A Discussion on an Urban Layout Workflow Utilizing Generative Adversarial Network (GAN)

With a focus on automatized labeling and dataset acquisition

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Deep Learning (DL) has recently gained widespread attention in the automation of urban layout processes. This study proposes a rule-based and Generative Adversarial Network (GAN) workflow to automatically select and label urban datasets to train customized GAN models for the generation of urban layout proposals. The developed workflow automatically collects and labels urban typology samples from open-source maps. Furthermore, it controls the results of the GAN process with labels and provides real-time urban layout suggestions based on a co-design process. The conducted case study shows that the average value of the GAN results, trained from an automatically generated dataset, meets the site's requirements. The developed co-design strategy allows the architect to control the GAN process and perform iterations on urban layouts. The research addresses the research gap in GAN applications in the field of urban design and planning. Many studies have demonstrated that training the (GAN) model by labeling enables machines to learn urban morphological features and-urban layout logic. However, two research gaps remain: (1) The manual filtering of GAN urban sample datasets to fit site-specific design requirements is very time-consuming. (2) Without a suitable data labeling method, it is difficult to manage the GAN process in such a manner to facilitate the meeting of overriding design requirements.

Keywords: *Deep Learning, Generative Adversarial Network (GAN), Urban Layout Process, Automatic Dataset Construction, Co-design*

INTRODUCTION

Since the 1960s, many studies have used rule-based approaches to achieve automated urban and architectural design layout and optimization (Anderson et al., 2018, Fricker et al., 2007). Compared to the rule-based approach, the Deep Learning (DL) method can recognize the dataset's features and generate output without explicitly formulated rules (Zheng and Yuan, 2021). Therefore, it has great potential in overcoming complex urban and building problems with difficult-to-discern objective constraints (Zeiler and Fergus, 2014). Regarding the fast development of DL, more recent research analyzes the potential and challenges of DL-generated urban design based upon human decision-making. The Generative Adversarial Network (GAN), a DL model, demonstrates huge potential for automated design and planning processes. GAN enables machines to learn the interrelationships of urban morphological features and urban layout logic by labeling (Liu et al., 2021). Although GAN models are adapted to quickly produce results similar to historical urban samples, it is still a challenge to integrate architects' decisions for producing solutions that meet urban future development requirements. At the same time, for generating results that meet our standards for future designs, we need numerous manual filtering processes to ensure that the historical cases that are entered into GAN meet the designer's requirements, rather than random sampling. Two areas need to be addressed in further research on the application of GAN to urban layout studies: (1) the manual selection of urban samples meeting the criteria to create a qualitative suitable dataset is tedious and repetitive; (2) without a suitable data labeling method, it is difficult to manage the GAN process in such a manner to facilitate the meeting of overriding design requirements.

To solve the outlined problem of generating datasets rapidly, some recent studies have applied Data Augmentation (DA) and Automated Data Acquisition methods (ADA). However, it is challenging to accurately represent the diversity of GAN results with the DA approach (Liao, 2021). Tian proposed an ADA method by automatically acquiring samples from GIS platforms to train GAN models for urban planning purposes (Tian, 2020). However, this kind of ADA method does not filter samples that meet the architect's requirements. Compared to the previous method, there is still potential for adding an Automatic Selection Component (ASC) to obtain only samples that meet architect/urban designer-defined criteria.

To solve the problem of managing the GAN label process to facilitate the meeting of overriding design requirements, many studies have experimented with different GAN Data Labeling Setting (DLS) approaches. DLS is an important GAN data-processing process that can influence the way people collaborate with DL models. For example, architects can control the urban layout of GAN by inputting different labels, such as the road network (Shen, 2020) or the shape of urban elements, like ponds, paths, and site boundaries (Liu et al., 2021). However, these labelling rules, consisting only of simple physical constraints, make it difficult for the GAN to produce layout results that incorporate the architect's subjective speculations. Compared to the previous studies, an enhanced DLS approach is needed to integrate the existing physical information (like road networks, public spaces, and green and blue infrastructure elements) and the architect’s speculation label as GAN’s input to enhance the architect’s decision-making in GAN applications.

Therefore, this research aims to provide a discussion on a hybrid workflow that can automatically select and label sample datasets instead of the manual training of a customized DL model for a co-decision urban design process. Co-design in this paper means, that the machine completes the automatic layout task based on the architect's decision-making. The aim is to train a DL model to assist architects in completing urban design tasks, such as road network layout and building layout; the machine also can give suggestions for building function, height, density, etc. Architects can co-operate with the GAN by inserting the physical constraints and design speculation labels of the current site as input to the GAN model. This lowers the threshold of accessibility and fosters the integration of automized design processes into traditional workflows.

Our proposed method makes it possible to generate solutions that better match site-specific requirements by automatically filtering samples using ASC, in comparison with Tian's (2020) method. The GAN will thus be more easily programmed to provide appropriate answers to urban layout tasks.

PREVIOUS RESEARCH

In this section, we summarize relevant research on urban data collection and data labeling.

Application of GAN in urban and architectural design

GAN is a DL framework designed by Lan Goodfellow and his colleagues in 2014 (Goodfellow et al., 2014). A GAN consists of two deep networks, the generator, and the discriminator. Both networks are trained to compete with each other in order to improve themselves. Recently, many studies have applied GAN models in architecture and urban design tasks. Hartmann et al. (2017) developed Street GAN for road network synthesis with nearly 500 samples. ArchiGAN generates furnished apartment floor plans using about 700-floor plans as samples (Chaillou, 2020). Fedorova (2021) used a GAN, which can adapt to a city's UMF to generate urban block design.

The aforementioned research highlights the advantages of GAN methods to enable machines to learn and generate architectural and urban layouts without any precise constraint rules. However, procuring enough training examples is a key challenge in working with GANs, according to Newton's research (2019). Peak performance in image synthesis tasks can contain 10,000 to 50,000 images (Im et al., 2018). As discussed in the introduction section, the manual generation of datasets remains a considerable challenge and is therefore the main aspect addressed in the conducted research.

Dataset in GAN for urban layout generation

Recent research has experimented with new methods for acquiring higher-quality datasets for DL models. For example, Newton used only 45 hand-drawn drawings of Le Corbusier as samples and successfully expanded them to 540 samples using the Data Augmentation (DA) method (2019). However, the DA method expands the sample size but does not significantly contribute to sample diversity. For example, Liao's experiments noted that enhanced samples are obtained by cropping, flipping, and adding noise to existing samples in order to add variation in the replications (Liao, 2021). Besides, Tian (2020) used an ADA method, which automatically obtained almost 4000 data samples from a GIS platform to train the GAN model instead of manually producing the dataset.

However, the architects are not able to filter the data qualitatively in Tian's method, which minimizes the application potential of the method. For example, it is still difficult to generate a qualitative high-density urban layout by using low-density urban layout datasets to train the GAN model (Shen et al., 2020). Therefore, in this study, an automatic selecting component (ASC) is designed to obtain a large amount of data while filtering samples for fulfilling site-specific requirements.

A labeling method for urban layout tasks utilizing co-decision elements

Previous research has shown that training a GAN with labeling allows the ML algorithm to learn the interrelationships of urban spatial elements (Liu et al., 2021). The DLS methods with GAN offer a new co-design possibility. The architect inputs design decisions (labels) to meet the urban design task, and the GAN quickly generates urban design proposals based on the chosen labels. However, in the current DLS approach, most of the inputs to the GAN are existing physical conditions of the site, such as existing boundaries (Tian, 2020), entrances (Liu et al., 2021), and roadway networks (Shen et al., 2020). These DLS methods lack the subjective speculative labeling of architects as input, in addition, there is a need for a systematic and automated method to replace manual labeling. The discussed enhanced DLS method is expected to automatically connect existing site-specific constraints and architects' design intentions as GAN 's input to form the co-design framework in which architects can better control the layout details compared to the previous method.

PROBLEM STATEMENT

Based on the above-outlined research gap, this research aims to support the GAN dataset generation through a workflow for fast filtering and crawling of data from OSM using the rule-based approach. The second goal is to define a new automatic DLS method. We are addressing the following research question: How do we enhance architects' design decisions in the GAN generation to facilitate the meeting of overriding design

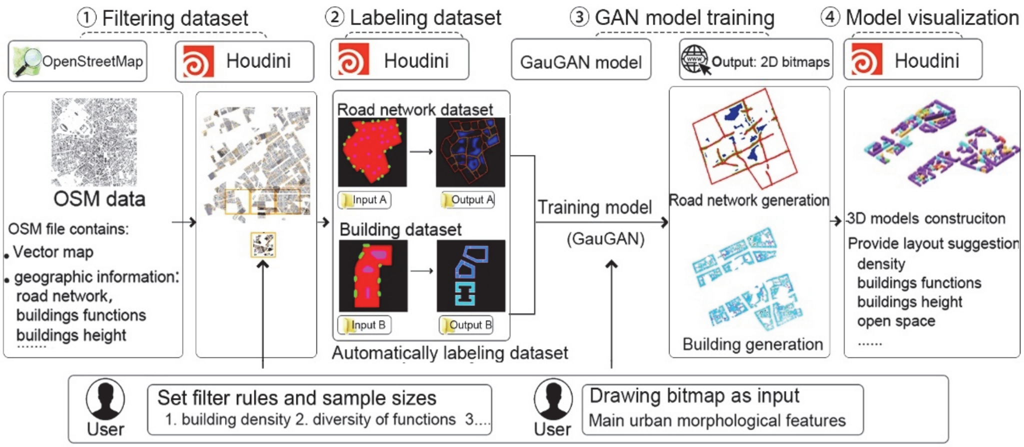


Figure 1
Workflow diagram outlining the automated data filtering process, GAN model training, and the co-design process.

requirements, rather than just using AI to find similar solutions from data sets?
Research Objectives:

1. Development of an automated process to filter different urban data samples (based on density, height, functions, diversity, etc.).
2. Development of an automated algorithm to calculate the urban spatial elements of selected samples (In this paper, urban spatial elements are defined as attributes of the urban structure defined by the architects, such as borders, openings, road networks, etc.).
3. Utilizing a GAN model to train the datasets to generate urban layout bitmaps.
4. Development of a process transferring bitmaps into 3d models, providing height and program suggestions for the generated layout.

The further discussion will mainly focus on the first and second objectives.

METHOD

This section focuses on the data generation process and GAN training.

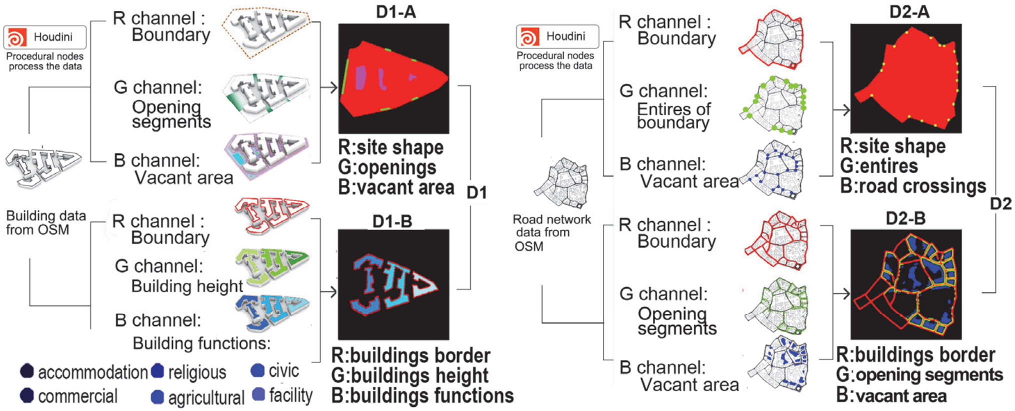
Framework

We propose a rule-based method containing an automated sample collection (ASC) and automatic label component (ALC) utilizing the Houdini modeling software. ASC filters the samples from the open street map platform, and ALC automatically completes the architect-defined DLS process that enables the architect to control the GAN results. The generated dataset is used to train a GAN model, further assisting the architects in the design process through urban proposal generation and visualization (Figure 1).

Automatized filtering of urban sample data with customized rules

OSM, an open-source geographic database, contains urban vector maps and information on cities. We first utilized Houdini OSM nodes to
automatically scan the given area on OSM vector maps for detailed information such as urban road networks, vacant areas, building functions, building height, etc. In our experiment, we collect two different groups of datasets for urban site-planning tasks. The building dataset (D1) is collected for generating building layouts on a single-block scale. The road network dataset (D2) is collected for road network generation on a multi-block scale. These

Figure 2
Automatic labeling process and color-coding rules of the dataset D1and D2



datasets are used to train two different GAN models. After the training, the GAN generates D1-models and D2-models. These two models can be used individually or together, which greatly extends the range of design scales and avoids generative size limitations (Sinha et al., 2020).

We set up a 3D bounding box in Houdini procedural nodes to filter the raw OSM with a custom set criterion. Users can customize the size of the box. Within the bounding box, the algorithm selects and calculates the suitable data meeting the filtering criteria in the specified area

as samples. The 'filtering criteria' is the raw data in OSM, redefined by architects by adding additional information, including density, diversity of building functions, plan area ratio, and green area in the bounding box. Next, the data that meet the set criteria will be entered into the system for automated labeling. Both D1 and D2 fetch samples with this filter.

Automatic labeling process of datasets

Our data labeling method reads and computes OSM metadata using the Houdini procedural node to calculate and collect the urban spatial elements to label the data. The selection and processing of the urban spatial elements in the data labelling process are inspired by the figure-ground map concept. The figure-ground map proposed by Colin Rowe contains physical information and subjective speculation, showing built and unbuilt, and are widely used in the urban analysis process. (Boca & Korolija, 2019). For example, the architect's analytical markers for road nodes, building boundaries and open spaces are superimposed on the existing building map. Finally, our DLS method selects road network nodes, borders, openings, entries, vacant land, and functions as additional labels, offering more input choices to control the layout. Such labelling method also allows GAN to make visual suggestions beyond the physical layout. Houdini's nodes can work automatically with the following colour coding ways.

Color-coding: To generate a computer-recognizable dataset, we convert the filtered graphics to bitmaps paired in RGB color mode in a batch in Houdini. We define three-color channels in the input bitmaps as different elements on the map separately. The three-color (RGB) channels represent different information in

different databases and the RGB channels merge into bitmaps (Figure 2). The dataset consists of a pair of bitmaps which are labeled as vector maps and stored in the training and testing folders of D1 and D2. All bitmap pairs are 512px * 512px in size which 1px is defined as 1.5 meters in scale.

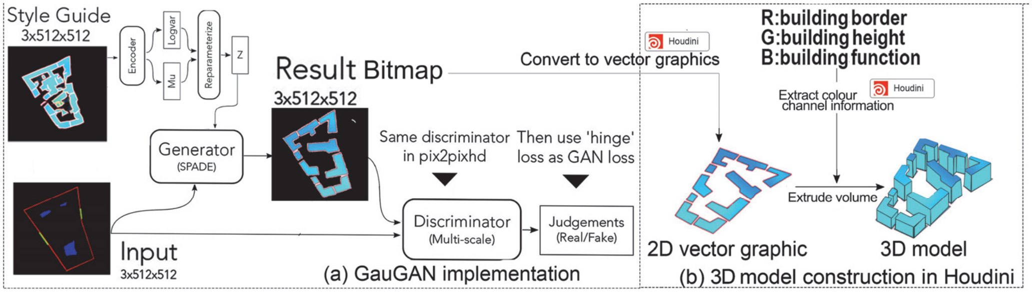


Figure 3
GAN model training process and 3Dmodel construction based on the color information of output bitmaps

D1-A describes the input rules of building layout: R channel represents the site shape based on road lines, G channel represents the open boundary, and B channel represents the vacant areas.

D1-B describes the layout and suggestions of buildings: the R channel represents the building footprint, and the G channel represents building height information. The height value of the building is reduced equivalent to a value between 0 and 1 using a Houdini vex function called the ‘clamp’. The B channel represents the function of the building. Different building functions represent different values in the B channel: Accommodation = 0/6, Commercial = 1/6, Religious = 2/6, Civic = 3/6, Agricultural = 4/6, Facility = 5/6, others = 6/6.

D2-A describes the input rules of road networks, R channel represents plots shape, G channel represents the entries, and the B channel represents the crossings of roads.

D2-B describes the layout of road networks and uses the same color label rules as D1-A.

GAN model training and vectorized model generation

In this part of the research, we chose the GauGAN neural network for machine learning. GauGAN is an image translation algorithm published by Nvidia Lab in 2019 to achieve multi-modal synthesis (Park et al., 2019). Compared to the Pix2pix model, the GauGAN model is much more precise, allowing the generated bitmap to be more easily converted into a vector graph (Pan et al., 2020). The resulting GAN bitmaps are converted back to a 3D model, as shown in Figure 3.

GAN model evaluation. We used the Fréchet Inception Distance (FID) model to evaluate GAN training accuracy. The FID can efficiently calculate the similarity of the generated image to the real image (Heusel et al., 2017). The dataset is divided into validation datasets and training datasets in a ratio of 1:9 (Park et al., 2019). The model is used on different sites to test the robustness of the model. Simultaneously, we quantified the building metrics (density, diversity of functions) of the final layout results to evaluate whether the results meet specific requirements. Finally, we published our training models on the following website:
http://show.fujiazhiyu.cn/gantrans/modeltype

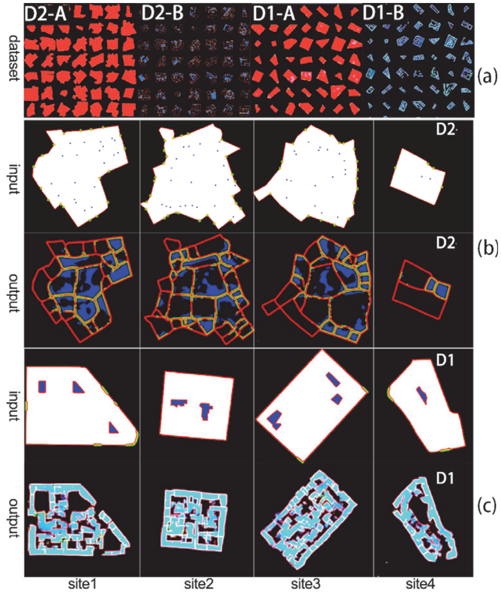
CASE STUDY

This section applies the defined workflow to a design competition in Milan to test its feasibility and practicality.

Main goal and settings

The site is in the Naviglio area under the context of the international design competition "Attraverso San Cristoforo" held by the City of Milan in 2018. The government's expectations for the competition are summarized as follows: (1) enhance road network links, (2) increase density and functional diversity of buildings, and (3) create more openings. We choose this case to verify whether specific design requirements can achieve the initial layout intention

Figure 4
(a) Generated D2 dataset, (b) Input and output of road network layout tested with GAN (c) Generated D1 dataset (d) Input and output of building layout tested with GAN



using the GAN model. Specifically, our experimental goals are as follows:

1. Fast and automatic generation of urban datasets for GAN training.
2. The trained GAN model can initially rationalize an urban layout, and architects can control different layouts through morphological rules.
3. Adaption of the generated GAN model to other sites.

The workflow process and settings are shown in Figure 1. The size of the screener is 768m (to completely cover the site). The building's functional diversity is defined as the number of building functions divided by the total number of buildings, which we set to greater than 0.07. The building density selection rules are set to greater than 0.3, attempting to enable the machine to learn samples that meet our screening criteria.

CASE STUDY RESULTS AND DISCUSSION

This section demonstrates the case study results and the process of co-design.

Testing the trained GAN model

We automatically collected 2012 samples as shown in Figure 4 (a). We selected 200 cases from the database as a test set to evaluate the model's accuracy. The model is trained for 400 iterations. The final FID score is 15.7. Figure 4 (b) and (c) display the road network and urban layout for the chosen sites generated by the GAN model. To verify the stability of the GAN, we chose four completely different site shapes and completely different input rules.

In addition, Table 1 shows the average value of the density and diversity of the generated results for 200 test data. The results demonstrate that the mean building density and functional diversity of our generated layouts are higher than the criteria of the ASC module in the case study process. Therefore, the GAN can generate a preliminary urban layout that meets site-specific needs by filtering the urban samples through ASC even before the training process, which realises the workflow of automatically sample filtering.

Table 1
Comparison of mean value test dataset generation results and selection criteria

	Functional diversity	Density
Selection criteria	0.07	0.3
Mean value of Result	0.0951	0.357

Road network layout

Figure 5 shows the co-design interface (Figure 5(a)) and different results (Figure 5(b)) of road network generation. In our input interface, architects firstly use red lines to outline the current site boundary, secondly use green dots to place the intended entrance location, and place intended road network nodes using blue dots. Then the GAN can generate a corresponding road network Layout. The red line represents the road network layout of the GAN output, at the same time the GAN suggests open boundaries (green) and open space layout in current solutions (blue).

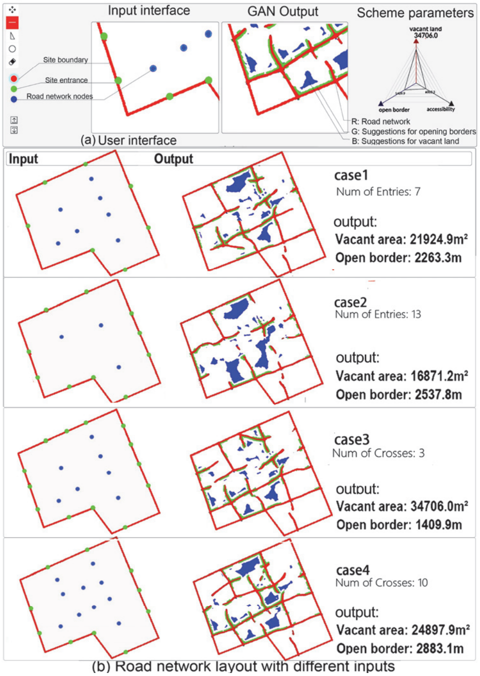


Figure 5
Comparison of the results of road network layout and suggestions by different inputs

Different numbers of entrances and nodes inputs in different positions will generate different results, as shown in Figure 5(b). Case 4 has better road network links and accessibility than case 3. This result is due to the manual modification of local interaction points by the architect. In contrast to case 2 and case 3, the architect can control the division of the urban layout by determining the location of the entrance within the boundary condition.

Compared with Liu (2021), the results show that GAN not only can learn the current road network relationship from historical examples but also allows the architect interactively adjust the details of the layout by controlling the inputs .The architect's site-specific decisions play an important role in the Gan iteration process and directly determine whether the GAN-generated results will meet the requirements of the urban design.

Building layout and suggestions

In Figure 6, architects firstly outline the plot physical boundary in red lines, then draw the intended locations of openings (green lines) and intended vacant land (blue blocks). Then the GAN can generate the corresponding building layout, The cases in Figure 6(b) display that the architect can control the entrance to the building group through open boundaries (green). By reducing vacant land in the co-design phase, the architect is able to create a difference between case 3 and case 1. In the next phase, the building layout is iterated, resulting in a density increase from 0.37 to 0.39. Figure 6(c) displays the synthesized 3D model based on the generated results, providing suggestions about the functions, height, and layouts. With the output of the

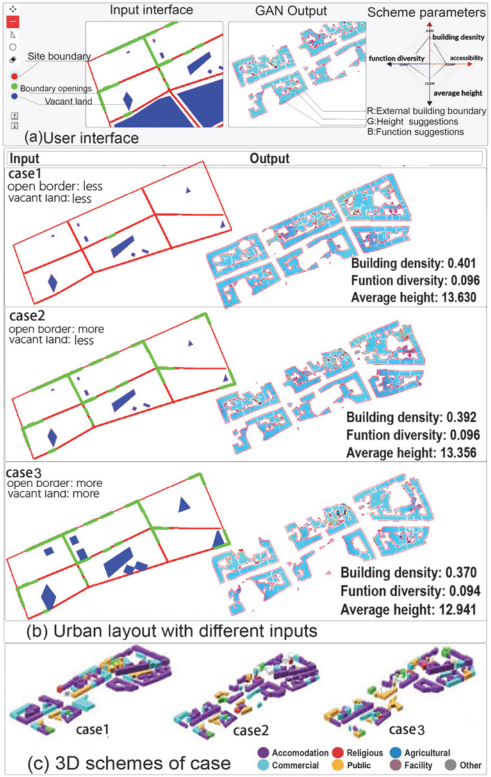


Figure 6
Comparison of urban layout generation according to varying input criteria.

GAN, the architect can modify the initial decision in real time to find a solution that meets the functional and height requirements. The generated results from case1 to case3 show residential buildings account for the largest proportion, followed by commercial buildings, without industrial buildings. With the intervention of the architect, gan can generate functional suggestions that are more in line with the requirements of the site.

Limitations

The current atomized dataset labelling approach is currently only able to solve basic urban layout tasks. There is a need for enhanced methods to face complex urban layout tasks with GAN, such as the precise control of road widths, building boundaries, green areas, etc. The combination of GAN methods and multi-objective optimization algorithms is visualized as viable urban designs. Additional experiments and comparisons are needed to verify which kinds of urban spatial elements can assist the architect in controlling the quality of urban layouts and which will potentially create conflicts. Scale limitation is still a challenge for GAN applications. Although we applied two databases to generate layouts in different scales, the process is not able to handle the requirements of dealing with multiple scales in the actual design process. The current research attempts to solve this problem using a rule-based algorithm combined with GAN.

CONCLUSION

This study adds new contributions to GAN's application in the automatized urban design process. The case demonstrates the ability to quickly automate the generation of datasets to save manual production time. The result shows it
is possible for GAN to generate solutions that better match site-specific requirements (density and functional diversity) by automatically filtering samples.

In addition, our DLS approach provides a co-design workflow by superimposing the physical constraints of the existing site and the subjective speculations of the architects as input to the GAN. The output of the GAN also contains the physical site layout and predictive suggestions for helping architects optimize their decision-making. Compared to previous methods, the co-design workflow offers the possibility to simultaneously solve complex urban design tasks during the design process. This method has the potential to introduce an intermediate bridge to enhance human design decisions to link physical maps and human willingness in AI instead of just letting AI generate similarities. In the future, the dimensional constraints in GAN will be discussed in-depth to apply the workflow to real design projects.

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