Research on the Rapid Method for Delineating the Boundaries of Urban Historic Areas based on Graph Theory and Graph Neural Networks

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Abstract. Delineating the boundaries of Urban Historic Areas is regarded as an important part of urban planning. However, existing identification methods have been criticized for their high subjectivity, low efficiency, and weak correlation with urban morphology, which could hinder the formulation of subsequent urban protection policies. This paper proposes a method based on graph theory and graph neural networks (GNNs) to objectively and efficiently delineate the boundaries of urban historic areas. The proposed method first constructs a graph that represents the urban structure with systems such as roads and water systems that can indirectly reflect the spatial structure of the city. Urban Historic Area-related information is then assigned to the corresponding nodes, and the node feature matrix of the graph is obtained. The node feature matrix is then fed into a graph neural network for computation to filter out the nodes that meet the requirements of Urban Historic Areas. Finally, the boundary of the Urban Historic Area is drawn according to the relationship between the node connections. To evaluate the accuracy of irregular boundary extraction, this study designed a metric called the Hausdorff distance-similarity ratio and tested it on several historical and cultural cities, including Quanzhou, Fuzhou, Yangzhou, Kaifeng, and Chaozhou. The experimental results demonstrated that the proposed Graph Neural Network-based method for delineating Urban Historic Areas effectively addressed the aforementioned problems. The method performed well in tests on five well-known historical and cultural cities. The differences between the official Urban Historic Areas boundaries released by these cities and the calculation results of this method were analyzed at the end of the paper.

Keywords: Graph neural networks, Urban morphology, Graph theory, Urban Historic Areas, Urban calculation
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1 INTRODUCTION

Delineating the boundaries of Urban Historic Areas is considered to be an important part of urban planning. However, for a long time, the official demarcation of Urban Historic Areas boundaries is the result of the game of political, historical, economic and other factors, which is not completely consistent with the demarcation from the perspective of urban morphology. This distinction will persistently influence the scientific basis of subsequent policies and strategies aimed at safeguarding Urban Historic Areas. Figure 1 shows the examples of St. Petersburg and Beijing, which show the gap between the perspective of government departments and that of urban morphology researchers.

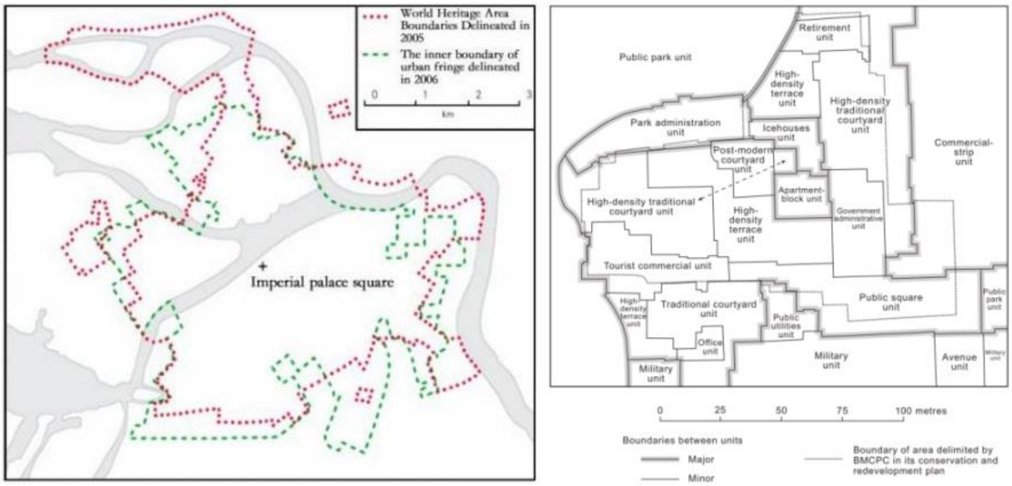


Figure 1: Comparisons of boundaries of Urban Historic Areas by urban morphology perspective with officially drawn boundaries: (a) the boundary of the World Heritage Site in St. Petersburg, Russia, versus the inner boundary of the middle-level urban fringe zone, (b) the boundary between landscape units and morphological units delineated by Beijing in 2006.[1][2]

The existing methods for delineating Urban Historic Area boundaries have limitations. These include lack of objectivity due to variability in evaluation criteria, over reliance on subjective weighting schemes, failure to establish definitive correlations between supporting datasets and drawn conclusions, and minimal consideration of urban morphology and spatial structures.

In recent years, the deep learning technologies represented by Convolutional Neural Network (CNN), Generative Confrontation Network (GAN) and Recurrent Neural Network (RNN) have made remarkable achievements in the tasks of urban element image extraction, urban texture darning, etc.

Classical deep learning technology mainly focuses on processing data with Euclidean spatial characteristics or temporal structure characteristics (such as images and texts). However, city is a complex system rich in structural-level information. This large amount of information cannot be applied to Euclidean space conditions and temporal structure conditions. How to make full use of this structural-level information has always been a difficult problem.

This study aims to establish a comprehensive and objective method for delineating the boundaries of Urban Historical Areas based on diverse datasets such as road system data, public transport network data, and river network data. Leveraging the capabilities of Graph Theory and Graph Neural Networks in processing structural-level information, this innovative approach is grounded in urban morphology and urban spatial structure. Compared to traditional methods, it offers enhanced speed, greater objectivity, and maintains a high level of accuracy in its results.

2 REVIEW

Before formally describing the methodology of this study, it is necessary to briefly review the current mainstream methods for delineating urban historic area boundaries.

Initially, government departments often directly used the existing ancient city walls as the boundaries of urban historic areas [3]. This method is relatively simple and straightforward, but it is only suitable for cities with well-preserved city walls. Subsequently, government departments adopted the Delphi method to determine the boundaries of urban historic areas for some well-known historical and cultural cities with incomplete city walls. The Delphi method is a widely used method in management science for soliciting expert opinions in a written format.[4]

In addition, some quantitative analytical techniques have also been adopted in relevant academic research. In their study on the delineation of historical and cultural blocks in Xiaoxian County, Gan et al. [5] employed the analytic hierarchy process (AHP) to determine the boundary location. This method essentially establishes a quantitative model for the grading of cultural relics protection units. The model assigns a weight to each building based on several indicators, including the grade of the cultural relics protection unit and the degree of building damage. The grade of the cultural relics protection unit is then determined based on these weights, and the boundary line is finally determined by combining the morphological characteristics of the courtyards and alleys and the boundaries of the natural environment such as rivers.

Gao et al. [6] proposed a method for demarcating historical urban area boundaries using a multi-factor grading evaluation system (MGES). This system consists of dozens of evaluation factors, such as architectural style, structure, artistic level, scientific research value, surrounding traffic conditions, and ownership. Each factor has its own weight, and the scores are determined through field and literature surveys. Finally, the final result is calculated by a formula.

In the work of identifying the boundary of Jianchuan urban historic area in Dali, Yunnan, Feng Haoyu relied on the massive data obtained from on-site data collection and local historical document research, and integrated several different methods, including the Delphi method, AHP method, MGES method, and GIS data method[7] .

It is obvious that the aforementioned methods all require extensive preliminary investigation and acquisition of very detailed data before they can proceed, which will take a lot of time. Another more significant drawback is that these methods all require artificial pre-definition of some weights, proportion factors, and indicators. Such definitions are artificial, based on experience, and have great subjectivity. It usually takes several months for these methods or even longer to demarcate the boundary of an urban historic area from scratch. In the context of significant advancements in neural network-based artificial intelligence technologies, this study attempts to design a method for delineating the boundaries of Urban Historic Areas by leveraging graph theory and graph neural network techniques. This method will strive to achieve the unity of objectivity, efficiency, accuracy, digitization, and dependence on a relatively small amount of data.

3 METHOD

3.1 Graph Theory and Graph Neural Networks

Grounded in Graph Theory, Graph Neural Networks (GNNs) are specialized deep learning architectures adept at extracting insights from graph-structured data. In mathematics, graphs comprising interconnective nodes and edges can represent abstract information and capture underlying structural relationships. Urban systems research indicates graph theoretic excel in numerous applications.[8][9][10]

Synthesizing graph theory and neural networks, GNNs perform feature aggregation and propagation across nodes and edges of complex graph topologies. This facilitates learning latent patterns within the networks at deeper levels. The approach overcomes the limitations of applying conventional deep learning directly to graph data, unlocking new capabilities [11].

3.2 Methods of Characterizing Urban

This study aims to develop a digital and semi-automated approach for the rapid delineation of the boundaries of urban historic areas. To achieve this goal, a data-driven and structured method for characterizing urban is required.

Despite the intricate nature of urban spatial typologies, which can be categorized as radial, linear, concentrated, star-shaped, or clustered, the spatial form of urban areas can be readily discerned through the observation of road patterns. Kevin Lynch, in his seminal work "The Image of the City", attributes this phenomenon to a deeper rationale: roads serve as the skeletal framework of cities.[12]

Within urban confines, a myriad of information is bound within the flow of the road network: people, vehicles, and goods. The morphology of roads in the central urban area exhibits a marked distinction from that of the periphery. Consequently, the spatial structure of roads serves as a proxy for revealing the underlying spatial structure of the urban areas to a certain extent.

The spatial structure of urban roads can be readily represented in a data-driven manner via a graph-based approach. Intuitively, urban streets themselves can be directly regarded as edges of the graph, while intersections of streets serve as the nodes. This approach can be designated as Method A.

Method A possesses the merits of being readily comprehensible and capable of maximally preserving the spatial structural relationships of the urban. However, it also suffers from the drawback of generating an excessively large number of nodes and edges in the overall graph. In reality, it is practically infeasible and unnecessary to thoroughly investigate every single alley and intersection within a urban historic area.

To address the limitations of Method A, an alternative approach is proposed, which considers specific points on the road network (e.g., bus stops, bridges) as nodes and constructs edges based on other explicit connections (e.g., bus routes, subway lines, urban canals). This approach is designated as Method B. (Figure 2)

Method B offers the advantage of simultaneously reducing both the number of nodes and edges in the overall graph while maximally preserving the spatial structural information of the urban, as long as an appropriate amount of route data is selected. Information regarding public transit routes and water systems within a city can be readily obtained from government websites or navigation applications. It suffices to supplement this information with historical entity data pertaining to the vicinity of these stations.

In practice, both methods are employed in a complementary manner. Method B serves as the primary approach for representing the overall spatial structure of the urban. However, in cases where streets lack bus routes or waterways lack bridges due to specific circumstances, Method A is utilized to supplement the data.

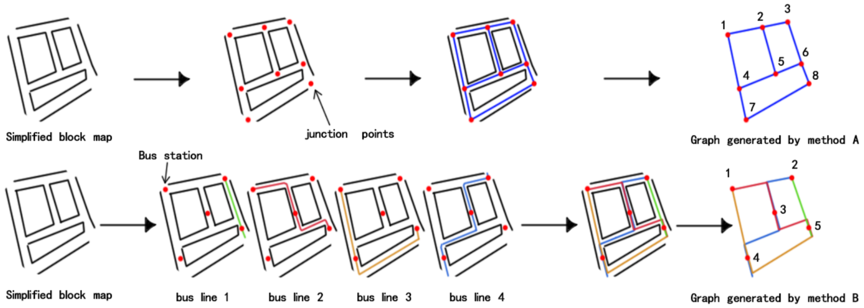


Figure 2: Comparison of two methods of transforming the urban spatial structure into a graph.

3.3 Preparations

The collected urban multi-source data is organized into formatted files, as shown in Tables 1 and 2. Table 1 stores the connectivity information and edge attributes of each node in the urban spatial structure graph, while Table 2 stores the urban historic area-related attributes of each node.

Leveraging the NetworkX open-source library in Python, a multiplex graph that reflects the urban structure can be constructed from Tables 1 and 2. The edges of this graph represent roads and water systems, while the nodes represent specific points on these networks. Each node possesses its own attributes, such as the number of surrounding historical buildings, temples or shrines, and ancient trees. Additionally, each edge carries its own attributes, such as the bus route number.

Previous node	The latter node	Line name	Spacing(km)
Ximen	Hutou steet	1	0.211
Hutou steet	Guangrong road	1	0.294
Guangrong road	Lu zhuang	1	0.462
Lu zhuang	Gaofeng bridge	1	0.149
......			

Table 1: Example of link relationship between nodes.

Node name	Region	Number of surrounding historical sites	Number of ancient and famous trees
Ximen	Gulou	6	4
Hutou steet	Gulou	0	0
Guangrong road	Gulou	0	0
The People's hospital	Taijiang	4	1
......			

Table 2: Example of node attributes.

The constructed multiplex graph typically encompasses hundreds of nodes and edges. Three distinct matrices are extracted from this graph: the adjacency matrix A that depicts the connectivity between nodes, the one-hot encoding matrix B that captures information that cannot be quantitatively computed, and the feature matrix C that reflects quantifiable information characteristics. The initial feature matrix H^0 is constructed by horizontally concatenating the three aforementioned matrices. This concatenation process yields a rich information representation, as illustrated in Figure 3.

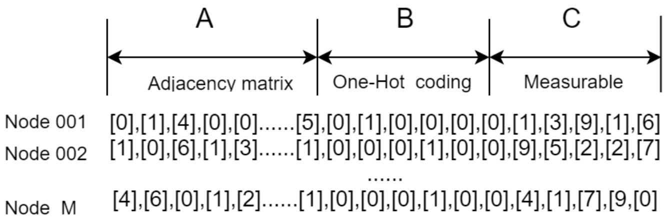


Figure 3: Schematic diagram of the different components of the initial feature matrix.

Adjacency matrix：$A \in R^{N \times N}$, N is the total number of nodes.

One-heat coding matrix： $B \in R^{b \times N}$, b represents the number of terms in the one-hot encoded attributes.

Quantifiable information feature matrix.： $C \in R^{c \times N}$, c denotes the number of quantifiable information feature terms.

The initial feature matrix H^0:

$$H^0 = [A|B|C]$$

To facilitate the training process, it is necessary to simultaneously construct a mask matrix and a label matrix. The formats of these matrices must be consistent.

Three types of labels were designed to classify the urban historic areas based on the number of historic sites within a 500-meter radius. Specifically, a node with no more than two ancient buildings is considered a non-historical area, a node with 3 to 5 historic sites is considered an edge area of an urban historic area, and a node with more than six historic sites is considered a core urban historic area.

This task utilizes labels as a reference, not aiming for the model to identify all nodes matching the labels flawlessly. The underlying objective is to "locate nodes belonging to the historic district," yet it is infeasible to acquire knowledge of all such nodes directly. Therefore, "the number of ancient buildings within a specific range" serves as a simplified surrogate. In fact, different datasets allow for further exploration with alternative reference labels related to historic districts, such as pedestrian traffic and the number of century-old shops.

3.4 Constructing Graph Neural Networks Model

After preparing the initial feature matrix, mask matrix, and label matrix, they are fed into the graph convolutional neural network model for training and computation. The information data of urban historic areas is not complex for computers, so it does not require a particularly complex neural network to achieve good results.

Graph neural networks (GNNs) essentially learn node representations by iteratively aggregating the representations of neighboring nodes and the node itself. The following presents a general framework for GNNs.[13]

H^0denotes the initial node representations；

$H^k \in R^{N \times F}, k \in \{1,2,3 \ldots K\}$ denotes the node representations at the kth layer；

K is the total number of layers in the GNN, and each layer has two core functions:

AGGREGATE, which aggregates information from each node's neighbor nodes.

COMBINE, which updates node representations by incorporating neighboring information.

For k=1,2,3...K：

$$a_v^k = AGGREGATE^k = \{H_u^{k-1}: u \in N(v)\} \qquad (3.4.1)$$

$$H_v^k = COMBINE^k = \{H_v^{k-1}, a_v^k\} \qquad (3.4.2)$$

Where $\mathrm{N}(v)$ denotes the set of neighbor nodes of the v th node. The node representations of the last layer can be regarded as the final node representations.

Given a set of labeled nodes, the entire model can be trained by minimizing the following loss function:

$$O = \frac{1}{\mathrm{n}_l} \sum_{i=1}^{\mathrm{n}_l} \mathrm{loss}(\hat{y}_i, y_i) \qquad (3.4.3)$$

Here, y_i is the label of node i , $\hat{y}_i$ is the prediction label of node i ,n_l is the number of label nodes, and loss() is a loss function, such as the cross-entropy loss function. The objective function O is minimized to optimize the entire neural network via backpropagation.

Node representations can be leveraged for downstream tasks. This study investigates a node classification task where the label attributes y_v of nodes v are predicted using the softmax function:

$$\hat{y}_v = Softmax(WH_v^T) \qquad (3.4.4)$$

Here, $W \in R^{|n| \times F}$, $|n|$ denotes the number of labels in the output space, F denotes the number of dimensions in the node representation vectors. H_v^T denotes the representation vector of node v in the output layer.

3.5 Train

The scale of different cities varies greatly, and the complexity of the constructed graphs also varies. Therefore, it may take multiple attempts to find suitable parameters. Please refer to the GitHub project provided by the author for the specific parameter setting and code of this study. (https://github.com/LIANHUA2/-Boundaries-of-Urban-Historic-Areas-based-on-GNNs.git)

After training, the computer outputs an embedding for each node. The embedding is a collection of 3-6 specific numerical values that represent structural information and various data. We can observe the spatial distribution of the embeddings to determine which nodes belong to the urban historic area. Figure 4 shows the change of the spatial distribution of embeddings during the training process from a two-dimensional perspective. As the number of iterations increases, the graph neural network gradually separates the nodes belonging to the urban historic area from the initial confusion. In the figure, the green nodes clustered at the bottom are ordinary nodes, the nodes of other colors clustered at the top belong to the urban historic area, the nodes clustered at the upper left corner belong to the core nodes of the urban historic area, and the nodes clustered at the upper right corner belong to the edge nodes of the urban historic area. Fig 5(b) shows the spatial distribution of embedding after 500 iterations from a three-dimensional perspective.

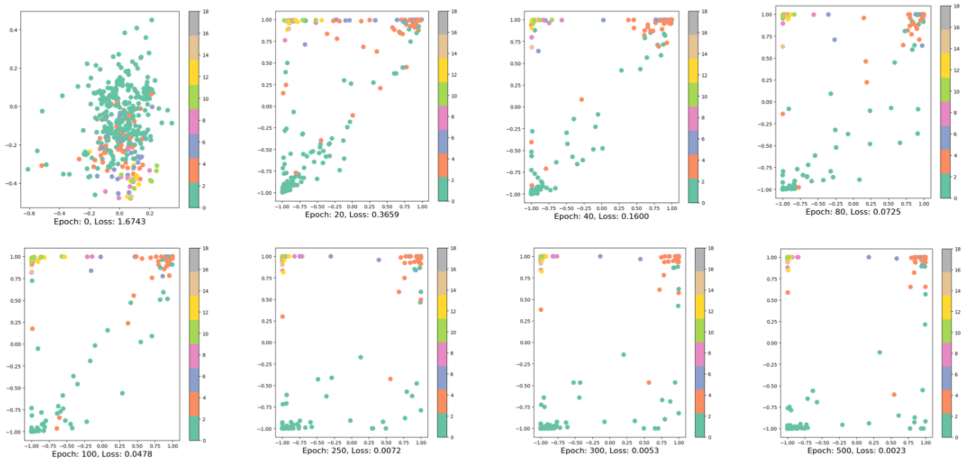


Figure 4: In two dimensions, observe the changes in the spatial distribution of embeddings during training.

The significance of not directly using urban historic area node labels for downstream tasks but adding the step of training a graph neural network model lies in the following. First, for a graph that represents a city, there are some nodes that, although they do not have strong historical features themselves, their neighbors and neighbors of neighbors all have strong historical features. In this case, such nodes should also be considered as urban historic area nodes. Similarly, some nodes, although they have labels that belong to urban historic areas, their neighbors and neighbors of neighbors do not have urban historic area labels. In this case, they should not be considered as nodes that belong to urban historic areas. Automatically distinguishing such nodes will greatly improve work efficiency. In addition, the original label attribute is essentially "an element that is positively correlated with urban historic areas", but it is not the "urban historic area" label itself. Therefore, it is necessary to train a graph neural network model to take the connectivity of the graph into account.

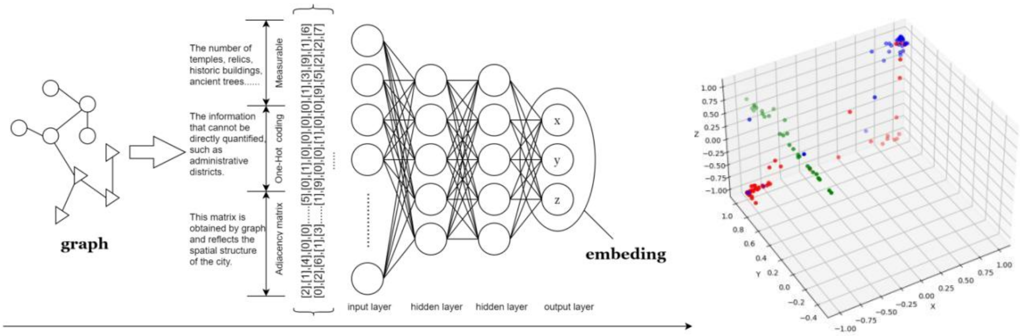


Figure 5: Coding and embedding process. (a) Acquiring node coding information from the graph and inputting to the neural network for embedding computation; (b) Visualization of three-dimensional node embeddings, with red indicating modern urban nodes, green denoting core Urban Historic Area nodes, and blue representing marginal Urban Historic Area nodes.

3.6 Translate into a Visual Image

The connectivity information is extracted from the initially constructed graph. Based on the connectivity, nodes identified by the computer as belonging to the Urban Historic Area are connected, and the resulting graph outline serves as the boundary of the urban historic area. This step requires manual annotation of the computer-calculated locations on the map, and the program will provide prompts on which nodes each node should be connected to.

Automatic generation of directly visualizable images is feasible, but it requires investigating the latitude and longitude coordinates of tens of thousands of bus stops in the city and verifying their correctness one by one. However, the following situations often occur: 1. The crawled latitude and longitude information is significantly different from the actual location. 2. Two bus stops in different locations have the same name.

Considering efficiency, manual annotation is the most convenient way. In fact, for a medium-sized city like Fuzhou and Quanzhou in Fujian Province, the number of nodes that meet the requirements is only about 100, and it can be completed by one person in just 1 hour.

Figure 6: The process of translating calculation results into visible images.

3.7 Complete Process

Figure 7 shows the complete flow of this method above. Firstly, the multivariate data is constructed into a graph. Then, get the required link relationship, adjacency matrix, and other information from the graph. Next, this information is input into the neural network model for calculation. Finally, the final result is obtained by synthesizing the output and link relationship of the neural network.

It can be seen that graphs play an important role in the aggregation and reorganization of information. The function of a graph neural network is to transform the reorganized information into an embedded vector that can be calculated mathematically.

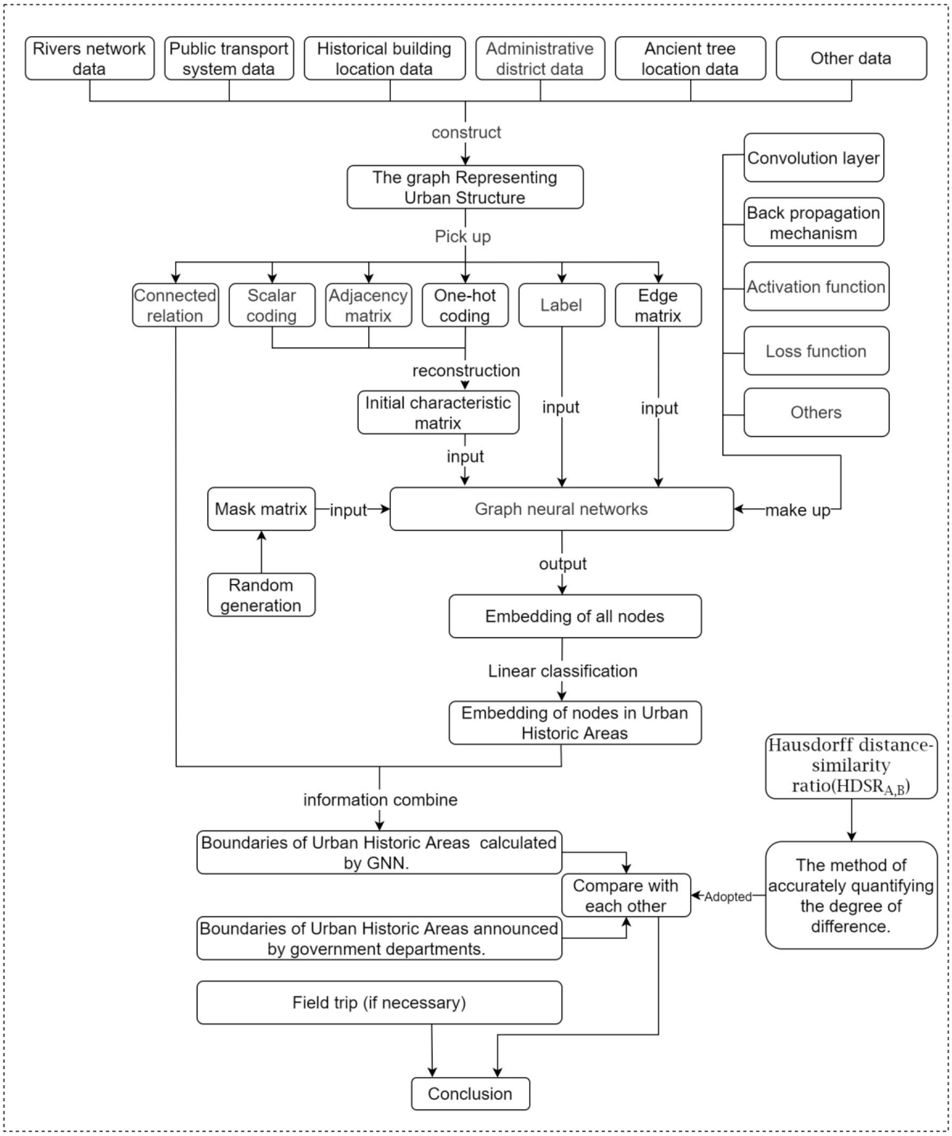


Figure 7: The complete step flow chart of this method.

4 HAUSDORFF DISTANCE-SIMILARITY RATIO

Since contours of most Urban Historic Areas manifest irregularly, a robust algorithm is required to quantify divergence between predicted boundaries and actual limits. We design such an algorithm, inspired by the Hausdorff distance method, to directly output the percentage similarity between new method judged boundaries and real delineations.

For the contour line of any irregular figure, it can be regarded as a point set composed of many points on the contour line. For any two point sets A and B, let n_A and n_B denote the number of points in A and B respectively. We define a metric called Hausdorff distance-similarity ratio ($\mathrm{HDSR}_{A,B}$), which can directly measure the similarity ratio between point set A and point set B in the form of percentage. It consists of the following parameters:

(1) The minimum distance from each point of point set A to point set B:

$$D^{\min}_{A\rightarrow B\,(i)},\ \ (i = 1,2,3...n_A) \quad (4.1)$$

Likewise, vice versa from B to A.

The average value of the global minimum distance :

$$D_{A,B}^{\text{Global Min-Avg}} = \frac{\sum_{i=1}^{n_A} D^{\min}_{A\rightarrow B(i)} + \sum_{j=1}^{n_B} D^{\min}_{B\rightarrow A(j)}}{n_A + n_B},\ (i = 1,2,3...n_A\,, j = 1,2,3...n_B) \quad (4.2)$$

(2) Within the A, the distance from the k-th point to the l-th point :

$$D_{A\ (k\rightarrow l)}\ ,\ (k, l = 1,2,3...n_A) \quad (4.3)$$

Each point has an average value of the distance to all other points. Add up these averages and then average again:

$$D_A^{\text{Avg-Avg}} = \frac{\sum_{k=1}^{n_A}\left(\frac{\sum_{l=1}^{n_A} D_{A(k\rightarrow l)}}{n_A - 1}\right)}{n_A},\ (k, l = 1,2,3...n_A) \quad (4.4)$$

Likewise, for point set B.

$D_A^{\text{Avg-Avg}}$ and $D_B^{\text{Avg-Avg}}$ represent intrinsic attributes reflecting the densities of point sets A and B respectively, which facilitates normalized comparison between A and B regardless of sparsity or density extremes.

(3) Final, Hausdorff distance-similarity ratio:

$$\mathrm{HDSR}_{A,B} = \max\left(1 - \frac{D_{A,B}^{\text{Global Min-Avg}}}{\left(\frac{D_A^{\text{Avg-Avg}} + D_B^{\text{Avg-Avg}}}{2}\right)}\ ,\ 0\right) \times \% \quad (4.5)$$

Where A and B are predicted and official boundaries respectively.

5 CASE STUDY

5.1 General Situation

To validate the reliability of the proposed methodology, this study selected five cities, namely Quanzhou, Fuzhou, Yangzhou, Kaifeng, and Chaozhou, for testing. These cities were chosen from the List of Famous Historical and Cultural Cities of China. They have diverse geographical and climatic conditions, and their urban historic areas possess distinct morphological characteristics, making them ideal test subjects for the methodology. Local urban planning departments have invested significant resources in surveying these cities, and their delineated urban historic area boundaries can be considered highly reliable.

The experimental results demonstrated that the proposed graph-based method can effectively delineate urban historic area boundaries. The delineated boundaries are generally consistent with the official ones, with some local discrepancies. The $\mathrm{HDSR}_{A,B}$ are both above 80%, indicating the strong adaptability of the proposed method. Moreover, the proposed method is highly efficient. It takes a team of two people, an average of only 3 to 4 days, to delineate the boundary of each city, including the time for data collection and preprocessing.

Table 3 compares the boundaries of the five cities delineated by the proposed method with the officially released urban historic area boundaries and presents the $HDSR_{A,B}$ between them.

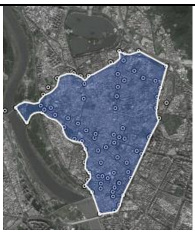
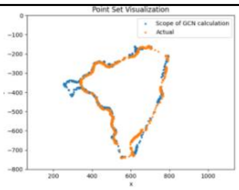
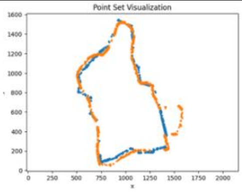
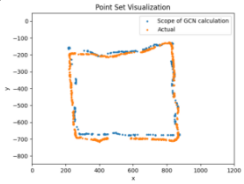
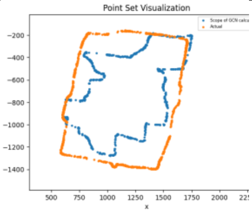
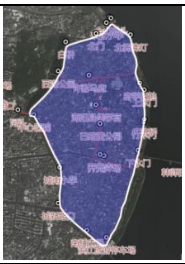
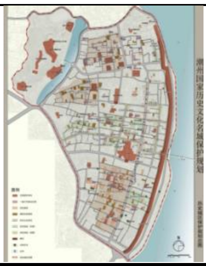
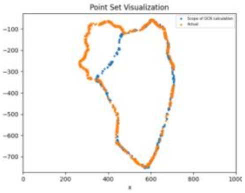
City name (Province)	The result of GNN calculation	The scope of government disclosure	Draw them on the same plane	Hausdorff Distance-Similarity Ratio	Geographical position
Quanzhou (Fujian)				95.62%	Southeast coast of China
Fuzhou (Fujian)				94.89%	Southeast coast of China
Yangzhou (Jiangsu)				95.43%	Eastern China
Kaifeng (Henan)				83.29%	Inland of China Central Plains
Chao Zhou (Guang Dong)				91.21%	South China

Table 3: Compares the results of Urban Historic Areas boundaries delineation in Quanzhou, Fuzhou, Yangzhou, Kaifeng, and Chaozhou using the proposed graph-based method with the officially released boundaries, and presents the $HDSR_{A,B}$ values between them.

5.2 Detailed Analysis of Cities

5.2.1 Quanzhou

In the case of Quanzhou, the urban historic area boundary delineated by the proposed method is largely consistent with the official one. But the graph neural network includes the Shisun Park area on the west side of Quanzhou Old City as part of the urban historic area, which slightly deviates from the official delineation result.

A field survey revealed that the area contains one provincial-level cultural relic protection unit, an ancient ferry port, a stone bridge relic, and two folk ancestral temples (Figure 8). This suggests that it could be a neglected historical area.

Government departments often directly designate the old site of the city wall as the boundary of the urban historic area, which may overlook some extended areas of the urban structure. Although these areas are located outside the ancient city wall, they also meet the criteria for Urban Historic Area.

Figure 8: The stalagmite park area in the west of Quanzhou ancient city contains many historical sites, but it has not been officially designated as a Urban Historic Area.

5.2.2 Fuzhou

In the test of Fuzhou, it can be clearly observed that the main difference between the calculation results of the graph neural network and the initially announced urban historic area by the official authority lies in the "Dong heng cheng" on the east side of the ancient city. According to the literature, "Dong heng cheng" was a sub-city built by Wang Gong, the capital commander of the Ming Dynasty, on the basis of the remains of the Song Dynasty city wall. It was built around 1374 AD and has been renovated since then, but its location has remained unchanged.

From the perspective of the city wall, this area should be included in the scope of the urban historic area. However, the calculation results of the graph neural network show that it should not be included. Figure 9(a).

The author conducted a field investigation and found that only the direction of the road here continues the characteristic direction of the city wall, and there are no historical relics left. Interestingly, the revised version of the urban historic areas protection scope published by the Fuzhou government in 2023 deleted "Dong heng cheng", which seems to confirm the reliability of the graph neural network in this type of task from another perspective.

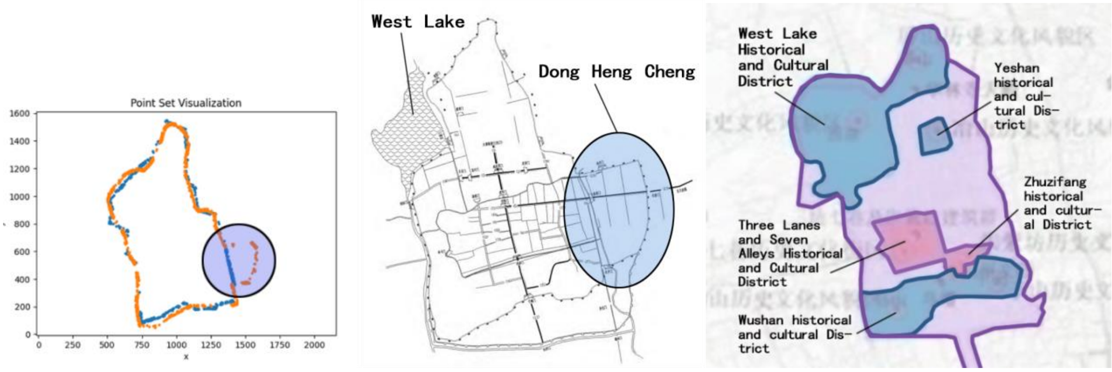


Figure 9: (a)Differences between GNNs calculation results (blue) and the location of Fuzhou ancient city wall (orange). (b)Location of Fuzhou Ancient City Wall in the Ming and Qing Dynasties[14]. (c)The latest official announcement of Fuzhou's Urban Historic Area boundary shows that the lavender is the urban historic area, and the blue area is the natural scenic area in the city.

5.2.3 Yangzhou

In the case of Yangzhou, the boundary delineated by the proposed method is almost completely consistent with the officially released urban historic area boundary. Yangzhou is a city surrounded by water systems, and a moat surrounds the outer side of the urban historic area, which was successfully captured by the graph neural network as a strong urban boundary feature. Figure.10c shows the present situation of Yangzhou moat. In fact, the river itself is a protected historical object.

Figure 10: (a)The boundary calculated by GNNs is compared with that officially announced by Yangzhou. (b)Comparison between the officially announced Urban Historic Area boundary of Yangzhou and the moat position of Yangzhou ancient city. (c) The present situation of architecture and moats in Yangzhou is an ancient city.

5.2.4 Kaifeng

Kaifeng is another example where the official government directly uses the old city wall site as the boundary of the urban historic area. Kaifeng is one of the oldest cities in China, and it has had multiple city walls in history. The city wall currently selected as the boundary of the urban historic area was built during the Qing Dynasty (around 1842 AD).

The $HDSR_{A,B}$ value of the graph neural network for Kaifeng, Henan Province is the lowest among the five cases. It can be observed that the urban historic area boundary delineated by the official is roughly a square, which is consistent with the existing remains of the city wall. The result of the graph neural network is an irregular polygon, which is closer to another boundary officially released than the historical and cultural block boundary.

Kaifeng, as a very old city and once the capital of feudal dynasties, has always been subject to multi-level protective control by the local government. The use of the city wall as the boundary of the urban historic area due to a certain policy inertia. Based on this, another boundary, the historical and cultural block boundary, has been established to better reflect the current status of historical relics for the purpose of actual protection. This viewpoint seems to be partially confirmed by the list of historical streets protection published by Kaifeng government.

Figure 11(c) shows the locations of the key protected historical streets, with red representing the first-level protected streets, light yellow representing the second-level protected streets, and light green representing the third-level protected streets. They are not evenly spread over the entire square space within the city wall, but are very close to the coverage area of the GNNs calculation results.

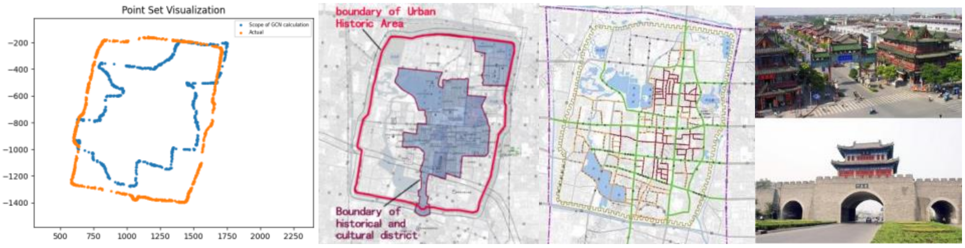


Figure 11: (a)The calculation result of GNNs method is compared with the position of Kaifeng ancient city wall.(b) Officially announced boundaries of urban historic area and boundaries of historical and cultural blocks in Kaifeng.(c) Officially announced the locations of the key protected historical streets.(d) Street view in the wall of Kaifeng ancient city and a well-preserved wall.

5.2.5 Chaozhou

Chaozhou is an example contrary to the other four cities. In fact, the boundary delineated by the graph neural network is almost identical to the location of the Chaozhou city wall. However, the boundary of the urban historic area by the local planning department of Chaozhou has been expanded to the northwest direction. The Hulushan Mountain was included on the northwest side of the ancient urban .

Hulushan Mountain is a local natural scenic spot with many famous modern cultural attractions. The local government has also invested a lot of money in repairing and maintaining the landscape inside it. The inclusion of Hulushan Mountain in the urban historic area is a consideration of the government for the development of tourism. (Figure 12b) This reflects the fact that the urban historic area boundary finally delineated by the government department may not necessarily reflect the urban morphology. Multiple factors, such as tourism policies, can affect the final official results. Therefore, from the perspective of academic research, it is still necessary to use objective methods to define the boundary of the urban historic area that truly reflects the urban form.

Figure 12c shows the relationship between the ancient city wall and the surrounding mountain water system. Figure 12d shows the present situation of the city wall and the street view in the ancient city. In this example, the city wall is well protected, so it is reasonable to use the ancient city wall as the boundary. This is also the judgment of GNN.

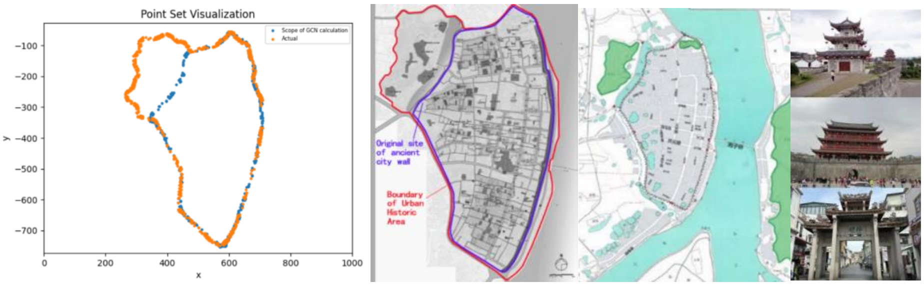


Figure 12: (a)The calculation results of GNNs method are compared with the officially published urban historic area boundaries. (b)The Urban Historic Area boundary was announced by the Chaozhou government. (c)The positional relationship between Chaozhou ancient city and its surrounding mountains and water systems.[15]. (d) The present situation of The ancient city wall of Chaozhou and the street view in the ancient city.

6 CONCLUSIONS

The results demonstrate that defining boundaries of Urban Historic Area via graph theory and graph neural networks is reliable. The method accurately identifies Urban Historic Area limits by fully exploring and leveraging abstract structural information of the city.

This new method can well avoid the limitations of traditional methods:

1. It is data-driven without dependence on expert scoring, enabling unified judgment criteria.

2. Graph neural networks can self-learn optimal weighting, eliminating the need for manual assignment weight as with traditional methods.

3. By adjusting the coding method of graph neural networks, we can easily identify which factors have greater influence on Urban Historic Area boundaries.

4. Urban morphology is incorporated by coding node information from graphs reflecting spatial structures.

The new method proposed in this study can provide a new perspective for understanding urban morphology and identifying urban historic areas.

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