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Transformation and Practice of Traditional Music Teaching Methods in Higher Music Education in the Digital Environment

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SUMMARY: *This paper focuses on the field of higher music education, designing a digital classroom teaching system comprising three core modules: piano simulation, score editing, and performance demonstration. By incorporating MIDI audio technology, it details the system architecture and API functions, providing teachers and students with powerful tools for digital music composition and performance. Furthermore, it innovatively constructs a membership function model based on an A-V two-dimensional emotional coordinate system, enabling the quantitative recognition and intelligent classification of diverse musical emotions. To validate the effectiveness of the emotion retrieval model, this study constructed an experimental corpus comprising 17,834 songs and 102 emotion tags sourced from Apple Music. The results show that the membership function model proposed in this paper is significantly better than the mainstream algorithm in two key indicators, P@N and NDCG@N, with the highest P@N value reaching 0.892 in the Top40 results and NDCG@N 0.878 in the Top5 results, which proves its superiority in retrieval accuracy and sorting quality. Finally, an application survey conducted among 104 vocal music students at a university revealed that over 75% of students favored and endorsed the digital teaching model centered on this technology. Among the 8 professional instructors, 75% observed significant improvements in students' creative abilities and learning motivation. This research not only achieved the digital transformation of traditional music teaching methods through its technical architecture but also demonstrated its technological advancement and pedagogical practicality through authentic experimental data and application surveys.*

KEYWORDS: *Higher Music Education; Music Teaching System; MIDI Audio; Music Emotion Retrieval*

1 Introduction

Over the past forty years of reform and opening up, China has risen to become the world's second-largest economy. Its journey toward cultural rejuvenation has also taken increasingly confident strides, with traditional music programs flourishing on social media platforms. Traditional music stands as a magnificent treasure of Chinese culture and serves as a vital means for fostering cultural confidence. Higher music education, as a cornerstone for cultivating professionals with specialized musical expertise, shoulders the mission of preserving China's traditional musical heritage [1-4].

Currently, music programs offered by various general higher education institutions constitute the primary form of music education. Music majors generally possess solid theoretical foundations and fundamental performance skills, forming the reserve force of

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China's musical talent. The music education they receive plays a pivotal role in preserving traditional music [5-8]. Although traditional music art forms have always been a core component of higher music education and remain popular among faculty and students in music programs, traditional teaching methods severely hinder improvements in educational quality [9-11].

Traditional teaching methods primarily emphasize the instructor's classroom delivery of musical knowledge through lectures and demonstration performances. All teaching objectives and content are determined by the instructor, resulting in a singular approach and a monotonous teaching process that fails to meet contemporary educational demands [12-15]. This necessitates a transformation in teaching methodologies, and the advancement of digital technology presents an opportunity for such change [16, 17]. Within a digital environment, multi-computer and multimedia technologies can be leveraged to conduct diverse instructional activities, enriching traditional music curricula and diversifying teaching formats [18-20]. Digital teaching methods more effectively enhance students' autonomous learning capabilities. Educators can adjust learning pacing according to individual student progress, significantly improving traditional music instruction outcomes while simultaneously alleviating teaching burdens [21-23].

This paper systematically outlines specific pathways for deeply integrating traditional teaching methods with modern technology in higher music education. Centered on the technical architecture and implementation of a digital music teaching system, it constructs a comprehensive technical support framework through three dimensions: system design, MIDI technology application, and musical emotion retrieval. First, it focuses on the overall architecture of the digital music classroom teaching system. Through functional structure design and module division, it clarifies the functions and interaction logic of three core modules: piano simulation, score editing, and performance demonstration. This provides an intuitive and operable technical platform for classroom instruction. Subsequently, it introduces MIDI audio technology, detailing the composition and common functions of computer music performance systems. This provides teachers and students with powerful tools for music composition and performance, enhancing the interactivity and creativity of teaching. Finally, the musical emotion retrieval model is designed based on the membership function, and the emotional states such as "happiness", "anxiety", "sadness" and "calm" are mathematically modeled and quantitatively identified by constructing the membership functions of A and V variables respectively through the quantification of A-V two-dimensional emotional coordinates, and the intelligent identification and classification of musical emotional states are realized through multi-factor comprehensive membership functions.

2 Technical Architecture and Implementation of a Digital Music Teaching System

2.1 Design of a Digital Music Classroom Teaching System

Given that the digital music classroom teaching system involves multiple modules encompassing diverse functions, this paper conducts an overall system design to ensure seamless coordination among modules. This design balances system stability and scalability while preserving comprehensive functionality, comprising two key components: functional structure design and functional module design.

2.1.1 Overall Functional Structure Design

Based on the practical requirements of the digital music classroom teaching system, this paper delineates the system's overall functional components. These primarily encompass three modules: the simulated piano template (including piano display control, piano performance, and piano sound processing), the music notation editing module (including editing initialization, score editing, and score display), and the music notation demonstration module (score playback control, score display control, and demonstration sound processing). The overall functional structure design of the system is illustrated in Figure 1.

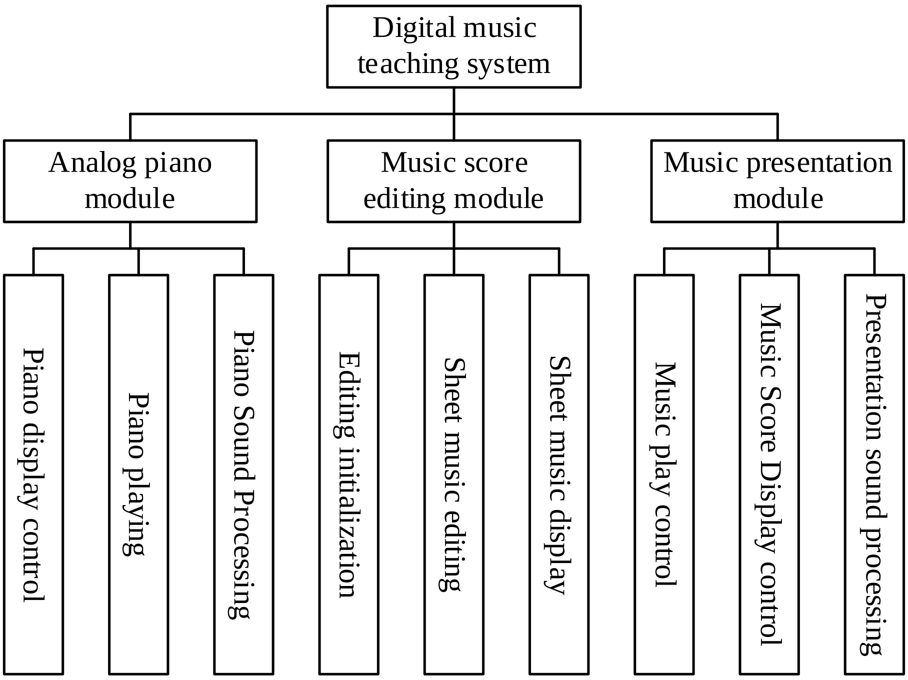

Figure 1: Overall design of the system's functional structure

2.1.2 Overall Functional Module Design

The three functional modules of the overall functional structure design are as follows: The Piano Playing Module must implement basic functions such as piano zoom, piano key panning, and piano playing. The Score Editing Module must implement fundamental functions including opening or creating scores, editing and previewing scores, and saving scores. The Score Demonstration Module must implement. The functional point designs for each module are shown in Figures 2 to 4.

(1) Piano Playing Module

The functionalities of the piano playing module are illustrated in Figure 2.

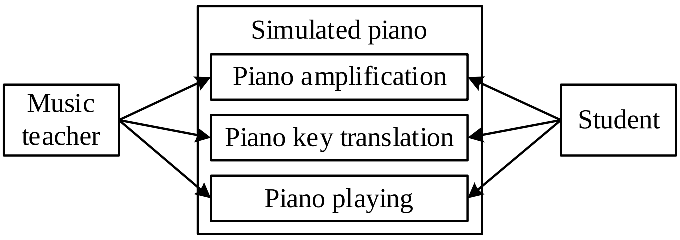

Figure 2: Function diagram of the piano playing module

(2) Music Score Editor Module

The functionality of the Music Score Editor Module is shown in Figure 3.

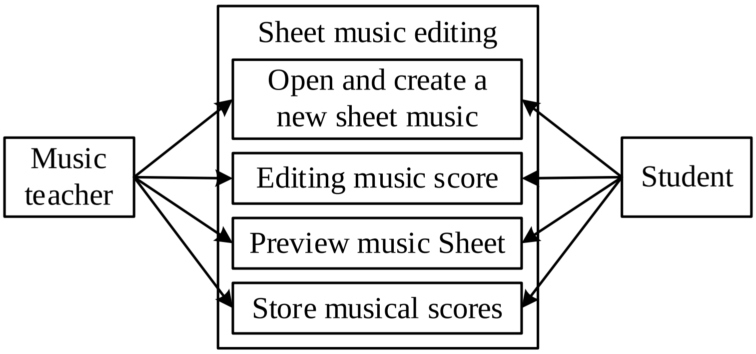

Figure 3: Function diagram of the music score editing module

(3) Sheet Music Demonstration Module

In music classroom instruction, playback demonstrations form a core component. During sheet music learning, playing corresponding scores for students not only promotes teacher-student interaction but also deepens students' understanding of the music. To enhance system integration with classroom teaching and ensure optimal playback quality, this system adapts to practical music instruction scenarios by expanding playback demonstration methods. These include single/multi-track playback, multi-instrument selection playback, transposed playback, and playback of specific measures. Special processing techniques guarantee high-quality playback outcomes.

The score demonstration module functions are illustrated in Figure 4.

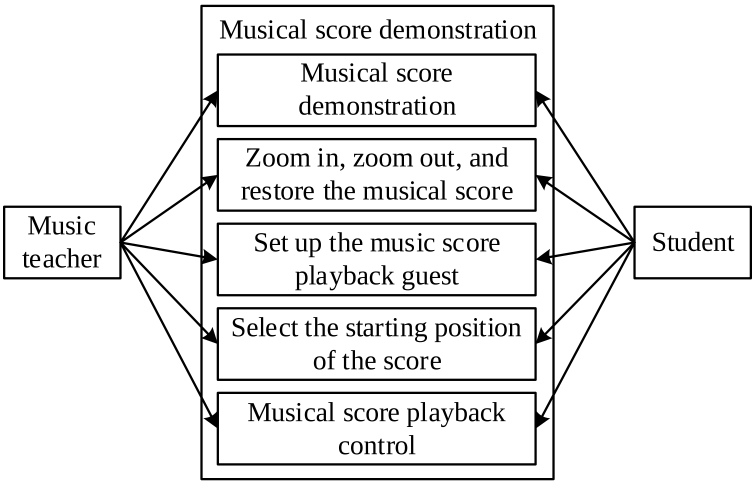

Figure 4: Functional diagram of the sheet music demonstration module

2.2 MIDI Audio Technology

After completing the functional structure and module design of the digital music classroom teaching system, this paper introduces MIDI audio technology as the core technical foundation to further enhance the system's music processing and performance capabilities. This section systematically outlines the composition of the MIDI system and its commonly used functions, providing the underlying technical support for achieving high-quality music input, editing, and output.

2.2.1 Computer Music Performance System

Computer music systems utilize a computer as the host, connecting external devices such as sound modules, music input systems, and effects processors via digital interfaces (MIDI) to enable music composition, production, and performance. Whether employing a computer or sequencer as the host, these systems are commonly referred to as MIDI systems due to their typical MIDI connectivity. Internationally, music created using computer music systems is collectively termed electronic music.

A computer music performance system consists of the following fundamental components:

(1) The music computer, which can be a dedicated sequencer or a personal computer (PC), serves as the central hub and brain of the MIDI system. Some PCs with robust music capabilities can function directly as sequencers, while others require an additional sound card (hardware).

Using a computer instead of a sequencer offers advantages such as greater storage capacity, more tracks, the ability to print sheet music, and larger screen displays, while retaining the computer's original functionalities. Music input methods for the computer are diverse, including keyboard input via synthesizers, computer keyboards, and even tape or floppy disk inputs.

(2) The sound source serves as the audio output for producing music within a computer music system, for real-time performance, and for outputting pre-produced music. Sound sources can be dedicated “sound modules”—such as drum machines, keyboard synthesizers, or digital pianos—which are synthesizers without keyboards.

For a keyboard synthesizer, while composing music, it can be freely modulated to produce various timbres. However, during playback, it can only function as one or two instruments (some synthesizers can divide the entire keyboard range into several timbre zones for separate control). Consequently, there was a period when achieving multi-instrument effects required purchasing numerous synthesizers. Later, multi-track sound sources were condensed into compact units without keyboards—sound modules. These not only function during music creation but also play back as multiple (typically at least eight) independent synthesizers during playback, effectively serving as a band of instruments with diverse timbres.

Digital pianos have gained increasing prominence in recent years due to their superior tone quality and diverse functionalities, such as transposition, auto-play, and composition. Their touch sensitivity and feel now closely resemble those of traditional pianos. Drum machines, or rhythm generators, are sound sources capable of producing various percussion or non-musical tones. They allow users to freely edit rhythms and patterns. However, since drum machines are now often integrated as a single sound channel within synthesizers, dedicated drum machines are gradually declining in popularity.

(3) Effects processors are accessories that manipulate audio signals to create artificial delays, reverbs, pre-delays, echo effects, chorus effects, pitch-shifting effects, and more.

(4) The audio output section includes the mixer, power amplifier, and speaker output. Mixers blend music recorded on various tracks while applying modulation processing and can also feed into multitrack recorders.

(5) MIDI cables: Dedicated MIDI cables connect components within the effects and audio output sections via MIDI ports.

The schematic diagram of this computer music performance system is shown in Figure 5:

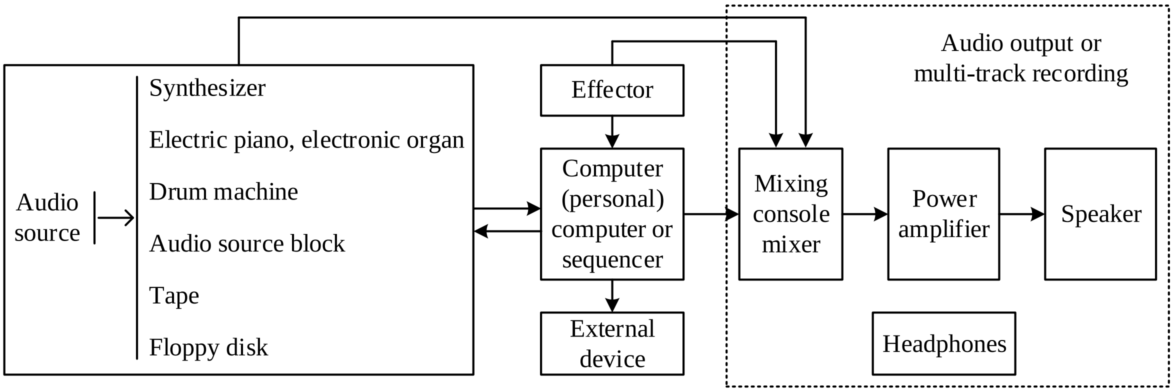

Figure 5: Computer music Performance System

2.2.2 Common MIDI Functions

Use MIDIAPI we can write a powerful electronic music program, here is an introduction to some common functions of MIDIAPI.

(1) midiOutGetDevCapS function is used to get the device description, which lpMidiOutCaps parameter for the device description structure;

(2) midiOutGetNumDevs function is used to detect waveform devices and MIDI devices, if the value of the function is 1 indicates that the computer detected a waveform device or MIDI device, usually the function is also commonly used and waveOutGetDevCaps () function to detect the computer whether or not the sound card;

(3) midiOutOpen function is used to open a device;

(4) midiOutClose function is used to close the device has been opened, the parameter hmo midiOutOpen function to obtain the Iphmo parameter;

(5) midiOutShortMsg function is used to play a specific sound, hMidiOut for the device number, dwMsg for the sound to be emitted. dwMsg function is also a 32-bit MIDI sound composition structure.

With MIDI audio technology, teachers and students will be able to compose their own music files. Through the study of this technology, the technology can be integrated in the song digital teaching aid system to provide teachers and students with a quick platform for song composition.

2.3 Digital music emotion retrieval method - affiliation function design

On the basis of mastering the MIDI technology, in order to further expand the system's capability in music emotion understanding and teaching personalization, this section will focus on the design of digital music emotion retrieval method, through the construction of the affiliation function model, to achieve the quantitative analysis and intelligent identification of the music emotion state, so as to provide possibilities for the accurate matching of the teaching content and emotional teaching.

In order to fit better with the fuzzy mathematics processing method, the AV model can be regarded as a two-dimensional plane coordinate axis. The horizontal coordinate Valence is abbreviated as V, the variable name is denoted as v, and the range from left to right is [-0.32, 0.32]; the vertical coordinate Activation is abbreviated as A, the variable name is denoted as a, and the range of values from bottom to top is [-0.27, 0.27] in order.

2.3.1 Affiliation functions for A variables

When the emotion is quite uplifting, such as "excited", the value of A is close to 0.27, while when the emotion is generally pleasant, the value of A is around 0.1. When people's emotional preferences are in the emotions of fear, anger, and nervousness, the value of A ranges from 0.25 to 0.14, or around 0.04. When in sadness, A takes values mainly in the region of -0.04-0.21. When the value of A is between -0.22 and -0.18, the emotional state is determined to be “calm”.

First of all, the affiliation function for the emotion “happy” is determined and denoted as Al. From the above, it can be determined that the fuzzy set “happy” corresponds to the domain [-0.27, 0.27]. Words with similar meanings to “happy” are almost concentrated in a certain range of segments, so it is determined that the overall structure of the affiliation function A11 should be intermediate. Next, the regions with an affiliation degree of 1 and 0 are identified. A region with an affiliation degree of 1 means that when the value of A of a certain song falls into this region, then the degree of affiliation of the emotion of this piece of music belongs to “happy” is 1. Similarly, a region with an affiliation degree of 0 means that when the value of A of a certain song falls into this region, then the degree of affiliation of this piece of music belongs to “happy” is 0. "Therefore, the domain of affiliation degree 1 is determined as (0.14, 0.07); the domain of affiliation degree 0 is [-0.27, 0.02). Then the transition zone is determined. By transition zone, we mean that it is difficult to say whether the emotion of the music is “happy” or not when the value of A falls into this region, and the transition zone domain of A11 is (0.02, 0.07) ∪ (0.14, 0.27). Since the relationship between A and people's emotional preferences is “inverted U-shaped”, the shape of the transition band should be a nonlinear up-convex transition. Finally, the functional form of the original A1 can be derived as A1', i.e., equation (1).

$$A1=\begin{cases}0,-0.27\le a<0.07\\ 2[(a-0.07)/0.02]^2,0.07\le a<0.08\\ 1-2[(a-0.09)/0.02]^2,0.08\le a<0.09\\ 1,0.09\le a<0.13\\ 1-2[(a-0.13)/0.04]^2,0.13\le a<0.15\\ 2[(a-0.17)/0.04]^2,0.15\le a<0.17\\ 0,0.17\le a<0.24\\ 1,0.24\le a\le 0.27\end{cases}\tag{1}$$

In order to follow up in the same level range to discuss the A variable and V variable in determining the weight of the affiliation need to ensure the consistency of the A variable and V variable in the range of values, it is necessary to change the range of values of A from [-0.27, 0.27] to [-0.32, 0.32], then the corresponding affiliation function should be transformed, that is, multiply each value of the value of the zero-boundary point of the value of the multiplication 32/27, and ultimately can be get the function of A1 as equation (2).

$$A1=\begin{cases}0,-0.32\le a<0.09\\ 2[(a-0.09)/0.02]^2,0.09\le a<0.10\\ 1-2[(a-0.11)/0.02]^2,0.10\le a<0.11\\ 1,0.11\le a<0.17\\ 1-2[(a-0.17)/0.05]^2,0.17\le a<0.19\\ 2[(a-0.22)/0.05]^2,0.19\le a<0.22\\ 0,0.22\le a<0.30\\ 1,0.30\le a\le 0.32\end{cases}\tag{2}$$

A similar method can be used to obtain the affiliation function A2 with emotion "anxiety", as in Eq. (3), the affiliation function A3 with emotion "sadness" as equation (4), and the affiliation function A4 with emotion as "calm", as eff. (5).

$$A2 = \begin{cases} 0, -0.32 \le a < 0.08 \\ 2[(a+0.08)/0.12]^2, -0.08 \le a < 0.02 \\ 1-2[(a-0.004),12]^2, -0.02 \le a < 0.04 \\ 1-02[a < a < 0.10 \\ 0, 0.01 \le a < 0.17 \\ 2[(a-0.17)/0.05]^2, 0.17 \le a < 0.19 \\ 1-2[(a-0.22)/0.05]^2, 0.19 \le a < 0.22 \\ 1, 0.22 \le a < 0.30 \\ 0, 0.30 \le a \le 0.32 \end{cases} \tag{3}$$

$$A3 = \begin{cases} 0, -0.32 \le a < -0.20 \\ 2[(a+0.20)/0.07]^2, -0.20 \le a < 0.17 \\ 1-2[(a+0.13)/0.07]^2, -0.17 \le a < 0.13 \\ 1, -0.13 \le a < -0.08 \\ 1-2[(a+0.08)/0.12]^2, -0.08 \le a < 0.02 \\ 2[(a-0.04)/0.12]^2, -0.02 \le a < 0.04 \\ 0, 0.04 \le a \le 0.32 \end{cases} \tag{4}$$

$$A4 = \begin{cases} 1, -0.32 \le a < -0.22 \\ 1-2[(a+0.22)/0.09]^2, -0.22 \le a < -0.18 \\ 2[(a+0.13)/0.09]^2, -0.18 \le a < -0.13 \\ 0, -0.13 \le a \le 0.32 \end{cases} \tag{5}$$

2.3.2 Affiliation functions for V variables

The V variable is linearly related to people's emotional preference P. When the value of V is small to large, the order of emotional state is sadness, anger, calmness, and happiness, and there are four fuzzy sets of V variable: happy, anxiety, sadness, and calmness, which are labeled as V1, V2, V3, and V4 in the order of their affiliation functions, and the range of the value of V is [-0.32, 0.32]. As with A, when the value of V is above 0.09, the emotion “happy” is more obvious as the value of V becomes larger. When V is around 0.1, the emotion tends to be calmer. When V is between -0.16 and -0.05, the emotions “nervousness, anger, and anxiety” are more likely to occur. When V is less than -0.16, the emotion “sadness” becomes more pronounced as V becomes smaller.

In determining the specific form of the four affiliation functions for the V variables, the same steps were taken as above for the A variables to determine the overall structure of the function. It can be roughly determined that V1 is a large function, i.e., above the value of 0.17, there will be “happy” or emotions similar to happy. Then, the domains with affiliations of 0 and 1 are identified. The domain of affiliation 0 is [-0.32, 0.09), and the domain of affiliation 1 is (0.19, 0.32). The range of the transition zone is [0.09, 0.19]. And the shape of the transition band is linear. So finally, the affiliation function of trapezoidal distribution is chosen and the function A21 is derived as shown in equation (6).

$$V1=\begin{cases}0,-0.32\le v<0.09\\(v-0.09)/0.10,0.09\le v<0.19\\1,0.19\le v\le 0.32\end{cases}\tag{6}$$

Similarly, based on the above method, the functional expressions of V2, V3 and V4 can be determined as Eq. (7), Eq. (8) and Eq. (9), respectively.

$$V2=\begin{cases}0,-0.32\le v<-0.20\\(v+0.20)/0.04,-0.20\le v<-0.16\\1,-0.16\le v<-0.06\\-v/0.06,-0.06\le v<0\\0,0\le v<0.32\end{cases}\tag{7}$$

$$V3=\begin{cases}1,-0.32\le v<-0.20\\(-0.16-v)/0.04,-0.20\le v<-0.16\\0,-0.16\le v<0.32\end{cases}\tag{8}$$

$$V4=\begin{cases}1,-0.32\le v<-0.04\\(v+0.04)/0.04,-0.04\le v<0\\1,0\le v<0.11\\(0.19-v)/0.08,0.11\le v<0.19\\0,0.19\le v<0.32\end{cases}\tag{9}$$

Finally, Eq. (10) is derived based on the realization of a multi-factor composite affiliation function.

$$P_i=m_iA_i+n_iV_i,(i=1,2,3,4)\tag{10}$$

where m_i and n_i represent the weights of the A-variable and the V-variable, respectively, at the ith type of emotion.

3 Experimental validation and analysis of music emotion retrieval model based on affiliation function

Through the design of the affiliation function in the digital music emotion retrieval model, this paper constructs a complete set of quantitative music emotion recognition model. This chapter will carry out an empirical study around the above model, and evaluate the comprehensive performance of the proposed method in music emotion retrieval accuracy and sorting quality with objective data by comparing it with mainstream retrieval algorithms.

3.1 Corpus Construction and Sentiment Label Similarity Calculation

3.1.1 Data corpus

A corpus of 18,342 music tracks from APPLE MUSIC and 157 emotion tags from the "Music Emotion" category were used as the experimental corpus. If a piece of music did not have a corresponding emotion label, it was filtered out. After processing 18,342 pieces of music, the remaining corpus consisted of meaningful emotion tags and music labeled with at least one emotion tag, including 17,834 pieces of music and 102 emotion tags. In order to evaluate the effectiveness of music retrieval, this paper sets 20 sets of labeled query strings, of which, 10 sets are positive emotions and the other 10 sets are negative emotions, and the number of labels in each set of query strings ranges from 1-5 labels. By letting the user score the music according to its relevance to the query string, a grade is set, and the user can choose the grade he thinks according to the degree of relevance, and then, the grade that has been labeled by the user the most times is chosen as the music's relevance grade for the query string. The grades are categorized from 1-5 in descending order.

3.1.2 Sentiment label similarity

In order to test the proposed music emotion retrieval method based on the design of the affiliation function for the emotion retrieval of different musical works, the article selects 100 pieces of music of different styles in the music library for the experiment, and each piece of music contains one or more emotion labels. Assuming that the decay coefficients c_1 and c_2 both take the value of 1, after the first iteration, the two-by-two similarity between each emotion label is shown in Fig. 6.

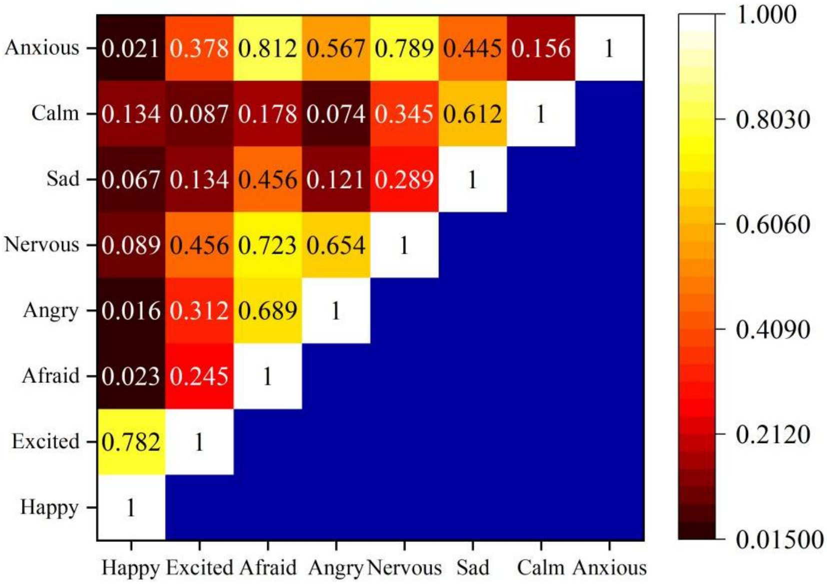

Figure 6: The similarity between each emotion label

From the emotion label similarity matrix in the figure, it can be seen that there are significant differences in the similarity between different emotion labels, reflecting the intrinsic connection between emotions in semantics and perception. The highest similarity between happy and excited is 0.782, indicating that these two emotions have a strong positive correlation in musical expression, which is consistent with their positive and elevated emotional characteristics. The similarity between fear and anxiety was also high at 0.812, indicating that these two negative emotions are often triggered or perceived simultaneously in music. There is also some similarity between sadness and calmness, with a similarity of 0.612 between the two emotion labels, which may be related to the coexistence of sadness and serenity as an expression of emotion in certain musical works.

In contrast, the lowest similarity between happy and scared was 0.023, reflecting the opposition between positive and negative emotions in the expression of musical emotions. The similarity between anger and calm was also low at 0.074, further confirming the complex relationship between activation (A) and validity (V) in the emotion dimensions. Overall, the similarity matrix better reflects the semantic structure of common emotion categories, providing a reliable data base for subsequent music emotion retrieval and categorization.

3.2 Comparison of music retrieval algorithms

3.2.1 Evaluation indicators

This paper uses two evaluation metrics, P@N and NDCG@N.

P@N is the evaluation of retrieval accuracy, evaluating the first N results in the returned results, labeling the correct results among them, and the evaluation system, based on the user's labeling, counts the number of correct results in the first N results of each query, and takes its proportion as the evaluation index of system performance. The more correct results in the first N results, the higher the value of P@N, the better the system performance. This method is relatively simple to implement, can highlight the accuracy of the retrieval system, and can reflect the user's satisfaction with the personalization of the retrieval system. In this paper, P@N refers to the proportion of music with relevance of 5 among the TOPN music returned.

NDCG@N is the normalized mean of the DCG formula. The method is based on the following two principles first, in information retrieval, relevance can be divided into several levels, highly relevant documents are more valuable than partially relevant documents, and their should be given a greater weight in the evaluation second, the later the position of the document in the sequence, the lower the value of this document, and from the user's point of view, due to the reasons of time, energy, and the information obtained from the documents that have already been read, the From the user's point of view, due to time, energy, and information obtained from documents already read, the user may not read these documents at all. In this method, the location and relevance of the document are taken into account, and the evaluation of the search results is more objective and accurate. In this evaluation method, each document has a certain contribution to its location, and its contribution value is related to the relevance of the document, and then, the contribution values of all the locations from 1 to n are added up as the final evaluation result. In this way, a sequence of documents of a certain length is converted into a sequence of correlation scores. The formula is shown in equation (11).

$$N_n = Z_n \sum_{i=1}^{n} \frac{\left(2^{r(i)} - 1\right)}{\log\left(1+i\right)} \tag{11}$$

where N_n is the normalization parameter that makes the value of NDCG@N of the optimal ranking always 1, and $r^{(i)}$ denotes the relevance of the ith returned result.

3.2.2 Analysis of comparison results

In order to further verify the superiority of the music sentiment retrieval model designed based on the affiliation function, the popular music retrieval algorithms cosine, Co_Tags, and T_SimRank algorithms are selected for comparison experiments in this paper.

In this section, the results of 8 sets of positive emotions and 8 sets of negative emotions for a total of 16 queries are selected as the training set, and the remaining 4 sets are treated as the test set. Fig. 7 and Fig. 8 show the music retrieval results under the four methods, respectively.

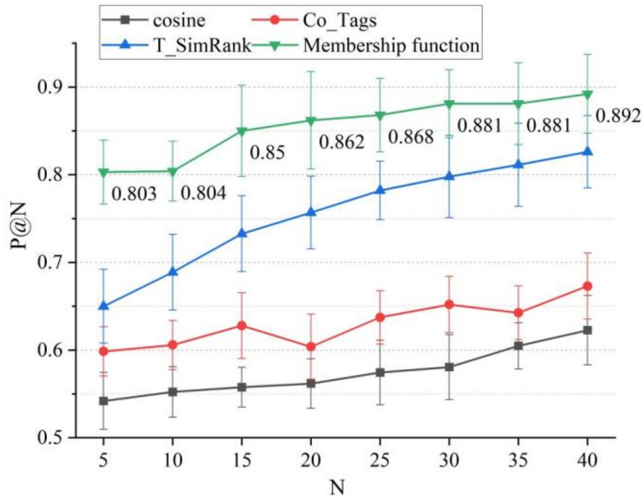

Figure 7: The P@N values under 4 methods

Figure 7 shows the P@N values of the four music sentiment retrieval algorithms for different numbers of returned results N, i.e., the proportion of music with a relevance of 5 in the first N results. From the overall trend, the P@N values of all algorithms show an increasing trend as the value of N increases, indicating that the retrieval systems are able to maintain a high accuracy rate when returning more results. Specifically, the membership function method performed best under all N values, and its P@N value gradually increased from 0.803 at N=5 to 0.892 at N=40, which was significantly higher than that of the other three methods. Especially at N=40, the P@N value is about 7.9% higher than that of the suboptimal T_SimRank method, reflecting the significant advantages of the method in terms of retrieval accuracy. The performance of Co_Tags and cosine methods is relatively weak, especially at smaller N values, indicating that these two methods are less accurate in TOP results. In summary, the music sentiment retrieval method based on the affiliation function performs best on the P@N metrics, has good accuracy and stability, and is suitable for high-precision music sentiment retrieval tasks.

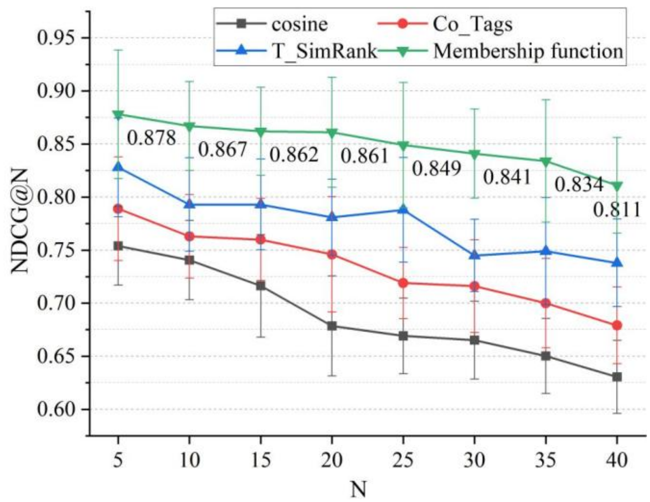

Figure 8: The NDCG@N values under 4 methods

Figure 8 shows the NDCG@N values of the four algorithms under different N values, which integrates the relevance and sorting position of the retrieval results and better reflects the overall retrieval quality of the system. From the data, it can be seen that the NDCG@N values of all algorithms show a decreasing trend as the N value increases, which is consistent with the actual situation that users are more concerned about the first few results.

The membership function method still performed best at most N values, especially when N=5 NDCG@N the value reached 0.878, which was significantly higher than other methods. Although its value gradually decreases with the increase of N, it remains at 0.811 at N=40, which is better than all other methods. This indicates that the method not only performs well in TOP results, but also maintains high ranking quality in the whole result sequence.T_SimRank method performs sub-optimally in NDCG@N index, especially at smaller N values, such as 0.828 for N=5, and the gap with the affiliation function method is small, but the gap is gradually widened as N increases.The cosine and Co_Tags methods' NDCG@N values are generally lower, especially at high N values the decline is more obvious, indicating that these two methods have some limitations in the result ordering and relevance judgment.

Overall, the affiliation function method also shows significant advantages in the NDCG@N metrics, further verifying its effectiveness and usefulness in music emotion retrieval.

4 Application of the digital music classroom teaching system in universities and colleges

This paper will further explore the application effect of the digital music teaching system based on this technology in real higher music education scenarios. Chapter 4 will take the sight-singing and ear-training course of a university as an example, and analyze in depth the specific impact of the system on students' learning attitudes, teachers' teaching evaluation, etc. through questionnaire surveys.

In order to better understand the current situation of the teaching of sight-singing and ear training in higher music education, as well as the change of the traditional music teaching mode and its positive effects by applying the digital music classroom teaching system in the teaching process. Taking the sight-singing and ear training class as the main body of research, we first investigate and analyze the current situation of sight-singing and ear training teaching in a university, and on the basis of this investigation, we apply the digital music teaching system designed in the article to the music classroom, and reform the teaching method of traditional music. Finally, the results of the practice are evaluated in all aspects.

4.1 Analysis of student-level surveys

The 2024 vocal performance majors of a university were used as the study population. The sample capacity was 107 people in total. The online questionnaire was distributed by class, and the author counted and organized the questionnaires after the students had filled them out. A total of 107 questionnaires were distributed, 104 questionnaires were returned, and 104 questionnaires were valid.

The direction of the survey is divided into two dimensions, students and teachers, students around the understanding of sight-singing and ear training, as well as students' attitudes towards digital teaching mode of the investigation of the two dimensions of the questionnaire survey.

4.1.1 Survey on Students' Attitude towards Sight Singing and Ear Training Learning

The survey on students' attitudes towards sight-singing and ear-training included the questions “Do you like sight-singing and ear-training?” and “Do you think that sight-singing and ear-training can improve music literacy?" The results of the surveys are shown in Figs. 9 and 10, respectively.

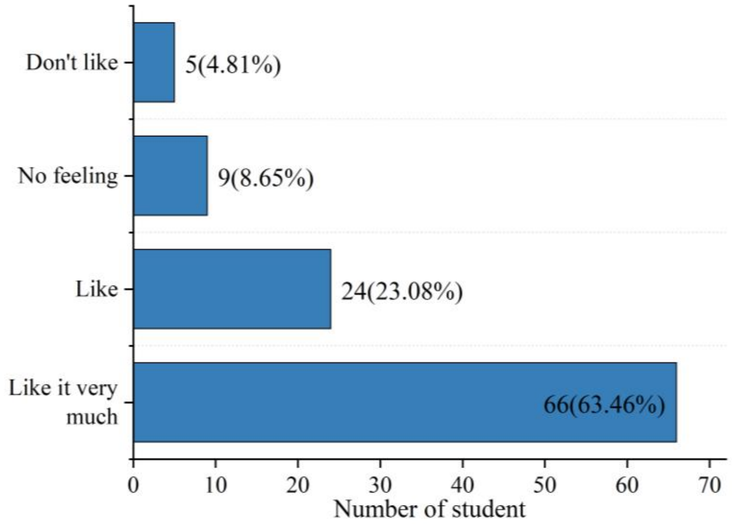

Figure 9: Results of whether students like the sight-singing & ear-training class

Among the 104 valid questionnaires, 63.46% of the students said they "like it very much" and 23.08% said they "like it", the total percentage of the two amounted to 86.54%. Only 4.81% of the students said "don't like", and another 8.65% of the students held the attitude of "don't feel". The data show that the majority of students have a positive attitude towards the sight-singing and ear-training course, reflecting the high acceptance and popularity of the course among students.

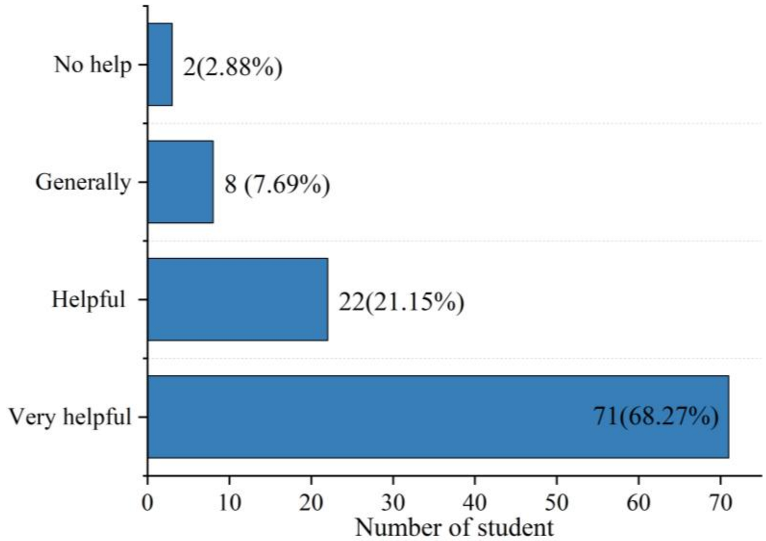

Figure 10: Results on whether sight-singing & ear-training can enhance musical literacy

Figure 10 shows the students' perceptions of the sight-singing and ear-training courses in improving their musical literacy. The data show that 68.27% of the students think that sight singing and ear training is "very helpful", 21.15% think that it is "helpful", and the total of the two amounts to 89.42%. Only 2.88% of the students thought it was "not helpful" and 7.69% thought it was "not helpful". The results show that the majority of the students recognized the role of sight-singing and ear-training courses in improving their musical literacy, indicating that the courses have an important value in music education.

4.1.2 Survey on Students' Attitude towards Digital Teaching Models

Students' attitudes towards the digital teaching mode were surveyed through the questions "Do you like the digital teaching mode?" and "Do you think the digital music classroom teaching system is helpful for sight-singing and ear-training?" The results of the survey are shown in Figures 11 and 12.

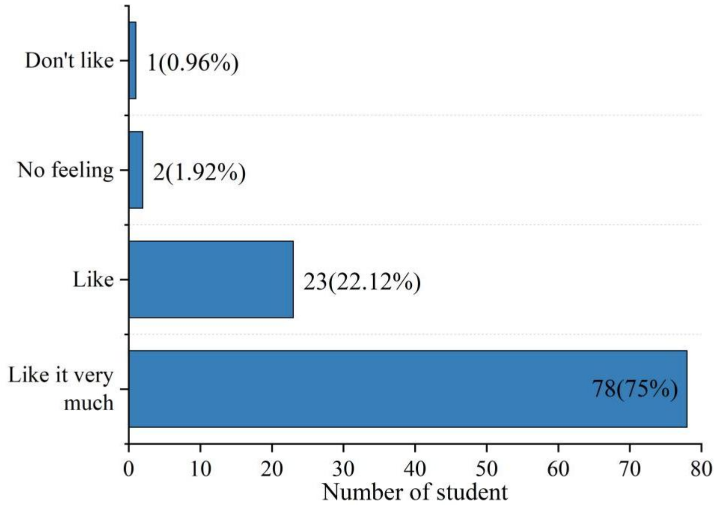

Figure 11: The results of the survey on whether students like the digital teaching mode

Figure 11 reflects the students' preference for the digital mode of teaching and learning. The survey shows that 75.00% of the students "like it very much" and 22.12% of the students "like it", which is 97.12% of the total. Only 0.96% of the students said "don't like", and 1.92% of the students held the attitude of "don't feel". This result is significantly higher than the preference of traditional teaching mode, indicating that the digital teaching mode has a high degree of acceptance and attraction among students.

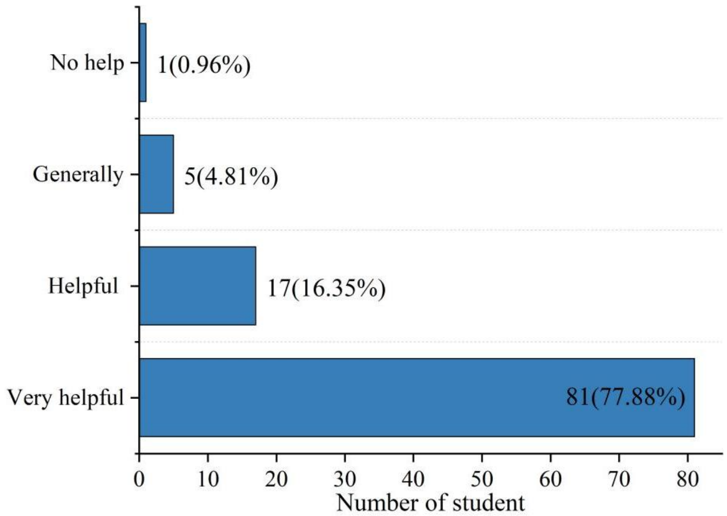

Figure 12: Results on whether the digital teaching system is helpful for music class

According to the students' evaluation of the degree of help of the digital music classroom teaching system in actual learning, 77.88% of the students think that the digital system is "very helpful” and 16.35% think that it is “helpful”, with the total approval rate as high as 94.23%. 94.23%. Only 0.96% of the students think it is “not helpful” and 4.81% think it is “average”. This shows that the digital system is widely recognized by students in enhancing learning effects.

4.2 Teacher-level survey analysis

There are eight tenured teachers of vocal performance majors in this university, and the teacher level mainly focuses on the two aspects of students' arranging ability and learning motivation under the teaching model of applying the digital music classroom teaching system. The results of the survey are shown in Table 1.

Table 1: The evaluation of students' creative ability and learning enthusiasm

Students' creative ability			Learning enthusiasm		
	Number of people	Percentage		Number of people	Percentage
Significant improved	5	57.5%	Very high	6	75%
Improved	2	25%	High	1	12.5%
No significant improved	1	12.5%	Generally	1	12.5%
Descend	0	0	Low	0	0

In terms of students' creative ability, 57.5% of teachers thought it was "significantly improved" and 25% thought it was "improved", with a total improvement rate of 82.5%, only 12.5% thought it was "no significant improvement", and no one thought it was "declining". In terms of learning enthusiasm, 75% of teachers thought that students' enthusiasm was "very high", 12.5% thought it was "high", the total positive rate reached 87.5%, and another 12.5% thought it was "average". The results show that the digital teaching mode has achieved remarkable results in improving students' creativity and learning motivation, and has been highly recognized by teachers.

5 Conclusion

This study systematically constructed a digital music teaching system integrating classroom teaching, music creation and emotion analysis, and empirically examined its core technology modules and teaching application effects.

The affiliation function model designed based on A-V (activation-valence) dimensions realizes intelligent and quantitative retrieval of music emotions. The model performs excellently in the music emotion retrieval task, with its P@N value reaching 0.892 in Top 40 retrieval results, and its NDCG@N value reaching 0.878 in Top 5 results, which is significantly better than the mainstream baseline algorithms, such as Cosine and Co-Tags, and verifies its significant advantages in improving the retrieval accuracy and the quality of result ordering.

After applying the system to the sight-singing and ear-training courses in colleges and universities, a questionnaire survey of 104 students found that more than 97% of the students (97.12%) expressed their fondness for the digital teaching mode, and as many as 94.23% of the students thought that the system was of practical help to their learning. Meanwhile, feedback from teachers was equally positive, with 75% observing that students' motivation to learn was “very high” and 82.5% believing that students' composing ability had been significantly improved. These data fully prove that the digital music teaching system has a significant positive effect on stimulating students' interest in learning, improving teaching efficiency and cultivating students' creative ability.

About the Author

Yuyang Xiao, a member of the Communist Party of China and a holder of a Master's degree in Art, serves as the deputy director of the Art Education Center at Bengbu Medical University. He also leads the Anhui Huagu Deng Dance and Song Theater. Having graduated from the Music College of Nanjing University of the Arts, where he specialized in Chinese Instrumental Performance, he is the sixth - generation direct disciple of Mr. Liu Tianhua, the pioneer of modern erhu.Xiao is actively involved in various musical associations. He is a member of the Anhui Musicians Association, a member of the Anhui National Orchestra Society, a council member of the Bengbu Musicians Association, and an examiner for social art level examinations at Xinghai Conservatory of Music.Since his graduation, he has mentored students to achieve over thirty national and provincial - level awards. He has received honors such as the Outstanding Communist Party Member and Outstanding Teacher titles.

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