

## Research Article

# Regional Patch Detection of Road Traffic Network

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Road traffic network (RTN) structure plays an important role in the field of complex network analysis. In this paper, we propose a regional patch detection method from RTN via community detection of complex network. Firstly, the refined Adapted PageRank algorithm, which combines with the influence factors of the location property weight, the geographic distance weight and the road level weight, is used to calculate the candidate ranking results of key nodes in the RTN. Secondly, the ranking result and the shortest path distance as two significant impact factors are used to select the key points of the RTN, and then the Adapted K-Means algorithm is applied to regional patch detection of the RTN. Finally, based on the experimental data of Zhangwu road traffic network, the analysis results are as follows: Zhangwu is divided into 9 functional structures with key node locations as the core. Regional patch structure is divided according to key points, and the RTN is actually divided into nine small functional communities. Nine functional regional patches constitute a new network structure, maintaining connectivity between the regional patches can improve the overall efficiency of the RTN.

## 1. Introduction

Road traffic network is an important infrastructure to serve the economy, society, and the public and is the backbone of the comprehensive transportation system. China is a big country in road traffic, with a total length of 4.8465 million kilometers at all levels, which constitutes a complex network system. The community is the dominant structure that exhibits different features and multifold functions of complex networks; accordingly, community detection is of critical importance in network science. In recent years, Newman [1] and Boccaletti [2] introduce the structure, dynamics, and function of complex networks. Newman [3] introduces the communities, modules, and large-scale structure in networks. Communities have intrinsic interest, they may correspond to functional units within a networked system, an example of the kind of link between structure and function that drives much of the present excitement about networks. Costa et al. [4] analyze and model real-world phenomena with complex networks. Fortunato et al. [5] present that community detection in networks is one of the most popular topics of modern network science. Communities, or clusters,

are usually groups of vertices having higher probability of being connected to each other than to members of other groups, though other patterns are possible. Yang et al. [6, 7] adapt the concept of community detection to the correlation network of urban traffic state and propose a new perspective to identify the spatial correlation patterns of traffic state. Real networks exhibit heterogeneous nature with nodes playing far different roles in structure and function, to identify vital nodes is thus very significant [8]. Liao et al. [9] introduce the problem of ranking the nodes and the edges in complex networks that is critical for a broad range of real-world problems, because it affects how we access online information and products, how success and talent are evaluated in human activities, and how scarce resources are allocated by companies and policymakers, among others. Agryzkov et al. [10] provide a method to establish a ranking of nodes in an urban network, with the main characteristic that is able to consider the importance of data obtained from the urban networks in the process of computing the centrality of every node. Yu et al. [11] say the identification of clusters or communities in complex networks is a reappearing problem. Kim and Kim [12] propose an algorithm that uses an interaction

optimization process to detect community structures in complex networks.

As community detection of complex network is one of the research hotspots, we proposed a Regional patch detection (RPD) analysis. Based on the idea of community detection of complex network, the regional patch detection of road traffic network (RTN) is put forward, which transcends the restriction of administrative division on RTN and fundamentally identifies the special common regional patch structure of RTN. Regional patch detection is applied to the RTN, the deep characteristic structure aggregation of the RTN is analyzed, the restrictions of the administrative division on the RTN are crossed, and the characteristic sharing area is detected according to the trend of the road network, ancillary facilities of the road network, service facilities, distance, and other influencing factors. To evaluate the rationality of traffic network planning, the rationality of road network structure design and the maintenance and maintenance of traffic network are theoretical and practical problems that need to be solved urgently.

The remaining of this paper is organized as follows: Section 2 constructs the road traffic network (RTN), considering the influence factor of weight and the regional patch detection of road traffic network are introduced. Section 3 presents the experimental results of a road traffic network (RTN) in Zhangwu of China. Finally, conclusions are provided in the Conclusion section.

## 2. Regional Patch Detection (RPD) from Road Traffic Network (RTN)

**2.1. The Construction of RTN.** The structure of RTN is always defined as followed due to its complexity. The RTN defined:

$$RTN = (N, E) \quad (1)$$

whereas:  $N = \{n_i | i = 1, 2, \dots, N\}$  is the set of nodes in the RTN,  $N = |N|$  is the number of nodes in RTN;  $E = \{e_{ij} | i \neq j, i, j \in \{1, 2, \dots, N\}\}$  is the set of edges.  $e_{ij} = 1$ , if there is an edge between nodes  $i$  and  $j$ , otherwise  $e_{ij} = 0$ ; weight factor: if each edge is given a corresponding weight, the network is called a weighted network; otherwise, it is called an unweighted network. An unweighted network can also be regarded as an equal-weight network in which each edge has a weight of 1.

**2.2. The Weighting Factors.** The influence of features, distance, and level of road traffic network play a key role in the geographical characteristics and traffic operation of road network. So we set the corresponding weight influence factors to analyze the core position distribution of the road traffic network. There are three weighting factors for the RTN:

**2.2.1. The Location Property.** The location property is an important factor in measuring the importance of a segment. Location characteristics are often related to the presence of facilities such as those in the hotel industry and the commercial sector. Suppose vector  $v$  is of size  $N \times 1$ ,  $N$  is the number of road nodes in the RTN. An element  $v_i = 1 (1 \leq i \leq N)$  that

TABLE 1: Road level weight distribution.

Road level	National road (G)	Provincial road (S)	County road (X)	Rural road (Y)	Village road (C)
Weight	0.6875	0.1875	0.075	0.025	0.025

represents the segment  $i$  is relatively important, and there are important ground feature service facilities around it. Otherwise,  $v_i = 0$ . The property matrix  $F$  defined as:

$$F = (v, v, \dots, v)_{1 \times N} \quad (2)$$

**2.2.2. The Geographic Distance.** For the geographical, a distance-decay characteristic displays significantly in the RTN. The correlation amplitude generally decreases with the increase of the distance between two nodes. Assumption, distance weight matrix  $W = (w_{ij})_{i,j=1}^N$ ,  $d_{ij}$  is the shortest path length between segments  $i$  and  $j$  in RTN and the unit is km:

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}} & i \neq j \\ 0 & i = j \end{cases}, 1 \leq i, j \leq N \quad (3)$$

**2.2.3. The Road Level.** The traffic road network is classified to five categories according to the road administrative level, which is divided into national road (G), provincial road (S), county road (X), rural road (Y), and village roads (C). According to the traffic volume, task, and nature of China's highway engineering technical standards (JTG B01-2014), different levels of traffic networks have different annual average daily traffic volume (ADT) [13]. Thus, the weights of different levels of traffic network are set as shown in Table 1.

Suppose, road level matrix  $L = (l_{ij})_{i,j=1}^N$ , element  $l_{ij}$  refers to the weighted value of road level in Table 1.

**2.3. Regional Patch Detection (RPD).** This community detection result is as a reference, we define the concept of geographic space road traffic network regional patch detection (RPD):

The regional patch is a subset of the RTN in the range of dividing the RTN at different levels. A regional patch contains nodes and the sections between nodes. The nodes in the regional patch are closely related to each other and have strong topological structure similarity and feature facility property similarity. The relation between regional patches is relatively sparse, and the close regional patches differ greatly, while the distant regional patches may have similar characteristics.

**2.4. RPD Method.** Complex networks have scale-free, small-world, and community characteristics. The characteristics of RTN are generally scale-free and small-world. Therefore, the community structure of RTN is analyzed based on the complex network, and the aggregation of road network is deeply explored.

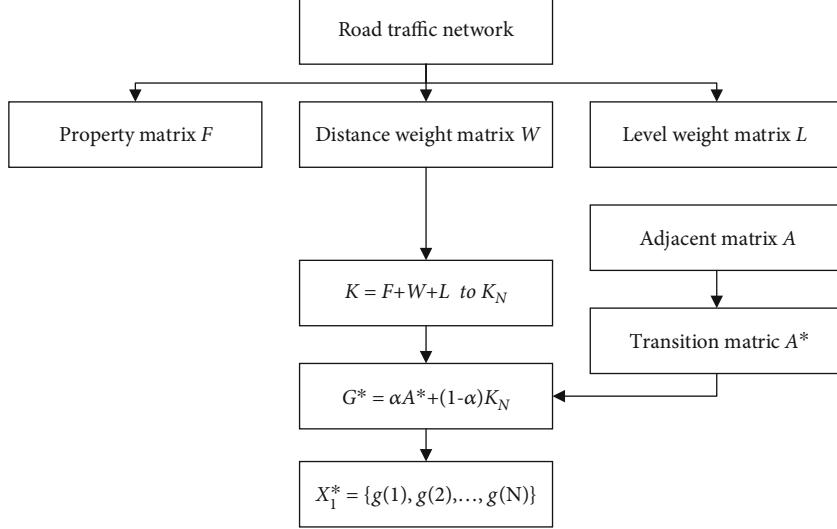


FIGURE 1: The Adapted PageRank algorithm.

TABLE 2: The Adapted K-Means Algorithm process.

Input: Road traffic network  $N = \{n_1, n_2, \dots, n_m\}$ ;  
Regional patch center (Decision Graph)  $k$ .

Process:

- 1: Select the regional patch center from the RTN as the initial value  $\{n_1, n_2, \dots, n_k\}$
  - 2: repeat
  - 3:  $C_i = \emptyset (1 \leq i \leq k)$
  - 4: for  $i = 1, 2, \dots, n$  do
  - 5:  $\arg \min_{C_k \in C} \|\hat{S}_i - C_k\|^2, i = 1, 2, \dots, N$
  - 6:  $C_k = 1/|Z_k| \sum_{\hat{S}_i \in Z_k} \hat{S}_i, k = 1, 2, \dots, K$
  - 7: Divide the sample  $n_i$  into corresponding regional patch  $C_{\lambda_i} = C_{\lambda_i} \cup \{x_i\}$
  - 8: end for
- Export: Regional patch detection  $C = \{C_1, C_2, \dots, C_k\}$

The Google matrix of PageRank, expressed in  $G$ , is defined as:

$$G = \alpha A^* + \frac{(1-\alpha)}{N} I_{N \times N} \quad (4)$$

In the paper, the refined Adapted PageRank algorithm is used to calculate the ranking results of key nodes of the RTN. The matrix  $(1 - \alpha/N)I_{N \times N}$  by adding a property matrix, a distance weight matrix, and a road level matrix. The weight influence factor set in Section 2.2 is applied to calculate the candidate location distribution of key nodes in the RTN.

Then, with the property matrix  $F$ , the distance weight matrix  $W$ , and the road level matrix  $L$ , a novel weighted

matrix  $K$  is defined, where  $k_j$  is the  $j$ th column of matrix  $K$ :

$$K = (k_1, k_2, \dots, k_j, \dots, k_N) = F + W + L \quad (5)$$

In order to make matrix  $K$  have column irreducibility and stochastically, every column vector  $k_j$  of matrix  $K$  should be normalized, Where  $\|k_j\|$  is the norm of column vector  $k_j$ .

A new matrix  $G^*$  in Equation. (6), the term  $(1 - \alpha/N)I_{N \times N}$  is replaced by  $(1 - \alpha)K_N$ . Calculate  $X_1^* = \{g(1), g(2), \dots, g(N)\} (\lambda = 1)$  of  $G^*$  are the rank of key nodes.

$$G^* = \alpha A^* + (1 - \alpha)K_N \quad (6)$$

The calculation rank of key nodes is described in Figure 1.

In this paper, the center points of regional patch detection are selected by the method of two-dimension decision graph. Thus, the number of centers can be determined by taking  $\rho$  and  $\delta$  into consideration,  $\rho$  as the horizontal axis and  $\delta$  as the vertical axis:

$$\gamma_i = \rho_i \delta_i, i \in I_S \quad (7)$$

The  $\rho_i$ , which is the  $i$ th vector  $X_1^*$ , the ranking value of key nodes.  $\delta_i$  represents the minimum shortest path length of RTN. The large  $\gamma$ , it may be the regional patch center. Therefore, it is necessary to arrange  $\{\gamma_i\}_{i=1}^N$  in descending order, and then intercept a number of data points from front to back as the regional patch centers. Therefore,  $C$  nodes distributed in the upper right of the graph were selected as the regional patch centers.

In the RTN, based on the Adapted K-Means algorithm to calculate the regional patches. The Adapted K-Means algorithm process are shown in Table 2. The Adapted PageRank algorithm uses the characteristic influence factor of RTN to calculate the ranking results of key nodes. The influencing factors include the location property, the geographic



FIGURE 2: Zhangwu road traffic network.

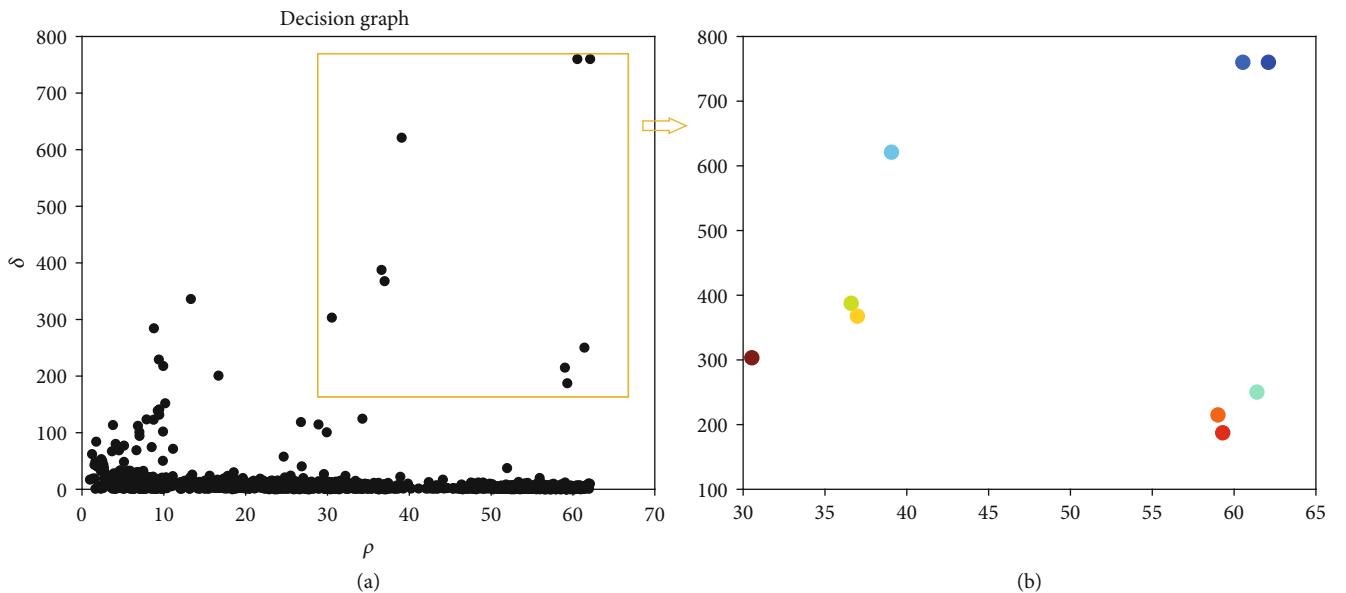


FIGURE 3: Initial cluster center selection results: (a) decision graph; (b) initial cluster center.

distance, and the road level. The method of two-dimension decision graph include the ranking value of key nodes as the horizontal axis and the minimum shortest path length as the vertical axis. The Adapted K-Means algorithm selected the center point of regional patch detection according to the two-dimension decision graph, so as to implement the regional patch detection of RTN. So, the RTN regional patch detection procedure as:

Step 1: in the RTN, calculate the adjacent matrix  $A$ , the property matrix  $F$ , the distance weight matrix  $W$ , and the road level matrix  $L$

Step 2: perform the Adapted PageRank algorithm to the ranking value of key nodes

Step 3: draw a decision graph with  $\rho_i$  and  $\delta_i$ , find the number of regional patches  $C$  and corresponding initial centroids

Step 4: perform the Adapted K-Means algorithm (Table 2) to detection the regional patches

Important key node locations are selected as the central point of regional patch aggregation in the RTN, and the Adapted K-Means algorithm is used to calculate the regional patch distribution. The key nodes of the RTN are taken as the basis of regional patch detection to identify the key locations of the overall RTN and divide the functional structure of the RTN. In the regional patches, the edge intensity is defined to quantify the relationship between each pair of connected

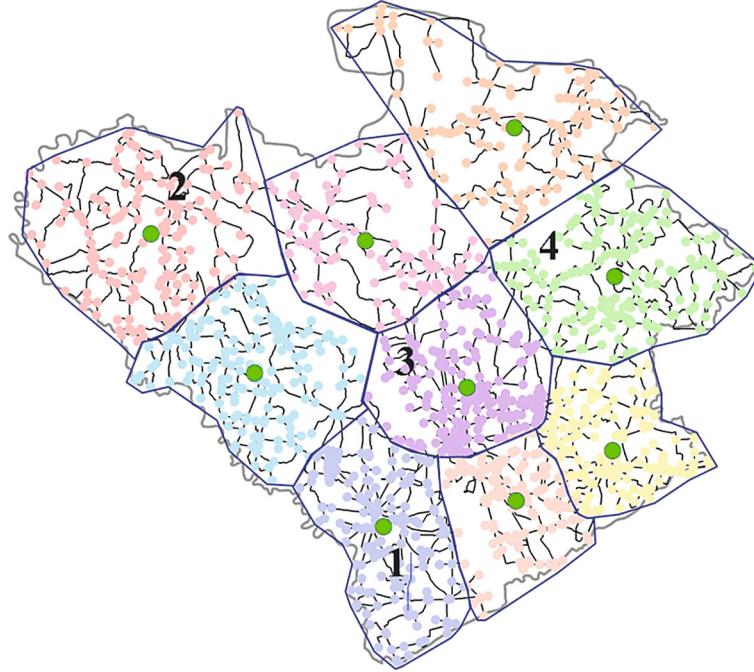


FIGURE 4: Zhangwu road traffic network regional patch detection.

nodes, and the vertical connected by the edges with higher intensities are denoted as core nodes, while the others are denoted as marginal nodes.

The regional patch can identify the key functional structure distribution of the RTN effectively and further understand the structural characteristics of the RTN. Those key nodes are as the center, the regional patch characteristics of the whole network are extracted. From the perspective of geographic space, the characteristic regional patches are detected across the administrative boundaries. The regional patch represents a novel research area and lays the foundation for in-depth analysis of the RTN.

### 3. Experiments and Analysis

The RTN comprised of national road (G), provincial road (S), county road (X), rural road (Y), and village road (C) in Zhangwu. The total number of nodes is 1750 and the total number of edges is 2053 in Zhuangwu road traffic network. As shown in Figure 2, Zhangwu road traffic network.

In the RTN, the number of nodes representing the national roads and provincial roads are only a small portion of number of nodes of the entire network. And most nodes representing the national roads and provincial roads have relatively low values of degree, and the nodes with large degree are mainly located on the county roads, rural roads, and village roads. Use the RTN regional patch detection to calculate the Zhangwu road traffic network. Get the location information of Zhangwu,  $v_i = 1$  and  $v_i = 0$  to distinguish the location of important and common features. After defining the property matrix  $F$ , computing the distance weight matrix  $W$ , and classification of the road level matrix  $L$ , we construct a refined matrix  $G^*$ .

Then, a vector, which represents the importance of road nodes in the RTN, is obtained. Figure 3 shows the result of the selection of the regional patch center of the RTN. Figure 3(a) shows that the center point of selection is shown in the orange box on the upper right side of the decision graph. The nine road nodes in Figure 3(b) are the number of differentiated regional patches. After this process, the number of regional patches were determined as the output parameters of the Adapted K-Means algorithm.

It can be seen from the decision graph that we calculate the classes of regional patch structures, the nodes with the same color are grouped into the same regional patch, and the number of regional patch structures in the RTN of Zhangwu is 9. As shown in Figure 4, the blue area is the Label 1 regional patch structure; pale orange pink area is the label 2 regional patch structure, and so on. Road nodes within a regional patch indicate that traffic state series on them have relatively high correlation compared with other road nodes in other regional patch. As shown in the results of regional patch detection, road nodes within a regional patch are necessarily connected to each other. The regional patch structure of the RTN in Zhangwu is drawn by the blue border, and the whole county is divided into nine regional patch structures. The structure state of the RTN is analyzed from the characteristics. From the figure, we can clearly find the central position of the nine regional patch. As geographical space structure, the connectivity and convenience of the nine regional patch can greatly improve the RTN of Zhangwu. The location of the center point in the connection diagram highlights the connected critical route, providing theoretical reference for the trend of improving the connectivity of the RTN, and the location of the key maintenance and improvement of the RTN can be determined on the road network

connected by regional patch structure. The RTN of Zhangwu can be better improved and maintain the overall network operating efficiency.

## 4. Conclusion

Based on the community detection of complex network, the application of Zhangwu RTN is analyzed, the regional patch structure of Zhangwu road traffic network is analyzed, the common aggregation regional patch of key points is drawn, and the functional structure of RTN is deeply analyzed. Key points are identified and analyzed to identify the important locations of the overall RTN. Based on the important locations, the common structure is drawn, and the network is divided into multiple functional regional patch. In RTN, the results of the regional patch detection of the road network system are determined by the influence of the property of ground object facilities, the distance between nodes, and the level distribution of the road network. However, community detection is rarely used in complex road traffic network. Road traffic network (RTN) rely on communities to play multiple roles and embody specific features, and different investigation levels may have different results and perspectives; hence, community detection is of critical importance for a better understanding of road traffic network.

Moreover, the modeling and analyzing methods are applied to the road network in Zhangwu. The results show that the method has a good regional patch detection effect and has great potential in identifying the aggregation degree of road network structure considering the special structural complexity of RTN from the perspective of geographic space. The analysis results can provide an effective theoretical basis for traffic management and operation analysis. However, the results can provide a basis for the regional patch identification of RTN, and the traffic network system can be studied according to the regional patch distribution trend. It provides a theoretical basis for the maintenance and reconstruction of traffic network in the future.

## Data Availability

The Zhangwu County Traffic Network data used to support the findings of this study have not been made available because the original road network data is the traffic situation of the real county location in China, and it is real and effective reality data. It can reflect the real data of China's geographical location. Therefore, it cannot be made public. However, the results of the later results can be referenced and applied.

## Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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