Synergistic Effect Generation of CAD and Reinforcement Learning in Ceramic Art Innovation

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Abstract. This article aims to explore the synergy between CAD (Computer Aided Design) technology and RL (Compensation Learning) algorithms in ceramic art innovation. In order to achieve this goal, an experimental framework integrating CAD design and RL optimization is constructed, and the effectiveness and innovation of this method are verified through a series of experiments. In terms of research methods, this article first configures the appropriate hardware and software environment to ensure the smooth progress of CAD design and the efficient operation of the RL algorithm. Subsequently, the data needed for the experiment were collected and preprocessed, including the ceramic design parameters generated by CAD and the state, action, and reward information in the RL process. During the experiment, the RL algorithm continuously optimizes its decision-making strategy according to the feedback of design parameters, thus gradually generating more innovative ceramic design schemes. The experimental results show that the combination of CAD and RL can significantly improve the innovation and practicality of ceramic design. CAD technology provides a convenient design tool for designers, while RL constantly taps the design potential through intelligent optimization algorithms. The two complement each other and jointly promote the innovative development of ceramic art.

Keywords: Computer-Aided Design; Reinforcement Learning; Ceramic Art; Innovate
DOI: https://doi.org/10.14733/cadaps.2024.S23.317-331

1 INTRODUCTION

As a treasure of human civilization, ceramic art bears a profound historical and cultural heritage. In the process of ceramic art production, surface roughness, vibration, and acoustic emission are key indicators for evaluating product quality and process effectiveness. These indicators not only affect the artistic effect of ceramics but are also closely related to their physical properties and durability. Traditional evaluation methods often rely on manual experience and subjective judgment, making it difficult to achieve accurate and efficient analysis. In recent years, with the rapid development of machine learning technology, its application in the field of ceramic art has gradually emerged. Asiltürk et al. [1] explored a comprehensive analysis method for surface roughness, vibration, and acoustic emission in ceramic art processes based on machine learning in order to improve the production level and product quality of ceramic art. Surface roughness is one of the important indicators for measuring the surface quality of ceramic artworks. Traditional surface roughness measurement methods are often time-consuming and have low accuracy. Machine learning technology can achieve fast and accurate prediction of surface roughness through training models. Lightweight ceramic materials have been widely used in 3D printed building products due to their excellent properties, such as lightweight, high strength, and thermal insulation. However, how to further improve the efficiency and quality of lightweight ceramic 3D printing has become a focus of current research. Beregovoi et al. [2] explored the application of computer-aided design (CAD) and reinforcement learning in lightweight ceramic 3D printing technology. It aims to improve the 3D printing efficiency and product quality of lightweight ceramics used in construction products. CAD technology plays an important role in the design of lightweight ceramic 3D printing. Through CAD software, designers can construct three-dimensional models of building products and perform precise size adjustments and design optimization. CAD technology not only improves design efficiency but also makes it more convenient for designers to modify and optimize models. In addition, CAD software can seamlessly integrate with 3D printers to achieve rapid conversion from design to production. Reinforcement learning is an artificial intelligence technique that learns optimal decisions through interaction between intelligent agents and the environment. In lightweight ceramic 3D printing, reinforcement learning can be applied to optimize printing parameters and control the printing process. From ancient painted pottery and celadon to modern art ceramics, its production technology and design concept are constantly developing and innovating. However, with the progress of science and technology and the change in social demand, the traditional ceramic art production method has made it difficult to meet the diversified and personalized needs of the modern market in some aspects [3]. Therefore, exploring new manufacturing techniques and innovative methods has become an important topic in the field of ceramic art.

With the continuous progress of technology, computer-aided design (CAD) and artificial intelligence (AI) technologies have penetrated various industries, including traditional handicraft industries. Ceramic art, as a treasure of Chinese culture, how to combine with modern technology and radiate new vitality has become a topic we are exploring. Cho [3] explored how CAD technology and reinforcement learning can play an extended and innovative role in integrating traditional ceramic art. CAD technology provides a new creative platform for ceramic art with its precise measurement, efficient design, and powerful simulation capabilities. Designers can quickly construct 3D models of ceramic works through CAD software and perform precise size adjustments and design optimization. In addition, CAD technology can also help artists achieve complex design concepts and overcome technical difficulties that are difficult to overcome in traditional handcrafting. Reinforcement learning, as a branch of artificial intelligence, simulates the interaction between intelligent agents and the environment to learn how to make the best decisions. In the field of ceramic art, reinforcement learning can be applied to the optimization of automated production lines, intelligent evaluation of work quality, and other aspects. CAD technology and reinforcement learning, as key technologies in mechatronics integration, are of great significance for improving production efficiency and optimizing product design. Meanwhile, as a representative of traditional art, the design and production of innovative products in ceramic art have also been deeply influenced by mechatronics technology. Cintra et al. [4] explore the scientific composition of CAD and reinforcement learning in the application of mechatronics, as well as their association with innovative ceramic art products. Through CAD technology, designers can more accurately draw and simulate the structure and motion of complex systems such as machinery and electronics, thereby optimizing design solutions and improving production efficiency. In addition, CAD can also achieve data sharing and collaborative design, allowing experts from different fields to participate in the design process together, improving the comprehensiveness and innovation of the design. CAD technology can help designers draw the shape and structure of ceramic products more accurately, improving the accuracy and aesthetics of design. Meanwhile, CAD can also achieve virtual simulation and optimized design of ceramic products, thereby shortening the production cycle and reducing production costs. Secondly, reinforcement learning technology can be applied to the intelligent manufacturing process of ceramic products.

In order to protect and inherit this precious cultural heritage, researchers are constantly exploring new technological means. In recent years, the emergence of digital stylization and expression re-materialization technology has provided new possibilities for the protection and inheritance of ancient ceramic art. Elran and Zoran [5] explored the digital stylization and expressive reification of ancient ceramic art with the theme of "ghosts in machines". Digital stylization is a method of using computer graphics technology to digitize the presentation of ancient ceramic art. Through high-resolution scanners and 3D modelling techniques, researchers can accurately capture the texture, colour, shape, and other details of ancient ceramic artworks and generate 3D digital models on computers. These digital models can not only be displayed on computers but also allow audiences to experience the charm of ancient ceramic art firsthand through technologies such as virtual reality and augmented reality. Expression re-objectification is a process of reshaping and re-creating ancient ceramic art using digital technology. Through techniques such as digital carving, texture mapping, and colour adjustment, researchers can digitally reshape ancient ceramic artworks while maintaining their original artistic style, giving them new vitality. In recent years, CAD technology has been widely used in the field of industrial design and artistic creation. CAD technology can greatly improve design efficiency, realize accurate modelling of complex shapes, and provide new possibilities for the innovation of ceramic art. Furthermore, RL, as a branch of artificial intelligence, learns strategies through the interaction between agents and the environment and realizes the optimization of goals. It has made remarkable achievements in the fields of games, autonomous driving, robot control and so on, and demonstrated its strong learning and decision-making ability.

In ceramic art innovation, the combination of CAD technology and RL has great potential. CAD technology can provide powerful design tools and realize the rapid design and modification of ceramic works. RL can explore new design concepts and innovative methods through intelligent learning and optimization. The combination of the two is expected to bring new breakthroughs to the innovation of ceramic art. The significance of this study is to explore the synergy between CAD technology and RL in ceramic art innovation. Through this research, I hope to promote the innovation and development of ceramic art, break the limitations of traditional production methods, and realize the diversification and personalization of ceramic art. Furthermore, this research is also helpful in promoting the application and development of CAD technology and RL in the field of artistic creation and provides reference and enlightenment for the innovation of other artistic forms.

Specifically, the combination of CAD and RL in ceramic art innovation may bring the following breakthroughs and innovations:

(1) Improvement of design efficiency: The rapid design and modification of ceramic works can be realized through CAD technology, which greatly shortens the design cycle and improves the design efficiency.

(2) Improvement of innovation ability: RL explores new design concepts and innovative methods through intelligent learning and optimization and provides new ideas and means for the innovation of ceramic art.

(3) Improving the quality of works: Through accurate modelling and optimization algorithms, precise control and high-quality production of ceramic works can be realized.

(4) Satisfaction with personalized demand: Through the combination of CAD and RL, customized design can be carried out according to market demand and personalized demand to meet the diverse needs of consumers.

The purpose of this study is to explore the synergistic effect of CAD and RL in ceramic art innovation so as to provide new ideas and methods for ceramic art innovation and promote the application and development of CAD technology and RL in the field of artistic creation. Firstly, this article introduces the research background and purpose and expounds on the importance of CAD and RL in ceramic art innovation. Then, the experimental process and results are described in detail, including the experimental environment setting, experimental data and pretreatment, experimental results and analysis. Then, a discussion is carried out to discuss the synergistic effect of CAD and RL in ceramic art innovation, the limitations of experimental results and the future research direction. Finally, it summarizes the research results, emphasizes the innovation and the enlightenment of the innovation of ceramic art, and points out the limitations and prospects of the research.

2 THEORETICAL BASIS

Ceramic art, as an important component of traditional craftsmanship, has always attracted people with its unique charm and rich cultural connotations. However, with the advancement of technology, traditional ceramic production methods are no longer able to meet the needs of modern design and production. Therefore, the introduction of advanced technologies such as computer-aided ceramic design (CAD Ceramic Design) and three-dimensional artificial/convolutional neural networks (3D CNN) provides new solutions for the digital synthesis and validation of ceramic art. Farook et al. [6] explored the applications and potential impacts of these technologies in ceramic design. Computer-assisted ceramic design is a process that utilizes computer technology to assist in the design and production of ceramic products. Through CAD software, designers can more accurately draw and simulate the shape, structure, texture and other features of ceramic products, greatly improving the efficiency and accuracy of design. In addition, CAD technology can also achieve design optimization and automation, providing technical support for the mass production of ceramic products. Nano ceramic art restorations, as a high-precision and high-performance dental restoration material, have received widespread attention in recent years. The introduction of computer-aided design (CAD) and computer-aided machining (CAM) technology provides more efficient and accurate solutions for the production of nano ceramic art restorations. Fasbind et al. [7] evaluated the application and effectiveness of CAD/CAM technology in the production of nano ceramic art restorations. CAD technology can be used in the design stage of nano ceramic art restorations. Through CAD software, designers can accurately draw three-dimensional models of restorations, simulate their effects in practical use, and communicate and adjust with patients. In addition, CAD technology can also optimize and customize the design of restorations to meet the needs of different patients. CAM technology is used to convert CAD designs into actual restorations. Through CAM equipment, nano ceramic restorations that are consistent with CAD design can be accurately processed, achieving efficient and accurate production. In addition, CAM technology can also automate post-processing tasks such as polishing and polishing restorations, improving production efficiency and quality.

Ceramics, as an ancient and charming art form, its aesthetic design education is particularly important in today's era. With the development of technology, product engineering modelling technology has gradually been introduced into ceramic aesthetic design education, injecting new vitality into traditional ceramic art. Furferi and Buonamici [8] explore the role of product engineering modelling in ceramic aesthetic design education and analyze how it can contribute to the development and inheritance of ceramic art. Product engineering modelling is a process of digital design and simulation of products using computer-aided design software (CAD) and 3D modelling technology. Traditional ceramic aesthetic design often relies on manual drawing and physical production, which is cumbersome and time-consuming. Product engineering modelling technology can achieve fast and accurate digital design, greatly improving design efficiency. Designers can quickly adjust and optimize design plans on the computer, reducing unnecessary modifications and rework. Traditional methods for manufacturing nanomaterials are often inefficient, costly, and may have adverse effects on the environment. Therefore, how to achieve green manufacturing of nanomaterials under the drive of digitization and innovation has become an important research topic at present. Konstantopoulos et al. [9] explored the digital innovation-driven nanomaterial manufacturing and the application of machine learning strategies while emphasizing the importance of a green perspective. By precisely controlling various parameters in the manufacturing process, such as temperature, pressure, reaction time, etc., digital technology can greatly improve the manufacturing accuracy and efficiency of nanomaterials. In addition, digital technology can also achieve intelligent and automated manufacturing processes, thereby reducing human errors and costs. By collecting and analyzing data during the manufacturing process, machine learning models can predict and optimize manufacturing parameters, thereby achieving optimization and automation of the manufacturing process. The manufacturing of nanomaterials driven by digital innovation, combined with machine learning strategies and green perspectives, is expected to bring revolutionary changes to the manufacturing of nanomaterials. Artificial intelligence (AI) has gradually penetrated into every aspect of our lives, bringing new development opportunities and innovation space to various industries. As a typical representative of the combination of tradition and modernity, ceramic art design has become a hot research topic on how to integrate modern technological elements while maintaining traditional charm. Liang [10] explored innovative thinking in ceramic art design based on artificial intelligence in order to provide new ideas and directions for the inheritance and development of ceramic art. The application of artificial intelligence in ceramic art design provides designers with creative inspiration and design suggestions through intelligent algorithms and big data analysis. It utilizes machine learning and other technologies to optimize design schemes automatically, improving the artistic and practical aspects of the work. By using virtual simulation technology to simulate the forming, firing, and other processes of ceramic works, experimental costs are reduced, and design efficiency is improved.

Ceramic materials have been widely used in industrial production due to their high strength, high hardness, good wear resistance, and corrosion resistance. However, the brittleness and poor tensile performance of ceramic materials limit their wider applications. In recent years, with the development of machine learning technology, more and more researchers have begun to explore the use of machine learning technology to optimize the performance of ceramic materials. Lolla et al. [11] investigated the influence of machine learning filling patterns on the tensile properties of ceramic materials in order to provide new ideas and methods for the improvement and application of ceramic materials. Machine learning technology is a data-driven model construction and optimization method. It can analyze and learn from a large amount of data to find the inherent patterns and connections between data, thereby achieving prediction and optimization of unknown data. Filling mode refers to adding a certain amount of filling agent to ceramic materials to improve their tensile properties. The type, particle size, and filling amount of fillers can all affect the tensile properties of ceramic materials. The traditional filling mode often relies on experience and practice, lacking scientific and precise accuracy. Ceramic materials have been widely used in toothbrush manufacturing due to their excellent physical and chemical properties. However, the wear resistance of ceramic toothbrushes has always been a key factor limiting their service life and performance. In order to improve the wear resistance of ceramic toothbrushes, Piva et al. [12] explored the application of computer-aided design (CAD) and reinforcement learning in optimizing the wear resistance of ceramic toothbrushes. CAD technology provides efficient and accurate tools for the design of ceramic toothbrushes. Through CAD software, designers can construct a three-dimensional model of toothbrushes and precisely control their shape, size, and structure. In addition, CAD can also perform simulation analysis to predict the performance of toothbrushes in practical use, including wear resistance, strength, etc. This provides strong support for optimizing toothbrush design and improving wear resistance. Combining CAD technology with reinforcement learning can further improve the wear resistance of ceramic toothbrushes. Firstly, use CAD software for preliminary design and simulation analysis of toothbrushes. Then, input the design parameters into the reinforcement learning model, and through the learning and optimization of the model, find the optimal combination of design parameters and manufacturing process parameters.

Digital Ceramic Additive Manufacturing (DCAM), as an emerging manufacturing technology, is receiving increasing attention. DCAM combines advanced technologies such as computer-aided design (CAD), numerical simulation, and additive manufacturing, bringing revolutionary changes to the production of ceramic products. However, the complexity and uncertainty of the DCAM process remain a challenge. To overcome these challenges, deep learning collaborative methods have been introduced into DCAM to improve its accuracy, efficiency, and stability. Pratap et al. [13] will provide an overview of deep learning collaborative methods for DCAM and explore relevant algorithms. Degree learning can identify key information such as geometric features and material properties of ceramic products through training a large amount of data, thereby optimizing CAD models and improving manufacturing accuracy. The traditional production process of all ceramic restorations is complex, and it is difficult to ensure the accuracy and aesthetics of the restorations. In recent years, the rapid development of 3D printing technology has brought revolutionary changes to the manufacturing of all ceramic restorations. The application of 3D-printed colour 3D models makes the production of all ceramic restorations more precise, efficient, and aesthetically pleasing. Schweiger et al. [14] explored the application of 3D printed colour 3D models in the manufacturing of all ceramic restorations. In traditional ceramic restoration production, temporary restorations are usually required for patients to wear, which not only increases production costs and time but may also affect the final effect of the restoration. By using 3D printing of coloured 3D models, temporary restorations that match the shape and colour of the final restoration can be quickly made for patients to wear, saving time and ensuring the restoration effect. Ceramic art, as an important component of human cultural heritage, has extremely high historical, cultural, and artistic value. However, due to various factors, such as time and environment, many precious ceramic artworks have suffered varying degrees of damage and destruction. In order to protect and restore this precious cultural heritage, researchers are constantly exploring new restoration technologies and methods. Srivastava et al. [15] proposed a ceramic art restoration scheme based on hybrid machine learning and metaheuristic algorithms, aiming to use advanced technological means for efficient and accurate restoration of ceramic art. Hybrid machine learning is a technology that combines multiple machine learning algorithms, which can fully utilize the advantages of various algorithms to improve the performance and generalization ability of models. In ceramic art restoration, hybrid machine learning can be used to identify and classify the degree and type of damage to ceramic artworks, providing accurate guidance for subsequent restoration work.

Metal ceramic restorations play an important role in dental restoration due to their combination of metal strength and ceramic aesthetics. However, interface fracture between metal and ceramic is a common failure mode, which affects the long-term effectiveness of restorations. In order to improve the strength of metal-exposed porcelain fracture repair, researchers are constantly exploring new adhesives and innovative manufacturing technologies. Tulga and Küçükekenci [16] explored how universal adhesives and innovative manufacturing technologies affect the strength of metal-exposed porcelain fracture repair in metal-ceramic restorations. Universal adhesive, as a key material for firmly bonding metals and ceramics, plays an important role in metal-ceramic restorations. The new adhesive material has higher bonding strength and corrosion resistance, which can effectively improve the interface bonding between metal and ceramics, thereby enhancing the fracture repair strength of metal-exposed ceramics. As a treasure of human civilization, the innovation and inheritance of clay ceramic art have always been the focus of attention for artists and researchers. With the rapid development of digital technology, advanced technologies such as computer-aided design (CAD) and reinforcement learning have provided strong support for the innovative digital construction of clay ceramic art. Yin et al. [17] explored the application and development of CAD and reinforcement learning in the digital construction of clay ceramic art innovation. Through CAD technology, artists can design the shape, structure, and texture of ceramic works more accurately, thereby improving the creativity and artistry of their works. In addition, CAD can also assist artists in material selection and process optimization, achieving more efficient and accurate ceramic production. Reinforcement learning is a machine learning technique that enables machines to learn and optimize decision strategies in interaction with the environment to achieve specific goals. In the innovation of clay ceramic art, reinforcement learning can be applied to optimize parameter settings, process paths, and defect detection in the ceramic production process. Through continuous trial and error and adjustment, reinforcement learning can help artists find the best ceramic production solutions to improve the quality and efficiency of their works. With the continuous development of technology, the development and application of functional materials have gradually become a research hotspot in the field of science and technology. Functional materials have broad application prospects in fields such as energy, medicine, and environmental protection due to their unique physical, chemical, and biological properties. In order to improve the development efficiency and performance of functional materials, Zheng et al. [18] explored the synergistic effect of computer-aided design (CAD) machine experiments and reinforcement learning in the development of functional materials. CAD machine experiment is a method that combines computer simulation with practical experiments to predict and optimize the performance of materials through simulation experiments. In the development of functional materials, CAD machine experiments can greatly shorten the experimental cycle, reduce experimental costs, and improve experimental efficiency. By constructing digital models of materials, simulating the preparation process, performance testing, and practical applications of materials, CAD machine experiments provide strong support for the development of functional materials.

3 RL ALGORITHM AND MODEL CONSTRUCTION

3.1 RL Algorithm and Model

Since its birth, CAD technology has been widely used in many industrial fields. In ceramic art, the application of CAD technology has injected new vitality into the traditional production process. The early research mainly focused on how to use CAD technology to realize the digital modelling of ceramic shapes so that designers can design more intuitively and efficiently. With the development of technology, the functions of CAD software are constantly enhanced, and the whole process, from preliminary design to fine adjustment, can be realized.

RL is a machine learning method that teaches strategies through interaction with the environment. In the field of artistic innovation, RL has been applied in many aspects, such as artistic creation and style imitation. Although CAD technology and RL have made remarkable progress in their respective fields, there are relatively few studies on combining them for ceramic art innovation. However, some preliminary studies have shown the potential and prospects of this combination. On a theoretical basis, the combination of CAD technology and RL can realize the intelligence and automation of the design and manufacturing process. The 3D model created by CAD technology can be used as the environment of the RL algorithm, and the algorithm can learn and optimize the design scheme in this environment. This combination can not only improve the design efficiency but also explore new design concepts and innovative methods. In practical cases, some studies have begun to try to apply CAD technology and RL to ceramic art innovation. By constructing appropriate reward function and state space, the agent is trained to learn and optimize the design parameters and production process of ceramic products. The experimental results show that this method can effectively improve the quality and production efficiency of ceramic products. These preliminary practical cases show that the combination of CAD and RL has broad application prospects in ceramic art innovation.

In this article, CAD technology and RL algorithms are applied to ceramic art innovation, and the design process is intelligent and optimized. This research not only expands the application scope of RL in the art field but also provides new ideas and methods for ceramic art design. In the future, we will continue to deepen this research and explore more optimization algorithms and application fields in order to further promote the innovation and development of ceramic art. In this study, the depth RL algorithm is applied to optimize the ceramic works designed by CAD software, aiming to realize the automation and intelligence of the design process. Specifically, this article constructs an RL model based on strategic gradient, which learns and optimizes the strategy of generating a ceramic design scheme through the continuous interaction between agents and the environment. In the aspect of model construction, the ceramic works designed by CAD software are regarded as the environmental state, which contains key design information such as the shape, size and proportion of the works. The adjustment of design parameters, such as changing the curvature of a certain part or increasing or decreasing the size of a certain feature, is defined as action space, and these actions directly affect the transformation of the environmental state.

Definition of state: A state s can be expressed as a set of design parameters of ceramic works, which describe the shape, size and proportion of the works. The state can be a high-dimensional vector, where each dimension corresponds to a design parameter.

$$s = (p_1, p_2, p_3, \ldots, p_n) \tag{1}$$

Where p_n represents the n th design parameter.

Action definition: Action a is the adjustment of design parameters, which can be expressed as an increment or relative change of parameters. The action can also be a vector, corresponding to the dimension of the state vector.

$$a = (\Delta p_1, \Delta p_2, \Delta p_3, \ldots, \Delta p_n) \tag{2}$$

Where Δp_n represents the variation of the n th design parameter. The optimal state value function and the optimal action-value function are as follows:

$$V^*(s) = \max_\pi V^\pi(s) \tag{3}$$

$$Q^*(s,a) = \max_\pi Q^\pi(s,a) \tag{4}$$

The optimal value function represents the highest value that can be obtained for each state or state-action pair among all possible strategies. In order to evaluate the influence of each action on the design effect, this article carefully defines a reward function. This function comprehensively considers the innovation, practicability, and aesthetics of the design and ensures that the model can evolve in a better design direction during the learning process. The reward function $\varepsilon R(s,a,s')$ evaluates the reward after performing the action a in the state s and transitioning to the state s'.

$$r = R(s,a,s') \tag{5}$$

Where r is the reward signal obtained? Bellman equation is the core formula in RL, which describes the recursive relationship between value functions. In this equation, for the state value function,

$$V^\pi(s) = \sum_{a \in A} \pi(a|s) \left(\sum_{s',r} p(s',r|s,a) \left[r + \gamma V^\pi(s') \right] \right) \tag{6}$$

For the action value function:

$$Q^\pi(s,a) = \sum_{s',r} p(s',r|s,a) \left[r + \gamma \sum_{a' \in A} \pi(a'|s') Q^\pi(s',a') \right] \tag{7}$$

Here $p(s',r|s,a)$ is the probability of moving to the state s' and getting the reward r after the state s performs the action a, and γ is the discount factor. Through continuous trial and error and learning, the model has gradually mastered the optimization strategy and can generate innovative and practical design schemes. The RL process is shown in Figure 1.

In the training process, the RL algorithm based on strategic gradient is used to update the parameters of the model. The strategy gradient method updates the strategy parameter θ by calculating the strategy gradient $\nabla_\theta J(\theta)$, which $J(\theta)$ represents the objective function of the strategy, usually the expected cumulative reward. The calculation formula of strategy gradient can be expressed as:

$$\nabla_\theta J(\theta) = E_{\pi\theta}\left[G_t \cdot \nabla_\theta \log \pi\theta(A_t|S_t) \right] \tag{8}$$

Where G_t represents the future cumulative prize from time t and $\pi\theta(A_t|S_t)$ represents the probability of executing the action A_t when the state S_t is given under the strategy $\pi\theta$.

In addition, this article also introduces some advanced training skills, such as experience playback and target network. Experience playback allows the model to learn from past experience and make full use of existing data resources.

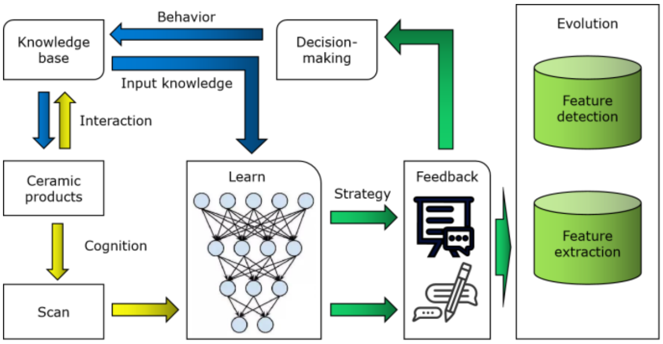

Figure 1: RL flow chart.

The target network reduces the fluctuation in the training process by stabilizing the learning target and further improves the stability of the model. After several rounds of iterative training, an RL model with stable performance is obtained. The model can automatically adjust the design parameters according to the given design objectives and constraints and generate an optimized ceramic design scheme. In the following experiments, this model will be used to optimize and explore the ceramic design further.

3.2 CAD Tools and Platforms

In this study, in order to realize the efficient and innovative design of ceramic art, professional CAD software Auto CAD is selected as the core tool and platform of design. Auto CAD software stands out for its excellent 3D modelling function, which can support all-around design from simple geometric shapes to highly complex artistic modelling. Its powerful modelling engine allows designers to create various ceramic shapes that are difficult to achieve by traditional processes through intuitive interfaces and precise numerical control. In addition to excellent modelling ability, the CAD software is also equipped with a rich material library and high-quality rendering function. Designers can choose virtual materials from the library that match the ceramic materials in the real world, such as glaze, texture, and gloss, to simulate the real appearance of ceramics. Through advanced rendering technology, designers can preview the final effect of ceramic works in real-time during the design process to find and correct potential design defects in the early stage. More importantly, Auto CAD software supports parametric design, which is a powerful and flexible design method. Designers can quickly generate different design schemes by defining and adjusting a series of parameters, such as size, proportion and shape details. This function is particularly important in ceramic design because it can significantly shorten the design cycle from concept to entity and help designers explore the possibility of innovation more widely in the design space. The 3D modelling process is shown in Figure 2.

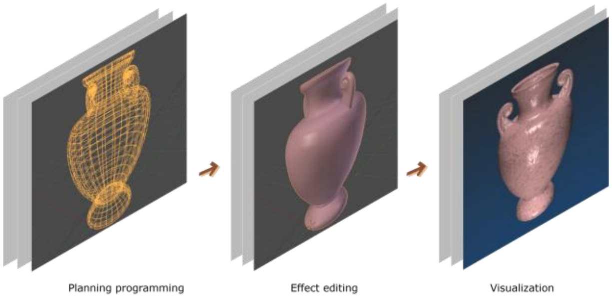

Figure 2: 3D modeling process.

In this study, the flexibility of parametric design laid a solid foundation for the subsequent RL optimization process. By combining design parameters with the RL algorithm, we can automatically adjust and optimize these parameters to find the best design scheme that meets specific design goals and constraints. This synergy not only improves the efficiency of design but also finds innovative design solutions that human designers may not find intuitively through intelligent search of algorithms.

4 EXPERIMENTAL PROCESS AND RESULTS

The hardware environment required for this experiment mainly includes high-performance computers, graphics processing units and ceramic manufacturing equipment (3D printers, CNC machine tools, etc.). High-performance computers are used to run CAD software and RL algorithms, providing powerful computing power and storage space. GPU is used to accelerate the training process of the RL algorithm and improve the computational efficiency. Ceramic manufacturing equipment is used to manufacture the optimized design scheme into solid ceramic works. In terms of software configuration, professional Auto CAD software is installed for the design of ceramic works, and the TensorFlow framework is used to realize the RL algorithm. In addition, necessary programming languages and development tools, such as Python and Jupyter Notebook, are installed for algorithm development and data analysis. In terms of network environment, ensure that the computers and servers in the experiment process can be permanently connected to the Internet to download the required software, data sets, and updates. Furthermore, an internal LAN has been established to share data and resources in the laboratory. After several rounds of experiments and optimization, this article obtained a series of optimized ceramic design schemes and solid works, as shown in Figure 3.

Figure 3: Ceramic design works.

These works are excellent in structural strength, aesthetics and innovation, which verifies the synergistic effect of CAD and RL in ceramic art innovation.

The following algorithm experiments are carried out. The experimental data mainly come from two aspects: one is the ceramic design data generated by CAD software, including 3D model, material information, design parameters and so on; The second is the data generated by the RL algorithm in the training process, including state, action, reward and so on. For CAD design data, this article has carried out necessary preprocessing operations, such as format conversion, data cleaning and normalization. Firstly, the 3D model generated by CAD software is converted into a unified OBJ format for subsequent processing and analysis. Then, the data is cleaned to remove invalid and redundant information. Finally, the design parameters are normalized and mapped to the same scale so that the RL algorithm can be better studied and optimized. The cumulative reward in the training process is shown in Figure 4.

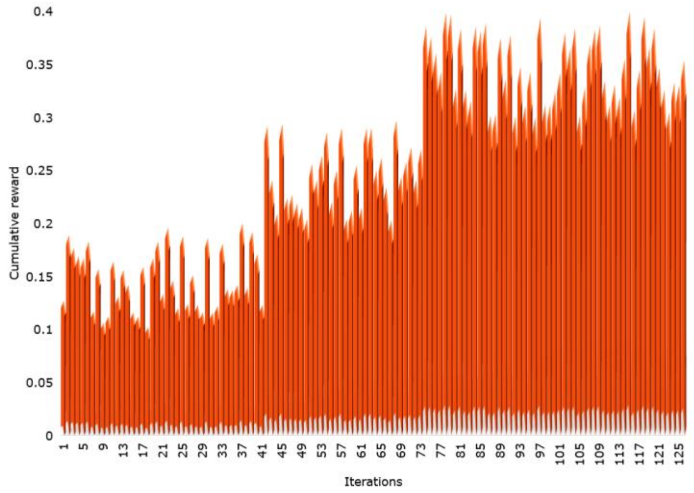

Figure 4: Cumulative reward chart during training.

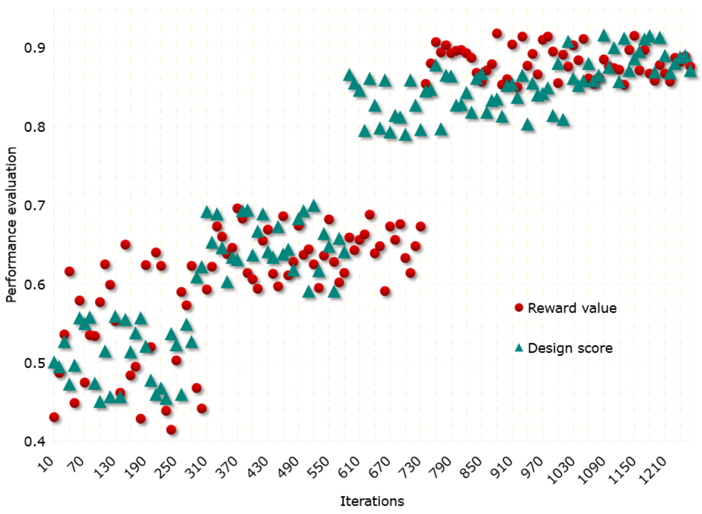

Figure 5: Design parameter optimization diagram.

This figure shows the changing trend of cumulative rewards obtained by the RL algorithm with the increase of iteration times in the training process. It can be seen that the cumulative reward increases with the number of iterations, which indicates that the algorithm is learning how to complete the task better. The optimization of design parameters is shown in Figure 5.

Each point set in the diagram represents the trajectory of a design parameter in the optimization process. As can be seen from the figure, with the increase in iteration times, the point set corresponding to this method shows an obvious upward trend. This shows that in the optimization process, the design parameters gradually tend to be more optimal, which significantly improves the performance evaluation index of ceramic design. The evaluation of design innovation and practicality is shown in Figure 6.

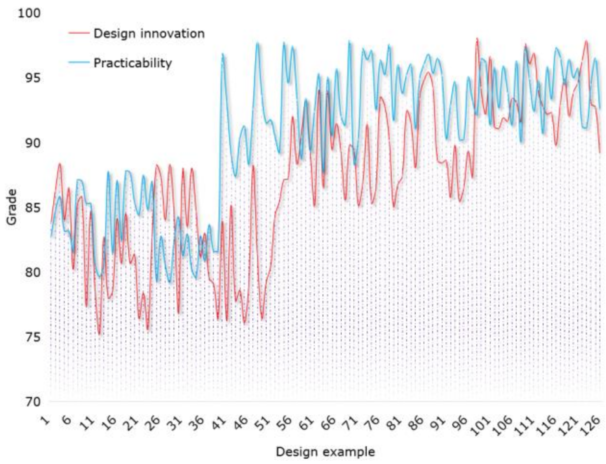

Figure 6: Evaluation of design innovation and practicality.

The results in Figure 6 show that the method in this article shows a high level of design innovation and practicality. By optimizing the design parameters, this method can maintain design innovation while taking into account the needs and limitations in practical application. Figure 7 shows the performance comparison of different algorithms.

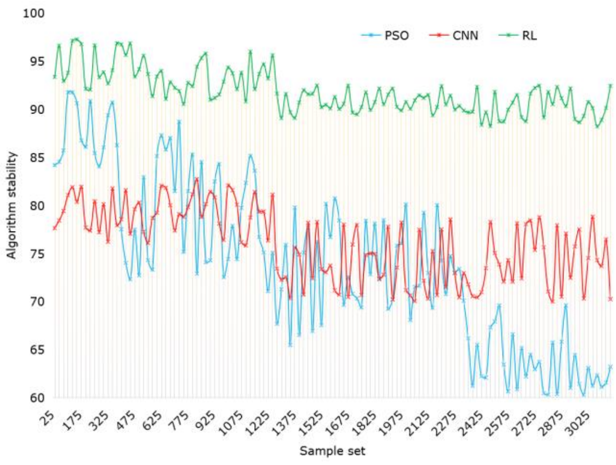

Figure 7: Performance comparison of different algorithms.

Stability is an important index to evaluate the performance of the algorithm, especially when dealing with complex and changeable design problems. In the performance comparison chart, the curve of this method is relatively stable, with small fluctuation, which is basically above 90%, so this method has good stability. Compared with other comparison methods, the curve corresponding to this method has a higher value on the ordinate. This means that under the same conditions, this method can obtain higher performance evaluation index values. This shows that this method has a better effect in optimizing ceramic design.

Based on the above experimental results, it can be concluded that the method in this article shows superior performance in the optimization of ceramic design parameters. This is mainly due to the innovative method of combining CAD technology and the RL algorithm proposed in this article, which can effectively explore the design space and find a better design parameter configuration.

5 DISCUSSION

5.1 Synergistic Effect of CAD and RL in Ceramic Art Innovation

According to the results, CAD technology and RL have shown remarkable synergy in the process of ceramic art innovation. CAD technology provides designers with powerful design tools, which makes the design of ceramic works more intuitive and efficient. Through CAD software, designers can easily create, modify and optimize design schemes and realize digital modelling and precise control of ceramic shapes. RL algorithm explores more innovative and practical design parameter combinations through intelligent learning and optimization, which provides designers with more design inspiration and optimization direction.

The advantage of this synergy is that it greatly improves the efficiency and quality of ceramic art innovation. The traditional ceramic design process often depends on the designer's experience and intuition and needs repeated trial and error and adjustment. The combination of CAD and RL enables designers to quickly generate a large number of high-quality design schemes on the computer and select the best scheme for manufacturing through intelligent optimization of algorithms. This not only shortens the design cycle and reduces the manufacturing cost but also improves the innovation and market competitiveness of ceramic works.

5.2 Limitation of Experimental Results and Future Research Direction

Although this experiment has achieved positive results, there are still some limitations to be noted. First of all, the sample size is relatively small, which may not fully reflect the full potential and advantages of CAD and RL in ceramic art innovation. The conclusion of this experiment can be further verified by expanding the sample size in the future. Secondly, algorithm selection and parameter setting may have an impact on the experimental results. Different RL algorithms and parameter settings may lead to different optimization effects and convergence speeds. Therefore, different algorithms and parameter settings can be tried to compare their performance and effect in future research.

In addition, this experiment mainly focuses on the application of CAD and RL in ceramic art innovation and does not involve other possible influencing factors and variables. For example, the creative level of designers, market demand, manufacturing technology and other factors may have an impact on ceramic art innovation. These factors can be considered comprehensively in future research to evaluate the role and value of CAD and RL in ceramic art innovation.

Because of the limitations and shortcomings of this experiment, future research can be carried out from the following aspects: First, the optimization algorithm is the key to improving the effect of CAD and RL in ceramic art innovation. You can try to use a more advanced RL algorithm and deep learning model to optimize the design scheme and improve the efficiency and accuracy of optimization. Secondly, expanding the application field is an important way to promote the application of CAD and RL in ceramic art innovation. This method can be applied to other types of art design and manufacturing processes, such as sculpture and painting, to verify its universality and expansibility. Finally, strengthening interdisciplinary cooperation is also an important direction for future research. Experts from computer science, art, design and other fields can be invited to participate in the research to make full use of their professional knowledge and experience to promote the development and application of CAD and RL in ceramic art innovation.

6 CONCLUSIONS

By combining CAD technology with the RL algorithm, this study deeply explored the synergy between them in ceramic art innovation. The results show that CAD tools provide designers with efficient and accurate design means, while RL significantly improves the innovation and practicability of the design scheme through intelligent optimization algorithms. This synergy not only shortens the design cycle of ceramic products and reduces production costs but also promotes the innovative development of ceramic art to a higher level.

The main innovation of this study lies in the successful application of the RL algorithm in ceramic art design, which realizes the intelligence and optimization of the design process. This innovation not only expands the application scope of RL in the art field but also provides new ideas and methods for ceramic art design. The results of this study have important enlightenment and significance to the innovative practice of ceramic art. First of all, it breaks the limitation of traditional ceramic design mode, introduces intelligent and data-driven design concepts, and injects new vitality into ceramic art innovation. Secondly, through the combination of CAD and RL, designers can explore the design space more efficiently and explore more innovative and practical design schemes. Finally, the methodology and experimental results of this study provide a useful reference for innovative practice in other art fields.

In addition, the results of this study also have a certain role in promoting related fields. For example, in industrial design, architectural design and other fields, we can also learn from the collaborative mode of CAD and RL to improve design efficiency and innovation. Furthermore, this study also provides a new perspective and research direction for the cross-study of computer science and art. With the continuous progress of science and technology and the increasing demand for art, the application prospect of CAD and RL in ceramic art innovation will be broader. It is believed that shortly, the synergy between CAD and RL will bring more breakthrough achievements and contributions to ceramic art innovation.

7 ACKNOWLEDGEMENT

This work was Funded by the 'Research Center for Cultural Construction and Social Governance in Ethnic Regions' of the Key Research Base of Humanities and Social Sciences in Guangxi Universities, Research on the Construction of Beiliu Ceramic Town under the Rural Revitalization Strategy, 2021YJJDZD01; The 2022 Guangxi Higher Education Undergraduate Teaching Reform Project, Research and Practice on the Integration of Industry and Education Talent Training Model for Arts and Crafts Majors in Normal Universities under the Background of New Liberal Arts, 2022JGB313; Funded by the Sichuan Cuisine Development Research Center Fund Project, Research on Modern Tableware Design under the Influence of Bashu Food Culture, CC23W34.

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