Urban Space Simulation Based on Wave Function Collapse and Convolutional Neural Network

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ABSTRACT

In this paper, we propose a pipeline of urban space synthesis which leverages Wave Function Collapse (WFC) and Convolutional Neural Networks (CNNs) to train the computer how to design urban space. Firstly, we establish an urban design database. Then, the urban road networks, urban block spatial forms and urban building function layouts are generated by WFC and CNNs and evaluated by designer afterwards. Finally, the 3D models are generated. We demonstrate the feasibility of our pipeline through the case study of the North Extension of Central Green Axis in Wenzhou. This pipeline improves the efficiency of urban design and provides new ways of thinking for architecture and urban design.

Author Keywords
Urban space synthesis; Wave Function Collapse (WFC); Convolutional Neural Networks (CNNs).

ACM Classification Keywords
J.6 COMPUTER-AIDED ENGINEERING: Computer-aided design (CAD)

1 INTRODUCTION

Around 54% of people in the world live in the urban areas in 2014 and the number of 66% is predicted in 2050 [24]. Modern cities exhibit increasing complexities and dynamics which demand for a fast adaption of urban design approach. However, traditional urban design method is still static, sectorial and time-consuming [18]. Thus, the computational generative urban design has become a hot research topic in recent years. The automatic generation has been addressed using approaches of procedural modeling and example-based modeling. Procedural approaches are based on the manually set design grammar or rule to generate design. In contrast, example-based approaches inspect examples and decompose them into a set of pieces of blocks, followed with a reorganization through algorithms, such as WFC, and the style of output is matched with the example statistically and perceptually [5]. Moreover, Nowadays, the artificial intelligence (AI) is developing rapidly and the application of deep learning technique for generation has been investigated. CNNs are utilized in the areas of computer graphics, such as texture synthesis.

In this work, we put forward an example-based approach for urban space synthesis which leverages the technique of WFC and CNNs. The first step is the establishment of urban design database. The second step utilizes WFC and CNNs to generate urban road networks, urban block spatial forms and urban building function layouts, followed with the evaluation and selection. The last step is the generation of 3D models.

The technique of WFC and CNNs are quite suitable for envisioned task as they learn the distribution underlying a set of images. With these techniques, the manual set of rules or parameters tuning which is tedious for non-experts will be no longer needed for generative design. The advent of AI techniques in urban space synthesis is still in early period, but it offers promising results. More than a simple opportunity, the potential of WFC and CNNs for the urban space synthesis is a major step ahead.

2 RELATED WORK

The first and second part of this section reviews procedural and example-based approaches focusing on urban space, texture and model synthesis. In the third part, we briefly review content generation approaches which leverages the technique of deep learning.

2.1 Procedural approach

In a comprehensive survey on procedural and inverse procedural modelling, Smelik et al. [23] survey procedural methods generating features of virtual worlds, including terrains, vegetation, rivers, roads, buildings, and entire cities. In general, procedural methods rely on the use of manually defined or automatically determined rule sets for content generation. Neil Leach and Weiguo Xu [12, 13] discuss the digital techniques for architecture in young architects' works and student architectural design works. Feng Yuan et al. [27] survey the different digital workshops in China. Yi Shi and Meipo Kwan [22] introduce the development of digital city in three American universities, namely, Massachusetts Institute of Technology, University of Illinois at Urbana-Champaign and University of Oregon. Ying Long [15] discusses the different approaches and applications of big data in urban planning and design and puts forward an approach of self-feedback urban design

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based on urban sensors and online platform. Reinhard Koenig [10] focuses on the evolutionary many-criteria optimization to improve urban design synthesis for building layout. In Yufan Miao et al. [18], the focus is on computational urban design prototyping. Decoding Space is used to generates urban layouts including street network, parcels and buildings according to designers' requirements.

2.2 Example-based approaches

Compared with procedural approaches, example-based methods do not need manual rules to generate content. It relies on analyzing the data such as urban morphology or road network to extract template or statistical information. Zheng Xie [26] explores the potential use of space syntax analysis in 3D parametric design. He extracts the correlation between urban morphology information and integration and generate urban form based on this parameter relationship. In Nishida et al. [19], road patches are extracted from real road networks and a new road network is generated. The terrain is taken into account to attach road patches to connector streets from an initial seed point. Heeger and Bergen [6], Portilla and Simoncelli [21] all try to match the large-scale random attributes of texture samples with the new texture. Vivek Kwatra et al. [11] use time as the third dimension to extend the texture synthesis and generate three-dimensional or multi-dimensional texture synthesis. Paul C. Merrell [17] simplifies texture synthesis technology by selecting samples with random shapes and then synthesizing larger texture output. Based on Paul C. Merrell's model synthesis study in 2009, the "Wave Function Collapse" algorithm by Python is published, which can generate similar images according to the input image [16].

2.3 Learning-based approaches

With the development of deep learning techniques, it has been used for procedural and data driven generation. In Yumer et al.'s research [28], the features of a low-dimensional generative model from high-dimensional procedural models is learned and new models can be generated. Nishida et al. [20] focus on interactive building modelling. CNNs are trained to classify the type of a rule snippet and to regress parameter sets. Then, the building mass, roof, etc. can be sketched iteratively. Results are classified and the parameters are inferred by CNNs. Stefan Hartmann [5] publishes StreetGAN. The road network is generated relying on GAN. A similar approach is leveraged by Adrian Albert et al. and he models urbanization patterns based on GAN. Stanislas Chaillou [2] puts forward an ArchiGAN which is a generative stack for apartment building design. A Pix2Pix GAN-model is trained to generate floor plan. Varshaneya V [25] leverages GANs to sketch in vector format and compare the generation results between GAN architecture SkeGAN and a VAE-GAN architecture VASkeGAN.

3 REVIEW OF WFC AND CNNS

3.1 WFC

WFC algorithm is widely used in the field of game and AI and it can randomly generate map according to custom rules. Similar images can be generated based on the input image by WFC algorithm. This algorithm is published on the website of github by Maxim Gumin [3]. He defines local similarity related to the following two aspects. Firstly, each N (feature parameter) ×N pixel module of the output image appears at least once in the input image. Secondly, the probability of appearance of each N*N pixel module in the output image is similar with the probability of appearance in the input image. Different styles of generated images can be generated by modifying the feature parameter N. There are five steps in this algorithm. Firstly, WFC learns the input and count N×N patterns. Secondly, an array with the output dimensions is created. The elements in the array represent the states of the outputs in region of N×N. Thirdly, the wave in the completely unobserved state is initialized. Fourthly, there is a cycle of observation and propagation. Observation includes the search of a wave element with minimal nonzero entropy and the collapse of the element into a particular state depending on coefficients and distribution of input. Propagation means propagating information observed. The cycle is repeated until all the wave elements are with zero or undefined entropy. Fifthly, if the wave element is in the observed state, then output is generated. If the wave element is in the contradictory state, then the work is ended without output.

The algorithm is mainly based on the discrete model synthesis study by Paul Merrell. He explores to propagate adjacency constraints in a simple tiled model [16]. This algorithm is also affected by declarative texture synthesis proposed by Paul Francis Harrison. He explains the adjacency data of tiles through the labels of these tiles' borders and fill the tilemap by backtracking search [4]. Isaac Karth and Adam M. Smith formulate WFC as an instance of constraint solving method for procedural content generation with multiple in-the-wild users in 2017 [8] and develop a system based on WFC trained on positive and negative examples and discuss this system in a general context with example based generators in 2019 [7]. Marian Kleineberg uses WFC algorithm to procedurally generate city based on the tiled model for Procjam 2018 [9]. It is the first step of application of WFC in the urban space generation.

3.2 CNNs

CNNs is a well-known deep learning technique in recent years. It is widely applied in the field of image recognition. Zhang Fang et al. [29] utilize CNNs to measure human perceptions towards a large-scale urban region. Zhou Bolei et al. [30] propose a novel method to recognize city identity through analysis of geo-tagged images and discuss the application of computer vision in urban planning. In 2016, Alex J. Champandard [1] proposes a semantic style transfer approach and turn two-bit doodles into fine artwork by

CNNs. In 2017 Li Chuan et al. [14] put forward the image synthesis method combining Makov random field and convolutional neural networks. This algorithm can be run by both GPU and CPU. GPU synthesis speed is much faster than CPU synthesis. This algorithm uses the several images as inputs to generate a new image and it depends on the original image style, original image's annotation and the target content image with its annotation. This algorithm extracts patch information from the style image and then transfers it to the target image according to the match degree. The matching effect is related to the number of iterations and computation speed. Within a certain range, the higher the number of iterations, the better the match, the longer the calculation time, but the matching effect will not increase after the number of iterations increases to a certain degree. Different number of iterations will result in different effects towards generated images.

4 URBAN SPACE SYNTHESIS BASED ON WFC AND CNNS

In this research, relevant theories and methods such as urban morphology, WFC, CNNs and urban design evaluation are applied. This research establishes a relatively well-developed urban design database, leverages WFC and CNNs for urban space synthesis, establishes the urban design evaluation system, and achieves the final urban design scheme through the interaction between designers and the pipeline (figure 1).

4.1 Establishment of urban design database.

The urban design database is established according to the international typical big data of urban space. The composition pattern of its spatial form is analyzed, contributing to basic type of the spatial prototype, which can be roughly divided into multi-center spatial pattern, grid pattern, annular radiation pattern and axis pattern. According to the classification of urban design cases, various urban design schemes are collected to establish the database. The urban design database includes three sub-datasets: urban road network database, urban block spatial form database and urban building function layout database.

The data of urban road network system is reflected by 2D maps of roads in different levels. The data of urban block spatial form is reflected by 2D maps with different colors to distinguish the square, green space and buildings in different heights. The data of urban building function layout is reflected by 2D maps that show different building functions by different colors.

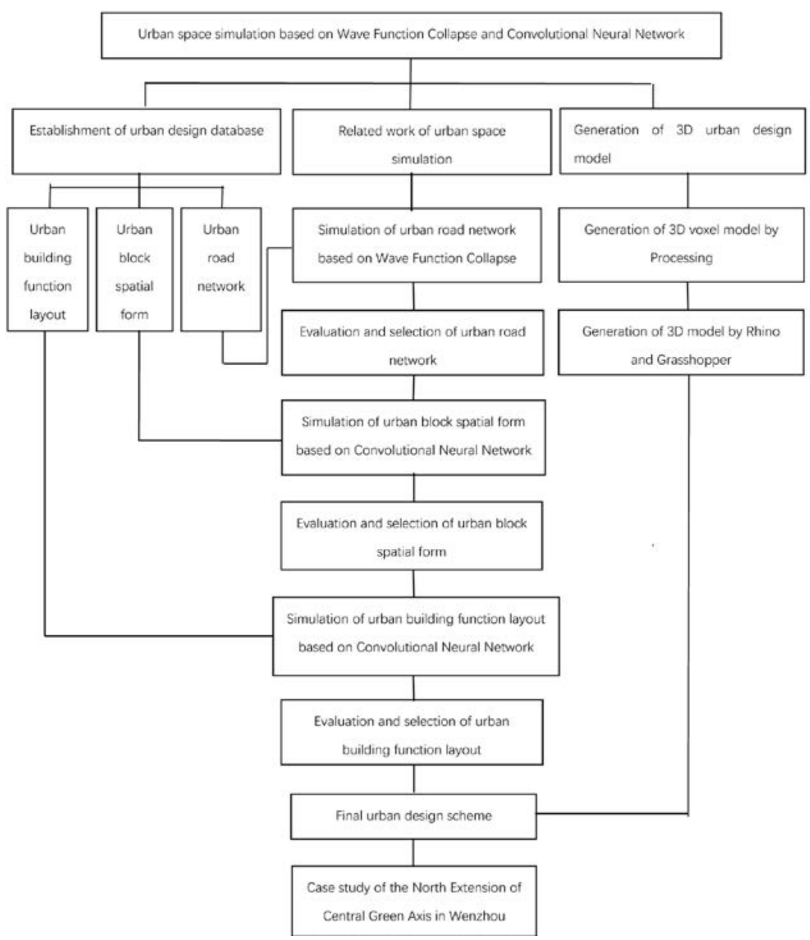


Figure 1. Research framework.

4.2 Urban space synthesis and scheme evaluation and selection.

The urban road network in the urban design database is the data source for synthesis by WFC and the characteristic parameter N is adjusted to generate multiple road networks. Then the generated road networks are evaluated and the optimal urban network is selected. Afterwards, the urban block spatial form in the urban design database is extracted for synthesis by CNNs, and the number of iterations is adjusted to generate multiple urban block spatial forms, followed with evaluation and selection, contributing to the optimal urban block spatial form. Finally, the urban building function layout in the urban design database is extracted, and the number of iterations is adjusted to generate multiple urban building function layouts. They are evaluated and the optimal urban building function layout is selected.

The evaluation and selection of urban design schemes can be divided into three steps. The first step is the evaluation of the urban road network. The second step is the evaluation of the urban block spatial form, and the third step is the evaluation of the urban building function layout. The evaluation indicators of urban road network include the density of the road network, the accessibility of the road network, the capacity of the road network and the integration degree of surrounding sites. The evaluation indicators of urban block spatial form include rationality of urban landmark layout, aesthetic quality of urban skyline, construction land rate, adaptability to topography, greening rate, rationality of urban square, variety of building form and variety of public spatial form. The evaluation indicators of urban building function layout include the diversity of urban building function and the rationality of urban building function layout.

4.3 Generation of 3D urban design models.

The data in three sub-databases are all 2D images, and the urban design schemes generated by WFC and CNNs are also 2D images. In this part, the 2D images are automatically generated into 3D urban design model by algorithm.

The different color in the generated 2D urban spatial block form represent squares, greening and building with different heights. The algorithm written by the software of Processing moves the pixels in generated 2D urban block spatial form to different heights according to their colors, contributing to 3D voxel model, and the 3D coordinate data of each voxel are exported. Then, the data are imported into the software of Rhino and Grasshopper and the 3D voxel model are changed to the 3D block model, which is the final 3D urban design model.

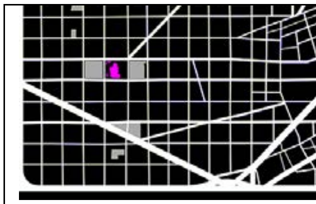
	
Barcelona	Hangzhou Qianjiang CBD
	
Paris	Venice
	
Washington	Wenzhou Ancient Town

Table 1. Sub-database of urban road network

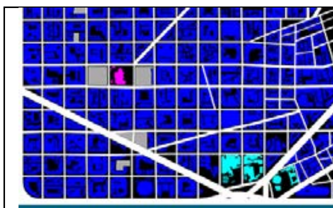
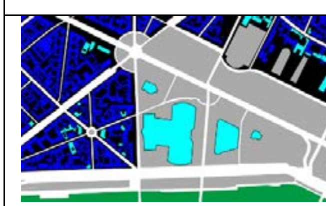
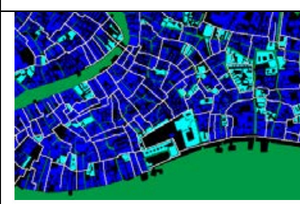
	
Barcelona	Hangzhou Qianjiang CBD
	
Paris	Venice
	
Washington	Wenzhou Ancient Town

Table 2. Sub-database of urban block spatial form

5 CASE STUDY: THE NORTH EXTENSION OF CENTRAL GREEN AXIS IN WENZHOU

In order to showcase the versatility of the urban space synthesis approach. It is validated on the case of the North Extension of Central Green Axis in Wenzhou. The central green axis is the main landscape axis through the north and south of Wenzhou, and the center of public culture and public activities. In this paper, we establish an urban design database, leverage WFC, CNNs and Processing algorithm to generate road network, urban block spatial form, building function layout and 3D spatial model.

5.1 Establishment of urban design database

According to the design vision and context, there are 6 urban space cases in the database, namely, Washington, Hangzhou Qianjiang Central Business District (CBD), Wenzhou ancient town, Venice, Barcelona, Paris. The design vision is the extension of central green axis. The cases with clear axis are selected, such as Washington, Barcelona, Hangzhou Qiangjiang CBD and Paris. In order to strengthen the identity of Wenzhou, the case of Wenzhou ancient town is selected. The selection of Venice is due to the similar topography. Both Venice and Wenzhou are watery place. The urban design database is divided into three sub-databases. Each case contains three parts of information, namely, urban road network (table 1), urban block spatial form (table 2) and urban building functional layout (table 3). Urban road network is reflected on figure-ground map. Urban block form uses different colors to distinguish buildings of different heights, squares, green Spaces and other public Spaces. Building heights can be divided into the 5 categories, namely, 1~3 story buildings, 3~8 story buildings, and buildings with more than 8 stories. Urban building function layout are divided into the following 5 categories, namely, cultural and educational areas, commercial areas, residential areas, office areas, and mix use of commercial and residential areas. Different colors are used to distinguish the different types of urban building functions.

5.2 Urban road network synthesis by WFC and scheme evaluation and selection

The urban road network in the database is extracted as data source for synthesis by WFC. The characteristic parameter N (3, 4 and 5) is adjusted to generate 3 different road networks. For scheme 1, the density of road network is appropriate; the accessibility of road network is high; the fit of surrounding sites is high. For scheme 2, the density of road network is high, the accessibility is appropriate, and the fit of surrounding sites is low. For scheme 3, the density of road network is high; the accessibility is low; the fit of surrounding sites is low. Thus, the scheme 1 is the optimal road network scheme (figure 2).

5.3 Urban block spatial form synthesis by CNNs and evaluation and selection

Urban block spatial forms from urban design database are learned and CNNs is leveraged to generate squares, green spaces and buildings with different heights. Each data source is learned in 3 different iterations (40, 60 and 80). The 6 cases are learned as data source separately and 18 schemes are generated. 2 of 6 cases are selected as data source to be learned afterwards. There are 15 case combinations totally and 45 schemes are generated. In other words, there are 21 different data sources to be learned and 63 schemes are generated. Then, in order to preserve the ecological structure, the constructions in Yangfu Mountain and Shangdoumen River in the schemes are replaced as green and blue. Finally, the urban block spatial form schemes are evaluated and selected. There are 8 evaluation indicators, namely, rationality of urban landmark layout, aesthetic quality of urban skyline, construction land rate, adaptability to topography, greening rate, rationality of urban square, variety of building form and variety of public spatial form. The highest score for each indicator is 10. The score is provided by urban designers. The final score is the sum of indicators above. Finally, 6 schemes whose final score in top 6 are picked out. These schemes are learned from the case of Wachingtom, the cases of Washington and Hangzhou Qianjiang CBD, the cases of Washington and Wenzhou ancient town, the cases of Washington and Paris, the cases of Hangzhou Qianjiang CBD and Wenzhou ancient town, the cases of Hangzhou Qianjiang CBD and Venice respectively.

	
Barcelona	Hangzhou Qianjiang CBD
	
Paris	Venice
	
Washington	Wenzhou Ancient Town

Table 3. Sub-database of urban building functional layout

5.4 Urban building function layout synthesis by CNNs and scheme evaluation and selection

The urban building function layout data of the 6 cases in the database are extracted and CNNs are leveraged to generate the building function layout. The iteration is adjusted as 40,

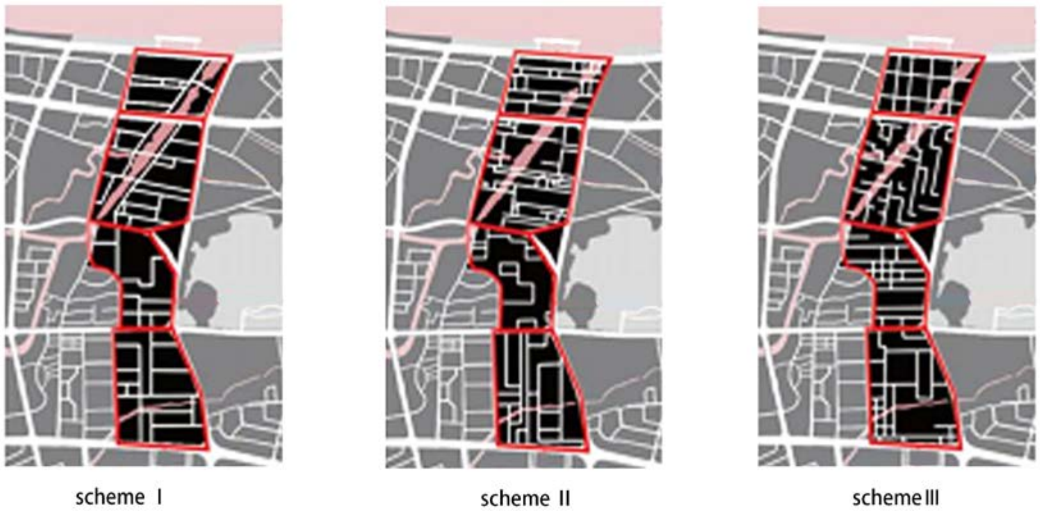


Figure 2. Generated urban road network.

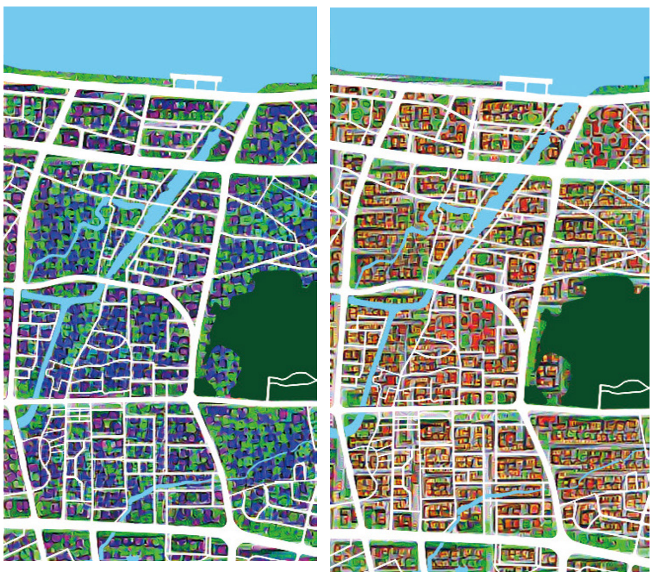


Figure 3. Optimal design of urban block spatial form and urban functional layout.

60 and 80. 18 urban building function layouts are generated for evaluation and selection. The evaluation indicators specified in this paper are as follows: the diversity of urban building function layout and the rationality of urban building function layout. The indicator of urban building functional diversity is the number of building functions and the indicator of the rationality of urban building functional layout depends on the distribution density of buildings with different functions and the coverage of building service radius. Based on the scheme, the designer will make an empirical score. The highest score for each indicator is 10 and the final score is the sum of two indicators. In the end, according to the final score, the best functional layout is generated by Hangzhou Qiangjiang CBD and Venice with iteration of 80 (figure 3).

5.5 Generation of 3D urban design models

The first step is writing the code in Processing. Pixels in the 2D urban block spatial form map generated in the previous stage are assigned to different heights according to their colors and a 3D voxel model is generated by algorithm (figure 4). Afterwards, the 3D coordinate information of each voxel point is exported. In the second step, the 3D coordinate information data obtained in the last step is imported in Rhino and Grasshopper to automatically generate the 3D block model of the North Extension of Central Green Axis in Wenzhou (figure 5).

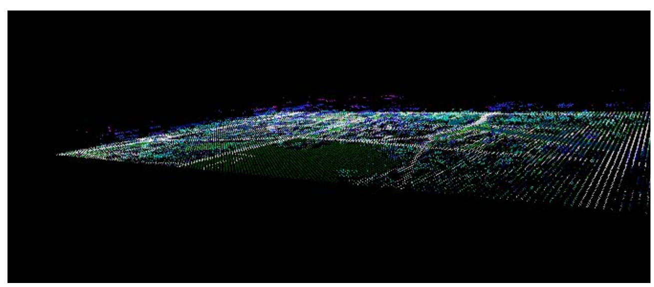


Figure 4. 3D voxel model.

Figure 5. 3D block model.

6 CONCLUSION

We have investigated the suitability WFC and CNNs for urban space synthesis. Firstly, an urban design database is established as the data source for generation. Then the road networks urban spatial forms and urban functional layout are generated by WFC and CNNs and evaluated by designer afterwards. Finally, the 3D models are generated. Our result demonstrates the feasibility of WFC and CNNs for fast prototyping of urban design. It can improve the design efficiency of urban designers and assist government's decision making.

However, we identified several limitations in our pipeline. Firstly, the schemes generated by this method are not accurate enough due to the limitations of computer hardware and algorithm. The boundaries between areas with different colors are not clear in the generated map by CNNs. Secondly, the process of scheme evaluation and selection is still subjective and empirical. The accuracy of evaluation and selection heavily relies on urban designers' ability and experience. Thirdly, the data format of the data source in the database and the generated results are all pixels. The resulting images produced in our pipeline can only be used for a preliminary planning concept and there is still a certain gap from the actual application of engineering projects. Transforming the format of output from raster to vector is a crucial step for allowing the pipeline to integrate with common architectural tools and practices. Fourthly, this pipeline is intended to be used for new spaces and cannot used for the management of the existing urban areas which is highly demanded in urban regeneration.

In order to solve the problems above, there are several interesting directions for future work. We plan to leverage Generative Adversarial Network for generation in order to improve the accuracy of image generated. Then, an optimization code, such as genetic algorithm, will be developed for evaluation and selection. Finally, we will investigate a new algorithm which can directly generate design output in the format of vector.

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