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Optimization Strategy of Ceramic Design Learning Using Reinforcement Learning

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Abstract. Under the background of economic development and the transformation of the ceramic industry, the requirements of ceramic design talent training have gradually increased, and the traditional talent training mode of colleges and universities can no longer meet the needs of the industry and the market. Ceramic design lacks innovation and can not meet the personalized needs of consumers. Therefore, this paper introduces reinforcement learning on the basis of CAD systems to build a training platform for ceramic design talents in universities, optimize the results of professional course scheduling, and improve the quality of ceramic design. The experimental results show that the platform has good performance of course scheduling and parameter optimization and can help students complete the corresponding tasks in a shorter time. In the application experiment, the course arrangement effect of this platform is better than the traditional course arrangement effect, and the result is more in line with the needs of talent training. In terms of parameter design optimization, the platform of this paper effectively realizes the optimization of the fit degree of basic ceramic design and ceramic modelling patterns and improves the quality of ceramic design. After the experiment, the students' personalized ceramic design performance significantly improved, especially in the three aspects of modeling design, market value, and innovation, taking into account the aesthetic value of ceramic design and market value.

Keywords: Reinforcement Learning; CAD Fusion; Ceramic Design; Personnel Training
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1 INTRODUCTION

Under the background of high-quality economic development and industrial technology upgrading, the transformation and upgrading of the ceramic industry is an inevitable trend of its future development, and the industry has an increasing demand for high-quality and high-skill design talents [1]. At the same time, with the improvement of people's living standards and the change in consumption concepts, higher requirements are put forward for the design sense, artistry, and practicality of ceramic products. Ceramic designers need to be able to create ceramic products that meet the needs of the market and meet the diverse needs of consumers. Compared with traditional ceramic design, the current cultivation of ceramic design talents needs to inherit ceramic culture, have solid professional knowledge and skills in ceramic design, and have an innovative spirit, innovative thinking, design ability and practical ability [2]. They can combine market demand and consumer preferences to create innovative and practical ceramic products and promote the development of the ceramic industry. Due to the limitation of environmental conditions, the traditional training mode of ceramic design talents in colleges and universities focuses more on the study of theoretical content and lacks sufficient practical links, resulting in insufficient practical ability of students and difficulty in transforming theoretical knowledge into practical ability [3]. There is a great contradiction between this mode and the characteristics of the ceramic design major. In addition, the ultimate goal of the cultivation of ceramic design talents is to cultivate professional talents who can be put into industrial production, drive industrial development with talents, and then feed back to colleges and universities to improve the standards of talent training to achieve a virtuous cycle of talent training. However, in practice, there is still a large distance between the cooperation between universities ceramic enterprises and scientific research institutions [4]. Problems such as poor information transmission, lack of cooperation mechanisms, and limited project research and development and technological innovation platforms make it difficult to carry out industry-university-research cooperation in depth. In terms of professional teaching content, many colleges and universities fail to consider the correlation between practical operation and theoretical knowledge, such as systematic course arrangement, overlapping of professional courses, unreasonable course arrangement, and incomplete professional courses [5]. The existence of these problems makes the training effect of ceramic design talents in universities not ideal, and can not meet the requirements of the ceramic industry and the market for talents.

As the intersection of traditional craftsmanship and modern design, the teaching process of pottery making is undergoing unprecedented changes. CAD technology can accurately simulate and create complex three-dimensional structures, allowing students to foresee the final product effect during the design phase. Reinforcement learning algorithms can provide students with intelligent design suggestions by analyzing a large number of design cases, and learning design rules and aesthetic standards [6]. Although traditional pottery classrooms can effectively teach basic skills, they have limitations in stimulating students' creativity, improving design efficiency, and implementing complex design concepts. On the CAD platform, students can not only sketch by hand but also generate preliminary design schemes using algorithms, greatly improving design efficiency and creative diversity. Reinforcement learning allows students to provide immediate feedback and adjustments during the design process [7]. Therefore, combining reinforcement learning with CAD technology and integrating it into a VR teaching environment provides new ideas and possibilities for the cultivation of ceramic design talents in universities. Students can continuously optimize their design plans based on algorithm evaluation results until satisfactory results are achieved. By combining reinforcement learning algorithms, students can challenge more complex and innovative design projects, such as asymmetric structures, complex textures, etc., which broadens the boundaries of design [8]. This "trial and error learning optimization" cycle promotes the improvement of students' innovative thinking and problem-solving abilities. In the VR environment, students can freely explore the impact of different materials and processes on design results, and even simulate challenges and solutions in practical operations [9]. Introducing VR-based ceramic production methods into university ceramic design courses not only enhances the fun of learning but also provides students with a more intuitive and immersive learning experience. This immersion encourages students to think more deeply about design details, stimulating their creativity and imagination [10]. In the VR environment, students can gain a deeper understanding of design principles and process flow by combining hands-on operations with intelligent assistance. Research has shown that using VR combined with reinforcement learning and CAD teaching methods can not only significantly enhance students' creativity, but also increase their learning engagement. At the same time, the design process of instant feedback and continuous optimization has stimulated their learning motivation and interest and increased their participation in various aspects such as behaviour, emotion, and social interaction [11].

With the development of CAD technology and computer technology, its application in ceramic design provides powerful technical support for the reform of the training mode of ceramic design talents. CAD technology, through computer-aided design software, makes ceramic design change from traditional hand-drawn way to digital design mode. This method greatly improves design efficiency, and designers can quickly transform their ideas into 3D models and preview the effects in real-time. Such a teaching model offers the possibility of visual design and adjustable parameters. At the same time, the application of CAD breaks the limitations of complex and unique ceramic design, providing designers with creative space to try different design schemes. However, the application of CAD technology can not solve the problem of the optimization of the training mode of ceramic design talents in colleges and universities. Therefore, this paper combines reinforcement learning to build a training platform for ceramic design talents and combines CAD systems to achieve the purpose of talent training optimization. In this study, the innovation of the reinforcement learning algorithm is that it can realize the optimization of ceramic design courses and improve the systematic, scientific and rational training mode. Secondly, the introduction of reinforcement learning can improve the automation and intelligence of ceramic design, help students achieve parameter optimization and design optimization, provide better solutions for ceramic design, and improve students' design thinking and innovative thinking.

2 RELATED WORK

The cultivation of ceramic design talents in universities has multidimensional and multi-level characteristics, involving multiple aspects such as educational philosophy, curriculum design, practical activities, and school-enterprise cooperation. In the previous talent cultivation model, some educators introduced the concept of factory time based on theory and practice, which means that students can understand the actual process of ceramic production by visiting and participating in the production. With the promotion of the "Three Innovations" educational concept, some educators propose school-enterprise cooperation, where enterprises provide more practical space for universities to help students improve their professional skills in the production process, and universities provide more high-quality talents for the industry, making talent cultivation more in line with market demand. With the continuous development and innovation of the ceramic industry, the demand for ceramic design talents is also growing. Especially interdisciplinary talents with innovative thinking, solid professional skills, and good comprehensive qualities. The training mode of ceramic design talents in universities is gradually showing a diversified trend. In addition to traditional school education, there are various forms of online education, seminars, and international exchanges. Each form has its own characteristics and can provide students with more flexible and diverse learning choices. Although significant achievements have been made in cultivating ceramic design talents in universities, there are still some problems and challenges. For example, there are still some unscientific aspects in the curriculum of some universities, leading to a disconnect between theory and practice; Some students need to improve their innovation ability. The breadth and depth of school-enterprise cooperation still need to be further expanded. With the development of computer technology, strong technical support has been provided for the cultivation of ceramic design talents. Ma et al. [12] used computer-aided design software for ceramic design, achieving ceramic modelling, rendering, and simulation, greatly improving design efficiency and allowing students to observe the ceramic design process more intuitively in the teaching process. In the future, the cultivation of ceramic design talents will introduce technologies such as virtual reality and artificial intelligence, creating a more realistic and practical ceramic design space for talent cultivation.

In ceramic design education, this technology can cultivate students' precise awareness and craftsmanship skills, laying a solid foundation for their future careers. In the later stages of ceramic design, precise image segmentation techniques (similar to image processing methods in mineral processing) can be applied to CAD models to achieve higher precision design and manufacturing. Marín et al. [13] analyzed students' behavioural data and feedback during the design process, and reinforcement learning algorithms can customize personalized learning paths for students. For example, based on students' performance in CAD operations, material selection, or design creativity, the system can recommend targeted learning resources and challenging tasks to accelerate students' growth and progress. This helps ensure a seamless transition from virtual design to physical design while reducing errors and waste in the manufacturing process. The integration of image segmentation technology in mineral processing and ceramic design education has also promoted interdisciplinary cooperation and innovation. Students can draw inspiration from different technical fields and combine various techniques such as image processing, machine learning, CAD design, etc. to create novel and unique ceramic works. This interdisciplinary collaboration not only broadens students' horizons but also stimulates their creativity and teamwork abilities. Reinforcement learning techniques can be applied in the early stages of ceramic design, and Ming et al. [14] simulate the design process through algorithms to automatically explore and optimize design solutions. This intelligent design exploration process not only improves design efficiency but also cultivates students' innovative thinking and problem-solving abilities. Combined with CAD software, students can quickly iterate multiple design options in a virtual environment without worrying about material waste or time consumption.

Augmented reality technology seamlessly integrates graphic information into physical environments, providing users with an unprecedented immersive experience. By combining AR and reinforcement learning, educational platforms can customize personalized learning content based on students' learning progress and interests. This' what you see is what you get 'experience enables students to have a more intuitive understanding of the effects of design in real space, thereby identifying and solving potential design problems in advance. In ceramic design education, this technology can greatly enrich students' learning methods and design practices, especially in the context of combining reinforcement learning and CAD technology. Shi et al. [15] recommend relevant AR case studies and design challenges based on students' design preferences and error patterns, promoting the development of deep learning and innovative thinking. Students can use AR technology to directly project CAD designs into a real environment for real-time visualization and validation. Meanwhile, reinforcement learning algorithms can assist in this process by simulating the physical characteristics and user feedback of different design schemes, providing intelligent design suggestions and optimization solutions. AR technology breaks the limitations of physical space and allows students and designers from different locations to participate in design projects together. In addition, AR technology can also help students adapt to the professional environment in advance and enhance their employment competitiveness by simulating real work scenarios. By sharing the AR environment, they can view and discuss design solutions in real-time, and collaborate remotely. This collaborative model not only improves design efficiency but also cultivates students' teamwork spirit and cross-cultural communication skills. AR technology also plays an important role in the development and sales stages of ceramic products. Meanwhile, reinforcement learning algorithms can analyze team interaction data, provide team collaboration optimization suggestions, and promote a more efficient and harmonious collaborative atmosphere. Tao [16] simulates the interaction scenarios between users and products, allowing designers to more accurately evaluate the usability, aesthetics, and comfort of products. By combining user feedback data and reinforcement learning algorithms, designers can continuously optimize product design and improve user experience and satisfaction. This AR-based user experience evaluation method also provides valuable teaching resources and practical cases for ceramic design education.

3 CONSTRUCTION OF CAD CERAMIC DESIGN TALENT TRAINING PLATFORM

3.1 Analysis of Training Mode of Ceramic Design Talents

Compared with the traditional ceramic design talent training mode, this training mode introduces the concept of "three innovations," which emphasizes the organic combination of creativity, innovation, and entrepreneurship in the education process to promote the all-round development of students. Among them, creativity is the soul, stimulating students' imagination and creativity; Innovation is the purpose, encouraging students to explore the unknown, to seek new breakthroughs; Entrepreneurship is practice, which translates creativity and innovation into practical results and cultivates students' market awareness and entrepreneurial ability. The creativity of ceramic design talents is based on the cultivation of the creative ability of innovative thinking, and innovative thinking is the driving force of technology and production innovation. Through design thinking training, creative workshops, and other ways to stimulate students' imagination and creativity. Students are encouraged to seek design inspiration from traditional culture, modern science and technology, social phenomena, and other perspectives to create unique and innovative ceramic works. The realization of innovation needs to guide students to innovate through iterative learning in the process of education and pay attention to cultivating students' innovative ability and critical thinking. Combined with project-based teaching, case analysis, and other methods, students are guided to understand the importance of innovation and its methods in depth. In the process of talent training, it is also necessary to integrate entrepreneurial education and cultivate students' market awareness and entrepreneurial ability so that students can grasp market changes, understand product development trends, and design ceramic designs that are more in line with industrial demand, market demand, and consumer demand. Figure 1 shows the design diagram of the teaching mode of the CAD ceramic design talent training platform based on reinforcement learning.

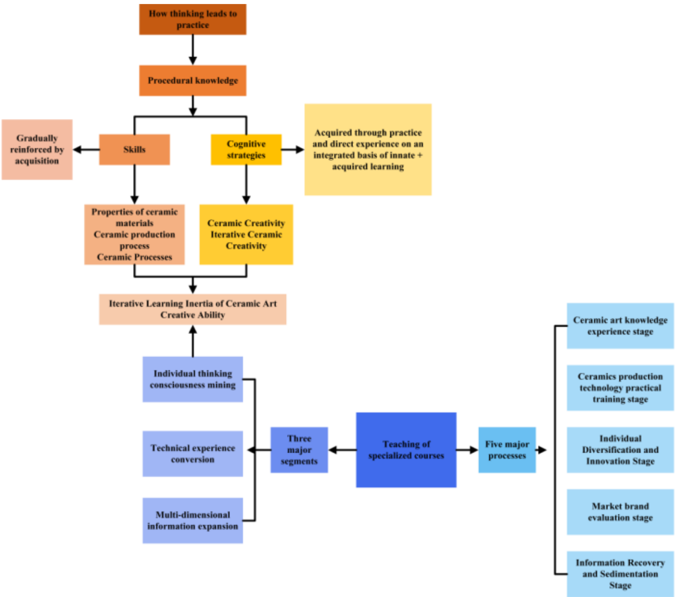

Figure 1: Design of teaching mode of CAD ceramic design talent training platform based on reinforcement learning.

The platform teaching mode of this paper is based on theory and practice and integrates entrepreneurial and innovative thinking. In the future, it needs to be optimized and adjusted for various teaching links. Among them, course arrangement is the basic and very important link in the process of talent training; the traditional training mode of course arrangement focuses on practical operation, ignoring the systematic, rational, and scientific curriculum. Reasonable curriculum arrangement and setting are the keys to achieving the goal of talent training and enhancing students' professional quality and practical ability. In addition, students need to realize the visualization of ceramic design through CAD systems in practice and achieve the best state of design through continuous parameter adjustment. Considering that students' own design level is uneven and there is no quality design standard for comparison, it is difficult for them to intuitively feel the shortcomings of their own design in the process of innovative design. External help is needed to find their own shortcomings. Therefore, this paper combines CAD systems and reinforcement learning to build two modules, course scheduling and ceramic design optimization, which will be introduced in detail below.

3.2 Ceramic Design Course Scheduling Module Based on Reinforcement Learning

Ceramic design not only attaches importance to students' historical and cultural heritage but also the combination of theory and practice, so the course covers a wide range. The basic courses include the fundamentals of fine arts and design, while the core courses cover all aspects of ceramic design, production, and technology. Courses from ceramic technology to modern ceramic creation are the core professional courses for colleges and universities to train ceramic design talents. The practical course includes practical training, special practical training, and comprehensive practical training. In the traditional training mode of colleges and universities, basic courses mainly focus on design and lack corresponding basic training in fine arts. The core courses of majors are not all regarded as main courses, and some courses are regarded as extension courses. The practical course is based on curriculum training or comprehensive practical training, lacks refinement, and takes a relatively short time. In essence, course scheduling is the optimal allocation of teaching resources; that is, training planning is realized through conditional constraints. Therefore, this paper introduces a genetic algorithm based on reinforcement learning to improve the module's course scheduling performance.

The elements of the ceramic design talent training course include curriculum, teacher, class, teacher and time, respectively expressed as $\{L,H,C,R,T\}$ The set representation of each element is shown in (1):

$$\{L,H,C,R,T\}$$
$$\begin{cases} L=\{l_1,l_2,\ldots,l_L\} \\ H=\{h_1,h_2,\ldots,h_H\} \\ C=\{c_1,c_2,\ldots,c_C\} \\ R=\{r_1,r_2,\ldots,r_R\} \\ T=\{r_1,r_2,\ldots,r_R\} \end{cases} \tag{1}$$

The scheduling decision variable is expressed as $X(l,h,c,r,t)$ Its objective function is shown in (2):

$$\min=\sum_{n=1}^{5}\sum_{l=1}^{L}card(\bigcap_{c=1}^{C}X_{t\in T^n}(l,h,c,r,t) \tag{2}$$

Its constraints are shown in (3):

$$\begin{cases} \forall n\in T,\forall m\in R,(\bigcap_{k=1}^{R}X_{k(n,m)})\le 1 \\ \forall n\in T,\bigcap_{m=1}^{R}H(n,R_m)=\varnothing \\ \forall n\in T,\bigcap_{m=1}^{R}C(n,R_m)=\varnothing \\ \forall n\in L,\bigcup_{k=1}^{5}T^k(n,C_m)=\varnothing \end{cases} \tag{3}$$

Among them, n Indicates the corresponding time range.

The application of a genetic algorithm can solve the above conditional programming problem and realize the heuristic search through the core idea of natural law. In terms of selection strategy, considering the practical application of the problem, the random traversal method was adopted in this paper; that is, the individual with the highest fitness in the sire was hybridized and mutated with the selected high-quality individual so as to select a new high-quality individual. The adaptive function is shown in formula (4):

$$f = \sum_{n=1}^{i} w_n f_n \tag{4}$$

Where each conflict factor is expressed as f_n, whose weight is expressed as w_n, its quantity is expressed as i.

The Q-learning algorithm used in the reinforcement learning module is a model-free reinforcement learning algorithm, which is used to learn how to take the optimal action in a given environment to maximize the cumulative reward. It is based on Markov decision process theory but does not need to know the full dynamic model of the environment. Q-learning works by learning an action-value function that estimates the expected value of future cumulative rewards that can be obtained by taking an action in a given state and following the optimal strategy. Locate in s State The execution is complete following the optimal policy. The expected cumulative reward after a the action is expressed as $Q(s,a)$ After the action is performed, observe the new status as $s^{'}$ Instant rewards are expressed as η Then the updated formula is shown in (5):

$$Q(s,a) \leftarrow Q(s,a) + \lambda[\eta + \beta \max_{a^{'}} Q(s^{'},a^{'}) - Q(s,a)] \tag{5}$$

Where the learning rate is denoted as λ, the discount factor is expressed as β, the best action of all actions in the new state is represented as $a^{'}$.

On this basis, this paper uses the average fitness of the population and the optimal individual fitness as the index of state set division. Let the sequence number be g. The sequence number in the iteration is n The individual adaptation function $G(x_n^g)$, the average adaptation function of its population is calculated as shown in (6):

$$G^g = \sum_{n=1}^{N} G(x_n^g) / N \tag{6}$$

Where the number of individuals contained in the population is denoted as N.

Then, the definition of the fitness function of the smallest individual in the population of the corresponding iteration generation is shown in (7):

$$M^g = \min G(x_n^g) \tag{7}$$

The representation vector of population status is shown in (8):

$$S = (G^g, M^g) \tag{8}$$

The reward function is shown in (9):

$$\eta = \frac{\sum_{n=1}^{N} G(x_n^g) - \sum_{n=1}^{N} G(x_n^{g-1})}{\sum_{n=1}^{N} G(x_n^{g-1})} \tag{9}$$

Where the number of sequences in the previous generation of the current iteration is n The individual fitness function is expressed as $G(x_n^{g-1})$.

Colleges and universities will arrange courses in different quantities according to students of different grades. In order to test the course scheduling performance of this module, this paper selected three groups of different course scheduling tasks to compare the course scheduling performance, and the control group was a classical genetic algorithm. Figure 2 shows the comparison results of the time and iteration times of the two-course scheduling methods under different task quantities. It can be seen from the results that when the number of scheduling tasks is low, the scheduling time of the two methods is similar, and the classical genetic algorithm is slightly faster. As the number of course scheduling tasks continues to increase, the advantages of this course scheduling method are gradually highlighted, and the time is obviously shortened. In terms of the number of iterations, the number of iterations of the proposed method is always less than that of the classical genetic algorithm.

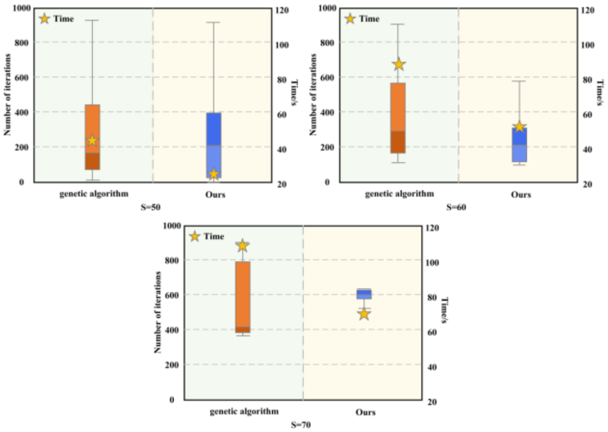

Figure 2: Comparison of the time and iteration times of two-course scheduling methods under different task quantities.

In order to further test the course scheduling performance of the module, the convergence curves of the two algorithms are compared in this paper, and the results are shown in Figure 3. The results show that the convergence rate of the proposed algorithm is faster and has an earlier convergence curve under a different number of scheduling tasks. This shows that the course scheduling performance of the proposed algorithm is better.

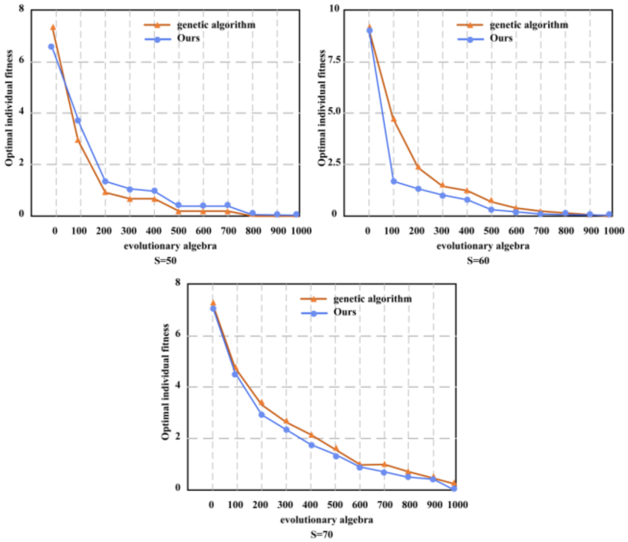

Figure 3: Convergence curves of the two algorithms with different numbers of tasks.

3.3 Ceramic Design Optimization Module Based on Reinforcement Learning

In the process of training ceramic design talents, it is not only necessary to pay attention to the learning of students' basic knowledge and traditional professional knowledge, but also to strengthen students' innovative thinking. Therefore, the ceramic design optimization module includes two aspects of optimization, one is the optimization of the parameters standardization of students' basic ceramic design, and the other is the optimization of students' personalized design.

In the standardization optimization of basic ceramic design parameters, considering that the optimization goal is clear and the standard is high, the strategy gradient algorithm in reinforcement learning is adopted to achieve the optimization purpose. The goal of the strategy gradient algorithm is to maximize the expected return, that is, to maximize the expected value of the cumulative discount return obtained from the initial state by the strategy. The change of state distribution will be affected by the change of strategy, so the expected maximization result can be obtained by calculating the gradient of the parameters in the strategy. Set policy parameters as θ , the objective function is expressed as $J(\theta)$, As shown in formula (10):

$$\nabla_{\theta} J(\theta) = E_{\tau \sim \pi\theta}[(\sum_{t=0}^{T} \nabla_{\theta} log\pi_{\theta}(a_t| \ s_t))(\sum_{t=0}^{T} \gamma^t r(s_t, a_t))] \tag{10}$$

Where the depreciation factor is expressed as γ .

In terms of optimization of personalized ceramic design, this paper adopts the Markov decision, the core of which is how agents choose actions according to the current state to maximize the cumulative reward in the environment with Markov properties. Let the quintuple be represented as (S, A, P, R, γ) , Where the finite set of states is denoted S , the finite set of actions is denoted as A , the state transition possibility is denoted as P , the return function is expressed as R . status $S \to A$ The mapping is represented as a policy π , which represents the possibility of a fixed action for each state, as shown in (11):

$$\pi(a|s) = p(A_t = a|S_t = s) \tag{11}$$

The sum of the ceramic designer's expected maximum discount rewards is shown in formula (12):

$$V^{\pi}(s) = \sum\nolimits_a \pi(s,a)[R(s,a) + \gamma \sum_{s'} \Pr(s'|s,a) V^{\pi}(s')] \tag{12}$$

Where the cumulative amount of future rewards that each possible decision in the present state can provide is expressed as $R(s,a) + \gamma \sum_{s'} \Pr(s'|s,a) V^{\pi}(s')$.

When students are in the moment t The current state is selected as the previous sequence state, which can be marked by positive and negative labels. At this time, all state sequences are shown as (13):

$$C = \{(s_1, l_1^+, l_1^-), ..., (s_t, l_t^+, l_t^-), ..., (s_n, l_n^+, l_n^-), where l_n^+, l_n^- \in (0, ..., 1) \tag{13}$$

Where positive and negative labels are respectively l^+, l^- .

Based on the above formula, the optimal framework of parameterized strategies based on student feedback can be obtained, as shown in (14):

$$G_{\varphi}(C, V) = \varphi \cdot T(\theta, V) - (1 - \varphi) \cdot L(\theta, C) \tag{14}$$

Where parameter θ the maximum discount reward is expressed as T The loss assessment function is expressed as L the regulatory factor is expressed as φ .

The solution by gradient descent method is shown in formula (15):

$$T(\theta, \ V) = \frac{1}{W(V)} \sum_{V_m \in V} w(V_l) R_l, where \quad W(V_l) = \frac{p_{\theta}(T_l)}{p_{\theta_l}(T_l)} and \quad W(V) = \sum_{V_l \in V} w(V_l) R_l \tag{15}$$

Where the student is recorded as l, the probability of getting the maximum reward is expressed as $p_\theta(T_l)$, a student's learning path of ceramic design is expressed as R_l.

$$L(\theta,C) = -\sum_{n=1}^{M} \log(E[\pi_\theta(O(s_n)\left|l_n^+,l_n^-)\right] \tag{16}$$

Where the student label condition possibility is expressed as $(O(s_n)\left|l_n^+,l_n^-)\right]$ And each student's feedback label is independent.

In order to test the performance of modular ceramic design optimization, this paper selects the compound shape method and genetic algorithm, which are commonly used to optimize the design parameters of ceramic design, and conducts optimization experiments on the shape parameters and the color parameters of ceramic, respectively. Figure 4 shows the comparison results of parameter optimization error curves of different algorithms. It can be seen from the results that among the three algorithms, the composite method has the largest error and the slowest convergence speed of the curve, while the error and convergence speed of the genetic algorithm have been improved to some extent. This shows that compared with other algorithms, the proposed algorithm has good parameter optimization performance, can reduce the optimization error, improve the optimization efficiency, and can meet the needs of practical applications.

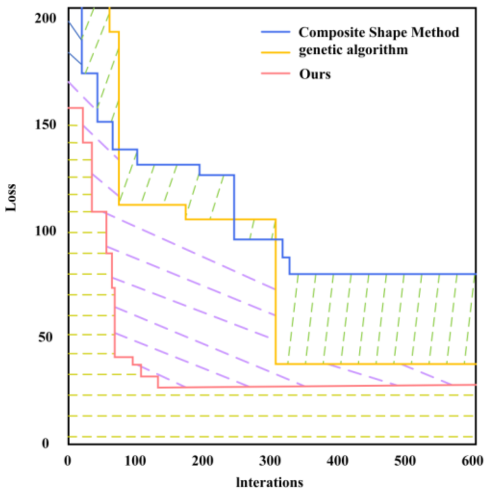

Figure 4: Comparison results of error curves of parameter optimization of different algorithms.

4 APPLICATION EXPERIMENT RESULTS OF CAD CERAMIC DESIGN TALENT TRAINING PLATFORM CONSTRUCTION BASED ON REINFORCEMENT LEARNING

The cultivation of ceramic design talents is systematic, and its optimization strategy should start from the training course arrangement. Therefore, in the application experiment, sophomore ceramic design students in a university are selected as the experimental objects, and the experiment contents include the optimization of professional course scheduling, the optimization of student basic ceramic design and the optimization of personalized ceramic design, and the comparison of student performance. The application experiment lasted for two months.

The core courses of the ceramic design major include Ceramic Technology A, Ceramic Modeling Design B, Ceramic Decoration C, Ceramic Molding Technology D, Modern Ceramic Creation E, Course Practice F, and Professional Practice G. Figure 5 shows the results before and after optimization of the two-week professional course of ceramic design. Figure (a) shows the result before the optimization of course scheduling. Due to the limitation of environmental conditions, the professional course AC has become an extended course, the professional course BDE has a tight theoretical schedule, and the corresponding course practice and professional practice are arranged in the same week. This kind of curriculum arrangement focuses on theoretical learning and lacks the importance of practice. Moreover, some professional curriculum arrangements have low requirements. Figure (b) shows the course scheduling results after optimization. The results show that the optimized professional courses all raise the course requirements and add other extension courses. In terms of practical courses, the correlation between curriculum practice and theoretical practice is stronger, and the professional practice time is increased, which is more in line with the needs of current ceramic design talent training.

9 weeks/session	Mon	Tue	Wed	Thu	Fri	Sat
1	B		D		B	A
2	B		D		B	A
3	C	D		C		
4	C	D		C		
5			B		D	E
6			B		D	E
10 weeks/session	Mon	Tue	Wed	Thu	Fri	Sat
1		F			F	A
2	F	F		F	F	A
3	F		F	F		
4			F			
5	G		G	F	G	E
6	G	G		F	G	E

(a)Optimization of pre-scheduling results

9 weeks/session	Mon	Tue	Wed	Thu	Fri	Sat
1	B	A	A	B	B	other
2	B	A	A	B	B	other
3	C	D		E	G	
4	C	D		E	G	
5	F	F	B	F	D	other
6	F	F	B	F	D	other
10 weeks/session	Mon	Tue	Wed	Thu	Fri	Sat
1	C	D	G	E	C	other
2	C	D	G	E	C	other
3	A	F	B	C		
4	A	F	B	C		
5	G	G		G	G	other
6	G	G		G	G	other

(b)Optimize Post-scheduling Results

Figure 5: Results before and after the optimization of the two-week professional course in Ceramic design.

In the experiment of basic ceramic design parameter optimization, this paper selects the classical ceramic design basic shape as the sample for parameter optimization. Figure 6 shows the comparison before and after the optimization of basic ceramic design parameters for some students. The results show that the platform in this paper can optimize basic ceramic parameters and realize subtle adjustments to make them more in line with standards. At the same time, students can intuitively find the problems in their own design according to the optimized results, and further make targeted adjustments.

Figure 6: Comparison before and after optimization of basic ceramic design parameters for some students.

Table 1 shows the comparison results of proportion and fit of some ceramic design patterns. It can be seen from the results that the proportion fit of ceramic design patterns after optimization is significantly higher than that before optimization. This shows that the platform can realize the effective optimization of students' design parameters according to the standardized parameter data so that it is more in line with the aesthetics and requirements of ceramic design.

Category	*group*	*Bottle height: bottle width ratio*	*Fit degree*	*Another ratio*	*Fit degree*
Pastel six peach drawing	Before optimization	3:2	84.5%	Abdomen and neck pattern ratio 2:1	90.7%
	post-optimization	3:2	99.6%	Abdomen and neck pattern ratio 2:1	98.3%
Blue and white bucket colour bottle	Before optimization	2:1	98.2%	The ratio of pattern area to blank area is 2:1	92.7%
	post-optimization	2:1	98.7%	The ratio of pattern area to blank area is 2:1	98.6%

Table 1: Comparative results of proportion fit of some classical ceramic design patterns.

Figure 7 shows the comparison results of some students' personalized ceramic design works and their scores before and after the experiment. In this experiment, students conducted ceramic designs on the same subject before and after the experiment and were graded by the teacher. The results show that the scores of students' ceramic design works after the experiment are all higher than those before the experiment, especially in the three aspects of ceramic modelling design, innovative design and market value. This shows that this system can help students improve their professional ability of ceramic design, develop innovative thinking of design, and make their design both aesthetic and market value.

5 CONCLUSIONS

The cultivation of ceramic design talents needs to break the restrictions of the traditional training mode, introduce the needs of the market, industry and consumers, improve the training requirements of design talents, and ensure that ceramic design talents can inherit the tradition while having innovative thinking. The traditional training mode focuses on theoretical teaching, lacks sufficient and systematic practical courses, and the course arrangement is not scientific and systematic, which does not meet the needs of talent training. Aiming at the problems existing in the traditional training mode, this paper combines reinforcement learning and CAD systems to build a training platform for ceramic design talents.

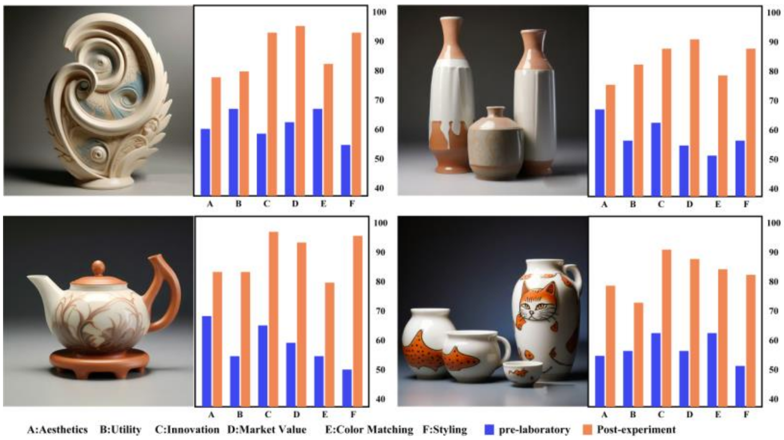

Figure 7: Comparison results of some students' personalized ceramic design work and their scores before and after the experiment.

On this platform, middle school students can realize the visualization of ceramic design through a CAD system, and realize the purpose of design optimization through the optimization module of ceramic design parameters based on reinforcement learning. In addition, the platform can also effectively and reasonably arrange professional courses according to the actual situation, making the courses more professional and systematic. The experimental results show that the platform in this paper has good course scheduling performance, which can complete the same number, of course, scheduling tasks in a shorter time, and the error curve convergence speed of parameter optimization is faster and the error value is lower, which can provide effective data support for application implementation. In the application experiment, the course scheduling results of this platform are more in line with the current talent training needs than those before optimization. At the same time, it can also help students optimize basic ceramic design parameters according to standardized parameters, help students find problems in modelling design and pattern design in a more intuitive way, and then make targeted improvements. Through the platform learning, the students' ceramic design performance after the experiment has been significantly improved, especially the design innovation, market value and modelling design have been greatly improved. This shows that the platform can improve the quality of ceramic design talent training and realize the optimization of talent training.

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