Automation of Design Innovation Process Based on CAD Technology and Reinforcement Learning

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Abstract. Design innovation is the core power that promotes the sustainable development of modern industry, architecture, science, technology, and many other fields. Computer-aided design (CAD) technology has developed from initial 2D drawings to powerful tools such as 2D modelling and simulation analysis, which provide designers with convenient design means. This article will discuss how to combine reinforcement learning (RL) algorithms with CAD technology to realize automatic image enhancement and Optimization. The experiment uses a large number of product modelling data to train the model and analyzes the convergence of the algorithm in the iterative process in detail. The results show that the new method has a high error in the initial iteration, but after about 20 iterations, the error gradually decreases and tends to be stable. In addition, through comparative experiments, it is found that this method has achieved a higher score in design performance, and its comprehensive performance is better than the traditional method. It is worth mentioning that this method has also achieved a significant improvement in user satisfaction, thanks to its Optimization in user experience, accuracy and reliability, and personalized and customized services. These advantages together reflect the practical application value and potential of the new method in the design field and provide strong support for future research and application.

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1 INTRODUCTION

Design innovation plays a pivotal role in propelling the sustainable advancement of various sectors, such as modern industry, architecture, and science and technology. Amidst the swift evolution of science and technology, CAD technology has emerged as an essential design tool, significantly enhancing both the efficiency and precision of the design process. As a key step in additive manufacturing, the design of grid filling mode directly affects the efficiency of material use and the performance of the final product. In recent years, machine learning technology has shown great potential in optimizing grid-filling patterns. Alejandrino et al. [1] explored how to use machine learning methods to improve material efficiency in additive manufacturing processes through grid-filling patterns. Additive manufacturing is a technology that uses layer by layer stacking of materials to create three-dimensional solids, widely used in aviation, automotive, medical and other fields. In additive manufacturing, the grid-filling mode determines how materials are distributed in three-dimensional space. The traditional grid-filling mode is often based on fixed algorithms and is difficult to adapt to changes in different materials and manufacturing requirements. Machine learning technology can provide new ideas and methods for optimizing grid-filling patterns by learning patterns and patterns from a large amount of data. CAD technology has developed from 2D drawing to 2D modelling, simulation analysis and other powerful tools, providing designers with convenient design means. However, CAD technology still needs designers to have rich professional knowledge and creativity in order to reach its greatest potential. In order to improve the positioning accuracy and operational efficiency of industrial robots, vision-based directional guidance technology has become a hot research topic. Ben and Cengz [2] discussed the method and technology research of implementing industrial robot visual directional guidance using CAD models under binocular vision. Binocular vision technology can obtain three-dimensional spatial information of objects by simulating the principle of stereo vision of the human eye, providing the possibility for directional guidance of industrial robots. As an accurate digital representation of objects, CAD models provide a benchmark for robot visual recognition. By combining binocular vision technology and CAD models, high-precision visual directional guidance for industrial robots can be achieved. Binocular vision technology captures two-dimensional images of objects from different angles using two cameras. By calculating the relative position relationship between two cameras and the matching points between images, the three-dimensional spatial information of objects, including their position, posture, and size, can be restored. As an accurate digital representation of an object, CAD models contain information such as the geometric shape, size, and position of the object. In visual directional guidance, CAD models can serve as benchmarks to match the actual object images obtained by the binocular vision system, thereby determining the precise position and posture of the object.

In addition, when dealing with complex design problems, CAD technology often needs to spend a lot of time and computing resources, which limits the efficiency of design innovation. Traditional automation systems often lack sufficient adaptability and flexibility to cope with uncertainty and changes in the production process. In order to solve this problem, researchers have begun to attempt to introduce reinforcement learning technology into the field of industrial automation. Through interactive learning between intelligent agents and the environment, automation systems can make optimal decisions based on real-time production data and environmental information. Chen et al. [3] explored how to utilize task modularity in reinforcement learning to achieve adaptive Industry 4.0 automation. Task modularization is a method of decomposing complex tasks into multiple simple subtasks, each of which can be independently learned and optimized. By combining reinforcement learning with task modularization, we can decompose complex industrial production processes into multiple simple sub-tasks, and then use reinforcement learning algorithms to independently optimize each sub-task. In this way, the entire production system can flexibly adjust the execution strategies of each sub-task according to actual needs and environmental changes, thereby achieving stronger adaptability and flexibility.

Against this background, how to combine advanced artificial intelligence technology, especially RL, to promote the automation of the design innovation process has become the focus of current research. Croce et al. [4] explored how to utilize reinforcement learning techniques to achieve semiautomatic transformation from semantic point clouds to BIM models. The traditional method of converting point clouds to BIM often relies on manual operations, which is inefficient and prone to errors. Reinforcement learning technology can complete this task automatically or semi-automatically through interactive learning between intelligent agents and the environment. By defining appropriate states, actions, and reward functions, reinforcement learning algorithms can learn the optimal transition strategy from semantic point clouds to BIM models. In the process of converting point clouds to BIM, reinforcement learning algorithms can be seen as agents that continuously optimize their conversion strategies through interactive learning with the environment (i.e. semantic point clouds). Design an appropriate reward function based on factors such as the accuracy and completeness of the BIM model to guide agents in learning the optimal transformation strategy. Train reinforcement learning models using historical data to learn the optimal transformation strategy from semantic point clouds to BIM models. As an important branch of machine learning, RL's unique trial-and-error learning mechanism enables agents to continuously optimize decision-making strategies in the interaction with the environment, thus realizing the automation of complex tasks. As an important component of injection moulding products, their quality and production efficiency are crucial to the competitiveness of enterprises. In recent years, the application of reinforcement learning technology in predicting the quality of injection moulded products has gradually received attention. It can not only improve product quality but also help promote the development of a sustainable manufacturing industry. Jung et al. [5] explored the application of reinforcement learning technology in the quality prediction of injection moulded products and its impact on sustainable manufacturing. The traditional quality control methods for injection moulded products often rely on manual inspection and post-processing, which have not only low efficiency but also make it difficult to ensure the stability of product quality. Reinforcement learning technology simulates the production process of injection moulded products by constructing models and training models using historical data to predict product quality. Specifically, reinforcement learning algorithms continuously adjust model parameters through interaction with the environment (injection moulding machines, raw materials, etc.) to optimize the accuracy of product quality prediction. This method can obtain a large amount of data in a short period of time and automatically adjust production parameters, thereby improving product quality and production efficiency. In image processing, RL-based image enhancement algorithms can adaptively adjust image parameters and improve image quality, which provides new ideas and methods for design innovation.

Traditional methods for identifying graphic defects mainly rely on manual visual inspection, but due to the complexity of wafer diagrams and the diversity of defects, manual visual inspection is not only inefficient but also prone to missed or false detections. Kim and Behdinan [6] use machine learning techniques to train models to learn the features and patterns of defects from a large amount of data, thereby achieving automatic defect recognition and classification. Using machine learning algorithms to extract effective features from wafer images, such as texture, shape, size, etc., for subsequent defect classification. Based on the extracted features, design appropriate classifiers, such as Support Vector Machine (SVM), Random Forest, etc., to automatically classify defects. Deep learning, as a branch of machine learning, can automatically learn hierarchical feature representations of data by constructing deep neural networks, thereby achieving better performance. The training and inference of deep learning models require a large amount of computing resources, such as high-performance computers and GPUs. How to achieve efficient training and inference under limited computing resources is also a challenge. RL (Reinforcement Learning) acquires the best decision-making approach through dynamic interactions between an agent and its environment, showcasing self-learning and adaptive adjustment abilities. In image processing, RL has proven effective in tasks like image classification, object detection, and image generation. The traditional industrial product design process often relies on the experience and intuition of designers, with a long design cycle and high optimization difficulty. In recent years, with the development of artificial intelligence and machine learning technology, reinforcement learning algorithms have achieved significant results in the fields of decision-making and control. Combining 3D CAD technology, Liu [7] has developed a fast design method based on reinforcement learning to achieve automation and intelligence in the design process. It uses 3D CAD software to establish a digital model of the product. These models not only contain the geometric shape of the product but also information such as materials and assembly relationships. On the basis of 3D CAD models, we introduce reinforcement learning algorithms to guide the design process. Reinforcement learning algorithms learn the optimal design strategy through trial and error, gradually approaching the ideal state of the design results. By continuously iterating and optimizing design strategies, achieve rapid product design. The optimization process can include multiple aspects, such as shape optimization, material selection, assembly sequence, etc.

Notably, RL-based image enhancement techniques can tailor enhancement strategies to image specifics, elevating visual appeal and quality. Digital twin technology, as a bridge connecting the physical world and the digital world, is gradually becoming an important tool in the field of industrial manufacturing. Digital twin technology can simulate and predict various behaviours in the production process without interfering with actual production by creating virtual replicas of the actual production environment. By combining reinforcement learning algorithms, digital twin technology can further optimize production control and improve production efficiency and product quality. Park et al. [8] explored the application of digital twins with horizontal coordination ability and how to use reinforcement learning to achieve intelligent control of workshop production. By using reinforcement learning algorithms, the control strategy of the device can be optimized, and the operational efficiency and stability of the device can be improved. For example, using deep learning algorithms to train the historical operational data of devices and learn the optimal control parameters and strategies. This article delves into the uses and constraints of CAD technology in design innovation and explores the strengths of RL in image processing. It proposes a novel integration of CAD and RL to automate the design innovation workflow. This approach aims to overcome CAD's traditional limitations and foster fresh design concepts, enhancing both efficiency and quality. We examine how RL algorithms can be paired with CAD technology to automatically refine and enhance images during the design process. Specifically, we investigate utilizing RL to adjust CAD model image parameters (e.g., brightness, contrast, colour) for more visually stunning designs. Additionally, we discuss optimizing CAD model structure and layout using RL for more rational and innovative designs.

This study focuses on the integration of CAD and RL to advance the automation and intelligence of the design innovation process. This integration promises to boost design efficiency, elevate quality, foster creativity, and breathe new life into fields like modern industry, architecture, and science and technology. Our contributions include:

(a) Introducing a CAD-RL integration method that pushes beyond traditional CAD limitations and offers fresh perspectives for design innovation.

(b) Automating the design innovation process through CAD-RL integration, minimizing manual intervention, and fostering design creativity.

(c) Utilizing RL algorithms for image enhancement and Optimization during the design process, adapting strategies to image specifics and meeting design quality demands.

(d) Addressing traditional CAD limitations in adaptability and complex design handling through our proposed CAD-RL fusion method, offering stronger support for design innovation.

In conclusion, this article outlines the uses and constraints of CAD in design innovation and RL's strengths in image processing. It presents a novel CAD-RL integration approach to automate design innovation, detailing image enhancement and optimization techniques. Finally, it summarizes the proposed method and offers future directions for this exciting field of study.

2 RELATED WORK

Digital twin technology achieves comprehensive monitoring and prediction of physical entities by constructing virtual models of physical entities. Reinforcement learning algorithms continuously optimize decision-making strategies to adapt to complex and ever-changing environments through interactive learning between intelligent agents and the environment. Combining digital twin technology with reinforcement learning algorithms can provide strong support for the flexible production control of micro-intelligent factories. Park et al. [9] analyzed the development of digital twin technology and reinforcement learning algorithms, providing new solutions for flexible production control in microintelligent factories. Reinforcement learning algorithms continuously optimize production control strategies through interactive learning between intelligent agents and the environment. In a micro intelligent factory, production control tasks can be viewed as a Markov decision process (MDP), where the intelligent agent is the production control system and the environment is the micro intelligent factory and its operating environment. By setting appropriate reward functions, reinforcement learning algorithms can learn the optimal production control strategy, enabling factories to maintain efficient and stable production in the face of uncertain factors such as market demand changes and equipment failures.

As one of the core tools of CAPD, 3D factory simulation software is increasingly widely used in industrial workplaces and process design. Pellicia et al. [10] explored the applicability of 3D factory simulation software in industrial workplaces and process CAPD. Using 3D factory simulation software, designers can simulate and optimize the factory layout in a virtual environment. This includes considerations such as equipment placement, material flow, and personnel access to ensure the operational efficiency and safety of the factory. 3D factory simulation software can provide detailed simulation of the process flow, including the operating status of equipment, material processing, and so on. This helps to identify problems and bottlenecks in the process flow, providing designers with a basis for improvement and Optimization. CAPD emphasizes multi-party participation and collaboration. 3D factory simulation software can provide a common virtual platform for all parties to communicate and exchange ideas. Through real-time updates and displays of simulation software, all parties can intuitively understand the latest progress and existing problems in the design and make timely adjustments and improvements. With the rapid development of artificial intelligence technology, the automation and intelligence of analog circuit design have become a research hotspot. The combination of CAD (computer-aided design) technology and reinforcement learning algorithms provides a new solution for the automation design of analog circuits. Settaluri et al. [11] explored how to use CAD reinforcement learning to achieve automated design of analog circuits and introduced its advantages and application prospects. The traditional analog circuit design process relies on the designer's professional knowledge and experience, with a long design cycle and a tendency to make mistakes. With the development of artificial intelligence technology, especially the successful application of reinforcement learning algorithms in decision-making and control fields, the automation and intelligence of analog circuit design have become possible. CAD technology, as an important tool for circuit design, combined with reinforcement learning algorithms, can achieve automated design of analog circuits and improve design efficiency and quality. CAD reinforcement learning methods can automatically complete the design process of analog circuits, reduce manual intervention, and improve design efficiency. By optimizing reinforcement learning algorithms, better circuit performance can be achieved, such as higher speed and lower power consumption.

The process parameters during 3D printing have a significant impact on product quality, production efficiency, and cost. Therefore, how to effectively monitor and optimize 3D printing process parameters has become a research hotspot. In recent years, the application of reinforcement learning technology in process parameter optimization has gradually received attention. Tamir et al. [12] explored a method for monitoring and optimizing process parameters of 3D printing products based on reinforcement learning. Reinforcement learning is a method of optimizing decision-making strategies through interactive learning between agents and the environment. In the Optimization of 3D printing process parameters, the printing process can be viewed as a Markov decision process (MDP), where the intelligent agent is the printing control system and the environment is the 3D printer and its working environment. By defining appropriate states, actions, and reward functions, reinforcement learning algorithms can learn the optimal combination of process parameters to achieve a balance between print quality and production efficiency. With the advent of Industry 4.0, the application of industrial robots on production lines is becoming increasingly widespread. To ensure the efficient, accurate, and safe operation of industrial robots, trajectory planning has become a key research field. CAD technology, as an important support for modern manufacturing, provides strong technical support for the trajectory planning of industrial robots. Wang and Arora [13] discussed the research status and development trends of continuous trajectory planning for industrial robots based on CAD technology. Industrial robot trajectory planning refers to planning the motion trajectory of the robot from the starting point to the target point according to task requirements. Continuous trajectory planning requires the robot to maintain continuity and smoothness of its trajectory throughout the entire motion process, avoiding sudden changes and shaking, thereby improving the robot's motion accuracy and stability. As a computer-aided design technology, CAD technology can provide accurate models, efficient data processing, and visual simulation environments for the trajectory planning of industrial robots.

Green design has become an important trend in product packaging design. The combination of CAD technology and reinforcement learning algorithms provides new possibilities for green design. Yu and Sinigh [14] discussed the application and advantages of CAD reinforcement learning based on green concepts in product packaging design. Traditional product packaging design often focuses on appearance and function while neglecting environmental impact. With the increasingly prominent environmental issues, green design has gradually become an important consideration factor in packaging design. CAD technology, as an important tool in modern design, combined with reinforcement learning algorithms, can provide more efficient and green solutions for product packaging design. By using reinforcement learning algorithms, we continuously optimize the design scheme to achieve the best green evaluation while meeting functional requirements. With the continuous progress of technology, the field of product design is undergoing a revolutionary change. Modular product design and computer intelligence design have become the core forces of this transformation, changing the way we design, manufacture, and use products. Zhao et al. [15] explored the strategies and methods of modular product design and computer-intelligent design, as well as how they jointly promote the future development of product design. Modular product design is a design method that breaks down a product into a series of independent and interchangeable modules. This design strategy helps to improve the flexibility, maintainability, and scalability of the product. Develop unified module standards and interface specifications to ensure compatibility and interchangeability between modules. This helps to reduce production costs and improve product maintainability and scalability. Design independent modules with clear functions and interfaces for replacement or upgrading when needed. This helps to improve the flexibility and maintainability of the product. Utilize big data and machine learning techniques to analyze user needs and product usage data to guide product design. This helps to design products that better meet user needs.

3 THE ADVANTAGES AND PRACTICES OF RL IN IMAGE PROCESSING

CAD technology allows designers to perform precise 2D and 3D modelling in computer environments. This ability greatly improves the accuracy and reliability of design, reducing the need for physical prototyping. Using CAD software, designers are able to effortlessly create intricate models, virtually assemble them, and conduct tests. Furthermore, CAD technology offers a range of simulation capabilities, including structural analysis and fluid dynamics simulation, enabling designers to foresee product performance during the initial design phases and consequently enhance design outcomes. CAD technology makes design optimization more efficient. Designers can quickly iterate and optimize design solutions through methods such as parametric modelling and variable design. In addition, CAD software also provides various automation tools, such as feature recognition, intelligent dimension annotation, etc. These tools can greatly reduce the time designers spend on tedious tasks, allowing them to focus more on innovative design. The combination of CAD technology and computer-aided manufacturing (CAM) technology has achieved a close integration of design and manufacturing. Designers can directly convert CAD models into G codes for CNC machining, thereby shortening the time from design to manufacturing of products.

Although CAD technology has brought many conveniences to design innovation, it also has certain technical barriers and learning costs. Mastering CAD software requires a certain amount of professional knowledge and practical experience, which may be a challenge for beginners. Although CAD technology provides powerful modelling and simulation capabilities, it also limits designers' creativity to a certain extent. Due to the fact that CAD software is usually based on parameterized and rule-based design ideas, designers may be limited by the software itself when pursuing innovative design. In large-scale design projects, data management and version control of CAD files may become a challenge. As multiple designers may be involved in a project at the same time, ensuring the consistency and freshness of CAD files has become an important issue. Although many CAD software supports standard data exchange formats (such as STEP, IGES, etc.), data loss or format conversion errors may still be encountered in practical operations. This may affect the collaboration efficiency of designers between different software platforms.

(1) the advantages of RL in image processing.

RL algorithm can adaptively adjust the processing strategy according to the actual situation of the image without setting fixed rules or parameters in advance. This adaptability gives RL great advantages in dealing with complex and changeable image problems. RL learns the optimal decision-making strategy through the interaction between agent and environment, which makes it have strong decision-making ability. In image processing, this decision-making ability can help the algorithm choose the optimal processing steps and operations so as to achieve better processing results. In addition, RL also considers long-term planning, which can take into account the future influence in the process of processing, thus avoiding falling into the local optimal solution. RL algorithm is robust to noise and interference and can resist the influence of these factors to some extent. This makes RL achieve better results when processing poor-quality images. At the same time, RL also has strong generalization ability, which can transfer the knowledge learned in one task to other related tasks.

(2) Practice of RL in image processing.

By instructing the agent to seek out and recognize the desired object within an image, the RL algorithm can precisely pinpoint its location and classify it within intricate settings. This approach not only enhances detection precision but also minimizes incorrect and overlooked detections. Additionally, by instructing the agent on how to modify parameters like brightness, contrast, and colour, the RL algorithm can flexibly tailor enhancement strategies to the specific conditions of the image, thereby elevating its visual appeal. This method is especially effective when dealing with low-quality images, which can significantly improve the clarity and recognition of images. In the aspect of image editing, RL can help users achieve finer and more natural editing effects, such as intelligent matting and automatic retouching. RL also has a broad application prospect in the field of video processing and understanding. For example, in the video surveillance scene, the RL algorithm can be used to realize functions such as automatic tracking and anomaly detection. In the aspect of video summary generation, we can learn how to select keyframes and clips by training agents to generate concise video summaries. In addition, in the video recommendation system, the RL algorithm can also be used to recommend appropriate video content according to the user's viewing history and preferences.

4 A NEW METHOD OF INTEGRATING CAD TECHNOLOGY WITH RL

As science and technology continue to evolve, the need for automation and intelligence in design innovation becomes increasingly significant. While traditional CAD technology remains a crucial aspect of the design landscape, its limitations become apparent when tackling intricate design challenges and the need for adaptive adjustments. RL, as an emerging machine learning technology, boasts strengths in autonomous learning and adaptive adjustment, exhibiting remarkable promise in image processing and beyond. Consequently, this article introduces an innovative approach that integrates CAD technology with RL, aiming to achieve automation and intelligence in the design innovation process.

(1) Fusion methods overview

The fusion methodology outlined in this article centers on merging CAD technology's precise modelling capabilities with RL's adaptive decision-making prowess. More specifically, CAD technology constructs an accurate model of the design challenge while the RL algorithm navigates the model space in search of the optimal design solution. This approach not only surpasses the limitations of traditional CAD methods when tackling intricate design challenges but also fosters fresh design concepts, ultimately enhancing both design efficiency and quality.

(2) Implementation steps of fusion method

Build a CAD model: First, use CAD technology to accurately model the product or system to be designed. This step includes determining the geometric shape, physical characteristics and constraints of the design problem and constructing the corresponding CAD model.

Defining the RL Environment: Utilize the CAD model as the RL environment, specifying the state space, action space, and reward function. The state space represents the current status of the design challenge, while the action space encompasses all conceivable design modification operations. The reward function assesses the quality of each action based on the predefined design objectives.

Training RL Agent: Through a large number of simulated interactive processes, training RL Agent to learn how to search the optimal design scheme in CAD model space. This step can adopt various RL algorithms, such as deep Q network (DQN) and strategic gradient method.

Optimization of design scheme: After the training, the RL agent is applied to practical design problems. The agent will search in the CAD model space according to the learned strategy, try different design adjustment operations continuously, evaluate the advantages and disadvantages of each operation according to the reward function, and finally find the optimal design scheme.

(3) Advantages of fusion method

Adaptability: The fusion method can deal with all kinds of complex design problems adaptively without manual intervention or preset rules. RL agents can make independent decisions and adjustments according to the actual situation of design problems, thus realizing real automatic design.

Innovation: Because the RL algorithm has strong exploration ability, the fusion method can stimulate new ideas and ideas in the design process. This is helpful to break the shackles of traditional design thinking and promote the development of design innovation.

Efficiency: The fusion method can improve the design efficiency through the autonomous learning and decision-making ability of agents. Compared with the traditional manual design or automatic design based on rules, the fusion method can find a better design scheme in a shorter time.

5 AUTOMATIC IMAGE ENHANCEMENT AND OPTIMIZATION

During the design innovation process, image quality plays a crucial role in effectively communicating design concepts and captivating the intended audience. Nonetheless, several factors, including lighting conditions and limitations of photographic equipment, often result in issues like reduced clarity and colour distortion in the original imagery. To address these challenges and elevate image quality to align with design specifications, this article introduces a method that seamlessly blends CAD technology with RL for automated image enhancement and Optimization.

In design, imagery serves as a visual representation of products, conveying their essence and alluring potential customers. The quality of these images is, therefore, intricately linked to the overall impact of the design and the emotional response it elicits from the viewer. To achieve this, images must exhibit clear details, accurate colour reproduction, and pleasing visual aesthetics. However, in practice, obtaining original images that meet these standards can be challenging, necessitating enhancement and optimization techniques. Figure 1 illustrates the fundamental principles of image enhancement using an RL-based approach.

This article proposes using the RL algorithm to achieve automatic image enhancement. We model the image enhancement task as a Markov decision process (MDP), where the state represents the current quality of the image, the action represents various enhancement operations performed on the image (such as adjusting brightness, contrast, etc.), and the reward is defined based on the enhanced image quality. Through this approach, RL agents can learn how to optimize image parameters to improve their quality through interaction with the environment.

Bellman equation (Equations 1 and 2) is a recursive expression of the value function, which reveals the relationship between current value and future value:

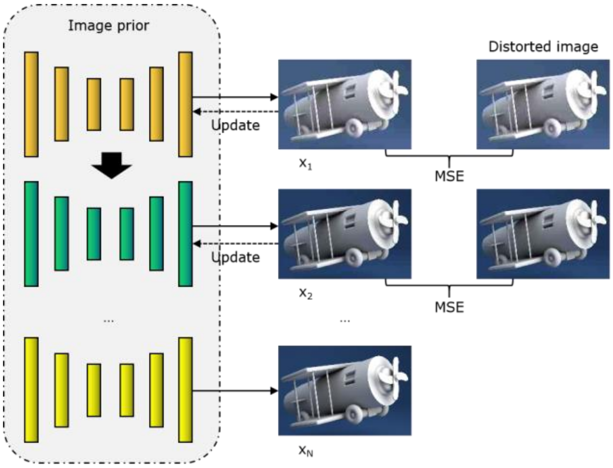

Figure 1: Schematic diagram of image enhancement principle based on RL.

$$V^{\pi}(s)=\sum_{a\in A}\pi(a|s)\left(R(s,a)+\gamma\sum_{s'\in S}P(s'|s,a)V^{\pi}(s')\right) \tag{1}$$

Here, $V^{\pi}(s)$ is the value of state s under strategy π, $R(s,a)$ is the immediate reward after state s performs action a, γ is the discount factor, and $P(s'|s,a)$ is the state transition probability.

$$Q^{\pi}(s)=R(s,a)+\gamma\sum_{s'\in S}P(s'|s,a)\sum_{a'\in A}\pi(a'|s')Q^{\pi}(s',a') \tag{2}$$

$Q^{\pi}(s)$ is the action value of the state s performing the action a under the strategy π.

The optimal value function (Equations 3 and 4) describes the optimal value of all possible strategies.

$$V^{*}(s)=\max_{a\in A}\left(R(s,a)+\gamma\sum_{s'\in S}P(s'|s,a)V^{*}(s')\right) \tag{3}$$

$V^{*}(s)$ represents the maximum value of state s in all strategies.

$$Q^{*}(s,a)=R(s,a)+\gamma\sum_{s'\in S}P(s'|s,a)\max_{a'\in A}Q^{*}(s',a') \tag{4}$$

$Q^{*}(s,a)$ represents the maximum action value of the state s performing action a in all strategies.

The strategy gradient (Equation 5) provides a method to optimize the strategy parameters by gradient rising.

$$\nabla_{\theta}J(\theta)=E_{\pi\theta}\left[\nabla_{\theta}\log\pi\theta(a|s)Q^{\pi\theta}(s,a)\right] \tag{5}$$

Here $J(\theta)$ is the performance of strategy π_{θ}, and θ is the parameter of strategy.

The dominance function (Equation 6) measures the superiority of a specific action relative to the average action and is often used to reduce variance in the strategic gradient method.

$$A^{\pi}(s,a)=Q^{\pi}(s,a)-V^{\pi}(s) \tag{6}$$

$A^{\pi}(s,a)$ indicates the advantage of performing the action a in the state s compared with the average.

Deterministic strategy gradient (Equation 7) and depth deterministic strategy gradient (DDPG, Equations 8-10) are variants of the strategy gradient method, which are suitable for continuous action space.

$$\nabla_{\theta} J(\mu_{\theta}) = E_{s\sim\rho^{\mu}}\left[\nabla_{\theta\mu\theta}(s)\nabla_{a} Q^{\mu}(s,a)\Big|_{a=\mu_{\theta}(s)}\right] \quad (7)$$

For deterministic strategy $\mu_{\theta}(s)$, this is the expression of its gradient.

$$L(\theta^{Q}) = E_{(s,a,r,s')\sim D}\left[\left(y - Q(s,a|\theta^{Q})\right)^{2}\right] \quad (8)$$

$$y = r + \gamma Q(s', \mu(s'|\theta^{\mu})|\theta^{Q}) \quad (9)$$

Where D is the experience playback buffer, and θ^{Q} is the parameter of the value network?

$$\nabla_{\theta_{\mu}} J \approx \frac{1}{N}\sum \nabla_{a} Q(s,a|\theta^{Q})\Big|_{s=s_i, a=\mu(s_i)} \nabla\theta^{\mu}\mu(s|\theta^{\mu})\Big|s_i \quad (10)$$

Here θ^{μ} is the parameter of the policy network.

The state transition probability (Equation 11) describes the dynamic characteristics of the environment, that is, how the state changes after performing an action.

$$P(s'|s,a) = \Pr(S_{t+1} = s'|S_t = s, A_t = a) \quad (11)$$

Describe the probability of state transition from s to s' after performing action a. In some cases, agents may need to learn environmental models to predict future state transitions and rewards.

The strategy entropy (Equation 12) measures the exploratory nature of the strategy and encourages agents to try different actions to avoid falling into local optimum prematurely.

$$H(\pi(\cdot|s)) = -\sum_{a\in A}\pi(a|s)\log\pi(a|s) \quad (12)$$

The entropy of the strategy in the state s is used to encourage exploring different actions.

In practical applications, a deep RL algorithm is used to train intelligent agents. By combining the representation learning ability of deep learning with the decision-making ability of RL, the deep RL algorithm can handle high-dimensional state space and action space and effectively learn the mapping relationship from the original image to the optimal enhancement strategy. Figure 2 shows the automated design interface of the product.

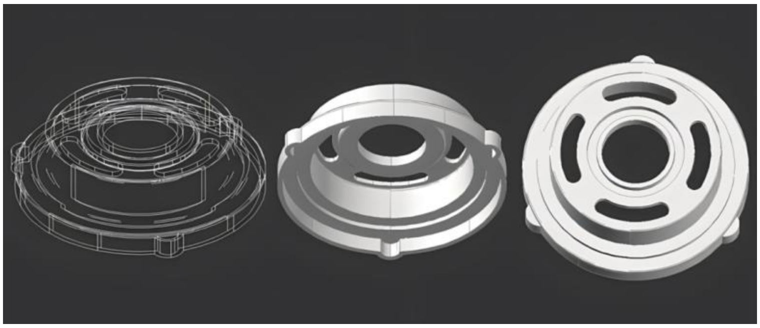

Figure 2: Product automation design interface.

On the basis of image enhancement using the RL algorithm, image optimization can be further combined with CAD technology. Specifically, by introducing the geometric information and physical characteristics in the CAD model into the image enhancement process, a more accurate and natural enhancement effect can be achieved.

6 EXPERIMENT AND ANALYSIS

During the experiment, we carefully adjusted the strategy of model training, especially how to select and add unlabeled samples to expand the training set. In each iteration, we decided to give priority to those sample instances that are the most uncertain in the model prediction. The reason for this is clear: these samples often contain important information or complex and subtle features that the model has not yet mastered. By incorporating these "difficult" samples into the training set, we expect the model to show better generalization performance when facing more extensive and challenging data.

In order to deeply understand the influence of different strategies on the model performance, this study designed a comparative experiment (Figure 3). In each iteration, we add 100, 200, 300 and 400 unlabeled samples with the highest confidence to the training set and record the experimental results in various situations. The "highest confidence" samples mentioned here actually refer to the relatively certain samples when the model predicts; that is, the model thinks that the labels of these samples are relatively reliable.

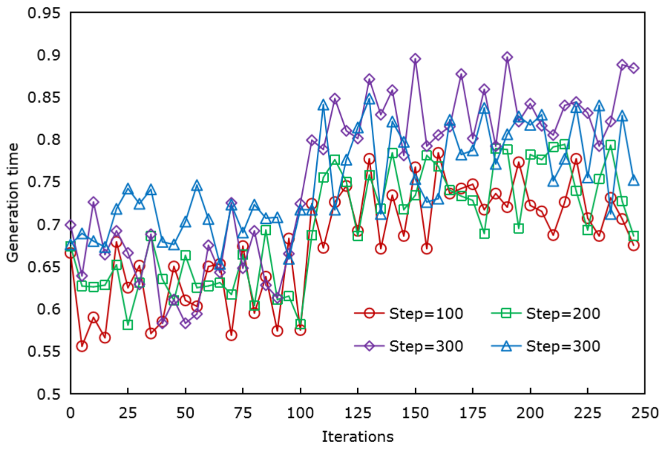

Figure 3: The correlation between the expansion of the training set utilizing active learning techniques and the resulting performance.

The results show that when only 100 high-confidence samples are added in each iteration, the performance of the model is relatively slow. This may be because the number of samples increased is small, and the new information learned by the model is limited, so the performance improvement is not obvious. However, when the number of high-confidence samples per iteration is increased to 400, the performance improvement of the model becomes more significant. This shows that increasing the number of samples with high confidence can improve the performance of the model more effectively. This may be because more samples provide more information for the model, which enables the model to learn in a wider feature space, thus improving its generalization ability. This does not mean that we can increase the number of high-confidence samples indefinitely. In practical application, we also need to consider the labelling cost, computing resources and model complexity.

In the experimental stage, in order to build a model that can efficiently analyze and optimize the whole design process, we use a large number of product modelling data as a training set. These data cover all kinds of design elements and features and provide rich learning resources for the model. Through continuous iterative training, the model gradually learned effective features and patterns from these data, thus improving its ability to predict and Optimization. Figure 4 provides a detailed depiction of the algorithm's convergence during the training process. Initially, the algorithm's output error is notably high due to the model's limited understanding of the input data's distribution and characteristics. Consequently, there is a substantial discrepancy between the predicted outcomes and the actual values. Nevertheless, as iterations progress, the model progressively acquires more information and patterns from the data, leading to a significant enhancement in its predictive capabilities.

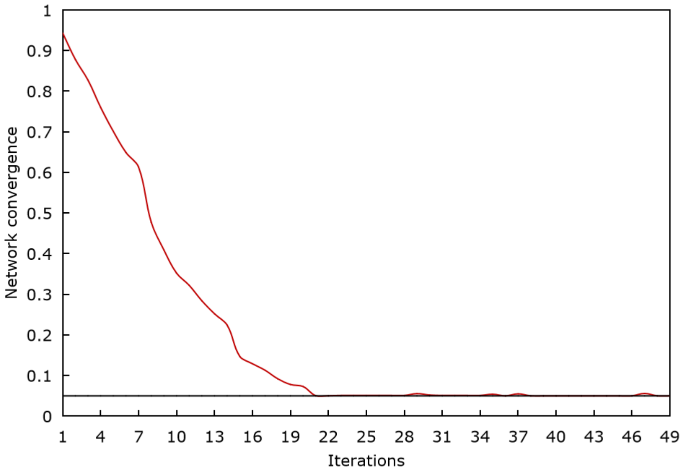

Figure 4: Convergence trend of the algorithm.

After about 20 iterations, the output error of the algorithm gradually decreases and stabilizes at a relatively low level. This indicates that the model has gradually found the intrinsic connection between input data and output objectives and can effectively utilize these connections for accurate prediction and Optimization. In addition, the stability of the error also means that the model has reached a relatively stable state, and further increasing the number of iterations may not significantly improve the performance of the model.

The findings presented in Figure 5 unequivocally demonstrate that our proposed approach attained superior ratings in terms of design performance. This accomplishment not only affirms the efficacy of our methodology but also underscores its preeminence in real-world implementations.

By effectively learning the features and patterns extracted from a large amount of product styling data, the model may achieve a better balance in terms of design novelty, practicality, aesthetics, etc., thereby obtaining higher ratings in design performance evaluation. By combining techniques such as RL, our method may be more efficient and comprehensive in searching for the optimal design solution and can discover excellent design areas that are difficult to reach by traditional methods.

Figure 6 reveals a noteworthy superiority of the proposed method over traditional ones in terms of comprehensive evaluation. This finding carries profound implications, as it underscores both the efficacy and potential benefits of the new approach in real-world scenarios. The proposed method may adopt a completely different algorithm design approach from traditional methods. This innovation may be reflected in multiple aspects, such as data preprocessing, feature extraction, model training, or optimization strategies. By introducing new mathematical tools, computational techniques, or model structures, new methods may better capture the essential characteristics of design problems, thereby achieving performance breakthroughs.

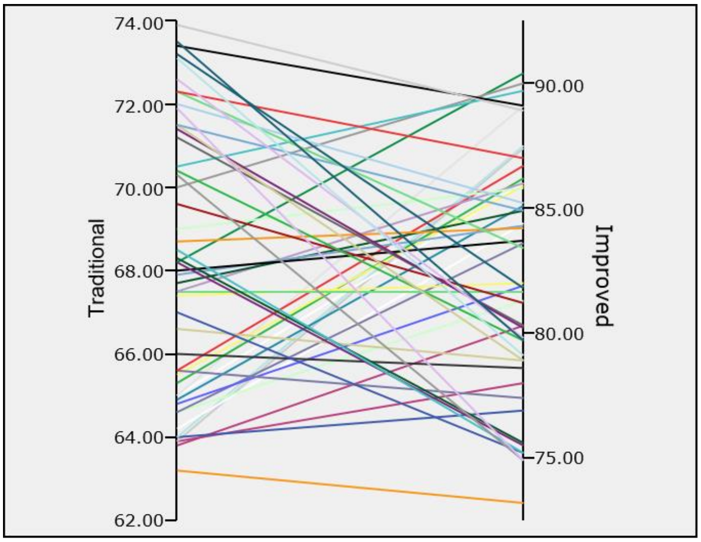

Figure 5: Design performance score.

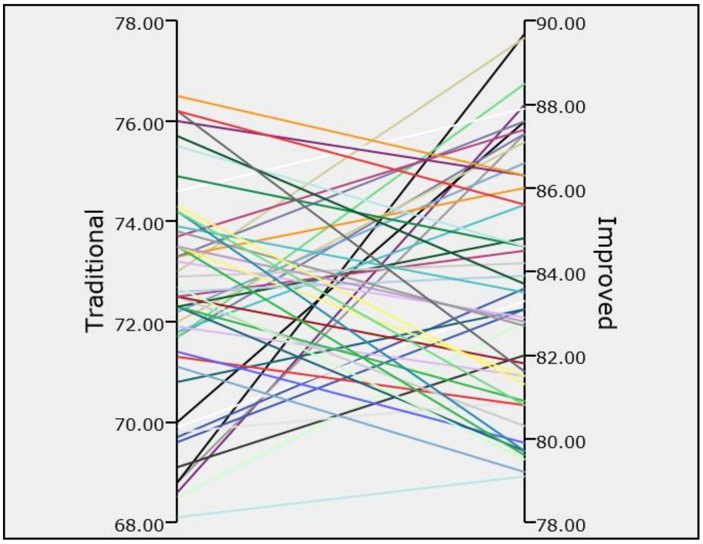

Figure 6: Comprehensive score.

In the field of modern design, data-driven methods are paid more and more attention. This method takes advantage of big data and improves the quality and innovation of the design scheme by learning design rules and patterns from massive data. As can be seen from Figure 7, this method is also significantly superior to the traditional method in terms of user satisfaction. This result is very important because user satisfaction is one of the key indicators to measure the success of a method or system. This method provides a more intuitive and easy-to-use interface and responds to users' operations and needs more quickly. As can be seen from Figure 7, the proposed method is also significantly superior to the traditional method in terms of user satisfaction.

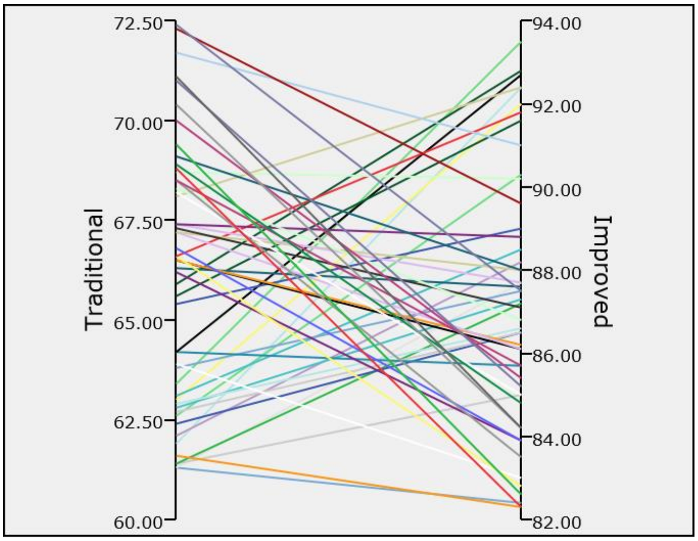

Figure 7: User satisfaction score.

The new method establishes an effective feedback loop so that users can easily provide feedback about their experiences. This kind of feedback not only helps developers to constantly improve their methods but also makes users feel that their voices are heard and valued, thus improving their satisfaction. These advantages not only prove the effectiveness of the new method but also lay a foundation for its wide popularity and use in practical application.

7 CONCLUSION

This article aims to promote the automation and intelligence of the design innovation process through in-depth research on the integration and application of CAD technology and RL. Through experiments and comparative analysis, the new method has shown significant advantages in design process optimization, comprehensive performance evaluation, and user satisfaction. The new method demonstrates higher flexibility and adaptability in complex and ever-changing design problems with advanced algorithms and excellent data processing capabilities. This not only improves the innovation of the design scheme but also effectively reduces the uncertainty and risks in the design process. By providing more intuitive and personalized services and establishing effective feedback mechanisms, this method has successfully improved user engagement and satisfaction, further enhancing its attractiveness and competitiveness in practical applications.

In summary, our proposed method has broad application prospects and enormous potential value in the field of design. In the future, with the continuous development and improvement of technology, we are confident in promoting this method to more design scenarios, providing designers and engineers with more powerful and intelligent design optimization tools, and jointly promoting innovation and development in the design industry.

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