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The Applications of Generative Adversarial Networks in Architecture Design: A Systematic Review

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Abstract: Purpose: To review and analyze the research status of the application of generative adversarial networks (GANs) in the field of architecture design. Methods: This study followed the latest PRISMA guidelines and systematically collected relevant research literature from domestic and international sources. In-depth analysis was conducted on 95 representative Chinese and English language articles. During the analysis process, three dimensions of intelligent architectural generation methods were comprehensively and deeply explored: the data application scale, algorithm type, and architectural design process. Results: (1) GANs have been applied to various processes in architectural design practice, from design generation, development, and evaluation to final solution expression; (2) GANs can be applied at different architectural scales, ranging from large-scale complex functional buildings to refined layout designs of residential units; (3) the appearance of GANs enables designers to quickly present design results at various stages, greatly improving work efficiency; and (4) at present, GANs also have many shortcomings, mainly reflected in the accuracy of the data and the usability of tools. Conclusion: Improvements in computer performance and the enrichment of data resources have promoted the widespread application of intelligent architectural generation methods. GANs have great potential in the field of architectural design and can provide a more efficient, flexible, and diverse design process. However, further research and development are needed to address the challenges and limitations of using GANs in this field.

Keywords: Generative Adversarial Networks; Architecture design; Deep learning; Intelligent buildings; Design methods

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Introduction

In recent years, deep learning technology has been applied widely across various domains, achieving significant breakthroughs. Particularly noteworthy is the generic adversarial network (GAN) framework, introduced by Ian J. Goodfellow and collaborators in 2014 [1]. The GAN framework comprises two crucial components: the generator and the discriminator. (**Figure 1**) The generator's primary objective is to assimilate the features of the data distribution from the training data and subsequently generate novel data samples. Conversely, the discriminator is tasked with discerning whether the samples produced by the generator closely resemble authentic data. During the training process, a zero-sum game dynamic emerges between the generator and discriminator. The generator and discriminator engage in an iterative training process, gradually converging toward equilibrium. The discriminator cannot distinguish between authentic data and generated samples after repeated iterations [2].

GANs have achieved significant advancements in image generation, translation, and enhancement across various domains [3]. Their proficiency in producing high-quality images has found utility in graphic design, game development, and related sectors [4, 5]. In addition to being proficient in computer graphics, GANs excel at creating top-notch visual content, particularly 3D modeling and animation [6]. GANs can accommodate diverse data formats beyond the visual domain. They are effective at manipulating textual data in fields such as natural language processing, machine translation, and text generation [7]. Additionally, GANs facilitate audio tasks such as music synthesis and speech synthesis. GANs can be applied across a variety of fields, making them capable of innovating and enhancing various aspects of data generation [8]. Due to the strong application potential of GANs, researchers in the field of global built environments are beginning to apply GANs to built environments. Architectural design plays an important role in the design of built environments.

At present, there are many problems in architectural design methods, including long design cycles, difficulty communicating design concepts and collecting feedback, difficulty in modification and high cost, and difficulties in cooperation, leading to design inconsistency and communication interruption. In addition, traditional design methods may be limited by designers' skills and creativity, and it is difficult to produce innovative or unique designs [9, 10]. Therefore, architectural design urgently needs technical innovation to change traditional design methods. The GANs can solve the above problems. At present, it has shown application potential in several fields, such as site environment analysis [11], 3D model creation [12], architectural style generation [13], and plane layout [14].

In this paper, we systematically reviewed 95 studies on the application of GANs in architectural design at home and abroad, covering new design methods applied in site design, architectural design, and interior design. This paper classifies and summarizes the work that GANs can perform in the current architectural design workflow and demonstrates the role of GANs in the architectural design workflow from multiple perspectives.

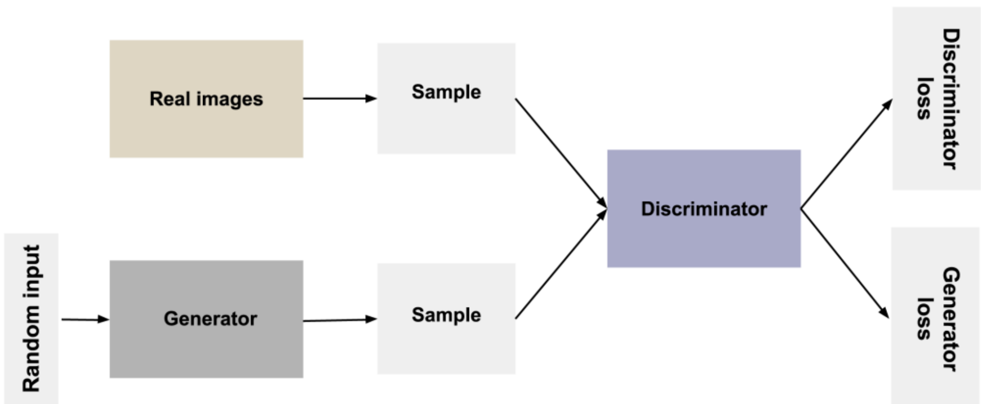

Figure 1. General architecture of a GAN (provided by Yang Xu)

This paper aims to explore the cutting-edge application of GANs in architectural design and further promotes the development of artificial intelligence in the field of architectural design. In the second section, we analyze the existing relevant literature. The third section introduces the methods of our review. The fourth section discusses the application potential of GANs in the architectural design process by analyzing the application of GANs in the architectural environment. Finally, the fifth section summarizes the main lessons and common limitations and outlines three research breakthroughs in the application of GANs in industry.

Literature Review

Current research into the application of GAN in the built environment spans multiple perspectives and has yielded fruitful results. Several researchers have systematically reviewed the research progress and limitations in this emerging field.

Based on the preliminary literature collection, five review papers supplemented our research work by looking at the topic of this paper from different perspectives.

This paper pays more attention to the combination of GANs and architectural design practice than the previous work and explains the application potential of GANs from the architectural scale. This article pays special attention to the application of GAN in various fields of the construction industry focuses on the application prospect of GAN in the architectural design method.

Wu et al. [15] introduced the application of GANs in the building environment. The author analyzes the architecture and applicability of the current GAN model and summarizes the relevant research. This paper introduces the application of GANs in urban, regional, and architectural levels from three topics: data integration, data enhancement and design automation. However, there is still a lack of high-quality data sets specifically for built environment issues, which may limit the potential of GANs in this field. As more data appear in the future, GANs can produce better results in the building environment.

Baduge et al. [16] conducted a comprehensive review of the application of artificial intelligence, machine learning and deep learning in the construction industry 4.0. This overview paper covers the application of these technologies in seven fields, including architectural design and visualization, material design and optimization, structural design and analysis, remote manufacturing and automation, construction management and safety, intelligent operation and building management, and durability and circular economy. This paper considers the application of these technologies in the whole building life cycle, and provides information on data collection and storage, as well as challenges and potential solutions involved in model development.

Hughes et al. [17] discussed the impact of artificial intelligence, especially GANs on creativity and design practitioners' work in improving creativity, productivity, and design vision. The study systematically reviewed publications indexed from various sources from 2015 to 2020, found 34 studies, and highlighted the main trend of using GANs in the design field. The review highlighted the limitations of these studies, including the lack of user research and the widespread small-scale examples or practices. The results of the study are summarized in the following table and areas for future research are identified.

Zhao Jing et al. [18] focused on the generation of small-scale spatial layout. This study proposes two types of problems in small-scale space design: convergence and divergence, explains the advantages of GAN in solving different problems from the perspective of algorithm principle, and clarifies the positioning and research significance of GAN in solving divergence problems in generative design. Based on the characteristics of GAN, the research demonstrates its application bottleneck, and summarizes the current situation and future development trend of GAN in application. Finally, the study proposed four specific future development directions: interpretability, controllability, achievement evaluation and experimental deployment.

Jiawei Yao et al. [19] explored a self-feedback architectural intelligent generative design workflow integrating shape generation grammar, multi-objective optimization, and evolutionary algorithms from "the perspective of environmental." material performance. The design process aims to solve the complex relationship and contradiction between the static architectural material space form and the dynamic environmental material performance, providing new theoretical and practical ideas for the future sustainable city and architectural design.

Data Types and Scales for Building Design

This paper discusses the multiple spatial scales of architectural design, which need to address different types of information and data. It is highly important to map the data to the appropriate scale to select the best GAN framework for tasks at different scales. **Figure 2** shows 11 data types, which can be divided into three scales: the block design scale, architectural design scale and interior design scale. Most data types are related to specific design metrics.

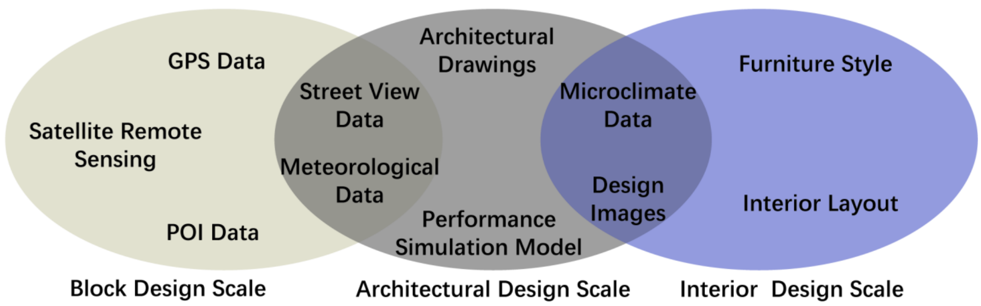

Figure 2. Data types at different scales in the architectural design process (provided by Nanqiao Shi)

This paper discusses the data types of different scales in architectural design and their application to GANs. At the scale of block design, GANs can use information such as population data, land use patterns, transportation networks and environmental characteristics to generate data-driven models to support decision-making throughout the whole design process. In architectural design and interior design, GANs can use a variety of data types, including 2D and 3D architectural drawings, BIM, images and videos of existing buildings and structures, GIS data, and text data such as building specifications and descriptions. The specific application of GANs depends on task requirements, such as style classification, damage recovery, material and texture generation, room layout generation, lighting simulation, indoor theme color and 3D modeling.

Types of Gans Used in Architectural Design

At present, many GAN algorithms have been applied to architectural design practice, but their generation conditions are different. Many powerful GAN models for different tasks have been open source, decreasing the threshold for scholars and designers to enter the GAN research field; moreover, researchers in the computer science field can use these algorithms. When applying GANs to architectural design, researchers at home and abroad have used these open-source libraries, which can be divided into the following three categories according to the literature.

The application of GANs in architectural design can generate architectural designs based on topological relationships. To this end, we need to construct a GAN architecture that can learn the relationships between various elements in architectural design, such as walls, doors, and windows. The building design dataset is used to train the GAN, the topological representation of the building is taken as the input, and the data are exported to the final design. GANs can then be used to generate a new design, taking the new topology representation as input, and generating the corresponding design [20].

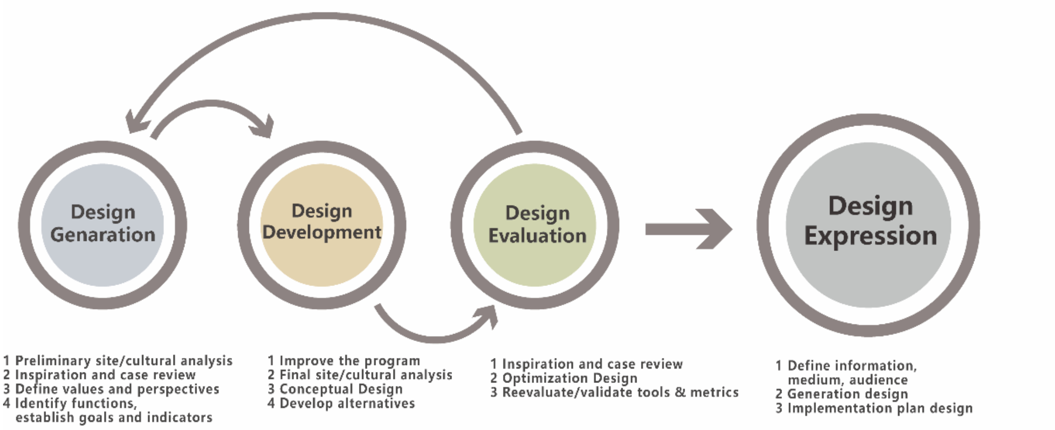

Figure 3. The architecture design process (provided by Nanqiao Shi)

In this paper, the GAN algorithm is applied to classify four stages of architectural design: design generation, design development, design evaluation and design expression (**Figure 3**). The design generation included a preliminary site survey and analysis, context analysis, preliminary design concepts, project function configuration, design objectives and design themes. The design development stage is the concept stage, and the design results are relatively complete. The design evaluation evaluates the design scheme based on the site conditions, needs and economic indicators. The design expression is the drawing and reporting stage after the final scheme is determined. The application of GANs can improve the creativity and productivity of designers [21].

Research Methods

This study used the latest PRISMA Guide [22] for literature screening to identify, select and review the Chinese and English literature containing the keywords "architectural design," "generation of confrontation network" and "GAN." The literature was retrieved from the CNKI and Web of Science databases. We determined the documents that met the requirements by searching and preliminary screening and further screened them according to the relevance of the research object and the architectural design, the applicability of the research conclusions, and that the language was Chinese or English.

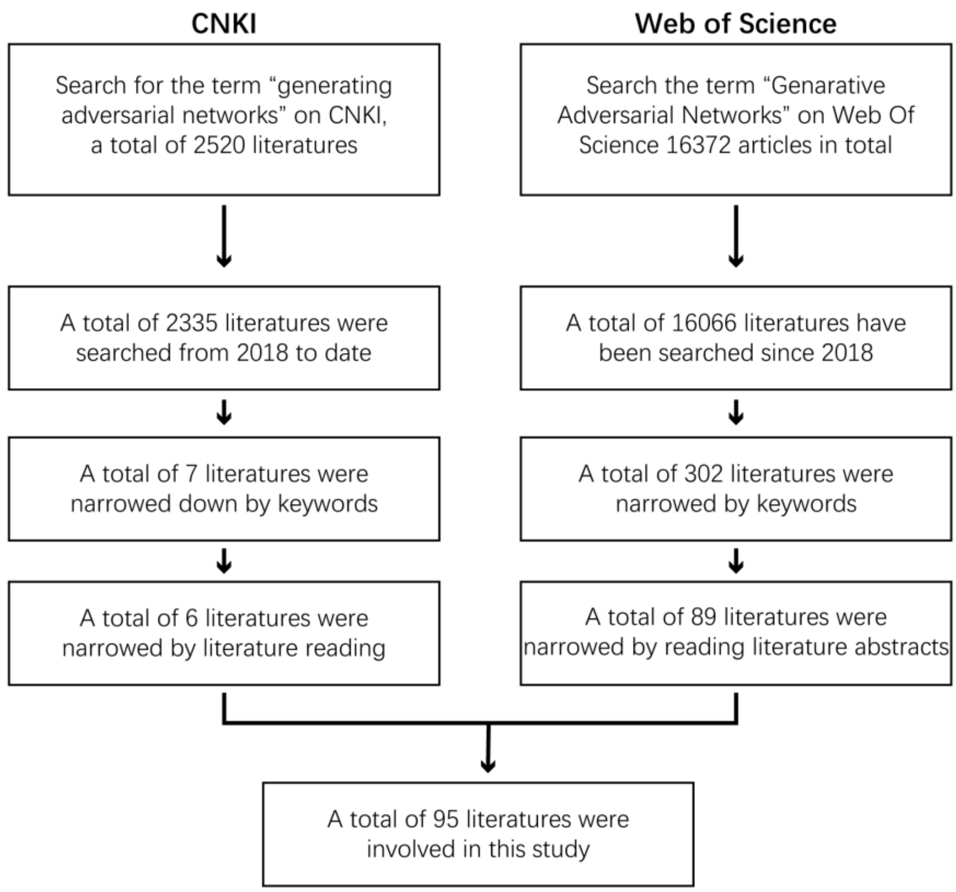

Figure 4. PRISMA flow diagram for literature selection (provided by Yang Xu)

This article introduces a search and filtering strategy, as shown in **Figure 4**. First, the paper titles, abstracts or keywords containing the keywords "General Adversarial Networks," "Generating Countermeasures Networks" and "GAN" were used for preliminary screening to ensure that papers with GANs as the main application mode were included. Next, the thematic keywords used were further selected for papers related to architectural design. The English keywords used were "3d building," "urban design," "architect," "site analysis," "building simulation," "building design," "layout," "façade," "material selection," "lighting design," "color," and "building structure." With these keywords, the research scope was narrowed, and 302 search records were obtained. The Chinese keywords used were "3D modeling," "structural design," "urban design," "architectural design," "plane layout," and "light environment." Using these keywords to narrow the scope of the research, a total of 7 search records were obtained. These keywords cover research from building block design to building interior design, as well as different types of applications from data processing to intelligent design. We read the qualified literature in detail and selected 95 representative Chinese and English studies from 309 studies for analysis. The screening criteria mainly include that the research object is related to the architectural design, and the research conclusions can be applied to the architectural design process. We are committed to demonstrating the application prospects of generative confrontation networks in architectural practice through careful screening and analysis.

Design Generation

In the early stage of architectural design, the design generation phase needs to balance diversity and complexity. The GANs can improve design efficiency. By analyzing historical data and current design requirements, a variety of possible design schemes can be generated to help designers quickly explore different options. In addition, GANs can also consider various factors, such as the design budget, environmental factors, and specifications, to help designers conduct more scientific and systematic design evaluations.

The GANs can generate new designs by using site data, which are determined by the unique characteristics and constraints of the site. The first is the site background analysis. GANs can be trained according to site data to generate designs provided by local environments (such as road networks, terrains, climates, and land use). This enables architects to quickly generate multiple designs based on site conditions, reducing the time and resources required for manual site analysis [23].

Data estimation refers to various applications that use GANs to predict missing data using the context information obtained from the training dataset. Zhang et al. [24] created a method to estimate changes in regional traffic conditions to help urban planners assess the impact of different traffic design schemes. The generator can generate real traffic conditions without observing the travel conditions. At the urban scale, Albert et al. [25] were among the first people to apply conditional GANs to simulate urbanization patterns under different urban conditions. Johnsen et al. [26] used a GAN to estimate the demographic data of urban residents in new community development (for example, family type and composition, income, and sociodemographic statistics) to measure the social impact of new real estate development. Recently, Ibrahim et al. [27] used a GAN to estimate the future housing growth patterns of different population groups in Doha, providing a new data-driven method for population and urbanization simulation. Sun et al. [28] studied the historical urbanization model from 1988 to 2015 and predicted future land use and land cover changes in Shenzhen.

Analysis of site performance. GANs can be used to generate designs that optimize specific performance indicators, such as energy efficiency, sunshine conditions, and ventilation conditions [29, 30]. This allows architects to quickly evaluate multiple design options and make informed decisions based on the performance requirements of a particular site. These are several ways for GANs to participate in site analysis in the process of architectural design.

In the early stage of design, architects often use sketches to think and deduce design schemes. The point of a sketch is that it can quickly express the inspiration of the designer at the initial stage of creativity, but there is still a large gap between the sketch and the final scheme. Experienced designers often have more accurate control over the site than young designers. A complete representation of the building in the sketch stage can improve the accuracy of the designer's judgment of the development direction of the scheme and further improve the work efficiency. At present, GANs have been able to carry out some preliminary processing [31, 32, 33] for designers' sketches.

Design Development

GANs can help designers explore different design schemes and find inspiration, which is very useful in the early stage of the design process. For example, in residential design, the process of designing modular housing is expensive and time-consuming and needs to be modified repeatedly to meet specific requirements, while meeting all functional requirements within a limited budget remains a challenge. Ghannad et al. [34] proposed a new CoGAN-based automated modular housing design generation framework, which includes a new module configuration algorithm to generate an optimal housing design layout. The framework is expected to contribute to the knowledge system of the generative design of modular housing for large-scale construction production and help architects and relevant clients communicate effectively in the design process.

GANs also play an important role in building appearance design. On the one hand, this approach can generate building elevations that conform to the surrounding environment. Kelly et al. [35] proposed a solution called FrankenGAN, which can create reasonable details on multiple scales of large neighborhoods and produce consistent styles between buildings and neighborhoods, while users can directly control the variability of output. This system allows users to specify styles interactively through images and control the variability of styles by manipulating the sliders corresponding to styles. This idea can also be widely used in the field of architectural heritage protection [36]. Lorusso et al. [37] provide a graphic decision support tool based on the generation confrontation network for urban renewal to formulate new color codes and respect the original color codes. The proposed method was tested in the historical center of Caggiano, Italy. The generated color code is evaluated and compared with the color plan adopted at that time, and the results are very close to those of the traditional design method.

Design Evaluation

During the assessment phase of the design process, conflicts often arise due to factors such as site conditions, building structure, client requirements, energy consumption considerations, economic constraints, and technical indicators. These conflicts may lead to evaluation outcomes that fall short of expectations, necessitating a return to the design generation stage for refinement. GANs offer valuable contributions by engaging in the evaluation and analysis of architectural designs. These methods achieve this through performance prediction, design optimization, and comparative analyses, thereby enhancing both the efficiency and quality of the design process.

GANs can undergo training on datasets comprising architectural designs and corresponding performance data, such as energy consumption or indoor air quality. This training equips GANs with the capability to generate architectural designs that adhere to specific performance criteria and subsequently evaluate the performance of the generated designs. In the context of energy consumption, Tian et al. [38] introduced a novel approach known as E-GAN, which was designed for predicting the daily power demand of large-scale buildings. E-GAN integrates a physics-based model (EnergyPlus) with a data-driven model (GAN). The methodology involves selecting a limited set of representative buildings, forecasting their power demand using the EnergyPlus model, and employing a GAN to extrapolate the power demand for a broader spectrum of buildings. The findings indicate that E-GAN yields precise power demand predictions, boasting an error rate of only 5%. Notably, compared to the computation time required by physics-based models, E-GANs complete calculations in only approximately 9% of the time.

In terms of structural design, Lu et al. [39] proposed a physics-enhanced GAN for the intelligent structural design of building structures. Research shows that, compared with the traditional data-driven design method, the proposed method can generate structural design more quickly and accurately from architectural drawings and specified design conditions. In terms of fire safety, Jin et al. [40] proposed a deep sequence learning model called the fire situation prediction network (FSFN), which uses regional urban fire alarm data to predict urban fires.

GANs can be used to optimize architectural design by training a GAN on a dataset of architectural design and related performance data and adjusting design parameters to generate designs that meet specific performance standards. Huang et al. [41] proposed using the generated adversary network as a substitute model to accelerate environmental performance-driven urban design. The GAN model can be trained to predict pedestrian altitude, wind speed, annual cumulative solar radiation, and the general thermal climate index in real time. The substitution model based on a GAN is combined with a multi-objective genetic algorithm to realize real-time optimization of urban morphology. The results showed that this method has a temporal advantage over traditional methods in outdoor environment optimization in urban design. Compared with numerical simulation methods, the GAN model can accelerate this process by 120-240 times. Kim et al. [42] used machine learning (ML) models to extrapolate unmeasured wind speeds around buildings to realize comprehensive analysis of the wind flow mode. He et al. [43]showed that these models can extract features from general architectural forms and provide accurate predictions, which may be integrated into automatic form finding and design optimization. Lu et al. [44] proposed a method that combines performance simulation, machine learning and algorithm generation with parametric design and optimization methods to optimize architectural design strategies according to specific environmental goals. The authors used a generated countermeasure network to predict environmental performance based on simulation results and carried out multi-objective optimization through the rapid evolution of a genetic algorithm combined with a database.

GANs can be used to compare and evaluate different design schemes. Designers need to compare different design schemes to make wise design decisions. Many scholars propose the use of virtual reality (VR) to assist in model performance evaluation.

Design Expression

Within the realm of architectural design, GANs find application in diverse facets of design communication and rendering. For instance, GANs are adept at transferring stylistic elements from one architectural design to another, thereby generating a novel design with a similar aesthetic [45]. Furthermore, to address 2D representations, Ye et al. [46] introduced an intelligent rendering tool named Masterplan GAN. This tool, grounded in crowdsourced data and the GAN framework, swiftly produces color master plan renderings within seconds, enhancing the efficiency of urban master plan visualization.

In indoor plan drawing, Kim et al. [47] used the conditional GAN to retrieve the indoor structure from complex plan images and unified the style of various plan formats before vectorization.

GANs can generate high-quality 3D visualizations of architectural design, which can help designers convey design ideas to customers more vividly and interactively in the design communication and rendering stages. Yang et al. [48] proposed a new GAN framework to automatically represent indoor images with realistic and aesthetic effects from ordinary images; this framework can convert original 3D geometry into indoor scenes with rendering effects without actual ray tracing calculations. GANs can be used to generate virtual reality (VR) experiences in architectural design so that designers and customers can experience design in a more immersive and interactive way.

Future Trends

For GANs to better play a role in the field of architectural design, this article proposes that improving the resolution, authenticity and accuracy of the generated architectural design data is necessary. These aspects are crucial for the application of GANs in different fields and scenarios. Therefore, this paper looks forward to several possible research directions and methods. First, multiscale generators and discriminators can be used, super-resolution methods can be used, or progressive training strategies can be used to improve the resolution of the generated architectural design data, thereby providing additional information, and increasing the suitability of complex architectural design and analysis. Conditional generative adversarial networks can be used, self-attention mechanisms can be used, or cycle consistency methods can be used to improve the authenticity of generated architectural design data, thereby allowing us to better reflect the architectural characteristics and laws of the real world and being more suitable for architectural design verification and evaluation. Variational autoencoders to generate adversarial networks can be used, knowledge distillation methods can be used, or multi-objective optimization methods can be used to improve the accuracy of generated architectural design data, thereby better meeting the goals and needs of architectural design; additionally, these methods are more suitable for the optimization and improvement of architectural design.

Another future trend is to use other data sources, such as satellite imagery or lidar, to enhance the information content and dimensionality of the architectural design data generated by GANs. This is a promising research direction because it can make the architectural design data generated by GANs richer and more diverse. Lidar data are used as input or auxiliary data for GANs to generate additional three-dimensional and detailed architectural design data, thereby improving the resolution and quality of the data. This helps designers express the form and structure of the building, as well as the building's materials and textures. Combined with street view 3D image data to generate more complete and accurate 3D architectural design data, 2.5 or 3D architectural design data can be generated to support research and applications in energy, climate, urban form, and other areas. This approach can help designers evaluate a building's performance and effectiveness, as well as its impact on the environment and society.

In addition to improving the resolution, authenticity, and accuracy of generated architectural design data, this article proposes that there are other challenges and opportunities for the application of GANs in the field of architectural design. The impact of breakthroughs in computer performance and changes in the underlying logic of GAN algorithms on the application of GANs in the field of architectural design can be explored. This allows GANs to process larger-scale and higher-dimensional data, thereby generating more refined and complex architectural design data. This also allows GANs to be trained more stably and efficiently, thereby improving the quality and diversity of generated architectural design data. The role and impact of GANs in architectural design and how GANs collaborate and interact with human designers and planners can be explored. This approach can help designers improve creativity and efficiency, as well as communication and coordination with other professionals and stakeholders.

This article hopes that these research directions and methods can lead to new breakthroughs and innovations in the application of GANs in the field of architectural design and provide new ideas and tools for architectural design practice and theory.

Conclusion

At present, there are many difficulties in the popularization of this technology. Most practitioners in architectural design-related fields are from architecture or design backgrounds. The professional education of these individuals is affected by traditional design education, and they often lack relevant professional knowledge in the computer field. Therefore, when using GANs, there are often high professional thresholds and high learning costs. However, designers often have good design modeling and drawing ability. At present, the mainstream modeling software used includes Sketchup and Rhino. Among these, Rhino's Grasshopper platform has powerful parametric modeling capabilities and can interface with various computer languages. The Grasshopper plug-in is expected to help realize the perfect link between GANs and design in the future, which depends on improvements in software development and algorithm accuracy [49].

Another limitation of GANs is the lack of accuracy of the results. In terms of building structure generation and plan generation, GANs usually can give vague results, reflecting rough estimation results. The implementation of architectural design still needs further optimization by designers. Especially in the absence of high-quality datasets, the results are not particularly good.

Another limitation of GANs is their high computing costs. Since GANs are equipped with two deep neural networks (generators and discriminators), the calculation cost of GANs is even greater than that of many other deep learning methods. Researchers must understand the costs of GANs and use them to perform the tasks that GANs are good at. At present, GANs in the field of application and architectural design can only aim at a specific design type, such as hospital, school, or residence. If new building types are to be included in datasets, considerable calculation time and commissioning time are needed, which undoubtedly increases the design cost.

GANs and the increasingly abundant data available in the building environment can be combined to create innovative solutions to help people understand cities. According to a review of 95 recently published papers, GANs can be used to solve problems that cannot be solved with traditional methods, while other studies utilize them to optimize existing processes. Data accuracy, high-quality datasets, and relevant software development are the main limitations hindering the wide deployment of GANs. Planners, analysts, and designers must also be able to interact with these technologies in a user-friendly way to incorporate these technologies into standard architectural workflows.

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