Hybrid Traffic Route Visual Recommendation Based on Multilayer Complex Networks

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Abstract

Urban traffic congestion is a major nuisance for residents' daily commute, but few studies have focused on the effective combination between urban traffic condition visualization and hybrid traffic travel route recommendation. In this paper, the visualization exploration of urban transportation patterns is realized by multilayer complex transportation networks, which are constructed by taxi transportation network, bike-sharing transportation network, and urban transportation community network. Based on multilayer complex traffic networks, a genetic algorithm modified by A* search algorithm is used to generate multi-modal travel routes. The case studies prove that this method can effectively reduce the time cost of commuting between congested areas by generating hybrid traffic routes.

Index Terms: Human-centered computing—Visualization—Visualization techniques—Network visualization; Human-centered computing—Visualization—Visual analytics

1 Introduction

The rapid development of urbanization in China has brought about a rapid increase in per capita car ownership. However, the resulting traffic congestion has a negative impact on the daily travel of urban residents and aggravates air pollution. Multi-modal travel with public transportation such as taxis as the primary mode and bike-sharing as a supplement, combined with reasonable travel route recommendations, can reduce the cost of travel time for residents while responding to the concept of "carbon neutrality" [1] and reducing personal travel carbon emissions.

Familiarizing with urban traffic conditions and choosing appropriate travel routes and modes of transportation can effectively reduce the impact of traffic conditions on commuting time. Liu [2] et al. proposed a system for unimodal and multi-modal travel route recommendation based on users' preferences and contexts. However, the system does not consider the impact of real traffic conditions on the recommended routes. Huang et al. [3] evaluated the importance of streets in cities through a dynamic network of real city traffic, which built by taxi trajectory data, Yildirimoglu et al. [4] used a multilayer complex networks to visualize the flow trajectories of different travel patterns and explore the potential connections among them. The aforementioned studies on urban traffic visualization are helpful for discovering urban traffic patterns, but lack further integration with traffic trip recommendations.

To address the above issues. Combining the characteristics of network visualization that can effectively tap the movement patterns, a real urban traffic operation network is constructed by applying complex network visualization to traffic trajectory data. The multilayer complex traffic networks are constructed by taxi data, bike-sharing data, and the urban transportation community network. Based on these networks, a multi-modal travel route recommendation method is proposed to reduce the impact of traffic congestion on commutes. Finally, the case studies based on real data from Xiamen city prove the method's effectiveness.

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2 Related Work

2.1 Trajectory Visual Analytics and Multi-Modal Route Recommendation

Vehicle trajectory data have a wide range of applications in popular traffic research areas such as road traffic prediction [5], route planning and navigation [6], and crowd movement patterns [7]. He et al. [8] provided a detailed review and evaluation of the relevant studies in recent years for the potential information in the visual exploration trajectory data. Luo et al. [9] proposed a visual analysis method to explore the similarity between road vectors based on cab GPS data for urban roads. Wang et al. [10] designed a GPS trajectory-based urban traffic congestion visualization and analysis system to explore urban traffic status and automatically detect traffic congestion events.

Multi-modal travel is less susceptible to urban traffic conditions than single-modal travel. Liu et al. [2] proposed a system for unimodal and multi-modal travel route recommendation based on user preferences and contexts. Bucher et al. [11] designed a heuristic multi-modal travel route generation algorithm to personalize the generated routes. Li et al. [12] proposed a multi-level hybrid logit model to solve the generalized overlap problem of multi-modal candidate routes.

2.2 Complex Network Applications

Network topology visualization combined with theoretical knowledge such as graph theory is an effective way to explore the analysis of complex network. Yildirimoglu et al. [4] assembled information about the flows of different entities in a multi-layered complex network structure and used it to identify the community structure in the urban network. Von et al. [13] proposed a method to visually explore dynamic, large-scale motion time-varying traffic data and reveal the masked motion patterns in the network. Zhang et al. [14] proposed multilayer networks topology visualization layout based on Louvain community detection to address the problem that existing multilayer networks visualization cannot clearly show the community structure.

In summary, based on the advantages of trajectory visual analytics and complex network theory in exploring urban traffic operation patterns, locating street congestion events and mining traffic flow patterns are achieved. Meanwhile, the quality optimization of recommended routes is achieved by further combining multi-modal route recommendation algorithms.

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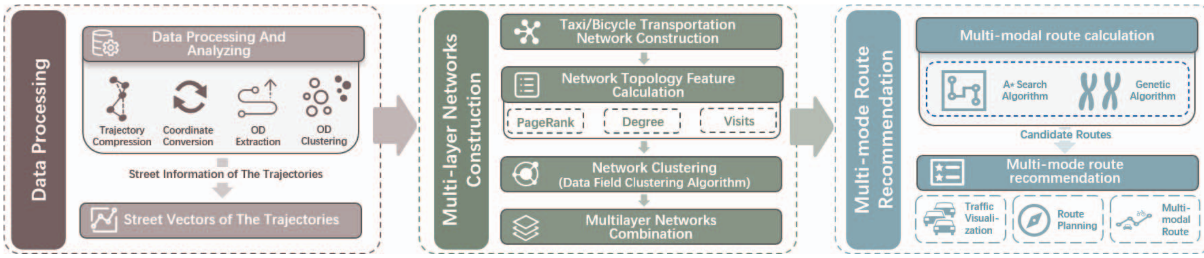

Figure 1: Multi-modal recommendation method based on multilayer complex networks, which consists of three parts: data processing, multilayer networks construction, and multi-modal route recommendation.

3 Multilayer Complex Networks-Based Route Recommendation Method

The method proposed in this paper consists of three main parts: data processing, multilayer networks construction, and multi-modal route recommendation, as shown in Fig. 1.

3.1 Trajectory Data Processing and Analysis

Taxi and bike-sharing trajectory data in Xiamen, China, are used as sample datasets (Table 1). Xiamen is an important central city and tourist city on the southeast coast of China. Taxis and bike-sharing are essential means of transportation in the city. Since Xiamen Island is the economic center of Xiamen City and is relatively isolated from the mainland, the traffic patterns are relatively independent, the trajectory data of Xiamen Island are taken as the focus of the analysis.

Table 1: Details of the data set

Data Type	Sample Size	Sample Properties
taxis trajectory	6742 taxis, about 18 million samples	taxi ID,time, coordinate,speed
bike-sharing trajectory	78,860 bikes, about 2.5 million samples	bike ID,time, coordinate

In order to complete the data preparation for the construction of the multilayer networks model, the process of analysis and processing of the raw trajectory data is as follows.

(1) Inspired by Douglas-Peucker algorithm [15], compression of trajectory data and processing of exception data are completed.

(2) Obtain street information of sample point coordinates in bulk by an online map service provider. Convert the latitude and longitude trajectories into street text vectors for building urban traffic networks.

(3) OD (origin-destination) extraction and trajectory data clustering. The DBSCAN clustering algorithm is used to cluster the OD distribution points, and the clustered hotspot distribution is visually analyzed to locate the popular commuting areas in the city. The OD clustering of taxis on Xiamen Island is shown in Fig. 2, where the colors in the map are only used to distinguish the different class clusters.

3.2 Construction of Multilayer Networks Model for Urban Traffic

The multilayer complex networks model is shown in Fig. 3. The second layer of the taxi traffic network and the third layer of the bike-sharing traffic network are formed by abstracting from the real geographic street information and trajectory data in the lowest layer. The second layer network is overlapped with the third layer network according to the same nodes (e.g., red nodes in Fig. 3), and different nodes (e.g., green nodes in Fig. 3) are added to generate a complete urban multi-modal transportation network, which is the fourth layer. To reduce the visual occlusion problem of complex traffic (Fig. 4a), the complex network in the fourth layer is clustered to generate the traffic community network in the fifth layer. Finally, based on the multilayer complex traffic networks, a multi-modal route recommendation is performed.

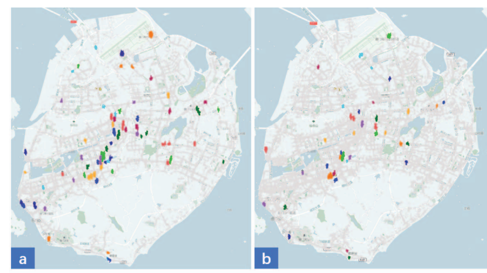

Figure 2: Xiamen Island taxi OD clustering. (a) Pick-up hotspot. (b) Drop-off hotspot.

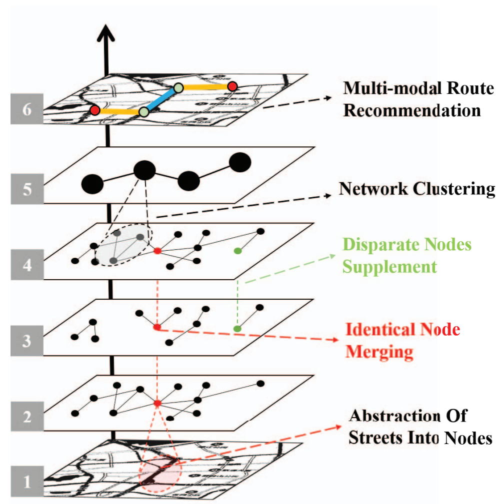

Figure 3: Multilayer complex traffic networks model.

The similarity measure in complex network clustering includes the distance between nodes and the weights of nodes and edges. In the traffic network, the nodes with high traffic volume are usually the city's main roads, which are closely related to the secondary arteries and streets distributed around. In other words, the nodes of the main roads in the urban transportation network have a ”cohesive” effect on the nodes of the secondary roads and smaller streets around them.

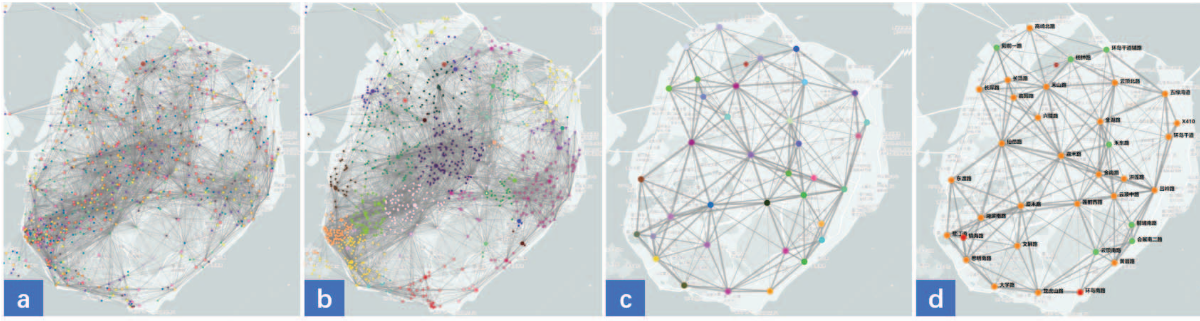

Figure 4: Complex traffic network clustering. (a) Real traffic network. (b) Clustering of complex network. (c) Traffic community network. (d) Overview of the average traffic speed of the community.

Traditional clustering algorithms do not reflect this ”cohesion” in the clustering results.

To address the above issues, the data field clustering algorithm [16] is introduced and improved to complete the clustering of complex traffic networks. Before performing the clustering calculation, the initial cluster center nodes need to be specified. In order to accurately extract the important backbone nodes of the traffic network, we normalize the PageRank value of the nodes, the degree, and the number of vehicle visits, respectively, then perform a weighted sum as the weights of the nodes. According to the calculated node weights, the top 5% [17] of nodes are extracted as the backbone nodes of the network. The weight value of node p_i is calculated by the formula:

$$w_{p_i} = \alpha PR_{p_i} + \beta D_{p_i} + \gamma V_{p_i} \tag{1}$$

where PR_{p_i} denotes the PageRank value of node p_i, D_{p_i} denotes the sum of the out degree and in degree of node p_i, V_{p_i} the total number of vehicle visits, respectively, α, β and γ are their respective corresponding weights. The PageRank value of node p_i is calculated by the formula:

$$PR(p_i) = \frac{1-d}{N} + d \sum_{p_j \in M(p_i)} \frac{PR(p_j)}{L(p_j)} \tag{2}$$

where d is the damping factor, which indicates the probability of continuing to visit the next node at the current node. N is the total number of all nodes in the network. $M(p_i)$ is the set of all nodes pointing to node p_i. $L(p_j)$ is the out degree of node p_j.

Comparison of the experimental results obtained by adjusting the algorithm weights several times, we found that the backbone nodes obtained when setting the values of α, β and γ to 0.8, 0.05, and 0.15, can represent the backbone structure of complex traffic networks.

Finally, the backbone nodes of the network are used as the initial input to the clustering algorithm for complex network clustering. The potential function of node p_i in the network is:

$$\varphi(p_i) = \max_{j \in [1,n]} m_{c_j} e^{-\left(\frac{\|p_i - c_j\|}{\sigma}\right)^2} \tag{3}$$

where m_{c_j} is the quality of the backbone node c_j. $\|p_i - c_j\|$ denotes the distance between the backbone node c_j and node p_i. σ is the influence factor, which is used to control the influence of the backbone node on the surrounding nodes. The Potential functions value $\varphi(p_i)$ is the combined traction force on node p_i. The backbone node with the highest traction on node p_i is the cluster to which node p_i belongs.

To avoid the possible existence of empty clusters after the first network clustering, the backbone nodes without subsidiary nodes are clustered twice. Finally, the nodes in the same clusters are merged into one community node, and the connected edges between communities are retained to generate the urban transportation community network. The effect of network clustering and the generated community network are shown in Fig. 4b and Fig. 4c, where the color of the nodes is only used to distinguish different class clusters.

As shown in Fig. 4d, the communities are divided into congestion, slow and smooth traffic conditions according to the average speed using three color codes: red, orange and green. Facilitates visual exploration of community traffic states.

3.3 Multi-Modal Route Recommendation Based on Multi-layer Complex Networks

Inspired by Abbaspour’s work [18], a genetic algorithm is introduced to solve multi-modal route recommendations. As a method that simulates searching for optimal solutions by simulating natural evolutionary processes, genetic algorithms are capable of solving complex combinatorial optimization problems while generating solution spaces that contain multiple candidate solutions.

The greedy strategy is employed to choose the travel method that takes the shortest time to pass between two nodes in the network. Combined calculation of multiple travel modes in the route is avoided, thus improving the algorithm’s efficiency. The main steps of the modified genetic algorithm are shown in Fig. 5.

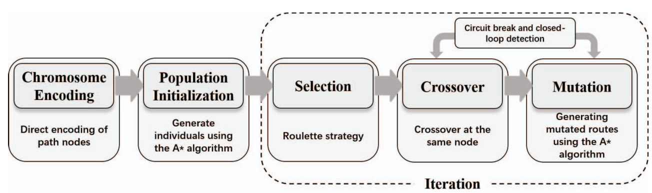

Figure 5: Modified genetic algorithm for computing multi-modal travel routes.

The quality of the initial population is the key to improving the speed of convergence and the set’s quality. Since the A* search algorithm has the advantage of solving the shortest path quickly, when generating the initial population of individuals, several intermediate nodes are randomly selected between the start and end points, and connected as a path by using the A* search algorithm. The numerical numbers of the network nodes in the path are also arranged sequentially as the chromosomes of the population individuals, avoiding repeated encoding and decoding steps.

In the natural selection phase, individuals of the population are selected using the roulette wheel selection algorithm. The probability that an individual is selected to be inherited to the next generation is inversely proportional to the route time.

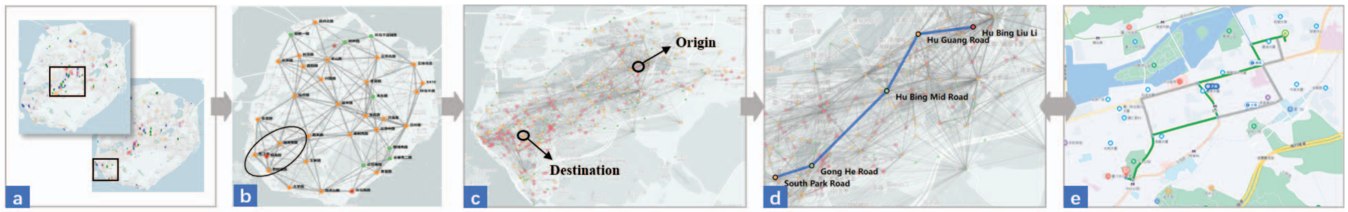

Figure 6: City's popular commuting area positioning and commuting route recommendation.

The random crossover method for route-encoded chromosomes is prone to breakage and loop closure. Therefore, in the crossover phase, the crossover is restricted only at the duplicated nodes of the two chromosomes, and only single-point crossover is performed. Meanwhile, the connectivity of the newly generated individual routes is checked after the crossover completion.

To enrich the diversity of the population, the individual route after mutation needs to be divergent and reasonable. The mutation algorithm for the population individuals is as follows:

(1) Randomly select a path node between start node and end point as the pending mutation node.

(2) Construct the set of candidate nodes. Add the neighboring nodes of the pending mutation node and all nodes separated by one node to the set of candidate nodes, then remove the original path nodes that may exist in the set.

(3) Generate an individual mutation route. The neighboring nodes of the pending mutation node are selected as the starting node and the target node. Several intermediate nodes are randomly selected in the set of candidate nodes and are sequentially connected into a new variant path using the A* search algorithm.

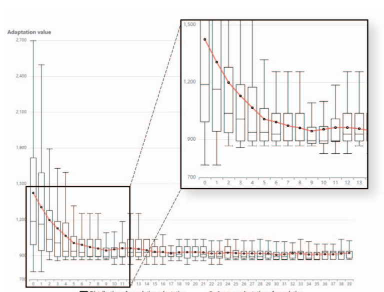

Figure 7: Population quality details for each iteration.

A community transportation network containing 354 nodes and 7098 edges is chosen as an example, in which a randomly selected start and end point are used to calculate the recommended route. The algorithm basically converges after 10 iterations, and the details are shown in Fig. 7. The black box-and-whisker plot and the red line indicate the fitness distribution and the average quality change of the candidate route populations generated by each iteration of the algorithm, respectively.

4 CASE STUDIES

To verify the effectiveness of the proposed method in solving the daily commuting problem of urban residents, the morning rush hour data are screened for traffic network construction and route recommendation.

4.1 Exploring Commuting Patterns and Recommending Commuting Routes for Urban Residents

To locate the popular commuting areas in the city, the distribution of pick-up hotspots (Fig. 2a) and drop-off hotspots (Fig. 2b) are analyzed. The adjacent areas with dense hotspots, as shown in Fig. 6a, are the popular commuting areas of the city.

Community nodes in popular commuting area locations are selected in the city's transportation community network to explore intra-community traffic conditions, as shown in Fig. 6b. Then a residential area in the region, "Hubingliuli," is selected as the starting point of the simulated residential commute, and a street near the commercial area and school, "Park South Road," as the destination of the commute to verify the rationality of the algorithm's recommended route, as shown in Fig. 6c.

The recommended route generated by the algorithm is shown in Fig. 6d. The route passes through several main and secondary roads. Basically, each intermediate street is clear, and due to the long distance of the actual street (about 5 km), there is no bike-sharing in the recommended route. Comparing this recommended route with the navigation results of an online map, as shown in Fig. 6d and Fig. 6e, the composition of the two routes is almost the same, which proves the feasibility and effectiveness of the method.

4.2 Multi-Modal Travel Route Recommendation

We chose "Fujing Street," a residential area with traffic congestion, as the starting point, and "Zhongshan Road Pedestrian Street," which has the same traffic congestion, as the destination. The recommended routes given by the algorithm are shown in Fig. 8. The yellow part of the routes is recommended for bike-sharing trips, and the blue part is recommended for taxi trips. The other two gray routes are the candidate routes given by the algorithm.

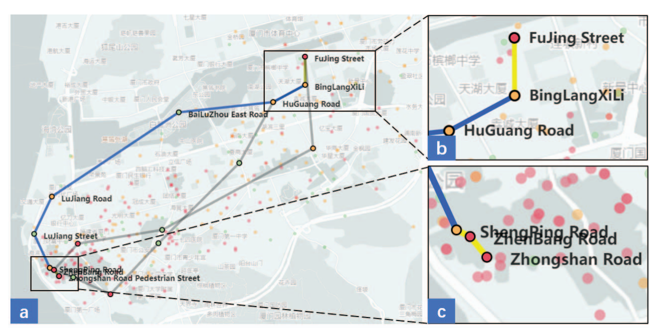

Figure 8: Multi-modal travel routes recommendation in congested areas.

The optimal route shown in Fig. 8b suggests riding the bike from the congested "Fujing Street" to the nearby "Binglangxili," then taking a taxi and getting off at "Shengping Road" near the destination, and finally riding the bike through the congested area of "Zhenbang Road" to the destination of "Zhongshan Road Pedestrian Street." This recommended route effectively reduces the cost of commuting between congested areas by avoiding taking taxi through congested streets.

4.3 Recommended Routes for Short-Distance Travel

In order to verify the effectiveness of the algorithm for short-distance travel route recommendation in areas with dense street distribution and complex traffic conditions, we choose "Siming North Road" and "Hequn Road" in the commercial district as the starting and ending points, respectively, and the recommended routes given by the algorithm are shown in Fig. 9b.

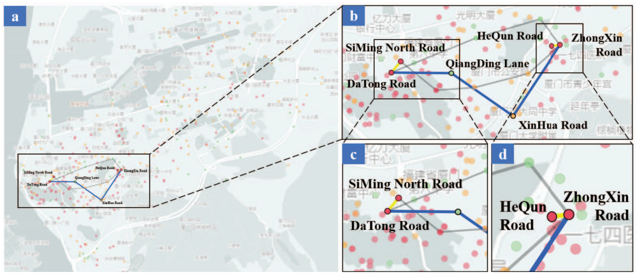

Figure 9: Short-distance travel routes recommendation.

In this route, the bike is used to go through the complicated traffic condition of the alley to the nearby "Datong Road" (Fig. 9c), and then take a taxi, get off early near the end of the road where taxis are not easily accessible, and use the bike-sharing to finish the last part of the journey (Fig. 9d). The route avoids the time spent waiting for a taxi to arrive in complex neighborhoods and takes less time than using a bicycle for the entire trip.

5 Limitation and Future works

In the actual route evaluation and selection, since the user's budget will directly influence the composition of the multi-modal route, the travel route overhead is also worth considering. We have not included the overhead of the route in the algorithm variables yet. In addition, we find in our experiments that the recommended routes sometimes have frequent interchanges, which increases the physical exertion of the travel process and is not conducive to the simplification of the user travel process.

In future work, the overhead criterion of the route will be added to the route evaluation of the algorithm, and a time penalty is applied to each interchange to limit the number of interchanges for the algorithm-generated route. On the other hand, we envision to develop our work into a complete visualization system to support more feasible interactions.

6 Conclusion

In this paper, a hybrid traffic visual recommendation method based on multilayer complex networks is proposed to reduce the impact of traffic congestion on commutes. By combining taxi traffic network, bike-sharing traffic network, and urban traffic community network into multilayer complex traffic networks, a genetic algorithm modified by A* search algorithm is used to generate multi-modal travel routes. The case studies prove the multi-modal travel routes generated by this method can effectively reduce the time cost of commutes in congested areas.

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