m(r). \tag{4}$$

Step 5. Similarly, repeat steps 1 to 4 and define $B^{m+1}(r)$ as

$$B^{m+1}(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} C_i^{m+1}(r). \tag{5}$$

Step 6. Define SampEn as

$$SampEn(m, r, N) = -\ln\left[\frac{B^{m+1}(r)}{B^m(r)}\right]. \tag{6}$$

In our work, each IMF generated by EMD contains 1152 data points due to the sampling rate of 128 Hz and 9 s signals collected for each channel. For the collected data points of each channel, an IMF is split into several segments each containing N data points. After feature extraction by EMD and SampEn, each trial for each participant will generate a feature vector. For example, if the value of N is 128, then an IMF will be split into 9 segments and generate 9 SampEn values (features) correspondingly for each channel. Therefore, there are 72 features (9*4*2 = 72) to form a feature vector for 4 IMFs and 2 channels. Obviously, the total number of samples for 32 participants watching 40 videos is 1280 (32*40 = 1280).

2.4. Support vector machine

SVM has shown promising empirical results in many fields. Based on statistics learning theory, SVM can construct an optimal separating hyperplane in a high-dimensional space to classify new samples.

Given a training data set $\{(x_1, y_1), (x_2, y_2), \ldots, (x_l, y_l)\}$, where $x_i \subset \Re^n$ denotes a sample with n-dimension, and $y_i \in \{+1, -1\}$ is the class of sample x_i. In order to find the optimal hyperplane, the training samples are first transformed into a higher dimensional feature space by a mapping function ϕ. Then, a possible separating hyperplane can be represented by [14]

$$w \cdot \phi(x) + b = 0 \tag{7}$$

The SVM decision function is represented as

$$f(x) = sign(\sum_{i=1}^{l} y_i K(x, x_i) + b) \tag{8}$$

where l is the number of support vectors, and $K(x_i, x_j)$ is the kernel function,$K(x_i, x_j) = \phi(x_i)^T\phi(x_j)$.

Considering the possible imbalance of samples, we employed a weight SVM classifier in this paper. Its main idea is to allocate a large punishment factor to the minority class, whereas a small punishment factor to the majority class.

3. Results

3.1. Experiment settings

In the experiments, we first use EMD to decompose EEG signals and then calculate features using SampEn. According to data acquisition, this paper mainly takes 4 types of emotions into account, such as HAHV, LAHV, LALV, and HALV. Their sample sizes are 458, 266, 260 and 296, respectively. We construct 4 binary classification tasks to evaluate the classification performance, namely, HAHV/LAHV (task 1), LAHV/LALV (task 2), LALV/HALV (task 3) and HALV/HAHV (task 4). It is obvious that the classes in tasks 1 and 4 are imbalanced. Therefore, a weight SVM is employed as the classifier in our experiments.

This paper uses 10-fold cross validation to evaluate the classification performance. The weight SVM with Gaussian kernel involves the penalty parameter C as well as the kernel parameter to be optimized. The grid search is used to tune both parameters. The search space is set as $\gamma = [2^{-10}, 2^{-8}, \ldots, 2^8, 2^{10}]$ and $C = [2^{-10}, 2^{-8}, \ldots, 2^8, 2^{10}]$. We used LIBSVM [15] to implement the weight SVM in our experiments.

For feature extraction, we only use the first 4 IMFs to calculate SampEn values. In the process of SampEn calculation, the value of r is varied from 0.10 to 0.25 and the value of m is set at 1 or 2.

3.2. The results of the experiment

In order to select suitable parameters N, m and r in SampEn, we consider 4 types of segments with different data points (N = 128, 192, 384, 11520). When we take 128 data points (N = 128) as a segment, an IMF will be divided into 9 segments for each channel (1152/128 = 9). Then there are the total 72 segments for 4 IMFs and 2 channels (9*4*2 = 72). When the values of N are 192, 384 and 1152, the number of segments are 48, 24 and 8, respectively.

SampEn values of channels F3 and C4 are employed to form input vectors of SVM for emotion recognition. The proposed method is run 10 times and the average accuracies (%) on 4 binary classification tasks are reported in Fig. 1, respectively. All the horizontal axes in Fig. 1 represent the value of r varying from 0.10 to 0.25. For each binary classification task, we reported 4 results for different lengths of segments in the case of different parameters m and r.

For task 1 and task 2, as shown in Fig. 1A(a), A(b), B(a) and B(b), the accuracies of m = 2 are superior to those of m = 1 in the cases of N = 1152 and N = 384. For task 3, the accuracies of m = 2 are slightly inferior to those of m = 1 in the case of N = 384, but they have no obvious difference in the case of N = 1152 as shown in Fig. 1C(a) and C(b). The observation result of task 4 shown in Fig. 1D is just the opposite of task 3. In the case of N = 1152, the classification accuracy of m = 2 outperforms that of m = 1. The two accuracy curves are intertwined while N = 384.

We also observe from Fig. 1A(c) and A(d) that, the classification accuracies are significantly lower, only about 50%, when r value is small, especially for N = 128. The similar results are observed from Fig. 1B–D.

We further illustrate the effects of the length of segment N on the classification results as shown in Fig. 2. We can see from Fig. 1 that the classification performance of 4 tasks tends to be stable when the value of r is from 0.16 to 0.20. Therefore, we only calculate average accuracies of different lengths for r falling in the range of 0.16–0.20. It is obvious that the performance of the proposed method in terms of average accuracy is significantly improved with the decrease of the length of segment N, especially for LAHV/LALV, LALV/HALV and HAHV/HALV tasks. When the length of segment is 128, the classification performance is the best and 8 average accuracies are all over 90%.

Our proposed method is also compared to other methods on DEAP database. Among these methods of comparison, Mohammadi et al. [12] employed DWT to decompose EEG signals and extracted several features. Five pairs of channels (F3–F4, F7–F8, FC1–FC2, FC5–FC6, FP1–FP2) are used in their experiments. The time windows are set at 2 s and 4 s. Emotion states in Ref. [12] contains high/low valence and high/low arousal. The best accuracies are 86.75% and 84.05, respectively. Jie et al. [13] used Kolmogorov-Smirnov (K-S) test to select SampEn values of several EEG channels and took them as the inputs of SVM. For the HAHV/HALV classification task, channels F3, CP5, FP2, FZ, and FC2 are selected while channels FP1, T7, and AF4 are selected for the LALV/HALV classification task. The results of 80.43% and 71.16% are reported. For

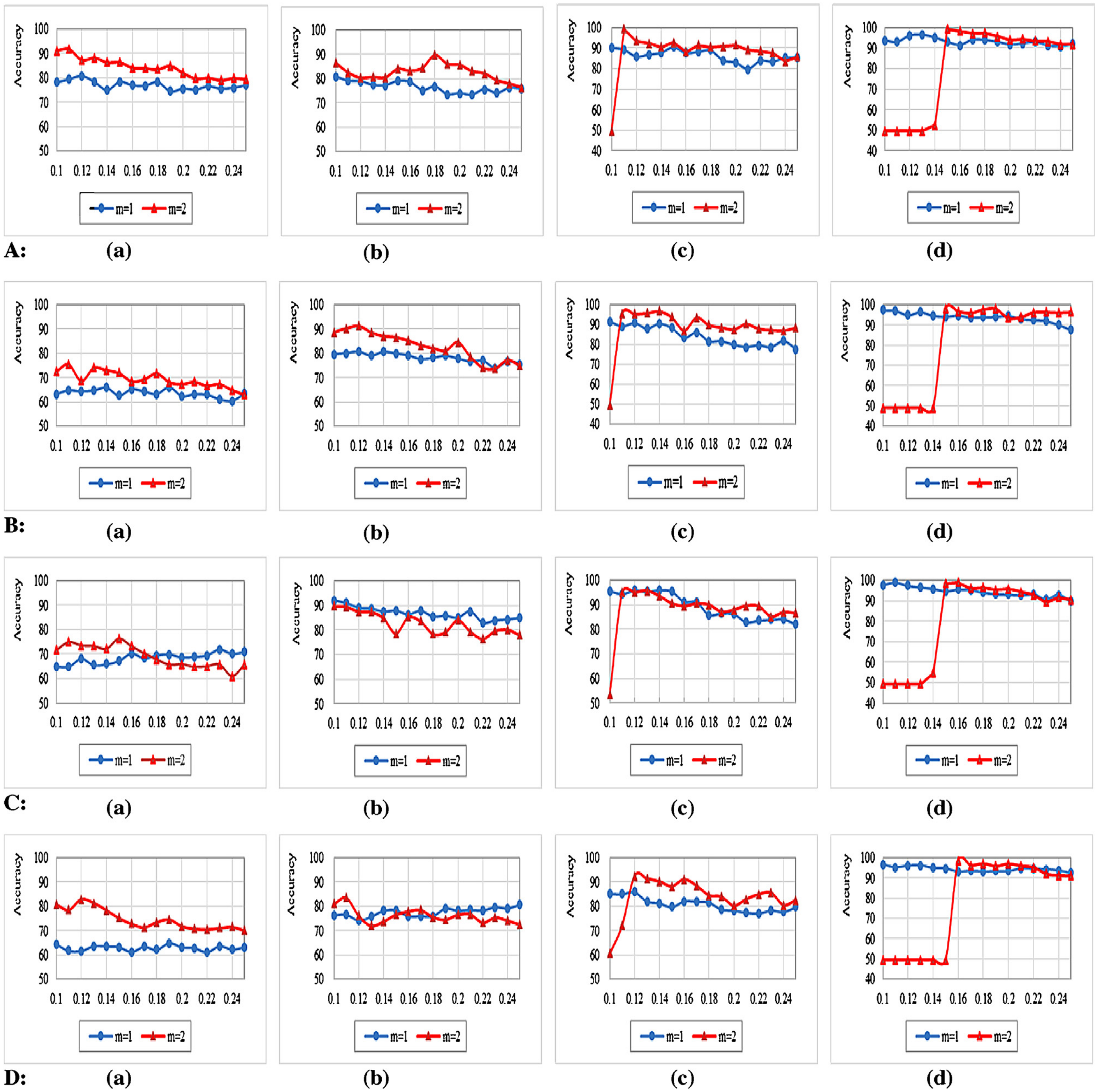

Fig. 1. Accuracies on different lengths of segments: A for task 1 (HAHV/LAHV), B for task 2 (LAHV/LALV), C for task 3 (LALV/HALV), and D for task 4 (HAHV/HALV). In each task, (a) 1152 points of each segment, (b) 384 points of each segment, (c) 192 points of each segment, and (d) 128 points of each segment.

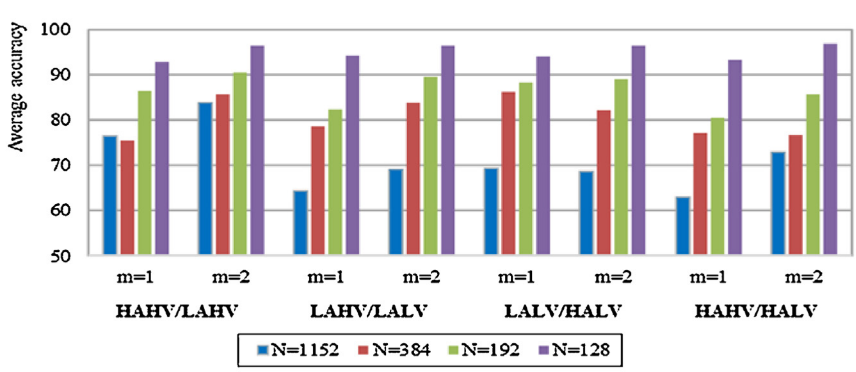

Fig. 2. Average accuracies in different length cases for *r* in the range of 0.16–0.20.

Table 1
Classification results of multi-class problem.

	r = 0.10	r = 0.11	r = 0.12	r = 0.13	r = 0.14	r = 0.15	r = 0.16	r = 0.17
m = 1	92.03	88.36	87.97	87.97	86.02	85.23	84.92	83.98
m = 2	23.13	23.13	23.13	23.13	26.56	93.20	91.25	90.63

	r = 0.18	r = 0.19	r = 0.20	r = 0.21	r = 0.22	r = 0.23	r = 0.24	r = 0.25
m = 1	84.69	82.73	82.34	81.48	77.89	77.73	74.77	74.45
m = 2	92.42	89.69	89.38	88.28	88.28	86.17	83.91	84.53

comparison to the method in Jie et al. [13], we reported the results in the case of $m = 2$ and $r = 0.20$, which is the same parameters with Ref. [13]. In addition, the length of se gment N in our proposed method is 128 in this experiment. The 4 results of our proposed method are 93.92% for HAHV/LAHV, 93.40% for LAHV/LALV, 95.63% for LALV/HALV and 96.96% for HALV/HAHV.

It is obvious that our proposed method evidently outperforms the comparison methods on classification accuracy. Our average accuracy is 94.98% which is about 8.2% and 14.5% higher than the best accuracy (86.75%) of Ref. [12] and the best accuracy (80.43%) of Ref. [13], respectively. Moreover, our proposed method uses 2 channels to extract features, while Ref. [12] used 10 channels and Ref. [13] used 5 (and 3) channels to obtain the best accuracies.

Finally, we report a multi-class classification problem containing 4 categories, such as HAHV, LAHV, LALV, and HALV. Table 1 shows the classification results in the case of $N = 128$. As shown in Table 1, when the value of r is less than 0.15, the classification accuracies are very poor in the case of $m = 2$, while they are quite good in the case of $m = 1$. When the value of r is no less than 0.15, the classification performance in the case of $m = 2$ is obviously better than that of $m = 1$. The best classification accuracy 93.20% appears in the case of $m = 2$ and $r = 0.15$. It is also worth noting that the classification accuracy gradually decreases as the value of r increases in the case of $m = 1$.

4. Discussion

Many studies show EEG signals can provide useful information of brain activities to recognize the emotional states [6,16,17]. Lots of researchers try to classify emotional states through extracting features from EEG signals. At present, multiple feature extraction methods have been proposed for human emotion recognition. Among these methods, wavelet transform [18–20] and autoregressive (AR) [6,21] are widely used. In addition, the entropy is a nonlinear parameter that reflects the complexity of the EEG signal, and has been widely used to differentiate EEG signals [22,23]. Non-linear Higher Order Spectra (HOS) is also a promising approach to feature extraction. Acharya et al. [24] proposed the method to extract HOS cumulant features from EEG segments and used significant features to classify EEG signals.

The present study employed EMD and SampEn to perform feature extraction from emotional EEG signals. In the calculation of SampEn, parameters have a certain influence on the performance of emotion recognition. Generally speaking, the classification accuracy is gradually increased with the decrease of N, as shown in Fig. 1. Four tasks have achieved good classification results in the combination of $m = 2$, $r = 0.16$ and $N = 128$, suggesting that the parameter combination of SampEn is suitable for emotion recognition of DEAP database. It is worth noting that the choice of m and r will affect the classification performance. For the same length of segment N, choosing a smaller m ($m = 1$) obtains a relatively low accuracy and the performance decreases slightly with the increase of r value. Conversely, choosing a higher m ($m = 2$) can lead to a superior accuracy, but the performance becomes unstable with respect to changing r value.

From average accuracies for r ranging from 0.16 to 0.20 shown in Fig. 2, it is reasonable to speculate that the classification performance is sensitive to the length of segment. Nevertheless, when the length of segment is smaller, the number of segments divided by our proposed method is more. Obviously the computation cost is greater. We also can see from Fig. 2 that, in the smooth classification trend (r is from 0.16 to 0.20), the average accuracy of $m = 2$ is superior to that of $m = 1$ in the same length N for these 4 classification tasks. There are only two exceptions, that is, LALV/HALV task of $N = 1152$ and HAHV/HALV task of $N = 384$.

For binary emotion recognition, the results show that our approach is very competitive in terms of accuracy, against several of the most popular techniques in the literature. For multi-class emotion recognition, when the r value is smaller than 0.15, the performance is very bad, consistent with previous reports, while our method obtains about 90% accuracy when using $m = 2$ and a range of r values from 0.15 to 0.20.

5. Conclusions

In this paper, we propose an emotion recognition method based on EMD and SampEn. The proposed method can recognize 4 categories of emotional states, such as HAHV, LAHV, LALV, and HALV, on the DEAP benchmark database. We employ EMD method to decompose EEG signals only containing channels F3 and C4. A series of IMFs obtained by EMD are used to calculate SampEn values and to form feature vectors. These vectors are fed into SVM classifier for training and testing. The average accuracy of the proposed method is 94.98% for binary-class tasks and the best accuracy achieves 93.20% for the multi-class task on DEAP database, respectively. It is confirmed that the proposed method is effective to recognize emotion, compared to other methods. Future studies will concentrate on the influence of other features. Also, improving the calculation cost of SampEn will be focused.

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