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A Review of the Research and Development of Adversarial Generative Networks in Interior Graphic Design

Haonan Yang*

Beijing University of Posts and Telecommunications, International School, 100876 Beijing, China

Abstract. This study provides a comprehensive overview of the research and development of adversarial generative networks in interior graphic design. With the continuous development of adversarial generative networks, the level of Generative Adversarial Networks (GAN) has reached a very outstanding level, and it has also developed in interior graphic design. This article will be divided into four categories: early research, optimization methods for refining workflows, optimization methods for introducing graph networks, and other optimization methods. The framework, characteristics, advantages, and disadvantages of these methods will be introduced. Early research mainly focused on two relatively simple frameworks based on CGAN. The optimization methods for refining workflow are based on the degree of refinement, with a focus on introducing two representative articles and also mentioning some outstanding research results. The graph network section focuses on two studies, House GAN and House GAN++, while also mentioning FlooPlan GAN. The other optimization methods section introduces the introduction perspective of ActFloor GAN technology and energy-saving strategies. The final section summarizes the work of this article and provides prospects for future development.

1 Introduction

In recent years, with the rapid development of computer vision and artificial intelligence, Generative Adversarial Networks (GAN) have achieved remarkable results in the field of image generation. GAN can generate very realistic images through adversarial training of generators and discriminators. However, in the traditional field of interior graphic design, it still relies on designers and traditional homework software to complete the work, which not only requires a lot of time and energy, but also has low efficiency, and the design results lack creativity and diversity. So, how to quickly and efficiently generate interior design solutions that meet standards and aesthetics has become an urgent problem to be solved.

The core task of using adversarial generative networks to generate interior graphic design schemes is to divide the graphic space and generate graphic renderings. The difficulty of the task lies in how to interpret and control the experimental process, how to constrain and

* Corresponding author: 2023213681@bupt.cn

standardize the experimental results, and how to improve practicality. This task can be traced back to 2018, with the two most representative articles being the research by Hao Zheng and the collaboration between Weixin Huang and Hao Zheng [1, 2]. These two articles established the connection between indoor functional zoning and design drawing generation, and trained the GAN model accordingly. This framework is not complex but lays an important foundation for this field. In 2019, Yang Liu and Stanislas Chaillou each proposed a plan based on refining the workflow [3,4]. By splitting the experimental steps, the transparency and standardization of the GAN network have been improved, making the experimental process controllable and practical. In 2020, the House GAN and House GAN++ schemes introduced the design strategy of graph networks, which transform the spatial relationships of the network into the spatial relationships of a planar graph, providing constraints on the spatial pattern of the image [5,6]. In 2021, ActFloor GAN introduced the concept of human flow activities, providing a new solution for the task and being highly innovative [7].

Since 2018, this topic has been developing for six or seven years, during which there have been many solutions from different perspectives, and over time, it has been constantly innovating and improving. This article will divide them into four categories and analyze and introduce them, namely: early research, optimization methods for refining workflows, optimization methods for introducing graph networks, and other optimization methods.

2 Early Studies

2.1 Build a correlation model between the core information of the floor plan and the drawing of the floor plan

Zheng wants to build a correlation model between the core information of the floor plan and the overall drawing of the floor plan. Zheng's first plan is to establish the connection between the design boundary and the drawing of the floor plan. Based on CGAN and pix2pix technology, Zheng trained on a dataset of 800 graphic design drawings from Columbia University (Fig. 1), establishing a connection between the design boundaries and the floor plan. It can quickly generate the internal structure of the floor plan by inputting randomly generated design boundaries. The result is a good generation effect on the wall, but the internal structure is still blurry (Fig. 2) [1].

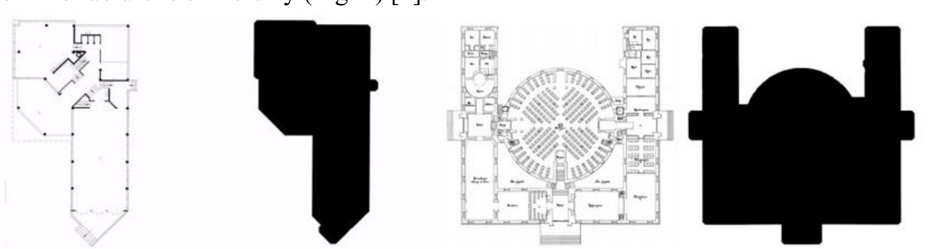

Fig. 1. The Columbia University dataset and its processed boundaries [1]

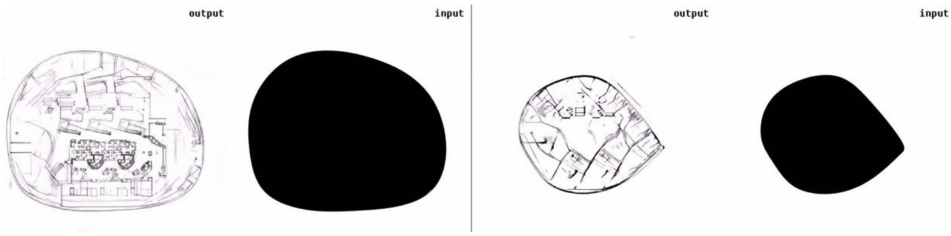

Fig. 2. the result of training, that is, inputting random boundaries can generate its internal structure [1]

ZHENG's second plan is to establish a connection between the partition of design drawings and the drawing of floor plans.

Based on CGAN and pix2pix technology, 800 floor plans from Columbia University were used as data, and functional zoning was performed on them (black represents interior boundaries, yellow represents interior areas, cyan represents furniture areas, and red represents building axes). Finally, this dataset was used for training [1]. This time ZHENG established the relationship between functional zones and core information. The input was the color blocks marked in the functional zones and the annotations of the building axis (Fig. 3), and the output was the internal structure of the floor plan. And this time the results are better, the predicted content is more detailed, and the performance is better

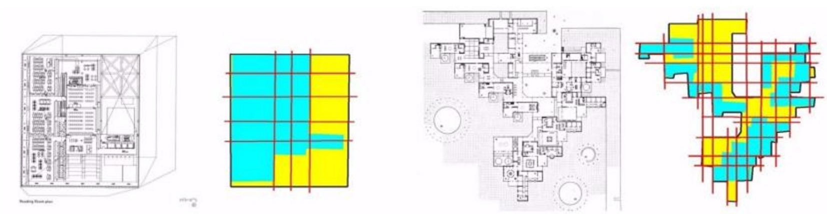

Fig. 3. with the original plan view on the left and the annotated image on the right [1]

This is a very successful attempt that proves that constraints can promote the progress of results, which points out a very good direction for future development. However, there are still some shortcomings. ZHENG's second model is superior to the first model, but its second model only has two functional partitions, which is clearly insufficient. ZHENG and HUANG's research will improve this point in the future.

2.2 Further refine the improvement plan for functional partitioning

Similarly, HUANG and ZHENG are based on CGAN and pix2pixHD technology. researchers processed 100 sets of color floor plan design data from Lianjia (in order to distinguish as much as possible, researchers used 7 combinations of RGB values of only 0 or 255 to mark corridors, bedrooms, living rooms, kitchens, bathrooms, and dining rooms, respectively. 2 combinations of RGB values of only 0 or 128 were used for windows, doors, and doors. The window and door drawing layers are located at the top of other areas as connections between areas), and trained them on the dataset [2]. HUANG and ZHENG then established the connection between internal functional zones and floor plans, which can generate floor plans by inputting the design of functional zones. Conversely, inputting floor plans can also generate their corresponding functional zones. The result is that the wall generation effect is very good, even with a small amount of data, the effect is still good, but the internal structure is still blurry (Fig. 4).

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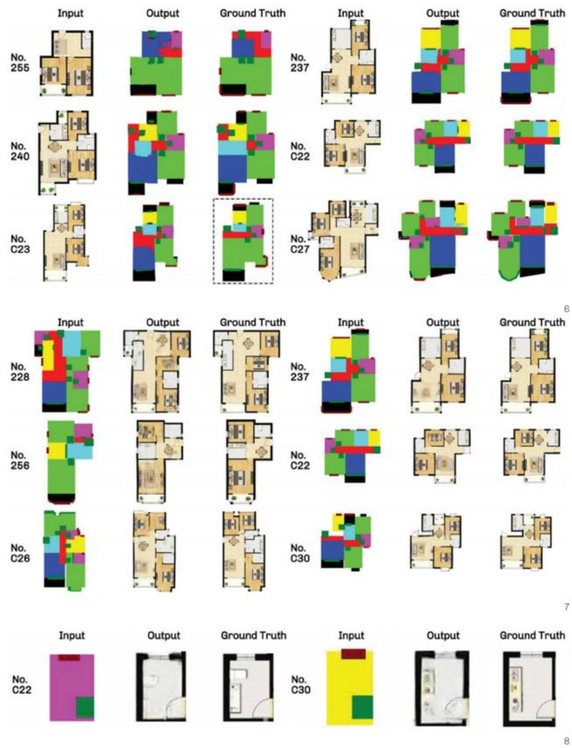

Fig. 4. shows the annotation based on the floor plan, the generation of the floor plan based on the annotation, and the detailed display of the toilet and kitchen [2]

In addition, this study also visualized the feature extraction process of each convolutional layer during the training process. As the network deepens, it can be seen that convolutional layers gradually shift their focus from single local information to more abstract information such as wholeness and spatial composition. This is very helpful for us to understand the essence of GAN for generating planar graphs.

3 Optimization Methods for Refining Workflow

GAN is an end-to-end model, where "end-to-end" refers to simplifying many steps of a task into a single starting and ending step. Essentially, it is to establish a mapping relationship between the input and output terminals. However, our task is engineering and rigorous, and researchers need to generate architectural plans rather than just images. So researchers need to impose certain frameworks and requirements, and researchers need to break down the experimental steps in order to improve the transparency, practicality, rigor, and standardization of GAN networks. Essentially, researchers need to make the experimental process controllable and practical.

3.1 Design concept of two-step splitting

In 2019, Yang Liu from South China University of Technology made progress on the basis of his predecessors by breaking down the task into two steps. Firstly, he generated a annotated plan layout based on the designed boundaries, and secondly, he generated a plan layout based on the annotated plan [3]. Yangliu's algorithm is still based on PIX2PIX. Regarding the dataset, he first used PS to export the borders and selected special colors for labeling (Table 1) (similar to the approach taken by Weixin HUANG and Hao ZHENG).

Table 1. Color chart for marking functional zones on a flat surface

	(255,0,0):bedroom		(0,255,0):living room		(0,0,255):kitchen
	(255,255,0):door		(255,0,255):window		(0,255,255):toilet
	(128,0,0):corridor		(0,128,0):balcony		(0,0,128):dining room
	(128,0,128):study		(128,128,0):other		

The first step of experimental training for image annotation is essentially training the neural network's ability to partition buildings and process spatial partitions. The experiment was conducted for 5000 generations, taking 13.5 hours, and the results gradually improved with the addition of generations.

The second step of the experiment is to train the use of annotated maps to generate flat maps. Essentially, this is to train the neural network's ability to generate details such as furniture in different areas, so that its expression of the content of the picture details can also be improved. The experiment was conducted for 3000 generations and the results were also quite impressive [3].

Finally, by cascading the two models, the results can be visualized in one go, which is quite impressive (Fig. 5). Yang Liu's progress lies in breaking down one experiment into two steps. Although it is not a qualitative leap in terms of improvement, his ideas are very visionary.

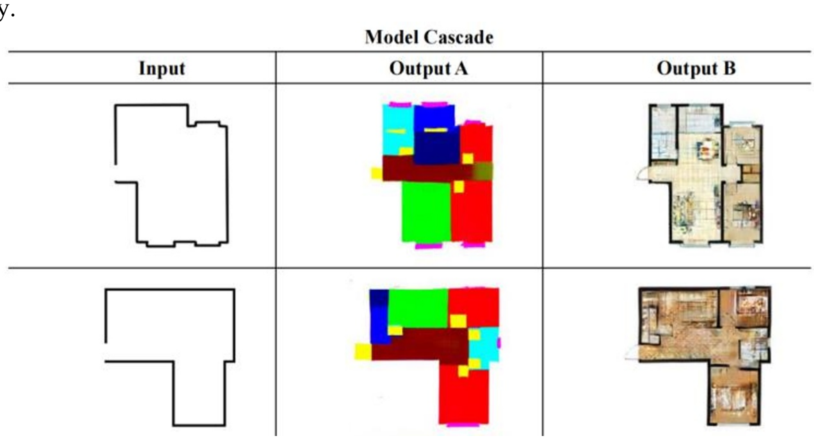

Fig. 5. Demonstration of the effect after cascading the first and second level experiments [3]

3.2 Design concept of two-step splitting

In 2019, Stanislas Chaillou from Harvard University went further by dispersing the process into more discrete steps, allowing users to intervene throughout the entire process. Each step represents a part of the architecture expertise, and these steps can be trained and intervened separately. Users can select the output of a model and edit it before handing it over to the next model. These models include "footprints" (indirectly representing the style and spatial shape of the building), room segmentation and window opening, and furniture (Fig. 6)[4].

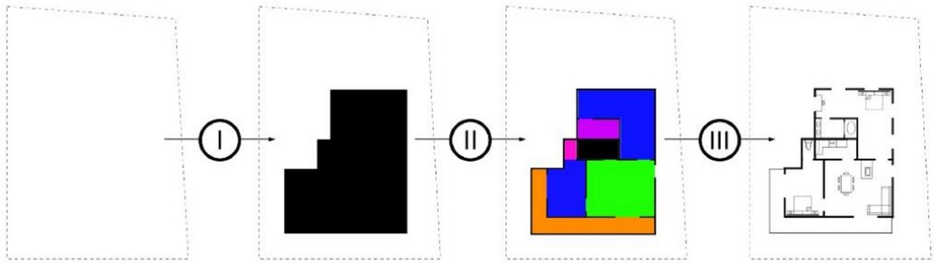

Fig. 6. Demonstration of Phase wise Generation of Floor Plans [4]

Subsequently, Stanislas Chaillou extended the shape of the room to an irregular situation, and the adaptability of the model was very good. The usage scenarios were extended (Fig. 7).

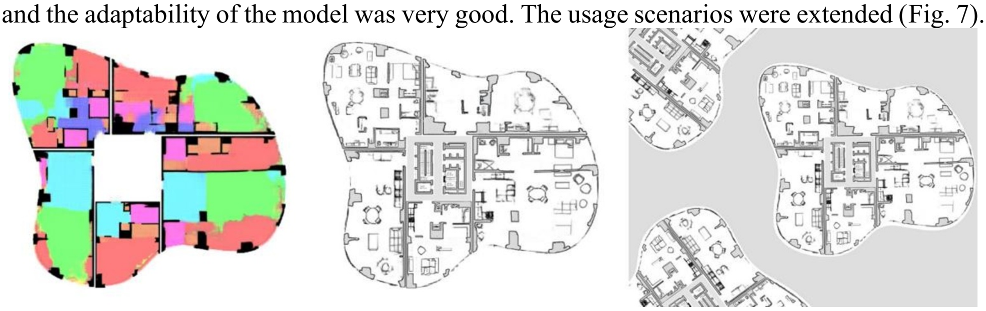

Fig. 7. Demonstration of Generating Irregular Boundaries [4]

It is also worth mentioning that Stanislas Chaillou has proposed a very comprehensive system for our customized, controllable, and transparent generation. He first proposed six aspects of graphic design, corresponding to six indicators, namely footprint, room type, wall orientation, thickness and texture, connectivity, and "flow line" (used to consider human activities) (Fig. 8).

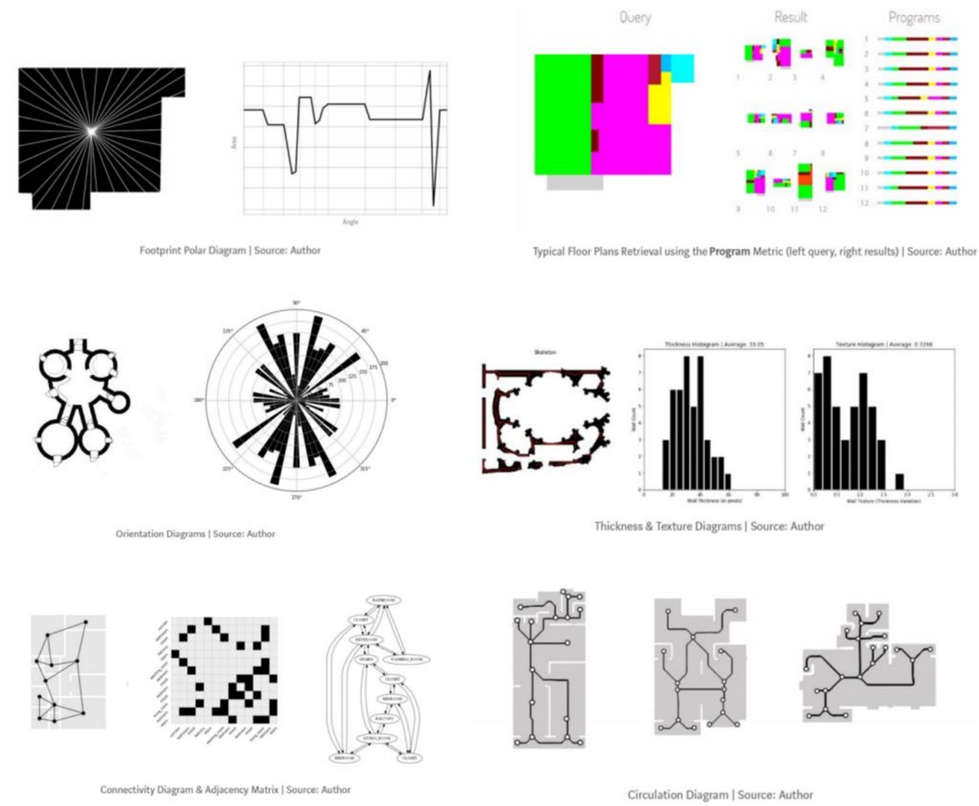

Fig. 8. six indicators, namely footprint, room type, wall orientation, thickness and texture, connectivity, and "streamline" [4]

At each step of the generation process, GAN outputs multiple design options that users can choose and modify. And the six indicators are used to quickly narrow down the scope and facilitate user screening and selection. Once the user filters according to the given criteria, a tree diagram can be generated for the user. Users can use it to further narrow down the search scope or choose other options to recalculate (Fig. 9)[4].

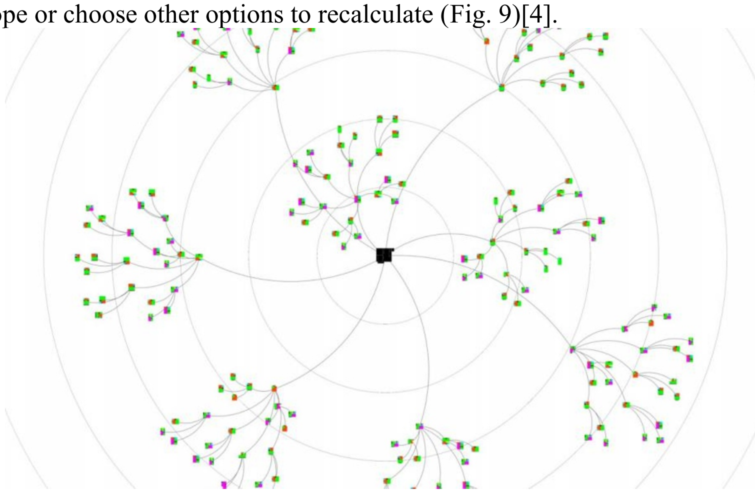

Fig. 9. tree diagram display [4]

Stanislas Chaillou's research has been very successful, as he has excelled in segmenting workflows. In the generation stage, he can achieve highly customized, transparent, and controlled generation. Based on this, he also designed a relatively complete selection system to help quickly select the results that users want. Stanislas Chaillou's progress is very significant.

3.3 CSID-GAN Technology: Optimization Scheme for Two Step Splitting

A two-stage plan similar to Yangliu first generates a reasonable indoor layout plan, and then personalizes the style (Fig. 10). The innovation lies in its cross scale structure. In order to avoid the common distortion problems of traditional GANs, CSID-GAN technology enhances image details and global consistency by optimizing at multiple image resolutions. Meanwhile, cross scale optimization has been innovatively introduced in image domain mapping, resulting in a more balanced representation of global and local details in the image. This also makes CSID-GAN technology more suitable for complex image generation tasks [8].

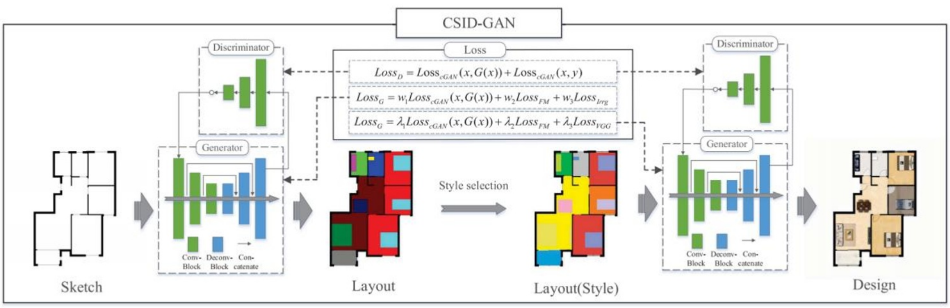

Fig. 10. CSID-GAN Network Framework [8]

4 Introducing Optimization Methods for Graph Networks

The introduction of graph networks as a data structure provides us with new ideas. The spatial relationships of graph networks can be transformed into the spatial relationships of planar graphs, which enables us to provide spatial constraints for image production and better achieve our goal of making our tasks controllable and practical.

4.1 Introducing House GAN Technology with Graph Networks

In 2021, Nelson Nauata, Sepidehsadat Hosseini, Kai Hang Chang, Hang Chu, Chin Yi Cheng, Yasutaka Furukawa proposed improvements to House GAN and created House GAN++. Similarly, inputting a bubble chart can output a realistic and compatible house layout (Fig. 11).

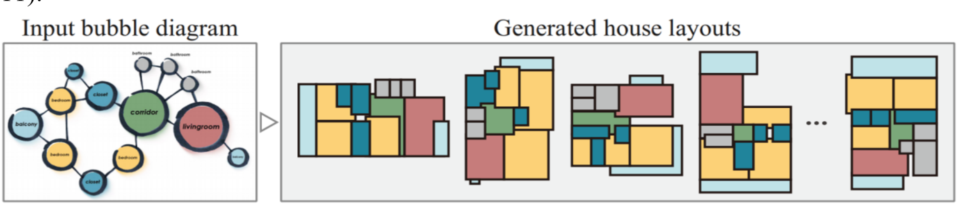

Fig. 11. inputting a bubble chart can output a spatial design diagram [5]

House GAN is a relation generative adversarial network (Fig. 12). The key lies in the relationship generator and discriminator, where input graph constraints are encoded into the graph structure of the relational network. Specifically, the author employed Conv MPN, which differs from GCN in that nodes store feature quantities in the design space and convolutions update features (as opposed to one-dimensional latent vector space) [5].

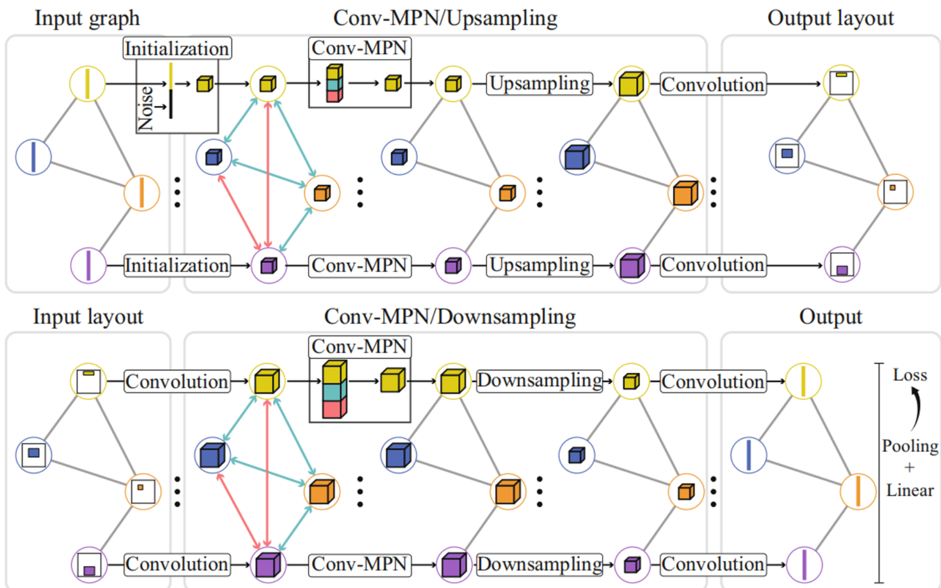

Fig. 12. House GAN Network Framework [5]

4.2 House GAN++: Improvement and Upgrade of House GAN Technology

In 2021, Nelson Nauata, Sepidehsadat Hosseini, Kai Hang Chang, Hang Chu, Chin Yi Cheng, Yasutaka Furukawa proposed improvements to House GAN and created House GAN++. Similarly, inputting a bubble chart can output a realistic and compatible house layout (Fig. 13).

Fig. 13. inputting a bubble chart can output a spatial design diagram

Three improvements: Firstly, in addition to nodes, edges also have the feature of generating gates; Secondly, each node/edge adopts a two-dimensional segmentation mask as an additional input constraint and has related new losses; Thirdly, the Conv MPN feature pool has been redefined to allow for feature exchange between nodes and edges.

House GAN++has improved both compatibility and diversity. Diversity is evaluated by FID scores, while compatibility is evaluated by image editing examples (Fig. 14) [6].

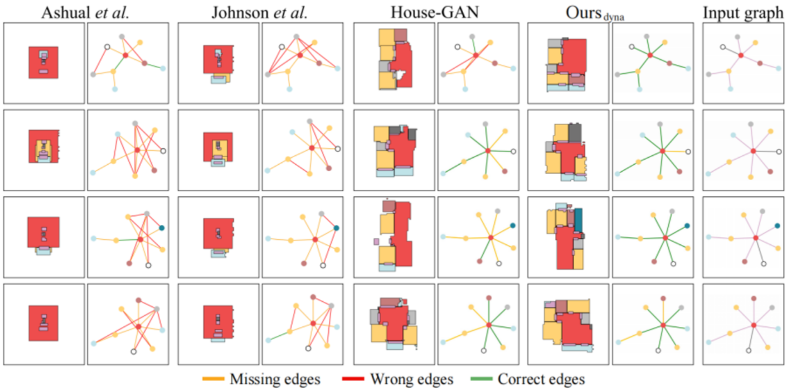

Fig. 14. Accuracy of Bubble Chart Generation [6]

4.3 FloorplanGAN: A more convenient solution

By entering the form, a bubble chart can be automatically drawn, which will be used to generate spatial layout and floor plans (Fig. 15). FloorplanGAN can not only generate floor plans, but also perform spatial optimization, such as adjusting room layout, furniture configuration, etc. By comparing the generated design with real-world architectural data, FloorplanGAN can make the design more rational and practical during the generation process [9].

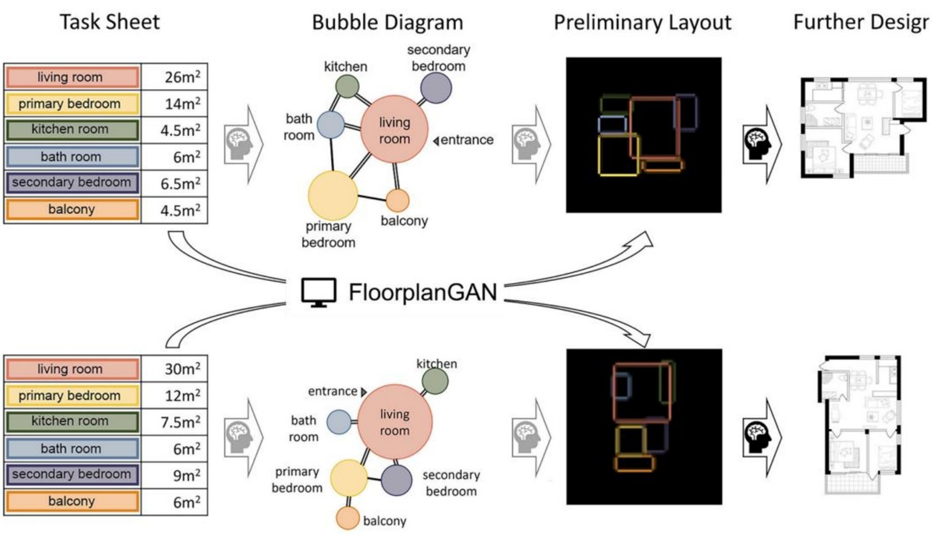

Fig. 15. FloorplanGAN Network Framework [9]

5 Other Types of optimization methods

5.1 ActFloor GAN technology introducing crowd flow activity strategy

In 2021, Shidong Wang, Wei Zeng, Xi Chen, Yu Ye, Yu Qiao, and Chi Wing Fu introduced the concept of induced abortion. They used the bi RRT algorithm to simulate and generate indoor pedestrian activity models, and used them as constraints and guidance conditions. At the same time, based on the overall idea and framework of CycleGAN, they created ActFloorGAN (Fig. 16). It consists of two stages, the first stage is to generate a flow activity map, and the second stage is to generate a floor plan. The first stage includes automatic generation or semi-automatic generation in an interactive interface [7].

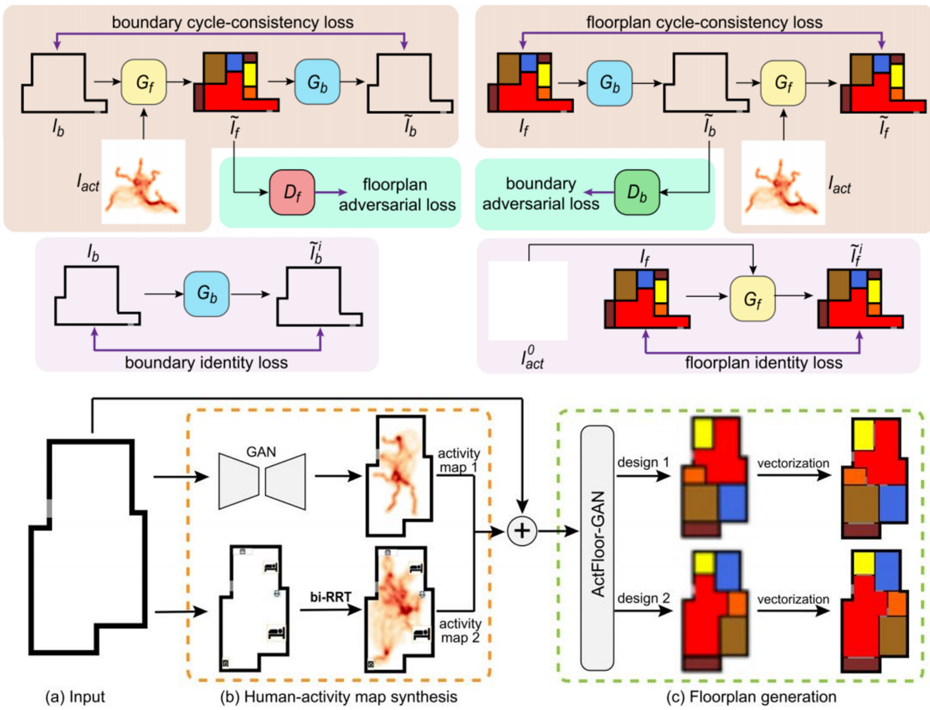

Fig. 16. Network Framework of ActFloor GAN [7]

In the stage of generating pedestrian activity maps, researchers first decompose the activity map into two parts. The first part is the activity trajectory left between each room in the living room area, as well as the trajectory between each room and the entrance. The second part is the activity trajectory inside each room. Firstly, in the RPLAN dataset, they extracted the locations of rooms and doors. Then, a bidirectional connection graph was constructed sequentially. And further, the bi RRT algorithm was used to simulate the movement of residents in the living room, generating an image that can represent the intensity of activity. Then, they continued to simulate the movement of people in other rooms. And merge these two results to generate the final flow activity map. And a GAN model was trained based on this (Fig. 17). The synthesis of flow activity maps can indirectly reflect the relationship between rooms and between rooms and furniture. In addition, in the semi-automatic generation of interactive interfaces, users can place various furniture at the boundaries of the building, and then the system generates corresponding pedestrian activity maps. This method helps to improve the controllability and flexibility of our tasks.

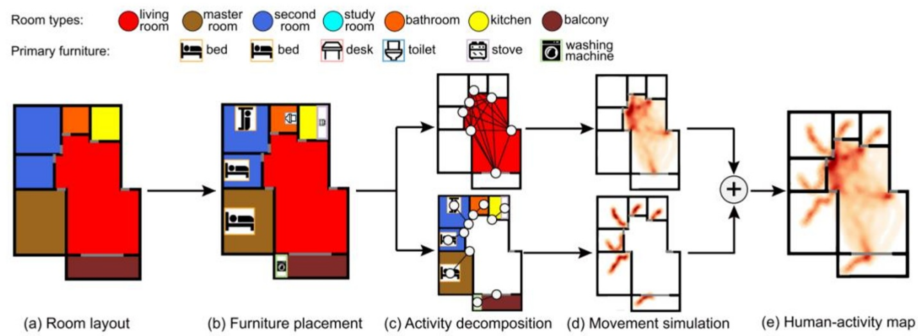

Fig. 17. Framework for Generating Flow Activity Maps [7]

In the floor plan generation stage, they trained the ActFloorGAN model to predict pixel by pixel room types and reconstructed the cyclic consistency constraint, using the crowd activity map to predict room types as a whole. Subsequently, they used processing modules to optimize these predicted house types into vector floor plans (Fig. 18) [7].

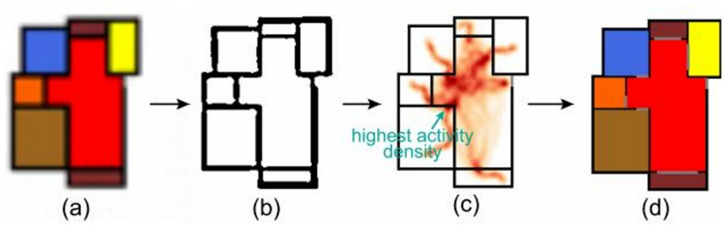

Fig. 18. Demonstration of Vectorization Process

ActFloorGAN stands out from other studies in that it does not adhere to rigid conditions, but instead creates an innovative approach based on human needs in practical use, which is highly progressive.

5.2 Training perspective on energy-saving strategies

Similar to Yang Liu's work, it is also divided into two parts: spatial division and plan generation. However, the difference is that the dataset used in this experiment is from entries in the Solar Decathlon (SD) competition between 2007 and 2018, which contain energy-saving design strategies [10]. Using this dataset for training, the generated results can save energy consumption and design more reasonable design methods for real-world situations.

6 conclusion

This article provides a comprehensive overview of the research and development of adversarial generative networks in interior graphic design from four perspectives: early research, optimization methods for refining workflows, optimization methods for introducing graph networks, and other optimization methods. It analyzes different optimization schemes and their respective development trajectories over the past seven years.

The goal of this task is to generate architectural plans rather than simply images, and to obtain engineering drawings with controllable processes and practical results. So the direction of this task must be to make the work process transparent and rigorous, and the work results standardized and practical. In the future, the goal of developing this task must also be to further enhance controllability and constraint, and improve the practicality of the results. In this regard, it is evident that the optimization method of refining workflow is the most effective.

However, Stanislas Chaillou also proposed that the principle of spatial design is more important than the method. This also inspires researchers to start from the core and focus on the principle issues of design in order to improve the research topic, followed by the methods and means of implementation. From this perspective, introducing graph networks and other optimization methods is clearly more outstanding.

This article believes that this study will provide certain assistance for subsequent scientific research work and lay a foundation for the future development of this field.

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