Hindawi
Scientific Programming
Volume 2023, Article ID 9767390, 1 page
https://doi.org/10.1155/2023/9767390

Retraction

Retracted: A Method of Extracting and Identifying College Students' Music Psychological Features Based on EEG Signals

Scientific Programming

Received 18 July 2023; Accepted 18 July 2023; Published 19 July 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. Liang, "A Method of Extracting and Identifying College Students' Music Psychological Features Based on EEG Signals," *Scientific Programming*, vol. 2022, Article ID 1503757, 10 pages, 2022.

Hindawi
Scientific Programming
Volume 2022, Article ID 1503757, 10 pages
https://doi.org/10.1155/2022/1503757

Research Article

A Method of Extracting and Identifying College Students' Music Psychological Features Based on EEG Signals

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Received 2 July 2022; Revised 13 August 2022; Accepted 16 August 2022; Published 12 September 2022

Academic Editor: Lianhui Li

With the development of information technology, music education in universities is also changing. Traditional music education can not effectively explore the feature of students, resulting in the quality of music education being restricted. The rapid development of Electroencephalogram (EEG) signals has brought a new educational model to music education. Through the extraction of students' psychological features of music by EEG, psychological features can be identified and different educational programs can be formulated according to the results. Multifeature extraction and combination method can improve the accuracy of EEG feature extraction. Using empirical mode decomposition and wavelet packet decomposition of the two kinds of methods to analyze EEG data, respectively, then the average energy, volatility index, sample entropy, and approximate entropy and multiscale features such as permutation entropy and Hurst index, select features in combination, to classify the feature set after the combination, so as to find out the feature of the performance of the optimal combination. The experimental results show that the feature combination of sample entropy and approximate entropy can better represent the main features of EEG psychological characteristic signals after wavelet packet decomposition, and the recognition accuracy is more than 90%.

1. Introduction

In the teaching of traditional music, most of the teachers have followed the same approach as in general subjects, from concept to illustration and back to the concept. This teaching method is dull and inflexible, and students can only passively accept knowledge. If the teacher can not design the teaching plan according to the characteristics of students, music teaching will become the 'stumbling block' of aesthetic education. The quality of music education can be effectively improved if the psychological characteristics of students learning music can be fed back at any time. [1, 2] Musical psychological feature refers to the psychological process including various human psychological factors generated during the interaction between people and music. [3] It includes the mood, preference, interest, and attitude related to music practice. It is a kind of special psychological fuzzy quantity, which includes both the psychological feature component caused by sound directly and the psychological component produced by the subject's thinking about the content of social life. [4–7] It is a current synthesized from two sources. Musical psychological feature is a kind of realistic psychological features with special concretization and music images. Music psychological feature is a kind of artistic psychological feature, which is contained in music and reflected by music, and is also the artistic expression of realistic psychological features in music. [8] Its form and existence have their own feature. Compared with the real psychological feature, musical psychological feature is not only a means of communication between people, but also the connotation of art for people to appreciate. It is expected to arouse the sympathy of others. Therefore, it is more concentrated and generalized than the natural outpouring of psychological feature, and thus has a stronger susceptibility. [9, 10]

psychological feature recognition aims to establish a harmonious man-machine environment and make the computer have higher and more comprehensive intelligence by giving the computer the ability to recognize, understand and adapt to the psychological feature of college students.

psychological feature recognition is an interdisciplinary research field integrating cognitive science, psychology, computer science, and neuroscience. [11–15] It is a difficult and hot topic in the field of cognitive science. With the enhancement of the computing power of computer, the cost of machine learning algorithms is greatly reduced, which lays a solid foundation for the rapid development of machine learning algorithms. Building an appropriate machine learning algorithm model can effectively improve the accuracy of the psychological feature recognition system. [16, 17] At the same time, the development of noninvasive sensing technology and human-computer interaction technology, it also provides a new idea for the development of psychological feature recognition. psychological feature recognition has a broad application prospect, and it can be potentially applied to the field of education. [18].

The modes of musical psychological feature recognition can be divided into physiological signals and non-physiological signals according to the source of signals. In recent years, with the development of wearable and non-invasive physiological signal acquisition devices, the real-time performance and accuracy of physiological signal acquisition are greatly improved, which promotes the development of physiological signals in the field of music psychological feature recognition. Physiological signals such as EEG signals, eye-tracking, and Electrodermal activities (EDAs) are widely used in psychological feature recognition. [19, 20] The reason why EEG signals play an important role in psychological feature recognition based on physiological signals is that the amygdala located deep in the brain is closely related to feelings and psychological features. Multichannel EEG signals can record the measurement results of different parts of the brain including the amygdala, and this information can closely reflect the psychological featured state. With the rapid development of EEG signal acquisition technology, brain-computer interface technology, and artificial intelligence technology, the study of EEG signals has gotten great attention in many countries. [22–26] The US government launched the Human Brain Initiative in 2013 to explore brain mechanisms, advance neuroscience research and develop new treatments for brain diseases that currently have no cure. In the same year, the European Union and Japan also announced their respective “Brain Project”. The European Union’s Brain Project research focuses on brain-like computing, which uses supercomputers to simulate brain functions; Japan’s Brain program focuses on the medical field, studying brain diseases and developing new treatments. In 2016, China listed “brain science and brain-like research” as a major national scientific and technological innovation and engineering project in its planning outline. For the “China Brain Project”, experts jointly proposed the layout of “one body and two wings”: the “main body” of the research on the neural principles of brain cognition, and the “two wings” of the research on the treatment and diagnosis of major brain diseases and the new technology of brain intelligence. Brain planning has provided impetus for the development of cognitive science and neuroscience. Therefore, psychological feature recognition based on EEG signals has attracted the attention of many scholars. [27–30].

In this paper, we study a kind of effective EEG music psychological characteristic feature extraction algorithm, study how to extract a variety of electrical features and combinations, to seek the feature of the optimal combination, and to improve the accuracy of electrical psychological feature classification, based on EEG signals of music college students psychological feature extraction and recognition technology development to provide technical basis.

2. Brain Electricity

2.1. Acquisition Method of EEG Signal. Dry electrodes are used to collect EEG signals. The electrodes on the device that touches the scalp do not need to be coated or added with conductive materials and can be worn directly on the head to collect EEG signals. The method is easy to operate in the experiment and the equipment is easy to carry, which provides theoretical basis and technical support for the development of portable EEG psychological feature detection therapeutic instruments in the future. However, the cuticle of the scalp has a large impedance, so the extracted EEG signal is not strong.

The other is to obtain EEG signals from a wet electrode, which is attached to the scalp via a conductive paste to reduce the impedance of the cuticle. This collection method can collect more stable and effective EEG signals, but this collection method is not conducive to the application of real life in terms of convenience and comfort.

2.2. EEG Preprocessing. Early EEG research usually involved manual detection and discarding of parts of the signal that contained artifacts, or EEG acquisition experiments designed to avoid artifacts. However, in the actual EEG collection, artifact generation is inevitable. Three methods are commonly used for artifact removal:

(1) Artifact subtraction. Assuming that the collected EEG signal is a linear combination of EEG signal and artifact signal and that the EEG signal is not correlated with the artifact signal, the artifact can be obtained by measurement. This method was used to remove electro-ophthalmic artifacts in the early stage. It is intuitive and has a clear physical meaning, but may lead to the loss of some useful EEG data.

(2) Principal component analysis. The EEG signal is decomposed by the orthogonal principle and the artifacts are removed according to the energy proportion of each EEG component. This method is only related to the covariance matrix of the signal, and although it is better than the pseudo-trace subtraction method, there is still high-order residual information between the signal components because it does not involve the high-order statistical feature of the signal.

(3) Independent Component Analysis (ICA). This blind source separation method has been widely used in EEG for artifact removal and feature extraction. Since this method does not have various noises of

physiological signals, and the sequence of separation signals cannot be determined, this method needs several iterations to obtain a separation matrix, and whether the independent components are artifacts needs manual judgment.

2.3. Feature Extraction Method. EEG feature extraction mainly involves noise reduction, reduction, and correlation removal. In the present research, the commonly used feature extraction methods are divided into time domain frequency domain analysis, space domain analysis, and nonlinear dynamics analysis.

2.3.1. Time Domain Frequency Domain Analysis. Frequency domain analysis of EEG signals mainly focuses on the statistical and geometric feature of EEG signal waveforms. Common analysis methods include probability density, time domain waveforms, autocorrelation, and cross-correlation. The analysis of EEG signals usually focuses on the amplitude, peak, waveform, histogram, mean, and variance of EEG signals. Although the time domain analysis of EEG has the advantage of intuition, it lacks objectivity. At present, the most common time-domain features in research are amplitude feature and amplitude energy feature (Band power, BP), while the most common filtering methods in time domain analysis are: band-pass filter, Laplace filter, full-lead average reference method, Kalman filter and moving average filter. Frequency domain analysis of EEG signals is usually to analyze the correlation and power spectrum of EEG signals. Frequency domain features usually use fast Fourier transform, Adaptive Antoregessive (AAR) model and wavelet transform to extract Power spectral density (PSD), AAR parameters or wavelet frequency band energy. Frequency domain analysis, known as power spectrum estimation, converts EEG signals based on the corresponding relationship between EEG power and frequency, making it easier to observe the distribution and variation of rhythm, as well as the energy distribution of each frequency. However, variance estimation is prone to fluctuation, so it will lead to the loss of higher-order information. Although autoregressive model is easy to estimate parameters, its parameters do not have specific physical meaning, so it cannot be extended in practice. The common time-frequency analysis of EG signal includes short-time Fourier transform, wavelet transform, wavelet packet decomposition, empirical mode decomposition, global empirical mode decomposition and local mean decomposition. What time-frequency analysis has in common is its powerful energy gathering ability. Even if it is impossible to know the relationship between signal changes over time, the corresponding time-frequency relationship can be obtained within a certain range of SNR. This method can easily describe the transient feature of EEG signals, but cannot describe the trend changes of EEG signals.

2.3.2. Airspace Analysis. Spatial domain analysis is to optimize the weighted combination of multilead EEG signals to obtain signal feature with higher signal-to-noise ratio. Common spatial analysis algorithms include principal component analysis (PCA), independent component analysis (ICA), common space model (COSPATIAL mode), Fisher's Criterion (FC), spatial adaptation of data and Canonical correlation analysis (CCA), etc.

2.3.3. Nonlinear Dynamics. In recent years, nonlinear dynamic analysis method has been widely used in EEG signal analysis because EEG signal is a collection of nonlinear coupling by a large number of nerve cells. In nonlinear analysis of EEG signals, one method is to analyze EEG signals through mixed pure theory. The common methods include Lorenz scatter diagram, maximum Lyapunov exponent, correlation dimension, and Hurst exponent. The other method is to analyze EEG signals by information theory. Common methods include permutation entropy, singular value decomposition entropy, LZC complexity, approximate entropy, and sample entropy.

3. Music Psychological Feature of EEG

3.1. Empirical Pattern Decomposition Algorithm of EEG. Empirical Mode Decomposition (EMD) algorithm does not need to set a basis function in advance, and it can decompose EEG signals according to the time-scale feature of EEG signals. Compared with Fourier decomposition which requires pre-setting of harmonic basis function and wavelet decomposition which requires pre-setting of wavelet basis function, the empirical mode decomposition algorithm does not need to set the feature of basis function, so its algorithm can be applied to any type of signal decomposition. EMD algorithm is suitable for the analysis of nonlinear and nonstationary signal sequences and has a high signal-to-noise ratio, so it has obvious advantages in processing nonstationary and nonlinear data. Since the EMD decomposition algorithm is based on local feature of EEG signal time scale, the EMD algorithm is adaptive. EMD algorithm can decompose THE EEG signal into several Intrinsic mode functions (IMF), and each IMF component covers local characteristic signals at different time scales of the original EEG signal. EMD can transform all the time domain signals of EEG signals into a linear steady state, and stabilize the nonstationary EEG data, so that more processing methods can be applied to EEG signals.

3.2. Eigenmode Functions. If the original EEG signal is decomposed by EMD, the original EEG signal can be reconstructed. The instantaneous frequency of a function is meaningful only when it is symmetric and its amplitude is 0 on average over local time periods, and when the point at which its amplitude is 0 is the same as the number of points at the minimax. The instantaneous frequency of each point in the eIGen mode function is meaningful, so the eigen mode function after EMD decomposition of EEG signal needs to satisfy 2 points. First of all, in the time period when the signal exists, the number of maximum and minimum points of the eigenmode function can differ at most by one in the local time period. Secondly, at any time point, the average value of the envelope of the maximum and minimum values of the eigenmode function in the local time is 0.

The first point to be satisfied is similar to the narrowband requirement for stationary Gaussian signals. The second point that needs to be met is that the instantaneous frequency does not vary with the fluctuation of the asymmetric signal over a local time period. The second point can also be explained by the fact that the local mean of the data is zero, but for nonstationary EEG data, calculating the local mean involves local time scales, which are difficult to define. Therefore, the average value of the envelope formed by the local maximum and the envelope formed by the local minimum is zero, so that the waveform of the EEG signal is locally symmetric. IMF represents the intrinsic vibration mode of the EEG data, where each vibration period of IMF defined by zero crossing has only one vibration mode and does not contain other complex odd waves. IMF may be frequency and amplitude modulated or unsteady and not constrained to be a narrowband signal, while a signal modulated only by frequency or amplitude may also be called IMF.

3.3. Empirical Mode Decomposition Implementation Method. EMD algorithm considers the oscillation in EEG signal as local oscillation. If the evaluation signal $x\ (t)$ is a variation between two adjacent minimum points at t^- and t^+, a locally high-frequency component $d\ (t)$ corresponding to the oscillation is defined, where $t^- \leq t \leq t^+$ where the oscillation is between two minimum values and passes through the maximum. At the same time, it is still necessary to define a local low-frequency component $m(t)$, where $t^- \leq t \leq t^+$, then $x(t) = m(t) + d(t)$. This method can be used to decompose all the oscillating components of the EEG signal. It can also be applied to all the residual components of the local signal. Therefore, the components of the EEG signal can be decomposed by an iterative method, a process called EMD decomposition. EMD decomposition is performed for a given EEG signal, and the decomposition process is shown in Figure 1.

The EMD decomposition process of EEG signals is as follows:

(1) Find all extreme values of $x(t)$.

(2) The envelope of extreme points is formed by interpolation method. The minimum point forms the lower envelope, which is expressed as $E_{\min}(t)$. The maximum point forms an upper envelope and is expressed as $E_{\max}(t)$.

(3) Calculate the mean value of upper and lower envelope $m(t) = (E_{\min}(t) + E_{\max}(t))/2$.

(4) Extract details $d(t) = x(t) - m(t)$.

(5) Repeat the above steps for residual $d(t)$ until the mean value of $d(t)$ is 0, and the iteration ends.

A screening process is needed during EMD decomposition, and the above EMD decomposition steps are redefined. In this screening process, steps 1–4 of EMD decomposition above are repeated for detail signal $d(t)$ at first, and iteration is not stopped until the mean value of detail signal $d(t)$ is 0 or meets the stop criteria. The detail signal $d(t)$ after iteration stop is called IMF, and the residual signal of detail signal $d(t)$ can be calculated through the fifth step of EMD decomposition above. After the above calculation process, with the generation of residual signals, the number of extreme points gradually decreases. After completing the EMD decomposition of the whole EEG signal, several IMF will be generated.

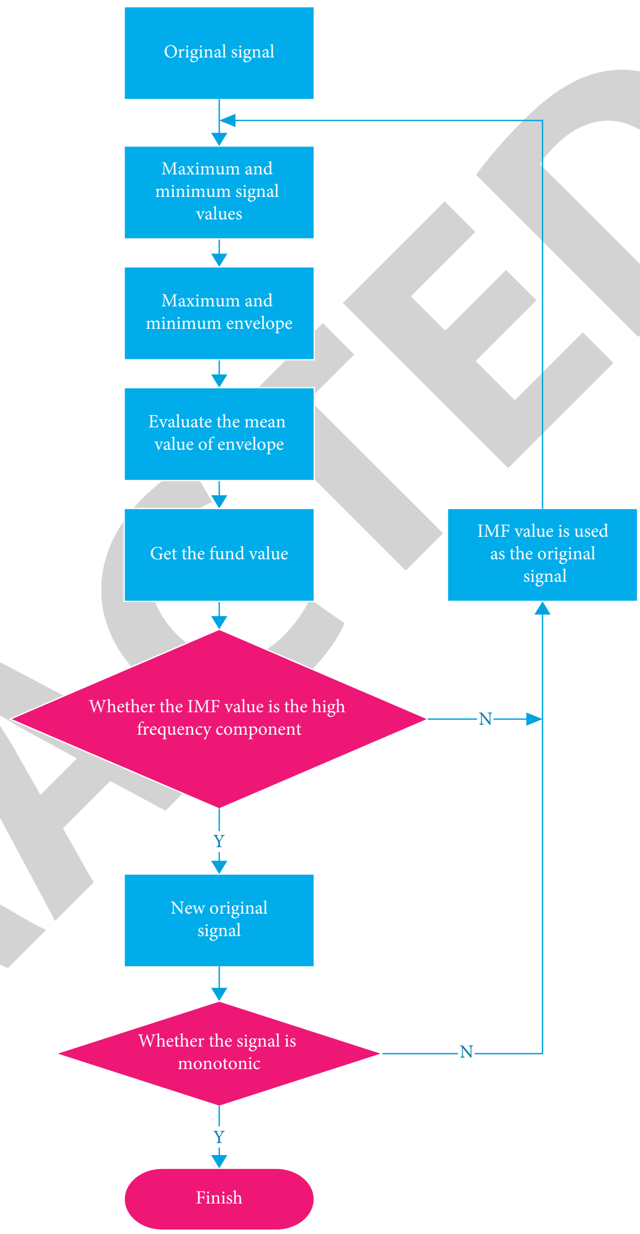

Figure 1: Empirical pattern decomposition process.

3.4. Feature Extraction Algorithm. The EEG signal will produce signal components after decomposition, and the EMD decomposition algorithm is used as an example to solve the average energy and fluctuation index of each component. Through the decomposition of the original EEG signal by the EMD algorithm, the l-order IMF components can be obtained, but the difference between the frequencies of the IMF components of each order is relatively large, so there is an energy difference between the IMF components of each order, and the average energy of the IMF components of each order can be used as a characteristic value of the EEG signal. The average energy per order IMF component is calculated as follows:

$$E_l = \frac{1}{n}\sum_{t=1}^{n}\left|S_l(t)\right|^2, \tag{1}$$

where S_l is the lth IMF component, n is the number of IMF component data points; E_l is the average energy characteristic of the lth IMF component.

According to the feature of each order IMF component after EMD decomposition, the representative first m-order IMF components are selected for feature extraction so that m average energy feature values can be extracted for each EEG data. Since the amplitude of brain waves varies with changes in musical psychological feature, the average of the sum of amplitude differences of adjacent IMF components is extracted as an eigenvalue, which characterizes the fluctuation intensity of the signal and is called the fluctuation index. Since the intensity of EEG signal changes varies across psychological feature states, the fluctuation index can be used as a measure of the intensity of EEG signal changes, which is defined as:

$$H_{i,j} = \frac{1}{n}\left(\sum_{t=1}^{n}\left|S_i(t) - S_j(t)\right|\right), \tag{2}$$

where $S_i(t)$ is the i-th IMF component after EMD decomposition; $S_j(t)$ is the j-th IMF component; n is the number of data points of the IMF component; H_{ij} is the average of the sum of the absolute values of the differences between the i-th and j-th IMF components, which is the fluctuation index.

The most representative top m-order IMF components are selected for feature extraction after EMD decomposition, so that $m-1$ IMF fluctuation index feature values can be obtained for each EEG data.

Approximate entropy (ApEn) is a nonlinear kinetic parameter that can be used to measure the pattern of EEG signal waveform changes and the unpredictability of EEG signal changes. ApEn characterizes the complexity of an EEG signal by a nonnegative number that is also used to indicate the probability of a change in the EEG signal, whose magnitude increases with the complexity of that EEG time series. Approximate entropy does not require a large number of data points for calculation in practical applications, and approximate entropy can suppress the mixed noise signals in EEG signals and has a strong resistance to interference signals. Since ApEn can analyze single or superimposed random signals, it is very suitable to be used for analyzing EEG signals. Denote a set of original EEG signals by $x(i)$, where $i = 1, 2, \ldots, n$, and n is the number of data points. The detailed steps to extract ApEn from EEG signals are as follows.

(1) This set of EEG signals $x(n)$ is converted into a set of vectors with dimension d according to the sequence of serial numbers.

$$Y(i) = X(i), X(i+1), \cdots, X(i+d-1), \tag{3}$$

where d is the window length, i is satisfying $i = 1,2, \ldots, n-d+1$.

(2) Calculate the distance between the i-th vector $Y(i)$ and the j-th vector $Y(j)$.

$$D\{Y(i), Y(j)\} = \max\{|Y(i+k) - Y(j+k)|\}, \tag{4}$$

where i is satisfied by $i = 1, 2, \ldots, n-d+1$, j is satisfied by $j = 1, 2, \ldots, n-d+1$, and k is satisfied by $k = 0, 1, \ldots, d-1$.

(3) When the threshold r is known and r is a nonnegative number, if the number of $D\{Y(i), Y(j)\}<r$ in a set of data points is denoted by $N^d(i)$, and the number of total vectors is denoted by $N-d+1$, and the ratio of these two is denoted by $C_i^d(r)$, the formula for calculating $C_i^d(r)$ for each EEG data series is shown below.

$$C_i^d(r) = \frac{N^d(i)}{(N-d+1)}, \tag{5}$$

where i is satisfied with $i = 1, 2, \ldots, N-d+1$.

(4) The natural logarithm is taken, and then the average of all the i's is found for the requested logarithm.

$$\phi^d(r) = \frac{1}{N-d+1}\sum_{i=1}^{N-d+1}\ln C_i^d(r). \tag{6}$$

(5) Then the data sequence $X(N)$ is further composed into a set of vectors of dimension $d+1$ according to the serial number, and $C_i^{d+1}(r)$ and $\phi^{d+1}(r)$ can be obtained after repeating the above steps.

$$\mathrm{ApEn} = \phi^d(r) - \phi^{d+1}(r). \tag{7}$$

Since the length of the processed EEG data points is set, the value of the original data point length N is not discussed for the time being. The window length d is also called the embedding dimension, and if the value of d is set larger than 2, the calculated approximate entropy is not used to accurately characterize the EEG signal. If the EEG signal is reconstructed when the value of d is set to 2, the EEG information obtained after reconstruction is more detailed than that portrayed when the value of d is 1, so the value of d is set to 2. The value of the threshold r, also known as the similarity tolerance, is related to the ability of the requested approximate entropy to discriminate between EEG categories. the size of r is more relevant to the scenario of practical application, and $r = 0.2 * std$ is usually chosen, where std denotes the standard deviation of the original time series.

3.5. Holdings of Sample Entropy. Sample entropy (SampEn), which transforms some of the steps in approximate entropy calculation, is also used to measure the complexity of time series and is commonly used in the assessment of physiological time series complexity and in the diagnosis of case states.

Sample entropy algorithm is expressed as follows:

(1) If the time series of an N-dimensional EEG signal is $u(1)$, $u(2)$, ..., $u(N)$, the sequence is obtained by sampling at equal time intervals.

(2) The parameters that determine the calculation results of the sample entropy algorithm are integer d and real number r, where d is the length of the comparison vector and r is the measure of similarity.

(3) Reconstruct d vector $X(1)$, $X(2)$, ..., $X(N-d+1)$, where $X(I) = [u(i), u(i+1), \ldots, u(i+d-1)]$.

(4) For $1 i \leq N-d+1$, count the number of vectors that meet the following conditions:

$$B_i^d(r) = \frac{(X(j), D[X(i), X(j)] \leq r)}{(N-d)}, i \neq j. \tag{8}$$

Among them, the $D[X, X*]$ is defined as $D[X, X*] = \mathrm{Max}|u(a) - u*(a)|$, indicates $X \neq X*$. $u(a)$ represents the element of vector X, and D represents the distance between vector $X(i)$ and vector $X(j)$, which is determined by the maximum difference of the corresponding element. The value range of j is $[1, N-d+1]$, but $j \neq i$.

(5) Find the average value of $B_i^d(r)$ over all I values, denoted as $B^d{}_i(r)$.

$$B^d(r) = (N-d+1)^{-1} \sum_{i=1}^{N-d+1} B_i^d(r). \tag{9}$$

(6) let $k = d+1$, repeat steps 3–4, get $A^k(r) = (N-k+1)^{-1} \sum_{i=1}^{N-k+1} A_i^k(r)$. Among them: $A_i^k(r) = (\text{number of } X(j) \text{ such that } d[X(i), X(j)] \leq r)/(N-k), i \neq j$.

(7) Sample entropy (SampEn) is defined as:

$$\mathrm{SampEn} = \lim_{N \longrightarrow \infty} \left\{ -\ln\left[\frac{A^k(r)}{B^d(r)}\right] \right\}. \tag{10}$$

3.6. Multiscale Permutation Entropy. Permutation entropy (PE) is also a nonlinear parameter that can be used to characterize the complexity of an EEG signal. It has the advantages of simple calculation procedures and a strong ability to suppress the mixed noise in EEG signals. Multiscale permutation entropy is calculated on the basis of PE, and its calculation steps are as follows, as shown in Figure 2.

First, the EEG psychological feature time series were coarse-grained. If a group of EEG psychological feature time series is $\{x(i), i = 1, 2, \ldots, n\}$, then the coarse-granulating method is as follows:

$$y_i = \frac{1}{s} \sum_{i=(j-1)s+1}^{js} x_i, \; 1 \leq j \leq \frac{N}{s}, \tag{11}$$

where s is a multiscale factor, and y_i is a multiscale time series.

When the scale factor s is 1, it means that the EEG psychological feature time series is the original EEG psychological feature time series, and the entropy calculated by the multiscale permutation entropy algorithm is the permutation entropy value.

Spatial reconstruction time series $\{y(i), i = 1, 2, \ldots, N\}$, and you get the matrix Y. The length of the time series is N.

$$Y = \begin{bmatrix} y(1) & y(1+\tau) & \ldots & y(1+(d-1)\tau) \\ y(2) & y(2+\tau) & \ldots & y(2+(d-1)\tau) \\ y(j) & y(j+\tau) & \ldots & y(j+(d-1)\tau) \\ \vdots & \vdots & \ldots & \vdots \\ y(k) & y(k+\tau) & \ldots & y(k+(d-1)\tau) \end{bmatrix}, \tag{12}$$

where d is the embedding dimension; τ is the delay factor; k is $k = N-(d-1)$; $y(j)$ is the j-th row component of the reconstruction matrix.

Consider $N-(d-1)\tau$ rows in the above formula as $N-(d-1)$ reconstruction components. The first j a, matrix component $\{y(j), y(j+\tau), \ldots, y(j+1)\ (d-1)\tau\}$, arranged in ascending order, is available:

Consider the $N-(d-1)\tau$ rows in the above equation as $N-(d-1)\tau$ reconstructed components. Then, the j-th component of the matrix $\{y(j), y(j+\tau), \ldots, y(j+1)\ (d-1)\tau\}$, rearranged in ascending order, gives the following equation.

$$\% \; y(i+(j_1-1)\tau) \leq y(i+(j_2-1)\tau) \leq \cdots \leq y(i+(j_d-1)\tau), \tag{13}$$

where $j_1, j_2, \cdots, j_d$ is the index value of the column where each element is located in the reconstructed component. If $y(i+(j_p-1)\tau) = y(i+(j_q-1)\tau)$ exists in the reconstructed component and p≠q, then it is necessary to sort the values of j_p and j_q by their magnitude. If $j_p < j_q$, then there is $y(i+(j_p-1)\tau) < y(i+(j_q-1)\tau)$.

Each row of an arbitrary reconstruction matrix has a sequence of reconstruction symbols corresponding to it.

$$S(i) = (j_1, j_2 \cdots, j_d), \tag{14}$$

where i is satisfied by $i = 1, 2, \ldots, k$, where the value of k is less than d.

Since the dimension of the reconstructed EEG component is d, the arrangement can be obtained as d kind.

If $p_1, p_2, \ldots, p_k$ is used to denote the probability of occurrence of sequence S(i), the permutation entropy of EEG sentiment time series $x(i)$ can be expressed as the following equation.

$$\mathrm{MPE} = -\sum_{j=1}^{k} P_j \ln P_j. \tag{15}$$

The formula for calculating PE and the range of values of probability P_j shows that MPE is maximum when $P_j = 1/d$ and its value is $\ln(d)$.

$$0 \leq \mathrm{MPE} \leq 1. \tag{16}$$

FIGURE 2: Multiscale permutation entropy calculation process.

The numerical size of the ranking entropy measures the complexity of the EEG signal $\{x(i),\ i = 1, 2, \ldots, N\}$. a larger value of PE indicates a more complex and random EEG signal, and vice versa.

The three parameters, embedding dimension d and delay factor as well as scale factor, will have an impact on the accuracy of the multiscale alignment entropy calculation results. An EEG psychological feature signal containing high and low arousal is selected from the DEAP database, and the appropriate parameters d, τ, and s are found experimentally. When $d = 3$ and $\tau = 1$, the absolute value difference of the amplitude of the two types of signal alignment entropy with different scale factors s is shown in Figure 3 below. From the figure, it can be seen that the magnitude difference is the largest when s is 1, so $s = 1$ is chosen. According to the previous research, it is known that when $2d \leq 5$ can make a good approximation to the asymptotic distribution by finite series.

Therefore, when $s = 1$ and $\tau = 1$, the absolute value difference of the amplitude of the two types of signal alignment entropy under different d is shown in Figure 4 below. From the figure, it can be seen that the amplitude difference is the largest when d is 5, so $d = 5$ is chosen.

Therefore, when $s = 1$, $d = 5$, the absolute value difference of the amplitude of the two types of signal alignment entropy under different d is shown in Figure 5 below. From the figure, it can be seen that the amplitude difference is the largest when $s = 1$, so it is chosen $\tau = 1$.

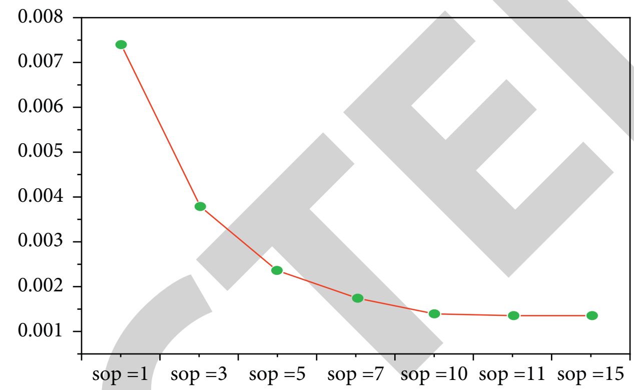

FIGURE 3: The difference of the average amplitude difference between the two categories at different s values.

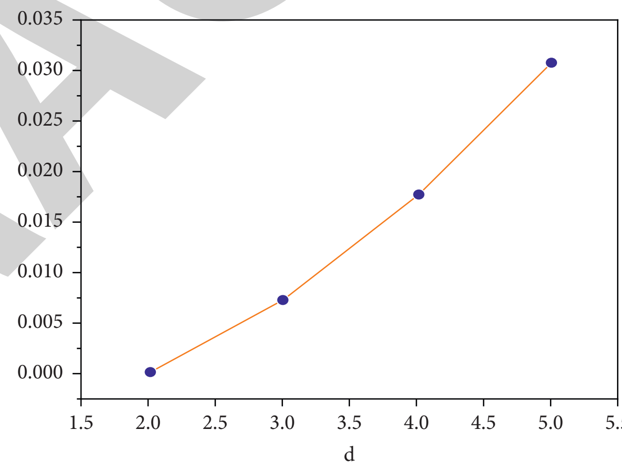

FIGURE 4: The difference of the average amplitude difference between the two categories at different d values.

3.7. Hurst Index. There are seven main methods for calculating the Hurst index: Aggregate variance method, R/S analysis method, Periodogram method, Absolute value method, Variance of residuals method, Abry-Veitch method, and Whittle method (Whittle estimator). R/S analysis is also called rescaled polar variance analysis, which is usually performed for only a few representative indices due to the complexity of the calculation method.

The Hurst index, calculated by R/S analysis, enables a quantitative description of the long-term dependence of time series information. The Hurst index is able to predict the trend of the EEG signal, but not the duration of new changes. In practical applications usually the system beyond a certain time scale shows a random behavior that is not correlated with the past. The quantity R for determining whether the EEG signal has acyclic cycles can be calculated by the following equation.

$$R_n = \frac{(R/S)_n}{\sqrt{n}}. \tag{17}$$

On the curve plotted by the relationship with lnn, if the curve is a horizontal line, it means that the signal is random and the Hurst exponent is equal to 0.5; if the curve slopes downward, it means that the signal has inverse persistence and the Hurst exponent is less than 0.5; if the curve slopes upward, it means that the signal has persistence and the Hurst exponent is greater than 0.5.

4. Experimental Results Analysis of EEG Psychological Feature Extraction

The EMD decomposition algorithm was used to process the EEG signals to obtain the IMF components of each order, and the 11-order IMF components were obtained after the 1-second EEG psychological feature signals on channel Fp1 were decomposed. Fourier transform algorithm was used to transform the IMF components of each order into the frequency domain, and the spectrum graph of each order IMF was obtained. After EMD treatment, the frequency range of each order IMF component is different. The

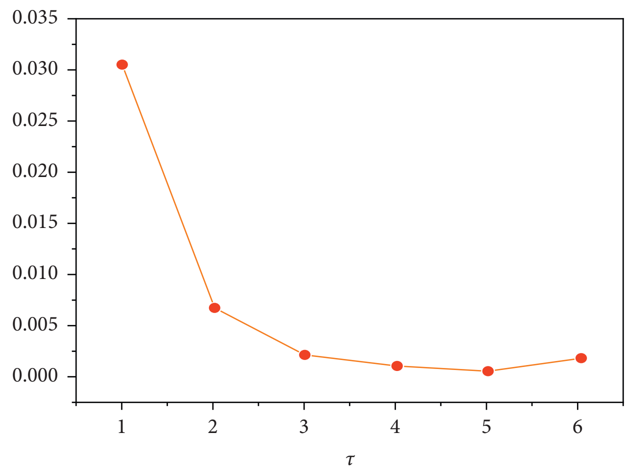

FIGURE 5: The difference of the average amplitude difference between the two categories at different τ values.

frequency of each IMF component decreases gradually with the increase of the order, and the higher the order IMF component, the lower the corresponding frequency. If the relevant features of each order IMF component are extracted, the obtained feature vector dimension will be very high, and these feature quantities will also contain many EEG features with little correlation with psychological features, thus reducing the accuracy of EEG psychological feature recognition. Since the frequency range of the EEG, rhythm wave is between 0.5 Hz and 45 Hz, and the IMF components obtained after EMD decomposition, in which the first 6th order IMF components occupy almost 90% of the energy of the EEG signal, the first 6th order IMF components are reconstructed with the original EEG signal on channel Fp1 for 1 second and the EEG signal on channel Fp1 for 1 second after reconstruction. The first 6 orders of IMF components can show the features of the original EEG signal on channel Fp1 for 1 second, so the first 6 orders of IMF components are selected for feature extraction respectively.

The data from the pre-processed DEAP dataset were analyzed in the time-frequency domain, and the EEG data of 32 subjects on 32 channels were decomposed into several eigen-simulation functions using the EMD algorithm. Based on the analysis of appropriate order IMF components, the first 6 order IMF components were selected for time-frequency analysis after EMD decomposition of EEG data from 32 subjects on 32 channels. The average energy features and fluctuation index features are first extracted for each order of IMF components selected as feature set 1 and feature set 2, respectively, and then the FFT transform is applied to the first 6 orders of IMF components after EMD decomposition, and the average energy features and fluctuation index features are extracted as feature set 3 and feature set 4, respectively. Finally, the sample entropy, approximate entropy, multiscale alignment entropy, and Hurst index of the first 6 order IMF components after EMD decomposition are extracted as feature set 5, feature set 6, feature set 7, and feature set 8, respectively. 80% of the extracted EEG

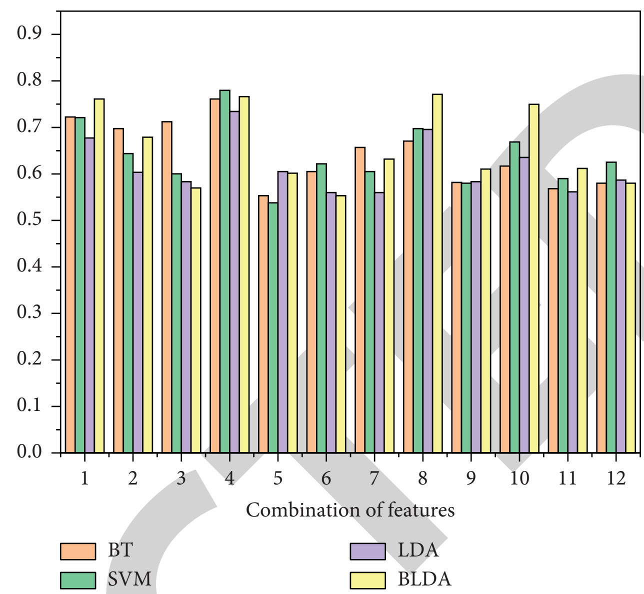

FIGURE 6: Average classification accuracy of feature combinations.

sentiment feature set is selected as the training set and 20% as the validation set, respectively. High/low arousal binary classification is performed by four classical classification methods, BT, SVM, LDA, and BLDA, one by one.

As can be seen from Figure 6, the classification accuracy of these features combined is not high, and the accuracy of EEG emotion classification after feature combination is lower than that before feature combination. The highest classification accuracy for the combination of all features is only 77.68%. It is 12.32% lower than the best result of 90% for classification by single features. The possible reasons for this phenomenon are: (1) the combined features produce redundant data, which affects the classification results; (2) when individual features are classified, the amount of feature data is relatively small compared to the combined features, and the classification results of the combined features may be oversaturated; (3) when each feature is classified individually, the feature values of the two categories have certain differences, but after combining them together, the differences between the two The difference between the feature values is reduced.

5. Conclusion

The psychological features of the music of college students are related to their preferences in learning music. It can effectively extract the psychological feature of music, identify and analyze the preferences of students, and develop different learning programs according to different students by combining their own features, so as to maximize the advantages of students. In this paper, multifeature extraction and combination methods are studied to improve the accuracy of mental feature extraction from EEG signals. The EEG emotion data after DEAP centralized preprocessing is processed by the Empirical Mode Decomposition algorithm. Through verification, it is found that the multifeature extraction method can effectively extract psychological feature data, better reflect the psychological feature of students, and provide good data support for the development of music education programs [21].

Data Availability

The dataset can be obtained from the author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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