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Research on Automatic Identification and Digital Preservation of Musical Intangible Cultural Heritage Performance Techniques Based on Deep Learning

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ABSTRACT The preservation of musical intangible cultural heritage requires effective approaches for identifying and documenting complex performance techniques that are often transmitted through tacit knowledge and oral instruction. To overcome the limitations of manual annotation, low-dimensional recording methods, and insufficient quantitative analysis, this study proposes a deep-learning-based automatic recognition framework for musical intangible cultural heritage performance techniques. A multi-source dataset containing representative performance recordings from guzheng, Nanyin, Finnish fiddle, and other traditional musical forms is first established. A hybrid architecture integrating cascaded convolutional gated neural networks and fully convolutional networks is then developed to capture local acoustic features and long-range temporal dependencies. Furthermore, note-onset information is incorporated to improve technique-boundary localization accuracy. Experimental results demonstrate robust recognition performance across diverse musical styles and performance conditions. The proposed framework supports digital archiving, intelligent retrieval, and interactive learning applications while providing methodological references for audio signal processing, pattern recognition, and intelligent cultural-information preservation systems.

INDEX TERMS deep learning, performance technique recognition, audio signal processing, pattern recognition, digital preservation

I. INTRODUCTION

INTANGIBLE Cultural Heritage (ICH) embodies the living diversity of human culture. Among them, musical ICH, with its unique sonic structure and performance techniques, has become an important media for carrying the national memory and emotional nature. From the ritual songs and dances of the indigenous people in southern Africa, to the urban cultural identity of Berlin's techno dance music, and the contemporary spreading of Cantonese opera in China, the same problem of preserving the authenticity and vitalism of musical ICH under the pressures of globalization and modernization has always been the core issue. Existing research shows that the protection of ICH has moved away from its simple archival recording to multidimensional, interdisciplinary collaborative innovation.

However, digital preservation of intangible cultural heritage related to music, which is a key subject of contemporary preservation, is mainly targeted at collecting and storing audio and video, having no proper methods to explore and capture the core "tacit knowledge" of performance techniques. Performance techniques are not simply the sequences of notes, but rather a total projection of the performer's bodily memory, aesthetic preferences and cultural context. For example, the subtle variations in the "vibrato, rubbing, pressing and sliding" on the left hand in guzheng playing, or the unique style of syncopation rhythmic and inverted bowing techniques in Finnish fiddle music, are not easy to be fully presented through traditional notation or written descriptions. This division of "technique" and "principle" often leads subsequent students to carry out imitations by oral transmission, and it becomes difficult for students to create a quantifiable, inheriting knowledge system.

The rapid development of artificial intelligence technology, especially the breakthroughs in the fields of deep learning in audio signal processing and music information retrieval, have opened up the new possibilities of overcoming this dilemma. From timbre classification using convolution neural networks to performance technique recognition combining temporal modeling to semantic parsing systems oriented towards intangible cultural heritage contexts technology is moving from "hearing" to "understanding". However, existing research is essentially targeting Western classical music or popular music and specific research work on the intangible cultural heritage concerning music has not yet been robust, especially in aspects such as the construction of datasets, multiple techniques jointly recognized and deep combination of technology and conservation practices where there is still much room for research.

Based on this, this study proposes an automatic identification method for musical intangible cultural heritage performance techniques based on deep learning, aiming to construct an end-to-end mapping model from audio signals to technique labels. The research will focus on three core issues: how to construct high-quality, multi-type intangible cultural heritage music datasets to support model training; how to design a deep learning architecture suitable for the characteristics of intangible cultural heritage music to improve identification accuracy; and how to transform the identification results into practical applications for digital preservation. Through the above research, this paper hopes to provide a computationally achievable and reproducible technical path for the living transmission of musical intangible cultural heritage, promoting the intelligentization of intangible cultural heritage preservation.

II. RELATED WORK

The study of Intangible Cultural Heritage (ICH) is increasingly showing a complex interdisciplinary and multidimensional aspect. Gwerevende and Mthombeni [1] emphasized the inherent synergy between language, dance and music in the protection of intangible cultural heritage. Wissmann [2] pointed out that the application for the Berlin Dance of Technology to be listed as an intangible cultural heritage is not only an endorsement of a musical style, but also a social process full of tension. Mathioudakis et al. [3] successfully developed and verified the InCulture platform, and concluded that the platform can effectively support and enrich the narrative expression of intangible cultural heritage. In China, the recognition of intangible cultural heritage is regarded by governments at all levels as an important means to promote local cultural identity and economic development, but its specific impact mechanism and effect on the tourism industry still need to be empirically tested. Tan et al. [4] found that the recognition of intangible cultural heritage has a significant positive impact on China's tourism economic growth in general. Chung [5] focused on the dilemma of the dissemination of intangible cultural heritage in contemporary society, and analyzed several innovative practices of applying technology to the dissemination of Cantonese opera as a case study.

Lázaro Ortiz and Jimenez de Madariaga [6] believe that tensions have arisen between the core concepts and specific operations of the Convention in its implementation, especially in the definition of heritage, the authenticity of community participation, and the scientific nature of the list compilation. Tan et al. [7] depicted the panorama of metaverse empowering the study of intangible cultural heritage. Howard [8] analyzed specific cases of musical instrument protection under different cultural backgrounds and explained how musical instruments both carry the material traces of history and exist as a medium for living music practice. Starčević et al. [9] showed that rural tourism enterprises that actively integrate intangible cultural heritage elements have a significant positive impact on financial results. Hsu et al. [10] revealed the complex interaction patterns of decision-making behavior of various stakeholders in the development of intangible cultural heritage tourism. This paper aims to penetrate the cultural appearance and reach the core of the skills through artificial intelligence technology, and provide a calculable and reproducible technical path for the living inheritance of intangible cultural heritage.

III. METHODS

A. CONSTRUCTION AND PREPROCESSING OF DATASET FOR INTANGIBLE CULTURAL HERITAGE MUSIC PERFORMANCE TECHNIQUES

High-quality datasets are fundamental to the performance of deep learning models. For the task of recognizing intangible cultural heritage (ICH) performance techniques in music, this study constructs a multi-source ICH music dataset, taking into account factors such as instrument type, technique diversity, and recording environment. The data sources mainly include three parts: first, publicly released ICH music databases; second, authentic performance audio recorded in collaboration with professional music academies and ICH inheritors; and third, live performance and teaching recordings obtained from publicly available online channels. This multi-source data acquisition strategy is designed to mitigate the risks of overfitting and provide a baseline for cross-domain generalization, although instrument timbre and recording quality remain significant variables. In terms of technique selection, the study focuses on the most representative intangible cultural heritage instrumental performance forms. Taking the guzheng as an example, eight core techniques were selected, including vibrato, upward glissando, glide, and slide in the left hand technique, and glissando, tremolo, harmonics and single-note plucking in the right hand technique. For Nanyin, a special dataset containing the performance features of gongche notation was constructed around the pipa, the core instrument. All audio data were resampled using a uniform sampling rate (44.1kHz) and quantization precision (16bit) to eliminate the format differences of data from different sources [11].

Data annotation is a crucial step in constructing a high-quality dataset. This study invited intangible cultural heritage inheritors and music school teachers with professional backgrounds to form an annotation team. They employed a combination of manual annotation and semi-automatic proofreading to perform dual annotation on audio files, assigning both technique category labels and time boundaries. To ensure consistency in annotation, each audio sample was independently annotated by at least two annotators. For samples with differing annotations, the final labels were determined through expert discussion. After annotation, all audio files were segmented into fixed-length short segments and divided into training, validation, and test sets in an 8:1:1 ratio.

To improve the robustness of the model, a series of data augmentation operations were introduced in the data preprocessing stage. First, Wiener filtering was used to denoise the original audio and reduce the interference of environmental noise on feature extraction. Second, by means of temporal stretching, pitch fine-tuning and background noise superposition, more diverse training samples were generated while keeping the technique categories unchanged. In addition, in view of the problem that the number of samples of some rare technique categories is small, the method of combining oversampling and synthetic minority class samples was adopted to balance the sample distribution of each category. Table 1 shows the sample distribution of the main technique categories in the dataset. It can be seen from the table that after data augmentation, the number of samples of each category tends to be balanced, providing a good data foundation for model training [12].

B. FEATURE EXTRACTION OF PERFORMANCE TECHNIQUES BASED ON HYBRID NEURAL NETWORKS

To address the acoustic characteristics of intangible cultural heritage music performance techniques, this study constructs a hybrid cascaded convolutional gated neural network as the core feature extractor. The design of this network is inspired by the successful application of hybrid cascaded convolutional gated neural networks in the retrieval of Xinjiang-style guzheng music, while also incorporating the advantages of fully convolutional networks in variablelength audio processing.

The network input receives two forms of audio representation: the original waveform and the Mel spectrogram. The original waveform preserves the complete phase information of the audio signal, which is especially important for capturing techniques with drastic transient changes (such as the guzheng tremolo and complex Pipa fingering transitions); the Mel spectrogram, by simulating the characteristics of human hearing, maps the frequency axis to the Mel scale, which can more effectively characterize the timbre and harmonic structure. The two inputs are respectively fed into parallel convolutional neural network branches for preliminary processing [13], [14].

In the feature extraction stage, a cascaded convolutional neural network module is responsible for extracting short-term acoustic features from local time windows. This module consists of multiple stacked convolutional layers, each followed by a batch normalization layer and a modified linear unit activation function to enhance non-linear expressiveness. Through the design of convolutional kernels of different sizes, the network can simultaneously capture subtle temporal variations (such as the periodic oscillations of vibrato) and broad frequency domain features (such as the continuous scale glissando of a glissando). The feature maps output by the convolutional layers are then fed into a temporal modeling module composed of gate-controlled recurrent units and recurrent neural networks. This module is specifically designed to capture long-term dependencies in musical performance—such as the complete trajectory of an upward glissando from its starting note to its target note, or the continuous transitions between multiple techniques within a musical phrase. To improve the model's accuracy in locating technique boundaries, this study adopts a strategy of fusing note start point detection information. In the performance of intangible cultural heritage instruments such as the guzheng, each technique typically corresponds to a note unit, and the note start point is often accompanied by a significant energy surge or spectral change. Therefore, in addition to the backbone network, a separate start point detector is trained, and a bidirectional long short-term memory network is used to predict the frame-level start probability of the audio sequence. The output of the start point detector is then fused with the technique classification predictions of the backbone network: for each note segment identified by the detector, the probabilities of various techniques in all frames within that segment are accumulated, and the technique category corresponding to the highest probability is taken as the final recognition result for that note. This fusion strategy effectively alleviates the classification ambiguity problem in the transition region between adjacent techniques and significantly improves the accuracy of notelevel recognition.

C. MULTI-TASK LEARNING AND MODEL TRAINING STRATEGIES

Considering the potential inherent connections between techniques of intangible cultural heritage music performance (e.g., the similarities of glissando and slur in pressing motions but in opposite directions), this study proposed a multi-task learning framework by making multiple parallel classification branches on top of the backbone network. The major branch is responsible for fine-grained classification of technique categories, and the minor branches are responsible for technique family classification (e.g. left-hand techniques versus right-hand techniques). By sharing underlying feature representations and jointly optimizing multiple, related tasks, the model is able to learn more generalizable feature representations.

In the model training phase, a hierarchical transfer learning strategy is used. First of all, the model is first pretrained on a large-scale general audio dataset to learn basic audio representation capabilities. Then, it is optimized on a pre-constructed intangible cultural heritage music dataset. Differential learning rate is adopted during fine-tuning: a smaller learning rate is used for the pre-trained layers to maintain the already learned knowledge, while a larger learning rate is employed for the newly added classification layers to perform fast adaptation for intangible cultural heritage specific tasks.

The loss function is designed as weighted sum of losses of multiple tasks, the main task of technique classification is focus loss, which is to ease the sample imbalance, and make the model pay more attention to the sample that is

TABLE 1. Sample distribution of the dataset for intangible cultural heritage music performance techniques

Techniques	Original sample size	Number of samples after augmentation	Average duration (seconds)	Labeling consistency (%)
Guzheng - Vibrato	234	892	3.2	94.5
Guzheng - Upward Glissando	536	1024	3.8	96.2
Guzheng - Glide	384	876	3.7	95.8
Guzheng - Glissando	366	854	3.4	93.6
Guzheng - Scraping	358	912	4.2	97.1
Guzheng - Tremolo	228	896	4.5	96.4
Guzheng - Harmonics	379	898	2.8	98.3
Guzheng - Single-note pizzicato	339	1105	2.1	97.5
Nanyin - Pipa Fingering	287	834	3.6	94.2
Finnish fiddle style	156	612	5.2	92.8

hard to classify, and the auxiliary tasks are cross-entropy loss and mean squared error loss, respectively. The total loss is dynamically balanced by learnable weights parameters in order to consider the contribution of each task. The optimizer is AdamW with an initial value of 0.001 and a cosine annealing is employed to vary the learning rate. The batch size is set as 32, maximum number of training epochs is 100 and an early stopping mechanism is introduced: training is stopped if validation set loss does not decrease for 10 epochs for preventing overfitting.

In order to objectively assess the model performance, accuracy, precision, recall, and F1 score were chosen as the key evaluation measures. Frame-level accuracy describes the recognition precision of the model in the temporal granularity while the note-level F1 score is more concerned about the recognition effect of the technique instances. In addition, based on the characters of intangible cultural heritage music, the Note F1 value was utilized as the primary metric to remove the effect of sample size difference on the overall metrics and more realistically reflect the ability of the model to recognize various techniques.

IV. RESULTS AND DISCUSSION

A. MODEL RECOGNITION PERFORMANCE EVALUATION AND COMPARATIVE ANALYSIS

To comprehensively evaluate the effectiveness of the proposed method, this study conducted systematic quantitative experiments on a constructed intangible cultural heritage music dataset. Multiple baselines were established for comparison, including traditional support vector machine classifiers, sliding window-based convolutional neural network methods, and end-to-end fully convolutional networks without incorporating inception information. All methods were trained and evaluated on the same training and test sets to ensure fairness in the comparison.

Table 2 shows the overall recognition performance of different methods on the test set. As can be seen from the table, the hybrid cascaded convolutional gated neural network proposed in this study, which incorporates starting point information, significantly outperforms the comparative methods in all evaluation metrics. Specifically, it achieves a frame-level accuracy of 97.5%, an improvement of over 15 percentage points compared to traditional methods; and a note-level F1 score of 95.2%, which is more practically meaningful, verifying the effectiveness of incorporating starting point information in improving the accuracy of technique boundary localization. Compared to traditional two-stage methods, this hybrid gated architecture avoids the error propagation problem; compared to methods without the fusion of note start point detection, the fusion strategy improves the classification accuracy at note boundaries by approximately 8%, indicating that utilizing the structural prior of “one note, one technique” in intangible cultural heritage music can indeed bring performance gains.

Further analysis of the model’s performance in recognizing different technique categories is shown in Figure 1, which displays the precision and recall for each technique. The results indicate that for techniques with distinct acoustic features, such as overtones and glissando, the model achieved a precision of nearly 98%. For vibrato, which has some spectral similarity to single-note pizzicato, the recall was slightly lower, suggesting that the model still has room for improvement in distinguishing subtle differences. The recognition rates for glissando and slide notes in the lefthand technique were both high, validating the effectiveness of the temporal modeling module in capturing pitch change trajectories.

B. MODEL GENERALIZATION ABILITY AND CROSS-DATASET VALIDATION

To check the generalization ability of the model across different recording environments and stylistic variations, further validation was conducted on independent test subsets containing instrument types and recording conditions not encountered during the training phase. The test data consisted of Nanyin pipa and performances excerpts and recordings from the Finnish fiddle music archive. These two data sets had a large difference from the training data in terms of instrument timbre, technique systems, and quality of the recording as well, which is a severe problem for the model’s generalization ability.

Experimental results demonstrate that, without any targeted fine-tuning on the test dataset, the model has good recognition performance in the cross-dataset test. For the Nanyin Pipa dataset, the model achieves an accuracy of 85.7% in identifying core right hand techniques at an F1

TABLE 2. Comparison of recognition performance of different methods on intangible cultural heritage music datasets (%)

Method	Frame-level accuracy	Accuracy	Recall rate	Note F1 value
SVM + Handcrafted Features	82.3	79.6	75.4	77.4
Sliding Window CNN	89.7	88.2	86.5	87.3
FCN (Fuse Without Start)	93.5	92.8	91.3	92.0
The method proposed in this study	97.5	96.8	95.2	96.0

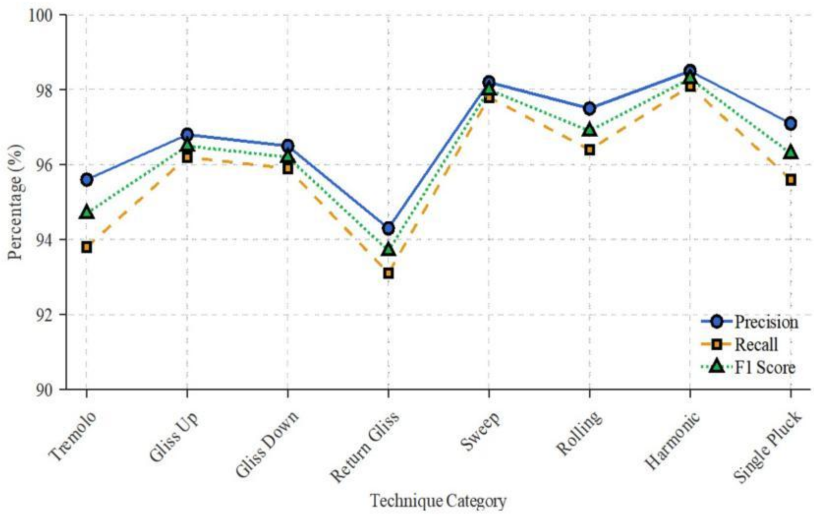

FIGURE 1. Precision and recall (%) of various performance techniques

score of 83.2% and in the case of the style recognition task of Finnish fiddle music, accuracy reaches 82.4%. This result shows that the model learns universal acoustic features that are independent of particular instruments during training, including attack transients, trajectories of pitch change, and vibrato cycles. These features show cross-cultural consistency between different intangible cultural heritage forms of music.

Further analysis has produced two principal problems to the performance degradation: 1) The timbre variation between different instruments caused a change in the distribution of the underlying acoustic features. 2) The non-standardization of technique definitions, for example, the discrete variation in the specific implementation of "vibrato" of different cultures. For the former,because of the effective gradual adaptive fine-tuning with a small number of target domain samples, it can improve the performance by more than 90%; for the latter, due to the urgent need for a cross-cultural technique ontology system, the technique categories must be reconstructed with the commonalities of the performance movements and acoustic effects.

C. ANALYSIS OF DIGITAL PROTECTION APPLICATION SCENARIOS

The ultimate goal of this research is to translate automatic identification technology into practical applications. Based on the above model, the research further constructed a prototype system for the digital preservation of intangible cultural heritage music, which includes three core functional modules: intelligent archiving, precise retrieval, and interactive teaching.

TABLE 3. Performance Test Results of Intangible Cultural Heritage Music Content Retrieval

Search methods	Top-1 hit rate (%)	Top-5 hit rate (%)	Average search time (seconds)
By technique type	89.3	96.8	0.8
By sentiment tag	78.5	88.2	1.2
According to the melody fragment	85.6	92.5	2.5

In terms of intelligent archiving, the system can automatically analyze uploaded intangible cultural heritage music recordings and output a structured annotation file containing technique type, time location, and confidence level. This file can be converted into a standardized metadata format and stored in a digital resource library along with the original audio and video.

In terms of precise retrieval, the system supports users to search for content by technique type combination, emotional tags, or melodic fragments. For example, users can search for "all slow passages containing glissando" or upload a humming melody, and the system will return performance recordings containing similar technique fragments through feature matching. Table 3 shows the performance test results of the retrieval function. As can be seen from Table 3, the content-based retrieval achieved a Top-5 hit rate of 92.5%, which can effectively support the comparative analysis needs of musicology researchers.

V. CONCLUSION

This study addresses the practical needs of digital preservation of intangible cultural heritage in the music field by proposing an automatic identification method for performance techniques based on deep learning. By constructing a multi-source intangible cultural heritage music dataset and designing a hybrid neural network architecture that integrates starting point information, this research achieves high-precision automatic identification of performance techniques in various intangible cultural heritage music genres, including Guzheng and Nanyin. The results show that deep learning methods can effectively uncover tacit knowledge within intangible cultural heritage music, transforming ineffable performance skills into calculable and reproducible digital representations. Based on this, an intelligent archiving, precise retrieval, and interactive teaching system is constructed, providing a practical technical path for the living transmission of intangible cultural heritage. However, this study also has certain limitations. First, the dataset's coverage needs further expansion, encompassing more regions and types of intangible cultural heritage music. Second, the model currently relies primarily on audio signals and has not yet fully integrated multimodal information such as sheet music and performance videos. Third, how to effectively connect the results of technique identification with intangible cultural heritage protection policy-making, community participation, and educational practices still requires interdisciplinary collaborative exploration. Future research will continue to delve into areas such as multimodal fusion recognition, lightweight model deployment, and the construction of community-participatory conservation platforms, so as to promote artificial intelligence technology to truly serve the protection and inheritance of cultural diversity.

AUTHOR CONTRIBUTIONS

Lu Xu designed, collected and analyzed the data, and drafted the manuscript. Lu Xu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Lu Xu participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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