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Computer-Aided Cultural and Creative Product Design Based on Reinforcement Learning

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Abstract. This article aims to investigate the design method of computer-aided cultural creative products (CCP) utilizing reinforcement learning, with a focus on the appearance design of woodcarving crafts as an illustrative example. Aiming at the limitation of the existing CCP design method in the design of woodcarving crafts, this article puts forward an innovative design scheme based on reinforcement learning. This method realizes the automatic optimization and design of the appearance of woodcarving crafts by constructing a suitable reinforcement learning model. Experiments and case studies show that the proposed method performs well in dealing with complex woodcarving design scenes and has significant rendering efficiency advantages while ensuring the accuracy and integrity of the design scheme. Regarding recall and accuracy, the improved algorithm has also improved significantly. To sum up, the research in this article provides a new method for CCP design, promotes the integration and innovation of traditional technology and modern technology, and expands a new research direction for the use of reinforcement learning in optimization design. The research results prove the practical application value of the computer-aided CCP design method based on reinforcement learning.

Keywords: Strengthen Learning; Computer-Aided; Cultural and Creative Products; Woodcarving Crafts
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1 INTRODUCTION

In today's cultural and creative industries, CCP design, as a bridge between traditional culture and modern aesthetics, increasingly shows its unique charm and huge market potential. CCP carries rich cultural connotations and attracts consumers' attention with its unique design style and aesthetic value. With the increasingly fierce market competition and the diversification of consumer demand, CCP design is facing unprecedented challenges. How to keep the essence of traditional culture, integrate modern design concepts, and create a CCP that meets the market demand and has a unique charm has become an urgent problem for designers. As a significant bearer of traditional culture, woodcarving crafts are cherished and sought after for their exquisite craftsmanship, unique modelling, and profound cultural connotations [1]. However, under the influence of modern production modes and consumption concepts, the design of woodcarving crafts faces numerous challenges. As a way of inheriting and innovating traditional culture, cultural and creative products are deeply loved and recognized by the public. However, currently in China, most cultural and creative products are displayed in the form of display cabinets, shelves, and other carriers, which only allow consumers to observe their external image [2]. Moreover, the incomplete dissemination of cultural information results in a contradiction between macro-level display needs and micro-level display techniques. Or it can only be roughly understood through the product manual and the interpretation of store staff, which has significant limitations in the era of human-computer interaction [3]. Intelligent algorithm technology has the characteristics of virtual real integration, virtual real synchronization, and natural interaction, which can effectively solve the display of cultural and creative products. Problems such as ineffective interaction and lack of user experience. Building a museum's cultural and creative product display and interaction system based on emotional design by combining intelligent algorithm technology to expand display methods and expression features [4]. Then, using service design tools such as empathy maps and user experience maps, a needs analysis is conducted to ultimately output a museum cultural and creative product design strategy based on intelligent algorithm technology from three levels: underlying mechanisms, dynamic gameplay, and aesthetic experience. The study focuses on digital cultural and creative industries, deconstructing the underlying mechanisms, dynamic gameplay, and aesthetic models within the MDA framework to decode the new connotations of digital cultural and creative industries in terms of functionality, interaction, and appearance [5]. Taking the cultural and creative products of Shaanxi Provincial History Museum as a case study, intelligent algorithm technology is used as the technical support, and MDA theory, emotional design theory, user behaviour analysis, service design tools and other methods are applied to the intelligent algorithm. Based on the practical application of AR cultural and creative technology in museums, taking the Shaanxi Provincial History Museum as an example, this study explores user needs through scene deconstruction and uses the Carnot model to rank the importance of needs [6]. Based on MDA theory, a reconstruction of cultural and creative product display and interaction system supported by intelligent algorithm technology. User demand analysis and conversion for intelligent algorithmic cultural and creative products for museums. Finally, test and evaluate the plan to confirm its effectiveness [7].

In response to the limitations of current computer-aided cultural and creative product design in terms of creative inspiration, design optimization, and user feedback processing. Combining the advantages of reinforcement learning in complex decision-making and continuous optimization, some scholars have proposed a computer-aided cultural and creative product design method based on reinforcement learning. Utilizing deep learning techniques such as Generative Adversarial Networks (GANs) to generate diverse preliminary design concepts, while introducing reinforcement learning to intelligently screen the most promising creative directions, reducing designers' blindness in the initial ideation stage [8]. Collecting feedback data through simulating user behaviour or actual user testing, using reinforcement learning models to analyze and predict the impact of different design adjustments on user satisfaction, and guiding subsequent design optimization directions. This method aims to broaden the creative boundaries of designers through intelligent means, accelerate the design iteration process, and enhance the market adaptability and user satisfaction of the final product [9]. This method constructs a computer-aided platform integrating reinforcement learning algorithms, which can simulate the "trial and error learning optimization" cycle in the design process, and automatically explore and optimize design solutions. Reinforcement learning teaches how to make optimal design decisions by interacting with the environment (i.e. design requirements, user preferences, market trends, etc.) to maximize the innovation and practicality of design. Designers input design requirements through a graphical user interface (GUI), and the system automatically executes reinforcement learning algorithms on the backend, exchanging real-time data with the front end to display the design iteration process and final results. By selecting representative cultural and creative product design cases (such as cultural derivatives, creative home products, etc.), this method is applied to carry out a full process practice from creative inspiration to design optimization. The results show that this method not only significantly improves design efficiency and innovation, but also enhances the market adaptability of the design through precise user feedback processing [10].

Constructing an appropriate reinforcement learning model can facilitate the automatic optimization and design of woodcarving crafts' appearance. In this process, the agent persistently experiments with various design schemes and adjusts its behaviour strategy according to environmental feedback reward signals, gradually approaching the optimal design scheme. Consequently, this article aims to delve into the computer-aided CCP design method leveraging reinforcement learning, using the appearance design of woodcarving crafts as an example [11]. The article initially reviews the fundamental principles and prevalent methods of CCP design, analyzing the application of existing methods in woodcarving crafts design. Subsequently, it introduces the basic principles and core elements of reinforcement learning. Based on this foundation, a design method for woodcarving crafts' appearance using reinforcement learning is proposed, with detailed descriptions of its implementation steps and key technical aspects. Ultimately, the validity and feasibility of the proposed method are substantiated through experiments and case analyses, and its application prospects in the CCP design field are discussed [12]. This research aims to introduce a novel idea and method to the CCP design field, fostering the integration and innovation of traditional and modern technologies. Furthermore, by applying reinforcement learning to the specific challenge of woodcarving crafts' appearance design, it hopes to uncover new application scenarios for reinforcement learning in the optimization design domain.

2 LITERATURE REVIEW

In the realm of CCP design, scholars have conducted extensive discussions on various topics, including the application of CAD, the exploration of product innovation design systems, and the integration of digital art. Xu and Jiang [13] deeply integrated theoretical knowledge of design and psychology when exploring computer-aided cultural and creative product design methods based on reinforcement learning, and combined the author's rich experience in the field of visual project design. The application of reinforcement learning algorithms in cultural and creative product design is not limited to static visual presentation but also involves dynamic adjustment and optimization of the design decision-making process. The core elements of data visualization include data distribution, temporal representation, domain comparison, spatial representation, local and global relationships, and relationships between data. Based on this, guide the design iteration. This "trial and error learning optimization" loop mechanism greatly expands the creative space of designers and accelerates the optimization process of design solutions. As the foundational framework for design inspiration, these elements are innovatively applied to cultural and creative product design through intelligent optimization using reinforcement learning algorithms. These sub-patterns not only help designers understand the operational mechanism of reinforcement learning in product design. By analyzing user behaviour, market feedback, and other data in real time, reinforcement learning models can automatically explore and learn which combinations of design elements are most attractive to users and meet their needs. This model elucidates the various design stages from requirement analysis, creative inspiration, and design optimization to user validation, and elucidates the reinforcement learning-driven design methods and key points that can be adopted in each stage. It also provides specific design insights, such as how to balance innovation and practicality in design, and how to dynamically adjust design strategies based on user feedback. On the basis of an in-depth analysis of the visual presentation and interactive factors of data visualization expression, Zhang [14] further established the deep correlation between abstract sub-patterns of reinforcement learning (such as exploration, utilization, balance, adaptation, etc.) and image sub-patterns. In the creative stimulation stage, deep learning techniques such as generative adversarial networks, combined with reinforcement learning screening mechanisms, are used to quickly generate and optimize creative solutions. In the design optimization phase, reinforcement learning models are used to continuously iterate design parameters to maximize the innovation and market adaptability of the design.

In the long history of China, traditional Chinese patterns, as cultural treasures, not only carry a profound cultural heritage but also surpass time and space boundaries with their unique artistic charm, exerting a profound influence on the field of modern design. Zhao and Sahari [15] delved into the artistic features of traditional Chinese patterns, their integration with modern design, and their specific applications and extensions in emerging design methods for computer-aided cultural and creative product design based on reinforcement learning. Reinforcement learning, as a machine learning technique, enables intelligent agents to continuously experiment, learn, and optimize decision-making processes in interaction with the environment to achieve specific goals. Chinese traditional patterns are renowned for their rich and diverse forms, profound connotations, and exquisite craftsmanship. In the traditional field of cultural and creative product manufacturing, the production methods of cultural and creative products have problems such as long production cycles, high costs, and low colour reproduction accuracy. Full-colour 3D printing technology can achieve integrated production from complex geometric shapes to precise colour gradients, which is particularly crucial for achieving colour reproduction in the intelligent manufacturing of cultural and creative products. To address this issue, Zhou et al. [16] fully utilized colour 3D printing technology to design colour-rich 3D cultural and creative digital files. Accurately predicting and reproducing colours in the field of intelligent manufacturing through colour 3D printing can enhance product attractiveness, increase product value, meet personalized colour needs, and achieve design freedom in intelligent manufacturing to meet different market demands. And use colour 3D printing equipment to output it, in order to achieve accurate reproduction of the colours and features of intelligent manufacturing cultural and creative products. By studying the principles and influencing factors of full-colour 3D printing reproduction, optimize the base colour rendering model. The research results of the paper are of great significance for improving the colour reproduction quality of Chinese creative products in the field of intelligent manufacturing and achieving predictability and controllability of colour 3D printing. However, 3D cultural and creative products have the characteristics of varied product shapes, complex colour response, diverse printing methods, complex post-processing, and single-colour printing materials. Zhao et al. [17] aimed to achieve colour reproduction prediction and control for colour 3D printing of cultural and creative products in the field of intelligent manufacturing. The problem faced by its colour reproduction and control is similar to that of colour 3D printing in other fields, that is, it cannot accurately predict and control its colour reproduction. The achievement of accurate colour reproduction in colour 3D printing provides a new research approach for improving the predictability and controllability of colour reproduction in full-colour 3D printing. Based on this, propose colour prediction and reproduction evaluation based on a multiple linear regression model and multi-layer BP neural network model. With the rise of the times, the value of intangible cultural heritage is increasingly evident, and qipao craftsmanship, as an intangible cultural heritage project, is receiving more and more attention from government departments. However, the development of qipao culture is relatively traditional and has a single form. Zhou et al. [18] broke the traditional design pattern of mobile apps by exploring the interface design of intelligent robot-related apps and studying the symbolic expression of app interfaces for this type of product. The rapid development of Internet information technology and the increasing popularity of mobile applications have brought opportunities for the spread of cheongsam culture. Analyze user needs based on accurate user profiles, establish user groups based on user needs, and construct an APP information framework and interaction model.

3 WOODCARVING CRAFTS APPEARANCE MODELING DESIGN METHOD

At present, research on process route planning is mainly limited to specific parts in fixed machining environments, making it difficult to quickly respond to dynamic changes in machining environments and personalized product customization in flexible machining systems. Therefore, it is urgent to carry out research on process route planning methods for flexible machining systems.

A process route planning method based on a deep O network is proposed to address the problem of dynamic changes in the processing environment. Considering that the action selection in Deep Reinforcement Learning (DRL) is similar to the selection of decision variables in process route planning. DRL can store previously learned strategies in the form of neural network parameters, which can be used to improve decision-making speed when dealing with problems with similar feature structures. Therefore, this article conducted research on the DRL-based process route planning method for machining systems to improve the response speed of flexible machining system process route planning. At the same time, an S-function exploration mechanism is proposed to accelerate the convergence speed of the algorithm for the selection problem of "exploration" and "utilization" of DON intelligent agents. Based on the meaning of process route planning, the execution status of part feature operations is mapped as a state vector, and the set of part feature operations is mapped as an action space. The proposed method effectively solves the process route planning problem of dynamic changes in the processing environment. In order to improve the utilization rate of reasonable experience by intelligent agents and accelerate the speed of avoiding part feature constraints, the weighted experience pool technology is proposed. The meaning of combining part feature reconstruction is based on the Markov Decision Process (MDP), which defines the state vector, action space, and reward function. At the same time, in order to avoid A3C agents getting stuck in local optima when selecting processing resources for parts. A random greedy strategy was proposed, and a fast failure strategy was proposed to address the problem of a large number of trial and error actions that may reduce the response speed of the algorithm when feature reconstruction agents select actions for parts. Figure 1 shows the neural network diagram.

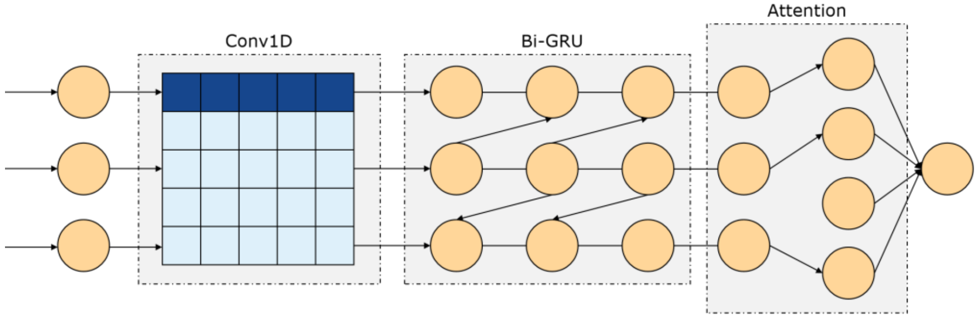

Figure 1: Neural network diagram.

Then, the deep Q-network (DQN) is used to train the agent, so that it can choose the optimal design action according to the feature vector.

The input layer receives a vector $x_1, x_2, \cdots x_n \,|\, x_i \in R$, where each input pair is assigned a weight w, and another offset is denoted as b, typically valued at 1 and recorded as w_0. To calculate the sum of the weight values, use the formula:

$$z = \sum_{i=1}^{n} w_i x_i + b \tag{1}$$

Record the output value as y, and calculate the value of y by activating function $g\ z$:

$$y = g\ z \tag{2}$$

Like a human neuron, the activation function transforms input signals linearly or nonlinearly. To enhance the network's expressive and learning abilities, a continuous nonlinear activation function is typically used, such as the Sigmoid function defined as:

$$\sigma(x) = \frac{1}{1+\exp(-x)} \tag{3}$$

When the input value diminishes, the output value tends towards 0; conversely, as the input value augments, the output value inclines towards 1. In situations where the input value is proximate to 0, the sigmoid function exhibits behaviour akin to a linear function. Meanwhile, the loss function is responsible for computing the discrepancy between the anticipated output r and the actual output y. In classification problems, the cross-entropy cost function is commonly used, especially in binary classification, where it calculates the loss. The loss function E is defined as follows:

$$E = -\sum_{n=1}^{N}\left[r_n \ln y_n + (1-r_n)\ln(1-y_n)\right] \tag{4}$$

Cross entropy, a concept in information theory, measures the distance between two probability distributions:

Figure 2 depicts the process of point cloud loading. With the passage of time, the data load increases, just as in the process of reinforcement learning, where agents approach the optimal solution through continuous trial and adjustment. The number of loaded points in Figure 2(b) is increased compared with Figure 2(a), and the number of loaded points in Figure 2(c) is further higher than that in Figure 2(b), while Figure 2(d) shows the largest number of loaded points, which reflects the continuity and dynamics of data loading.

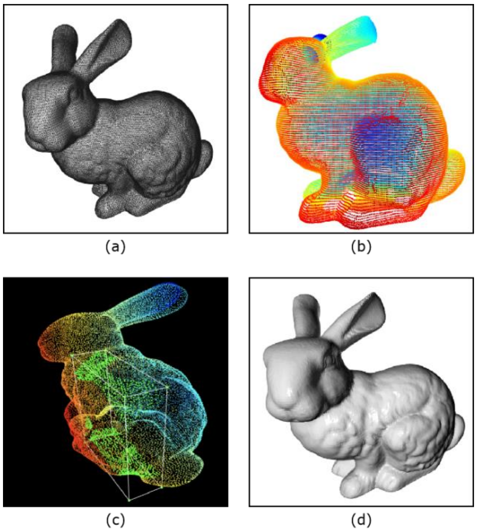

Figure 2: Loading principle of data points in dynamic loading of point cloud model.

In this dynamic loading process, the dynamic loading algorithm plays a core role. This algorithm is very important for loading data; it can load large-scale point cloud data into internal memory continuously according to its characteristics and provide strong data support for subsequent CCP design. The algorithm can also determine the best degree of loading to ensure the best balance between loading speed and loading efficiency. By traversing the point hierarchy to construct a tree, the algorithm ensures that the point cloud loading process has a good transition, thus realizing the rapid and dynamic loading of the point cloud.

To ensure the reinforcement learning model converges towards the global optimal value, intelligent initialization of weights is crucial. In the convolution layer of reinforcement learning, these weights are represented as convolution kernels (or filters) and are randomly initialized following a uniform distribution:

$$W \sim U\left[-\frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}},\frac{\sqrt{6}}{\sqrt{n_{in}+n_{out}}}\right] \tag{5}$$

Where n_{in}, n_{out} represents the number of input and output neurons corresponding to the weight of the convolution kernel. This layer constitutes an innovation in the proposed model, distinguishing it from traditional fully connected neural networks. Its primary objective is to extract features from the woodcarving process. By introducing two theoretical innovations: local perception and parameter sharing, it successfully achieves automatic feature extraction.

$$X^L = f\ Z^L\ = f\ X * K^L + b^L \tag{6}$$

Here, $*$ represents the convolution operation, Z^L denotes the input value for the L layer convolution, X^L signifies the feature mapping value obtained after applying the nonlinear activation function, and f represents the activation function.

Assuming I represents all pixels in the entire image and $I_{c\ i}$ represents all pixels with color $c\ i$, the color correlation diagram can be expressed as:

$$\gamma_{i,j}^{k} = \underset{P_1 \in I_{c\ i}, P_2 \in I}{P_r}\left[\left|p_1 - p_2\right| = k\right] \tag{7}$$

$i, j \in\ 1,2,L,N\ , k \in\ 1,2,L,d$ and $\left|p_1 - p_2\right|$ represent the distance between pixels p_1, p_2 . Considering colour correlation complicates and enlarges the colour correlation diagram. A simplified version is the colour autocorrelation graph, examining only the spatial relationship between same-colored pixels. CAD displays the output image in full-screen mode, matching the display's resolution. After constructing the pattern structure, the polygon area of each pixel within the output image is computed and documented. Subsequently, objects present in the 2D scene are mapped into the real 3D scene by utilizing depth relationships. These objects are then re-projected through the real 3D scene, taking into account their relative position to the virtual viewpoint. This process facilitates the calculation of depth information for each pixel in the actual scene, providing a comprehensive understanding of the spatial layout:

$$Z = \frac{Z_{\min} - Z_{\max}}{255} d + Z_{\max} \tag{8}$$

The formula d denotes the grey value of image depth information, linearly transformed to a 0-255 range for real-scene mapping. The minimum depth value d represents the farthest scene, while the maximum depth value $Z_{\max}$ represents the nearest. Z signifies the depth value of the current pixel in the real scene.

A Gaussian filter can eliminate Gaussian noise in images and is considered a smoothing filter. This article proposes using a Gaussian filter in the depth image preprocessing step, effectively smoothing the depth image and making it more aligned with the real scene depth. In two-dimensional space, it is defined by the following formula:

$$G\ u,v\ = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\ u^2+v^2\ /\ 2\sigma^2} \tag{9}$$

σ represents the standard variance of normal distribution. The filter radius is:

$$r^2 = u^2 + v^2 \tag{10}$$

In 2D space, the contour lines of the surface generated by this formula take the shape of concentric circles, exhibiting a normal distribution emanating from the centre. To transform the original image, a convolution matrix is employed, which is constituted by pixels possessing a nonzero distribution. This application of the matrix facilitates the alteration of the image according to the specified formula.

In the design process, the basic requirements and constraints of the vase, such as height, diameter, material, and so on, are first inputted through the design input module. Then, the feature extraction module transforms these requirements and conditions into high-dimensional feature vectors. Next, the reinforcement learning model module begins to select the optimal design action according to the feature vector and gradually generates the design scheme. Finally, the design output module converts the generated design scheme into a 3D model for users to evaluate and provide feedback.

4 EXPERIMENT AND CASE ANALYSIS

In order to fully verify the practical application effect and efficiency of computer-aided CCP design method based on reinforcement learning in dealing with complex woodcarving design scenes, this study carefully selected several representative woodcarving design scenes for testing. These scenes not only cover different complexities and unique features, such as fine texture carving, complex spatial structure, and the integration of diverse cultural elements but also specially select scenes that can reflect the combination of traditional woodcarving techniques and modern design concepts to ensure the comprehensiveness and depth of the test. Through this choice, the purpose is not only to verify the applicability of the reinforcement learning method in the field of woodcarving design but also to fully demonstrate the remarkable advantages of real-time rendering algorithm in animation rendering by comparing rendering speed, design optimization degree and user satisfaction, and then to explore its potential in improving CCP design efficiency and creativity.

Figure 3 shows the algorithm's rendering speed in different complexity woodcarving design scenes. The real-time rendering algorithm proposed in this article shows excellent rendering efficiency, whether in scenes with rich details or in scenes with complex structures, which fully proves its excellent performance in dealing with complex woodcarving design scenes.

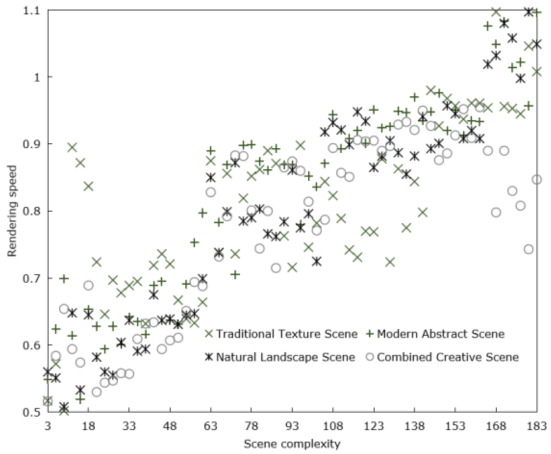

Figure 3: Algorithm rendering speed.

Figure 4 shows the effect of the dynamic loading algorithm proposed in this article in practical application. Figure 4(a), Figure 4(b) and Figure 4(c) constitute a group, which clearly shows the state of the rough die in different processing stages. Among them, Figure 4(a) shows the initial loading data model of the rough model, showing the unprocessed original form; Figure 4(b) shows the shape of the rough model reconstructed by the algorithm, and it can be observed that the algorithm has effectively optimized and adjusted the model; Figure 4(c) is the enlarged effect of the top point group in Figure 4(a), and it can be clearly seen that there is a big gap between the point groups in the initial loading data model.

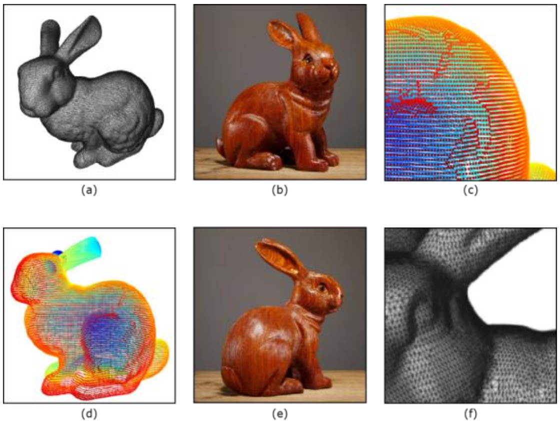

Figure 4: Image loading experiment.

Figures 4(d), 4(e), and 4(f) also constitute a group, but they represent the point cloud form of the fine mode. In Figure 4(d), the initial loading data model of the fine die is shown, and its details and accuracy have been obviously improved compared with that of the coarse die. Figure 4(e) shows the fine die shape reconstructed by the algorithm, and it can be observed that the algorithm further optimizes the details and shapes of the model; Figure 4(f) is the enlarged effect of the top point group in Figure 4(d). Compared with the enlarged effect of the coarse die, it can be clearly seen that the point group gap of the fine die is relatively small, and more points are loaded, which fully proves the remarkable effect of the dynamic loading algorithm proposed in this article in improving the accuracy and details of the model.

To further ascertain the precision and reliability of the algorithm in practical scenarios, advanced 3D laser scanning technology is employed. This technology swiftly captures and accurately reconstructs a 3D model that closely mirrors the object's shape, size, texture unevenness, and direction. As evident in Figure 5(a), the 3D model obtained through this technology exhibits a high degree of visual similarity with the real object. To ensure the model's accuracy, the measurement function provided by the 3D laser scanning technology is utilized to precisely measure the distance, with the results displayed in Figure 5(b). The minimal error between the 3D model and the real object underscores the accuracy and reliability of the method in model reconstruction.

In the process of verifying the performance of the algorithm, we also pay special attention to the recall and accuracy of the automatic generation of woodcarving. The recall rate reflects the ability of the algorithm to successfully recall the relevant design elements when generating the woodcarving design scheme, while the accuracy rate reflects the degree of conformity between the design scheme generated by the algorithm and the expected goal. As shown in Figure 6 and Figure 7, the experimental results of recall and accuracy of automatic generation of woodcarving are shown, respectively.

As can be seen from Figure 6, the improved algorithm shows obvious advantages in recall rate. Compared with the improved algorithm, the improved algorithm can recall the elements related to woodcarving design more accurately, thus improving the integrity of the design scheme.

As can also be seen from Figure 7, the improved algorithm has also achieved significant improvement in accuracy. Compared with the improved algorithm, the design scheme generated by the improved algorithm is more in line with the expected goal and has higher accuracy. This result further proves the superiority of this method in improving the accuracy of woodcarving design schemes.

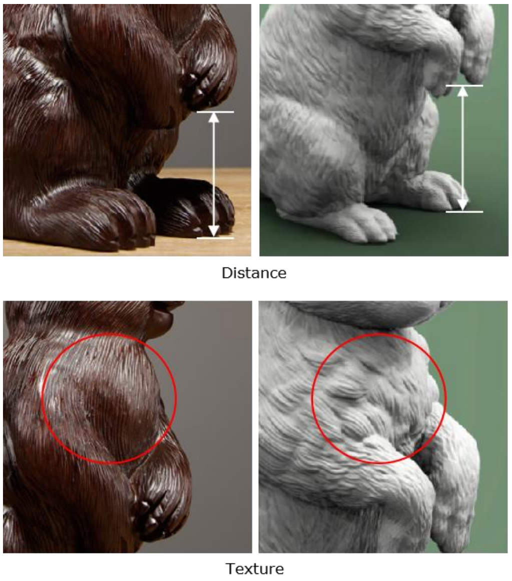

Figure 5: Comparison between physical object and model.

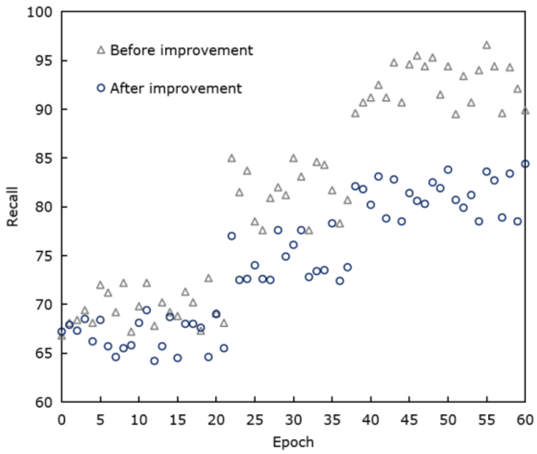

Figure 6: Automated generation of recall rate for woodcarving.

A process route planning method based on the CCP design method is proposed for the problem of feature reconstruction of parts. When part feature reconstruction occurs, the proposed method has the fastest response speed and obtains the best quality solution. At the same time, in order to avoid local optima caused by the optimal selection of machine tools, cutting tools, and feed directions by CCP design agents, a random greedy strategy is proposed, and a dictionary is maintained for each operation to record the minimum energy consumption and corresponding processing resources. Then, a fast failure strategy was proposed to solve the problem of CCP agents getting stuck in a lot of trial and error when selecting actions due to complex feature constraints caused by feature reconstruction of parts.

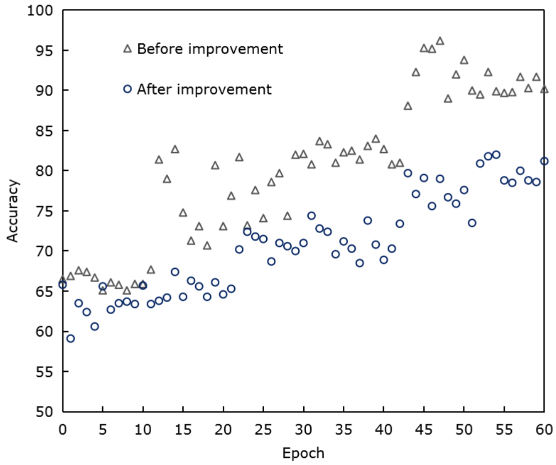

Figure 7: Automated generation accuracy of woodcarving.

In the context of feature reconstruction of parts, state vectors, action spaces, and reward functions are defined based on Markov decision processes. A process route planning method based on DPPO is proposed to address the problem of dynamic changes in the processing environment and simultaneous reconstruction of part features in process route planning. In the context of dynamic changes in the machining environment and simultaneous reconstruction of part features, utilizing the dynamic generation of nodes and edges in the graph structure can reduce the impact of dynamic changes in the machining environment and feature reconstruction on the description of part machining status. At the same time, the high-dimensional information in the graph structure is transformed into low-dimensional vectors, and then the candidate node set in the part processing state graph is mapped to the action space. Simulation experiments have shown that the proposed method effectively solves the process route planning problem that occurs simultaneously with dynamic changes in the machining environment and feature reconstruction of parts.

5 CONCLUSIONS

In this article, the computer-aided CCP design method based on reinforcement learning is deeply explored, and the appearance design of woodcarving crafts is studied in detail. By examining the fundamental principles and prevalent methods of CCP design, this article delves into the application and limitations of existing techniques in woodcarving crafts design, while highlighting the potential value of reinforcement learning in this domain. Subsequently, a novel design method for woodcarving crafts appearance, grounded in reinforcement learning, is proposed. The article elaborates on the implementation steps and pivotal technical nuances of this method. Through rigorous experiments and case analyses, the effectiveness and feasibility of the proposed method are confirmed, demonstrating its notable advantages in enhancing the rendering efficiency of woodcarving design schemes, ensuring model accuracy, and improving recall and precision.

In summary, this study introduces a fresh perspective to the CCP design field, fostering the integration of traditional and modern technologies. It also opens up new avenues for the application of reinforcement learning in optimization design. With ongoing research and practice, the computer-aided CCP design method based on reinforcement learning is poised to play a pivotal role in the cultural and creative industries, breathing new life into the preservation and innovation of traditional culture.

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