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Computer-Aided Design AND APPLICATIONS

3D Effect Image Solution of Landscape Design Model Based on Generative Adversarial Networks

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Abstract. This article analyzes CAD's computer-aided creative design by utilizing the landscape architecture's adversarial network. An intelligent structural optimization of landscape design has been constructed through an in-depth investigation of generative adversarial networks. Compared to traditional methods, The generation scheme of CAD has constructed a 3D effect image solution by analyzing the practicality of image clarity. It utilizes image landscape creation based on CAD performance to optimize the clarity of design effects. While maintaining artistic value, the algorithm proposed in this article intelligently improves the quality of artistic works. It constructs novelty and advantages in efficient design processing. The comprehensive evaluation of the proposed landscape design model constructs the artistic integrity value of innovative elements. Through the analysis of the effectiveness of the model, the algorithm has also made significant improvements in landscape innovation.

Keywords: Landscape Design; Art Style; Generative Adversarial Networks; CAD
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1 INTRODUCTION

Bianconi et al. [1] focused on the important role of visual perception in landscape design quality assessment. By training an advanced artificial intelligence system, we enable it to accurately identify and quantify various design elements present in images, such as vegetation, water bodies, hard paving, etc. It is committed to defining a set of digital methodologies and standards for evaluating the quality of landscape design, all based on utilizing geographic reference images along roads as open-source big data resources. These L values not only reflect the physical characteristics of landscape design but also contain elements of visual perception, such as spatial layout, colour matching, scale ratio, etc. Through comprehensive analysis of a large amount of image data, we have obtained a comprehensive landscape quality index (L value), which comprehensively reflects the overall quality of landscape design. However, as urbanization intensifies and people aspire for a superior lifestyle, traditional design methodologies reveal shortcomings, primarily in terms of efficiency, innovation, and ecological sustainability. Fortunately, the swift advancements in information technology have introduced artificial intelligence (AI) as a novel opportunity in landscape design. AI's robust data processing and learning capabilities offer unprecedented prospects. Specifically, GAN, a significant breakthrough in AI, have achieved remarkable feats in image processing and natural language handling, attributed to its unique generative prowess and adversarial training framework. Da et al. [2] delved into the characteristics of the Rain classroom and addressed the limitations of flipped classroom teaching. The graduate group of landscape design students who participated in the Rain Classroom-based flipped classroom showed significantly better academic performance than the control group in the computer-aided landscape design course. In terms of landscape design expansion analysis, it was found that the Rain classroom teaching mode has a positive promoting effect on landscape design learning. By conducting a questionnaire survey on students who have participated in the Rain Classroom learning model and comparing it with the control group of traditional lecture-style teaching methods, significant differences in academic performance were found. This technology generates highly realistic and varied images through the adversarial interplay between generators and discriminators, thereby presenting fresh design perspectives and techniques for landscape architecture.

Moreover, GAN possesses the ability to autonomously produce a diverse array of potential design solutions by studying existing landscape designs. This process significantly reduces the design cycle, as designers only need to select the desired works from these proposed schemes. Felbrich et al. [3] summarized the current technological status in the field and explored how to combine their advantages to achieve higher levels of autonomy and efficiency in landscape design and construction. It demonstrates how to train robot agents through model-free DRL algorithms such as TD3 and SAC, enabling them to autonomously plan and construct landscape structures. The first case study focuses on verifying the universal applicability of DRL training in landscape design computing environments and comparing the learning success rates of different algorithms. The second case study focuses on demonstrating the advantages of our framework in tool path planning, geometric state reconstruction, manufacturing constraints, and action evaluation. In the interdisciplinary fields of landscape design, robot computing design and manufacturing (CDRF), and deep reinforcement learning (DRL), it explores a new way to achieve autonomous robot additive manufacturing to drive innovation in the landscape design and construction industry. Landscape design is an art that needs constant innovation, and GAN can generate diverse and novel design schemes, providing designers with more inspiration. Although these designs generated by GAN may not completely conform to the designer's style, some novel elements and ideas can often stimulate the designer's creative thinking, thus producing more excellent design works.

Hussein [4] delved into the integration of augmented reality (AR) technology into landscape design education and its potential advantages. In landscape design education, traditional two-dimensional drawings and oral explanations often struggle to visually display the three-dimensional effects and spatial relationships of the design. By introducing AR technology, we hope to create a more attractive learning experience for students, deepen their understanding of the landscape design process, and stimulate innovative thinking and practical abilities. By wearing AR devices, students can directly observe, interact, and operate landscape design projects in a virtual three-dimensional environment, thereby obtaining a more intuitive and in-depth learning experience. During the landscape design process, designers must thoroughly consider ecological elements like topography, vegetation, and climate to ensure a harmonious blend with nature. GAN can harness vast natural environment and landscape design data to create an eco-compliant design. Jahani et al. [5] extensively drew on environmental behaviour and aesthetic theories and incorporated them into the study of intelligent interactive landscape design. Based on practical cases, explore the impact of new perspectives and the application of new technologies on intelligent interactive landscape design. This illustrates the prospects of interactive landscape design after the application of intelligent and digital technologies. In the context of rapid economic development in modern society, in the intersection of big data information, the internet and virtual communities have not made human relationships closer but rather highlighted the lonely personal experience and personalized way of life. Thus reflecting humanistic care. The proposal of "human landscape intelligent interaction" design is based on the experience of people in the environment. The human experience provides new ideas for landscape design, enabling designers to discover new problems and find solutions. In the era of the knowledge economy, aesthetic design and modern landscape design not only need to conform to modern aesthetics in appearance but also fully consider the personalized psychology and habits of users. By advocating for harmonious coexistence between people and nature in the landscape, we aim to promote the concept of people-oriented and sustainable development in landscape design.

Jing et al. [6] took the research on landscape planning and design of commercial pedestrian streets based on intelligent interactive experience as the starting point. Research methods and content, and derive an overall technical roadmap based on the research framework of proposing, analyzing, and solving problems. By analyzing a large number of existing cases both domestically and internationally, starting from well-known commercial pedestrian streets in China, the problems in landscape planning of commercial pedestrian streets in China are summarized. Starting from the current development status and prospects of intelligent interaction, this paper provides a detailed interpretation of the landscape planning and design of commercial pedestrian streets for intelligent interaction experience, clarifying the research purpose and theoretical-practical significance. Finally, analyze the commonalities between intelligent interaction and commercial pedestrian streets, and summarize the design steps, strategies, and principles of landscape planning and design for commercial pedestrian streets based on intelligent interaction experience. A complete planning and design process system, including design techniques, provides new ideas and methods for the intelligent interactive experience design of commercial pedestrian streets in the future. Lavorel et al. [7] explored the management innovation of design crowdsourcing models in the field of landscape design, focusing on the design pattern based on network crowdsourcing. Through investigation and research methods, they conducted an in-depth analysis of the structure and operational mechanism of designing crowdsourcing patterns and proposed corresponding solutions and suggestions. By reviewing relevant literature and cases on design patterns, crowdsourcing patterns, and landscape design patterns. To gain a more comprehensive understanding of the application and development of design crowdsourcing models in the field of landscape design, this study employed literature review and case comparative analysis methods. In the field of landscape design, the design model based on online crowdsourcing can bring together design thinking, cultural elements, and practical experience from around the world, providing diversified solutions for projects. This model breaks down geographical and professional limitations, allowing designers, scholars, hobbyists, and even the general public to participate in the process of landscape design.

The objective of this study is to devise an innovative GAN-based CAD landscape design model. This model integrates AI technology with traditional design tools, leveraging GAN's generative prowess and CAD software's efficient modelling capabilities to achieve efficient, innovative, and eco-sustainable landscape design. The research offers the following advancements:

(1) The introduction of GAN, an advanced AI technology, into landscape design disrupts traditional design paradigms.

(2) The study constructs a GAN-based CAD landscape design model, integrating GAN's generative abilities and CAD's modelling functionality to automate and intellectualize the landscape design process.

(3) The generating ability of GAN provides abundant inspiration for landscape design, and it can generate highly realistic and diverse design schemes.

(4) Aiming at the problems of traditional landscape design methods in design efficiency, innovation and ecological sustainability, the model proposed in this study provides effective solutions.

In this study, a large number of landscape design data is collected to train the GAN model; Then, a variety of possible design schemes are generated by using the trained GAN model; Finally, combined with CAD software, the generated design scheme is further optimized. In this way, the intelligent landscape design process can be realized, the design level can be improved, and the feasibility of the design scheme can be ensured.

2 LITERATURE REVIEW

The CGAN model demonstrates strong capabilities in understanding and calculating the external spatial layout of nursing homes. Although there are certain differences between the landscape design schemes generated by the CGAN model and the actual designs, most of the design elements and layout principles exhibit a high degree of similarity. The questionnaire survey in the study shows that architects are highly satisfied with the landscape design schemes generated by the CGAN model and believe that these schemes have high reference value. By studying historical data and design rules, The CGAN model can automatically generate layout plans for the external space of nursing homes, including gardens, walkways, leisure areas, etc. These solutions not only consider functional requirements but also incorporate aesthetic elements, providing valuable references for landscape designers. This indicates that the CGAN model has great potential for intervention between indoor space design and landscape design [8]. Lochhead and Hedley [9] conducted an exploratory study aimed at developing an innovative workflow to address the need to fully capture complex institutional spatial geometries and topological structures in landscape design. Not only does it focus on the internal design of institutional spaces, but it also emphasizes the role of landscape design in it. In the process of combining 3D data collection methods with geographic information science theory, 3D game engines, 3D evacuation simulation, and spatial analysis, we have paid special attention to the role of landscape design. Through 3D modelling and photogrammetry techniques, it evaluated real-world features in digital space and explored how these features affect the decision-making process of landscape design. The modelling of elements such as terrain, buildings, and facilities in landscape design also requires high-precision 3D data capture and processing techniques. This is particularly important in modelling complex structures such as terrain undulations and building contours in landscape design. Rough registration stage, Moritani et al. [10] employed a technique based on random sample consistency and a three-dimensional hash table, which not only improved registration efficiency but also ensured registration accuracy. In the fine registration and modelling stage, high-precision modelling is achieved by minimizing the fitting error of the cylinder as a nonlinear function of the position and geometric parameters of the scanner and cylinder. These technologies can effectively capture and model these subtle bending features, making landscape design models more realistic and refined. In landscape design, the three-dimensional reconstruction of ancient buildings with high historical or cultural value not only helps to protect and inherit this precious cultural heritage but also provides rich inspiration and reference for modern landscape design. In order to improve the performance of image matching in the 3D reconstruction of ancient buildings, Nie et al. [11] proposed a new method called FM_GMC based on grid partitioning and high-density clustering of key points in the grid. Divide the image into multiple grids and calculate the density of key points in each grid. Based on the density value, divide the grid into anchor elements, adjacent elements, and boundary elements. Image-based 3D reconstruction of ancient Chinese architecture is a challenging task, and image matching, as a key link, has a significant impact on the accuracy and precision of the reconstruction results.

In the field of landscape architecture, research through design (RTD) is not only a common practice but also a core driving force for continuous innovation and development in this field. In the current academic and professional context, although landscape architecture design practices are diverse, there is still a lack of literature on using design behaviour as a systematic research process. Nijhuis and Vries [12] aim to explore in depth how spatial design can be applied as a research strategy, in order to contribute new perspectives to research and education in the field of landscape architecture. In the design process, we may use sociological methods to study the relationship between human behaviour and space or use ecological methods to evaluate the impact of design on the environment. The article also delves into the design process and methods of landscape architecture. The design process is a cyclical process from problem identification, concept generation, scheme optimization, and implementation evaluation, each step requiring the use of scientific research methods and rigorous thinking. With the rapid development of technologies such as deep learning (DL) and generative adversarial networks (GANs), The application of AI in fields such as architectural design and urban planning has shown enormous potential. Senem et al. [13] constructed a large dataset containing approximately 100000 front-end and backyard layout images.

These images not only incorporate visual aesthetic considerations but also incorporate functional and structural evaluation scores. The results show that the garden layout design generated using GANs is visually attractive, while also meeting high standards in terms of functionality and structure. In landscape architecture, especially in the design of two-dimensional garden layouts, The application research of AI is still in its early stages, but this is exactly the focus of our research. This provides landscape architects with a new design tool that they can further refine and optimize based on.

Shan and Sun [14] delved into the auxiliary usage patterns and detail optimization processes of VR technology in landscape design. And further validated its effectiveness through comparative experiments of indoor and outdoor landscape design. The Lumion platform provides a rich library of materials and powerful rendering capabilities, allowing designers to quickly generate high-quality virtual landscape images. The spatial data obtained through GIS systems can be visualized and analyzed in VR environments, helping designers more accurately grasp the relationship between geographical environment features and landscape elements, and providing a scientific basis for design. In the process of optimizing the details of landscape design, special attention is paid to the energy-saving optimization of the data collection system. For outdoor landscape design, VR technology can simulate a wider natural environment and landscape elements, helping designers better grasp the overall landscape effect. With the vigorous development of the social economy and the rapid advancement of computer software and hardware technology, computer technology is increasingly widely used in various industries, greatly promoting innovation and progress in the industry. Through virtual reality technology, designers and homeowners can immerse themselves in the future landscape environment, which will undoubtedly greatly improve the efficiency and effectiveness of landscape design. This software can not only achieve highly realistic virtual reality effects but also combine virtual design with real environments, providing a brand-new immersive experience for landscape design. In the landscape architecture industry, computer-aided design software has become an indispensable tool for landscape designers due to its precise, efficient, and convenient characteristics, and is widely used in fields such as interior decoration, advertising design, and urban planning [15].

With the progress of the times, people's lives have entered the information age, and urban commercial pedestrian streets have become one of the most frequent public spaces in people's lives. The landscape quality inside commercial pedestrian streets is also considered to represent the level of urban economic development and the level of intelligent popularization, by adding intelligent interactive experiences based on the principles and techniques of the original commercial pedestrian street landscape planning and design. To play a bridging role in the research of intelligent interaction and the planning and design of commercial pedestrian streets in China. Integrating intelligence and intelligence into urban public space planning and design, thereby providing a more refined design basis for the intelligentization of urban commercial pedestrian streets. Summarize and summarize a set of landscape planning and design processes suitable for the current information age for commercial pedestrian streets. Zeng et al. [16] used deep learning techniques and combined forest landscape geotagged photos from six case locations in China to explore preferences for different forest landscape scenes. This discovery has guiding significance for landscape design, suggesting that designers should fully consider the viewing habits and aesthetic preferences of tourists when planning forest recreation paths and observation platforms, ensuring that tourists can easily enjoy the most attractive forest landscapes. From the perspective of aesthetic space, research has found that people tend to prefer forest landscapes in flat views, such as overhead and forward views, while their attention to elevated views is relatively low. The study also found that although there is a certain preference for the internal landscape of forests, there is a lower preference for individuals, details, and the overall landscape. In green space planning, landscape design factors should be fully considered, such as landscape diversity, connectivity, and aesthetic value. Based on the spatial distribution characteristics of TDGV, it is possible to reasonably lay out green space in urban planning, ensuring the balanced distribution and efficient utilization of green resources. In the process of urban development, the impact of human factors such as urban planning and construction activities on green space cannot be ignored. Compared to the traditional role and artistic form of landscape design, designers will focus on considering factors such as user behaviour and habits when conducting interactive design. To immerse users in the landscape environment as tourists rather than spectators, the intelligent and interactive application of landscape design needs to be diverse and interdisciplinary. Unlike traditional design, interaction design is more concerned with the user's experience. Experience is first and foremost about experience, followed by perception, and only by placing users at the core. And we will study how to provide users with high-quality enjoyment in their interactions. Because of the development of Internet technology, the number of digital products is increasing, and there are more and more intelligent interactive landscapes between users and products [17]. As a densely populated public space in a city, commercial pedestrian streets are the most able to reflect the economic development level and social and cultural charm of a city. The emergence of these intelligent interactive technologies has gradually influenced the landscape architecture profession, providing many interesting and feasible design ideas for the landscape planning and design of commercial pedestrian streets. So every city should have at least one unique commercial pedestrian street that exudes its urban charm, which can be any aspect of the city. Whether it is cultural heritage or historical background, whether it is celebrities or strange stories, they can become highlights in commercial pedestrian streets in cities and be integrated into landscape design. It has received praise from visitors and tourists, further promoting and encouraging the development of intelligent interaction technology in the landscape planning and design of commercial pedestrian streets. At the same time, the rapid development of modern science has given birth to a large number of intelligent interaction technologies. However, its influence and popularity are still insufficient, and compared to foreign research processes, it is still in the early stages of development and has not formed a relatively complete theoretical system. Although intelligent interaction technology has been widely promoted and applied in landscape design in China. Therefore, it is urgent to incorporate intelligent interactive experiences into the landscape planning and design of commercial pedestrian streets.

3 INNOVATIVE MODEL OF CAD LANDSCAPE DESIGN BASED ON GAN

3.1 Model Design Principle

The foundational design tenet of this model draws inspiration from the core precept of GAN, wherein adversarial training enables the generator to fabricate lifelike design visualizations. Concurrently, the discriminator functions to discern between authentic and generated imagery. Within the realm of landscape design, the GAN's generative component crafts potential landscape design representations, while the discriminative element evaluates the logic and aesthetic merits of these depictions.

The goal of this model is to train the generator so that it can output images in China landscape painting style, and the whole training process can improve the level of the generator. Let $M = m_1, m_2, \ldots, m_n$ represent China landscape painting image data set, D represent the discriminator and G represent the generator. Where D is a function with a single image as the independent variable, that is, $D: M \rightarrow [0,1]$. Input an image and output the probability that this image is true. G is a function with a random vector as input, and the output is an image with the same size M as the image in Figure 1 shows the overall frame structure of this model.

The essence of GAN revolves around the creation of novel data via the interplay between its generative and discriminative components. Within the innovative CAD-integrated landscape design paradigm, the generative module crafts original landscape design proposals, whereas the discriminative module undertakes the task of distinguishing these proposals from authentic landscape design data. This dynamic interplay can be mathematically expressed by a specific formula:

$$G^* = \arg\min_G \min_D V\ D, G \tag{1}$$

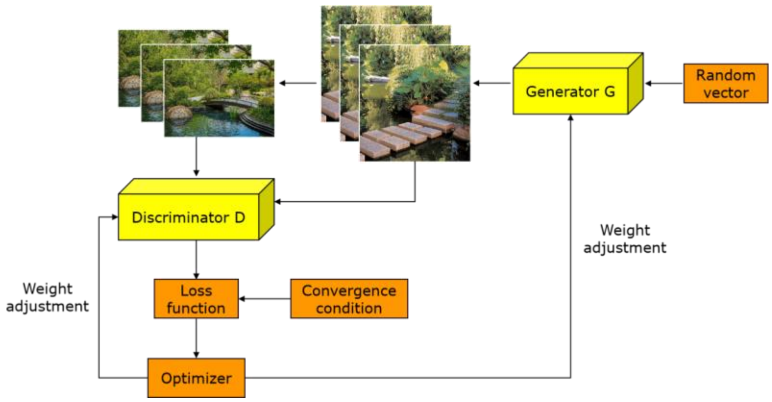

Figure 1: Integral frame structure.

Among them, G stands for generator, D stands for discriminator, and $V(D,G)$ is a value function, which is used to measure the game effect between discriminator and generator. In the actual training process, the value function $V(D,G)$ can be defined as:

$$V(D,G)=E_{x\sim p_{data}(x)}\left[\log D(x)\right]+E_{z\sim p_z(z)}\left[\log(1-D(G(z)))\right] \tag{2}$$

Here, $p_{data}(x)$ is the distribution of real landscape design data, and $p_z(x)$ is the noise distribution input by the generator. By minimizing the loss of the generator and maximizing the loss of the discriminator, GAN can gradually improve the authenticity and diversity of generation schemes.

When realizing the innovative model of CAD landscape design based on GAN, the network structure design of the generator and discriminator is very important The network structure of the generator can be expressed as:

$$G(z)=f_G(z;\theta_G) \tag{3}$$

Where f_G stands for the neural network of the generator, z is the random noise input, and θ_G is the parameter set of the generator.

Accordingly, the network structure of the discriminator can be expressed as:

$$D(x)=f_D(x;\theta_D) \tag{4}$$

Where f_D stands for the neural network of the discriminator, x is the input data (which can be real data or generated data), and θ_D is the parameter set of the discriminator.

It can be seen that under the new trend, intelligent interactive landscapes have two attributes: physical space and digital space. Digital space can serve as a new manifestation of the urban landscape in the new era. This viewpoint is not only a metaphor but has also become a reality. And here we are exploring more about the digital space of intelligent interactivity. The importance of its interface in constructing digital space cannot be overstated, as it takes various forms and can serve as a bridge between urban physical space and digital space - a low-dimensional and multi-dimensional connection. Here, space refers to the urban landscape space where information devices and multi-channel sensors are embedded. As a carrier of information transmission, this landscape scene is not only a traditional physical space but also a medium for digital space.

3.2 Model Architecture and Implementation

Scale is a crucial factor in intelligent interactive landscape design. We use scale research to grasp the overall interaction design. Therefore, the author hopes to explore from both macro and micro perspectives and analyze the impact of scale on intelligent interactive landscape design. The landscape space domain has three-dimensional properties. When the landscape domain is considered as a "point", it will draw attention from the "points" in the landscape. Sometimes the landscape field is viewed as a "line", dominated by linear factors, and the dimension that determines landscape concepts is a unidirectional dimension; When the landscape field triggers the audience's conscious behaviour with the characteristic of "surface". Intelligent interactive landscape design cannot escape the three-dimensional macro scale, and its constituent relationships must also be considered in the design process, and cannot exceed the three-dimensional category of matter. The landscape dimension is a two-dimensional dimension; When the landscape domain triggers the audience's perception of the overall space, that is, "domain", it is the three-dimensional dimension of space. This has a macro control over the scale of interactive facilities in landscape design.

Generator loss:

$$\xi_G = -E_{z\sim p_z(z)}\left[\log D(G(z))\right] \tag{5}$$

Discriminator loss:

$$\xi_D = -E_{x\sim p_{data}(x)}\left[\log D(x)\right] - E_{z\sim p_z}\left[\log(1 - D(G(z)))\right] \tag{6}$$

The parameters are updated by the gradient descent method, and the specific updating steps are as follows:

Generator parameter update:

$$\theta_G \leftarrow \theta_G - \alpha \nabla_{\theta_G} \xi_G \tag{7}$$

Discriminator parameter update:

$$\theta_D \leftarrow \theta_D - \alpha \nabla_{\theta_D} \xi_D \tag{8}$$

For the implementation of this model, TensorFlow serves as the framework for its construction and training. Initially, the model undergoes pre-training to familiarize itself with fundamental terrain and vegetation data. Subsequently, genuine landscape design data is employed to fine-tune the model, enhancing its generative capabilities. The training process incorporates an alternating optimization strategy, wherein the discriminator is first trained to accurately discern between authentic and generated imagery, followed by the generator's refinement to craft more convincing visuals that can deceive the discriminator.

3.3 Data Set and Model Training

The data used in the model training comes from the Internet, and 1359 images with Chinese classical garden style were successfully obtained by using the crawler program, as shown in Figure 2. These images will serve as the basis of the training data set.

To accommodate varying image sizes, we employ scaling, cropping, and flipping techniques to standardize the images and enrich the dataset. For images where the short side's length falls below 80% of the long side, we randomly extract three square regions, each measuring the same length as the short side. Conversely, we crop the image based on 80% of the long side's length. Then, the cropped images are rotated by 90, 180 and 270 and flipped horizontally, and finally, all the images are processed to the size of 200*200 pixels. After the above operations, our training data set has been expanded to 19,920 images. Figure 3 shows some image samples that have been cropped, rotated, and flipped. Before training, all images are normalized. The normalization formula is m'=(m-127.5)/127.5, where m represents the original pixel value (range 0-255), and the normalized pixel value is limited in the interval of [-1,1].

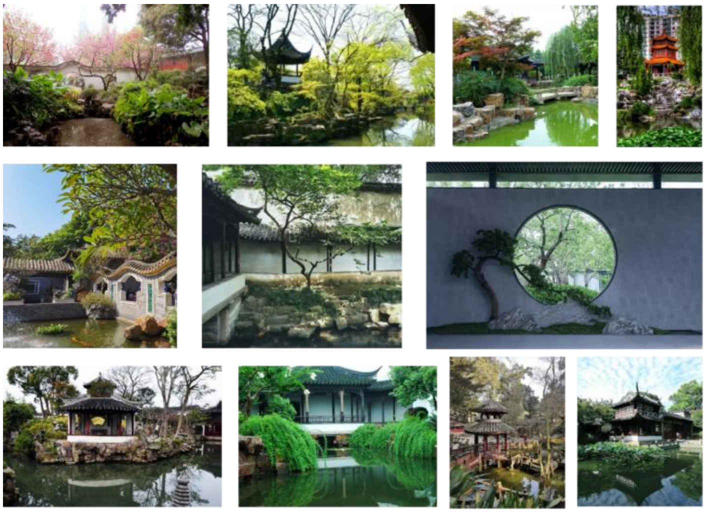

Figure 2: China classical garden style image training data set.

Figure 3: Example of image rotated and flipped after cropping.

Next, the processed images are divided into several batches for training, and each batch contains 16 images. In each training, a set of noise data is generated, which consists of a 100-dimensional real-valued vector, and each element of the vector is in the [0,1] interval and obeys the standard normal distribution. These noise data are input into the generator, and then the discriminator will score the image output by the generator and the real image. According to the scoring results, the respective loss function values and gradient values are calculated and optimized by the optimizer. Every 100 training sessions, the model will be automatically saved.

The model is implemented in Python programming language and based on TensorFlow 2.0 deep learning framework. The training of the model was executed on a computer equipped with an Intel i7 CPU, 32GB of RAM, and an NVIDIA GeForce 1080 Ti graphics card with 11GB of memory. Throughout the training cycle, TensorBoard provided real-time oversight, documenting the fluctuations in the loss values of both the generator and discriminator. As illustrated in Figure 4, as the training advanced, these loss values gradually converged towards stability.

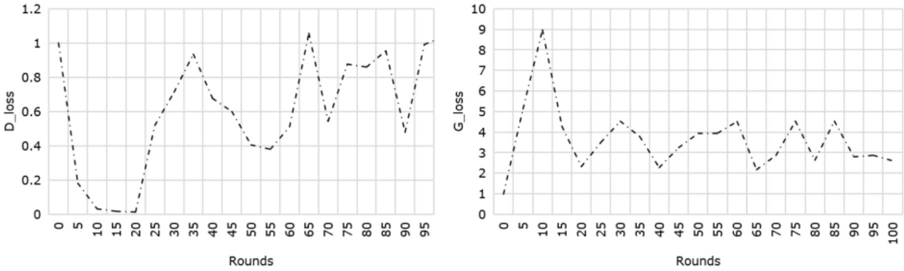

Figure 4: Variation of loss function value.

During the training phase, the output of the generator evolved significantly, transitioning from an initial random and unordered state to a distinct image embodying the classic Chinese garden aesthetic. This transition process is essentially a process in which the initial parameter distribution of the generator gradually approaches the probability distribution implied in the training data set. Figure 5 shows some output images of the generator during training.

Figure 5: Partial image output during the generator training process.

After sufficient training, the generator can output image samples in China's classical garden style, as shown in Figure 6.

By reducing the channel count in each layer of the discriminator and generator by half, we scale down the model's capabilities and parameters, ultimately speeding up the training. Nevertheless, this adjustment comes with a trade-off: a decline in the quality of the generated images. Upon retraining the model, an image sample, as depicted in Figure 7, reveals that with half the channels, the image quality noticeably diminishes, exhibiting more blank spaces and a less pronounced style that characterizes classical Chinese gardens.

4 EXPERIMENT AND ANALYSIS

The data presented in Figure 8 aptly captures the observer's subjective evaluation of the innovative GAN-based CAD landscape design model against the conventional CAD design approach. The results indicate that the new model garners a higher rating, suggesting significant advantages from an observer's perspective over the traditional methodology.

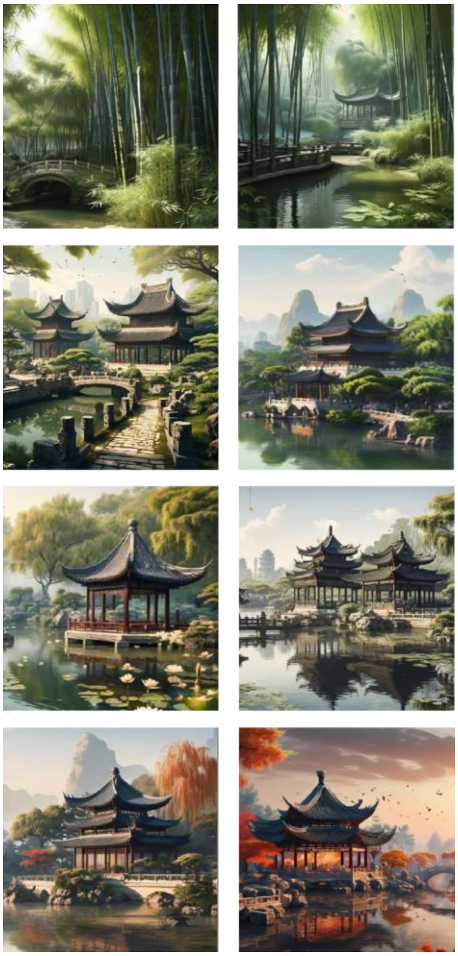

Figure 6: Example of classical garden-style image output by the generator.

Figure 7: Image generated by the model under the condition of a small parameter scale.

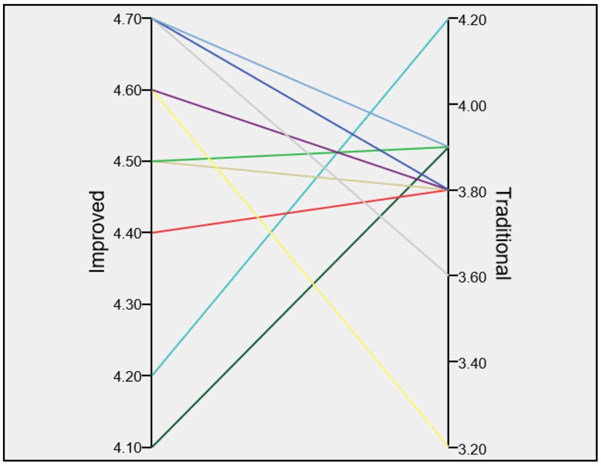

Figure 8: Subjective assessment of landscape design given by observers.

Figure 8 quantitatively presents the subjective evaluation comparison between the new GAN-based CAD landscape design model and traditional CAD design methods by observers. From the data in the figure, it can be seen that the new GAN-supported design model significantly received higher evaluations, which clearly indicates that from the observer's perspective, the new model demonstrates significant advantages compared to traditional methods. This advantage is not only reflected in the technical aspect, but the introduction of GAN technology in the new model makes the landscape design process more intelligent and efficient. The generative ability of GAN ensures the diversity and innovation of design works. At the same time, its powerful learning ability enables the model to continuously learn and optimize itself from data, thereby generating more realistic and artistic landscape design solutions.

Figure 9 provides a stark comparison between the GAN-based CAD landscape design approach introduced in this article and alternative algorithms in terms of image clarity and 3D impact.

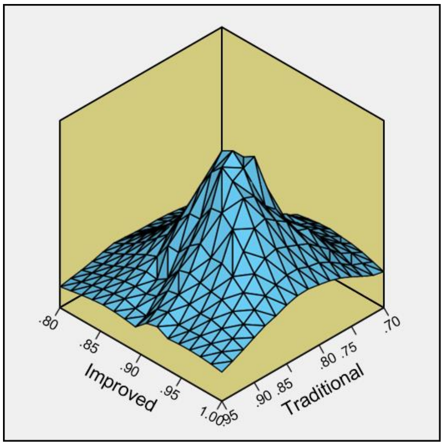

Figure 9: Accuracy results of different algorithms.

Figure 9 visually illustrates the excellent performance of the GAN-based CAD landscape design method compared to other algorithms in terms of image clarity and 3D impact, as introduced in this article. From the data in the figure, it can be seen that our new method has achieved significant results in overcoming common problems such as image blur and lack of depth perception. Of particular note, compared to traditional methods, our method has improved accuracy by 28.47%, which significantly validates the enormous potential of GAN in the field of CAD landscape design. When analyzing this result in depth, we can find that GAN's unique structure brings unprecedented advantages to CAD landscape design. Through adversarial training between the generator and discriminator, the GAN model can learn more realistic and delicate image features, thereby generating landscape design images with higher clarity and three-dimensional sense. This ability enables designers to achieve more realistic and engaging design results in a shorter period of time, greatly improving design efficiency and quality. In CAD landscape design, the introduction of GAN can significantly improve the clarity and 3D sense of the image. Through the game between generator and discriminator, the model can learn more realistic image features, thus generating high-quality design images. This advantage enables designers to obtain more satisfactory design results in a shorter time.

Figure 10 illustrates a comparative analysis of the time efficiency of various approaches in CAD landscape design. As the intricacy of the design escalates, reflected in the proliferation of feature pixels, the processing duration for CAD landscape design also extends. Nonetheless, amidst this trend, the algorithm introduced in this article demonstrates a remarkable edge in terms of efficiency.

Figure 10 provides an intuitive data display of the comparative analysis of different methods in processing time in CAD landscape design. With the gradual increase in design complexity, such as the sharp increase in the number of feature pixels, the processing time of CAD landscape design software is also showing an upward trend. In this generally extended processing time, the algorithm proposed in this article demonstrates significant efficiency advantages compared to traditional methods. The complexity of design is not only reflected in its final presentation of beauty and precision but also closely related to the diversity of internal composition elements and the richness of details.

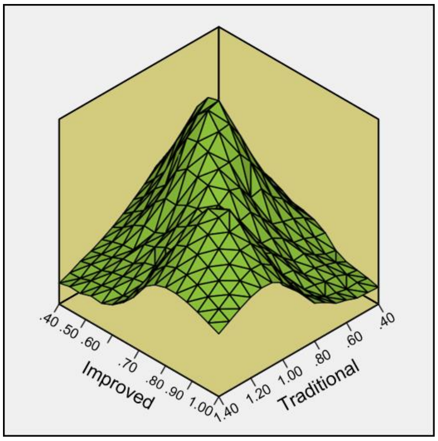

Figure 10: The processing time of CAD landscape design using different methods.

These detailed elements, such as trees, flowers and plants, water bodies, buildings, etc., need to be accurately represented through a large number of pixels in CAD design software. Therefore, as the complexity of the design increases, the amount of data that needs to be processed also increases sharply, leading to an increase in processing time. The intricacy of a design often correlates directly with the abundance of its constituent elements and detailing. As these factors proliferate, the volume of data requiring CAD software processing grows, inevitably augmenting both processing duration and computational resource expenditure. Nevertheless, within comparable complexity levels, our proposed algorithm demonstrates a notably shorter processing time than its counterparts. This edge translates into swifter design task completion and heightened efficiency, enabling designers to cater more effectively to client demands.

5 CONCLUSIONS

This study explores the innovative application of Generative Adversarial Networks (GANs) in computer-aided design (CAD), particularly in the field of landscape architecture, and successfully develops a new landscape design model. This model effectively combines the generation ability of GAN with the precision and practicality of CAD technology, providing new creative sources and efficient tools for landscape design. This study delves into the practical application of Generative Adversarial Networks (GANs) in the field of landscape design and significantly validates their outstanding ability to create highly artistic and innovative landscape design solutions. These design schemes generated by GAN not only retain the integrity of art but also achieve significant improvements in novelty and quality, meeting the high requirements of contemporary landscape design for diversity and personalization. Furthermore, this study innovatively combines GAN with computer-aided design (CAD) technology, achieving a rapid transition from design concepts to practical applications. Through deep learning of a large amount of design data and artistic styles, GAN can generate design schemes that comply with design rules and are full of innovative inspiration, greatly enriching the diversity and expressiveness of landscape design. The perfect combination of technology and art not only greatly improves design efficiency and reduces design costs, but also brings new development opportunities and broad market prospects to the landscape design industry. The introduction of CAD technology ensures the accuracy and practicality of design schemes, enabling innovative designs created by GAN to be smoothly transformed into actual landscape works. Through this study, we look forward to the further integration of GAN and CAD technology, bringing more innovation and breakthroughs to future landscape design.

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