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Computer-Aided Design AND APPLICATIONS

High-Quality Graphic Rendering and Synthesis of Design Graphics Using Generating Adversarial Networks

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Abstract. High-quality graphic rendering can accurately show the appearance, material, and lighting effects of design objects, thus improving the accuracy of design decisions. Image synthesis technology can skillfully integrate multiple design elements, create a harmonious and unified scene, and then strengthen the overall sense and visual impact of design. In this article, we innovatively propose an algorithm for image generation by using the Generating adversarial network (GAN). This algorithm can deeply learn the internal distribution law of real images and then produce high-quality rendering results. By constructing a reinforcement learning (RL) model, we skillfully transform the generation process of GAN into a series of decision-making problems and constantly seek the optimal generation strategy with the help of real-time interaction between agents and the environment. In the experiment, we made a comprehensive comparison with the traditional method. The findings indicate that the novel approach has attained a notable advancement in rendering velocity, accompanied by an enhancement in rendering quality exceeding 10%. This remarkable achievement is mainly attributed to the perfect combination of real-time rendering technology and dynamic adjustment strategy. This research not only injects new vitality into the field of graphic rendering but also provides solid technical support for improving efficiency and quality assurance in design practice.

Keywords: Graphic Rendering; Reinforcement Learning; Generating Adversarial Networks; Computer-Aided Design
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1 INTRODUCTION

As information technology rapidly progresses, the significance of computer-aided design (CAD) in various fields, such as architectural design, industrial manufacturing, and film and television animation, among others, is growing exponentially. CAD systems can help designers complete the complex process from conceptual design to detailed design in a virtual environment, in which the rendering and synthesis technology of graphics and images is the key link to realizing design visualization. Computer-assisted graphics and image rendering have become key tools in multiple fields. In this article, Alique and Linares [1] explore the importance of fast and meaningful feedback for achieving high-quality graphics and image rendering and analyze how to utilize this feedback mechanism in practical applications effectively. Fast and meaningful feedback is crucial for improving drawing quality and efficiency in computer-aided graphics and image rendering processes. The feedback mechanism can provide timely information about the drawing results, help users adjust parameters, optimize the drawing process, and ultimately generate high-quality graphics and images. Meaningful feedback refers to the ability of feedback information to accurately and concretely reflect the quality of the drawn results and the existing problems. This feedback not only informs the user of the results of the operation but also provides directions and suggestions for improvement. Meaningful feedback can help users better understand and control the drawing process, thereby improving drawing quality. In graphics and image drawing software, a real-time preview function can be designed to allow users to see the effect immediately when adjusting parameters. At the same time, provide detailed error prompts and suggestions to help users solve problems encountered during the drawing process. In addition, machine learning and other technologies can be used to intelligently analyze user drawing behaviour, providing personalized feedback and suggestions. The material prediction and recommendation technology in computer-aided design provides strong support for achieving high-quality graphic and image drawing hierarchical learning. CAD technology provides designers with precise and efficient design tools through its powerful computing and graphic processing capabilities. In CAD technology, material prediction and recommendation is a key links, which is of great significance for achieving high-quality graphic and image drawing hierarchical learning. High-quality graphics and image rendering are one of the core goals of CAD technology. To achieve this goal, the selection of materials is crucial. Through material prediction and recommendation techniques, designers can choose materials more accurately, resulting in more realistic and vivid rendering effects. In addition, with the development of technology, CAD systems are constantly improving their ability to draw graphics and images. For example, by introducing more advanced rendering algorithms and improving model accuracy, CAD systems can more accurately simulate the texture and lighting effects of materials, resulting in higher-quality graphics and images [2]. High-quality graphics and image rendering can truly reflect the appearance, material and lighting effects of design objects, and improve the accuracy of design decisions; Image synthesis technology can fuse multiple elements into a coordinated and unified scene, and enhance the overall sense and artistic expression of design.

With the deepening of biomedical research, fluorescence microscopy imaging technology is playing an increasingly important role in the field of life sciences. However, due to the weak fluorescence signal and the limitations of the imaging environment, traditional fluorescence microscopy imaging often faces problems such as low resolution and noise interference. In order to improve these issues, researchers have begun exploring the use of adaptive image sampling techniques using deep learning to enhance the quality of fluorescence images. Dai et al. [3] provided a detailed introduction to the application of this technology in fluorescence image reconstruction. Deep learning is a powerful machine learning technique that can learn complex feature representations and mapping relationships in images by training large amounts of data. Adaptive image sampling is a technique that can dynamically adjust sampling strategies based on image content and requirements. Combining deep learning with adaptive image sampling can intelligently select key information for acquisition during the imaging process, thereby improving the quality and efficiency of image reconstruction. Image registration is a key task in medical image processing and analysis, which involves aligning images of different patterns, times, or perspectives for further diagnosis, treatment, and research. In this process, selecting the appropriate algorithm is crucial for achieving high-quality graphics and image rendering. Elkeshreu and Basir [4] explored the optimal algorithm selection for achieving high-quality graphics and image rendering in multimodal medical image registration. High-quality graphics and image rendering are one of the important goals of medical image registration, which helps doctors diagnose diseases more accurately, formulate treatment plans, and evaluate treatment outcomes. However, medical image registration faces many challenges, such as grayscale differences between images, changes in anatomical structures, and interference from noise and artifacts. Therefore, selecting the appropriate algorithm is the key to achieving high-quality graphics and image rendering. At present, commonly used algorithms in image registration include grayscale-based methods, feature-based methods, and deep learning-based methods. The grayscale-based method utilizes the grayscale information of images to calculate the similarity between images, such as mutual information, mean square error, etc. They have high accuracy and robustness, but they require a large amount of computation and have a slower computation speed. Feature-based methods register images by extracting feature points or regions. They have high computational efficiency and stability but may be affected by factors such as image quality and anatomical changes. Convolutional neural networks (CNNs) have achieved significant success in the fields of image processing and analysis. Especially in sensing systems, CNN-based image synthesis and rendering technology is becoming a hot research topic. Frolov et al. [5] explored how CNN-based sensing systems can achieve high-quality image synthesis pipelines and image rendering. Sensing systems are widely used in various fields, such as autonomous driving, security monitoring, medical imaging, etc. In these fields, the quality of images directly affects the accuracy and effectiveness of subsequent processing. As a powerful deep learning model, CNN can effectively process image data, extract useful features, and perform accurate prediction and classification. A CNN-based sensing system can achieve high-quality image synthesis pipelines. In the process of image synthesis, multiple images need to be fused to obtain more comprehensive and accurate information. However, due to various factors such as lighting conditions and changes in perspective, there are often significant differences and noise between different images. To address these issues, CNN can be used for image fusion and denoising. By training a large amount of image data, CNN can learn the similarities and differences between images, thereby achieving more accurate image fusion. Meanwhile, CNN can also be used to remove noise and interference from images, improving image quality and clarity.

Image reconstruction refers to the process of restoring the original image from a series of projection or measurement data. Therefore, developing efficient and accurate image reconstruction techniques is of great significance. Gothwal et al. [6] reviewed how to use CAD and RL algorithms to achieve high-quality academic image reconstruction techniques, and explored relevant engineering calculation methods. CAD technology provides powerful support and tools for image reconstruction. Reinforcement learning algorithms provide a new solution for image reconstruction. By simulating the human learning process, reinforcement learning algorithms can automatically learn and optimize image reconstruction strategies without prior knowledge. In image reconstruction tasks, reinforcement learning algorithms can adjust parameters and strategies based on the quality feedback of the reconstructed image to gradually improve the reconstruction effect. Combining CAD and RL algorithms can fully leverage their advantages in image reconstruction. CAD provides precise modelling and optimization tools, providing reliable problem descriptions and constraints for RL algorithms. The RL algorithm can automatically learn and optimize reconstruction strategies based on the models and feedback provided by CAD, thereby improving the quality and efficiency of reconstructed images. In terms of rendering, the traditional physics-based rendering method can simulate real-world lighting and material effects, but it takes a lot of calculation and time, and it is difficult to meet the needs of real-time rendering and interactive design. For the performance of complex scenes and diverse materials, traditional rendering methods often need to manually adjust a large number of parameters, lacking intelligence and automation. In the aspect of image synthesis, traditional image editing and synthesis software usually requires users to have professional image processing knowledge, and the operation is cumbersome, so it is difficult to realize an efficient and automatic image synthesis process. The rise of deep learning technology has brought new opportunities to the field of graphics and image rendering and synthesis. GAN, as an important model in the field of deep learning, has made remarkable progress in image generation, style transfer and super-resolution. GAN enables the generator to learn the distribution of real data through confrontation training, thus generating realistic images. At the same time, RL, as a branch of machine learning, has made breakthrough achievements in the fields of game AI, autonomous driving and so on by learning the optimal decision strategy through the interaction between agents and the environment. Applying RL to the process of graphics and image rendering and synthesis is expected to realize automatic and intelligent parameter adjustment and optimization.

The purpose of this study is to explore a new method of rendering and synthesizing graphics and images by combining GAN and RL algorithms. By designing an image generation algorithm based on GAN and optimizing the generation process of GAN by using RL, the high-quality rendering and synthesis of 3D graphic images in the CAD process can be realized. The significance of the research lies not only in proposing a new method of rendering and synthesizing graphics and images but also in its potential wide application prospect. High-quality graphics and image rendering and synthesis technology can enhance the realism and immersion of design effect display in the field of architectural design and can assist product design and quality inspection in the field of industrial manufacturing; In the field of film and television animation, more realistic and fascinating virtual scenes can be created.

(a) This article proposes an image generation algorithm based on GAN, which can learn the distribution of real images and generate high-quality rendering results. Through the confrontation training between generator and discriminator, the algorithm can automatically adjust parameters, reduce manual intervention, and improve the efficiency and automation of rendering.

(b) In this article, RL is innovatively introduced into the field of graphics rendering to optimize the generation process of GAN. By constructing the RL model, the generation process of GAN is regarded as a sequential decision-making problem, and the optimal generation strategy is learned through the interaction between agents and the environment.

This study will focus on the following aspects: firstly, analyze the advantages and disadvantages of existing graphics and image rendering and synthesis technologies, and make clear the research problems and challenges; Secondly, the image generation algorithm framework and network structure based on GAN are designed, and how to generate high-quality images through confrontation training between generator and discriminator is discussed. Thirdly, the RL model is constructed to optimize the generation process of GAN, and how to define reward function, design exploration and utilization strategy and realize efficient training of algorithm is studied. Finally, the effectiveness and superiority of the proposed method are verified by experiments, and its potential in different application scenarios is discussed.

2 RELATED WORK

Traditional image encoding methods mainly focus on pixel-level compression, while understanding and processing at the semantic level are relatively limited. In recent years, the rise of deep learning technology has provided new possibilities for image semantic encoding, enabling us to efficiently and high-qualityly encode and decode images from the semantic level. Huang et al. [7] explored image semantic encoding technology based on deep learning and how it drives us toward more intelligent semantic communication. Image semantic encoding aims to extract key semantic information from images and represent this information compactly and understandably. In this way, even in low bandwidth or high noise environments, the main semantic content of the image can be maintained, thereby achieving high-quality image transmission and storage. However, image semantic encoding faces many challenges, such as the complexity, subjectivity, and variability of semantic information. The experimental results show that compared with traditional image encoding methods, deep learning-based image semantic encoding methods can achieve higher compression rates and lower transmission errors while maintaining the main semantic content of the image. With the rapid development of information technology, the security and concealment of image information have become increasingly important. Lechlek et al. [8] proposed a high-quality uncovered image information rendering and hiding algorithm based on fractal theory, aiming to achieve effective hiding and confidentiality of image information. This algorithm combines the self-similarity of fractal theory with advanced techniques in image processing and can embed secret information into carrier images without introducing obvious distortion or coverage. Image information hiding technology is a method of embedding secret information into a carrier image, allowing it to be transmitted and saved without arousing suspicion. Traditional image information hiding methods often lead to distortion or coverage of the carrier image, reducing the quality and usefulness of the image. Therefore, developing a high-quality image information-hiding algorithm without coverage is of great significance. It uses fractal theory to generate texture images that are similar to the carrier image. This can be achieved by adjusting the parameters and iteration times of the fractal transformation. Combine the fractal texture embedded with secret information with the carrier image to generate the final hidden image. The synthesis process needs to maintain the overall visual effect and detailed information of the image without being affected. Li and Li [9] discussed how to use virtual reality technology to construct image scenes in virtual healthcare systems, including scene design, model creation, and interactive implementation, and analyzed their potential impacts on medical education, surgical simulation, and remote healthcare. The construction of image scenes is an important component of virtual medical systems. By constructing realistic surgical scenes, doctors can conduct surgical simulations, and operational training, and even provide remote surgical guidance. Aiming to explore the construction methods and applications of animated image scenes in virtual medical systems under the background of virtual reality technology. The construction of animated image scenes in virtual healthcare systems has had a profound impact on medical education, image simulation, and remote healthcare.

Convolutional neural networks (CNNs) have achieved significant success in the fields of image processing and analysis. Especially in sensing systems, CNN-based image synthesis and rendering technology is becoming a hot research topic. Li et al. [10] explored how CNN-based sensing systems can achieve high-quality image synthesis pipelines and image rendering. Sensing systems are widely used in various fields, such as autonomous driving, security monitoring, medical imaging, etc. In these fields, the quality of images directly affects the accuracy and effectiveness of subsequent processing. As a powerful deep learning model, CNN can effectively process image data, extract useful features, and perform accurate prediction and classification. A CNN-based sensing system can achieve high-quality image synthesis pipelines. In the process of image synthesis, multiple images need to be fused to obtain more comprehensive and accurate information. However, due to various factors, such as lighting conditions and changes in perspective, there are often significant differences and noise between different images. To address these issues, CNN can be used for image fusion and denoising. By training a large amount of image data, CNN can learn the similarities and differences between images, thereby achieving more accurate image fusion. Meanwhile, CNN can also be used to remove noise and interference from images, improving image quality and clarity. To address this issue, researchers have begun exploring the use of deep neural networks (DNNs) to improve the quality of PET image reconstruction. Li et al. [11] introduced how to use DNN techniques, especially Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN), to reconstruct high-quality PET images in a large axial field of view. Deep neural networks are powerful tools that can learn complex patterns from large amounts of data and are used for various tasks, including image classification, generation, and reconstruction. In PET image reconstruction, DNN can learn to extract useful information from low-quality PET data and generate high-quality images. Convolutional neural networks are a type of neural network that is particularly suitable for image processing. In PET image reconstruction, CNN can learn to extract features from raw PET data and generate high-quality images through layer-by-layer convolution and pooling operations. In addition, by training a large amount of PET image data, CNN can learn the spatial structure and texture information in the image, further improving the quality of reconstructed images.

The dual diffusion model is a mathematical model based on physical processes used to describe how pixel intensity in an image diffuses in space and time. In the context of fMRI data processing, the dual diffusion model can be used to simulate the diffusion process of neural activity in the brain when processing visual information. By simulating this diffusion process, we can better understand and reconstruct the brain response patterns under visual stimuli, thereby obtaining more natural and high-quality images. Meng and Yang [12] introduced an image reconstruction and rendering method based on a dual diffusion model, which can combine fMRI data under visual stimuli to generate images that are closer to real perception. Before performing image reconstruction and rendering, it is necessary first to obtain fMRI data under visual stimuli. This typically involves presenting a series of images to the subjects while utilizing activity patterns recorded by fMRI scanners. By analyzing these activity patterns, they can extract signals related to visual stimuli. The application of dynamic scene generation and image rendering in multiple fields is becoming increasingly widespread. Nasir and Ali [13] discussed how to use the Addie model to develop dynamic scene generation and image rendering applications that combine packaging design. In the integration of digital media and packaging design, dynamic scene generation and animation drawing techniques have brought new possibilities to packaging design. The Addie model, as a classic instructional design model, can also be applied throughout the entire process of software development. It will provide a detailed introduction to how to use the Addie model to develop dynamic scene generation and image drawing applications that combine packaging design. In the design phase, we need to develop application architecture, interface design, interaction design, etc., based on the results of the analysis phase. The application architecture needs to support efficient scene generation and image rendering. The interface design needs to be intuitive, user-friendly, and convenient for users to get started quickly. Interaction design needs to be smooth and natural, providing rich customization options. Backend development requires processing data logic and generating dynamic scenes and images. Database design requires storing user data, scene templates, etc. Server deployment needs to ensure the stability and scalability of the application.

With the rapid development of deep learning and reinforcement learning (RL), their applications in the field of image processing are becoming increasingly widespread. Especially when facing complex problems such as image restoration, intelligent models combined with reinforcement learning algorithms can demonstrate strong potential and advantages. Yu et al. [14] explored how to use reinforcement learning models to achieve learning network path selection in image restoration processes. Image restoration refers to the restoration of original high-quality images from damaged or degraded images. This is a complex optimization problem that typically requires consideration of multiple features of the image, such as pixel values, textures, edges, etc. Traditional image restoration methods often rely on manually designed features and optimization algorithms, but these methods are often difficult to handle complex image restoration tasks. Reinforcement learning is a method that allows machines to learn how to make optimal decisions through trial and error. In image restoration tasks, reinforcement learning models can be seen as intelligent agents that can learn how to choose appropriate image restoration paths to maximize the quality of restored images. With the rapid development of digital image processing technology, image restoration technology has become a research hotspot in the field of image processing. Image restoration aims to restore high-quality original images from degraded or damaged images. In recent years, image restoration methods based on sparse representation have achieved significant success, among which the sparse representation method based on joint patch groups has received widespread attention. Zha et al. [15] explored the application of sparse representation based on joint shards in high-quality image restoration. Sparse representation is a signal processing technique that utilizes a small number of non-zero elements to represent the main features of a signal or image. In image restoration, sparse representation approximates the original image by finding a sparse set of basis vectors, thereby achieving image restoration. Compared with traditional image restoration methods, sparse representation-based methods can better preserve the structure and texture information of images, thereby achieving higher-quality image restoration. Joint sharding refers to the process of dividing an image into multiple small image blocks (i.e. shards) during image restoration and utilizing the correlation between these shards to jointly represent and restore the image. By combining image sets, redundant and structural information within the image can be fully utilized to improve the accuracy and robustness of image restoration.

The application of deep reinforcement learning in the field of image processing is becoming increasingly widespread. Especially in the field of image cropping, how to automatically crop high-quality image segments that conform to human visual perception is an important research direction. Zhang et al. [16] explored how to use attention-aware collaborative deep reinforcement learning to achieve high-quality image cropping. Image cropping refers to selecting and extracting regions of interest from the original image to highlight key information in the image. Traditional image cropping methods often rely on manually designed features or fixed cropping rules, which are often difficult to adapt to different scenes and complex and ever-changing image content. Deep reinforcement learning combines the advantages of both deep learning and reinforcement learning, enabling adaptive learning and decision-making in complex environments. In image cropping tasks, deep reinforcement learning models can learn how to automatically crop high-quality image segments based on image content and human visual attention. The attention module is used to simulate human visual attention mechanisms and identify important areas in images. By introducing an attention mechanism, the model can focus on key parts of the image during the cropping process, thereby avoiding pruning important information. With the rapid development of information technology, the security and concealment of image information have become increasingly important. Zhang et al. [17] proposed a high-quality uncovered image information rendering and hiding algorithm based on fractal theory, aiming to achieve effective hiding and confidentiality of image information. This algorithm combines the self-similarity of fractal theory with advanced techniques in image processing and can embed secret information into carrier images without introducing obvious distortion or coverage. Image information hiding technology is a method of embedding secret information into a carrier image, allowing it to be transmitted and saved without arousing suspicion. Traditional image information hiding methods often lead to distortion or coverage of the carrier image, reducing the quality and usefulness of the image. Therefore, developing a high-quality image information-hiding algorithm without coverage is of great significance. It uses fractal theory to generate texture images that are similar to the carrier image. This can be achieved by adjusting the parameters and iteration times of the fractal transformation.

3 METHODOLOGY

(1) Research the status of graphics and image rendering technology.

Graphic image rendering technology is the core field of computer graphics, which aims to generate realistic or artistic images through computers. With the rapid improvement of computer hardware performance and the continuous innovation of graphics algorithms, graphics rendering technology has experienced the evolution from simple ray tracing to complex global illumination simulation.

Traditional graphic rendering methods, such as rasterization and ray tracing, generate images by simulating the propagation of light and the material properties of the object's surface. These methods have made remarkable achievements in visual effects, but they are often accompanied by high computational costs. When scene complexity increases—with numerous geometric shapes, intricate materials, and dynamic lighting—traditional rendering methods' computational demands skyrocket, making real-time rendering challenging.

In recent years, graphics rendering leveraging deep learning has emerged as a focal point of research. Models like Convolutional Neural Networks (CNN) and GAN excel in image generation, style transfers, and super-resolution tasks. By training on vast datasets, these models grasp intricate input-output mappings, yielding high-quality imagery. Wang et al. introduced an image synthesis approach that combines GAN with conditional batch normalization. This innovative method generates a range of rendering outcomes based on varying conditions, enhancing flexibility and control in image synthesis endeavours. In the field of graphic rendering, deep learning techniques are used to accelerate ray tracing, predict global lighting effects, and generate realistic materials. For example, some studies use neural networks to approximate complex lighting models, significantly improving rendering speed without sacrificing too much visual quality. In addition, there are studies combining deep learning with traditional rendering methods to achieve more efficient global lighting simulation and real-time rendering.

(2) The current research status of GAN

GAN, consisting of a generator and a discriminator, is a deep learning model that creates new data through adversarial training. The generator aims to produce realistic samples, fooling the discriminator, while the discriminator strives to differentiate between real and generated ones accurately. This adversarial process drives both components to enhance their abilities until equilibrium is reached. GAN's capacity to learn from vast image datasets allows it to capture the essence of real images and produce innovative, similarly styled ones. Moreover, its conditional generation capability—tailoring outputs to specific conditions or constraints—grants GAN versatility in tasks like image editing, style transfers, and super-resolution.

(3) The current research status of RL in image processing

RL is a machine learning algorithm that learns the optimal decision strategy through interaction between intelligent agents and the environment. In the field of image processing, RL is used to solve a series of complex tasks, such as object detection, image segmentation, image generation, etc. By defining appropriate state space, action space, and reward function, the RL algorithm can automatically explore the intrinsic structure of image data and learn effective processing strategies.

In terms of image generation, RL is used to optimize the parameters and generation process of the generation model. Unlike traditional gradient descent-based optimization methods, RL explores the parameter space through trial and error and adjusts parameters based on reward signals feedback from the environment. This method has higher flexibility and robustness in handling complex generation tasks.

Some studies combine RL with GAN to achieve more efficient image generation. For example, guiding the generation process of GAN towards specific goals by defining appropriate reward functions, or using RL to automatically adjust the network structure and hyperparameters of GAN. These attempts have brought new ideas and methodological innovations to the field of image generation. When exploring methods for high-quality rendering and synthesis of 3D graphic images in the CAD process, this study adopted a GAN-based image generation algorithm and combined it with RL to optimize this generation process.

3.1 Image Generation Algorithm Based on GAN

GAN, a deep learning model, has exhibited significant promise in image generation. It comprises two primary components, a generator and a discriminator, which undergo adversarial training together. The generator strives to produce highly realistic images to fool the discriminator, while the discriminator aims to differentiate between authentic and generated images precisely. The comprehensive structure of this model is depicted in Figure 1.

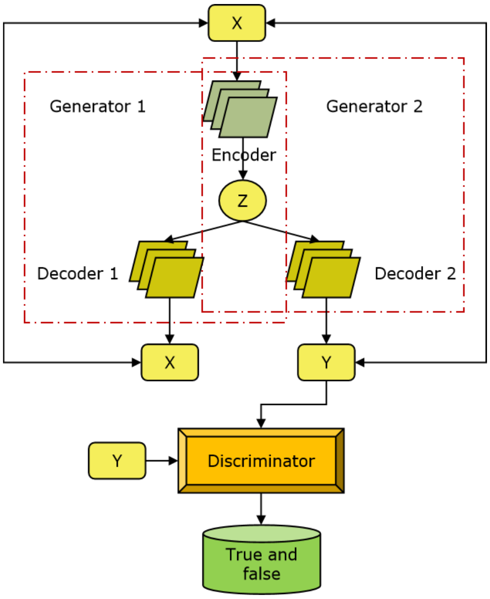


Figure 1: Overall architecture of the model.

In this study, we designed a GAN-based image generation algorithm aimed at generating high-quality 3D graphic images. Firstly, a deep convolutional neural network was constructed as the generator, which receives random noise vectors as input and outputs the generated image. The network structure of the generator has been carefully designed, including multiple convolutional layers, activation functions, and batch normalization components, to ensure the generation of images with rich details and textures. The architecture of the generator for adversarial training is shown in Figure 2.

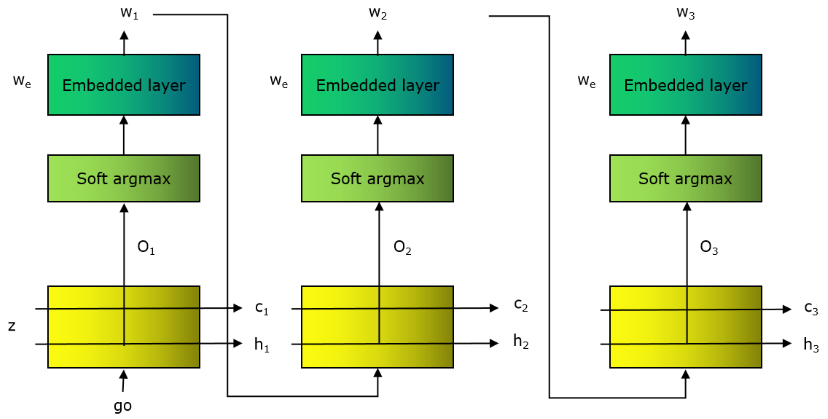


Figure 2: Generator architecture of confrontation training.

At the same time, a discriminator network is constructed to distinguish the real image from the generated image. The discriminator also adopts the structure of the deep convolutional neural network and is trained by supervised learning. In the training process, the real image is marked as a positive sample and the generated image is marked as a negative sample. The goal of the discriminator is to maximize the discrimination accuracy of positive samples and minimize the misjudgment rate of negative samples. The model structure of the discriminator is shown in Figure 3.

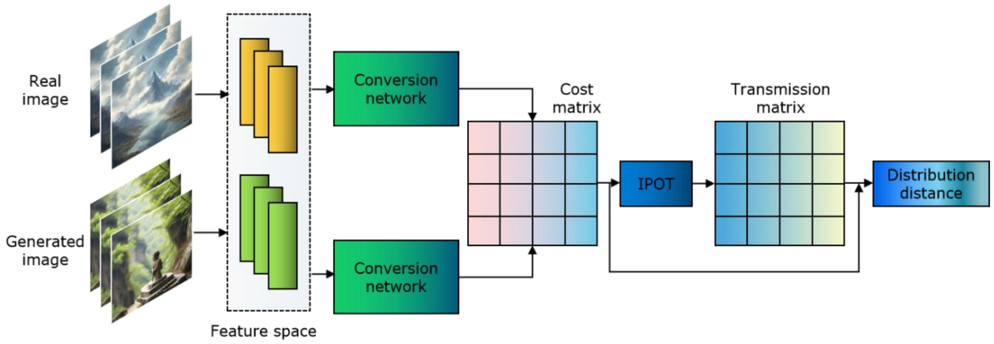


Figure 3: Discriminator model structure.

Through adversarial training, the generator progressively enhances its ability to produce realistic images, while the discriminator sharpens its skill in recognizing generated ones. This continuous interplay gradually leads to a scenario where the discriminator can no longer discern between the generator's highly realistic images and actual ones, indicating that the GAN has achieved a dynamic equilibrium.

3.2 RL Optimizes GAN Generation Process

Although GAN-based image generation algorithms can generate high-quality images, they may still face the problem of unstable or lack of diversity in certain complex scenes. To address these issues, this study introduces RL to optimize the generation process of GAN. We consider the generation process of GAN as a sequence decision problem and treat the generator as an agent and the rendering environment as an external environment. At each moment, the generator selects an action (i.e. the next generation operation) based on the current state (i.e. the generated image part) and receives a reward signal returned by the environment (i.e. the quality evaluation result of the generated image).

Given that the encoder and discriminator have identical weights, excluding the final layer, they can be combined. The portion of the network they share is represented by H. Subsequently, the Encoder can be described using formulas (1) and (2), while the discriminator D is represented by formula (3).

$$\mu = f_1 \; H \; X \tag{1}$$

$$\log \sigma^2 = f_2 \; H \; X \tag{2}$$

$$D = f_3 \; H \; X \tag{3}$$

f represents distinct mappings from the network's final layer.

To mitigate the issue of fuzzy image synthesis, the inference network assesses image fidelity. Specifically, it aims to assign a "true" label to a genuine training sample x and a "false" label to a generated sample x_f. Meanwhile, the generating network strives to produce image samples that the network prediction deems as "true." The respective introspective confrontation losses for the inferred and $z_{a,f}$ generated networks are expressed as follows:

$$L_{adv}^{G} = L_{KL} \; z_{a,f} \tag{4}$$

$z_{a,f}$ signifies the authenticity component of the produced sample.

To ensure colour consistency between the transformed and original images, we employ an identity loss function:

$$L_{identity} \; G_1 \; = E_{x \sim p_{data} \; x} \left[\left\| G_1 \; x \; - x \right\|_1 \right] \tag{5}$$

Where $x \sim p_{data} \; x$ represents that the picture originated from the source domain X to be transformed, and $G_1 \; x$ represents the forged result synthesized by the generator G_1.

To optimize the generation process, we designed a reward function to measure the quality of generated images. The reward function can consider multiple factors, such as image fidelity, diversity, and consistency with the target. By carefully designing the reward function, the generator can be guided towards evolving towards generating high-quality images. In the selection of the RL algorithm, we adopted a policy gradient-based algorithm to update the parameters of the generator. The policy gradient algorithm estimates the direction of parameter updates by calculating the policy gradient and uses the method of gradient ascent to maximize the expected reward. In this way, the parameters of the generator can be effectively adjusted to optimize the generation process and improve the quality of the generated images.

The traditional rendering process typically involves multiple steps and complex parameter adjustments. This study utilized deep learning technology to automate some rendering processes and optimized the setting of key parameters through RL. These optimization measures reduce the need for manual intervention and improve rendering efficiency and automation.

Let's assume that $f^{"}\ x,y$ denotes the initial 3D image, $x^{'}_{jui}$ signifies the vicinity of an arbitrary pixel $c^{'}_{sg}$ within the 3D image, $w^{'}_{wer}$ is representative of the number of values of each 3D feature, and $b^{'}_{wep}$ designates the overall count of pixels in 3D. The enhancement of the image takes place in the frequency domain:

$$E^{'}_{qwu} = \frac{b^{'}_{wep} \times f^{"}\ x,y}{x^{'}_{jui} * c^{'}_{sg}} \times\ w^{'}_{wer} \oplus e^{'}_{gtu} \tag{6}$$

$e^{'}_{gtu}$ denotes the distribution pattern of image grey values. Let $\xi^{'}_{uio}$ represent the frequency of each grey value in the image, $O^{'}_{hjk}$ stand for the image's grey level, x,y designate any image point, $x+a,y+b$ indicate the image's disturbance point, and $x+a,y+b^{\ kl}$ correspond to points x,y and $x+a,y+b$. These elements collectively establish a new image grey scale.

$$b^{"}_{poi} = \frac{x+a,y+b^{\ kl}}{x,y\ \times\ x+a,y+b} \oplus \frac{\xi^{'}_{uio}}{O^{'}_{hjk}} \tag{7}$$

Let $\iota^{"}_{pol}$ denote the image's first-order differential function, $v^{'}_{wer}$ signify the image's inherent attribute, and $d^{'}_{sgh}$ represent the amplitude-frequency characteristic function. Together, they outline the grey characteristics of the image.

$$e^{'}_{yup} = \frac{d^{'}_{sgh} \pm \iota^{"}_{pol}}{v^{'}_{wer}} \mp d^{'}_{sgh} \tag{8}$$

Assume that $\partial^{'}_{uip}$ represents the variance of the original image block merged with each adjacent basic image block, and $c^{'}_{wepp}$ represents the proportion of each image block in the whole image. The enhancement function of image edge grey contrast is obtained:

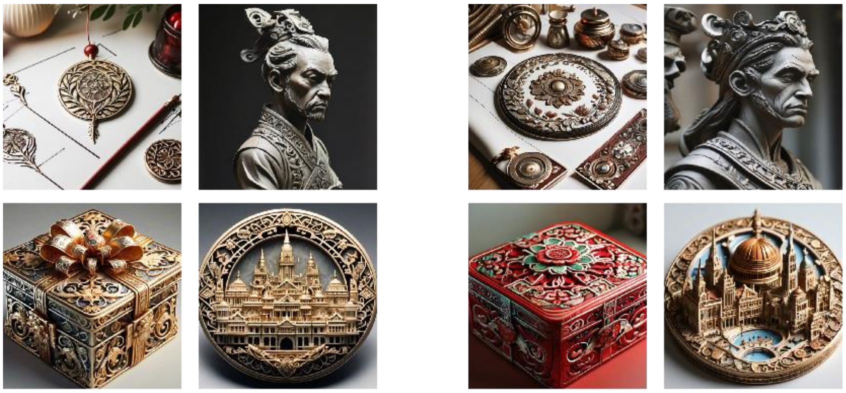
$$r^{'}_{rti} = \frac{c^{'}_{wepp} \pm \partial^{"}_{uip}}{h^{'}_{tu}} \times f^{'}_{rty} \tag{9}$$

Where $h^{'}_{tu}$ stands for mask operator and $f^{'}_{rty}$ stands for texture feature of low-frequency part.

4 EXPERIMENTAL RESULTS

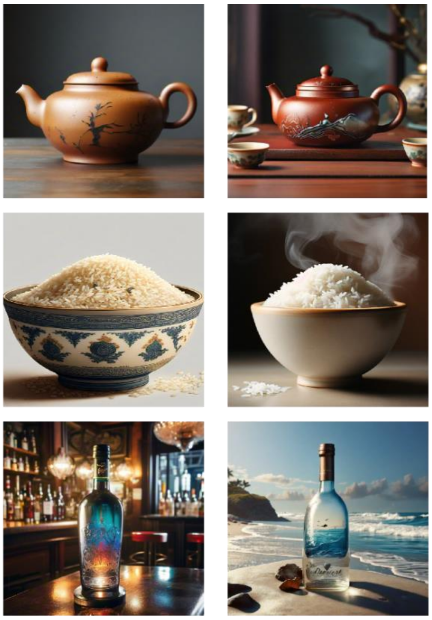
4.1 Dataset and Experimental Design

The experimental design is committed to an in-depth exploration of the application and effects of real-time rendering and dynamic adjustment technology in image design. Through a carefully constructed experimental plan, we compared the differences between traditional rendering methods and works using real-time rendering technology in multiple dimensions, aiming to comprehensively evaluate the potential of new technologies in enhancing audience appeal and information dissemination effects. A dataset of design works covering multiple types and styles was selected in the experiment, ensuring the breadth and representativeness of the research. By utilizing the real-time rendering function of CAD software, we simulated a real design environment and made preview and detailed adjustments to the work. At the same time, combined with dynamic adjustment strategies, key elements such as colour, lighting, and materials of the work were optimized to achieve the best visual effect. After in-depth analysis and comparison of experimental data, it was found that image design works that have been dynamically adjusted and rendered in real-time have significantly enhanced their ability to attract audience attention and improve information dissemination. The real-time rendering function of CAD provides designers with the convenience of previewing and adjusting the final effect of graphics in real time during the design process. Partial samples of the selected dataset are shown in Figure 4.



(a) Normal sample (b) Negative sample

Figure 4: Partial sample of data set.



Before optimization After optimization

Figure 5: Comparison of image rendering effects.

4.2 Results and Analysis

The test results captured in the real-world scenario depicted in Figure 5 unequivocally demonstrate the superior performance of the method introduced in this article for image defogging and preserving intricate details. In contrast to conventional defogging techniques, this approach not only eliminates fog from the image efficiently but also preserves a higher level of detailed information, resulting in a clearer and more natural-looking processed image. Traditional defogging methods often face an unavoidable problem when processing images: the loss of details. This is because these methods may destroy or lose some fine structures in the image, such as edges and textures, in the process of removing fog. These details are very important for the overall visual effect of the image and the complete transmission of information. Once lost, the image will become blurred and lose its original sense of hierarchy and three-dimensional sense. The image defogged by this method still maintains rich detailed information. This is due to the innovation and optimization of the algorithm design of this method, which can keep the original details of the image to the greatest extent while defogging.

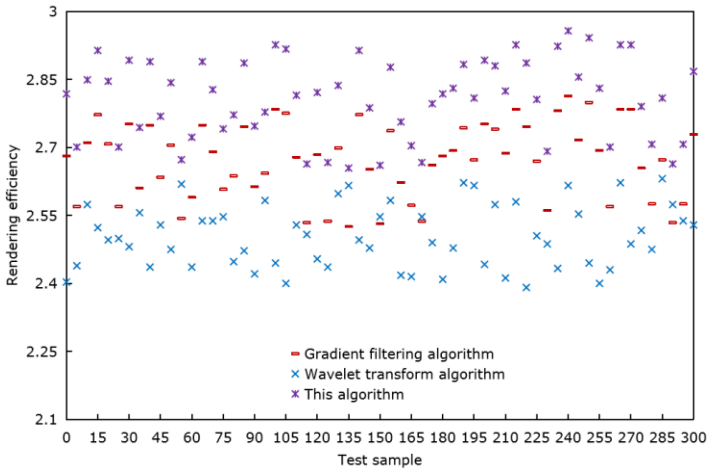


Figure 6: Rendering efficiency of different methods.

Figure 6 shows the comparison of rendering efficiency between the optimized model and traditional methods in this article. The optimized model in this article has significant advantages in rendering time compared to traditional methods. For scenes or models of the same complexity, the method proposed in this article requires a shorter rendering time, which means that designers can obtain previews or final rendering results in a shorter time, thereby improving the efficiency of design work. This advantage is mainly attributed to the real-time rendering technology and dynamic adjustment strategy adopted in this article to optimize the model. Real-time rendering technology can fully utilize computer hardware resources to achieve fast rendering and preview of graphics. The dynamic adjustment strategy can adjust rendering parameters in real-time according to changes in the scene or model, avoiding unnecessary computation and rendering time waste. The combination of these technologies and strategies has achieved significant breakthroughs in rendering efficiency for the method proposed in this article.

Figure 7 shows the comparison results between the optimized model and traditional methods in terms of rendering quality in this article. Compared to traditional methods, the optimized model in this article has significantly improved rendering quality by more than 10%. This improvement is mainly reflected in the authenticity, detail preservation, and colour restoration of images. The optimization model in this article can simulate light propagation and material performance more realistically by introducing advanced graphics rendering algorithms and image processing techniques, thereby generating more realistic image effects. At the same time, this method also focuses on preserving details, ensuring the complete presentation of detailed information in the image by optimizing rendering parameters and using high-resolution mapping techniques.

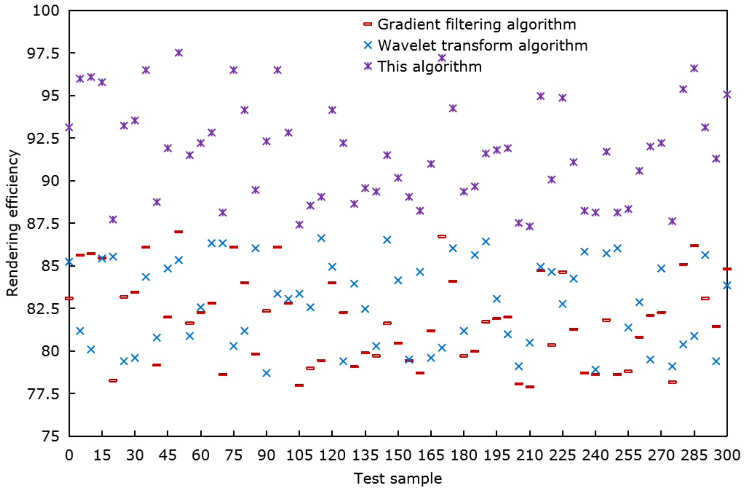


Figure 7: Rendering quality of different methods.

Table 1 shows the comparison of image rendering performance between our algorithm and two common algorithms (gradient filtering algorithm and wavelet transform algorithm). The algorithm in this article performs excellently in the image PSNR index, with significantly higher PSNR values compared to the other two algorithms. This indicates that the algorithm proposed in this article has significant advantages in image rendering quality, as it can better maintain the details and clarity of the image. Gradient filtering algorithms and wavelet transform algorithms may introduce certain distortions or noise in image processing, leading to a decrease in the quality of rendering results. The algorithm in this article effectively reduces these distortions and noise by optimizing the rendering process and improving computational efficiency, thereby improving the PSNR value of the image.

Iterations	*Gradient filtering algorithm*	*Wavelet transform algorithm*	*This algorithm*
1	25.8	27.5	28.6
2	26.1	26.5	27.8
3	27.5	29.1	28.8
4	30.7	32.3	30.5
5	9.8	16.5	16.9
6	16.7	16.2	18.8

Table 1: Comparison of PSNR of image rendering with different algorithms.

Table 2 shows the running time comparison of the three algorithms under different iterations. With the increase in iteration times, the running time of the three algorithms increases. However, under the same number of iterations, the running time of this algorithm is relatively short, which has certain advantages. This shows that the algorithm in this article performs well in computational efficiency and optimization, and can reduce computational time and resource consumption while ensuring image rendering quality.

Iterations	*Gradient filtering algorithm*	*Wavelet transform algorithm*	*This algorithm*
1	0.09	0.15	0.09

2	0.15	0.21	0.16
4	0.12	0.29	0.26
8	0.25	0.57	0.32
16	0.37	0.91	0.32
32	0.77	1.55	0.61

Table 2: Comparison of image rendering running time of different algorithms.

Compared with traditional rendering methods, this article verifies the effectiveness and superiority of the proposed method. The experimental results show that in terms of rendering efficiency, the optimized model in this article significantly reduces rendering time and improves the efficiency of design work. This advantage is mainly attributed to the application of real-time rendering technology and dynamic adjustment strategy, which can make full use of computer hardware resources, realize fast rendering and preview of graphics, and adjust rendering parameters in real-time according to the changes of scenes or models, thus avoiding unnecessary calculation and waste of rendering time. In the aspect of rendering quality, the optimized model of this article has also achieved obvious improvement, which is more than 10% higher than the traditional method. This improvement is mainly reflected in the authenticity of the image, detail preservation and colour restoration. By introducing advanced graphics rendering algorithms and image processing technology, this method can simulate light propagation and material performance more realistically and generate more realistic image effects.

This study not only provides a new and effective method for the field of image design but also provides strong support for improving image quality in practical applications. The combination of real-time rendering technology and dynamic adjustment strategy enables designers to obtain high-quality rendering results in a shorter time. This is of great significance to the high efficiency and high-quality requirements of modern design work. However, there are still some limitations and shortcomings in this study. For example, for extremely complex or large-scale scenes or models, real-time rendering may still face certain challenges. In addition, with the continuous development and progress of technology, there may be more advanced rendering methods and algorithms in the future, so it is necessary to constantly update and optimize the methods in this article to meet the new requirements.

5 CONCLUSION

CAD systems can help designers complete the complex process from conceptual design to detailed design in the virtual environment, in which the rendering and synthesis technology of graphics and images is the key link to realizing design visualization. In this article, the high-quality rendering and synthesis of graphic image CAD are studied compared and analyzed with traditional gradient filtering algorithm and wavelet transform algorithm. The results show that the algorithm proposed in this article has obvious advantages in image rendering quality and computational efficiency. In terms of image rendering quality, this algorithm effectively reduces the distortion and noise that may occur in the image processing process by optimizing the rendering process and improving the calculation efficiency. This advantage makes our algorithm more practical when dealing with complex images or demanding rendering tasks. In terms of computational efficiency, this algorithm reduces unnecessary computational steps and resource consumption by improving the algorithm structure and optimizing the computational process. This advantage makes the algorithm in this article more efficient when dealing with large-scale image data or real-time rendering tasks, and can meet the requirements of speed and performance in practical applications.

To sum up, the real-time rendering method of graphic image CAD proposed in this article has shown remarkable advantages in image rendering quality and computational efficiency. In the future, we will continue to optimize and improve the algorithm to further improve its performance and scope of application, and provide more and better solutions for practical applications.

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