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Minimal Cost Vector Travel Navigation Method

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***Abstract*—This paper proposes a minimum cost vector navigation mode based on a distance vector navigation model to address the lack of applicability of traditional path planning methods for short-distance travel in urban transportation networks. By incorporating travel cost into the distance vector navigation model, a new vector navigation mode is developed to overcome the issue that traditional vector navigation algorithms fail to meet users' demand for short-distance travel. Using the distance vector navigation model, the urban traffic network data is transformed into a complex network diagram, and a path planning model is established with the objective function of minimizing travel cost. The model path is solved by a greedy algorithm. The model is then applied to the Sioux Falls road network for travel route planning. The effectiveness and accuracy of the model are evaluated based on two factors: the weighted centrality of the path and the similarity of the actual path. The results indicate that the model achieves higher scores in centrality and similarity with actual paths for shorter travel distances, which better aligns with actual travel patterns.**

Keywords*—*urban transportation, path planning, vector navigation, complex networks, minimum cost

I. Introduction

How travelers plan their travel paths in urban transportation networks has been a hot topic studied by many scholars, especially in large-scale urban road networks. Although there are many types of route planning methods, and the demand for different routes has increased with the rapid development of the number of travelers and the logistics and transportation industry, most of the route planning methods can meet the daily needs of people [1-9]. However, the traveler's psychological preferences during the actual trip also have a great impact on route planning.For example, after analyzing a large amount of GPS dataand statistics of different street networks, JAVADI A H[10] concluded that although the system plans very effective routes, when the travel distance is short, travelers take many factors into consideration when planning the route, such as the cost of the route, time cost, road conditions, road scenery, etc. These factors are considered to be psychological mechanisms of the organism itself. Based on this, Liu[11]developed an opportunity model that takes into account the curiosity and caution of travelers when traveling and has been shown to be a better predictor of travelers' movements than the expected IO-like model. Understanding this psychological mechanism can help inform real-time route planning effectively, allowing better integration of artificial intelligence with urban transportation. Through the study of a large number of actual travel trajectories, it was found that the path planning approach caused by this mental computer system is similar to a vector navigation approach with direction. Based on this, BONGIORNO C[12]proposed a distance-based vector navigation approach that takes into account the path length of the road section and the angle between the road section and the destination. Through a large number of experiments and actual data comparison, it was found that travelers tend to have more directional navigation when traveling short distances.

The research content of the above researchers can be summa rized as follows: the path planning method without considering the psychological preference factor is more suitable for long-distance travel, while the distance-based vector navigation method obtained from the psychological computer system is a good solution for short-distance travel. However, in actual travel, travelers usually consider the travel cost as an influencing factor. Therefore, in this paper, we propose a vector navigation method based on the distance-based vector navigation approach to better simulate the traveler's path planning method. This approach takes into account the traveler's path length and directionality, and integrates the travel cost to make it more consistent with the actual travel mode for short-distance travel. This improves the applicability of the distance-based vector navigation method in actual travel. Additionally, the proposed method improves the distance-based vector navigation method in actual travel.

II. Model Construction

To further enhance the distance-based vector navigation model, we have added the street segment cost to the model. This has transformed the model into a cost vector navigation model, which relies on the angular deviation of the street segment cost from the destination.

$$C_{dir}(P)=\sum_{S_{ij}\in P} c(\theta_{ij},L_{c_{ij}}) \tag{1}$$

$$c(\theta_{ij},l_{ij})=e^{N(\log(|\theta_{ij}|\times L_{c_{ij}}),\sigma)} \tag{2}$$

$\theta_{ij}\in[-\pi,\pi]$ is the angle between the tangent of the street that where S_{ij} is located and the straight line of the travel destination, N is the number of nodes in the road network, σ is a parameter of the model, specifically the impact of the psychometric mechanism on the model, the size of which is based on likelihood value of model to:

$$\log L=\sum_{i=1}^{N}\log P(OD^{(h)}\mid OD,C,\sigma) \tag{3}$$

where $P(OD^{(h)} \mid OD, C, \sigma)$ is the probability of the traveler choosing the actual travel path among all paths in the OD pair[12].

$L_{T_{ij}}$ (Link Travel Time) is the travel time parameter for the current road section obtained by calculating the statistics of vehicle free-flow travel time, traffic flow size, and road section capacity for each road section in a specific time period within the urban road network. The calculation is performed as follows:

$$L_{T_{ij}} = F_{T_{ij}} * (1 + B_{ij} * (F_{ij} / Q_{ij})^{P_{ij}}) \tag{4}$$

where $L_{T_{ij}}$ is the travel time (h) from node i to node j of the current road section, $F_{T_{ij}}$ is the free flow travel time (h) of the current road section, B_{ij} is the current network weighting factor, F_{ij} is the traffic volume (pcu/h) of the current road section, Q_{ij} is the capacity of the road section (pcu/h), P_{ij} is the road class from node i to node j (four classes according to international standards). After calculating the travel time of the road section,the travel cost of the road section $L_{C_{ij}}$ (Link Cost) is obtained.

$$L_{C_{ij}} = L_{T_{ij}} + \mu C_{ij} + hL_{ij} \tag{5}$$

In the above equation, h is the current section length weighting factor, L_{ij} is the current section length (km), μ is the cost factor of the section, and C_{ij} is the travel cost of the section (cent). The travel cost of road segment is related to the traffic volume of the road segment, the free-flow travel time of the vehicles on the road segment, the cost of the road segment and the length of the road segment.

III. Evaluation Indicators

To further illustrate the similarity between the model and the actual paths, we define the similarity jaccard score between the paths obtained from the model and the actual travel paths.

$$J(P_1, P_2) = \frac{|P_1 \cap P_2|}{|P_1| + |P_2| - |P_1 \cap P|} \tag{6}$$

P_1 and P_2 are two different paths,if the value of $J(P_1, P_2)$ equal 1,it means that these two paths are completely identical, and if the $J(P_1, P_2)$ is 0,it means that these two paths are completely different.

To determine the extent to which the paths obtained from the model perform statistically, we define a measure of paths $L(p)$,it is the weighted centrality score of a path, the value is the sum of the weighted centrality scores of each section of:

$$L(p) = \sum_{i=1}^{N} P(OD \mid C(P)) \tag{7}$$

$$P(OD \mid C(P)) = \sum_{s,t \in V} \frac{C_{\sigma(s,t|e)}}{C_{\sigma(s,t)}} \tag{8}$$

By calculating the minimum weighted paths of all OD pairs in the network, counting the number of times each edge appears in the minimum weighted path $C_{\sigma(s,t|e)}$,and normalizing the number of minimum weighted paths between each pair of nodes to obtain the weighted centrality score of the road segment, the weighted centrality score of the path is the sum of the weighted centrality scores of each road segment on the path.

IV. Experimental Analysis

In this paper, the SiouxFalls road network was used as the experimental network for the experiments. To select the parameters of the network, the weighting coefficients and spending coefficients of road sections were obtained from the public data of the network. After analyzing the travel trajectory data of actual travelers, 7 actual travel trajectories with the highest travel frequency were selected as the experimental comparison data. The SiouxFalls network includes 24 nodes and 76 road sections, and the same start and end points as the actual trajectories were selected to facilitate the data comparison. The nodes with node numbers 1 and 6 were used as the starting points, while the nodes numbered 7, 11, and 15 were used as the end points. The paths were compared with the actual travel paths using the vector navigation method based on the minimum cost, the vector navigation method based on the distance, and the shortest path navigation method, respectively.

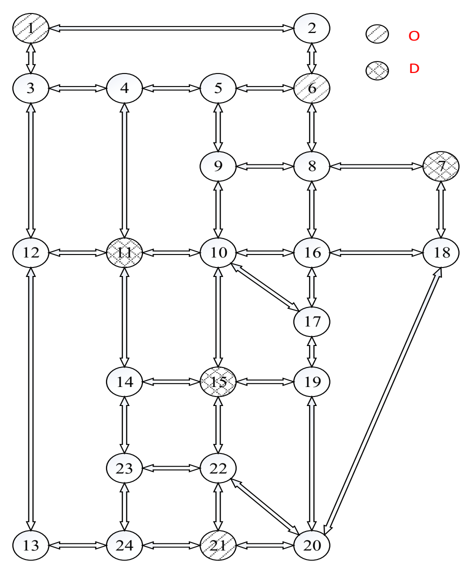

Fig. 1. SiouxFall network

TABLE I. Actual Routes

Number	OD	Path
1	1-11	1-3-4-5-9-10-11
2	1-15	1-3-12-11-14-15
3	6-15	6-8-9-10-15
4	1-7	1-3-4-5-9-8-7
5	21-7	21-22-15-14-11-10-16-18-7
6	21-11	21-22-15-10-11
7	15-1	15-10-9-5-4-3-1

By analyzing the OD pairs in this network, it can be observed from Figure 2 that the majority of OD pairs have a length of 4km. OD pairs with shorter or longer lengths account for a minority of the network. Moreover, the spending on OD pairs is proportional to the change in OD pair length, which is reflective of the actual situation. In terms of model parameter σ selection, for OD pairs with a length of 3~5km, when the travel distance is short, the changes in travel cost and travel distance are similar,it suggesting that they are affected by the same psychological calculation mechanism. Therefore, the experimental parameter σ for the minimum cost-based vector navigation approach in this range can be the same as that of the distance-based vector navigation. In this paper, for the sake of comparison, the same parameter σ values as in the literature are chosen for the effects of experimental parameters on distance-based and least-cost model-based path planning. Specifically, the values of 0.44 and 1.06 are selected as the parameters σ for this experiment.

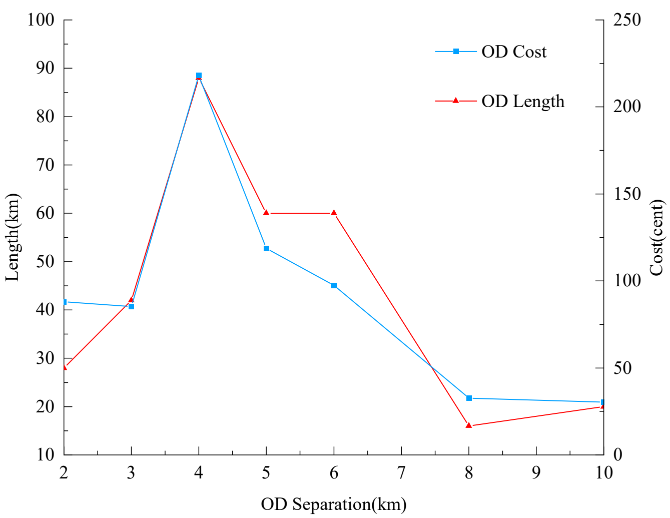

Fig. 2. OD pair length and cost

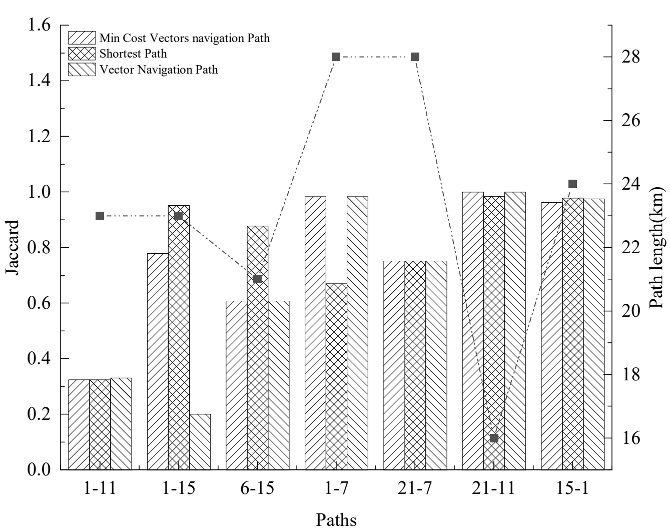

Fig. 3. Path similarity Jaccard score

To verify the practical applicability of the paths obtained by different models, the similarity scores between the paths obtained by different models and the actual travel paths were experimentally compared. Figure 3 shows that when the travel path is short, the similarity score between the actual travel path and the path obtained by the model is close to 1, indicating that the path obtained by the model is very similar to the actual path. However, as the travel distance increases, the similarity score between the path obtained by the model and the actual path decreases, while the score of the shortest path increases, suggesting a shift from directional to distance-based choice of travel mode. Although there are still some deviations between the paths obtained from the model and the actual paths, the seven paths obtained from the model have an average similarity score of 10% higher than that of the shortest path model and the actual paths, which is a good predictor of the actual travel situation even at shorter distances.

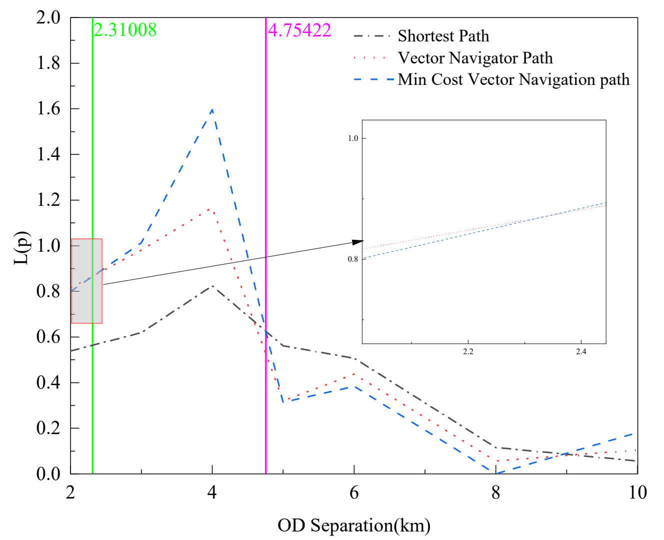

Fig. 4. The $L(p)$ scores for different Models with OD distributions with $\sigma = 0.44$

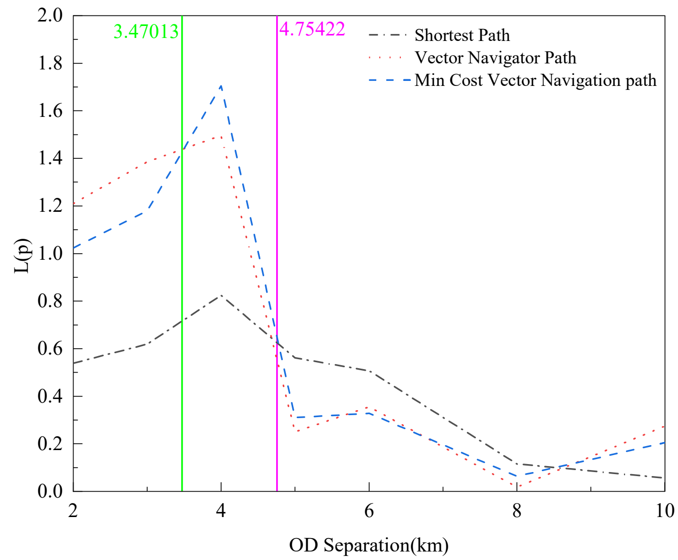

Fig. 5.The $L(p)$ scores for different Models with OD distributions with $\sigma = 1.06$

After simulating travel path planning between all OD pairs in the Sioux Falls network, a relationship between the distance of the OD pair distribution and the weighted centrality score of the OD pairs was obtained. When the σ value is 0.44,from the Fig4, the weighted centrality score of the vector navigation model is highest. when the distance of the OD pair is within 2.31 km, it indicating a preference for the vector navigation strategy with the smallest distance. The weighted centrality scores of the minimum-expenditure vector navigation and vector navigation models are higher than the shortest path navigation model. when the distance of the OD pair is within 2.31 km to 4.75 km, with the weighted centrality score of the minimum-expenditure vector navigation model being the highest. However, the weighted centrality score of the least-cost vector navigation model is the highest, indicating that travelers are influenced by the psychological computation system and choose the path with the least directional cost. Similarly, when the σ value of is 1.06,from the Fig5,the distance of the OD pair tends to be within 3.47 km, and the distance of the OD pair tends to be between 3.47 km and 4.75 km. When the OD pair distance is greater than 4.75 km, the weighted centrality scores of the shortest path model are higher than the weighted centrality scores of the vector navigation and vector navigation models based on the minimum cost model, indicating that travelers are more likely to choose the shortest path as the travel mode.

As the travel distance increases, the traveler's choice of travel mode gradually changes from the direction-optimized path strategy to the shortest path optimization strategy, consistent with the findings in the literature[12]. This also supports the accuracy of the model proposed in the paper.

V. Conclusion

Based on the psychological mechanism of travelers' path selection, a new quantitative model is established on the distance-based vector navigation model. This model is validated to be closer to the actual travel behavior of travelers for short travel distances. However, it is also found that the distance-based vector navigation method alone cannot meet the complex and diverse travel needs, thus requiring optimization. The proposed minimum-cost-based vector navigation method integrates road segment costs and quantifies the path cost function based on the psychological computational mechanism for short-distance travel, simulating the actual path planning process in the traveler's brain and making travel directional. This approach adjusts the path planning process based on actual needs, which is also a new extension of the distance-based vector navigation method.

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References

[1] LIU Q,HOU P,WANG G,et al. Intelligent route planning on large road networks with efficiency and privacy[J]. Journal of Parallel and Distributed Computing,2019,133: 93-106.

[2] GAO L N,TAO F,MA P L,et al. A short-distance healthy route planning approach[J]. Journal of Transport & Health,2022,24: 101314.

[3] ZENG Y,TONG Y,SONG Y,et al. The simpler the better: An indexing approach for shared-route planning queries[J]. Proceedings of the VLDB Endowment,2020,13(13): 3517-3530.

[4] YAO Y,PENG Z,XIAO B. Parallel hyper-heuristic algorithm for multi-objective route planning in a smart city[J]. IEEE Transactions on Vehicular Technology,2018,67(11): 10307-10318.

[5] LIU B,LONG J,DENG M,et al. An Adaptive Route Planning Method of Connected Vehicles for Improving the Transport Efficiency[J]. ISPRS International Journal of Geo-Information,2022,11(1): 39.

[6] Nie Qinghui,Long Xiujiang,Liang Cheng,Xia Jingxin,Ou Jishun. Optimal allocation and path planning of sanitation vehicles on urban roads under multiple constraints[J]. Transportation Systems Engineering and Information,2022,22(5): 273-284.

[7] Kumar S, Awasthi P. Navigation architecture for autonomous surveillance rover[J]. International Journal of Computer Theory and Engineering, 2009, 1(3): 231.

[8] Kazemi M, Banaeyan M, Pourmohammad A. UAV Navigation Based on PIIFD/INS Method[J]. International Journal of Computer Theory and Engineering, 2012, 4(2): 283.

[9] Park C H, Kim N H. Analysis of Navigation Error of an Integrated GNSS-Vision System Based on Geometric Allocation of Landmarks via Modelling of the Urban Environment[J]. International Journal of Computer Theory and Engineering, 2017, 9(2).

[10] JAVADI A H ,EMO B,HOWARD L R,et al. Hippocampal and prefrontal processing of network topology to simulate the future [J]. Nature communications,2017,8(1): 1-11.

[11] LIU E J,YAN X Y. A universal opportunity model for human mobility[J]. Scientific reports,2020,10(1): 1-10.

[12] BONGIORNO C,ZHOU Y,KRYVEN M,et al. Vector-based pedestrian navigation in cities[J]. Nature Computational Science,2021,1(10): 678-685.