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Article

Constructing a Digitalized Timbre Feature Library for Suona Music of Intangible Cultural Heritage Using Random Forest Classifier

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Abstract: As an important part of the intangible cultural heritage, the digital development of the suona is an innovative combination of modern technology and intangible culture, which can be regarded as one of the ways to inherit the intangible culture in the new era. This paper recognizes the existence of the diversity of suona in traditional applications, and proposes to improve the suona timbre recognition method of random forest according to the musical characteristics of suona. Comparing My SQL and Oracle databases, My SQL is selected as the main technology of digital timbre feature library for suona music, and the functional modules of digital timbre feature library for suona music are designed to be composed of two systems: portal subsystem and background management subsystem. Analyze the accuracy of the suona timbre recognition model of residual network combined with random forest model. Analyze the experience of using the digital display design of suona music database by combining the sensory, emotional, interactive, thinking, aesthetic and entertainment dimensions of experience design. Experiencers were able to gain some gains from sensory, emotional, thinking, aesthetic, and entertainment dimensions, and the mean score of the experience of the digital display design of non-heritage suona music was 4.30.

Keywords: random forest; residual network; My SQL database; suona

1. Introduction

In the vast river of culture, intangible cultural heritage is not only the witness of history, but also the inheritor of national spirit, carrying rich cultural memory and artistic value. Among them, suona art is unique among many intangible cultural heritages, which is loved by people all over the world. The suona belongs to the music category of intangible cultural heritage, and there are a number of traditional tunes handed down to date, and its music form and performance form have obvious geo-cultural characteristics, which can be seen from its playing techniques, melody, rhythm, timbre and other aspects of its cultural characteristics [1-3]. Suona music is not only a form of musical performance, but also a cultural symbol, which has been integrated into the daily life of local people, witnessed countless joyful and sad moments, and become an important bridge connecting the past and the future, inheritance and innovation [4-6]. Meanwhile, as an intangible cultural heritage, suona music has special cultural, economic and social values, and it is an invaluable treasure in the spiritual home of mankind [7-8]. Therefore, exploring the inheritance of suona skills from the perspective of intangible cultural heritage is not only respecting and promoting the art of suona itself, but also a powerful impetus to the inheritance and development of Chinese excellent traditional culture [9-11].

As we all know, sound is the soul of a musical instrument, and timbre is the core of a musical instrument, and the study of timbre characteristics of suona music will directly reflect the cultural background and aesthetic accumulation of different periods and ethnic groups [12-14]. Therefore, the establishment of suona music timbre characteristics database can be along the lines of music and culture data collection, focusing on instrumentation, performance method and so on [15-16]. In addition, since most of the database contents in the field of music information retrieval (MIR) are pure instrumental sound databases with annotations or instrumental sound clips from music databases, etc., used for the extraction of information such as pitch, timbre, melody, rhythm, harmony, etc. [17-19]. Therefore, the construction of suona music timbre feature database also occupies an extremely important position in content-based music information retrieval [20]. It can be seen that it is of great significance to construct a digital timbre feature database of intangible cultural heritage suona music through the use of cutting-edge computer sound analysis technology.

This paper analyzes the traditional application of suona and the modern evolution of the rhythm, according to the musical characteristics of suona and the timbre performance characteristics of the instrument, through the improvement of the random forest model, puts forward a suona timbre recognition method. Combined with the feature selection of the random forest model, the random forest is used as a model classifier in the timbre recognition algorithm to alleviate overfitting and improve the audio recognition accuracy of the music. Then the residual network model is added as the feature extractor of audio, which utilizes the feature learning advantage of the deep learning model to strengthen the feature grasping ability. My SQL is selected as the sound system database of suona music, and the functional module framework of digital sound feature library of suona music is designed. Analyze the timbre recognition effect of the proposed algorithm, and carry out the digital display of suona music database, and analyze the effect of digital display of suona music database.

2. Suona Music Digital Timbre Feature Library Construction

2.1. Traditional Use and Modern Evolution of the Suona

The suona, as a traditional national instrument, carries a deep historical and cultural heritage, and its traditional applications are wide and varied. In modern music, it has also undergone significant evolution. In the following, the traditional application and modern evolution of suona will be discussed in detail from various aspects.

2.1.1. Traditional Applications of the Suona

(1) Representation of regional and national music

As one of the national instrumental music with a long history, suona profoundly embodies the characteristics of national culture. The existing traditional repertoire is rich in the essence of national spirit and culture, which all reflect strong aesthetic ideas, from the emotional connotation, rhythmic mood to the playing style, all of which are branded with traditional aesthetic ideas. It is not only a tool for musical expression, but also a symbol of national history and cultural memory, carrying the cultural characteristics of a particular region.

(2) Diversity of solo and ensemble performance

In traditional music culture, suona has a significant position. With its rich expression and penetrating sound, suona is widely used in solo, ensemble and accompaniment, and is widely popular in folk music in the form of wind and percussion. Especially in solo performance, suona can not only show its high and exciting tone, but also express the soft and sad emotion through the delicate playing technique. In the ensemble, suona often forms a sharp contrast or perfect integration with other instruments, adding layers and colors to the overall music.

(3) Wide range of musical styles and themes

As a traditional folk music, suona contains deep national traditions and is known to the world for its unique sound. The suona has a variety of performance forms and a highly recognizable sound, which can express loud, cheerful and high-pitched tones, as well as soft, sorrowful and even tragic musical emotions.

2.1.2. Modern Evolution of the Suona

(1) Innovation of production technology

The modern suona has made significant improvements in the production technology. The application of new materials, such as the use of synthetic materials, makes the sound of suona more beautiful and stable, and at the same time, it is more convenient to play. These technological innovations provide a better foundation for the application of suona in modern music.

(2) Expansion of playing techniques

Modern suona players continue to expand their playing techniques to adapt to the rhythm and style of modern music. In addition, the mastery of difficult scales, rapid changes and other techniques also make the suona more flexible and diverse in modern music.

(3) Changes in roles and positioning

Besides retaining the traditional solo and ensemble forms, it has gradually developed new ways of application. At the same time, suona also appears as a harmonic instrument, forming a complex harmonic structure together with other instruments to enhance the overall expressiveness of the orchestra.

(4) Expansion of musical styles and themes

With the diversified development of modern music, suona is gradually used in more diverse musical styles and themes. For example, in modern creative music, the integration of suona and modern instruments has given birth to novel music forms and styles. In movies, TV dramas and other media music, suona is also often used to create a specific atmosphere and emotion.

2.2. Sound Color of Suona Music

2.2.1. Musical Characteristics of Suona

The suona consists of five parts: the reed, the air plate, the core, the suona pole and the suona bowl. Due to the special structure of the suona and the different materials of each part, the suona has outstanding characteristics in rhythm, melody, range and timbre, and has become an indispensable accompanying instrument in many opera music.

(1) Rhythmic characteristics of suona

Rhythm, as an important part of music, directly affects the expression of music. As one of the most frequently used musical instruments in opera music accompaniment, suona has distinctive characteristics. It has a strong sense of rhythm, which can harmonize and echo with the music style, and can enhance the musical expression of the piece while improving the aesthetic effect of the music.

(2) Melodic characteristics of suona

Melody can highlight the emotions and thoughts expressed in the music. The introduction of melody can make the whole piece have a strong sense of rhythm, and better express and express the music emotion. The melody of suona is mainly affected by three factors: pitch, volume and sound color. Due to the high volume and strong rhythmic sense of suona, the player can handle the melody in detail according to the style, emotion and mood of the performance to emphasize the sense of atmosphere. In the opera repertoire, the addition of suona special effects can promote the development of the plot, active atmosphere, but also for the storyline to bring a more three-dimensional sense, more diverse and rich in the content of the effect.

(3) As the accompaniment of opera music

As a national wind instrument with strong skills, suona is widely used in many art forms, and its expression is vivid, rich, interesting and rhythmic, which can show the music mood well. The suona has various forms and styles of performance, which can be widely adapted to different types of music. In addition, suona can fit its melodic lines to specific music styles, showing a unique musical image. Suona has a unique charm of cultural flavor and rich regional color, in the opera music accompaniment, suona is an important part of it, which directly affects the mood of the plot, the emotional direction. Suona has three ranges of high, medium and low, namely, a1-b3 for treble, a-a2 for alto and A-d2 for bass.

2.2.2. Tonal Performance Characteristics

The special nature of sound color makes it must go through the process of people's perception in order to have the existence, in order to express the information that the sound wants to express. People with normal hearing have the ability to perceive sound, and feel differently about different timbres, and thus emotionally different. When you hear a sound that is cheerful in tone, the whole person will burst with joy from the heart. When the sound is sad, the person will fall into a depressed mood, and inexplicable sadness will come to his heart.

Similarly, the sound presented in the process of vocal performance, the timbre of the conversion will allow the audience to carry out their own sense of association, originally facing the empty stage, may be brought into the sound of some specific scenarios in the blink of an eye, through the timbre of the expression of the characters constructed one after another story and immersed in a story of nothingness. There are also sounds that will make people instantly happy, but also make people suddenly fall into tears, which is not only the feelings brought by the sound, but also the magical effect caused by the change of timbre. So, although timbre is something invisible and untouchable, through the real reaction of the listener, one can truly see the existence of timbre, feel the expression effect of timbre, and enhance the infectious power of vocal performance.

2.3. Techniques for Constructing Digital Timbre Feature Libraries of Musical Scores

2.3.1. Random Forest Model

The core of a random forest lies in the words “random” and “forest”. Among them, “forest” refers to a collection of hundreds or even thousands of regression or classification trees, a structure that fully embodies the "integration idea" followed by random forests.

The process of Random Forest Modeling (RF) is to first create n sets of sample sets with samples for training using bootstrap, each with a consistent amount of data. Next, a decision tree is trained on the sample set individually. Finally, based on the classification of the decision tree, the prediction results are made explicit by the final vote [21-22].

Having constructed partially interconnected and independent decision trees enhances the internal variability of the model, which helps the RF model to accurately discriminate complex datasets. By bootstrap sampling, n datasets are obtained, which in turn are trained to form a decision tree $\{h_1(X), h_2(X), \cdots, h_n(X)\}$, which constitutes a combinatorial classification modeling system, which determines the final outcome based on the principle of majority voting for its classification decision:

$$H(x) = \arg\max \sum_{i=1}^{k} I(h_i(x) = Y) \tag{1}$$

$H(x), h_i, Y$ represent the combined classification model built with n decision trees, individual decision trees within the set of models, and model output variables, respectively.

(1) Convergence, Strength and Association Coefficient of Random Forests

The original dataset (X,Y), from which the set of classifiers $\{h_1(x), h_2(x), ..., h_k(x)\}$ of the training set samples are made explicit, and the gap function formula is obtained as specified below:

$$mg(X,Y) = av_k I(h_k(X) = Y) - \max_{j \neq Y} av_k I(h_k(X) = j) \tag{2}$$

where $I(\cdot), av_k(\cdot)$ denote the bootstrap function, and the finding of the mean, respectively. The formula for averaging the difference between the number of judgmental votes and the maximum misclassification category gives an idea of the relatively higher number of modeled judgments compared to the level of the mean of the number of judgments, and the magnitude of the resulting value is directly proportional to the categorical confidence. The specific generalization error formulas are shown below:

$$PE^* = P_{X,Y}(mg(X,Y) < 0) \tag{3}$$

RF reduces the generalization error by adding decision trees until it stabilizes. This is one of the reasons why RF can avoid "overfitting".

The upper bound of the generalization error of RF is usually based on the correlation coefficients and strengths, where the classification strengths of individual decision trees and inter-decision tree relationships are positively and negatively correlated with the classification effectiveness of the model, respectively.

Define the interval function of RF:

$$mr(X,Y) = P_\theta[h(X,\theta) = Y] - \max_{j \neq Y} P_\theta[h(X,\theta) = j] \tag{4}$$

The set of classifiers $h(X,\theta)$ intensity s:

$$s = E_{X,Y}\, \mathrm{mr}(X,Y) \tag{5}$$

Chebyshev's inequality based on the condition that s is not less than 0:

$$PE^* \leq var(mr) / s^2 \tag{6}$$

Order:

$$\hat{j}(X,Y) = \arg\max_{j > Y} P_\theta[h(X,\theta) = j] \tag{7}$$

There are upper bound constraint equations for the mr variance:

$$\begin{aligned} mr(X,Y) &= P_\theta[h(X,\theta) = Y] - P_\theta[h(X,\theta) = \hat{j}(X,Y) \\ &= E_\theta\{I[h(X,\theta) = Y] - I[h(X,\theta) = \hat{j}(X,Y)]\} \end{aligned} \tag{8}$$

Define the meta-interval function:

$$rmg(\theta, X, Y) = I[h(X,\theta) = Y] - I[h(X,\theta) = \hat{j}(X,Y)] \tag{9}$$

The expectation of $rmg(O, X, Y)$ over θ is calculated to be the mr variance $mr(X,Y)$. The constant is found for all functions f:

$$\left[E_\theta f(\theta)\right]^2 = E_{\theta,\theta'} f(\theta) f(\theta') \tag{10}$$

where θ, θ' is independently and identically distributed, based on which the expression can be obtained:

$$mr(X,Y)^2 = E_{\theta,\theta'} rmg(\theta, X, Y) rmg(\theta', X, Y) \tag{11}$$

Derived:

$$\begin{aligned} \text{var}(mr) &= E_{\theta,\theta'}[\text{cov}_{X,Y}\, rmg(\theta, X, Y) rmg(\theta', X, Y)] \\ &= E_{\theta\theta'}[\rho(\theta,\theta') sd(\theta) sd(\theta')] \end{aligned} \tag{12}$$

Eqs. $\rho(\theta,\theta'), sd(\theta)$ and $sd(\theta')$ represent the correlation, standard deviation of $rmg(\theta, X, Y)$ and $rmg(\theta', X, Y)$, respectively, when θ, θ' is held constant as a precondition. Based on this it can be understood:

$$var(mr) = \bar{\rho}[E_\theta sd(\theta)]^2 \le \bar{\rho} E_\theta var(\theta) \tag{13}$$

where $\bar{\rho}$ denotes the mean value of the correlation coefficient ρ, which can be calculated by the following formula:

$$\bar{\rho} = E_{\theta,\theta'}[\rho(\theta,\theta') sd(\theta) sd(\theta')] / E_{\theta,\theta'}[sd(\theta) sd(\theta')] \tag{14}$$

can be obtained by substituting it into the above equation:

$$E_\theta \text{ var}(\theta) \le E_\theta [E_{X.Y} rmg(\theta, X, Y)]^2 - s^2 \le 1 - s^2 \tag{15}$$

The final upper bound on the generalization error is calculated as:

$$PE^* \le \bar{\rho}(1 - s^2)/s^2 \tag{16}$$

By observing the expression of the upper bound of the generalization error, it can be found that in order to further optimize the Random Forest algorithm and reduce the generalization error, it is necessary to start from two aspects: on the one hand, it is to improve the classification ability and accuracy of a single decision tree, and on the other hand, it is to reduce the correlation between the decision trees, which also indicates that the classification of the RF is more accurate compared with the Bagging algorithm.

(2) Random Forest Feature Selection

Compared with other classification algorithms, RF differs in its ability to measure variable importance, which is mainly realized in two ways: average Gini index reduction, precision reduction method, the latter is to add noise interference to any variable in the OOB set to get the RF classification accuracy reduction.

The method based on RF variable importance measurement first performs a descending order ranking of all variable importance. Then the weight of rejection is determined, features are removed and new features are created, the previous process is repeated, and the optimal set of features is selected using the OOB error rate as a criterion, which is used to complete the feature selection.

2.3.2. Random Forest-Based Tone Recognition

(1) Data Preprocessing

The specific process of pre-emphasis is usually filtered so that the input signal $x(n)$ passes through a high-pass filter when $0.9 \le a \le 1.0$, and the formula for the filter in the time domain is:

$$y(n) = x(n) - ax(n-1) \tag{17}$$

The formula in the frequency domain is:

$$H(z) = 1 - a * z^{-1} \tag{18}$$

After splitting the frames, it is necessary to add a window operation to each audio frame to facilitate the subsequent Fourier expansion to further analyze the audio. The time-domain signal is $x(n)$, the window function is $w(n)$, using the wear function to truncate the time-domain signal $x(n)$, we can get the N-point sequence $x(n)$, and we can get the expression:

$$x_n(n) = w(n)x(n) \tag{19}$$

By Fourier transform, this can be converted to an expression:

$$x_n(e^{jw}) = \frac{1}{2\pi}\int_{-\pi}^{\pi} X(e^{j\theta}) \cdot W(e^{j(w-\theta)})d\theta \tag{20}$$

In this paper, the audio signal is converted using a short-time Fourier transform. Through the audio signal preprocessing is more convenient for audio time-frequency domain conversion analysis.

The Meier filter consists of multiple triangular bandpass filters, which can perform certain smoothing operations on the spectral signal, reduce the impact of harmonics, and highlight the resonance peaks of the original speech. The center frequency of the triangular filter is shown in the following equation:

$$f(m) = \frac{N}{F_s} B^{-1}(B(f_1(m)) + m\frac{B(f_h(m)) - B(f_1(m))}{M+1}), m = 1, \ldots, M \tag{21}$$

where $f_h(m), f_1(m), B(f)$ are the upper limit frequency of the triangular filter m, the lower limit frequency of the triangular filter m and the Mel frequency, respectively. Meanwhile the conversion relation between $B(f)$ and the frequency Hz in Eq. can be obtained from Eq:

$$f_{Hz} = 700(e^{f_{mel}/1127} - 1) \tag{22}$$

The frequency response $H_m(k)$ of the triangular filter is:

$$H_m(k) = \left\{ \begin{array}{l} 0, k < f(m-1) \\ \dfrac{2(k - f(m-1))}{(f(m+1) - f(m-1))(f(m) - f(m-1))}, f(m-1) \le k \le f(m) \\ \dfrac{2(f(m+1) - k)}{(f(m+1) - f(m-1))(f(m+1) - f(m))}, f(m) \le k \le f(m+1) \\ 0, k > f(m+1) \end{array} \right\} \tag{23}$$

Eq. $H_m(k)$ is satisfied:

$$\sum_{m=0}^{M-1} H_m(k) = 1 \tag{24}$$

Taking the log logarithmic energy, the logarithmic energy of the m th Mel filter output is shown in the following equation:

$$S(m) = \ln\left(\sum_{k=0}^{N-1} E(k)H_m(k)\right) \tag{25}$$

where m denotes the number of Mel filters and corresponds to m logarithmic energy per frame after setting the number of m. After extracting the logarithmic energy of each frame, the final Mel sound spectrogram can be obtained by giving the cascade in the form of frames.

(2) RNRF algorithm

This paper mainly proposes an audio recognition algorithm based on residual network and random forest. The innovative residual network is introduced into the algorithmic process of audio recognition, taking advantage of the feature learning of the deep learning model. Feature extraction is performed on the Mel sound spectrogram of audio, and its extracted deep features are more representational. The combination of residual network and random forest further improves the accuracy of audio recognition, and the introduction of random forest mitigates the negative impact of overfitting.

Residual cell structure: In the residual cell structure, the connection from the input to the output on the right side is called a shortcut connection, and the mapping of this connection is a constant mapping. With such a connection, the formula in the forward propagation of the network is:

$$x_{i+1} = x_i + F(x_i, W_i) \tag{26}$$

$$x_{l+2} = x_{l+1} + F(x_{l+1}, W_{l+1}) = x_l + F(x_l, W_l) + F(x_{l+1}, W_{l+1}) \tag{27}$$

Then the forward propagation formula from the input of the l layer to the output of the L layer is:

$$x_L = x_l + \sum_{i=l}^{L} F(x_i, W_i) \tag{28}$$

The forward arithmetic process is a concatenated addition operation, while the traditional neural network is a concatenated multiplication operation, and the computation is obviously different.

The residual network effectively solves the problems of gradient vanishing and gradient explosion in the process of backpropagation. Specifically, the backpropagation formula for residual networks is shown in the following equation:

$$\frac{\partial E}{\partial x_l} = \frac{\partial E}{\partial x_L}\left(1 + \frac{\partial}{\partial x_l}\sum_{i=1}^{L-l} F(x_i, W_i)\right) \tag{29}$$

From the formula, it can be seen that the residual network only seeks the front part of the chain law when back propagating, i.e., the gradient from the L th layer can be passed to the lth layer backward process basically keeping stable. Based on this, the experiments in this chapter utilize the residual network model as a feature extractor for audio.

Random Forest is used as the final classifier of the model in the RNRF algorithm, which mainly aims to further alleviate the overfitting and improve the accuracy of audio recognition, and Random Forest is able to deal with high-dimensional features without the need of dimensionality reduction process.

Random Forest uses the self-sampling method to draw samples, according to the bootstrap algorithm, let the current dataset containing m samples, due to the fact that there is a put back to the sampling, the probability of drawing samples x in each round of sampling is m one part. That is:

$$\lim_{m\to\infty}\left(1 - \frac{1}{m}\right)^m \approx \frac{1}{e} \approx 0.368 \tag{30}$$

The generalization error formula for random forest is shown by the following equation:

$$error \le \frac{\overline{p}(1 - s^2)}{s^2} \tag{31}$$

where error is the generalization error of the random forest, $\overline{p}$ is the average correlation coefficient between the trees, and s is a measure of the strength of the tree classifier, and the model performance is measured by a probabilistic algorithmic measure formulated as:

$$M(X,Y) = P(\overline{Y}_\theta = Y) - \max(\overline{Y}_\theta = Z) \tag{32}$$

where $\overline{Y}_\theta$ is the prediction category of the classifier, the larger $M(X,Y)$, the greater the probability that the classifier's prediction is correct, as shown by Eq. As $\overline{p}$ increases, the upper bound of the generalization error increases. As a result, the randomization of the random forest helps to reduce the correlation $\overline{p}$ between the trees, thus improving the generalization error of the model.

2.4. Suona Music Database System Design

2.4.1. Database Technology

This system as a music database system must use a database to manage music resource data, the more commonly used mainstream databases are My SQL and Oracle.

A comparison of the two database technologies is shown in Table 1. According to the above comparison, My SQL database is easier and more convenient in database management and data recovery, its database connection speed is faster, in addition, it occupies less resources and requires less hardware. Combined with the needs of this system in terms of database management, My SQL is adopted as the system database.

Table 1. Different database techniques.

	Oracle database	My SQL database
Database management	Management is complex and requires higher management technology	Simple management and low management requirements
Data recovery cost	Because a lot of data is stored in memoryIt's a high	Easy to recover and lower cost
Database connection	Slow	Fast speed
Hardware requirements	More resources, high requirements for hardware	Less resources, low requirements for hardware
Safety	High safety	Low safety

2.4.2. Functional Modules

The functional module framework of the digital timbre feature library for suona music is shown in Figure 1.

Derived from the functional module framework diagram, this system is divided into two subsystems, which are the portal subsystem and the background management subsystem. A large number of music resources as well as the corresponding public data element standards for music data elements serve as the basis for resource management, which provides a basic guarantee for other functional applications of the system.

The portal subsystem is the interactive interface between the music database system and the users, and it is the window to show the system services to the users. The portal subsystem not only provides users with an entrance to retrieve music resource data in an all-round way, but also displays various music resources in a good way.

The functional modules of the portal subsystem are divided into two main modules: the user information module and the all-round retrieval module. The user information module consists of two sub-modules, namely: registration, login module and account management module. The omni-directional retrieval module is the core module of the portal subsystem, responsible for the omni-directional retrieval of all system resources and resource information viewing functions. According to user requirements, the omni-directional search module contains four sub-modules, namely: resource global search module, resource advanced search module, resource single category query module and detailed information browsing module.

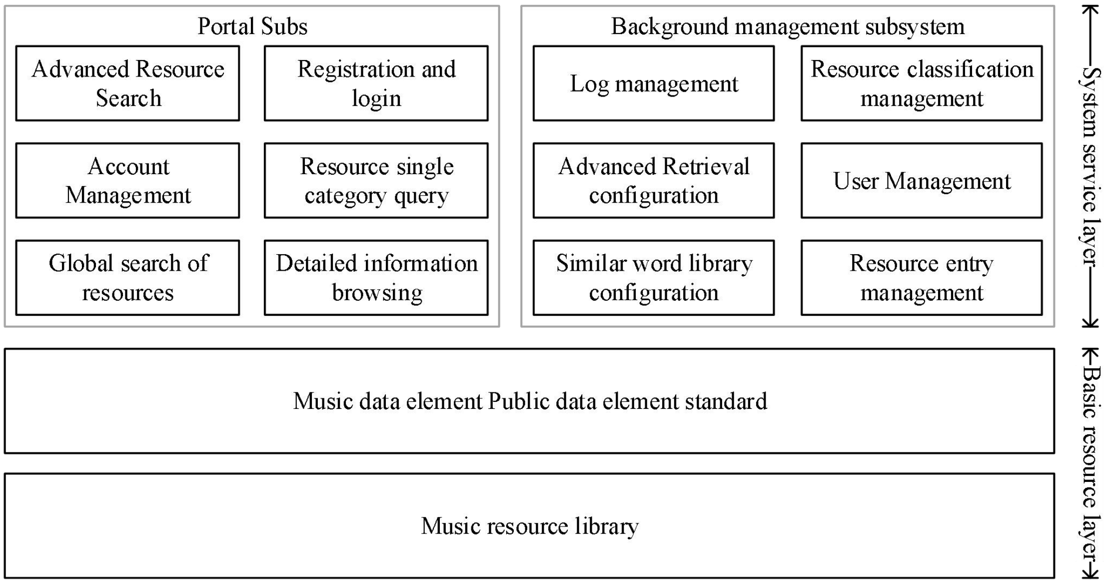


Figure 1. The functional framework of the digital phoneme library of the suona music.

3. Digital Display Design Experience of Suona Music

3.1. Random Forest Algorithm Based Suona Timbre Recognition

The experiments were performed using 6 hours of audio clips of suona performances. The data is about 782M, and the full dataset has nearly 18020 sound symbols. This training set meets as many different musical features as possible, and with a sampling rate of 56.74kHz and 18-bit quantization, 8 bass segments are filtered out to obtain the test sample set, which has a total of 84 humming segments, including 1206 sound symbols.

Then, the vocal note data were preprocessed so as to eliminate the Gaussian noise as well as to normalize them, and a comparison of the effect of the audio signal data set before and after preprocessing is shown in Fig. 2, with Figs. (a) and (b) before and after normalization, respectively.

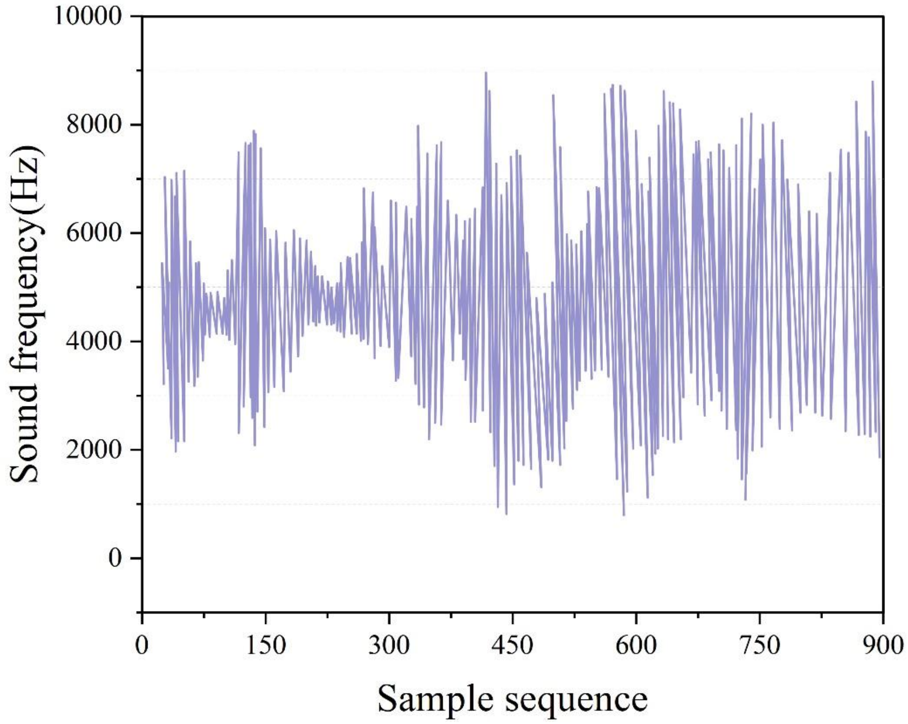
After the pre-processing of the acoustic frequency, the method not only removes the industrial frequency noise in the acoustic frequency, but also removes the Gaussian white noise, so as to make it close to the non-interference state, and accordingly selects a model applicable to the fundamental frequency characteristics of a large number of acoustic symbols, and reduces the influence of noise on the interference of the fundamental frequency by the fundamental frequency identification of the filtered frequency domain, thus improving the recognition accuracy.

Here, the changes in model error accuracy before and after preprocessing are investigated, and the comparison of the mean square error between the pre-preprocessing model and the post-preprocessing model in the test set is shown in Fig. 3. Figures (a) and (b) are before and after preprocessing, respectively.

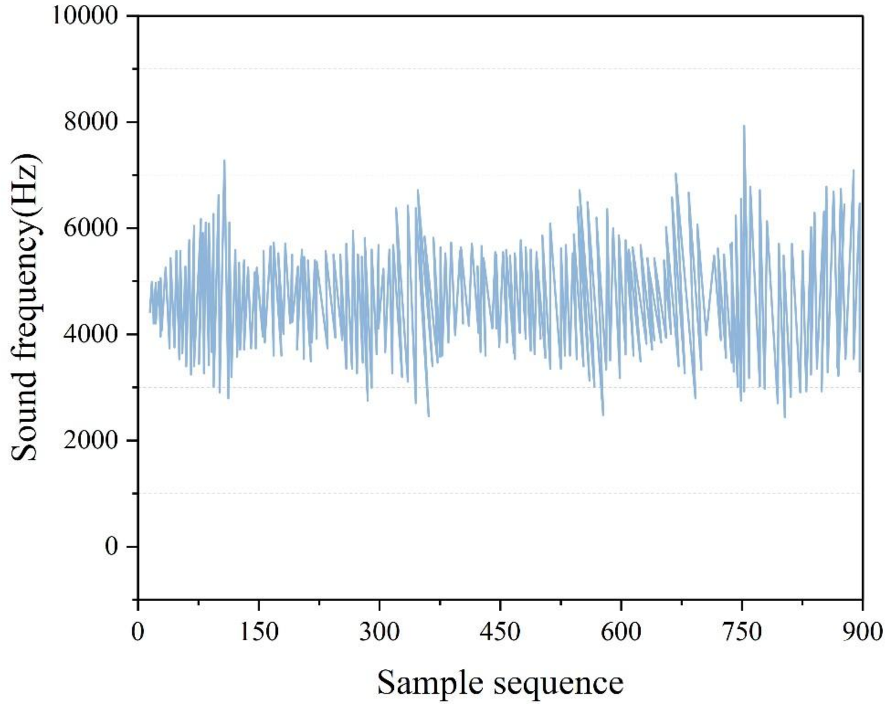
Among them, Fig. (a) shows the MSE change of the pre-preprocessing model of the data with the increase in the number of iterations. The pre-preprocessing model reaches the target MSE when it is iterated up to 80 times, which is also the best value of the pre-preprocessing model in 80 iterations.

Figure (b) shows the variation of MSE with increasing number of iterations for the preprocessed model. In the same 80 iterations, the data preprocessed converges at 10 iterations and reaches the target MSE value. And the data preprocessed model reaches the optimal MSE value of 1.31×10^{-12} at 12 iterations, which is much smaller than the optimal MSE value of the preprocessed model in 80 iterations.

In addition, the convergence speed of the preprocessed model is 80% higher than that of the preprocessed model, indicating that the model with data preprocessing not only improves the prediction accuracy of the model, but also improves the convergence speed of the algorithmic model.

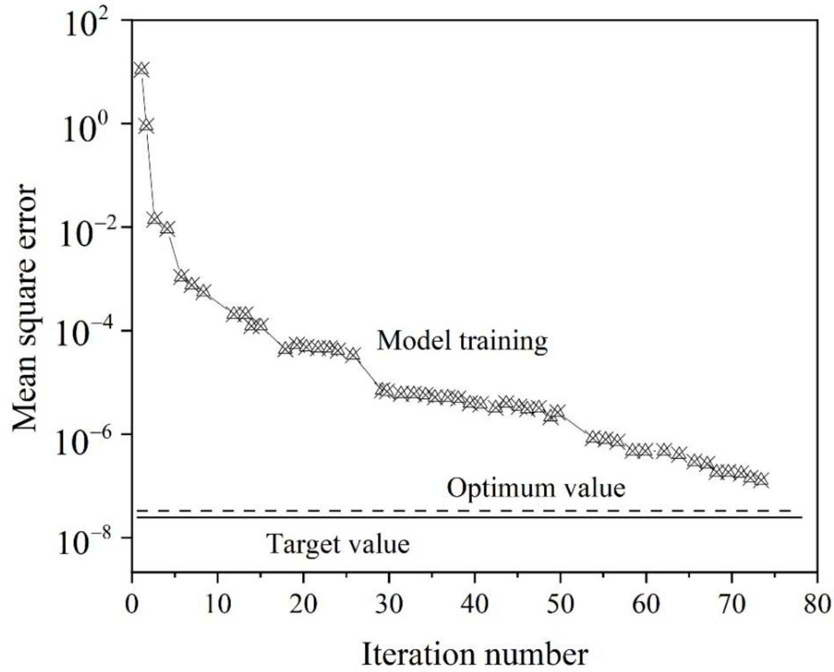


(a) Before normalization

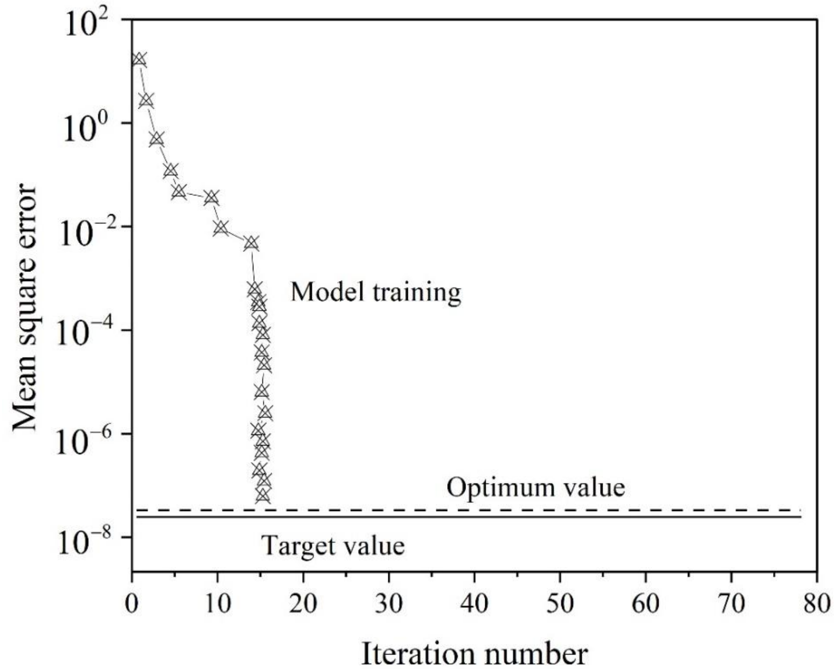


(b) normalized

Figure 2. Contrast of audio signal data sets before and after preprocessing.



(a) preprocessing



(b) After preprocessing

Figure 3. Comparison of training results.

In order to compare the oboe tone recognition accuracy of the RNRF algorithm constructed by the study in different parameter sets, this paper compares it with Adaptive Boost algorithm (Ada Boost), Plain Bayesian (NBC) algorithm, Support Vector Machine (SVM), and Back Propagation Neural Network (BPNN), and the results of the comparison are shown in Figure 4.

From the seven parameter sets of tone recognition accuracy, it can be seen that the recognition rate of the RF algorithm proposed by the study within each set is the highest value compared to the other algorithms, and the accuracy of tone recognition reaches more than 400 in all cases. This shows that the random forest algorithm proposed in this paper has the highest recognition rate.

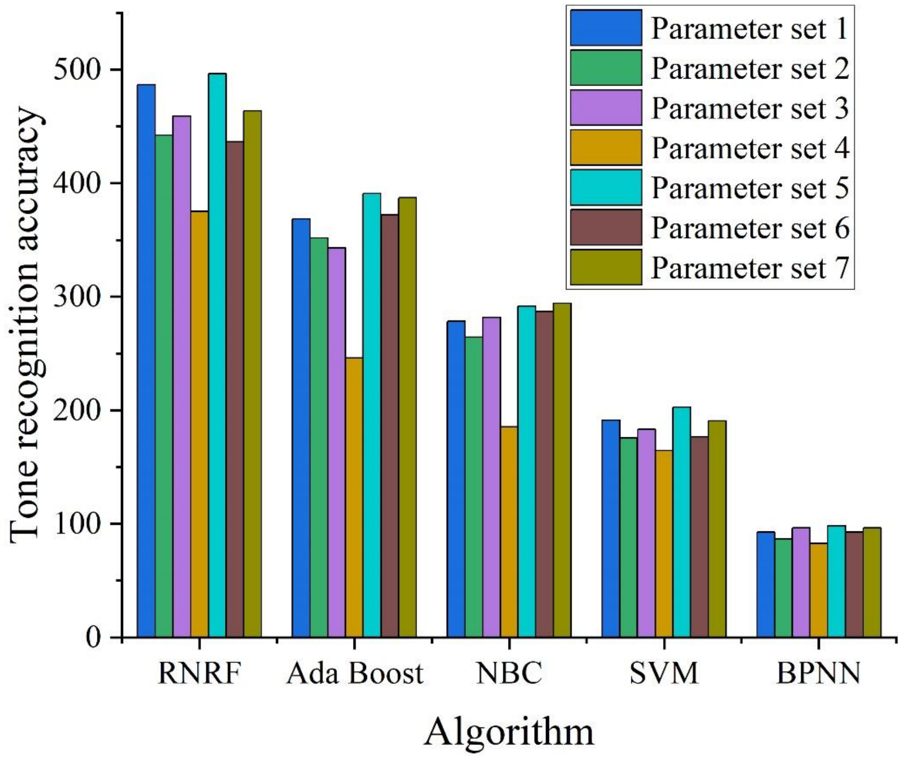


Figure 4. Comparison result.

In order to facilitate the description, the study arranges the collected sound note fragments in order, which are A, C, B and D. The base frequency identification of the base frequency spectrum is performed by adaptive filtering, base frequency feature identification and the method proposed by the study (RNRF), and the recognition effects of the three methods are compared, and the comparative results are shown in Table 2, where ①, ② and ③ represent the elimination of errors/%, insertion of errors/%, and the correct rate/%, respectively.

The combination can be seen that in the four suona timbre segments, the elimination error ability and correct recognition rate of the acoustic character fundamental frequency feature method are the lowest, followed by the filter method.The elimination error ability, insertion error rate and correct recognition rate of RNRF are the best values, and the mean values of the elimination error ability, insertion error rate and correct recognition rate are 55.86%, 1.27% and 96.11%, respectively.

This shows that the RNRF algorithm is better than the other two methods in terms of insertion error and insertion error, as well as elimination error and correct recognition, and is more accurate.

Table 2. Comparison result.

Suona tone classification	The results of different methods for the recognition of the suona tone								
	Filter method			Phonon frequency characteristic method			RNRF		
	①	②	③	①	②	③	①	②	③
A	40.52	3.01	90.24	34.21	1.96	86.75	62.21	1.21	96.24
B	37.19	4.57	87.36	30.76	1.82	82.31	57.68	1.03	95.03
C	35.05	4.82	85.16	33.14	2.35	84.96	53.14	1.54	97.49
D	37.21	3.66	90.03	36.87	2.13	89.34	50.39	1.29	95.66

The comparison of the effectiveness of the four algorithms in evaluating the indicator models is shown in Figure 5.

From the figure, it can be seen that the values of RNRF algorithm on all three evaluation metrics are less than the other three models. From the error values of the specific prediction models in the figure, it can be calculated that on the MSE evaluation metrics the RNRF model reduces 1.86%, 0.27%, and 1.09% compared to SVM, AdaBoost, and BPNN, respectively. In RMSE evaluation indexes are reduced by 4.74%, 2.06% and 5.11% respectively. 10.39%, 1.74%, and 5.11% reduction in MAE evaluation metrics, respectively. Because the smaller the value of the model evaluation index, the better the model prediction.

So as a whole, BPNN model has the worst prediction effect, RNN model has moderate prediction effect, AdaBoost model has better prediction effect and RNRF algorithm has the best prediction effect.

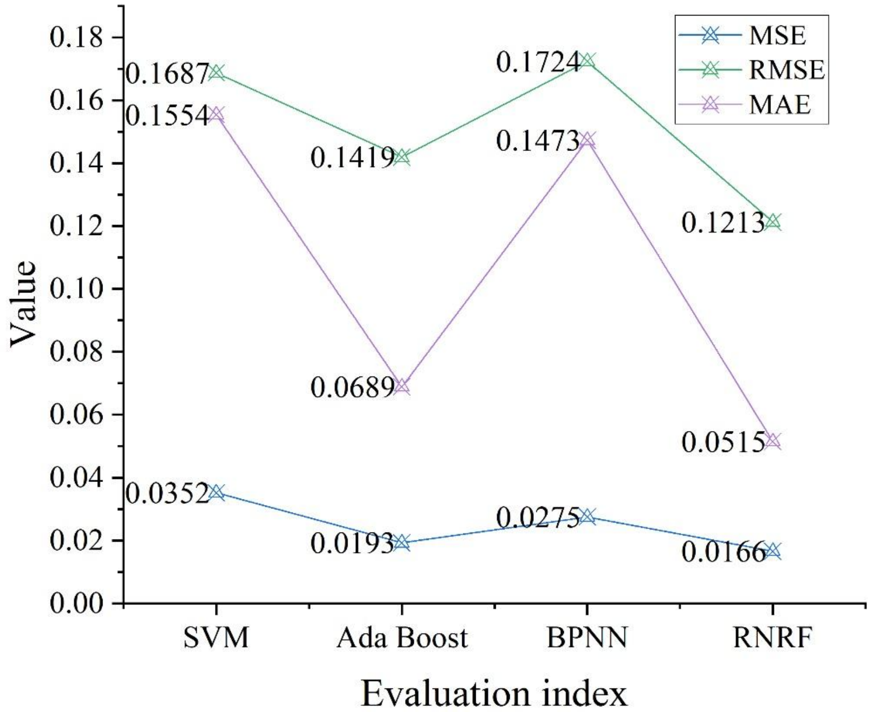


Figure 5. The four algorithms evaluate the effect of the index model.

3.2. The Use of the Suona Music Timbre Feature Library

The fundamental of the non-heritage exhibition space is to create excellent "interpretation" space environment for the content and exhibits of non-heritage, and the essence of its exhibition experience design is to convey information, using various information carriers as a means. Display space is also one of the forms of expression of non-legacy space-time art.

The suona instrument display is combined with interactive technology for display. This two-way display mainly hopes that the audience can understand the real form, type, usage of the instrument in the evolution of suona musical instruments, as well as the tone of the instrument, the way of playing, production techniques and other information. In the design of the display of musical instruments, it is necessary to interpret the playing techniques and production techniques of the instruments. Among the many digital technologies, it is necessary to integrate the sound, visual performance, and cultural story of musical instruments into one, and here we chose a multi-point high-definition interactive screen to combine with the exhibits for progressive display.

The interface of the interactive screen displays all types of suona instruments, while the lower part of the interactive screen is equipped with multiple headphones that can be used by more than one person at a time, making it easy for the audience to listen to the sound and interpretation of the suona instruments. Next to the screen are clickable interactive demonstrations of timbre, instrument performance and production techniques, which can be viewed by clicking on each of them. Through visual demonstrations and auditory experiences, the charm of suona instruments in historical activities is comprehensively demonstrated. In the visual, auditory and interactive experience to make up for the audience in the process of visiting the information communication is not comprehensive due to the information fault experience.

In order to further understand the experience of using the digital display design of suona musical instruments, a survey was conducted on the respondents' experience. The questionnaire survey was distributed in two forms, one is the field distribution of the questionnaire, after the field observation and research, the audience was randomly selected to fill in the questionnaire. Due to the limited sample size of the field questionnaire, it is not enough to analyze the audience's more in-depth demands, so we chose to issue the questionnaire in the form of network questionnaires, where the questionnaires firstly require the respondents to answer whether they have "experienced the design of the digital display of the non-heritage musical instruments", and if they have visited the exhibition, we will continue to answer the questions in depth, and if they haven't visited the exhibition, then we will ask them the reasons and expectations for this kind of exhibition. If they have visited the exhibition, they will continue to answer the question in depth. In the end, 328 valid questionnaires were obtained.

Respondents' scores on the various dimensions of the digital display design of non-heritage are shown in Table 3.

From the respondent group's scoring of the final gain from visiting the digital display design of non-legacy suona instruments, it seems that the public's demand for the digital display and inheritance of non-legacy suona music is very comprehensive, and they hope to gain something relatively from the sensory, emotional, thinking, aesthetic and entertainment aspects. The average score of respondents' experience of digital display design of non-legacy suona music was 4.30. Respondents' acceptance of digital design of non-legacy suona musical instruments is high, which contributes to the effective inheritance of non-legacy cultures, including the suona.

Table 3. The respondents rated the design of non-reprinted digital display (N = 328).

Topic	1	2	3	4	5	Mean
Senses	10	15	43	102	158	4.25
Affections	7	22	55	83	161	4.34
Interacts	9	21	86	105	107	4.19
Thinking	23	45	70	121	69	4.06
Aesthetic	3	9	51	159	106	4.45
Entertainment	5	6	23	143	151	4.51
Total	57	118	328	713	752	4.30

4. Conclusion

In this paper, we design and construct a digital timbre library of suona music, propose a suona timbre recognition method by combining residual network and random forest model, and store the recognized data of suona music to form a database. Analyze the feasibility of suona timbre recognition method based on random forest model and investigate the digital display design of suona music timbre library.

By comparing the recognition accuracy of suona timbre recognition method combining residual network and random forest model with different algorithms, the method proposed in this paper is optimal in the three dimensions of error elimination ability, insertion error rate and correct recognition rate, and the correct recognition rate can reach 96.11%. The algorithm proposed in this paper can more accurately identify suona timbre and promote the establishment of suona timbre feature library.

The suona music database is digitized for display design, using interactive forms to allow the audience to participate in experiencing the uniqueness of suona music and timbre. In the survey, the average value of the respondents' rating of the digital display design of suona music feature library is 4.30, which indicates that the digital display design of suona music and timbre is recognized by the market, and it can help to disseminate the suona and other non-heritage cultures.

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