

# International Journal for Housing Science and Its Applications

Publish August 3, 2025. Volume 46, Issue 3 Pages 816-826

https://doi.org/10.70517/ijhsa46361

# Research on the Construction of Music Teaching System and Interaction Mode by Integrating Deep Reinforcement Learning and Virtual Reality Technology

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Abstract A music teaching system based on virtual reality technology can virtualize teacher resources and teaching environment resources. Through the unique immersion, interactivity and conceptualization of virtual reality technology to create the environment needed for music learning, thus making the use of resources more convenient. This paper constructs a music teaching system that includes teaching content and teaching form, music teaching system, and teaching evaluation system. Among them, the music teaching system allows online instruction, virtual environment learning, and human-computer interaction. In order to create a good simulation environment, lightweight deep reinforcement learning method is proposed for the problem of high requirements of deep reinforcement learning training resources in virtual resources, and a deep separable convolutional deep reinforcement learning model is designed. Compared with the deep reinforcement learning model, this model can obtain a higher reward value when the learning rates are all 0.001, and is more suitable for the construction of the simulation environment of the music teaching system. After the teaching practice for freshmen majoring in music in S school, the comprehensive evaluation score of teaching effect is 84.29, which indicates that the teaching system designed in this paper can ensure the quality of music teaching.

Index Terms virtual reality, deep reinforcement learning, human-computer interaction, music teaching system

# I. Introduction

Virtual Reality (VR), a medium consisting of interactive computer simulation that senses the location and movements of participants, replacing or augmenting one or more sensory feedbacks to produce a sense of mental immersion or presence in a simulated environment [1], [2]. Literally speaking only, i.e., a discipline that allows one to produce the sensation of reality while at the same time being virtual. To let people produce virtual reality of this technology, need to use three-dimensional image technology, simulation technology, electronic information, and most importantly, also supports the completion of this technology, computer technology, with the help of computers so that people can realize the real experience of sight, sound, touch and so on so that people do not leave the house and have the feeling of being in the realm of reality [3]-[5].

Nowadays, quality education as the top priority in the field of education, and music plays an indispensable role in quality education [6]. However, there are still problems of backward music teaching facilities and single form of music teaching system. Music is a discipline with openness and the ability to cultivate students' creativity and imagination, and education should always be inspiring, exploring the unknown and the infinite, rather than conclusive [7], [8]. Therefore, the problem we urgently need to solve is precisely how to make students' thinking become more creative and divergent, which requires schools and teachers to optimize and improve the music teaching facilities and the form of teachers' teaching, so as to guide students to imagine and think in the classroom without being confined to the teacher's lectures [9]. The VR technology can, through the use of projection equipment, form the artist's superb performances three-dimensionally in each student (such as theater performance, folk music singing and playing), ensuring that each student can appreciate the artist's singing expressions and movements in an all-round way. They can even imitate their performance forms at will, which to a certain extent makes up for the deficiency of the limitation of the teacher's demonstration skills in the traditional music classroom, and enables the teacher to better observe, evaluate, and correct the deficiencies presented by each student in the imitation, thus enhancing the teaching effect [10]-[13]. In addition, VR technology can also create an "immersive" virtual scene for students, which can bring students into exotic places that are inaccessible in reality, and feel the music styles of different regions and nationalities, so that students can deeply participate in them and deepen their musical experience and perception [14]-[16]. For example, teaching foreign or ethnic minority genres of music, you can



virtualize the scene of an ethnic minority singing and dancing, bring students into a specific musical environment, feel the music style, help students more accurately experience the elements of music and understand the music style [17]. By these cases, we have reason to believe that VR technology can be applied to music teaching, compared with a single teaching mode, this new music teaching system, for the attention is not focused, low efficiency of the traditional music teaching difficult to provide a new solution [18].

The study firstly carries out the preliminary construction of the music teaching system from three aspects, namely, optimizing the teaching content and teaching form, building a music teaching system, and establishing a teaching evaluation system. The constructed music teaching system integrates deep reinforcement learning and virtual reality technology, which can better realize the virtual environment teaching. Then this paper proposes a lightweight deep reinforcement learning method to solve the problem of high requirements of deep reinforcement learning training resources in virtual video. The method designs a deep separable convolutional deep reinforcement learning model from the perspective of model structure. The standard convolution operation in the model is split into deep convolution operation and point convolution operation, which can reduce the number of parameters and computational complexity of the model after the split. Finally, the effect of the constructed music teaching system is evaluated using hierarchical analysis.

# II. Music Teaching System Construction

This paper constructs the music teaching system from three aspects: updating and optimizing the teaching content and teaching form, building a music teaching system, and establishing a scientific, standardized and clear teaching evaluation system, respectively.

### II. A. Updating and optimizing teaching content and forms of teaching

Integrate and optimize the teaching resources of music skills courses, so as to enable quality curriculum resources to play their positive role. Sweep away the problem that the stereotyped singularity of teaching resources is not compatible with practical teaching. Combined with the actual situation, explore the diverse forms of music to enrich the teaching content. In terms of enriching teaching methods, more extracurricular practical activities can be organized to enhance students' perceptual ability. Encourage students to freely create a variety of works, exercise students' abilities and cultivate their sense of innovation at the same time. Combined with virtual reality technology, 3DMax is used to create a virtual learning environment [19], which dynamically displays the results of audio processing in the virtual scene and increases the interactivity of learning in the virtual scene. The development of Unity3D is used to realize the display of the results of audio processing in the virtual scene prompt information. Use Unity3D development to play the teaching video in the virtual scene.

# II. B. Establishment of a music teaching system

### II. B. 1) System architecture

The music teaching system provides a variety of music learning services, online instruction, virtual environment learning and human-computer interaction [20]. In order to realize its functions, the whole platform adopts a five-layer architecture, from bottom to top: access layer, data processing layer, data storage layer, scene management layer and application layer, and the architecture of the music teaching system is shown in Figure 1.

- (1) Access layer: the access layer mainly includes audio access and video access. Audio access is realized through voice capture devices (e.g. microphone) to input sound. Video access through the video capture device (eg: camera) to realize the video input.
- (2) Data processing layer: It includes audio processing system and teacher guidance system. The audio processing system realizes the extraction of sound characteristic data and the comparison of two sets of fundamental sound data.
- (3) Data storage layer: realizes the storage of audio and audio feature data and video storage. The storage interface adopts the commonly used ODBC and JDBC data access methods, and the audio and video file interfaces provide file access services through the encapsulated file IO system of the Java platform.
- (4) Scene management system: including virtual scenes and real scenes. The virtual scene is a virtual learning environment and characters created by the software. Realistic scenes are realized by accessing realistic videos.
  - (5) Application layer: realizes regular online instructional learning, virtual environment learning and interaction.



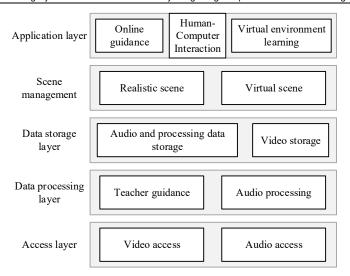


Figure 1: Music teaching system architecture

## II. B. 2) Audio processing

The audio processing system includes two parts, the feature extraction module and the feature processing module. The feature extraction module includes a fundamental frequency recognizer and a tone length acquirer, and the feature extraction module is shown in Figure  $\boxed{2}$ . The fundamental frequency recognizer has built-in fundamental frequency recognition methods: cepstrum method, harmonic peak method, cyclic straight method, wavelet transform method and parallel processing method. The extraction of fundamental frequency data features is carried out according to the method selected by the teacher in the teacher instruction system for acquiring fundamental tones. The tone length acquirer uses the algorithm  $T = \Delta N \cdot 1/(f_s/2^q)$  to extract the hourly value of the tone length, where  $\Delta N$  is the number of samples between the two note endpoints, q is the wavelet decomposition scale, and f, is the frequency of the signal when it was initially sampled.

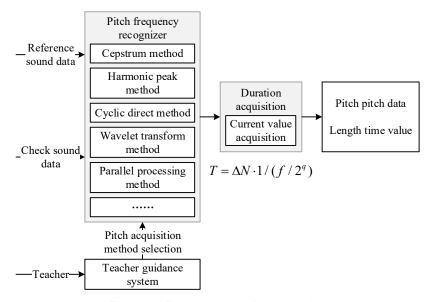


Figure 2: Feature extraction module

The feature processing module includes a frequency pitch converter, a pitch comparator, and a tone length comparator, and the pitch tone length comparator is shown in Figure 3. The frequency pitch converter converts the

$$X = [12 \times \lg(y/27.5)]/\lg 2 + 1 \tag{1}$$

where  $\mathcal{Y}$  is the frequency of the fundamental sound, X is the corresponding pitch, and the pitch comparator compares in a way H = A - B, where A is the pitch of the sound to be examined, B is the pitch of the



fundamental sound, and H is the pitch difference. The pitch comparator compares L = C - D, where C is the pitch of the sound to be checked, D is the pitch of the reference sound, and L is the pitch difference.

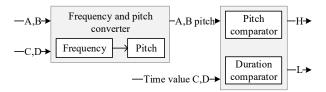


Figure 3: Pitch length comparator

### II. B. 3) Interaction modes

The participation of "human-computer interaction" mode provides diversified choices of teaching resources for the development of the music discipline, and at the same time expands the space for the development of music subdisciplines [21]. The application of the "human-computer interaction" model in the field of music mainly involves the following aspects: research on interactive electronic music, research on the teaching of music with intelligent instruments, and the application of multimedia classroom. Different music sub-disciplines provide a new platform for the development of "human-computer interaction" technology, and "human-computer interaction" technology expands new research paths for music sub-disciplines, and the two interact with each other to make progress together, which provides a powerful technical support and theoretical support for the development of the new mode of music education. Both of them interact and progress together, providing powerful technical support and theoretical support for the development of the new model of music education.

### (1) Interactive Electronic Music

The rapid development of information has opened up new horizons for the creation and presentation of "interactive electronic music". The creation concept of "interactive electronic music" is more in line with the trend of the times, and the scope of people who can participate in it is gradually widening. Taking music as the main body, on the interactive platform through modern technological means, music information is inputted into interactive devices (such as computers, MIDI devices, iPads, etc.) through different types of sensors, and through the corresponding software programs, music information is captured, identified, analyzed and processed, and finally various music art forms are integrated in three-dimensional form, presenting a multi-dimensional comprehensive art with a sense of hierarchy and three-dimensional space. Comprehensive art.

### (2) Intelligent Musical Instrument Music Teaching

The development of "human-computer interaction" brings new opportunities for music teaching. In the "humancomputer interaction" mode, the emergence of intelligent musical instruments has injected new vitality into music teaching. The setting of the teaching system requires that the teacher is still the main body of teaching, and the visualization of the teaching content is realized through the picture displayed by the musical instrument equipment, so that the students can visualize the picture of the learning content, and the learning content can be decomposed by the picture, so that the students follow the content of the picture to learn. Students can follow the content of the screen to learn, which can reduce the difficulty of students to understand the teaching content and improve the efficiency of students to master knowledge. At present, the common intelligent musical instruments on the market are: intelligent piano, intelligent drums, these intelligent musical instruments through the computer system settings, to achieve "human-computer interaction" visualization, audible, teaching system will be the integration of traditional music teaching lesson plans, classification, in the form of animation on the unified screen, the teacher through the interactive interface of teaching tips, can follow the teaching content, the students follow the content of the screen to learn, can reduce the difficulty of students to understand the content, improve the efficiency of students to master knowledge. Teachers can guide students to learn new knowledge step by step through the teaching hints in the interface, which ensures that teachers teach in an organized way. At the end of the course, a game will be played to assess the mastery of knowledge. In the process of learning, students can also give instructions to the interactive machine, according to their own learning situation for knowledge practice.

### (3) Multimedia Music Teaching

In the new "interactive" teaching environment, educators can not only improve the efficiency of the transmission of educational information, interactive devices set up a variety of interactive ways to improve the initiative of students to participate in learning activities, vivid interactive interface can stimulate students' interest in learning, in the process of interaction to improve students' learning concentration, the use of interactive electronic devices with superior interactivity. The use of interactive whiteboards with superior interactivity for teaching effectively enhances teacher-student communication and student interaction, and also simplifies and humanizes the learning mode of "human-computer interaction". Educators use the "human-computer interaction" teaching interface to effectively



convey the information process at the same time, but also through the collection of student assessment data, through the analysis of assessment data, the problems found to be summarized, and can make appropriate adjustments and improvements to the "human-computer interaction" mode of teaching, and to improve the "human-computer interaction" mode. By analyzing the assessment data and summarizing the problems found, we can make appropriate adjustments and improvements to the "human-computer interaction" mode of teaching, and adjust the teaching steps and teaching methods with students as the main body, so as to enrich the way of acquiring knowledge under the "human-computer interaction" mode and reduce the difficulty of learning.

Interactive whiteboard, a large amount of rich teaching information through the memory classification loaded into the interactive system, in the implementation of the teaching process, in order to facilitate the supplementation of the teaching content, can be combined with more interactive software, so that the classroom teaching in an orderly manner to inject new vitality. In the process of teacher-student exchanges, you can enrich the breadth of knowledge of students, thereby enhancing the students' knowledge horizons, greatly stimulate students' interest in learning, improve students' learning efficiency, not only to achieve the active participation of students in the initiative of learning, but also to achieve the enhancement of students' interest in learning. The storage function of the interactive device can also realize the classroom generative teaching.

# II. C.Establishment of an evaluation system

The study used the hierarchical analysis method to evaluate the effectiveness of the music classroom. The evaluation method includes the following steps:

(1) Establishing a recursive hierarchical structure

According to the principle of hierarchical analysis, the evaluation indicators are grouped according to their attributes, and each group constitutes a recursive hierarchical structure to form a multilevel evaluation indicator system [22]. The classroom teaching effect evaluation indexes constructed in this paper are divided into three levels of recursive hierarchy, and the constructed evaluation index system is shown in Table 1. Among them, the index level contains nine evaluation indexes such as teaching design with innovation, breaking through the teaching interaction mode, cultivating students' creative ability, reflecting the teaching focus, rich and diversified teaching resources, providing activities such as simulation games, teaching methods that arouse students' interest, friendliness of teaching tools, and possessing artistic level.

Target layer	Criterion layer	Index layer		
		Teaching design is innovative (C1)		
Evaluation of classroom teaching effect	Teaching design (B1)	Breakthrough teaching interaction mode (C2)		
		Cultivate students' ability to create (C3)		
		Reflect the teaching focus (C4)		
	Teaching mode (B2)	Rich and diverse teaching resources (C5)		
		Provide simulation games and other activities (C6)		
		Teaching methods cause students to be interested (C7)		
	Teaching tool (B3)	Teaching tool friendliness (C8)		
		Artistic level (C9)		

Table 1: Evaluation index system

# (2) Constructing a two-by-two comparison judgment matrix

In order to compare each factor or indicator to find its relative weight, the relative importance scale is introduced. The scale of 1 to 9 is used. The judgment matrix is derived from the two-by-two comparison method.

- (3) Hierarchical single sorting and consistency test
- 1) Calculate the product of each row of the judgment matrix M:

$$M_i = B_{i1}, B_{i2}, \dots, B_{in} \quad (i, j = 1, 2, \dots, n)$$
 (2)

2) Compute the nth root of  $M_i$ :

$$\overline{W_i} = \sqrt[n]{M_i} \tag{3}$$

3) Normalize the square root vector:

$$W_i = \overline{W_i} / \sum_{i=1}^n \overline{W_i}$$
 (4)



Get the sorting weight vector:

$$W = (W_1, W_2, \cdots, W_n) \tag{5}$$

4) Determine the maximum eigenvalue of the matrix into  $\lambda_{max}$ :

$$\lambda_{\max} = \sum_{i=1}^{n} \left[ \left( AW \right)_{i} / nW_{i} \right] \tag{6}$$

where:  $(AW)_i$  - the *i* th element of the vector AW.

To ensure the reasonableness of the obtained weights, a consistency test is usually performed on each judgment matrix to see if it has satisfactory consistency. Otherwise, the judgment matrix should be modified until the consistency requirement is satisfied. The calculation formula is as follows:

$$CR = \frac{\lambda_{\text{max}} - n}{(n - 1)RI} < 0.1 \tag{7}$$

where: RI - average random consistency index. For each judgment matrix CR is less than 0.1.

(4) Total ranking and total consistency test

The synthetic weights are calculated from top to bottom, and the weights of a single criterion are synthesized and carried out layer by layer until the weights of the elements in the bottom layer and the total consistency test are calculated, i.e.:

$$W^{(k)} = [W_1^{(k)}, W_2^{(k)}, \cdots, W_{nk}^{(k)}]$$

$$T = p^{(k)}W^{(k-1)} = p^{(k)}$$

$$[W_1^{(k-1)}, W_2^{(k-1)}, \cdots, W_{nk-1}^{(k-1)}]^T$$
(8)

Where,  $W^{(k)}$  - a synthetic ranking weight vector of nk elements on the k th layer with respect to the total objective,  $p^{(k)}$  - the vector of sorting weights of nk elements on the k th layer with respect to all elements on the k-1 th layer for the criterion,  $W^{(k-1)}$  - a vector of synthetic ranking weights of nk-1 elements on the k-1th layer for the total objective.

# III. Deep Reinforcement Learning in Virtual Teaching and Learning

The system to be built in this paper involves a large number of virtual videos, which provide an excellent training and testing platform for deep reinforcement learning algorithms. In virtual videos, deep reinforcement learning (DQN) models have good or even perfect simulation environments, and the simulator can generate unlimited data. This all lays a solid foundation for deep reinforcement learning training. Aiming at how deep reinforcement learning models can reduce computational resources in virtual video, the study proposes a lightweight deep reinforcement learning method to create a better simulation environment for music teaching systems by constructing a deep separable convolutional reinforcement learning model.

### III. A. Deep reinforcement learning methods

The basic elements of reinforcement learning include observation, behavior, and reward function, which are often used to solve sequential decision-making problems. In the reinforcement learning paradigm, an intelligent body obtains immediate reward or punishment items through interaction with the external environment as quantitative feedback from the environment on its behavior. Then it adjusts its own strategy according to the feedback value and iterates repeatedly until it realizes the optimal decision [23], and the basic learning model of reinforcement learning is shown in Fig. 4.

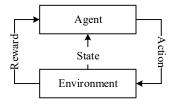


Figure 4: Basic learning model of reinforcement learning



First, the intelligent body obtains the perception state  $S_t$  by observing the external environment. Then, according to the existing strategy, it selects the action  $a_t$  from the action space A to be executed, and the external environment will give the corresponding feedback according to  $a_t$  to obtain the immediate return  $r_{t+1}$  and update the state to  $S_{t+1}$ . Eventually the intelligent body adjusts its own policy parameters according to the reward function and continues to make new decisions about the new state  $S_{t+1}$ . The goal of the reinforcement learning task is to find the optimal policy  $\pi^*$  that allows the intelligent body to obtain the optimal cumulative return in any state:

$$\pi^* = \operatorname{argmax} E_{\pi} \left\{ \sum_{k=0}^{\infty} \gamma^k r_{t+k} \mid S_t = S \right\}, \forall S \in S, \forall t \ge 0$$
(9)

where  $\pi^*$  denotes the strategy of the intelligent,  $\gamma \in [0,1]$  is the discount factor, k is the future time step, and S is the state space.

According to whether the model is known or not, existing reinforcement modeling algorithms can be divided into two categories: model unknown and model known. According to the way of behavior selection can be divided into policy-based and value-based reinforcement learning. According to whether the learning strategy and execution strategy are the same or not can be categorized into heterogeneous strategy and homogeneous strategy learning approaches.

# III. B. Deeply Separable Convolutional Reinforcement Learning Models

The part of the deep reinforcement learning model that observes the environment consists of convolutional neural networks. In this section, depth-separable convolution is introduced into deep reinforcement learning to construct a lightweight deep reinforcement learning model (LQN).

Deep separable convolution decomposes standard convolutional operations into deep convolutional operations and pointwise convolutional operations. Deep convolution applies convolution operations only to each feature map on each channel and does not involve convolution operations on features between each channel. The pointwise convolution operation is only used to merge features between channels of the feature maps output from deep convolution, and does not operate on a single layer of features on each channel. The convolution operation for standard convolution, on the other hand, is computed both on features on each channel and between individual channel features.

Let  $H_k$  and  $W_k$  be the height and width of the convolution kernel,  $N_c$  and  $N_k$  be the number of channels in the input, the number of convolution kernels, and  $H_f$  and  $W_f$  be the height and width of the feature map of the input mapped by the convolution layer. The equation for the computational complexity of the standard convolution is (10):

$$H_{k} * W_{k} * N_{c} * N_{k} * H_{f} * W_{f}$$
 (10)

In deep separable convolution, the equation for the operational complexity of deep convolution is equation (11):

$$H_k * W_k * N_c * H_f * W_f$$
 (11)

In deeply differentiable convolution, the equation for the arithmetic complexity of pointwise convolution is equation (12):

$$N_c * N_k * H_f * W_f \tag{12}$$

The ratio of the complexity of the deep separable convolution to the standard convolution operation is (13):

$$\frac{H_k * W_k * N_c * H_f * W_f + N_c * N_k * H_f * W_f}{H_k * W_k * N_c * N_k * H_f * W_f} = \frac{1}{N_k} + \frac{1}{H_k * W_k}$$
(13)

From the above calculations, it can be seen that the LQN method can reduce the amount of standard convolutional operations to  $\frac{1}{N_k} + \frac{1}{H_k * W_k}$ . In the model of this section, the amount of three-layer convolutional

calculations can be reduced to 
$$\frac{1}{32} + \frac{1}{8*8} = \frac{1}{64} + \frac{1}{4*4} = \frac{5}{64}$$
 and  $\frac{1}{64} + \frac{1}{3*3} = \frac{73}{576}$ , respectively.

Meanwhile, in terms of the number of parameters of the model, this split method can reduce the number of parameters of the model at the same time. The formula for the number of parameters of a standard convolutional layer is (14):



$$H_k * W_k * N_c * N_k \tag{14}$$

The number of parameters in a convolutional layer in a deeply separable convolutional model is given by (15):

$$H_{k} * W_{k} * N_{c} + N_{c} * N_{k} \tag{15}$$

The ratio of the complexity of the deep separable convolution to the standard convolution operation is (16):

$$\frac{H_k * W_k * N_c + N_c * N_k}{H_k * W_k * N_c * N_k} = \frac{1}{N_k} + \frac{1}{H_k * W_k}$$
(16)

As with the ratio of operational complexity, the number of parameters of the depth separable convolution can be reduced to the original  $\frac{1}{N_k} + \frac{1}{H_k * W_k}$ , so the ratio value of the specific number of parameters reduced by the LQN method is the same as the specific value of the reduction of operational complexity described above.

# III. C. Analysis of experimental results

### III. C. 1) Convergence behavior

In this section, an insight into the convergence behavior of the selected LQN algorithm in the task of reducing the virtual video computational resources will be presented and it will be compared with the DQN algorithm in solving this problem.

The convergence behavior of the DQN algorithm at different learning rates is shown in Fig. 5. The vertical axis is the average of cumulative rewards and the horizontal axis is the number of epochs for a fixed training of 100000 times. (Same as below) It can be observed that after training, the intelligence has learned the whole network system. The reward obtained from each experiment is dynamically changing, and the mean value of the reward is gradually stabilized, i.e., the algorithm is gradually converging. And according to the simulation results, the convergence is most obvious and the best performance is achieved when the learning rate is 0.001. The higher number of different epochs under the same number of training times indicates that fewer training steps are required in one round of training and the performance is better.

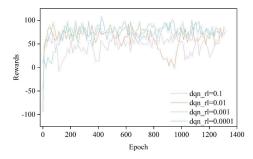


Figure 5: DQN increases the value of the average in different learning rates

The training results of the LQN algorithm at different learning rates are shown in Figure 6. The number of training sessions is also fixed at 100000. It is observed that the cumulative reward averages are higher at both learning rates of 0.01 and 0.001, and in comparison, the number of epochs is slightly higher at a learning rate of 0.001, so it is considered that the LQN algorithm performs better at a learning rate of 0.001.

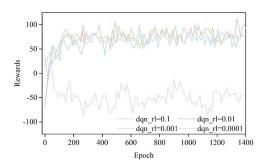


Figure 6: LQN increases the value of the average in different learning rates



# III. C. 2) Performance Comparison of LQN Algorithm with DQN Algorithm

We compared the reward value performance of the two algorithms with fixed learning rate of 0.001 for both DQN and LQN algorithms with the best results, and the statistical results are shown in Fig. 7 for the cases of less, average, and more number of interferences. In our simulation results, it is consistent with the rule that the lower the number of interferences, the higher the reward value. Our chosen LQN algorithm has reward values ranging from 100 to 120 in all three cases, which are significantly better than the DQN algorithm. The study shows that the LQN algorithm is more suitable for the construction of the simulation environment of the music teaching system.

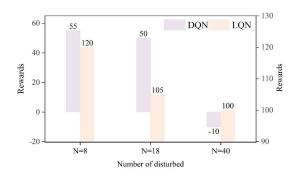


Figure 7: The algorithm rewards the comparison

# IV. Evaluation of the effectiveness of the application of the music teaching system

The music teaching system integrating deep reinforcement learning and virtual reality technology was designed in the previous paper, and this chapter evaluates the application effect of the system. Taking the freshmen majoring in music in S school as the experimental subjects, the teaching system designed in this paper was used to teach music in the first semester of 2024, and after the semester ended, the students' music learning effect was evaluated based on the teaching effect evaluation index system constructed in Table 1. In-depth weighting analysis and quantitative research were conducted on these dimensions and their detailed indicators, and finally the level of integration effect was determined by calculating the scores and according to the evaluation criteria of experts.

### IV. A. Calculation of weights

Using the hierarchical model as a basis, we compared the indicators for evaluating the teaching effectiveness of the music course for freshmen music majors in School S two by two to determine the relative importance between them, and generated a judgment matrix accordingly. Typically, we use a scale from 1 to 9 to compare indicators: scale 1 means that between two indicators, A and B have the same importance. Scale 3 means that between two indicators, where A is slightly more important than B. Scale 5 means that A is more important compared to B. Scale 6 means that A is more important compared to B. Scale 7 means that A is more important compared to B. Scale 7 means that between the two evaluation indicators, A has more importance than B. Scale 9 means that between the two evaluation indicators, A has more importance than B. Scales 2, 4, 6, and 8 represent the values of the scales corresponding to the intermediate states between the judgments described above. The importance of B over A can be expressed by the inverse of the scale.

After index weights, synthetic weights calculation and consistency test. The three-level index weights of the teaching effect evaluation system are shown in Figure 8. Among them, the weights of the indicators of teaching interaction mode (C2) and teaching design (C1) are relatively high, 19.2% and 17.5% respectively. This indicates that the interaction mode and instructional design in the music teaching system designed in this paper have the greatest influence on the music teaching effect.

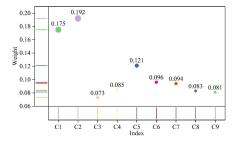


Figure 8: The teaching effect evaluation system three level index weight



# IV. B. Evaluation analysis

Five experts  $(E_1, E_2, \cdots E_5)$  were invited to evaluate the nine indicators according to their own satisfaction with them using a semantic scale of excellent, good, moderate and poor. The qualitative indicators are assigned values to make them quantitative, and the lower limit of the assignment is set to 60, with the formula excellent = 95, good = 85, medium = 70, and poor = 60. The evaluation results of the weights of the indicators by the five experts are shown in Table 2. The composite ratings of the five experts are =  $87.25 \times 0.175 + 87.5 \times 0.192 + 86.75 \times 0.073 + 84.5 \times 0.085 + 77.5 \times 0.121 + 83.25 \times 0.096 + 78.5 \times 0.094 + 84.25 \times 0.083 + 86 \times 0.081 = 84.29$ , and the result of the comprehensive evaluation is "good".

Index	$W_{i}$	$E_1$	$E_2$	$E_3$	$E_4$	$E_5$	Average score
C1	0.175	85	91	85	88	87.25	85
C2	0.192	76	92	93	89	87.5	76
C3	0.073	87	90	85	85	86.75	87
C4	0.085	91	88	84	75	84.5	91
C5	0.121	70	86	72	82	77.5	70
C6	0.096	85	81	91	76	83.25	85
C7	0.094	73	73	81	87	78.5	73

Table 2: The evaluation results of the evaluation of the index

In conclusion, the teaching system designed in this paper has been applied well and can be used as a reference to apply to daily music teaching.

### V. Conclusion

The music teaching system constructed in this paper contains a large number of virtual video applications, accordingly, the study proposes a lightweight deep reinforcement learning method to create a good simulation environment. The lightweight deep reinforcement learning model has a reward value ranging from 100 to 120 with a learning rate of 0.001, which can obtain a higher reward value and is more suitable for the construction of the simulation environment of the music teaching system than the deep reinforcement learning model. The weights of teaching interaction mode and teaching design in the teaching system designed in this paper are 19.2% and 17.5%, respectively, and the two have the greatest influence on the music teaching effect. After the freshmen majoring in music in S-school apply the teaching system constructed in this paper for music learning, the comprehensive evaluation score is 84.29, which indicates that the teaching system designed in this paper can realize a relatively good music teaching effect.

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