Construction of Generative AI Piano Improvisation Accompaniment Teaching System Based on Fine-Tuned Music Large Model

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ABSTRACT Current approaches to piano improvisation accompaniment teaching are hampered by such aspects as delayed feedback or inadequate personalized instruction and digital tools are also limited technically in terms of music theory constraints and realtime interaction. This research builds a generative artificial intelligence teaching system using a large-scale music model fine-tuned. The system front-end obtains the student playing data through the Web MIDI API and extracts the features of non-stationary tempo and dynamic using the temporal difference normalization algorithm and exponential moving average algorithm respectively. The main accompaniment engine is based on the large-scale model ChatMusician and is fine-tuned with datasets using LoRA to generate the accompaniment in a grammatically correct way by applying harmonic constraints by implementing the Top-p sampling strategy. The back-end is dedicated to the integration of the dynamic time warping algorithms and visualization charts to give multi-dimensional quantitative feedback. The results of the experiments after 8 weeks of teaching indicated that the error rate for the experimental group was reduced to 7.6%, fluency score was 86.7 and the system usability scale score was 82.4. It has the ability to effectively reduce the harmonic grammar error in this system, enhance the playing fluency and learning independence of music learners, and offer a practical technical solution for intelligent music education.

INDEX TERMS Generative artificial intelligence; piano improvisation; large-scale music model; real-time interactive feedback

I. INTRODUCTION

PIANO improvisation accompaniment instruction is undergoing a profound transformation from an experience-oriented traditional model to a modern teaching model that is technology-enabled and supported by diverse theories.

In this study, a piano accompaniment teaching system for improvisation using generative AI is developed by fine-tuning a large-scale music model. The major contributions of the present work are threefold: firstly, a non-stationary feature extraction technique for the edge-side of the MIDI signal is proposed, which is based on the Temporal Difference Normalisation algorithm and the Exponential Moving Average algorithm and which is able to accurately transform the student's playing signal into the model input representation; secondly, a new approach to generating the input signal to the model is presented; thirdly, the transformed input signal is then used to drive a suitably trained model to predict the next note to be played. Second, it is based on the open source large-scale model ChatMusician, adopts low rank adaptation (LoRA) strategy, fine-tunes the model with 15,000 regular accompaniment scores, and proposes a Top-p sampling decoding strategy to combine TSDT harmonic function constraints, which can better guarantee the diversity of improvisation and the grammatical correctness of the accompaniment to be generated. Thirdly, it adopts a dynamic time warping (DTW) algorithm and a multi-dimensional visualization feedback module to allow students to receive quantitative feedback on rhythmic and harmonic accuracy in real time.

This paper reviews the existing research on reform of piano improvisation accompaniment teaching and intelligent music processing, elaborates the core methods of the system such as edge data acquisition, large model fine tuning, dynamic generation interaction, quantitative evaluation mechanism, and discusses the application effect of the system from quantitative and qualitative perspectives based on experimental design and data analysis, the conclusion and future development directions are given.

II. RELATED WODR

Piano and improvisation accompaniment teaching is undergoing a profound transformation from an experience-oriented traditional model to a modern teaching model that is technology-enabled and supported by multiple theories. Yuan [1] introduced knowledge graphs and AI technology into the curriculum system construction and tried to build an intelligent system that recommends personalized learning paths; Wang [2] returned to the essence of teaching and extracted the three core elements of harmony theory, accompaniment texture and melody analysis, emphasizing their coordinated development; Liu [3] focused on the vocational orientation of higher vocational colleges and proposed that piano teaching should shift from the cultivation of advanced skills to the cultivation of practical keyboard skills; Ke [4] used constructivism as a theoretical framework to explore the innovation of student-centered teaching models; Guo [5] developed an improvisation accompaniment teaching platform based on Logic Pro software and promoted the in-depth application of digital tools in the entire teaching process. Isarathikul et al. [6] developed an intermediate classical piano teaching guide for the Bangkok Piano Academy, emphasizing the systematization of teaching standards; Madapatha [7] revealed the irreplaceable nature of individual teaching and group teaching in terms of technical precision and collaborative learning through qualitative research; Choi and Lim [8] explored the innovative application of digital technology in group piano teaching, verifying the positive role of technology in improving interactivity and learning effectiveness; Chen and Phongsatha [9] and Liu and Phongsatha [10] respectively used Guangdong University of Petrochemical Technology and Yunnan University as cases to empirically test the effectiveness of mobile blended learning and video conferencing-based blended learning in non-piano major students. In summary, the above studies show that existing work has made beneficial accumulations in the reform of piano improvisation accompaniment teaching mode, the construction of digital platforms and the verification of blended teaching effects, but their common limitation is that they lack real-time modeling of the dynamic decision-making process of harmonic function progression and texture generation, and have not deeply embedded music theory prior knowledge into the generative interaction mechanism. Therefore, existing tools struggle to provide dynamic accompaniment support that conforms to harmonic grammar while offering personalized responses to the non-stationary tempo fluctuations and improvisations in students' playing. This study introduces a fine-tuned music model, injecting functional constraints such as -TSDT into the -decoding -process to construct an end-to-end real-time generation and feedback system, aiming to fill the gaps in current research in terms of technological approach.

III. METHOD

A. END-SIDE MIDI ACQUISITION AND NON-STATIONARY FEATURE EXTRACTION

Using the browser's native Web MIDI API, the edge-side acquisition module directly monitors the port status of external MIDI inputs, capturing and processing key MIDI events like Note On, Note Off, Pitch and Velocity while the student plays. Given the dynamic changes and speed changes that cannot be completely controlled during the beginner playing, the system adopts the timing difference algorithm for dynamic normalization in real-time, to improve the performance of the system to a certain extent.Insufficient control for the beginner playing causes the speed to change continuously and the performance to fluctuate, the system adopts the timing difference algorithm for real-time dynamic normalization to increase the performance of the system to a certain extent. First, the algorithm sets up a time window of 4 notes at the front end, and will calculate the first order difference of the timestamp of two neighboring notes in real-time, to get the instantaneous speed change rate corresponding to the current playing. If a speed deviation greater than a set dynamic threshold (25% above or below the standard note's time value) is detected, the system no longer uses absolute time values, but uses a ratio of the time value of the current note to the average time value of the notes within the window, and maps this to the relative time value of the standard note (quarter or eighth note). If the playing dynamics are not stationary, then the system applies a method called exponential moving average (EMA) to smooth the Velocity value. The smoothing coefficient is 0.3, so that dynamic changes that occur due to student's sometimes unstable finger touch (dynamics noise) is removed, but that the conscious musical expression technique (crescendo and diminuendo) remains intact. The smoothing features removed are, at last, correctly mapped to the back-end large model providing high fidelity input representation in the form of a triplet time series data containing absolute pitch, time value and the standard relative time value, as well as the smoothing dynamics[11] .

B. CORE ENGINE: LORA FINE-TUNING OF CHATMUSICIAN'S LARGE MODEL

The main accompaniment engine of this system is a modified ChatMusician-Base, an open-source symbolic music language model. A Low-Rank Adaptation (LoRA) strategy is used for efficient high-level fine-tuning to allow the model to learn the standard piano accompaniment textures and strict harmonic connections of piano improvisation more deeply. The fine-tuning dataset consists of 15,000 carefully chosen and cleaned standard music accompaniment scores, with accompanying symbols, for various common improvisational accompaniment textures, including block chords, Alberti bass and arpeggios. All data is converted to a common representation in ABC notation text format. For the LoRA fine-tuning configuration, the rank of the bypass low rank matrix is set to 16, the scaling factor is set to 32, and the module to fine-tune is specified as the Attention layer matrix in the Transformer architecture. A single NVIDIA A100 GPU is used to perform the fine-tuning, and the optimizer is AdamW. Initial learning_rate is given as 2×10^{-4} and Cosine learning_rate_decay is given. The batch size is 64 and the training will be conducted for 10 epochs. At the data representation level, by explicitly splicing some specific prefix words of the prompt (e.g., "Style: Classical, Texture: Broken Chord") before the main melody text, the model is made to establish a strong relationship between the tonality and chord progression of the main melody and the multi-part accompaniment texture during training, which successfully injects the explicit music theory prior knowledge into the low-rank matrix parameters of the large model [12] .

C. DYNAMIC ADAPTIVE GENERATION AND REAL-TIME INTERACTION MECHANISM

During the interactive generation phase, the system instantly converts the MIDI timing of the student's playing transmitted from the front end into an ABC text sequence, which is then fed into the fine-tuned model as a prompt. To ensure that the AI-generated accompaniment possesses both improvisational diversity and strictly adheres to traditional harmonic grammar without detonation, the system introduces a harmonic-constrained Top-p sampling strategy at the decoding end. When the decoder predicts the probability distribution of the next note token at each time step, the system first activates a harmonic constraint filter. Based on the tonality prediction of the current measure and the previously generated chord progressions, it automatically calculates the set of candidate pitches that conform to the TSDT (Total-Subdominant-Dominant-Total) regular harmonic functional order, and directly clears the probability of candidate pitch tokens that do not conform to this music theory rule to zero. Subsequently, Top-p sampling is performed on the filtered valid probability distribution, with the p-value dynamically set to 0.85 and the temperature coefficient set to 0.7 to balance the richness and accuracy of the accompaniment. The accompaniment token stream generated by the model's autoregression is then decoded into a standard MIDI stream in real time. The front end uses the Web Audio API in conjunction with a lightweight AudioContext object to load a Soundfont sound library containing high-quality piano samples. The multi-texture piano accompaniment is rendered and output on the browser with an extremely low latency of less than 20 milliseconds, perfectly realizing an intelligent dual-piano interactive experience of "playing as you play".

D. QUANTITATIVE EVALUATION AND VISUAL FEEDBACK BASED ON DTW ALGORITHM

The visualization feedback module utilizes the Dynamic Time Warping (DTW) algorithm to provide precise, multi-dimensional quantitative evaluation of students' performance. Because students may exhibit spontaneous rhythmic stretching or slight tempo fluctuations during improvisation, traditional point-by-point time comparisons cannot objectively assess accuracy. The system transforms the student's actual single-melody MIDI timing sequence and the system's built-in expected standard score (or optimal harmonic skeleton) into two-dimensional feature vector sequences, with vector dimensions including pitch features and standardized timestamps. The DTW algorithm constructs a distance matrix and uses dynamic programming to calculate the minimum cumulative distance between two timing paths, automatically aligning the student's playing with the corresponding points on the timeline of the standard reference score. After alignment , the system outputs quantitative indicators in two dimensions: rhythmic accuracy is calculated using the curvature and root mean square error of the aligned path on the timeline; harmonic accuracy is derived by comparing the overlap between the student's playing pitch (and implied chords) and the standard harmony. The data from these two dimensions are ultimately mapped to standard scores of 0-100, and presented in real time on the web interface through the ECharts chart component on the front end as a dynamically scrolling staff heatmap (with red text indicating wrong notes) and radar chart, allowing students to clearly and intuitively see the specific problems in their accompaniment practice.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL DESIGN AND IMPLEMENTATION

This study selected 60 second-year piano students from a music academy as experimental subjects. All students had completed Czerny 740 or higher level etudes and possessed basic harmonic knowledge (able to identify and play I, IV, and V triads and their inversions), but had not previously received systematic training in improvisation. Before the experiment, all participants completed a pre-test: they were given an 8-bar C major melody to play on the spot, had 3 minutes to prepare, and then improvised an accompaniment. Three independent judges (an associate professor of piano, a full-time improvisation teacher, and a researcher specializing in music education) scored the participants on a 100-point scale based on four dimensions: chord selection accuracy, texture richness, rhythmic stability, and overall fluency. The Cronbach's α coefficient of the three judges' scores was 0.91, indicating good consistency. Pre-test results showed no significant difference between the experimental group (n=30, mean 67.3, standard deviation 8.1) and the control group (n=30, mean 66.9, standard deviation 7.8) (p=0.85), indicating that the baseline levels of the two groups were balanced. Subsequently, the experimental group entered a smart practice room equipped with this AI teaching system for 8 weeks, totaling 16 lessons (2 lessons per week, 45 minutes per lesson). Each lesson included 15 minutes of system-guided melody analysis, 20 minutes of human-computer interactive accompaniment practice, and 10 minutes of system feedback review. The control group received regular instruction with the same syllabus (teacher demonstration, classroom practice, and one-on-one guidance) in an adjacent traditional practice room. The instructor was the same teacher with 12 years of experience in teaching improvisation accompaniment, to control for teacher variables. The two sets of teaching content are completely identical, covering eight units in sequence each week: C major triad progressions, transposition in G major and F major, dominant seventh chord resolution, K46 chord application, arpeggio texture (Alberti bass), block chord texture, semi-arpeggio texture, and comprehensive improvisation. Each week, an equal amount of practice homework (3 melodies of 8 to 16 measures) is assigned after class.

B. ANALYSIS OF QUANTITATIVE EXPERIMENTAL RESULTS

To assess the system's impact on the mastery of improvisational accompaniment skills, weekly in-class tests were conducted over eight weeks. MIDI analysis was used to determine the error rate (the percentage of unexpected off-key notes), and three judges blindly evaluated fluency (out of 100), with the average score taken. Figure 1 shows the error rate of chord progressions and the fluency scores for the two groups in each week.

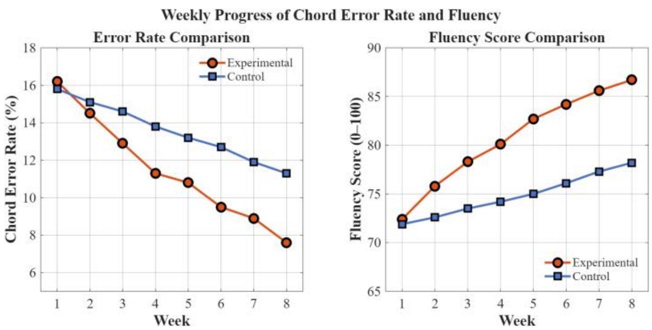

FIGURE 1. Error rate (%) and fluency score for each week.

The experimental group showed a continuous and accelerating decline in the error rate, decreasing from 16.2% in the first week to 7.6% in the last week, a drop of 8.6 percentage points. In contrast, the control group only saw a slow decrease from 15.8% to 11.3%, a drop of only 4.5 percentage points. This indicates that the AI system's real-time error marking and harmonic constraint sampling effectively disrupted the inertia of incorrect harmonic connections; the control group, on the other hand, fell into the gradual bottleneck of traditional teaching, characterized by "repeated trial and error but difficulty in precise positioning." In terms of fluency score, the experimental group achieved 86.7 points in the last week, far exceeding the control group's 78.2 points, reflecting a substantial enhancement in the coherence and richness of multi-part texture development. In summary, the experimental data fully demonstrates that this system, through precise music theory prior input and real-time audio rendering, can effectively promote students' deep internalization of harmonic function progressions, significantly reduce harmonic grammar error rates, and improve the textural fluency of improvisation, verifying its significant effectiveness in establishing multi-part thinking.

To test dynamic accompaniment ability, after week 8, melody accompaniment with speed fluctuation ranges (0%, ±10%, ±20%, ±30%, ±40%) was set, and rhythmic coordination accuracy (out of 100, 100 being perfect synchronization) was calculated based on DTW. Figure 2 shows the mean accuracy and improvement rate of the two sets under different fluctuation ranges.

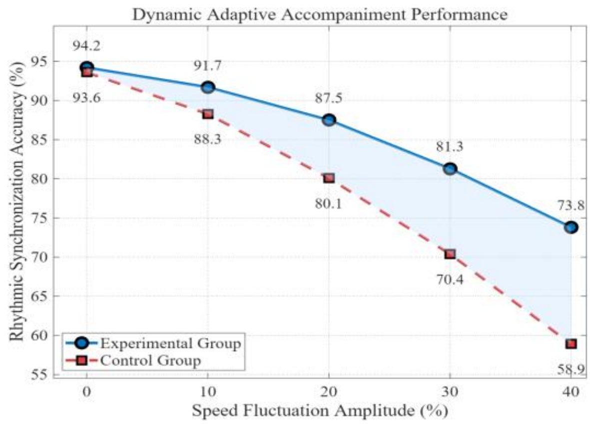

FIGURE 2. Rhythm Coordination Accuracy under Different Speed Fluctuation Amplitudes.

When there are no velocity fluctuations, the accuracy rates of the two groups are essentially the same (94.2% vs 93.6%), eliminating the interference of baseline rhythm capability. As the fluctuation amplitude increases, the accuracy rate of the control group drops precipitously, from 88.3% at ±10% to 58.9% at ±40%, a drop of nearly 30 percentage points; while the experimental group, benefiting from the joint calibration of temporal difference normalization and dynamic time warping, sees its accuracy rate only steadily decline from 91.7% to 73.8%, a drop controlled within 18 percentage points. Under the extreme non-stationary state of ±40%, the absolute accuracy rate of the experimental group is 14.9 percentage points higher than that of the control group. The average accuracy rate for each fluctuation amplitude is calculated as follows: 85.7% for the experimental group and 78.26% for the control group , a relative improvement of 7.44 % . This result verifies the robustness of the front-end sliding window difference and EMA strength smoothing algorithm in capturing real-time velocity pulsations. In conclusion, the system can act as an intelligent dynamic beat calibrator, improving students' rhythmic coordination and error tolerance in non-steady playing states, and providing reliable technical support for adaptive follow-along playing of improvisational accompaniment in real performance scenarios.

C. QUALITATIVE TEACHING FEEDBACK AND BEHAVIORAL ANALYSIS

In order to carry out the comprehensive appraisal of the effectiveness of application of the system in real teaching, this study used two aspects of qualitative analysis: subjective experience and behavioral engagement. After the teaching experiment, the students in the experimental group (N = 30) completed an online survey on the subjective experience level with the System Usability Scale (SUS, 10 items, 5-point rating) and a self-designed teaching satisfaction questionnaire (5 dimensions, 7-point rating). The questionnaire had an α of 0.89 and 30 valid questionnaires were returned. The smart practice room's back-end log system automatically captured the time students in the experimental group spent on the site each week, and the number of times they viewed feedback, for 8 weeks. This data was then compared to the paper practice logs returned for the control group (control group log return rate 100%). In addition, the learning engagement of the two groups was assessed using an overall assessment of the quality of homework completed (3 blind judges on a 100% scale) and the amount of independent practice. The above data are summarized in Table 1 .

TABLE 1. Comparison of Learning Experience and Behavioral Engagement Between the Two Groups

Indicator	Experimental (n=30)	Control (n=30)	Difference
System Usability Scale (SUS) score	82.4	—	—
Teaching satisfaction (7-point scale)	6.2	5.1	1.1
Willingness for autonomous practice (7-point scale)	6.5	5.3	1.2
Weekly autonomous practice hours (h/week)	4.8	3.9	0.9
Homework blind-review average score (100-point scale)	84.5	77.3	7.2
Daily feedback-viewing / review frequency (times/day)	4.2	—	—

The experimental group responded favorably to the usability of the system (mean SUS score 82.4), which reflects the high acceptability on the functional completeness and user-friendliness of the system. In terms of teachers' satisfaction with the teaching process, the experimental group achieved a 1.1 point difference, which shows the great benefit of the AI system in providing immediate feedback and dynamic accompaniment to enrich the learning process. The students in the control group typically indicated that they "did not feel like they were playing right after practicing. The experimental group's willingness to practice independently scored 6.5 points whereas the control group scored 5.3 points. This, together with the experimental group's log data (the average of weekly independent practice was about 0.9 hours longer than that of the control group), suggests that the instant quantitative feedback and visual review function was effective in stimulating students' intrinsic learning motivation, creating a positive learning loop of "playing → feedback → correction → playing again. In addition, the average score of the experimental group in the blind evaluation of homework is significantly higher than that of the control group, which shows that the subjective learning willingness of the former is improved and the skill progress is reflected in measurable score. The experimental group looked at feedback an average of 4.2 times per day, and again, visual heatmaps and radar chart-based scoring of the feedback proved to be valuable in guiding learners' self-correction behavior. As a whole, the system proved to be effective for increasing students' self-engagement and better improving teaching satisfaction and out-of-class practice efficiency to solve the "in-class and out-of-class connection" issue that existed in improvisation teaching.

V. CONCLUSION

This study addresses the technical challenges of delayed feedback and lack of real-time generation with music theory constraints in piano improvisation instruction. It constructs a generative AI teaching system based on a fine-tuned large-scale music model. Through edge-side non-stationary feature extraction, model fine-tuning and decoding incorporating harmonic functional constraints, and visualized feedback driven by dynamic time warping, the system demonstrates significant effects in reducing harmonic grammar errors, improving performance fluency, and stimulating self-directed practice motivation. This verifies the feasibility and pedagogical value of injecting music theory priors into the large-scale model generation process. However, this study still has certain limitations: the experimental subjects are concentrated in a single institution with a limited sample size, and the teaching period is relatively short. The applicability of the system to more complex tonalities, non-Western musical styles, and learners of different age groups remains to be tested. Future work will expand the diversity of datasets, explore multimodal input (such as audio and sheet music) fusion and lighter edge-side deployment schemes, and conduct long-term tracking experiments across institutions and cultures to promote the application of this system in a wider range of music education scenarios.

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