Exploration of Campus Layout Based on Generative Adversarial Network

Discussing the Significance of Small Amount Sample Learning for Architecture

Yubo Liu, Yihua Luo, Qiaoming Deng(✉), and Xuanxing Zhou

School of Architecture, South China University of Technology, Guangzhou, China
dengqm@scut.edu.cn

Abstract. This paper aims to explore the idea and method of using deep learning with a small amount sample to realize campus layout generation. From the perspective of the architect, we construct two small amount sample campus layout data sets through artificial screening with the preference of the specific architects. These data sets are used to train the ability of Pix2Pix model to automatically generate the campus layout under the condition of the given campus boundary and surrounding roads. Through the analysis of the experimental results, this paper finds that under the premise of effective screening of the collected samples, even using a small amount sample data set for deep learning can achieve a good result.

Keywords: Deep learning · Layout design · Campus planning · Generate design · Small amount sample

1 Introduction

In recent years, with the improvement of computing power, the emergence of more data and more effective algorithms, Artificial Intelligence (AI) has once again ushered in a development boom. Among them, deep learning, which overcoming the limitations of high-dimensional data processing and feature extraction, is widely used in the field of computer vision, audio, and natural language processing, and further promotes the development of AI.

The models and methods of machine learning are mainly based on the theory of statistical learning. Currently popular machine learning models, especially the deep learning, generally need a large number of sample data to ensure that the models are fully trained to achieve the learning effect and obtain universal rules. However, in the field of architectural design, the design issues we are concerned with are not only related to the universal rules, but also related to the value orientations and aesthetic tendencies of specific architects. The particularity and difference of these design works result in the variety of architecture. This characteristic of architecture design makes it possible for the training of small amount chosen sample data sets to achieve a relatively ideal effect.

By taking the campus layout as the pointcut, this paper discusses the ability of Pix2Pix model to automatically generate the campus layout under the condition of the

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given campus boundary and surrounding roads, which is based on deep learning and artificial chosen small amount sample data sets. With the premise of effective screening of the collected samples, we succeed in the experiment by using a small amount chosen sample data sets.

2 Related Work in the Field of Architectural Layout

Layout design has always been a research hotspot in the field of AI, such as: document layout, game map layout, cover layout, interior furniture layout, etc.

In the field of architectural layout, Merrell et al. (2010) propose a method of automatically generating residential building layout based on Bayesian networks. They select 120 residential building layouts from the 1500 best-selling residential building layouts for machine learning. Fan et al. (2014) propose a method to complete the missing or unoccluded facade layouts with a statistical model and a planning algorithm. They selected 100 complete and unoccluded building facades with uniform style as the data set of training. The author with his team also try to expand the existing 15 samples to 140 samples in the form of artificial data augmentation, and explore the generation of specific architectural forms through the neural network method (Liu et al. 2019).

In recent years, the development of deep learning has provided new ideas and methods for the field of architectural layout. Huang and Zheng (2018) use Generative Adversarial Network (GAN) for the recognition and generation of apartment floor plans. A total of 115 samples were collected, including 100 training samples and 15 testing samples. Wu et al. (2019) propose a CNN-based method of generating floor plans for residential buildings with given boundaries and they select more than 80K floor plans from more than 12K collected floor plans of the Asian real estate market to construct a database named RPLAN, of which 75K floor plans are used as training samples, half of the left is used as testing samples and the other half is used as verification samples. Chaillou (Chaillou 2019) chooses nested GANs to generate a furnished floor plan from the parcel, using about 700 floor plans as samples. Newton (2019) trains GAN to generate floor plans with the style of Le Corbusier and discusses the effectiveness of different augmentation techniques when dealing with small data sets, using 45 hand-drawn drawings of Le Corbusier as samples and expanding the samples to 135/180/540 through different augmentation techniques.

In the above work, we found two ways to collect and filter data samples as datasets: 1) One is using tens of thousands of samples for training to obtain the universal rules in a statistical manner, the specificity of specific samples is neutralized through the mass of sample data, such as Wenming Wu's research (Wu et al. 2019). 2) The other is using a small amount chosen samples which meet the training standards data set for training, only to obtain the rules of its particularity, such as David Newton's research (Newton 2019). This paper adopts the latter method, constructs specific chosen sample data sets through artificial screening according to the value orientations and aesthetic tendencies of specific architects, finally get relatively ideal results with small amount chosen sample data sets for deep learning training.

3 Methods

The main process of campus layout generation based on deep learning with small amount chosen samples data sets is as follows:

1) *Expected goal.* Automatically generate a reasonable campus layout under the condition of the given campus boundary and surrounding roads.
2) *Data screening.* According to the characteristics of the campus layout and the value orientations and treatment methods of specific architects, we have screened 85 university samples and 302 primary school samples. The specific screening rules are as follows:

The specific screening rules for the primary school:

1. The site plan is clear.
2. Decentralized campus design.
3. An independent playground.
4. Single-loaded teaching building connected by corridors.
5. A basketball court or scale is used as a scale reference.
6. The campus is located in the subtropical monsoon climate zone with balanced economic development.
7. The campus land is flat, avoiding the special terrain such as slopes or water.

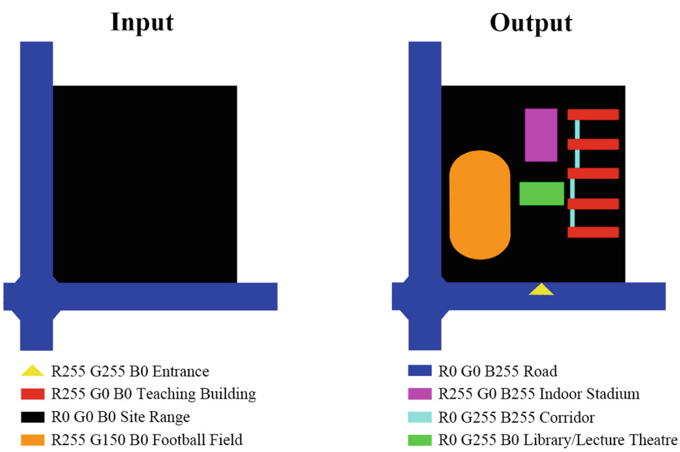

Fig. 1. Training data of the primary school, top: input and output, bottom: labeling rule

The specific screening rules for the university:

1. The site plan is clear.

2. The campus layout conforms to the design concept of a specific design company.
3. The loop traffic system and the central area.
4. A basketball court or scale is used as a scale reference.

3) *Model construction.* This paper selects the Pix2Pix model based on Generative Adversarial Networks to complete this research. The generator uses the U-net framework and the discriminator uses the Patch-GAN framework (Isola, et al. 2017). By inputting pictures of the actual campus boundary and surrounding roads and outputting corresponding pictures of the actual campus layout (Fig. 1, 2, and 3), this model is trained to learn the rules of actual campus layouts and generate campus layout automatically. It is worth noting that the color selection is related to the RGB value interval to avoid recognition errors. Appendix provides more details.

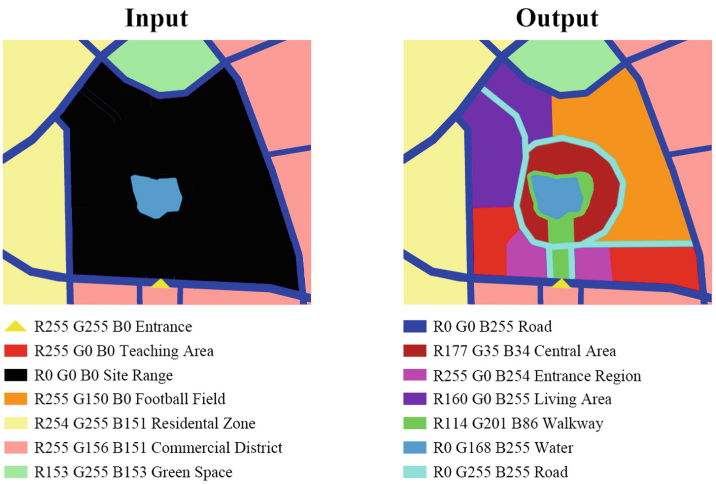

Fig. 2. Training data of the university for step 1, top: input and output, bottom: labeling rule

4) *Experimental test.* Use the testing set to test the trained Pix2Pix model, analyze and evaluate the training effect of the model by comparing the generated campus layout with the actual campus layout.

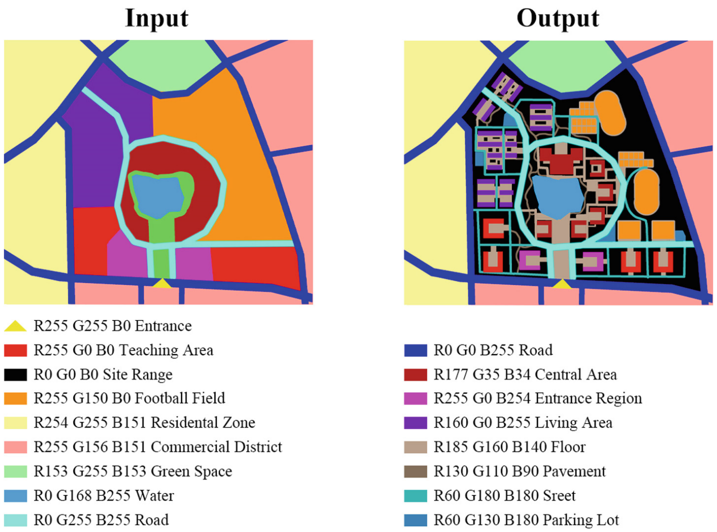

Fig. 3. Training data of the university for step 2, top: input and output, bottom: labeling rule

4 Experimental Results and Analysis

First, we tried to train a model that automatically generates the campus layout of the primary school from the campus boundary and surrounding roads. The experimental results show that the model we trained has learned the rules of the layout of the primary school to some extent. Figure 4 shows the selected results from the testing set.

Compared with the actual layout, the layout generated in No. 265 has a more reasonable relationship between the teaching building, the gymnasium and the stadium, leaving a transition road in the middle. The layout generated in No. 301 pays more attention to the north-south orientation of the teaching building than the real layout. There are also some poor layouts. For example, the layout in No. 275 fails to generate a complete teaching building group, and as for the layout in No. 294, the campus entrance is not reasonable enough at the intersection of roads, but the main building chooses to strive for north-south orientation instead of parallel to the surrounding road.

On the basis of some achievements in the campus layout of the primary school, we tried to automatically generate the campus layout of the university. Due to the complexity of the campus layout of the university, we split the training process into two steps: The first step is to train a model that generates the main functional zoning of the campus based on the campus boundary, surrounding roads and surrounding functional distribution. The second step is to train another model which is based on each functional zoning of the campus and generates the internal architectural layout of the them. In this way, a complete campus layout of the university is achieved.

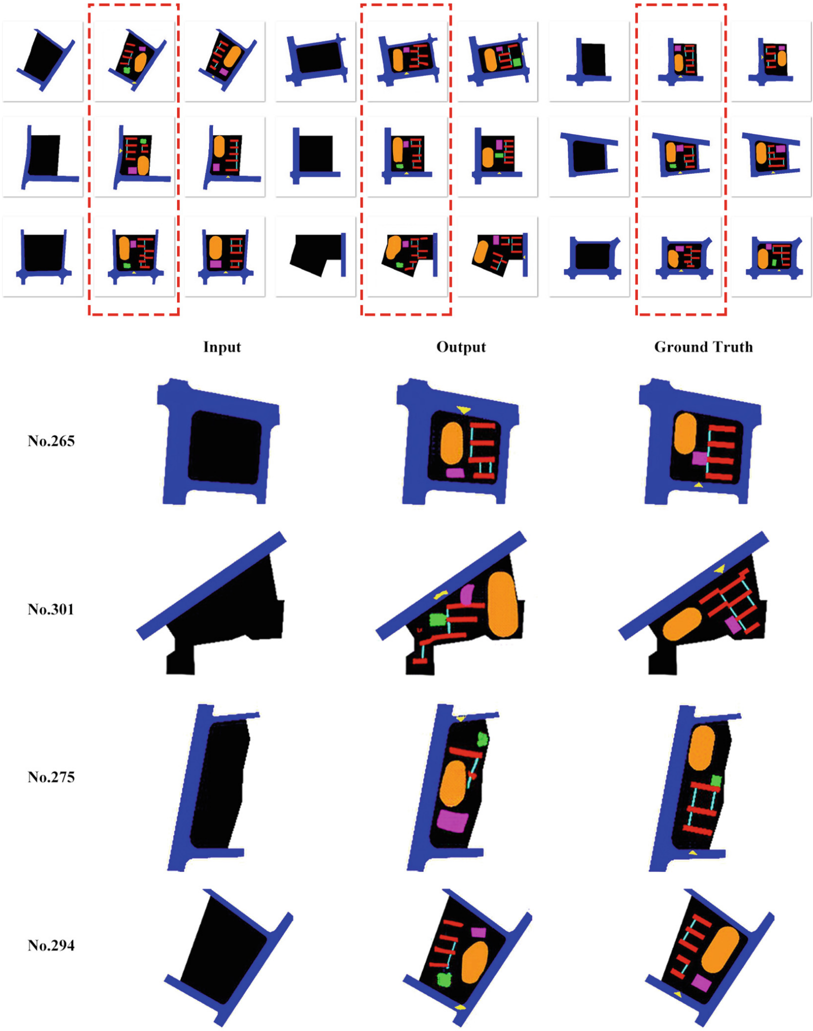

Fig. 4. Selected results from the testing set of the primary school

In the first step, we chose the campus planning scheme with a specific style designed by a design company as samples, highlighting the team's adherence to the layout concept of the loop traffic system and the central area which emphasizes that teaching buildings and landscapes jointly shape the communication space, and the final effect reached the expected. From the perspective of functional zoning, the generated layout is highly consistent with the original plan, forming an obvious layout pattern of the loop traffic system and the central area. The relationship between each functional zoning and the external environment is relatively reasonable. Almost all the testing samples successfully output the loop traffic system, forming a continuous campus walkway from the entrance area to the central area (Fig. 5).

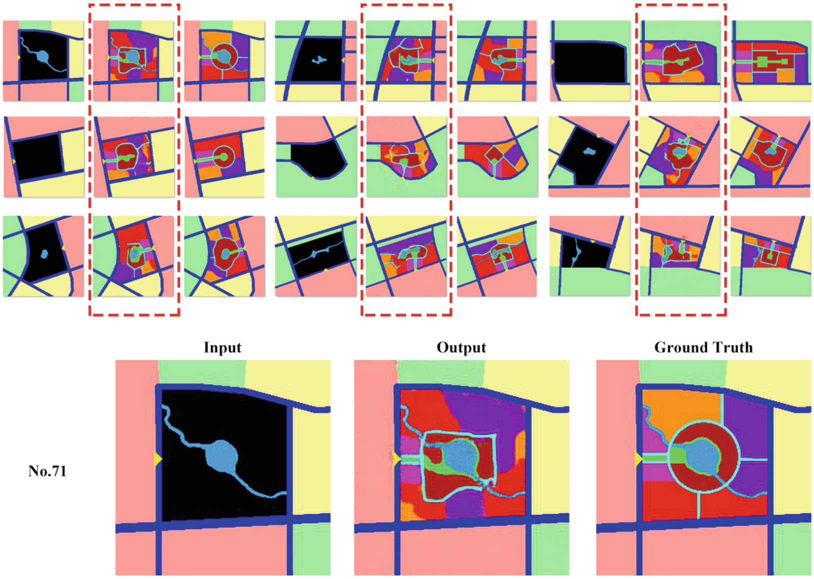

Fig. 5. Selected results from the testing set of the university in step 1

In the second step, we also continue to select samples that consistent with the design concept of the design company, which emphasized the organic combination of the architectural layout of the central area and the core open space of the campus, and emphasized that the layout of the dormitory area should be combined with the main pedestrian traffic roads to form the street space. The final effect is also relatively successful (Fig. 6). The output results not only grasped the laws of north-south orientation of building layout and stable building spacing, but also coordinated the relationship between the buildings, public space and water in the central area. The layout of the dormitory area has also initially formed the spatial relationship we want to shape. Unexpectedly, the layout of some buildings also initially reflects the overall style of lightness and flexibility, which is pursued by the design company. As discussed in the paper, in small amount sample learning, the clearer the layout rules of the samples are, the better the learning effect will be. For example, the layout of the dormitory area and sports area in the samples is simple and clear, the generation effect is good. But the central area is rich in architectural form and flexible in layout, there are fuzzy areas in the generated results. We can achieve improvement by adjusting the samples and enhancing the regularity of the layout of the central area. However, this fuzzy area is very similar to the sketch for the architect, and maybe has a stronger design inspiration. Related research attempts are still underway.

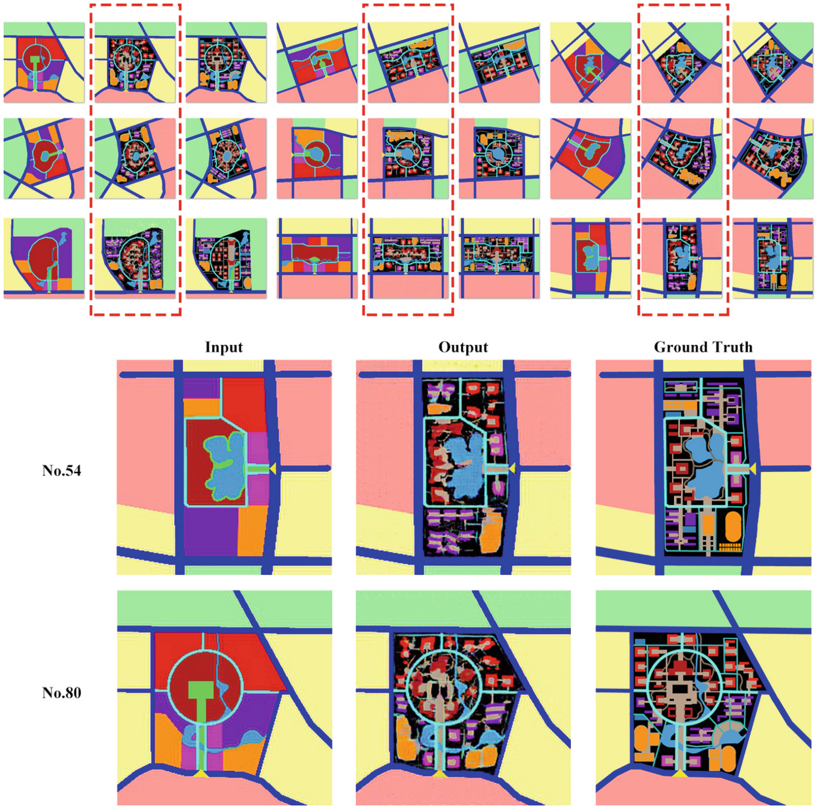

Fig. 6. Selected results from the testing set of the university in step 2

5 Discussion

This paper aims to explore the idea and method of using deep learning with a small amount sample to realize campus layout generation. The experimental results show that when the collected samples are screened by the characteristics of campus layout and the value orientations and treatment methods of specific architects, even using small amount sample data sets for deep learning can achieve a good result. The inspiration of this study is that when combining the field of architectural design and AI, we should pay attention to the particularity and difference in the architecture, found out own way, not just follow the way of computer discipline. From this point of view, we hope to find a way to deep learning based on small amount sample data sets which conforms to the characteristics of architecture discipline and points to specific design concepts and design techniques.

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Appendix

In the process of deep learning, each value of RGB values is divided into five intervals, 0–50, 51–100, 101–150, 151–200 and 201–255 (Fig. 7). At least one value of the RGB values of the two colors is in a different interval, so as to distinguish the colors, for example, the color (255, 255, 0) can be understood as (5, 5, 1).

RGB Values Interval	Classification
0-50	1
51-100	2
101-150	3
151-200	4
201-255	5

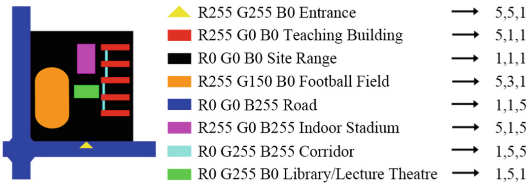

Fig. 7. Further explanation of the choice of colors used to label different elements

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