



An Extreme Learning Approach for Electronic Music Classification

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Abstract. In order to recognize different kinds of electronic music, an extreme learning based method is proposed. Firstly, the feature of different electronic music data are extracted from cepstrum coefficient. Secondly, the kernel principal component analysis is adopted to reduce the dimension of features. Thirdly, in order to select appropriate parameters for an extreme learning machine, the genetic algorithm is used. Finally, experiments are carried out to verify the performance of the proposed electronic music classification method. In the experiments, we have established a database including four kinds of electronic music, i.e., “Guzheng”, “Lute”, “Flute”, and “Harp”. The experimental results show that the classification accuracy of the proposed method can reach up to 96%, while the wrong classification rate of the proposed method is only 14% which is much lower than existing electronic music classification models.

Keywords: Electronic Music Classification · Kernel Principal Component Analysis · Extreme Learning Machine · Feature Extraction

1 Introduction

With the continuous development of information technology, and the combination of music more tight Dense, there have been many kinds of electronic music which are able to relieve people's life and work pressure. However, each user likes different types of electronic music, so it is important to find the music from the mass of the electronic music library [1]. Electronic music classification is the key to improve the efficiency of electronic music query and is becoming the focus of attention [2].

Electronic music classification studies can be divided into two phases: traditional stage and modern stage. For the traditional stage, it is a manual classification that they are divided into the corresponding category through the analysis of electronic music by some experts and professionals [3]. When the electronic music data is very small, the classification of traditional classification of high accuracy, can be a good explanation of the classification results. However, the defects of traditional method including high error rate, low classification efficiency, are gradually reflected with the continuous increase of music data [4]. For the modern stage, the classification of electronic is accomplished automatically by computer [5]. Electronic music automatic classification belongs to a pattern recognition problem. It is necessary to extracts the characteristic information that reflects the electronic music. It is prolonged and inefficient to classify

the electronic music automatically according to the original feature information because of the large number of original features. Therefore, the technology of principal component analysis (PCA) is used to screen out the most important features to reduce the dimension of feature vector in order to speed up the automatic classification of electronic music [6]. Principal component analysis is a linear approach and can't be used to extract nonlinear information that describes an electronic music label [7]. The kernel principal component analysis is an improved principal component analysis method. By introducing the kernel function, the nonlinear information is extracted, and the feature is better than the principal component analysis [8]. Electronic music automatic identification also need to design electronic music classifier including Hidden Markov Model [9], Neural Network [10] and Support Vector Machine [11]. However, these methods exist some deficiencies. For example, the hidden Markov model can only be linearly classified and the results of electronic music classification are unreliable. Although the artificial neural network can classify the electronic music non-linearly, it requires sufficient electronic sample data. Once the sample can't meet the sufficient conditions, the electronic music classification effect dropped sharply. Although the support vector machine does not have the requirements of the neural network for the sample data, the learning process is complicated, the time complexity is high, and the speed requirement of the mass electronic music classification can't be satisfied.

For the reason of the shortcomings of the traditional model in the process of electronic music classification, an electronic music classification model for improving the limit learning machine is proposed. Firstly, the cepstrum coefficient of electronic music is extracted, the characteristics of electronic music are selected by kernel principal component analysis, and then the classifier of electronic music is improved by the limit learning mechanism. Finally, the simulation results show that the improved extreme learning machine improves the average classification rate of electronic music, and electronic music classification performance is better than the other.

2 An Electronic Music Classification Model for Improving Extreme Learning Machine

2.1 The Extraction of the Characteristics of Electronic Music

The current electronic music has many characteristics to describe its type, and electronic music is actually a kind of sound, Mel cepstrum coefficient can describe the sound frequency of energy changes and extract features quickly. The Mel cepstrum coefficient is selected as electronic music Classification of the characteristics for this article, the specific steps are as follows:

- (1) The collected electronic music data is framed to remove the invalid frame.
- (2) The frame signals of electronic music are processed by Fourier transform to obtain their amplitude spectrum.
- (3) Through the Mel scale transformation of the amplitude spectrum, and the filter group is used to filter the spectrum, the energy value of the j th filter is

$$e[j] = \log \left(\sum_{k=0}^{N-1} w_j[k] \times |s[k]| \right), j = 1, 2, \dots, p \quad (1)$$

Where $w_j[k]$ is the weight of the filter, $|s[k]|$ is the Fourier transform spectrum amplitude and p represents the number of filters. The crosstalk MFCC coefficient of electronic music is obtained by performing cosine transform on Eq. (1), the specific formula is:

$$x_i = \sqrt{\frac{2}{p}} \sum_{j=1}^p (e[j] \times \cos(\frac{i\pi}{p}(j - 0.5))), j = 1, 2, \dots, L \quad (2)$$

where L describes the dimension of the coefficient.

2.2 The Selection of Characteristics of Electronic Music with PCA

A collection of electronic music samples is described by $X = \{x_1, x_2, \dots, x_m\}$, $x_k \in R^N$, and then $\varphi(x)$ is used for Non-linear mapping and $\sum_{k=1}^m \varphi(x_k) = 0$, the electronic music feature selection problem can be described as

$$\lambda w_\varphi = C_\varphi w_\varphi \quad (3)$$

C_φ represents the covariance matrix of all samples, computed by

$$C_\varphi = \frac{1}{m} \sum_{k=1}^m \varphi(x_k) \varphi^T(x_k) \quad (4)$$

and

$$w_\varphi = \sum_{i=1}^m a_i \varphi(x_i) \quad (5)$$

By introducing a kernel function $K_{i,j} = k(x_i, x_j) = \langle \varphi(x_i) \cdot \varphi(x_j) \rangle$, the original electronic music feature selection problem is transformed into:

$$m\lambda K\alpha = K^2\alpha \quad (6)$$

So

$$m\lambda\alpha = K\alpha \quad (7)$$

The feature vector of the characteristic value of electronic music $\lambda_1, \lambda_2, \dots, \lambda_m$ is described with $a = (a_1, a_2, \dots, a_m)$.

In order to speed up the selection of the feature, the eigenvector is normalized, and for the test sample, the w_φ projection can be calculated by:

$$h_k(x) = \langle w_\varphi \cdot \varphi(x_j) \rangle = \sum_{i=1}^m a_i^k (\varphi(x_i) \cdot \varphi(x)) = \sum_{i=1}^m a_i^k K(x_i, x) \quad (8)$$

2.3 Improved Extreme Learning Machine

In order to solve the traditional neural network convergence speed is slow and easy to result in over-fitting, complex network structure defects, Huang et al. propose the method of extreme learning machine. As long as the simple random set of weights and thresholds, and the hidden layer of nodes, the training process can be successfully completed and get the optimal solution to solve the problem [12]. Let the number of nodes with hidden layers be L , then the output function of the limit learning machine is:

$$f_L(x) = \sum_{i=1}^L \beta_i G(a_i, b_i, x), \quad x \in R^d, \beta_i \in R^m \quad (9)$$

Where g_i is the Implicit layer node output function $G(a_i, b_i, x)$. a_i , b_i are the Learning parameters and β_i is the Weight vector.

For the data $D = \{(x_i, t_i) | x_i \in R^d, t_i \in R^m, i = 1, 2, \dots, N\}$, we can get

$$H\beta = T \quad (10)$$

Where H is the hidden layer output matrix of the network and is defined as:

$$H = \begin{bmatrix} G(a_1, b_1, x_1) & L & G(a_L, b_L, x_L) \\ M & 0 & M \\ G(a_1, b_1, x_N) & L & G(a_L, b_L, x_N) \end{bmatrix} \quad (11)$$

Where β is the weight matrix between the hidden layer and the output layer and T is the output matrix, defined as follows:

$$\beta = \begin{bmatrix} \beta_1^T \\ M \\ \beta_L^T \end{bmatrix} \quad (12)$$

$$T = \begin{bmatrix} t_1^T \\ M \\ t_L^T \end{bmatrix} \quad (13)$$

The least squares algorithm is used to solve the matrix of β :

$$\beta = \|H\beta - T'\| \quad (14)$$

And then

$$\hat{\beta} = H^+ T' \quad (15)$$

In the process of the extreme learning machine, the parameters a_i , b_i directly affect its learning performance. In order to solve this problem, this paper presents the genetic algorithm to determine the parameters of the limit learning machine as Fig. 1:

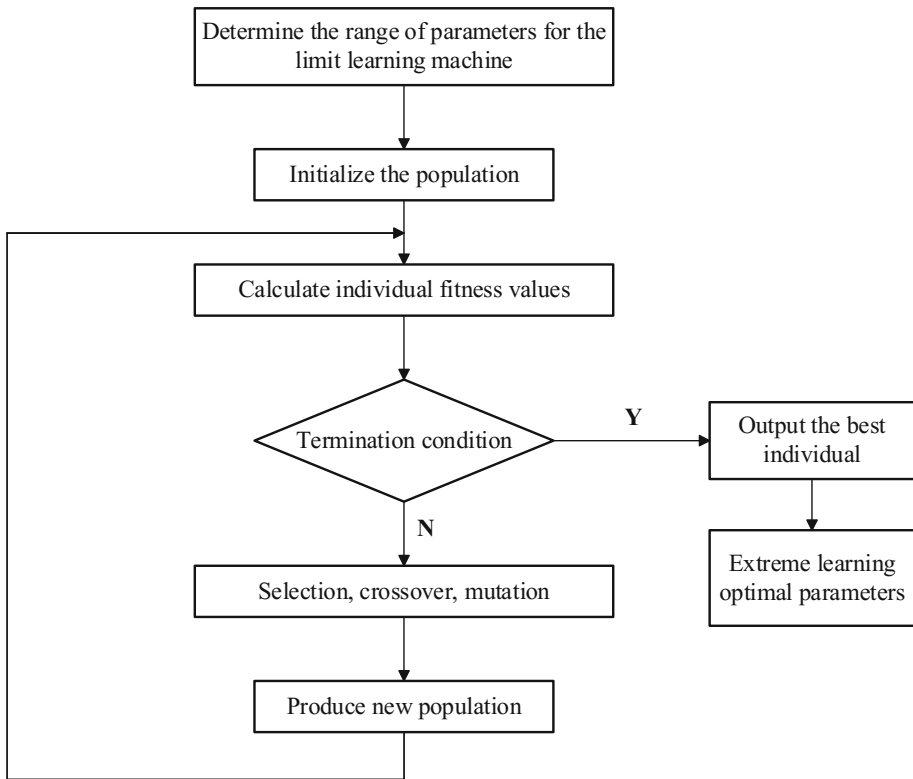


Fig. 1. The work flow of improved learning machine.

2.4 The Electronic Music Classification Steps of Improved Extreme Learning Machine

- (1) Collecting electronic music sample data to form an electronic music database.
- (2) Extracting the characteristics of the electronic music database which Composition feature vector library.
- (3) The characteristics of the electronic music database are normalized.

- (4) The kernel principal component analysis is used to select the characteristics of the electronic music database to form the optimal feature subset.
- (5) According to the optimal feature subset, the training samples and test samples are dimensioned to reduce the size of the data.
- (6) The training samples are input to the extreme learning machine for learning, and genetic algorithm is used to determine the optimal extreme learning machine parameters.
- (7) According to the optimal parameters, extreme learning is able to establish electronic music classification model.
- (8) Testing and analyzing the performance of electronic music classification models using electronic music test data.

3 Performance Testing of Electronic Music Classification

3.1 The Source of Electronic Music Data

In order to analyze the effect of improving the electronic music classification of the extreme learning machine, we choose a lot of data for simulation test. The data can be divided into four types of electronic music, such as GuZheng, Lute, Flute, and Harp. The number of samples is shown in Table 1. In order to make IELM electronic music classification effect is comparable, we designed two kinds of contrast model, described as follows:

Table 1. Number of training and testing samples in the experiments

Electronic music type	Number of training samples	Number of test samples
GuZheng	1000	250
Lute	800	200
Flute	500	125
Harp	200	50

- (1) Principal component analysis and ELM electronic Music Classification Model (PCA-ELM).
- (2) Kernel principal component analysis and Support Vector Machine's Electronic Music Classification Model (KPCA-SVM).

3.2 Results and Analysis

Each model runs 10 times to calculate their average. As are shown in Figs. 2, 3, and 4, the results of accuracy rate, error classification rate and average training time of electronic music classification between the KPCA-ELM and the contrast model is presented.

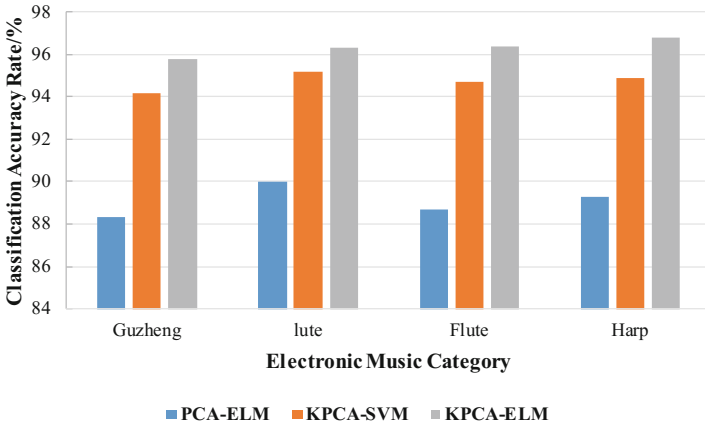


Fig. 2. The correct rate of electronic music classification.

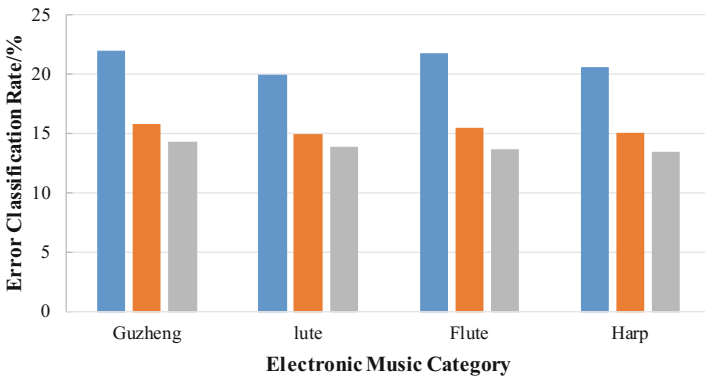


Fig. 3. The error rate of electronic music classification.

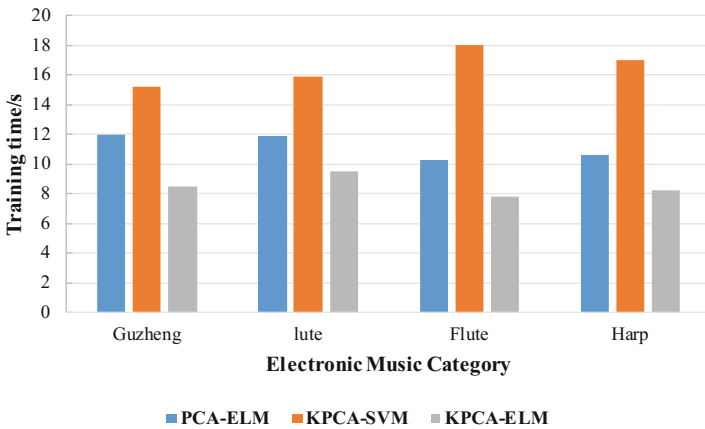


Fig. 4. The training time of electronic music classification.

Then we can make the conclusions that

- (1) Compared to PCA-ELM, KPCAELELM's electronic music classification rate has been improved, and the error classification rate is smaller. This is because KPCA can extract better non-linear features than PCA, making the feature more accurately reflect the type of electronic music.
- (2) Compared with KPCA-SVM, KPCAELELM electronic music classification rate has also been improved, effectively reducing the electronic music error classification rate. This is because ELM integrates the advantages of traditional neural networks and support vector machines, and establishes of a better performance electronic music classification model.
- (3) In all electronic music classification models, KPCAELELM has the least number of electronic music classified training sessions. This is because KPCA can effectively reduce the feature dimension, and ELM can obtain faster learning speed than support vector machine. In addition, it speeds up the training speed of electronic music classification and improve the classification efficiency of electronic music, and more suitable for mass electronic music classification.

4 Conclusion

Electronic music classification can broaden the scope of multimedia applications and has a very important application value. In order to solve the shortcomings of the current electronic music classification model, this paper proposes an electronic music automatic classification model for improving the extreme learning machine. The model integrates the advantages of kernel principal component analysis and extreme learning machine. At the same time, the genetic algorithm is used to select the parameters of the limit learning machine, which improves the accuracy of electronic music classification and has wide application prospect.

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