Title:
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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Introduction:
Delineating the boundaries of Urban Historical Areas is considered to be an important part of urban planning. However, for a long time, the official demarcation of urban historic areas has been the result 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.

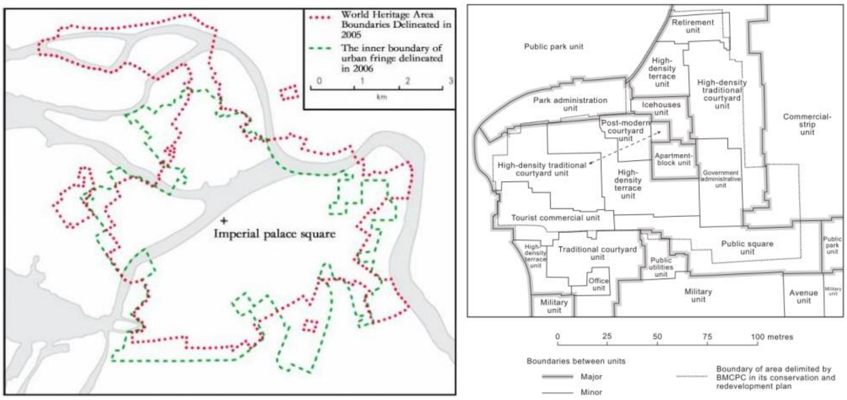

Fig. 1: Comparisons of boundaries of Urban Historic Areas by urban morphology perspective with officially drawn boundaries: (a) the boundary of the World Heritage Site in St. Petersburg, Russia, versus the inner boundary of the middle-level urban fringe zone, (b) the boundary between landscape units 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 Networks (CNN), Generative Confrontation Networks (GAN), and Recurrent Neural Networks (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, the 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 and greater objectivity and maintains a high level of accuracy in its results.

Main Idea:

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.[3][4][5]

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.[6]

Method

The proposed method based on Graph Theory and Graph Neural Networks (GNNs) has the potential to effectively overcome the limitations of existing approaches (Fig. 2).

Roads are the lifeblood of cities, carrying streams of people and flows of commodities and information vital for urban functioning. The layout of thoroughfares evolves across historical periods, each era imprinting distinct signatures onto the road network. Arterial width and density patterns transform through the ages, expanding or contracting as cities morph over time. Waterways have also been integral to urban development, as cities often emerge along inland rivers or lake shores, with moats typically demarcating the boundaries of ancient settlements.

Clearly, roads and waterways profoundly shape urban morphology. As they are intertwined with urban historic areas, roads, and water systems could provide vital spatial information to urban calculation. A promising approach is constructing graphs based on road network data and hydrographic data to represent the structural fabric of cities. Furthermore, information that strongly conveys historical significance ought to be incorporated into the graph, such as Buddhist temples, ancestral halls commemorating surname forebears, former residences of historical luminaries, and century-old trees. This graphical framework could help identify and demarcate Urban Historic Areas.

The introduction of GNNs can then facilitate quick analysis of these information-rich graphical models, identifying relationships between nodes without tedious manual examination.

The following are the specific steps:

1. The city's multivariate data are synthesized and constructed into a multigraph. The edges of this diagram represent roads and water systems, and the nodes represent special points on roads and water systems. Each node has its own attributes, such as the number of surrounding historical buildings, temples, ancestral halls, and ancient trees. Each edge also has its own attributes, such as bus line number.

2. Obtain the coding information of each node from this graph. This coding information can be spliced by an adjacency matrix, one-shot coding, and scalar data.

3. The coded information is constructed into an initial feature matrix. The initial characteristic matrix contains abundant information, and each row and column has its own special meaning. In addition, for the convenience of training, the mask matrix and the label matrix should also be made simultaneously. The formats of these matrices must be consistent.

4. Construct a graph neural network model and give these matrices to the model for training and calculation. The computer will output the embedding of each node. Embedding is 3-6 specific numerical values, which represent an aggregation of structural information and various data. We can judge which nodes belong to the Urban Historic Ares by embedding spatial distribution.

5. The link relationship is obtained from the graph constructed in the first step. According to the link relationship, the nodes judged by the computer as Urban Historic Areas are connected together, and the obtained graphic outline is the boundary of Urban Historic Areas.

At the end of this study, in order to prove the reliability of this method, the judgment result of this new method will be compared with the actual boundaries of Urban Historic Areas of several Chinese cities, such as Quanzhou in Fujian, Yangzhou in Jiangsu and Kaifeng in Henan. These cities are chosen as comparison objects because the local government has drawn a more accurate boundary of Urban Historic Areas after a lot of repeated research.

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)

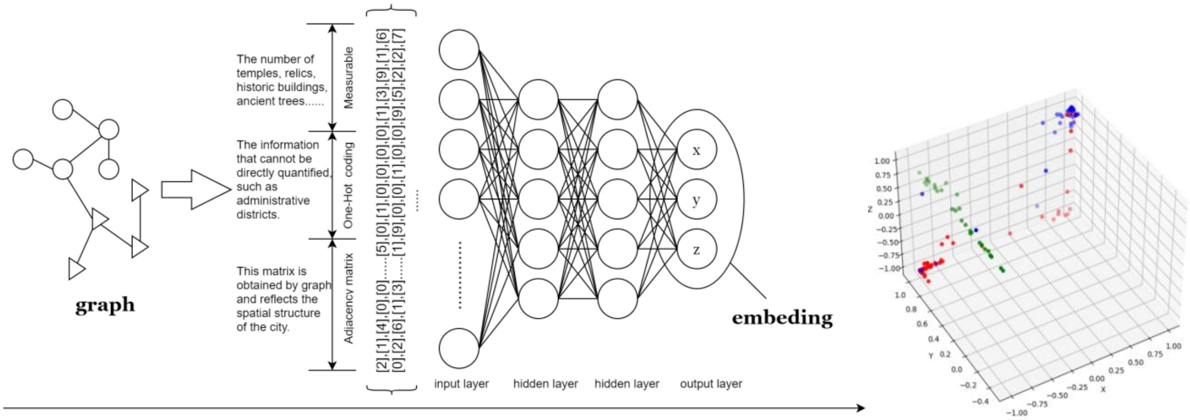

Fig. 2: Coding and embedding process. (a) Acquiring node coding information from the graph and inputting to the neural network for embedding computation; (b) Visualization of three-dimensional node embeddings, with red indicating modern urban nodes, green denoting core Urban Historic Area nodes, and blue representing marginal Urban Historic Area nodes.

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 ($HDSR_{A,B}$), 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 :

$$D^{min}_{A\rightarrow B\,(i)},\quad (i = 1,2,3\ldots n_A) \tag{1.1}$$

Likewise, vice versa from B to A.

The average value of the global minimum distance :

$$D^{Global\ Min-Avg}_{A,B} = \frac{\sum_{i=1}^{n_A} D^{min}_{A\rightarrow B(i)} + \sum_{j=1}^{n_B} D^{min}_{B\rightarrow A(j)}}{n_A+n_B},\ (i = 1,2,3\ldots n_A\ , j = 1,2,3\ldots n_B) \tag{1.2}$$

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

$$D_{A\ (k\rightarrow l)}\ ,\ (k, l = 1,2,3\ldots n_A) \tag{2.1}$$

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

$$D^{Avg-Avg}_{A} = \frac{\sum_{k=1}^{n_A}\left(\frac{\sum_{l=1}^{n_A} D_{A(k\rightarrow l)}}{n_A-1}\right)}{n_A},\ (k, l = 1,2,3\ldots n_A) \tag{2.2}$$

Likewise, for point set B.

$D^{Avg-Avg}_{A}$ and $D^{Avg-Avg}_{B}$ 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:

$$HDSR_{A,B} = max\left(1 - \frac{D^{Global\ Min-Avg}_{A,B}}{\left(\frac{D^{Avg-Avg}_{A} + D^{Avg-Avg}_{B}}{2}\right)}\ ,\ 0\right) \times \% \tag{3.1}$$

Where A and B are predicted and official boundaries respectively.

Case Study

Taking Quanzhou as an example, the boundary of Urban Historic Areas demarcated by the new method is shown in Fig 3, which is basically consistent with the official historical city boundary demarcated in reality. After many calculations, the $HDSR_{A,B}$ of Quanzheng is 95.62%.

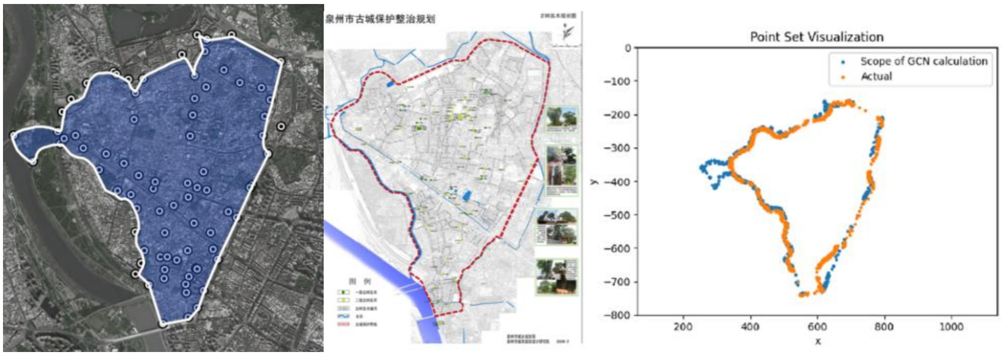

Fig. 3: Quanzhou, Fujian, China. Comparison between official and predicted Urban Historic Areas: (a) Urban Historic Area identified by graph neural network; (b) Urban Historic Area designated by the government;(c) The two areas depicted together on the same plane.

It is worth noting that the Stalagmite Park area on the west side of Quanzhou ancient city is also judged as an Urban Historic Area by the new method based on graph theory and graph neural network. It is different from the official demarcation result. We visited Stalagmite Park on the spot and found that it has a provincial cultural protection unit, an ancient ferry, a stone bridge relic, and two folk ancestral halls (Fig 4). We think this may be a historical area neglected by the government. Officials often directly designate the former site of the ancient city wall as the boundary for urban historic areas, regardless of whether the wall still exists. We hope this new method can provide a fresh perspective for understanding urban morphology and identifying Urban Historic Areas.

For more tests on other cities, please refer to the full article. The $HDSR_{A,B}$ values of these tested cities are all above 80%.

Fig. 4: The stalagmite park area west of Quanzhou ancient city contains many historical sites, but it has not been officially designated an urban historic area.

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.

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