Optimization Strategy of Design Innovation Based on Environment Interactive Learning

Bo Wang[1] and Yishuai Lin[2]

[1]Department of Architecture and Design, Qinhuangdao Vocational and Technical College, Qinhuangdao, Hebei 066100, China, wangbo@qvc.edu.cn
[2]Department of Architecture and Design, Qinhuangdao Vocational and Technical College, Qinhuangdao, Hebei 066100, China, linyishuai@qvc.edu.cn

Corresponding author: Yishuai Lin, linyishuai@qvc.edu.cn

Abstract. Considering the obstacles encountered in the present design domain, this article introduces a fresh design innovation model and integrates the RL (Reinforcement Learning) algorithm to refine the design process. In terms of experimental methods, this article first constructs a design innovation model based on CAD (Computer Aided Design) software, which combines innovative ideas and design parameters to improve the innovation and practicality of design. Subsequently, the RL algorithm is introduced to optimize the design scheme through interactive learning between the agent and the environment. The design and implementation of simulation experiments follow scientific principles, ensuring the reliability and repeatability of experimental results. The results show that compared with traditional design methods, the design innovation model based on CAD combined with the RL algorithm can significantly improve the design efficiency and quality. The proposed method shows superiority in the innovation index, performance index, and stability index, among which the innovation score is as high as 9.87. The results verify the effectiveness of the CAD-based design innovation model and RL in design optimization. This research not only provides new theoretical support and practical guidance for the design field but also lays a solid foundation for the future development of intelligent design.

Keywords: Computer-Aided Design; Reinforcement Learning; Design Innovation; Optimize
DOI: https://doi.org/10.14733/cadaps.2024.S23.284-299

1 INTRODUCTION

The swift advancement of science and technology has rendered CAD a vital instrument in contemporary design practices, thereby significantly enhancing design productivity and precision. Embedded systems and mobile devices have become an indispensable part of our daily lives. From smartphones and tablets to smart home devices, these systems not only change our way of life but also drive innovation in various industries. Ajani et al. [1] explored the application and optimization of CAD (computer-aided design) and reinforcement learning in the fields of embedded and mobile devices. CAD, as a widely used technology in engineering, construction, and manufacturing, is gradually emerging in embedded and mobile devices. By leveraging the powerful computing power and portability of these devices, CAD software can provide users with a more efficient and convenient design experience. In embedded systems, CAD software can be used for product prototype design and simulation. Designers can use these tools to accurately model, analyze, and optimize in virtual environments, thereby reducing the time and cost of physical prototype production. In addition, embedded CAD software can also be integrated with production equipment to achieve automated design and production processes. In the application of CAD technology, designers can use professional CAD software to draw two-dimensional drawings and three-dimensional models and carry out accurate dimensioning and material selection. Designing efficient analogue circuits has become a key challenge for electronic engineers to meet the growing demands for performance and reliability. In recent years, the rise of machine learning technology has provided new solutions for this field. Budak et al. [2] proposed an efficient simulation circuit design determination method based on machine learning-assisted global optimization, aiming to improve design efficiency and optimize circuit performance. Machine learning technology can extract useful information from a large amount of data and automatically optimize design parameters through learning algorithms. In analogue circuit design, machine learning can be used to predict circuit performance, optimize component parameters and topology structures, etc. By training machine learning models, we can achieve rapid evaluation and global optimization of circuit performance. It utilizes trained machine learning models to quickly predict circuit performance. Automatically adjust component parameters and circuit topology through global optimization algorithms to optimize circuit performance. Furthermore, CAD technology also supports the performance analysis and optimization functions of design schemes, such as finite element analysis and fluid mechanics analysis, which helps designers predict the performance and reliability of products in the design stage. Since its inception, 3D printing technology has had a profound impact in multiple fields, especially in manufacturing, healthcare, construction, and others. Among them, Fused Placement Modeling (FDM) is one of the most common and popular technologies. However, despite the maturity of FDM technology, there are still many areas that can be optimized during the printing process. With the rapid development of machine learning technology, more and more researchers are attempting to apply machine learning to 3D printing optimization to improve printing quality and efficiency. Dabbagh et al. [3] explored machine learning optimization methods for extrusion-based 3D printing. In the extrusion-based 3D printing process, there are many factors that affect printing quality and efficiency. In addition, due to the uncertainty and complexity of the printing process, it is difficult to find the optimal printing parameters through traditional optimization methods. Therefore, a more intelligent and adaptive method is needed to optimize the printing process. Machine learning can analyze historical data to find the optimal combination of printing parameters in order to improve printing quality and efficiency. For example, regression algorithms can be used to predict printing results under different printing parameters and find the optimal combination of parameters. However, traditional CAD technology still has some limitations in design innovation, such as a lack of intelligence and a low degree of automation.

In recent years, as a new machine learning technology, RL has been widely used in decision-making optimization, intelligent control and other fields. A computational design environment is a digital simulation environment used to simulate and predict the behaviour of actual systems. In additive manufacturing, the computational design environment can simulate the robot's motion trajectory, material stacking process, and changes in the manufacturing environment. By simulating and training in this virtual environment, it is possible to quickly validate and optimize the control strategy of robots, thereby improving the efficiency and quality of additive manufacturing. Traditional deep reinforcement learning methods typically rely on model learning, which involves predicting future states through dynamic models of the learning environment. However, in additive manufacturing, it is very difficult to establish accurate environmental models due to the complexity and uncertainty of the environment. Felbrich et al. [4] proposed a distributed model-free deep reinforcement learning method that does not require learning environmental models but directly learns the optimal decision strategy through trial and error. Distributed model-free deep reinforcement learning decomposes tasks into multiple subtasks, each of which is handled by an independent agent. These agents interact with the environment to learn how to complete their respective subtasks. RL algorithm usually includes three basic elements: state, action and reward. The state is a set of variables that describe the current situation of the environment; Action is a set of behaviours that agents can take; Reward is the feedback signal after the environment performs an action on the agent. The performance of CNN largely depends on the configuration of its hyperparameters. In order to find the optimal combination of hyperparameters, researchers have begun to explore the application of Multiagent Reinforcement Learning (MARL) to CNN hyperparameter optimization problems. Iranfar et al. [5] explored the methods and potential advantages of utilizing multiagent reinforcement learning for CNN hyperparameter optimization. Multiagent reinforcement learning is a technology that enables multiple agents to learn and collaborate together in the same environment. In CNN hyperparameter optimization problems, we can treat each hyperparameter as an agent and find the optimal combination of hyperparameters through the collaboration of multiple agents. Specifically, each agent is responsible for adjusting one or more hyperparameters and learning how to adjust these parameters to improve the performance of the model through interaction with the environment (i.e., the CNN model). Collaboration between intelligent agents can be achieved through sharing experiences, communication, or collaborative evolution. Multiagent reinforcement learning can explore different combinations of hyperparameters in parallel, greatly reducing optimization time. Through collaboration and sharing of experiences among intelligent agents, multiagent reinforcement learning can break out of local optima and achieve global optimization. RL learns the optimal strategy through continuous exploration and trial and error, that is, selecting the best action according to the current state to obtain the maximum cumulative reward.

With the rapid development of 3D printing technology, its application in the manufacturing industry is becoming increasingly widespread. However, with the expansion of the production scale, surface fault detection of 3D printed products has become an important issue. Traditional detection methods often rely on manual visual inspection, which is not only inefficient but also prone to missed or false detections. Kadam et al. [6] analyzed data-driven algorithms that can learn and extract useful information from large amounts of data. In the surface fault detection of 3D printed products, machine learning can identify various surface defects, such as cracks, bubbles, unevenness, etc., by training models. Specifically, machine learning algorithms can preprocess surface images of 3D printed products and extract features related to defects. Then, using these features, train a classifier to distinguish between normal surfaces and faulty surfaces. Then, use this dataset to train machine learning models that can accurately identify various surface faults. The application process of the RL algorithm in design optimization includes defining the state space, action space, and reward function of the design problem. Select the appropriate RL algorithm for strategy learning and optimization. The learned strategies are applied to practical design problems for verification and evaluation. Through iterative learning and optimization processes, the optimal design strategy can be gradually approached, and the design goal can be maximized or minimized. With the rapid development of technology, nanomaterials have shown enormous potential for application in multiple fields due to their unique physical and chemical properties. However, the manufacturing process of nanomaterials is complex and variable, requiring extremely high precision and efficiency. To address these challenges, Konstantopoulos et al. [7] explored the introduction of advanced technologies such as computer-aided design (CAD) and reinforcement learning into the field of nanomaterials manufacturing to achieve innovation-driven and sustainable green development. CAD, as a powerful design tool, can accurately simulate and optimize material structures at the nanoscale. In addition, CAD can also be used to automate and optimize the manufacturing process of nanomaterials, improving production efficiency and quality. Reinforcement learning is a machine learning technique that automatically finds the optimal strategy to complete a specific task through interactive learning with the environment. In the manufacturing of nanomaterials, reinforcement learning algorithms can learn how to adjust manufacturing parameters to achieve optimal material performance. Compared with traditional methods, reinforcement learning has stronger adaptability and higher efficiency and is expected to play an important role in the manufacturing of nanomaterials.

The aim of this research is to investigate the fusion of RL and CAD technology, proposing a design optimization strategy that leverages both to enhance design innovation and quality. Our investigation encompasses an analysis of CAD's current applications and limitations in design, an exploration of RL's fundamental principles and their potential in design optimization, and the formulation of a novel CAD-RL integration strategy. Simulation experiments validate the effectiveness and superiority of our approach, offering both theoretical enrichment and practical advancements in intelligent design methods. By incorporating RL, we enable automated control and intelligent optimization, ultimately enhancing design efficiency, fostering innovation, and reducing costs. This progress promises to catalyze technological and industrial advancements in the engineering design sphere.

In terms of novelty, this study introduces RL algorithms to the realm of CAD design, presenting a new optimization strategy. We frame design challenges using the MDP (Markov Decision Processes) model and employ RL to devise optimal design strategies, achieving automated and intelligent design process optimization. Compared to traditional CAD methods, our strategy offers superior intelligence and automation, significantly boosting design efficiency and fostering innovation.

The article is structured as follows: Section 1 introduces the research background, objectives, and key innovations. Section 2 reviews relevant literature. Sections 3 through 5 comprise the main body, detailing the CAD-based design innovation model, system calibration and image preprocessing, simulation experiments, and result analysis. Finally, Section 6 summarizes the findings and outlines future research directions.

2 RELATED WORK

In order to further improve the efficiency of the PBF process and the performance of manufactured parts, the application of machine learning technology in this field is gradually receiving attention. Liu et al. [8] reviewed various machine learning techniques applied in the PBF process and performance optimization in recent years, including supervised learning, unsupervised learning, deep learning, and reinforcement learning, and explored future development trends. Powder bed fusion (PBF) is an important additive manufacturing technology that constructs three-dimensional objects by layering and melting powders. However, the PBF process involves multiple complex physical and chemical processes, making the selection and optimization of process parameters very difficult. Traditional optimization methods are usually based on trial and error and expert experience, which are inefficient and difficult to achieve optimal solutions. Supervised learning builds prediction models by training labelled datasets. In PBF, supervised learning can be used to predict the performance of parts under different process parameters, such as density, strength, and surface quality. By constructing an accurate prediction model, it can guide the optimization of process parameters and improve manufacturing efficiency and quality. CAD, as a powerful design tool, provides great convenience for the manufacturing of ABS-Al composite structures. Engineers can use CAD software to design the shape, size, and internal structure of composite materials accurately, ensuring the performance and quality of the final product. In addition, CAD can be directly integrated with manufacturing equipment to achieve seamless integration from design to manufacturing, greatly improving production efficiency. Reinforcement learning is a machine learning technique that uses interactive learning with the environment to find the optimal decision strategy. In the manufacturing of ABS-Al composite structures, reinforcement learning algorithms can learn how to automatically adjust manufacturing parameters based on factors such as material properties, manufacturing processes, and equipment status to achieve optimal results. By interacting with the actual manufacturing environment, reinforcement learning algorithms can gradually learn the optimal manufacturing strategy, thereby improving product performance and production efficiency [9].

With the continuous advancement of technology, computer-aided design (CAD) has become an indispensable tool in the field of engineering. CAD technology can significantly improve design efficiency, optimize design solutions, and play a huge role in multiple engineering fields. However, facing complex and ever-changing design problems and constantly updating design standards, how to predict and ensure the success of CAD technology in engineering applications has become a worthwhile research topic. In recent years, reinforcement learning, as an advanced machine learning technology, has provided new ideas for predicting and evaluating the application of CAD technology in engineering. Singh et al. [10] analyzed machine learning methods that interact with the environment to find the optimal strategy for completing specific tasks through reinforcement learning. In CAD technology, reinforcement learning can be applied to predict and optimize the design process. Specifically, reinforcement learning algorithms can learn how to automatically adjust design parameters and strategies based on design specifications and goals to maximize design performance metrics. Through continuous trial and error and learning, reinforcement learning algorithms can gradually find the optimal design solution and predict the success probability of the solution in practical engineering applications. With the rapid development of additive manufacturing (AM) or 3D printing technology, its application fields are constantly expanding, from prototype production to final product manufacturing, demonstrating its enormous potential. However, multiple process parameters involved in the 3D printing process have a significant impact on the quality and performance of the final product. Therefore, Tamir et al. [11] analyzed the key impact of real-time monitoring and optimization of process parameters on improving 3D printing efficiency and product quality. Machine reinforcement learning is a machine learning technique that simulates human decision-making processes. It automatically finds the optimal strategy to complete a specific task through interactive learning with the environment. In 3D printing, it can be used to learn how to adjust process parameters to maximize printing quality or efficiency. Although machine reinforcement learning-based 3D printing process parameter monitoring and optimization has great potential, it still faces some challenges, such as data collection and processing, algorithm efficiency and stability, and feasibility of practical applications.

Compact heat exchangers, as an efficient heat exchange device, have a wide range of applications in multiple industrial fields. However, its performance is influenced by various parameters, including the physical properties of the fluid, operating conditions, geometric structure, etc. Traditional design methods often rely on experimentation and experience, which is not only costly but also inefficient. With the rapid development of machine learning technology, more and more researchers are attempting to apply these technologies to the performance prediction and optimization design of compact heat exchangers. Machine learning technology can achieve accurate prediction of complex systems by learning patterns and patterns from large amounts of data. In the performance prediction of compact heat exchangers, machine learning algorithms can establish a mapping relationship between input parameters and output parameters. Through training and optimizing models, Uguz and Ipek [12] have achieved rapid prediction and evaluation of the performance of compact heat exchangers. In order to accurately predict the performance of compact heat exchangers, it is necessary to construct appropriate machine-learning models. In the process of model construction, attention should be paid to data preprocessing and feature selection to improve the prediction accuracy and generalization ability of the model. With the increasing complexity of electronic systems, High-Level Synthesis (HLS) has become an important tool for designing complex digital systems. HLS allows designers to design at higher levels of abstraction, simplifying the design process and improving design efficiency. However, in HLS, exploring design space is a huge challenge as there are numerous potential design solutions, each with different performance, power consumption, and area goals. In order to explore this multiobjective design space effectively, Wu et al. [13] proposed a modelling method that combines reinforcement learning and graph neural networks. Reinforcement learning is a machine learning technique that learns optimal decision strategies through the interaction between intelligent agents and the environment. In the exploration of the HLS design space, each design scheme is regarded as an action, and the evaluation results of design goals are regarded as reward signals. Train agents to learn how to generate optimal design solutions that meet multiple design objectives through reinforcement learning algorithms. In order to more effectively evaluate design solutions, it proposes a modelling method based on graph neural networks. A graph neural network is a deep learning model that can process graph-structured data and capture complex relationships between nodes and edges. In HLS, we can represent design solutions as graph-structured data, where nodes represent hardware components (such as processors, memory, etc.), and edges represent the connection relationships between components.

With the rapid development of computer-aided design (CAD) and reinforcement learning (RL) technologies, their applications in antenna design are gradually receiving attention. Wu et al. [14] introduced the basic principles of CAD and reinforcement learning, then elaborated on their combined application in antenna design, and finally analyzed their effectiveness through practical cases. As a key component of wireless communication systems, the performance of antennas directly affects the transmission efficiency and quality of the entire system. Traditional antenna design mainly relies on the designer's experience and repeated experimentation, resulting in long design cycles and low efficiency. With the continuous advancement of CAD technology and reinforcement learning algorithms, new optimization methods have been brought to antenna design. Reinforcement learning is an algorithm that learns through trial and error, gradually learning the optimal decision strategy through interaction with the environment. In antenna design, reinforcement learning can be used to adjust design parameters automatically to optimize antenna performance. By constructing an appropriate reward function, reinforcement learning algorithms can guide the antenna design process and gradually approach the optimal solution. In the manufacturing process of variable components, the accuracy and consistency of geometric shapes are crucial for ensuring product quality and performance. In order to optimize the manufacturing process parameters of variable component geometries, reinforcement learning has become an effective solution. Zimmerling et al. [15] explored the use of reinforcement learning to optimize manufacturing process parameters for variable component geometries. In the manufacturing process of variable components, the selection of manufacturing process parameters has a significant impact on the accuracy and consistency of geometric shapes. However, the selection of manufacturing process parameters is a complex issue that involves the interaction and influence between multiple parameters. Traditional optimization methods often struggle to handle this complexity, resulting in less precise and efficient selection of manufacturing process parameters. Train intelligent agents using actual manufacturing data or simulated data, and learn the optimal manufacturing process parameter selection strategy through interaction with the environment. Deploy the trained, intelligent agent to the actual manufacturing environment and adjust and optimize according to the actual situation to achieve the best selection of manufacturing process parameters.

3 SYSTEM CALIBRATION AND IMAGE PREPROCESSING

The ongoing advancement of computer technology has led to remarkable enhancements in the capabilities and performance of CAD systems, enabling the shift from 2D drawings to 3D modelling, as well as the transition from static designs to dynamic simulations. However, there are still some problems and challenges that urgently need to be solved in intelligent and automatic design. Related research in the field of RL has made remarkable progress in recent years, and many new algorithms and theoretical frameworks have been put forward. RL has been successfully applied in many fields, such as game AI, autonomous driving, robot control and so on. In terms of design optimization, RL also shows certain application potential. For example, at present, the application of RL in design optimization is still in its infancy, and the related research results are relatively few. In the future, the integration of CAD technology with RL will grow increasingly tight as artificial intelligence technology continues to evolve and gain widespread adoption. Additionally, the ongoing advancement of simulation technology will lead to a surge in research interest and trends surrounding RL-based design optimization methods that leverage simulation experiments. System calibration is a key step to ensure that the image acquisition and processing system can work accurately and reliably. It involves accurate measurement and calibration of the parameters of the camera to improve the accuracy of subsequent image processing and analysis. The main purpose of system calibration is to eliminate or reduce the image error caused by camera lens distortion, lighting condition change, camera position deviation and other factors. Through calibration, the corresponding relationship between image coordinates and world coordinates can be established, which provides the basis for advanced image processing tasks such as 3D reconstruction and target tracking. Common system calibration methods include calibration based on a calibration board and self-calibration. The calibration method based on the calibration plate usually uses the calibration plate with known geometric characteristics and calculates the parameters of the camera by shooting the image of the calibration plate and extracting the feature points. The self-calibration method uses the redundant information in the image sequence to estimate the camera parameters without additional calibration objects.

The typical steps of system calibration include preparing the calibration board, shooting calibration images, extracting feature points, calculating camera parameters and verifying calibration results. In the preparation stage, it is necessary to select a suitable calibration board and determine its placement position. In the shooting stage, it is necessary to ensure that the calibration plate is clearly visible in the camera's field of view. When extracting feature points, image processing algorithms such as edge detection and corner detection can be used. When calculating camera parameters, optimization algorithms such as the least square method are usually used to estimate the parameter values. Finally, the accuracy of the calibration results is verified by shooting other objects with known geometric characteristics. Let f be the focal length of the camera lens and v and u be the image distance and object distance of the lens, respectively, and we can get their relationship:

$$\frac{1}{f}=\frac{1}{u}+\frac{1}{v} \tag{1}$$

Because the focal length of a camera lens is usually much smaller than the object distance, it can be regarded as $f \approx v$ the lens imaging model can be transformed into a pinhole imaging model, as shown in Figure 1.

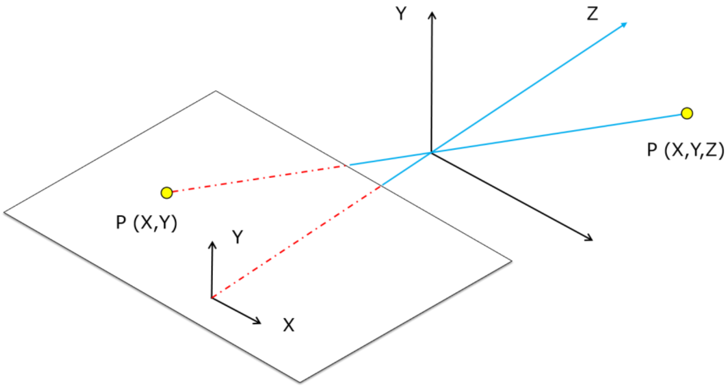

Figure 1: Principle of pinhole imaging.

In the process of converting CAD model data into virtual reality visual model data, the first task is to optimize and export CAD model data. This step is very important because it directly affects the quality and performance of the subsequent virtual reality scene. In the process of exporting, it is necessary to ensure that the geometric structure, texture, and material of CAD model data are consistent in the virtual reality platform. This includes maintaining the correct proportion, orientation and alignment. Furthermore, when exporting a CAD model, you need to make some settings as needed, such as selecting exported objects, setting export precision, and choosing whether to export materials and textures. These settings will directly affect the quality and size of the exported model. The method adopted in this article is to directly export CAD 3D model to VRML (.wrl) file in the CATIA environment. By parsing this VRML file, all the face and vertex information of the original model can be obtained, as shown in Figure 2.

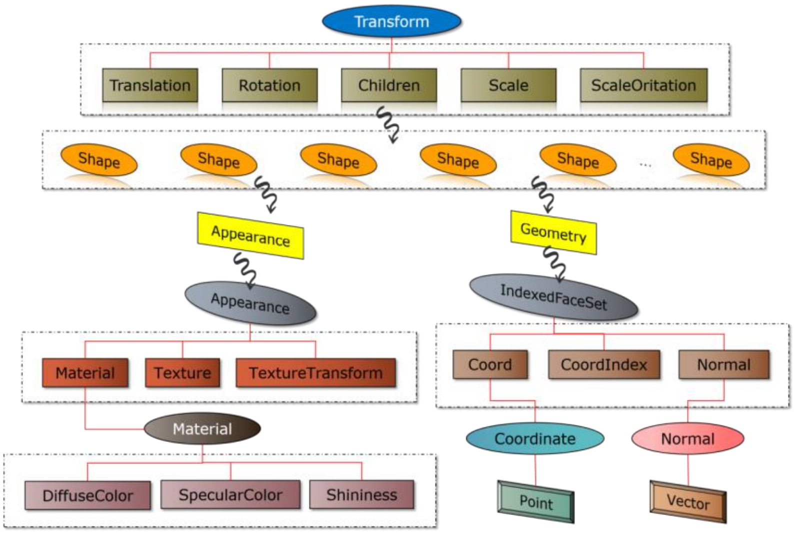

Figure 2: Nodes involved in exporting VRML files and the relationship between nodes.

In VRML, the IndexedFaceSet node is an important element in describing the geometric modelling of a surface. It describes a surface of a geometric model by collecting surfaces and can be used as the value of the geometry domain of the Shape node. The IndexedFaceSet node contains the main domains coord, normal and coordIndex.

Camera calibration is the key link of 3D reconstruction, and the accuracy of its results has a direct and far-reaching impact on the subsequent 3D reconstruction effect. Image preprocessing weakens the interference of ambient light and image noise to improve the recognizability of the image. Image preprocessing plays a crucial role in the image processing workflow. Its main objectives are to enhance image quality, emphasize features, minimize noise disturbances, and generally prepare the data for more advanced processing tasks. By improving the signal-to-noise ratio and contrast between the subject and its background, as well as smoothing out fine details, preprocessing helps mitigate issues stemming from uneven lighting, noise, camera shake, and other factors. Common preprocessing techniques include converting colour images to grayscale to simplify data and reduce computational demands, adjusting contrast, and detecting edges. The conversion to grayscale, often achieved through a weighted average of red, green, and blue colour values, is a particularly useful tool for streamlining image data:

$$Gray = 0.299 \times R + 0.587 \times G + 0.114 \times B \tag{2}$$

Enhance the contrast by stretching the histogram of the image. For example, using the linear stretching formula:

$$g\ x,y\ = a \times f\ x,y\ + b \tag{3}$$

The edge detection operator is applied to highlight the edge information in the image. For example, using the Sobel operator:

$$G_z = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{4}$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{5}$$

By calculating the convolution between the image and these operators, the edge strength in horizontal and vertical directions can be obtained. Then, the preprocessed image is saved to a file or transmitted to the next processing stage. In practical application, it is necessary to select appropriate preprocessing methods and steps according to specific image processing tasks and requirements.

4 CONSTRUCTION AND OPTIMIZATION OF DESIGN INNOVATION MODEL BASED ON CAD AND RL

4.1 Model Construction

Design innovation refers to the introduction of new ideas, methods or technologies in the design process to create unique, practical and advanced products or programs. In the CAD environment, design innovation is mainly reflected in the innovative thinking and realization of the shape, structure, function and material of the design object. Design innovation not only requires designers to have rich design experience and creativity but also to master CAD technology and be able to use various design tools and methods flexibly for innovative design. The design innovation in the CAD environment needs to consider the influence of many factors. These factors include the characteristics of the design object, the change in design requirements, the availability of design resources, the complexity of the design process and the innovative ability of designers. Specifically, the characteristics of the design object determine the difficulty and direction of innovation. The change in design requirements requires designers to constantly adapt to and meet the diverse needs of the market and users. The availability of design resources limits the possibility and implementation of innovation. The complexity of the design process requires designers to have systematic thinking and collaborative design ability. The innovative ability of designers is the key factor in realizing design innovation.

The design innovation model based on CAD is a complex system that contains many subsystems and elements. Supported by CAD technology, the model aims to design innovation and realize automation, intelligence, and innovation in the design process by integrating various design resources and innovative elements. Specifically, the model includes the following parts:

(1) Innovation demand analysis module: Responsible for collecting and analyzing the innovation demand of markets, users and technologies and providing guidance and support for innovative design. It can be expressed as a function of market and user input to innovation demand output:

$$\begin{gathered}\text{Innovation demand} = \mathrm{f}_{\text{Demand analysis}} \\ (\text{Market input, user input, technology input})\end{gathered} \tag{6}$$

(2) Innovative scheme design module: According to the analysis results of innovation demand, using CAD technology and innovative methods, multi-scheme innovative design is carried out, and several feasible, innovative schemes are generated. This can be expressed as a mapping with innovation demand as input and innovation scheme set as output:

$$\begin{gathered}\text{Collection of innovative solutions} = \mathrm{f}_{\text{Scheme design}} \\ (\text{Innovative demand, CAD technology, innovative methods})\end{gathered} \tag{7}$$

(3) Innovation scheme evaluation module: Establish evaluation index system and method, evaluate and compare multiple innovative schemes generated, and select the best innovative scheme for subsequent development and implementation. The evaluation process can be expressed as a function that accepts the set of innovative schemes as input and outputs the optimal scheme:

$$\begin{gathered}\text{Optimal innovation scheme} = \mathrm{f}_{\text{Scheme evaluation}} \\ (\text{Collection of innovative schemes, evaluation index})\end{gathered} \tag{8}$$

(4) Innovation process management module: Responsible for managing and monitoring the whole innovation design process to ensure the smooth progress and high-quality completion of innovation design.

The design innovation model based on CAD is effective and applicable in theory. Supported by CAD technology, the model can make full use of the powerful functions of CAD to carry out efficient and accurate innovative design. The model considers the influence of many innovative elements and can comprehensively and systematically support the realization of innovative design. Furthermore, the model has certain flexibility and expansibility and can be customized and expanded according to different design requirements and innovation goals.

4.2 Design Optimization Strategy Based on Rl

The design optimization problem refers to the problem that the design goal is optimized by adjusting the design parameters or changing the design scheme under certain constraints. In a CAD environment, design optimization usually involves the optimization of multiple design parameters and the balance of multiple design goals. There are often complex nonlinear relations and multiobjective conflicts between these design parameters and objectives, which makes the design optimization problem complicated. Aiming at the design optimization problem, it is necessary to choose the appropriate RL algorithm to solve it. When selecting an algorithm, several factors must be taken into account, including the specific nature of the design challenge, the speed of convergence, stability, and the computational demands of the algorithm. Additionally, to enhance both the efficiency and precision of the algorithm, further refinement and optimization are essential. The key to achieving optimal design lies in the strategic integration of RL and design optimization techniques. This requires a tailored approach that carefully considers both the unique aspects of the design problem and the distinct features of the RL algorithm.

In this article, the RL algorithm and ant colony optimization algorithm are combined to form a hybrid optimization strategy. At each time step, the RL algorithm is used to select the action A, and the new state S and reward $R\ s,a$ are observed. For Q-learning, the update rule of the value function $Q\ s,a$ is:

$$Q\ s,a\ \leftarrow\ 1-a\ \cdot Q\ s,a\ +a\cdot\left(R\ s,a\ +\gamma\cdot,\max_{a'\in A}Q\ s',a'\right) \tag{9}$$

Where s' is the state reached after the state s performs the action a. The updating rules of pheromones can be defined as:

$$\tau_{ij}\ t+1\ =\ 1-\rho\ \cdot\tau_{ij}\ t\ +\sum_{k=1}^{m}\Delta\tau_{ij}^{k}\ t \tag{10}$$

Where $\tau_{ij}^{k}\ t$ is the pheromone contribution of the k ant to the path i,j at time t. Combining RL and ant colony optimization algorithm, action selection can be based on the combination of Q value and pheromone:

$$a=\arg\max_{a'\in A}\ Q\ s,a'\ +\beta\cdot\tau\ s,a' \tag{11}$$

Or, more generally, using a weight product:

$$a=\arg\max_{a'\in A}\left(Q\ s,a'\ \cdot\tau\ s,a'^{\ \beta}\right) \tag{12}$$

Where β is a parameter to adjust the influence weight of the pheromone? $\tau\ s,a'$ Needs to be defined according to specific problem states and actions.

According to the observed reward and new state, the value function or strategy of the RL algorithm is updated. Furthermore, the pheromone mechanism of the ant colony optimization algorithm is used to influence the action selection, which tends to choose the state-action pair with a higher pheromone level. Update the pheromone level to reflect the success or failure experience gained through RL.

When implementing the application strategy of RL in design optimization, we need to follow certain steps and precautions. Specifically, it includes the following steps: (1) Defining the objectives and constraints of the design optimization problem; (2) Select the appropriate RL algorithm and improve and optimize it; (3) Establish the mathematical model and simulation environment of the design problem; (4) Implementing RL algorithm for strategy learning and optimization; (5) Evaluate and verify the optimization results; (6) Adjust and improve the strategy according to the evaluation results.

5 SIMULATION EXPERIMENT AND RESULT ANALYSIS

Simulation experiments play an important role in scientific research and technology development, and their purpose is to simulate the behaviour of real environments or systems in order to test, verify and optimize theoretical models, algorithms or designs. This section outlines the primary objective of the simulation experiment: to assess the efficacy of the aforementioned design innovation model and to determine the practical implications of implementing RL strategies in design optimization. To ensure robust and reliable findings, the experiment must adhere to principles of reliability, reproducibility, and scalability. Furthermore, the experimental setup should incorporate the principles of control and single-variable manipulation to measure the impact of both the design innovation strategy and the RL algorithm on the experimental outcomes precisely.

During the experiment, a total of 30 images were captured using two cameras positioned on the left and right sides. These images, taken from various angles of the calibration board, facilitated the identification of approximately 2000 corners within the coordinate systems of both cameras. Figures 3 and 4 illustrate the re-projection errors for the left and right cameras, respectively.

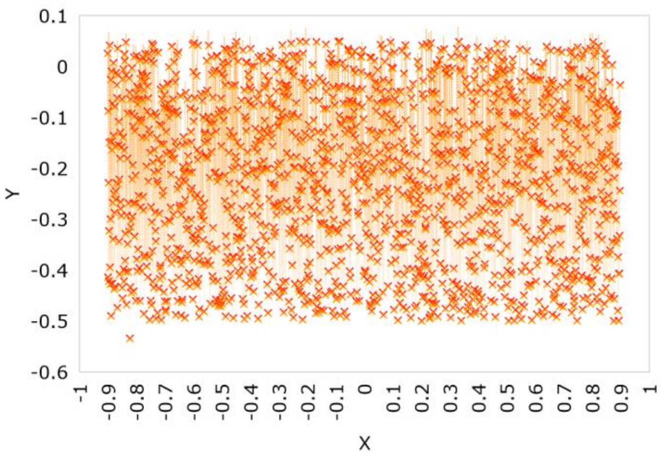

Figure 3: Re-projection error of left camera.

The data in the observation diagram shows that the errors of these corners are mostly concentrated around 0, and the maximum errors in the horizontal and vertical axes are not more than 1 pixel. This result is shown in Figure 3. Therefore, it can be concluded that the result of this calibration is quite accurate and fully qualified for the subsequent 3D reconstruction process.

For example, Table 1 shows the internal parameters of all cameras, and Table 2 shows the external parameters of the left and right cameras.

After processing and analysis, this section shows the experimental results intuitively and clearly. The contents of the exhibition include key indicators and comparison results. This article focuses on the key index of image quality -PSNR (Peak signal-to-noise ratio), which is an objective standard to evaluate image quality and is usually used to measure the quality loss after image compression, reconstruction or transmission. In the experiment, PSNR is shown in Figure 5.

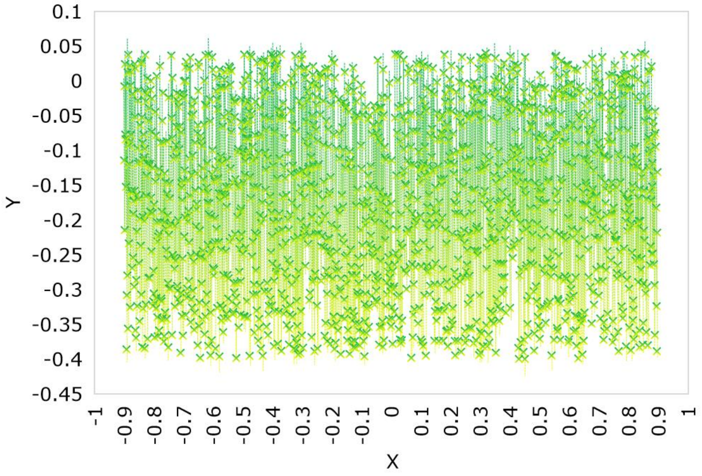

Figure 4: Re-projection error of the right camera.

	Internal parameter matrix	*Distortion parameter*
Left camera	$\begin{bmatrix} 1112.3 & 0 & 483.6 \\ 0 & 1208.8 & 322.4 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} -0.11875 & -0.27249 & -0.00039 \\ & 0.00045 & 0.00000 \end{bmatrix}$
Right camera	$\begin{bmatrix} 1207.8 & 0 & 410.3 \\ 0 & 1203.1 & 397.2 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} -0.17005 & -0.06311 & -0.00281 \\ & 0.00006 & 0.00000 \end{bmatrix}$
Auxiliary camera	$\begin{bmatrix} 1107.9 & 0 & 443.8 \\ 0 & 1204.5 & 359.7 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} -0.14558 & -0.15321 & -0.00386 \\ & 0.00031 & 0.00000 \end{bmatrix}$

Table 1: Internal parameters of all cameras.

	Spin matrix	*Translation vector*
The right camera relative to the left camera	$\begin{bmatrix} 0.9997 & -0.0141 & 0.0301 \\ -0.0149 & 0.9995 & -0.0354 \\ -0.0298 & 0.0361 & 0.09978 \end{bmatrix}$	$\begin{bmatrix} -129.0546 \\ -3.6705 \\ -2.3502 \end{bmatrix}$

Table 2: External parameters of left and right cameras.

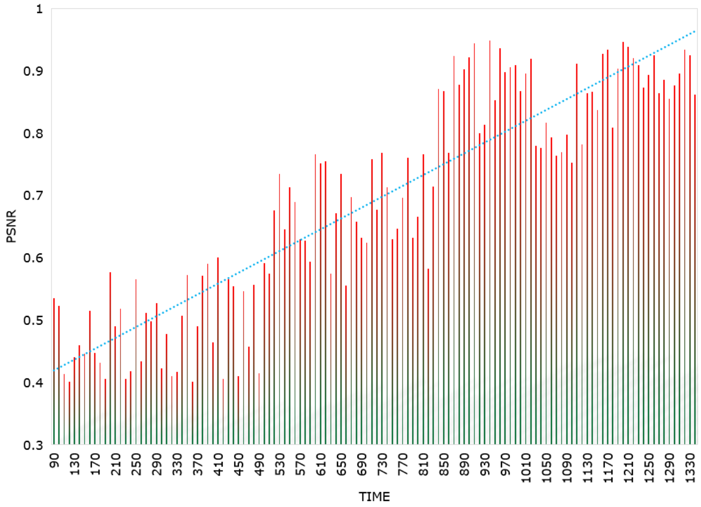

Figure 5: PSNR.

By comparing the PSNR values of different design methods, it can be clearly seen that the method of combining the CAD-based design innovation model with the RL algorithm has significant advantages in image quality. A higher PSNR value means that the reconstructed or processed image is closer to the original image with lower distortion. This result shows that the proposed method is excellent in preserving image details and structural information and can meet the requirements of high-standard image processing. Figure 6 shows the design efficiency and quality of different design methods.

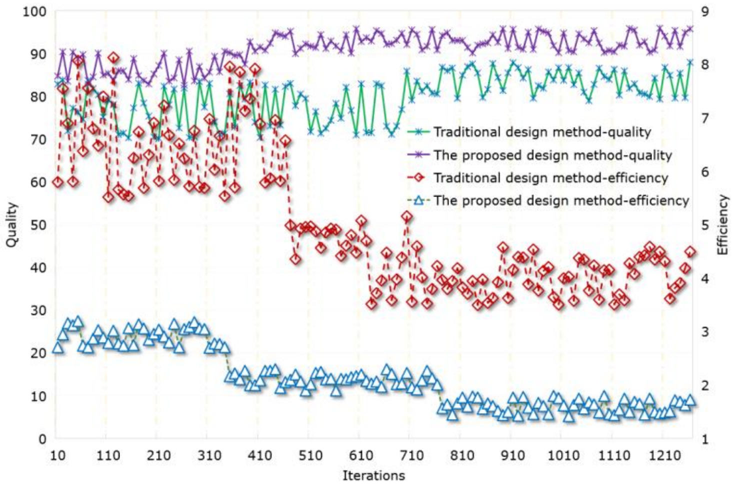

Figure 6: Design efficiency and quality of different design methods.

Compared with the traditional design method, the design method based on CAD and RL has significantly improved the design efficiency. This is mainly due to the efficient performance of intelligent algorithms in the process of automatic design and the reduction of dependence on manual intervention and trial and error. Furthermore, this method also performs well in terms of design quality and can generate more innovative and practical design schemes.

In order to comprehensively evaluate the innovation of different design methods, this section also compares the innovation scores. The innovation scores of different design methods are shown in Figure 7.

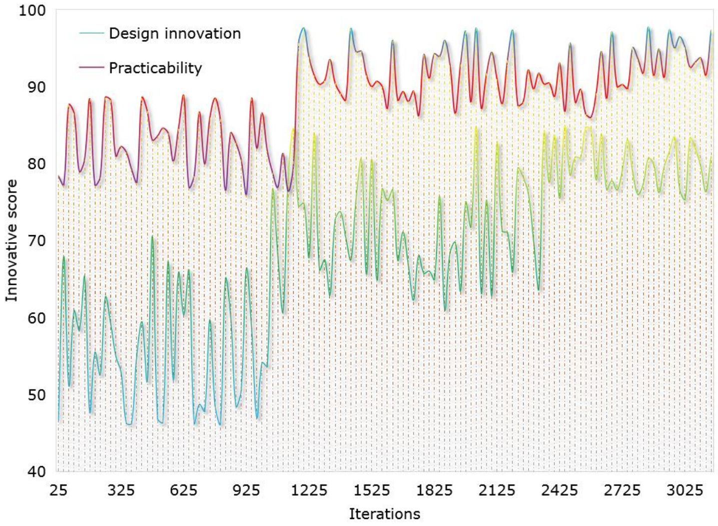

Figure 7: Innovation score of different design methods.

The figure unambiguously demonstrates that the design approach integrating CAD and RL significantly surpasses traditional methods in terms of innovation. This superiority primarily stems from the model's adaptability in incorporating innovative concepts and design parameters, coupled with the RL algorithm's proficiency in navigating the design space and refining innovative strategies.

The experimental findings presented in this section underscore the notable enhancement in design efficiency and quality achieved by the CAD-RL design innovation model when contrasted with traditional design methodologies. Specifically, the proposed methodology exhibits remarkable performance in both innovation and performance indices, boasting an impressive innovation score of 9.87. This score unequivocally validates the method's preeminence in image processing and design. The experimental outcomes unequivocally establish the excellence of the CAD-RL design innovation model in terms of image quality, design efficiency, overall quality, and innovation. This groundbreaking approach offers fresh theoretical underpinnings and practical direction for the realm of image processing and design, paving the way for potential advancements in related fields.

6 CONCLUSIONS

This article introduces the notion of design innovation, delves into the components of design innovation within a CAD setting, and successfully establishes a design innovation model. Additionally, it addresses the design optimization challenge by discussing the selection and enhancement of the RL algorithm, proposing an effective combination strategy. The efficacy and applicability of the presented approach are substantiated through the design and execution of simulation experiments.

Key accomplishments encompass successfully constructing a CAD-based design innovation model, offering fresh perspectives and techniques for design innovation. The RL algorithm's integration into design optimization enhances both the effectiveness and efficiency of the optimization process. Simulation experiments validate the proposed method's validity and applicability, bolstering research and practical endeavours in related domains. These achievements significantly contribute to advancing design innovation and optimization practices.

The CAD-based design innovation model empowers designers with novel ideas and methodologies, aiding them in tackling intricate and dynamic design challenges. The RL application strategy in design optimization provides valuable direction for selecting and refining optimization algorithms, thereby elevating the impact and efficiency of design optimization. Furthermore, the study's methodologies and insights offer valuable references and inspiration for research and practices in other fields.

As science and technology continually evolve, design innovation and optimization encounter new challenges and opportunities. Future research directions could focus on several trends: Firstly, the swift progression of intelligent design technology presents ample opportunities for design innovation. Secondly, the integrated utilization of big data and artificial intelligence techniques can provide robust support for design optimization. Lastly, interdisciplinary research emerges as a pivotal force in propelling the advancement of design innovation and optimization practices.

Bo Wang, https://orcid.org/0009-0008-2604-119X
Yishuai Lin, https://orcid.org/0009-0004-8523-3678

REFERENCES

[1] Ajani, T.-S.; Imoize, A.-L.; Atayero, A.-A.: An overview of machine learning within embedded and mobile devices–optimizations and applications, Sensors, 21(13), 2021, 4412. https://doi.org/10.3390/s21134412

[2] Budak, A.-F.; Gandara, M.; Shi, W.; Pan, D.-Z.; Sun, N.; Liu, B.: An efficient analog circuit sizing method based on machine learning assisted global optimization, IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 41(5), 2021, 1209-1221. https://doi.org/10.1109/TCAD.2021.3081405

[3] Dabbagh, S.-R.; Ozcan, O.; Tasoglu, S.: Machine learning-enabled optimization of extrusion-based 3D printing, Methods, 206(1), 2022, 27-40. https://doi.org/10.1016/j.ymeth.2022.08.002

[4] Felbrich, B.; Schork, T.; Menges, A.: Autonomous robotic additive manufacturing through distributed model-free deep reinforcement learning in computational design environments, Construction Robotics, 6(1), 2022, 15-37. https://doi.org/10.1007/s41693-022-00069-0

[5] Iranfar, A.; Zapater, M.; Atienza, D.: Multiagent reinforcement learning for hyperparameter optimization of convolutional neural networks, IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 41(4), 2021, 1034-1047. https://doi.org/10.1109/TCAD.2021.3077193

[6] Kadam, V.; Kumar, S.; Bongale, A.; Wazarkar, S.; Kamat, P.; Patil, S.: Enhancing surface fault detection using machine learning for 3D printed products, Applied System Innovation, 4(2), 2021, 34. https://doi.org/10.3390/asi4020034

[7] Konstantopoulos, G.; Koumoulos, E.-P.; Charitidis, C.-A.: Digital innovation enabled nanomaterial manufacturing; machine learning strategies and green perspectives, Nanomaterials, 12(15), 2022, 2646. https://doi.org/10.3390/nano12152646

[8] Liu, J.; Ye, J.; Silva, I.-D.; Vinel, A.; Shamsaei, N.; Shao, S.: A review of machine learning techniques for process and performance optimization in laser beam powder bed fusion additive manufacturing, Journal of Intelligent Manufacturing, 34(8), 2023, 3249-3275. https://doi.org/10.1007/s10845-022-02012-0

[9] Ranjan, N.; Kumar, R.; Kumar, R.; Kaur, R.; Singh, S.: Investigation of fused filament fabrication-based manufacturing of ABS-Al composite structures: prediction by machine learning and optimization, Journal of Materials Engineering and Performance, 32(10), 2023, 4555-4574. https://doi.org/10.1007/s11665-022-07431-x

[10] Singh, J.; Perera, V.; Magana, A.-J.; Newell, B.; Wei, K.-J.; Seah, Y.-Y.; Xie, C.: Using machine learning to predict engineering technology students' success with computer-aided design, Computer Applications in Engineering Education, 30(3), 2022, 852-862. https://doi.org/10.1002/cae.22489

[11] Tamir, T.-S.; Xiong, G.; Fang, Q.; Yang, Y.; Shen, Z.; Zhou, M.; Jiang, J.: Machine-learning-based monitoring and optimization of processing parameters in 3D printing, International Journal of Computer Integrated Manufacturing, 36(9), 2023, 1362-1378. https://doi.org/10.1080/0951192X.2022.2145019
[12] Uguz, S.; Ipek, O.: Prediction of the parameters affecting the performance of compact heat exchangers with an innovative design using machine learning techniques, Journal of Intelligent Manufacturing, 33(5), 2022, 1393-1417. https://doi.org/10.1007/s10845-020-01729-0
[13] Wu, N.; Xie, Y.; Hao, C.: IronMan-Pro: Multiobjective Design Space Exploration in HLS via reinforcement learning and graph neural network-based modeling, IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 42(3), 2022, 900-913. https://doi.org/10.1109/TCAD.2022.3185540
[14] Wu, Q.; Cao, Y.; Wang, H.; Hong, W.: Machine-learning-assisted optimization and its application to antenna designs: Opportunities and challenges, China Communications, 17(4), 2020, 152-164. https://doi.org/10.23919/JCC.2020.04.014
[15] Zimmerling, C.; Poppe, C.; Stein, O.; Kärger, L.: Optimization of manufacturing process parameters for variable component geometries using reinforcement learning, Materials & Design, 214(1), 2022, 110423. https://doi.org/10.1016/j.matdes.2022.110423