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Research on vehicle trajectory matching method based on improved HMM

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Abstract: Aiming at the problem that traditional vehicle trajectory matching algorithms based on hidden Markov model (HMM) cannot have both accuracy and time efficiency in complex and special road sections, a vehicle trajectory matching method based on improved HMM modeling was proposed. In the determination of candidate road sections, grid index was generated to improve the overall retrieval efficiency. The improved HMM model integrated heading angle factors in the calculation of launch probability, considered the deviation effect caused by vehicle speed on heading angle, and set empirical factors for adjustment. At the same time, considering the factors such as the excessive error of the observation value before and after and the curve section, the actual travel distance of the vehicle within the unit sampling interval was used instead of the observation distance value to ensure the accuracy of the calculation of the transfer probability. Finally, the measured data was used to conduct experiments to verify the performance of the improved algorithm. The experimental results indicated that the matching accuracy of this method was about 94.0%, which was 2.8% higher than that of the traditional HMM trajectory matching method. It also had certain advantages in improving time efficiency and matching accuracy of complex road sections. The single-point matching time was reduced by about 0.9 ms, suitable for matching under complex road conditions such as intersections, overpasses, and parallel sections.

Key words: vehicle trajectory; map-matching; hidden Markov model (HMM); road network

0 Introduction

GPS-based positioning technology has been widely used in services related to vehicle location in the field of intelligent transportation with the advantages of stability, reliability, and accuracy. Due to the complex urban road network and the multipath effect caused by the occlusion of high-rise tunnels, the positioning data is affected by noise and deviates from the correct driving section. The map matching algorithm aims to correct the uncertainty by establishing the connection between the spatial road network map data and the vehicle trajectory. The interference error caused by factors can accurately match the position of the vehicle to the driving section, and provide basic support for real-time navigation, trajectory, and traffic flow analysis[1-3]. Researchers have used different technologies to develop many map matching algorithms for their application requirements, such as topological analysis[4], curve fitting[5], D-S evidence theory[6,7], and machine learning methods[8,9]. The application of advanced technology in the map has improved the performance of these algorithms, but as the complexity of the algorithm increases, the overall efficiency has declined[10,11].

According to different application scenarios, various algorithms have their own advantages and disadvantages. It is necessary to weigh the two factors of time efficiency and matching accuracy. Therefore, it is a key issue to propose an efficient and accurate map matching algorithm. With the wide application of the hidden Markov model (HMM) -based map matching algorithm proposed by Newson et al.[12], the HMM provides a new idea in the solution of the trajectory matching problem. Luo et al.[13] and Hsueh et al.[14] used low-frequency sampling data and HMM for modeling and matching. It has good applicability to sparse trajectories, but the model is not flexible and it is difficult to introduce other sensor information. Yuan et al.[15] added an interactive voting link on the basis of the STM algorithm, and considered the correlation between observation points globally to reduce the complexity of the algorithm. Song et al.[16] combined the driver preference algorithm to improve the HMM algorithm to further ensure the accuracy of vehicle trajectory matching under low sampling frequency. Wu et al.[17] used genetic algorithm to optimize the process of Viterbi solving the maximum likelihood, and improved the matching accuracy. Che et al.[18] proposed an enhanced hidden Markov mapping matching (EHMM) model, which used explicit topological expressions and introduced historical FCD information and traffic rules to optimize overall performance. Goh et al.[19] proposed an online trajectory matching method based on HMM. In the calculation of the launch probability, the road topology relationship and the temporal and spatial characteristics of the positioning data were considered, and the support vector machine method was used in the calculation of the state transition probability. Finally, the matching result was output in real time through the variable sliding window. Jagadeesh et al.[20] introduced the idea of driver path selection and proposed an improved HMM online map matching algorithm that achieved good results in a high-noise environment. Aguchi et al.[21] used historical trajectory data to train a probabilistic route prediction model, and replaced future GPS points with the probabilistic route prediction model to solve the delay problem of the matching process. Due to the increasingly developed urban road network, the complexity of application scenarios puts forward higher requirements on the matching algorithm, so the environmental impact should be considered in the algorithm implementation[22]. Many scholars took the complex urban environment as an entry point to study matching strategies suitable for more application scenarios[23,24].

However, these methods are optimized based on the basic premise of the shortest driving path between the two positioning points, which cannot describe the specific changes of the road section. Therefore, it will reduce the actual travel route of the vehicle, especially the matching accuracy at the curved road section. The impact of the real-time running speed of the vehicle on the model parameters is not considered, which leads to the problem that the matching efficiency and accuracy cannot be balanced. It is not applicable to the matching of complex road sections such as intersections and overpasses.

The traditional vehicle trajectory matching method based on HMM is no longer based on the hypothesis of the traditional shortest path rule, but it is calculated based on the ratio of the distance between the vehicle's actual traveling distance and the candidate point. It is used as the probability calculation of the actual before and after, so as to ensure the accuracy of the distance calculation between adjacent observation points and improve the overall matching accuracy. Considering the influence of the heading angle factor and the vehicle speed on the heading angle deviation, the calculation of the optimal launch probability was adjusted by setting the empirical factor. Finally, multiple sets of experiments were set up to verify the algorithm.

1 Vehicle trajectory matching method based on HMM

Generally, the collected vehicle trajectory data to be matched is a known observation sequence, and the road section that the vehicle actually passes is an unknown hidden state. Using HMM to model and solve the problem of the vehicle's true driving trajectory sequence is equivalent to the known observation sequence and the relevant parameters of the model to obtain the maximum probability matching state sequence. As shown in Fig.1, the vehicle positioning data to be matched is regarded as an observation value, and its corresponding multiple candidate road sections are implicit states. The model parameters included initial distribution, emission probability B_{ij}, and state transition probability A_{ij}. Each observation value was corresponded to the implicit state. The state has its own emission probability, which also represents the probability that the model will obtain each observation from the current state. And the state transition probability was the probability of the model transitioning between the hidden states, which represented the vehicle passing between the actual road sections. The initial state probability is the probability of the appearance of each state at the initial moment, which is determined by the initial positioning point.

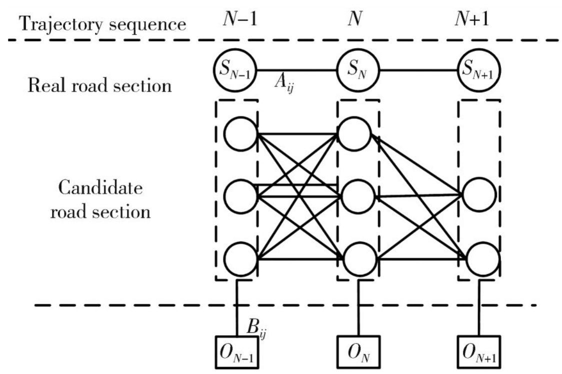


Fig. 1 Map-matching method based on HMM

The traditional HMM-based vehicle trajectory matching method[12] only considers the shortest distance to calculate the launch probability. Although some scholars consider the direction angle and other factors, the influence of vehicle speed on its deviation is not considered. When calculating the adjacent distances of observation points, the influence of curved road sections and large deviation observations is not considered, which will affect the overall matching accuracy. Especially for complex road conditions such as intersections, the matching time will be prolonged and the matching time efficiency will be reduced.

2 Improved HMM vehicle trajectory matching method

The method proposed in this paper mainly included three parts: data preprocessing, candidate road section selection, and trajectory matching. The overall algorithm flow is shown in Fig.2. The data preprocessing part included the establishment and generation of the electronic map grid index, and the candidate road sections were retrieved and selected by introducing the error confidence ellipse. The improved HMM vehicle trajectory matching method included the determination of the initial distribution, the calculation of the launch probability based on the direction and distance weights, and the calculation of the state transition probability considering the curvature of the road section. Finally, it was solved by the Viterbi algorithm to obtain the best matching result of the vehicle trajectory for output.

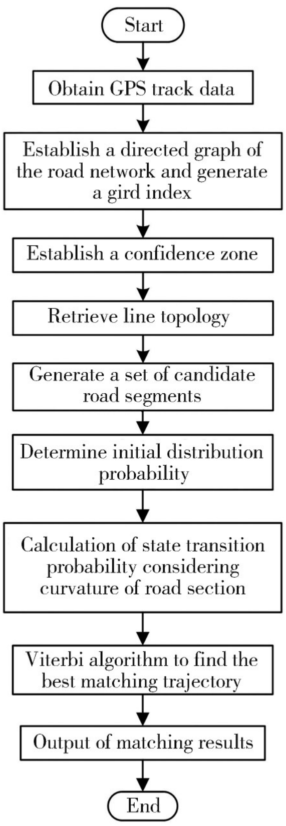


Fig. 2 Flow chart of map matching algorithm for improved HMM modeling

2.1 Road network data index generation

The road network data in shapefile format was read, the relevant information of the road network of the vehicle was obtained, and a directed graph of the road network was built to describe it. Before trajectory matching, it was necessary to obtain candidate road sections with current location information. If the road network data was inquired every time, it was effective but the matching time was inefficient. First, the road map information was divided into corresponding number of grids, and then the road section information contained in each grid was analyzed and calculated in advance. This method could effectively and quickly obtain the candidate road sections of the current positioning point, and improve the overall time efficiency of the matching process.

2.2 Selection of candidate road sections

As shown in Fig.3, the processing of the candidate road section is completed by establishing an error confidence area based on GPS positioning data and analyzing the topological relationship with the candidate road section. Construct an error ellipse for road segment retrieval, and set the current anchor point coordinate to (x, y) in the Gaussian plane coordinate system.

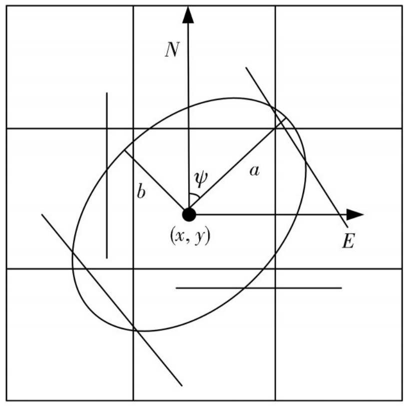


Fig. 3 Candidate area of road segment based on error ellipse

Taking the original positioning point as the center of the error ellipse, its parameters can be described as

$$\begin{cases} a = \sigma_0^2 \sqrt{\dfrac{\sigma_x^2 + \sigma_y^2 + \sqrt{(\sigma_x^2 - \sigma_y^2)^2 + 4\sigma_{xy}^2}}{2}}, \\ b = \sigma_0^2 \sqrt{\dfrac{\sigma_x^2 + \sigma_y^2 - \sqrt{(\sigma_x^2 - \sigma_y^2)^2 + 4\sigma_{xy}^2}}{2}}, \\ \phi = \left[\pi - \arctan\left(\dfrac{2\sigma_{xy}}{\sigma_x^2 - \sigma_y^2} \right) \right], \end{cases} \tag{1}$$

where a, b, ϕ are the error ellipse length, radius, and the deflection angle, respectively; σ_x^2 and σ_y^2 are the east and north measurement error variances of the positioning point

(x, y); σ_{xy} is the covariance, the value of which can be directly obtained by the measurement equation solved by GPS positioning; σ_0 is the posterior variance of the unit weight, and the σ_0 change caused by different credibility can adjust the size of the road segment retrieval area.

The current anchor point (x_i, y_i) and the midpoint (x_i, y_i) of the candidate road section need to satisfy

$$\frac{[(x_{OL}^i - x_i)\cos\phi + (y_{OL}^i - y_i)\cos\phi]^2}{a^2} + \frac{[(x_{OL}^i - x_i)\cos\phi - (y_{OL}^i - y_i)\sin\phi]^2}{b^2} \leqslant 1. \quad (2)$$

The set of candidate road sections could be obtained through the calculation of Eq. (2).

2.3 Vehicle trajectory map-matching method based on improved HMM modeling

2.3.1 Calculation of state transition probability

The state transition probability represented the transition probability between the two hidden states before and after. The traditional HMM trajectory matching method is mainly calculated by the distance between the two observation trajectory points and the distance between the two hidden states before and after the real road section.

$$a_{ij} = P(q_{t+1} = r_j | q_t = r_i) = \frac{\|O_t - O_{t+1}\|_{\text{dis}}}{\|r_i - r_j\|_{\text{route}}}, \quad (3)$$

where $\|O_t - O_{t+1}\|$ represents the distance between the front and back observations, and $\|r_i - r_j\|$ is the distance between the two candidate points corresponding to the real route.

However, there are measurement errors in the positioning points at road intersections or curved road sections. It will lead to the wrong match of the position of the vehicle on the curved road section by using the ratio of the distance between the two observation points to the distance of the corresponding candidate road section as the state transition probability.

As shown in Fig. 4, when the vehicle travels to the intersection, there are three candidate road sections. If the actual road section was route 1, its length was L_1. The straight line distance L between the front and back observation points O_i and O_j is affected by the error factor. The ratio of the distance between two candidate points L_2 on the road segment as the state transition probability will lead to the error of the position of the vehicle on the curved road segment, and the efficiency of matching time will be reduced.

Therefore, the ratio of vehicle driving distance within the unit sampling interval to the distance between the front and back candidate sections is used as the transfer probability. As shown in the Eq. (4), in the calculation of the distance between the front and rear observation points, the inaccurate measurement is avoided due to the influence of error factors, and the actual travel distance of the vehicle within the unit sampling interval is used instead of the observation distance value. To a certain extent, it can make the calculation of state transition probability in the model more accurate.

$$a_{ij} = P(q_{t+1} = r_j | q_t = r_i) = \frac{\overline{v_t}\Delta s}{\|r_i - r_j\|_{\text{route}}} = \frac{\overline{v_t}/f}{\|r_i - r_j\|_{\text{route}}}, \quad (4)$$

where f is the sampling frequency of the device, and $\overline{v_t}$ is the average speed of the vehicle traveling on the current road section.

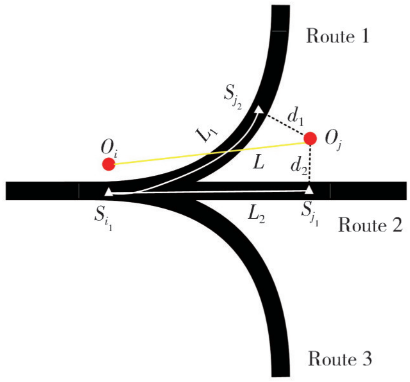


Fig. 4 Schematic diagram of intersection positioning point

2.3.2 Calculation of observation state probability

In the traditional HMM map matching algorithm, the emission probability is usually calculated by measuring the distance from the observation point to the candidate road section. The smaller the probability, the greater the probability. Newson[12] assumed the normal distribution and used the Gaussian density function to express the corresponding emission probability, as shown in Eq. (5).

$$b_j(k) = P(o_t = o_k | q_t = r_j) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{\|o_t - r_j\|^2}{2\sigma^2}}, \quad (5)$$

where σ is the standard deviation, which is determined based on the error measurement error of the actual equipment, and $\|o_t - r_j\|$ represents the projection distance from the actual measurement value to the candidate road section.

Lou et al.[13] calculated the ratio of the distance from the current observation to the candidate road section and the total distance as the emission probability by

$$b_j(k) = P(o_t = o_k | q_t = r_j) = \frac{1/d(o_k \to r_j)}{\sum_{i=1}^{k}(1/d(o_k \to r_i))}, \quad (6)$$

where $d(o_k \to r_j)$ is the distance from the current observation point to the candidate road section.

Both of the above methods use a single distance factor to calculate the launch probability. Usually under special road conditions such as intersections and overpasses, these methods may affect the calculation efficiency of the probability. Only matching them to the nearest road section is not conducive to real-time discrimination. Therefore, the variation of the heading angle and the deviation of the speed on the heading angle were considered, and the adjustment was made by setting the experience factor in this paper.

Calculate the angle between the current positioning point (x_i, y_i) and the north direction, that is, the GPS heading angle α_n, which is directly obtained by the device. The direction of the candidate road segment is specified as

$$\beta_n = \begin{cases} \frac{\pi}{2} - \arctan\left(\frac{y_i}{x_i}\right), x_i > 0, \\ \frac{3\pi}{2} - \arctan\left(\frac{y_i}{x_i}\right), x_i < 0. \end{cases} \tag{7}$$

The larger the direction deviation value, the smaller the weight function value, and W_ϕ is set as

$$W_\phi = w_\phi \cos(\Delta\phi) = \begin{cases} w_\phi \cos(|\alpha_n - \beta_n|), & |\alpha_n - \beta_n| < \pi, \\ w_\phi \cos(2\pi - |\alpha_n - \beta_n|), & |\alpha_n - \beta_n| > \pi, \end{cases} \tag{8}$$

where $\Delta\phi$ is the direction deviation; w_ϕ is the speed deviation threshold. Considering the different speeds of vehicles, the obtained heading angle has a certain deviation, that is

$$w_\phi = \begin{cases} 0, & V < V_{\text{low}}, \\ 0.4, & V_{\text{low}} \leqslant V \leqslant V_{\text{mid}}, \\ 0.8, & V > V_{\text{mid}}, \end{cases} \tag{9}$$

where V is the vehicle speed; V_{low} and V_{mid} are the set low-speed and medium-speed measurement thresholds, respectively, which are determined by multiple experiments according to the vehicle's real-time speed and the heading angle deviation range obtained by the GPS receiver.

The observation state probability obtained by combining the distance factor and the heading angle factor is shown as

$$W = \frac{W_{\text{d}} + W_\phi}{2}, \tag{10}$$

where W_{d} represents the weight function of the distance deviation between the current GPS positioning point and the candidate road section, and W_ϕ represents the weight function of the deviation between the GPS heading angle and the direction of the candidate road section, W_{d} and $W_\phi \in [0,1]$.

2.3.3 Viterbi algorithm to calculate maximum likelihood driving section

The process of solving the best matching road section through the hidden Markov model is mainly to gradually solve the state sequence $q_t, t \in (1, m)$ of the best matching of the observation sequence through the known parameters $\lambda = [A, B, \pi]$ and the observation sequence $o_t, t \in (1, M)$. First, given the GPS observation sequence $o_1, \cdots, o_t, \cdots, o_m$, as shown in Eq. (11), the maximum probability matching sequence is

$$P(\text{matching sequence}) = \text{Max}\{P(q_1, \cdots, q_t, \cdots, q_m | o_1, \cdots, o_t, \cdots, o_m)\}, \quad q_t \in V,\ 1 \leqslant t \leqslant M. \tag{11}$$

According to the definition of conditional probability in probability theory, the states of the hidden state sequence are independent of each other, as can be seen from Eq. (12).

$$P(q_1, \cdots, q_t, \cdots, q_m | o_1, \cdots, o_t, \cdots, o_m) = \frac{P(q_1, \cdots, q_t, \cdots, q_m, o_1, \cdots, o_t, \cdots, o_m)}{P(o_1, \ldots, o_t, \ldots, o_m)}, \quad q_t \in V,\ 1 \leqslant t \leqslant M. \tag{12}$$

Since each state of the hidden state sequence is independent, and the observed values of the trajectory are also independent of each other. Then Eq. (12) can be transformed into

$$\begin{aligned} & P(q_1, \cdots, q_t, \cdots, q_m | o_1, \cdots, o_t, \cdots, o_m) = \\ & P(q_1, \cdots, q_t, \cdots, q_{m-1}, o_1, \cdots, o_t, \cdots, o_{m-1}) \times \\ & P(q_m | q_1, \cdots, q_t, \cdots, q_{m-1}, o_1, \cdots, o_t, \cdots, o_{m-1}) \times \\ & P(o_m | q_1, \cdots, q_t, \cdots, q_{m-1}, o_1, \cdots, o_t, \cdots, o_{m-1}). \end{aligned} \tag{13}$$

Due to the special nature of the hidden Markov model, at any moment, the value of the track observation point corresponds to the real road section state sequence, and has nothing to do with other state variables and observations. And the state q_t at time t depends on the state at the previous time $t-1$, then the Eq. (15) can be obtained.

$$P(q_t | q_1, \cdots, q_{t-1}) = P(q_t | q_{t-1}),\ q_t \in V, 1 \leqslant t \leqslant M, \tag{14}$$

$$P(o_t | q_1, \cdots, q_{t-1}, q_t, o_1, \cdots, o_{t-1}) = P(o_t | q_t), \quad q_t \in V, 1 \leqslant t \leqslant M. \tag{15}$$

Substituting Eqs. (14) and (15) into Eq. (13), the Eq. (16) can be obtained.

$$\text{Max}\{P(q_1, \cdots, q_t, \cdots, q_m | o_1, \cdots, o_t, \cdots, o_m)\} = \text{Max}\left\{P(q_0) \prod_{t=1}^{m} (p(q_t | q_{t-1}) p(o_t | q_t))\right\}, \tag{16}$$

where q_0 is the initial state; $q_t, t \in (1, m)$ is the real road section state sequence; and $o_t, t \in (1, m)$ is the actual observation sequence.

3 Results and discussion

3.1 Experiment

The proposed algorithm was verified by taking part of the road network in a certain place as the experimental environment. The GPS receiver was used to collect vehicle trajectory data, the total length was about 15 km, the sampling frequency was set to 1 Hz, a total of 3 000 data points and the collected data included information such as location, vehicle speed, and time stamp. The road network data was obtained on Openstreet and contained 2 500 road section information. Fig. 5 shows the road network data displayed in Google earth and the measured vehicle trajectory data collected. The proposed algorithm was programmed in Python language and displayed visually through ArcGIS software. Finally, the matching accuracy and time efficiency were compared with curve fitting trajectory matching method, D-S evidence theory trajectory matching method, and traditional HMM map matching method.

Fig. 5 Measured vehicle trajectory data

3.2 Discussion

Generally, there are two kinds of indicators to measure the excellent trajectory matching algorithm.

$$CMP_i = \frac{C_p}{M_p} \times 100\%, \tag{17}$$

where C_p is the number of track points that are correctly matched, and M_p is the total number of track points to be matched.

$$CMP_j = \frac{C_s}{M_s} \times 100\%, \tag{18}$$

where C_s is the number of road segments that matched correctly, and M_s is the total number of road segments to be matched.

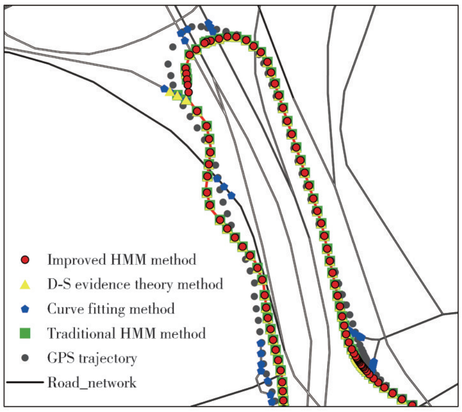
In this paper, Eq. (17) is chosen to calculate the accuracy rate. As can be seen from the statistical results in Table 1, the overall matching accuracy of the proposed algorithm could reach 94.0%, which was far better than curve fitting and D-S evidence theory trajectory matching methods, and the accuracy was 2.8% higher than that of traditional HMM matching methods. In terms of matching time, the proposed algorithm integrated heading angle factors, improved the calculation method of launch probability and state transition probability, shortened the matching time, and guaranteed the real-time and accuracy of judgment in complex road sections. The overall matching time of the method was shortened by about 2.7 s.

Table 1 Vehicle trajectory matching method results

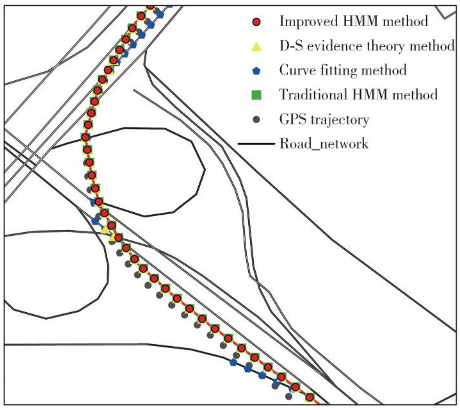
Trajectory matching method	Matching data points	Correctly matched data points	Matching accuracy/%	Match time/s
Curve fitting	3 000	2 351	78.4	19.5
D-S evidence theory method	3 000	2 647	88.2	17.6
Traditional HMM method	3 000	2 736	91.2	14.4
Improved HMM method	3 000	2 820	94.0	11.7

As shown in Table 2, the curve fitting method, the D-S evidence theory method, the traditional HMM trajectory matching method, and the proposed method are separately counted for the matching accuracy and the single-point matching time of the special road section indicated in Fig. 5. It could be verified that the improved HMM modeling method was suitable for complex road conditions such as intersections, overpasses, and parallel sections. It balanced the contradiction between the accuracy and time efficiency of the traditional HMM trajectory matching algorithm to a certain extent.

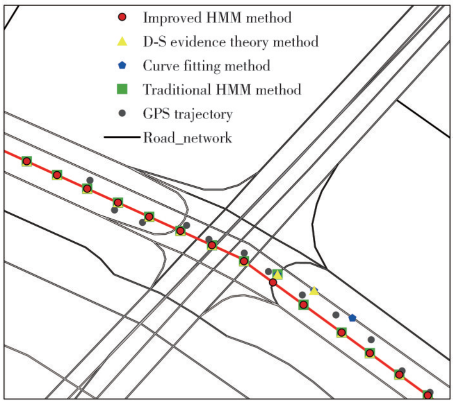
As shown in Fig. 6(a) — (d), all the four matching methods could match the original GPS track points with the road sections in the road network, eliminating the influence of measurement errors, but the matching accuracy of each method was greatly different. It could be seen from the partial visualization diagram that the proposed method was basically consistent with the real reference trajectory, while the curve fitting method did not perform well in multi-branch road sections. The D-S evidence theory and the traditional HMM trajectory matching method could cope with the matching of some complex road sections, but the matching errors still occurred on overpasses and parallel sections. In the face of increasingly complex road network environment, the proposed algorithm was suitable. Compared with the traditional HMM trajectory matching method, the proposed method not only had advantages in special road sections, but also improved the time efficiency.



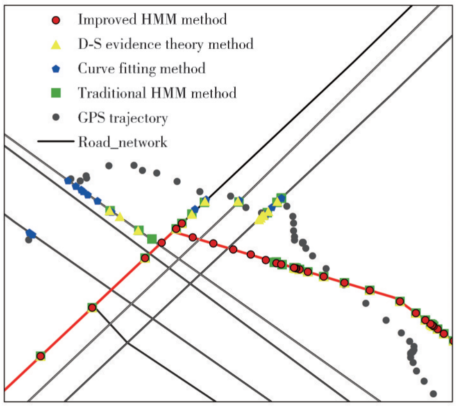
(a) Matching result of overpass Ⅰ



(b) Matching result of overpass Ⅱ



(c) Matching result of parallel road section



(d) Matching result of intersection Ⅱ

Fig. 6 Comparison of matching results of special road sections with local visualization diagrams

As can be seen from Table 2, the matching accuracy of the proposed method on special road sections is about 17.48% higher than that of the curve fitting method and 8.68% higher than that of the D-S evidence theory method. Compared with the traditional HMM method, it had obvious advantages in parallel road sections, the accuracy rate could be increased by 5.8%, and the average single-point matching time could be reduced by 0.9 ms.

Table 2 Map matching results at special road sections

Method	Intersection Ⅰ/%	Intersection Ⅱ/%	Overpass Ⅰ/%	Overpass Ⅱ/%	Parallel section/%	Average single point match time/ms
Curve fitting method	87.1	85.0	71.8	70.6	67.7	6.5
D-S evidence theory method	90.0	92.5	86.4	80.4	76.9	5.9
Traditional HMM method	92.9	92.5	92.7	90.2	85.0	4.8
Improved HMM method	94.3	95.0	95.4	94.1	90.8	3.9

4 Conclusions

In order to improve accuracy and time efficiency, the traditional vehicle track matching method based on HMM was improved. Firstly, considering the influence of course angle factor and vehicle speed on course angle deviation, the calculation method of launch probability was improved by setting empirical factors to adjust. At the same time, when calculating the transmission probability, the factors such as the front and back observations and the curve section error were taken into account to ensure the accuracy of the distance calculation between the adjacent observations. Finally, experiments were carried out using the measured data to verify the performance of the algorithm, and compared with curve fitting, D-S evidence theory, and traditional HMM trajectory matching methods. The experimental results indicated that the improved HMM modeling vehicle trajectory matching algorithm had a significant improvement in matching accuracy. Compared with the traditional HMM matching method, it also had certain advantages in improving time efficiency and matching accuracy of complex road sections. It was suitable for matching under complex road conditions such as intersections, overpasses, and parallel sections. It balanced the matching algorithm to a certain extent. The contradiction between accuracy and time efficiency had certain engineering practical value.

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Declaration of conflicting interests

The authors have no conflict of interests related to this publication.

References

[1] GAO W C, LI GUO L, TA N. Overview of road network matching algorithms. Journal of Software, 2018, 29(2): 225-250.

[2] FAN J C, FU C, STEWART K, et al. Using big GPS trajectory data analytics for vehicle Miles traveled estimation. Transportation Research Part C: Emerging Technologies, 2019, 103: 298-307.

[33] YU J, YANG Q, LU J F, et al. Advanced map matching algorithms: a survey and trend. Acta Electronica Sinica, 2021, 49(9): 1818-1829.

[4] WHITE C E, BERNSTEIN D, KORNHAUSER A L. Some map matching algorithms for personal navigation assistants. Transportation Research Part C: Emerging Technologies, 2000, 8(1-6): 91-108.

[5] BI J, ZHU Y, CHENG Y. A comprehensive map matching algorithm based on curve fitting and network topology. Journal of Transport Information and Safety, 2014, 32(6): 127-131.

[6] TENG Z J, ZHANG Y, LI H T. Improved D-S evidence theory map matching algorithm under the background of intersecting roads. Journal of Chinese Inertial Technology, 2020, 28(3): 380-385.

[7] TENG Z J, ZHANG Y, LI H T, et al. Adaptive D-S evidence theory map matching algorithm for complex road networks. Journal of Jilin University (Engineering and Technology Edition), 2021, 51(2): 524-530.

[8] SU H B, WANG G Z, WANG J D. Map matching algorithm based on fuzzy neural network. Journal of University of Science and Technology Beijing, 2012, 34 (1): 43-47.

[9] LU J P, LUO Y T, HUANG Z S, et al. An information fusion map matching method based on ranking learning. Journal of Zhejiang University (Science Edition), 2020, 47(1): 27-35.

[10] MOHAMED R, ALY H, YOUSSEF M. Accurate real-time map matching for challenging environments. IEEE Transactions on Intelligent Transportation Systems, 2017, 18(4): 847-857.

[11] ZHOU C, YUAN J Z, LIU H Z, et al. Survey of map matching algorithm for intelligent transport system. Computer Science, 2015, 42(10): 1-6.

[12] NEWSON P, KRUMM J. Hidden Markov map matching through noise and sparseness//The 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, November 4-6, 2009, Seattle Washington, US. New York: ACM. 2009: 336-343.

[13] LUO A, CHEN S H, XU B. Enhanced map-matching algorithm with a hidden Markov model for mobile phone positioning. ISPRS International Journal of Geo-Information, 2017, 6(11): 327.

[14] HSUEH Y, CHEN H, HUANG W. A hidden Markov model-based map-matching approach for low-sampling-rate GPS trajectories//2017 IEEE 7th International Symposium on Cloud and Service Computing (SC2), November 22-25, 2017, Kanazawa, Japan, New York: IEEE, 2017: 271-274.

[15] YUAN J, ZHENG Y, ZHANG C, et al. An interactive-voting based map matching algorithm//2010 Eleventh International Conference on Mobile Data Managemen, May 23-26, Kansas City, MO, USA, New York: IEEE, 2010: 43-52.

[16] SONG C B, YAN X F, STEPHEN N, et al. Hidden Markov model and driver path preference for floating car trajectory map matching. IET Intelligent Transport Systems, 2018, 12(10): 1433-1441.

[17] WU G, QIU Y J, WANG G R. Map matching algorithm based on hidden Markov model and genetic algorithm. Journal of Northeastern University (Natural Science), 2017, 38(4): 472-475.

[18] CHE M L, WANG Y L, ZHANG C, et al. An enhanced hidden Markov map matching model for floating car data. Sensors, 2018, 18(6): 1758.

[19] GOH C Y, DAUWELS J, MITROVIC N, et al. Online map-matching based on hidden Markov model for real-time traffic sensing applications//International IEEE Conference on Intelligent Transportation Systems, September 16-19, 2012, Anchorage, AK, USA. New York: IEEE, 2012: 776-781.

[20] JAGADEESH G R, SRIKANTHAN T. Online map-matching of noisy and sparse location data with hidden Markov and route choice models. IEEE Transactions on Intelligent Transportation Systems, 2017, 18(9): 2423-2434.

[21] TAGUCHI S, KOIDE S, YOSHIMURA T. Online map matching with route prediction. IEEE Transactions on

Intelligent Transportation Systems, 2019, 20(1): 338-347.

[22] YIN J C, WU F, LI A P, et al. Trajectory matching method considering speed and heading information. Geomatics and Information Science of Wuhan University, 2021, 46(11): 1774-1781.

[23] KONG X F, YANG J W. A scenario-based map-matching algorithm for complex urban road network. Journal of Intelligent Transportation Systems, 2019, 23(6): 617-631.

[24] MAAREF M, KASSAS Z M. Ground vehicle navigation in GNSS-Challenged environments using signals of opportunity and a closed-loop map-matching approach. IEEE Transactions on Intelligent Transportation Systems, 2020, 21(7): 2723-2738.

基于改进HMM的车辆轨迹匹配方法研究

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摘　要: 针对传统基于隐马尔可夫模型(HMM)的车辆轨迹匹配算法在复杂特殊路段无法兼备准确率与时间效率的问题, 提出了基于改进HMM建模的车辆轨迹匹配方法。在候选路段的确定上通过生成网格索引提高整体检索效率, 改进的HMM模型在发射概率的计算上综合航向角因素, 考虑车辆速度对航向角造成的偏差影响, 并设置经验因子进行调节。同时, 考虑前后观测值误差过大及曲线路段等影响因素, 采用单位采样间隔内的车辆实际行驶距离代替观测距离值, 以保证传递概率计算的准确性。最后, 利用实测数据进行试验, 验证算法的性能。实验结果表明, 所提方法匹配准确率约94.0%, 相较于传统HMM轨迹匹配方法提高了2.8%, 在提高时间效率及复杂路段的匹配准确度上也具有一定优势, 单点匹配时间减少约0.9 ms, 适用于交叉路口、立交桥、平行路段等复杂路况下的匹配。

关键词: 车辆轨迹; 地图匹配; 隐马尔可夫模型(HMM); 路网

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