Nolli Map: Interpretation of Urban Morphology Based on Machine Learning

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Abstract. Nolli map is the earliest diagram tool to simplify and quantify urban form, which most intuitively reflects the spatial layout of tangible elements in the city. The urban morphology contains its inherent evolutionary laws. Exploring the inner rules of cities is helpful for people to conduct urban research and design. Unlike the traditional research methods of urban morphology, the neural network algorithm provides us with new ideas for understanding urban morphology. In this experiment, we label 136 European cities samples in the rules of Nolli map as a training set for machine learning. We use Generative Adversarial Networks (GAN) for multiple mapping experiments. The generated images present recognizable and plausible images of the urban fabric. The results show that the machine can learn the inherent laws of complex urban fabrics, which expands a new applied method for the study of urban morphology.

Keywords: Nolli map · Urban morphology · Deep learning · GAN

1 Introduction

In 1736, Giambattista Nolli, the Italian architect and surveyor, was commissioned by Pope Clement XII to draw a plan of Rome (Fig. 1). Nolli recorded every part of the space of Rome, using complex iconographic schema, illustrative cartographic symbols to depict urban fabric, which comprehensively and effectively display the spatial elements of the city, reveal the urban structure composed of streets, squares, buildings, and show other tangible elements of the city. Nolli map now is the most widely used diagram method of urban morphology [7].

The urban morphology is the external presentation of the city which has developed in periods of years. Thus, the old fabric and the new one are intertwined [13]. In recent years, the development of open data platforms has provided numerous geographic information data resources for the quantitative investigation of urban morphology [18]. However, urban morphology is so complex that it is influenced by factors such as geography, socioeconomics, politics, etc. under nonlinear laws. The urban morphology research based on traditional statistical analysis fails to completely integrate all elements and to grasp the subtle characteristics of urban evolutionary laws.

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Fig. 1. Nolli map in 1748 and its sections *Source* https://nolli.stanford.edu/

With the rise of artificial intelligence especially deep learning technology, these problems may be solved. An important feature of deep learning is that machines can automatically extract general features from data through data learning, instead of extracting data features in a manual way and inputting them into machines like traditional research methods. It will provide a new way of urban morphology study. In this way, cities can be more accurately understood and represented.

2 Background

Before starting the experiments, we summarize the feature of Nolli map, propose the research implications, and analyse the existing researches on deep learning for city form.

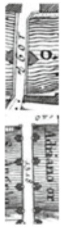
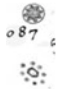
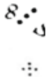
2.1 Nolli Map and Urban Morphology

Nolli chose the traditional Roman scale of 1:2750 to draw. The information of the whole map can be summarized according to different parts of the city and divided into the following three different spatial categories (Table 1). The first category is urban built-up area, which is based on the figure-ground plan concept: (1) public spaces such as streets and squares are depicted with a white background; (2) inaccessible private buildings are indicated with black blocks; (3) open artificial green lands are illustrated with light grey. The second category comprised natural environment elements like different types of hills, rivers, plants, which are distinguished through different fabrics. In addition, Nolli also made sketch drawings to describe municipal infrastructures such as bridges and street furniture in details.

From the perspective of urban design research, Nolli map can more comprehensively depict urban form. Nolli map distinguishes the urban fabric by figure-ground plan, fully indicating the relationship between the private building and the public space. Comprehensive information and clear morphological features would help the machine to learn the organic fabric of the city under machine learning method.

Other diagram methods for urban morphology may be not suitable for the rapid learning by machines. Conzen divided urban plans into buildings, plots and streets,

Table 1. Categories of diagram theory in Nolli map

Urban built-up area				Natural environment elements			Municipal infrastructure and street furniture		
Street	Square	Buildings	Artificial green area	Hill	River	Plants	Bridge	Fountain	Drain
									

marked them with linear elements and different fabrics [1], whose description of urban structure ignores other city elements, urban planners mark various macro quantitative indicators such as plot ratio, functional density and height in different colours, which do not reflect spatial characteristics. The research on the relationship between spatial policy and urban form use geometric elements of point, line and surface, which cannot show a tangible form of the urban fabric [9].

Research in the past enriches the diagram of Nolli map and proposes future research trends in digitization and machine learning. Venturi created a Nolli map of the Las Vegas Strip, integrating road elements into the map. Huimin Ji analyzed and proposed a new urban public space mapping method, and pointed out that Nolli-type maps can be efficiently created by using the data of urban maps and indoor maps in various digital maps [6]. Hwang and Koile [4] proposed an illustration of the public space of Boston's main streets, and discussed the role of machine learning techniques in that diagram.

2.2 Applications of Deep Learning in Urban Design

At the urban level, the initial applications of deep learning mainly focus on the generation of urban streetscape maps [15] and quick previews of urban block renovations [17]. Subsequent related research gradually emerges in the generation of floor plans at different scales. Liu et al. [8] used cGAN models trained from a database containing 85 pairs of samples to generate building layouts at different building densities within a plot. Shen et al. [14] applied GAN to create urban design solutions in small plots. Pasquero and Poletto [11] used cycleGAN to explore "non-human" urban forms by transferring biomorphic styles to the urban fabric. Pan et al. [10] trained a large sample of northern neighborhoods to generate diverse layouts within a plot [10]. Fedorova [2] used the model trained by five existing urban environments to observe the possibility of style transfer between different cities, and presented quantitative and qualitative evaluations of the results (Table 2).

Through the analysis of the above existing studies, it is easy to find that: (1) Most of the studies are not from an urban morphology perspective, but from image fitting

Table 2. Comparison of various studies in the research

Paper	Authors	Model	Application scenario	Sample size	City range	Image resolution
Urban Design process with conditional generative adversarial networks [8]	Yuezhong Liu, Stouffs Rudi	cGAN	Small plots: road boundaries generate building rows; not clearly imaged	85	~0.5 km (Image metering)	512 × 512
Machine learning assisted urban filling [14]	Jiaqi Shen, Chuan Liu, Yue Ren, Hao Zheng	Pix2PixHD	Small plots: road network generates building rows	/	~0.5–0.7 km (Image metering)	256 × 256
DeepGreen–coupling biological and artificial intelligence in urban design [11]	Claudia Pasquero, Marco Poletto	cycleGAN	An attempt to urban style transfer	/	/	256 × 256
Suggestive site planning with conditional GAN and urban GIS data [16]	Runjia Tian	Pix2Pix	Single plot: road boundaries generate building layouts	4400	~0.5 km (Image metering)	256 × 256
A Preliminary study on the formation of the general layouts on the northern neighborhood community based on GauGAN diversity output generator [10]	Yuzhe Pan, Jin Qian, Yingdong Hu	GauGAN Pix2PixHD	Single plot: road boundary generates building row; single function: residential area	167	0.11–0.33 km	512 × 512
Generative design of urban fabrics using deep learning [12]	Jinmo Rhee, Pedro Veloso	WGAN	Small plots: random urban fabric generation from noises; unsupervised learning	45,852	~0.15 km (Image metering)	512 × 512
Generative adversarial networks for urban block design [2]	Stanislava Fedorova	pix2pix	Small plots: road boundaries generate building layouts	/	~0.4 km (Image metering)	256 × 256

in computer graphics; the studies ignore the laws of urban evolutionary development. (2) Most of the studies stay in the relationship between boundaries and building layout, ignoring other elements which influence the development of the city, such as water system, green space. (3) The urban scope of the experimental sample is small, mostly within 0.5 km × 0.5 km, which is more like the internal generation of land parcels rather than urban-level studies; it is also because of the limitation of the image processing capability of deep learning models, that the image resolution is too small to show more details of the city.

2.3 Objective

The research is to explore the strategy of using GAN model to realize the automatic generation design of urban form. According to the evolution laws, the corresponding relationship between the pairs of data sets can be sorted out. The urban fabric is automatically generated based on the city's underlying structure. We adjust the model framework of GAN to fit high-resolution images, which enables a wide range of Nolli map images to be learned. The machine cognition of the laws of the overall shape of the city has made a breakthrough on a large scale, which proves that deep learning has great potential in urban morphological researches and design applications.

3 Methodology

The main process of exploration on machine learning generation of urban morphology is as follows: (1) Database establishment: Select city data which meet the standard and collect their relevant information. (2) Sample processing and labelling: Redraw and label samples on basis of Nolli Map. (3) Training and testing: Input one-to-one corresponding sample sets to train and test the machine learning model. (4) Evaluation and modification: Evaluating the results and putting forward further adjustment of labeling method to improve the final generation.

3.1 Model Architecture

In this experiment, based on the data type and the characteristics of neural networks, Image-to-Image Translation with conditional Generative Adversarial Networks [5] are used as the main learning model. Taking this model as a basis, we adapt its model architecture, such as the number of neural network layers, to compute images at higher resolutions (1024×1024).

The concept of Generative Adversarial Networks (GAN) was first proposed in 2014 by Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, and other scholars [3]. GAN consists of a Generator and a Discriminator. In the training process, the Generator first generates an alternative image from the latent space and passes it to the Discriminator. The Discriminator takes either the real image or the alternative image as input and tries to distinguish whether the current input is the real data or the alternative data. After the mutual game between Generator and Discriminator, the GAN model completes the effective learning of the data and finally synthetize the high-quality fake images.

3.2 Dataset Construction

According to the experimental objectives and the requirement of the deep learning model, we collect the urban data that meet the requirements; then sort, analyze and label them.

The original city data source is the open data from OpenStreetMap, and we use QGIS and python to download the OSM city data. We select 136 European city samples, which can represent the typical urban morphological feature (Fig. 2).

After the city data is collected, we complete the data analysis and graphical labelling of the data set (including training set A and training set B) and the export of images in the data processing stage. We make the cleaning of the city elements in the OpenStreetMap attribute table, and label the main elements of the city in the rules of Nolli Map.

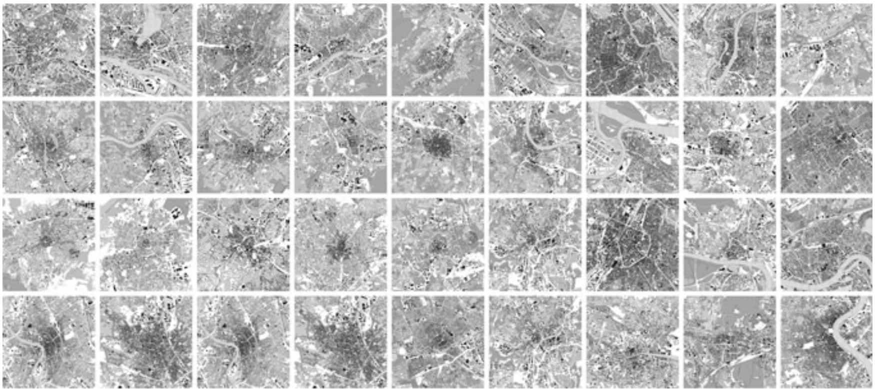


Fig. 2. Part of city dataset

In training set A, the basic data of roads, green areas, and water systems that affect the development of the city are retained in the OSM data attributes, and the artificial parts of green areas and water systems are deleted and the natural green areas are dissolved and expanded; in training set B, the data of existing buildings, green areas and water systems are retained in the OSM data attributes. Through the learning from training set A to training set B, the influence of the underlying information on urban morphology during urban evolution is explored.

The labeling method of the data is transformed from the Nolli map. In the labeled image (Fig. 3), different elements are represented by different labeling symbols: black blocks are buildings; diagonal filled and gray areas are green lands; dotted areas are water bodies; and blank areas are the places that are accessible to citizens.

Fig. 3. Training set A &Training set B

3.3 Training and Testing

After the construction of training sets A and B, the images of the training dataset are fed into the optimized GAN separately. To achieve the goal of learning large-scale urban fabric, the model is adjusted to handle and run 1024 × 1024 pixels images. In the optimizing process, we adjust the number of net layers and the number of neurons in each layer of the neural network, to help the computer power to meet with requirements of high-resolution images and avoid the frequent overfitting phenomenon in machine training.

During the training process, the generator and the discriminator play against each other. A higher discriminator loss value and a lower generator loss value means that the training process tends to succeed. The training gradient is set to a constant learning rate before 200 epochs, and a decaying learning rate is used after 200 epochs, which facilitates better fitting of the data. From the loss images, it can be found that the losses of the generator and discriminator stabilize after 680 epochs. The loss values of the generator and discriminator during the training process are recorded in Fig. 4.

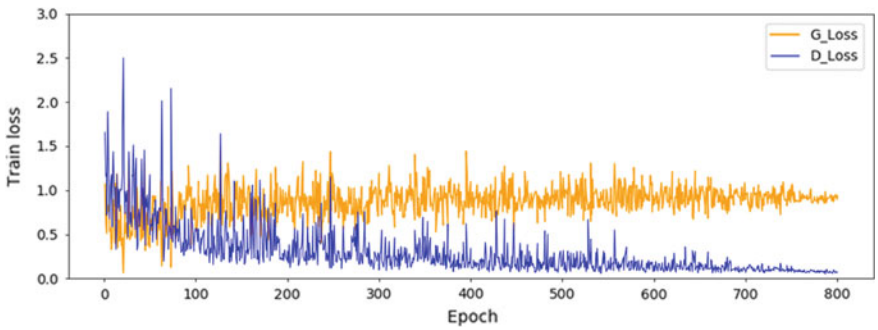


Fig. 4. Generator loss (G_LOSS) and discriminator loss (D_LOSS) during training

In addition, we set a monitor web to record and display the process of the generated images during the training. Figure 5 shows that the generated images are blurred before the 70th epoch; the generated images at the 70–470th epoch recorded are filled with the repeating blocks, which lacks the diversity of urban fabric; the generated images from the 470–770th epoch recorded are more reasonable and the city streets are more obvious. In the 770th epoch, the machine has grasped the more obvious urban morphological laws. Finally, we choose the 800th epoch trained model as the urban generated experimental model. After the model training is completed, inputting the testing data, the new urban form image responding to the base conditions can be quickly output.

4 Analysis of Results

Meantime, we make labelled maps that contain urban basic data from 25 European cities as the testing data inputting into the model. Then the synthesized city image is generated.

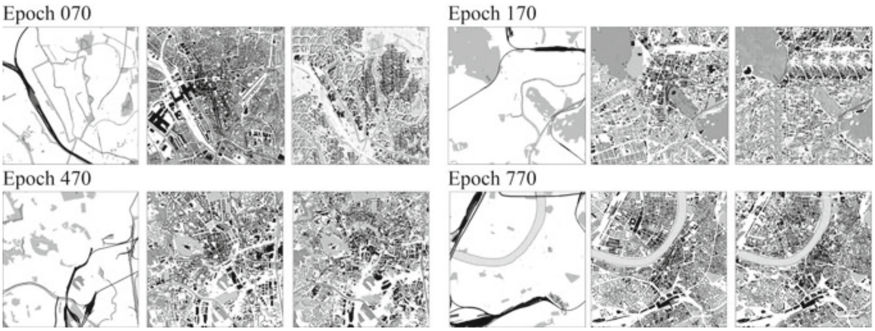


Fig. 5. Output results for each training epoch (input image; real image; synthesized image)

Compared with the real city's image, though the synthesized urban fabric is different, it retains the typological characteristics of the urban fabric (Fig. 6). In Frauenkirche's fabric comparison, the baroque radial street pattern in the real city is replaced by the natural organic pattern, while the synthetic fabric retains the morphological structure with a ring center and several radial axes as the skeleton. In the synthesized image of Leeds, the shape of the blocks and the shape of the secondary road network are quite different from the real ones, but the buildings layout is the same: the east and south parts are arranged with regular plots and large-scale buildings, which reveals the industrial area; the north part is arranged with residential areas with dot-like and strip-like buildings. In the comparison of the three pairs of images, the scales of buildings and street blocks are reasonable and the variation patterns are similar. The urban center is extremely in high density, with recognizable medieval city boundary patterns.

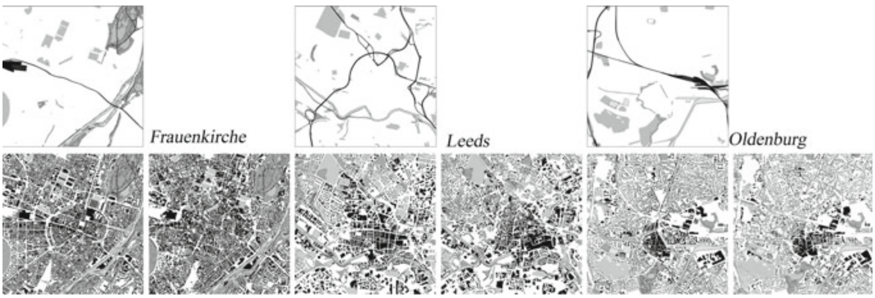


Fig. 6. Comparison between the real images and the generated images

We also input the urban initial condition to get the virtual city image (Fig. 7). The layout of the images maintains the main characteristics of the European cities: the street pattern conforms to the skeleton structure of the city. Most of the streets inside the skeleton have natural and organic morphological features with small radial structures inside; the street block scale is 50–100 m; high-density blocks exist in the center and low-density blocks are in the suburbs; buildings in the central area are dominated by enclosure groups, and more independent buildings appear in the suburbs. The simulated urban fabric also effectively responds to natural information such as water and green space: the building layout responds to the "Fixation line" elements (arterial roads, rivers) of the urban form; the edges of natural green spaces are eroded by buildings; more green space appears nearby the water bodies; buildings in the center enclose clear patterns of plazas.

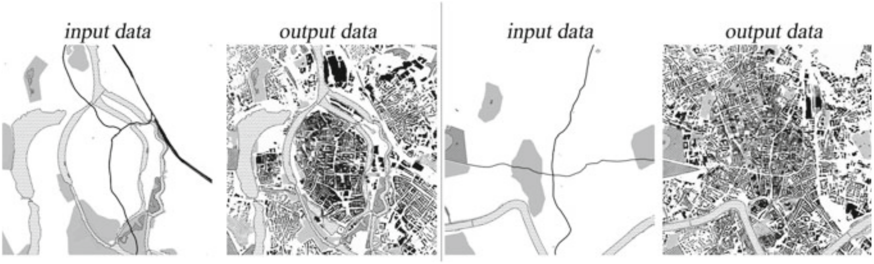


Fig. 7. Generated urban form

5 Conclusion

This experiment basically completes the generation of city form based on machine learning, and proves that the data-driven generative method is a new way of the cognitive research of cities. The diagram representation of Nolli Map fits well with the data training process of deep learning, and the clarity of figure-ground diagram facilitates the training of the city plan pattern and the features of the elements by the machine. Labeled city data is fed into GAN for training and rapidly predicts the city form based on the initial conditions. This experiment proves that Nolli Map as a classical urban research method still has important value in the era of artificial intelligence; machine learning will inject new vitality into urban morphology research.

References

1. Conzen MRG (1960) Alnwick, Northumberland: a study in town-plan analysis. Trans Pap (Inst Br Geogr) 27:111–122
2. Fedorova, S. (2021). Generative adversarial networks for urban block design. arXiv:2105.01727arXiv:2105.01727
3. Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, Courville A, Bengio Y (2014) Generative adversarial nets. Adv Neural Inf Process Syst 2014:2672–2680
4. Hwang JE, Koile K (2005) Heuristic Nolli Map: representing the public domain in urban space. In: Proceedings of CUPUM05, vol 1, p 16
5. Isola P, Zhu JY, Zhou T, Efros AA (2017) Image-to-image translation with conditional adversarial networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 1125–1134
6. Ji H, Ding W (2021) Mapping urban public spaces based on the Nolli map method. Front Archit Res 10(3):540–554

7. Li M, Feng J (2017) An analysis of the value of the Nolli Map's Analytical methods. New Archit 11–16
8. Liu Y, Rudi S, Yang Y (2018) Urban design process with conditional generative adversarial networks. Archit J 09:108–113
9. Liu Q, Ding W (2012) The graphical method and its significance in the study of urban fabric form. Architect 5–12
10. Pan Y, Qian J, Hu Y (2021) A preliminary study on the formation of the general layouts on the northern neighborhood community based on GauGAN diversity output generator. Springer Singapore, Singapore, pp 179–188
11. Pasquero C, Poletto M (2020) DeepGreen-coupling biological and artificial intelligence in urban design. In: 40th annual conference of the association of computer aided design in architecture (ACADIA), pp 668–677
12. Rhee J, Veloso P (2021) Generative Design of Urban Fabrics Using Deep Learning. In: 26th international conference on computer-aided architectural design research in Asia (CAADRIA), Hong Kong, pp 31-40
13. Saint A (1993) The city shaped: urban patterns and meanings through history
14. Shen J, Liu C, Ren Y, Zheng H (2020) Machine learning assisted urban filling. In: 25th international conference on computer-aided architectural design research in Asia (CAADRIA), Bangkok, Thailand, pp 679–688
15. Steinfeld K (2019) GAN Loci: imaging place using generative adversarial networks, Austin, pp 392–403
16. Tian R (2021) Suggestive Site Planning with Conditional GAN and Urban GIS Data. In: Proceedings of the 2020 DigitalFUTURES-The 2nd International Conference on Computational Design and Robotic Fabrication (CDRF 2020), Shanghai, pp 103–113
17. Xu H, Li L (2021) Research on analysis and generation of street view color based on deep learning. In: 2021 national conference on architecture's digital technologies in education research, Wuhan, China, pp 120–126
18. Ye Y, Zhuang Y (2016) The raising of quantitative morphological tools in urban morphology. Urban Design 4(006):56–65

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