Research and Application of Adaptive Projection Map Matching Algorithm under the Background of Complex Roads

xiaoxue fu
383431362@qq.com

Shanghai University of Medicine and Health Sciences

hongtao cheng
Shanghai University of Medicine and Health Sciences

yijin chen
China University of Mining and Technology

Short Report

Keywords: traffic safety, map matching, adaptive projection algorithm, intersecting road, candidate roads

Posted Date: June 4th, 2024

DOI: https://doi.org/10.21203/rs.3.rs-4465571/v1

Additional Declarations: No competing interests reported.

Research and Application of the Adaptive Projection Map Matching Algorithm under the Background of Complex Roads

FU Xiao-xue[1], CHENG Hong-tao[1], CHEN Yi-jin[2]

(1. Information Management Center, Shanghai University of Medicine & Health Science, Shanghai 201318, China;

2. School of Earth Science and Surveying Engineering, China University of Mining and Technology, Beijing 100083, China)

Corresponding author: FU Xiao-xue, Ph.D., Email: 383431362@qq.com

Abstract: To address the problems of easy volatility, empty matching, incorrect matching, and low matching accuracy, an adaptive projection map matching algorithm is proposed based on existing map matching algorithms for intersecting urban roads. First, the method of setting the distance threshold was used to eliminate abnormal location points. Then, by comparison with the AutoNavi map, the missing data in the OpenStreetMap were filled. To reduce the matching time, the grid index was generated, and the impossible methods were filtered by the error circle. Second, the probabilities of the projection distance and direction were assigned, and the corresponding weight coefficients were adjusted adaptively. Finally, the probabilities of the candidate methods were calculated by considering both the projection distance and direction, which helped to determine the actual road and improve the matching accuracy. At the same time, real-time driving data from Changzhou taxi vehicles were used for experimental verification. The results show that the adaptive projection map matching algorithm can increase the matching accuracy by approximately 4% compared with other existing matching algorithms and shorten the single-point matching time by approximately 1.5 ms, which realizes accurate map matching under complex intersecting methods.

Keywords: traffic safety; map matching; adaptive projection algorithm; intersecting road; candidate roads

1. Introduction

The applications related to intelligent transportation are all based on vehicle trajectories, the core of which is to accurately locate the GPS trajectory data of vehicles on roads via map matching [1-5]. A typical GPS trajectory includes a series of sequential track points. Each point collected from GPS consists of latitude, longitude, and timestamp information. However, due to the limitations of GPS, errors may occur in the sampling and calculation process of GPS data, as well as in the reception and return process of positioning data, leading to inaccurate GPS data [6-11]. Therefore, it is necessary to process the raw data and map it to the road network, which involves map matching. The input of the map matching algorithm should be the location information marked by GPS points, the adjacency information of the road network, and other driving data of the vehicle. The key issue is how to quickly and accurately infer the vehicle's driving route by integrating various data collected by vehicle terminal equipment with road networks downloaded from Open Street Maps[12-17]. At present, a variety of map matching algorithms have been researched and applied domestically and internationally [18-20].

The existing map matching algorithms have problems such as empty matching and false matching [21-28]. When the amount of data to be matched increases rapidly, the matching efficiency often decreases significantly. In response to the above issues, this article proposes an adaptive projection map matching algorithm against the background of intersecting road sections. Based on different types of roads, the weight and calculation variables are adaptively adjusted to achieve accurate map matching under complex urban road networks. Moreover, the single-point matching time can be reduced even when large-scale data are matched.

2. Algorithm Implementation

2.1 Data preprocessing

Map matching is the process of matching the vehicle's positioning information to the corresponding road. In this article, the positioning information of the vehicle is obtained through the on-board terminal device installed in the vehicle, and the map data information is downloaded from the official website of Open Street Map (OSM). OSM map data are free, open and provided by volunteers all over the world. The OSM data mainly fall into three types: node, way and relationship [29-31]. Due to the complexity of urban roads, vehicle positioning information often experiences certain errors as a result of building obstructions, overpasses, viaducts and underground tunnels, resulting in abnormal data. Therefore, to reduce the impact of abnormal positioning information on matching accuracy, it is necessary to preprocess the positioning information in advance. First, abnormal data are removed from the positioning information. Second, the interpolation method is used to fill in the missing positioning data. Through the onboard terminal device, the vehicle positioning information that we obtain includes the longitude and latitude, direction angle, speed and driving time [32-35]. The principle of removing abnormal data from the positioning information is shown in Figure 1.

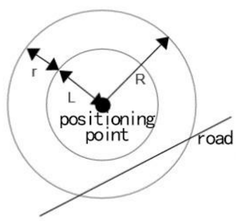

Fig. 1 Diagram of Elimination

The maximum distance is determined based on the positioning error and the maximum deviation of the vehicle. The positioning points whose distance between the roads is greater than the maximum distance are removed, and the maximum distance is also known as the distance threshold R_{max}. The calculation formula is as follows:

$$R_{max} = (V_{rmax} + V_s) * \delta t + r \qquad (1)$$

where V_{rmax} is the maximum speed limit on the road, V_S is the instantaneous velocity error, δt is the sampling interval time of vehicle positioning information, r is the radius of the error circle of positioning data at a certain confidence level, and $R_{max}$is the sum of the maximum deviation distance of the vehicle and the radius of the error circle. If the distance from the location point to the road exceeds R_{max}, the location point will be eliminated. Otherwise, the anchor point is retained.

In addition to removing positioning outliers, this article also uses interpolation algorithms to determine the coordinates of positioning points. The interpolation principle is shown in Figure 2:

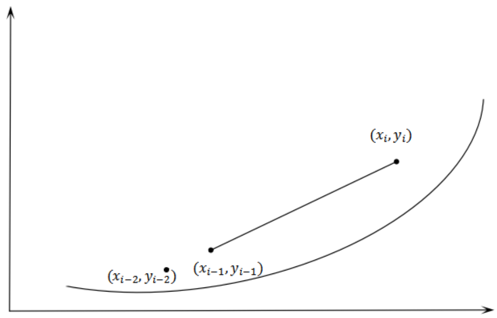

Fig. 2 Diagram of Interpolation

where (x_i, y_i) is the coordinate of the anchor point that needs to be completed, (x_{i-1}, y_{i-1}) is the coordinate of the positioning point from the previous time, v_{i-1} is the speed of the vehicle at the previous time, and φ_{i-1} and φ_{i-2} are the direction angles of the vehicle at the anchor points of the previous two moments, that is, the angles between the driving direction of the vehicle and the due north direction. Therefore, the calculation formula of (x_i, y_i) is as follows:

$$x_i = x_{i-1} + v_{i-1} * \delta t * \sin[(\varphi_{i-1} - \varphi_{i-2}) + \varphi_{i-1}] \quad (2)$$

$$y_i = y_{i-1} + v_{i-1} * \delta t * \cos[(\varphi_{i-1} - \varphi_{i-2}) + \varphi_{i-1}] \quad (3)$$

In addition to the data preprocessing of vehicle positioning information, it is also necessary to preprocess the original map data for matching. The map data used in this paper are downloaded from the OSM map website [36-37], so it is necessary to process the map data into the required map data to be matched, mainly for road detection and the completion of map information. In Figure 3, a represents the original map data of Changzhou city, and b represents the map data after adding new roads. After the vehicle positioning information and map data are preprocessed, the entire electronic map needs to be grid divided. During map matching, the grid where the positioning point is located will be determined first, and then all candidate road segments contained in this grid will be identified, which can greatly improve the speed of queries and shorten the time needed for road network matching.

Fig. 3 Diagram of the New Road Detection Experiment of Changzhou

2.2 Candidate Road Set R

After preprocessing the vehicle positioning data and map data, the entire electronic map was gridded to determine the approximate area of the actual road. Currently, the algorithm using error ellipses is used to determine an elliptical region. The calculation formulas are shown in (4), (5), and (6), where a is the major half axis of the ellipse, b is the minor half axis of the ellipse, and the standard deviation and covariance of the vehicle's longitude and latitude are $\sigma_X, \sigma_Y, \sigma_{XY}$, where σ_0

is a variable parameter, and the angle between the major half axis of the ellipse and the direction of the true north is represented by φ.

$$a = \sigma_0 \sqrt{\frac{1}{2(\sigma_X^2 + \sigma_Y^2)} + \sqrt{\sigma_X^2 - \sigma_Y^2 + 4\sigma_{XY}^2}} \quad (4)$$

$$b = \sigma_0 \sqrt{\frac{1}{2(\sigma_X^2 - \sigma_Y^2)} + \sqrt{\sigma_X^2 - \sigma_Y^2 + 4\sigma_{XY}^2}} \quad (5)$$

$$\varphi = \frac{\pi}{2} - \frac{1}{2}\arctan(\frac{2\sigma_{XY}}{\sigma_X^2 - \sigma_Y^2}) \quad (6)$$

According to the error ellipse calculation formula, if the error ellipse algorithm was adopted, the calculation would be more complicated. Therefore, in this article, the calculation method of the error ellipse was simplified by taking the coordinates of the location point (x_i, y_i) as the center of the ellipse, as shown in formula (8), where the major axis and focal length of the simplified ellipse are $2a'$ and $2c'$, respectively. The grid where the positioning point is located is determined by the grid index.

$$a' = R * \delta t \quad (7)$$

$$c' = \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \quad (8)$$

The roads contained in the error circle are selected as candidate road segments. The set of all candidate matching roads is R={R_1, R_2..., R_i... R_n | i=1,2..., n}.

2.3 Determine matching road sections

2.3.1 Probability function allocation

(1) Construction of the probability of the projection distance

The projection distance from the positioning point to a certain road can be divided into two situations, as shown in Figure 4. Therefore, the calculation method for the projection distance from the positioning point to a certain road can also be divided into two types. The projection distance is an important indicator in road network matching, which means that the smaller the projection distance from the vehicle to the candidate road is, the more likely the vehicle is to travel on that road.

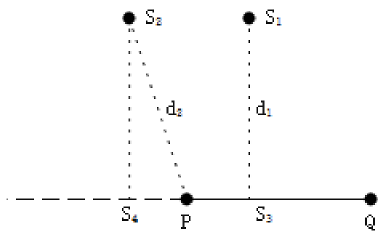

Fig. 4 Calculate the shortest distance

The shortest distance from positioning point S_1 to segment PQ is d_1, and the formula is as follows (9) [30]:

$$d_1 = \frac{|(y_2 - y_1)x + (x_1 - x_2)y + (y_1x_2 - y_2x_1)|}{\sqrt{(y_2 - y_1)^2 + (x_2 - x_1)^2}} \quad (9)$$

The projection of anchor point S_2 to section PQ is on the extension line of section PQ, so the shortest distance from S_2 to section PQ is d_2, and the calculation is shown in formula (10).

$$d_2 = \sqrt{(x_1 - x)^2 + (y_1 - y)^2} \quad (10)$$

Based on the grid index and error circle calculation, the set of candidate roads we obtain is R={R_1, R_2..., R_i... R_n | i=1,2..., n}; then, the probability of distance $\theta_1(R_i)$ is constructed as formulas (11) and (12):

$$\alpha_i = \frac{a'}{d_i} \quad (11)$$

$$\theta_1(R_i) = \frac{\alpha_i}{\sum_{j=1}^{n} \alpha_j} \quad (12)$$

(2) Construction of the Probability of the Angle between the Vehicle and Road

According to the positioning information collected by the vehicle navigation terminal device, the direction angle of the vehicle is also an important parameter for accurate road network matching. The angle between the vehicle's direction and the road's direction is assumed to be θ I, as shown in Figure 5:

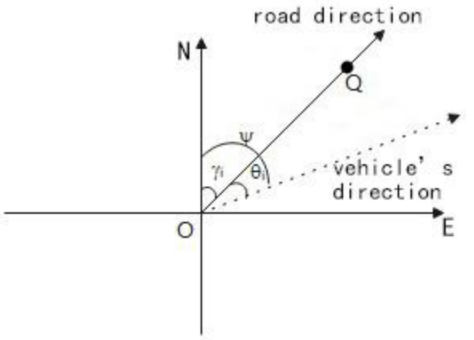

Fig. 5 Diagram of Road Direction and Vehicle Direction

In the figure above, assuming that the coordinate of point Q is (x,y), O is the origin of the coordinate, and the coordinate is (0,0), then the angle between road section OQ and the true north direction γ_i can be calculated according to formula (13) [11]:

$$\gamma_i = \begin{cases} \frac{\pi}{2} - \arctan(\frac{y}{x}), x > 0 \\ \frac{3\pi}{2} - \arctan(\frac{y}{x}), x < 0 \end{cases} \quad (13)$$

If x=0 and y<0, then $\gamma_i=\pi$; if x=0 and y>0, then $\gamma_i=0$; therefore, the calculation of θ_i can be derived as shown in formula (14):

$$\theta_i = \begin{cases} |\psi - \gamma_i|, |\psi - \gamma_i| < 180° \\ 360° - |\psi - \gamma_i|, |\psi - \gamma_i| > 180° \end{cases} \quad (14)$$

Suppose that the set of candidate paths obtained from the error circle is R={R_1,R_2..., R_i... R_n | i= 1, 2... n}; then, the probability construction formula of the direction angle is shown as (15) and (16):

$$\lambda_{\mathrm{i}} = \frac{\pi}{\theta_i} \quad (15)$$

$$p_2(R_i) = \frac{\lambda_i}{\sum_{j=1}^{n} \lambda_j} \quad (16)$$

2.3.2 Probability calculation of candidate road sections

The object of this article is map matching under intersecting road sections. After calculating the distribution probability of the distance and direction angle, we use the adaptive weight method to combine the two influencing factors to calculate the probability of the candidate section. The calculation formula is as follows:

$$\mathrm{p}_0 = \mu_1 p_1 p_2 + \mu_2 p_1 p_2 + \mu_3 p_1 p_2 + \mu_4 p_1 p_2 \quad (17)$$

In the above formula, from left to right, it is the probability that road Ri can be matched based on both distance and direction, the probability that the road RI can be matched only on the basis of distance, the probability that the road RI can be matched only based on direction, and the probability that the road RI is not matched according to distance and direction.

2.3.3 Steps and flowchart of the algorithm

The specific implementation steps of the algorithm are as follows:

Step 1: Remove the abnormal information of vehicle positioning, complete the OSM map, and grid the electronic map;

Step 2: Obtain the candidate matching path set;

Step 3: Calculate the distribution probability of the projection distance and direction;

Step 4: Determine the weight parameters adaptively according to the different types of roads;

Step 5: Calculate the probability of the candidate matching path.

The flow chart of the algorithm is shown in Figure 6.

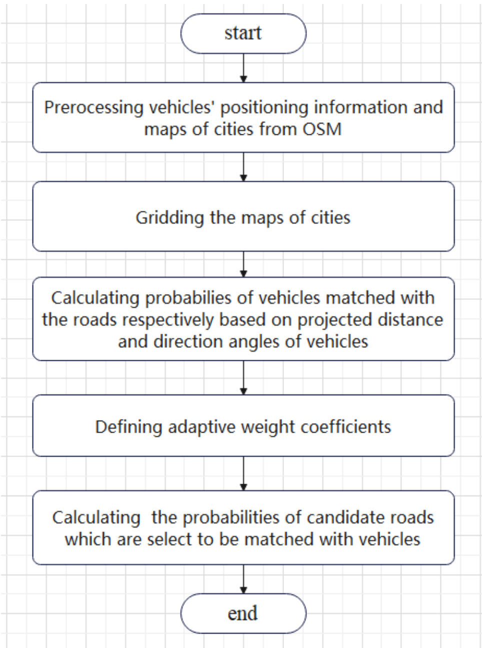

Fig. 6 Flowchart of the Improved Projection Distance Matching Algorithm

3. Verification

3.1 Experimental verification of the algorithm

To verify the performance of the adaptive projection map matching algorithm, real-time positioning information collected from more than 1800 taxis in Changzhou city was used to test and verify the algorithm. The positioning information of the vehicle is obtained through the vehicle navigation terminal, including the longitude and latitude of the vehicle, the speed of the vehicle, and the direction angle. The sampling interval is 10 seconds. The measurements were mainly carried out under the scenario of intersecting road sections. The matching results of the vehicles in a certain area are shown in Figure 7 below. It can be seen from the figure that against the background of complex intersecting road sections, each positioning point of the vehicles can be well matched to the road, with extremely high matching accuracy.

Fig. 7 Matching Trajectory of Vehicles

3.2 Analysis of Algorithm Results

In the context of complex urban intersections, the matching accuracies of four algorithms were compared: the adaptive projection algorithm, traditional projection algorithm, hidden Markov model algorithm, and curve fitting matching algorithm. The accuracy of the algorithm was calculated as the ratio of the number of correct matching points to the number of all positioning points. As shown in the figure, the matching accuracy of the proposed algorithm in this research on intersection sections is over 98%. Compared with the other three algorithms, the accuracy improved by at least 4%. Because the proposed algorithm increases the weight of the parameter of the vehicle direction angle at the time of calculating the probability of the candidate sections, the matching accuracy of the parallel sections is lower than that of the other three algorithms. However, in the scenario of combined road sections, the accuracy of our algorithm is significantly better than that of the other three algorithms, indicating that our algorithm has the highest matching accuracy in the case of intersection and combined road sections and is especially suitable for complex intersection road sections in cities.

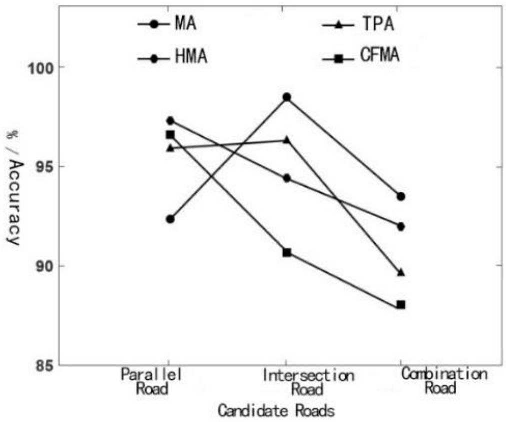

Fig. 8 Comparison of Matching Accuracy

To evaluate the matching algorithm, the single-point matching times of the four algorithms were also calculated in addition to determining the matching accuracies of the four algorithms. The single point matching time refers to the average time it takes to match the target point to a certain road segment. Figure 9 shows the matching times of the four algorithms for two, three, four, and five candidate roads. It can be concluded from the figure that when there are two candidate roads, the matching time of the algorithm proposed in this article is 3.8 ms. When there are five candidate roads, the matching time is approximately 5.5 ms. As the number of candidate roads increases, the single-point matching times of all four algorithms increase. However, the matching time of the algorithm proposed in this article is lower than that of the other three algorithms, and its single point matching time can be reduced by approximately 1.5 ms, indicating good real-time performance.

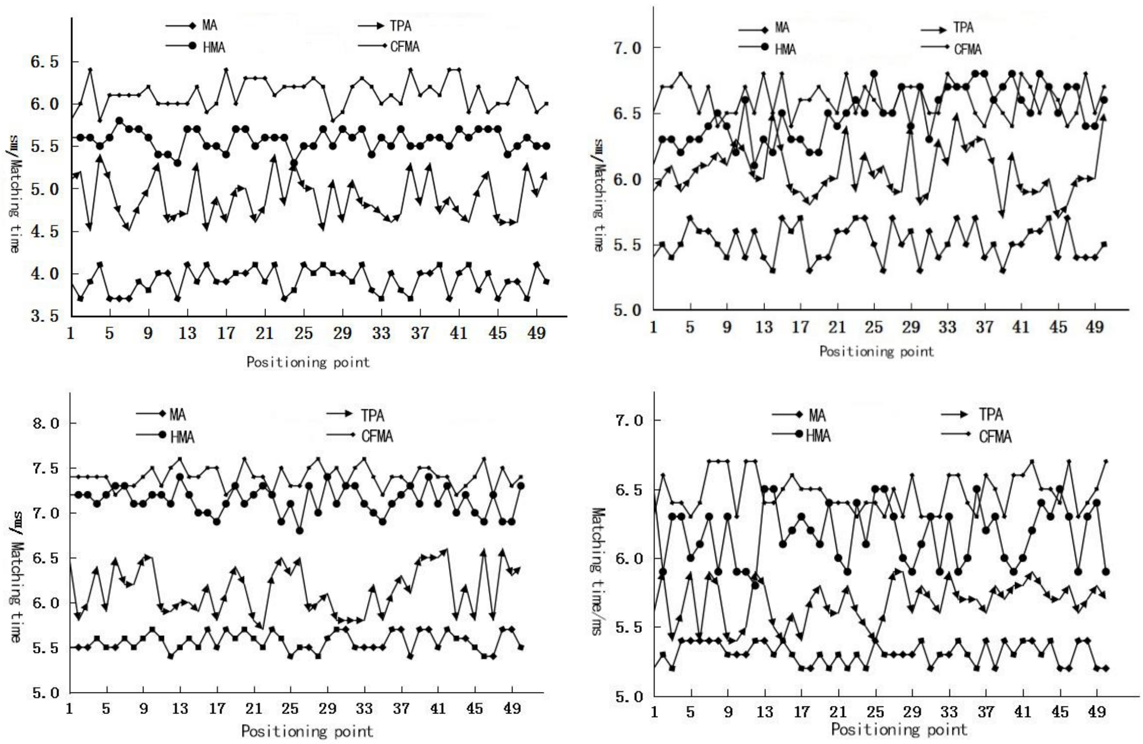

Fig. 9 Single-point matching time of different algorithms under two, three, four, and five candidate roads

4. Conclusion

This article focuses on the map matching of complex urban roads, including intersections; proposes an adaptive projection map matching algorithm for parallel and intersecting methods; removes positioning anomalies through the distance threshold method; and completes the missing road information of open street maps compared with Amap. The set of candidate roads is determined by gridding the city map downloaded from the OSM and calculating the error circle. The speed of map matching is improved by generating a grid index for the roads on the map. To select the optimal matching road segment, we determine the probability of candidates by adaptively adjusting weight coefficients according to the allocation probabilities of the projection distance and vehicle direction angle. The conclusions drawn through experimental verification are as follows:

(1) By setting the maximum distance, the abnormal positioning points are removed, and the positioning information of the collected vehicles is preprocessed. Moreover, by comparing the city map from the OSM with that from Amap, the missing roads in the OSM are replaced, providing precise map data for subsequent map matching. This is a crucial and important step for enhancing the accuracy of map matching.

(2) By generating grid indices on electronic maps of cities obtained from the OSM and calculating error ellipses, the approximate areas where candidate roads are located can be identified, which can improve the query efficiency of candidate road sets and greatly decrease the calculation time of map matching.

(3) Through the experimental verification of real-time driving data of taxi vehicles in Changzhou city and the simulation comparison of the four types of algorithms, the adaptive projection map matching algorithm proposed in this paper is compared with the other three map matching algorithms. Although this algorithm has a minor reduction in the matching effect under parallel roads, it has increased the matching accuracy by approximately 4% against the background of cross-roads, implying that difficult map matching on complex urban roads is effectively implemented.

(4) Compared with the other three types of map matching algorithms, by calculating the single-point matching time on two, three, four, and five candidate roads, the results show that the adaptive projection map matching algorithm not only decreases the single-point matching time by approximately 1.5 ms in the case of multiple candidate roads but also improves the algorithm performance and consequently realizes fast map matching in the context of intersections.

The main research of this article is about map matching algorithms and their application in the context of intricate networks of urban roads. Due to the diversity of urban roads, which contain a large number of viaducts and overpasses, the next stage of research will focus on how to precisely locate vehicles on elevated roads or overpasses and achieve high performance of the algorithm.

Declarations

The authors declare that they have no competing interests.

Authors' contributions section

Conceptualization, FU Xiao-xue; methodology, FU Xiao-xue and LUO Zan-wen. ; software, FU Xiao-xue and CHENG Hong-tao; validation, FU Xiao-xue and CHENG Hong-tao; formal analysis, FU Xiao-xue; data curation, FU Xiao-xue; writing-original draft preparation, FU

Xiao-xue and LUO Zan-wen. ; writing-review and editing, FU Xiao-xue and CHEN Yi-jin; supervision, FU Xiao-xue and CHEN Yi-jin.

Funding

No funds were received for this research.

Availability of data and materials

The data that support the findings of this study are available from Shanghai Super Star Information Science & Technology Co., Ltd., upon reasonable request.

Acknowledgments

The authors thank the Shanghai Traffic Big Data Institute for providing the floating car dataset. The authors would also like to thank the reviewers for the valuable suggestions that significantly improved this paper.

References:

[1] REN M, KARIMI H A. A hidden Markov model-based map-matching algorithm for wheelchair navigation[J]. Journal of navigation, 2009, 62(3): 383-395.

[2] LOU Y, ZHANG C, ZHENG Y, et al. Map-matching for low-sampling-rate GPS trajectories[C]//Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems. Seattle, Washington: ACM, 2009: 352-361.

[3] WHITE C E, BERNSTEIN D, KORNHAUSER A L. Some map matching algorithms for personal navigation assistants[J]. Transportation research part C: emerging technologies, 2000(8): 91-108.

[4] QUDDUS M, OCHIENG W Y, ZHAO L, et al. A general map matching algorithm for transport telematics applications[J]. GPS solutions, 2003, 7(3): 157-167.

[5] BRAKATSOULAS S, PFOSER D, SALAS R, et al. On map-matching vehicle tracking data[C]//Proceedings of the 31st International Conference on Very Large Data Bases. Trondheim, Norway: VLDB Endowment, 2005: 853-864.

[6] SCHÜSSLER N, AXHAUSEN K W. Map matching of GPS traces on high-resolution navigation networks using the multiple hypothesis technique(MHT), Working Paper 568[R]. Zurich: Institute for Transport Planning and System (IVT), 2009.

[7] VITERBI A J. Error bounds for convolutional codes and an asymptotically optimum decoding algorithm[C]//IISc Centenary Lecture Series, The Foundations of The Digital Wireless World. Singapore: World Scientific Publishing Co., Pte. Ltd., 2009: 41-50.

[8] MOHAMED R, ALY H, YOUSSEF M. Accurate real-time map matching for challenging environments[J]. IEEE transactions on intelligent transportation systems, 2017, 18(4): 847-857.

[9] HOU X T, LUO L B, CAI W T, et al. Fast online map matching for recovering traveling routes from low-sampling GPS data [C]//2018 IEEE SmartWorld, Ubiquitous Intelligence and Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, internet of People and Smart City Innovation. China:IEEE, 2018: 917-924.

[10] TANG J J, ZHANG S, ZOU Y J, et al. An adaptive map-matching algorithm based on hierarchical fuzzy system from vehicular GPS data [J]. PloS one, 2017, 12 (12):262-265.

[11] TENG Zhi-jun, QU Zhao-qiang, HOU Xue-yan, et al. Map matching algorithm based on curve fitting and topology [J]. Computer Engineering, 2018, 44(08): 291-295.

[12] LIU Wei, LI Mei, XU Xiao-yu, et al. An improved map matching algorithm based on HMM model [J]. Journal of Peking University(Natural Science Edition), 2018, 54 (06): 1235-1241.

[13] WU Gang, QIU Yu-jing, WANG Guo-ren. Map matching algorithm based on hidden Markov model and genetic algorithm [J]. Journal of Northeastern University (Natural Science Edition), 2017, 38(04): 472-475.

[14] XIE Jin-yun, TU Wei, LI Qing-quan, et al. Parallel map matching method for large-scale floating traffic data[J]. Journal of Wuhan University (Information Science Edition), 2017, 42(05): 697-703.

[15] YU L H, CHEN H C. Map matching for low-sampling-rate GPS trajectories by exploring real-time moving directions [J]. Information Sciences, 2018, 34(01), 433-434.

[16] CHEN Fei, ZOU Tao, WANG Lun. Improved projection-based map matching algorithm[J]. CEA, 2011, 47 (31): 242-244 + 248.

[17] ZHANG Y P,FU C Y,HU L W. Yellow Light Dilemma Zone Studies: A Review [J]. Journal of Traffic and Transportation Engineering: English Edition, 2014, 1(5):338-352.

[18] ZHU Shun-ying, JIANG Ruo-xi, WANG Hong, et al. Review of Research on Traffic Conflict Techniques[J]. China Journal of Highway and Transport, 2020,33(2):15-33.

[19] LAURESHYNA A, CEUNYNCK T D, KARLSSON C, et al. In Search of The Severity Dimension of Traffic Events: Extended Delta-Vas a Traffic Conflict Indicators[J]. Accident Analysis & Prevention,2017 (98):46–56.

[20] ZHANG K, ZHANG L, YANG, M H, et al. Fast Tracking via Spatiotemporal Context Learning[J]. Computer Science, 2013, 8693(1): 127-144.

[21] LI M, WANG X H, SHI K. Traffic Conflict Identification Technology of Vehicle Intersection Based on Vehicle Video Trajectory Extraction[J]. Procedia Computer Science, 2017, 109: 963-968.

[22] HO T D, GROTLI E I, SUJIT P B, et al. Optimization of Wireless Sensor Network and UAV Data Acquisition[J]. Journal of Intelligent & Robotic Systems, 2015, 78 (1): 159-179.

[23] XING L, HE J, MOHAMED A, et al. Examining Traffic Conflicts of Up Stream Toll Plaza Area Using Vehicles' Trajectory Data [J]. Accident Analysis and Prevention, 2019, 125: 174-187.

[24] LU G, YAN J, KOU Y, et al. Image Registration based on Criteria of Feature Point Pair Mutual Information[J]. IET Image Processing, 2011, 5(6): 560-566.

[25] FU X S, ZHU J. Research on Moving Vehicle Detection and Tracking Algorithm Based on Video Image[J]. Key Engineering Materials, 2011, 467-469:1488-1492.

[26] LI M, WANG X H, SHI K. Traffic Conflict Identification Technology of Vehicle Intersection Based on Vehicle Video Trajectory Extraction[J]. Procedia Computer Science, 2017, 109:963-968.

[27] LIU Y,CHANG G L, TAO R, et al. Empirical Observations of Dynamic Dilemma Zones at Signalized Intersections[J]. Transportation Research Record,2006, 2035: 122-133.

[28] LU G, CHENG B, KUZUMAKI S, et al. Relationship between Road Traffic Accidents and Conflicts Recorded by Drive Recorders[J]. Traffic Injury Prevention, 2011, 12(4): 320-326.

[29] QU Da-yi, HAN Le-wei, LIN Lu, HEI Kai-xian, ZHAO Zi-xu. Design of Vehicle-road Cooperative Auxiliary Decision-making System for Active Safety at Intersections. Journal of Highway and Transportation Research and Development, 2021, 38(5): 100-108,122.

[30] TENG Zhi-jun, QU Zhao-qiang, HE Yi-chang, et al. Expressway fast map matching algorithm

based on initial position [J]. Journal of Chinese Inertial Technology, 2017, 25(04): 461-465+472.
[31] ZHAO Xiao-yue, WANG Pan, ZHU Shun-ying, JIANG Ruo-xi, ZOU He. Spatial Distribution of Traffic Conflicts in Interchange Merging Area Based on Video Recognition. Journal of Highway and Transportation Research and Development, 2021, 38(5): 90-99.
[32] WANG Dong-zhu, SONG Xiang-hui, ZHU Shu-shan, et al. Merging Assistance Method Based on Vehicle-infrastructure Cooperative Technology[J]. Journal of Highway and Transportation Research and Development, 2012, 29(S1): 50-57,63.
[33] ZHU Di, LIU Yu. An incremental map matching algorithm under road network topology constraints [J]. Journal of Wuhan University (Information Science Edition), 2017, 42 (01): 77-83.
[34] MOHAMED R, ALY H, YOUSSEF M. Accurate real-time map matching for challenging environments[J]. IEEE transactions on intelligent transportation systems, 2017, 18(4): 847-857.
[35] LING Y, DAN L, SONG H. A map-matching algorithm with low-frequency floating car data based on matching path[J]. EURASIP journal on wireless communications and networking, 2018(1): 146-152.
[36] CAROLA B, JANA R, PABLO A M, et al. An instance specific parameter tuning approach using fuzzy logic for a postprocessing topological map-matching algorithm[J]. IEEE intelligent transportation systems magazine, 2018, 14(2): 136-141.
[37] ZENGYOU S, DONGNA Y. D2D wireless resource allocation algorithm based on overall equity[J]. Journal of Northeast Electric Power University, 2019, 39(1): 81-87.