An Improved Interactive-voting based Map Matching Algorithm Considering Path Correlation

Wei Zhang, Anchen Wang and Zhijun Teng

Abstract—**Map matching is a technology that aligns users' GPS position sequence with the road network on a digital map. Under low-sampling-rate conditions, existing interactive voting-based map matching algorithm leads to mismatching and low matching efficiency. Considering such problems, this paper proposes an improved interactive voting-based map matching algorithm considering path correlation by optimizing the observation probability and transition probability formulas to improve spatiotemporal analysis. Average speed and sampling time are used to estimate the path length and analyze the correlation between the estimated path and the actual path in order to reduce mismatching and improve the accuracy of matching. Utilizing three constraint conditions to filter erroneous candidate road segments improves accuracy and reduces matching time. The experimental results show that under various road conditions, the improved algorithm outperforms the compared algorithms. The matching accuracy can be maintained at over 90%, and the matching time is reduced by about 1ms compared to the comparison algorithms.**

Index Terms—**Path correlation; interactive-voting; map matching; low sampling rate; observation probability; transition probability**

I. Introduction

WITH the increasing popularity of GPS navigation devices, users can track moving objects in real time, but the positioning drift of GPS sensors will lead to different degrees of positional and sampling errors, seriously affecting the application accuracy of GPS [1]. Therefore, in order to improve the accuracy of GPS data application, many researchers "tie" the digital electronic map and GPS error data, that is, map matching. Its purpose is to identify the real road section of a moving object, which is a key process in many location-based information applications, such as vehicle navigation [2], fleet management [3], and intelligent transportation systems [4]. In order to comprehensively balance cost and demand, most civilian GPS devices lack sufficient accuracy. Therefore, it is essential to employ more robust map matching algorithms in location-based information services to enhance the accuracy of road network matching and establish a solid foundation for lower-level applications [5–7].

In practical situations limited by resources, map matching of low-sampling-rate data is often involved [8-10]. The ST-Matching (Spatial Temporal Matching) method by Zheng et al. [11] and the IVMM (Interactive Voting-Based Map Matching) algorithm by Yuan et al. [12] were representative map matching algorithms aimed at low-sampling-rate data. The ST-Matching algorithm used simple spatiotemporal analysis to construct a candidate graph based on weights and then evaluated the similarity between candidate paths and GPS tracks. However, when the trajectory is long and the vehicle passes through multiple lanes, the accuracy of the ST-Matching algorithm is not high. The IVMM algorithm was an enhanced version of the ST-Matching algorithm that considered the road network topology. It utilized the mutual influence relationship between global GPS tracking points and constructed a distance weighted matrix to indicate the influence degree between GPS points, enhancing the accuracy of matching. However, the accumulation of errors still easily leads to the mismatching of sampling points. Wang et al. [13] analyzed the driving time using the average speed between front and rear sampling points and the length of the driving path, correcting the mismatching caused by the IVMM algorithm but failing to eliminate the accumulation of errors. Zhang et al. [14] used a spatial analysis function, a temporal analysis function, and a road analysis function with two constraints to determine the relationship between consecutive candidate points in map matching for low-sampling-rate data of taxi GPS tracks. This approach reduced computation and enhanced algorithm accuracy. However, the above methods ignored the role of direction. Dogramadzi and Khan [15] proposed an accelerated map matching algorithm that made full use of the adjacency of road sections to avoid unnecessary route distance calculation, thus saving matching time. However, when the sampling rate was low, the connections between sampling points became weaker, and the effectiveness of this method decreased. Yan et al. [16] used the direction factor of sampling points in spatial analysis and constraint analysis. The reliability of the direction factor was high in some cases, but it was weakened when the speed was too low, and mismatching occurred when a long detour was needed between two sampling points.

Aiming at the problems of mismatching and the low efficiency of the above algorithms, this paper proposes an improved interactive voting-based map matching algorithm considering path correlation (PCIVMM). Utilizing geometric and topological information, real-time speed data, and other sampling-point factors improves the observation probability

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and transition probability. Introducing a similarity function between the estimated path and the actual path improves the accuracy of judging candidate roads. Additional limitations are implemented to filter out road segments with significant errors, thereby reducing cumulative errors, simplifying the computation of the transfer matrix, reducing the number of alternative routes for later voting, and ultimately improving matching efficiency and accuracy.

II. Map Matching Problem

Map matching is the process of matching the latitude and the longitude obtained by the vehicle trajectory with the road network presented by the digital map. Due to the Doppler effect and the positioning error of GPS, reproducing the real position of the tracking point becomes challenging, thereby adversely affecting subsequent applications like track mining. Therefore, a map matching algorithm is used to correct the tracking point, as shown in Fig. 1.

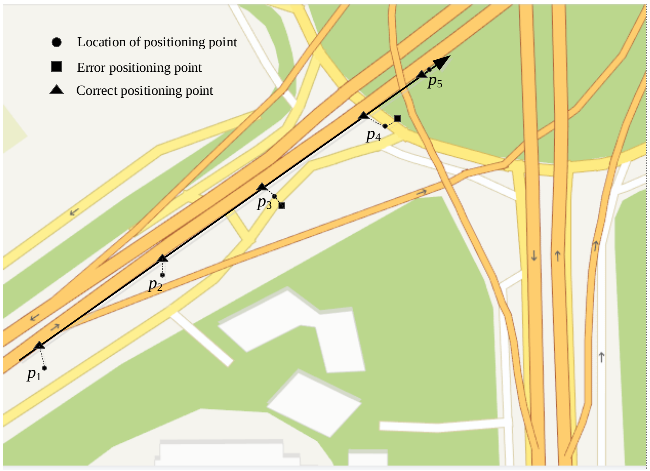

Fig. 1. Map matching example

The following is a brief introduction to the related concepts of map matching [1].

Definition 1 (GPS track) A GPS track $T: p_1 \rightarrow p_2 \rightarrow \ldots \rightarrow p_n, (i=1,2,\ldots,n)$ is a sequence of sampling points of the same moving object collected in order of time. A GPS point at timestamp i is defined as: $p_i = [t_i, lat_i, lon_i, \theta_i, v_i]$, where t_i is sampling time, lat_i is latitude, lon_i is longitude, θ_i is real-time direction, and v_i is instantaneous speed.

Definition 2 (Road network) A road network is a directed graph G={V, L}, where V is the set of vertices (i.e., road endpoints) and L is the set of all edges.

Definition 3 (Path sequence) A path sequence is defined as $P: l_1 \rightarrow l_2 \rightarrow \ldots \rightarrow l_n$, $(i=1,2,\ldots,n)$, where $l_i \in L$ represents the road segment which the moving object is located at time t_i, and the path consists of several sections.

Definition 4 (Candidate Segment Set) The candidate segment set refers to the selection of some possible matching segment sets within the threshold region around the currently collected GPS sampling points according to certain rules. The candidate points are the corresponding matching points on a candidate segment. In this paper, the point with the shortest Euclidean distance is selected as the candidate point set.

III. Research Method

The map matching algorithm proposed in this paper consists of four main steps as shown in Fig. 2: calculating the sum of candidate sets of sampling points, analyzing the characteristics of sampling points, conducting weighted analysis based on the relationship between sampling points, and performing interactive voting to determine the optimal matching path.

A. Candidate preparation

By reading the road network data file, information about road nodes and traffic attributes can be obtained, and the directed graph G={V, L} of the road network can be established, including the start node, the intermediate node, and the end node of the road segment.

The R-tree index of road networks is established to improve the searching efficiency of data in space. The buffer region R is set for each sampling point, and the corresponding candidate points are obtained by projecting the road segment M contained in R. If the projection point falls outside the road segment, the endpoint closest to the road segment is selected as the candidate point.

B. Feature analysis

1) Spatiotemporal analysis

The actual position of the moving object is closely related to its spatial characteristics to some extent. Geometric information is the most basic and effective information in map matching, and the full use of the features of a single sampling point can improve the accuracy of matching. Therefore, this paper first improves the observation probability.

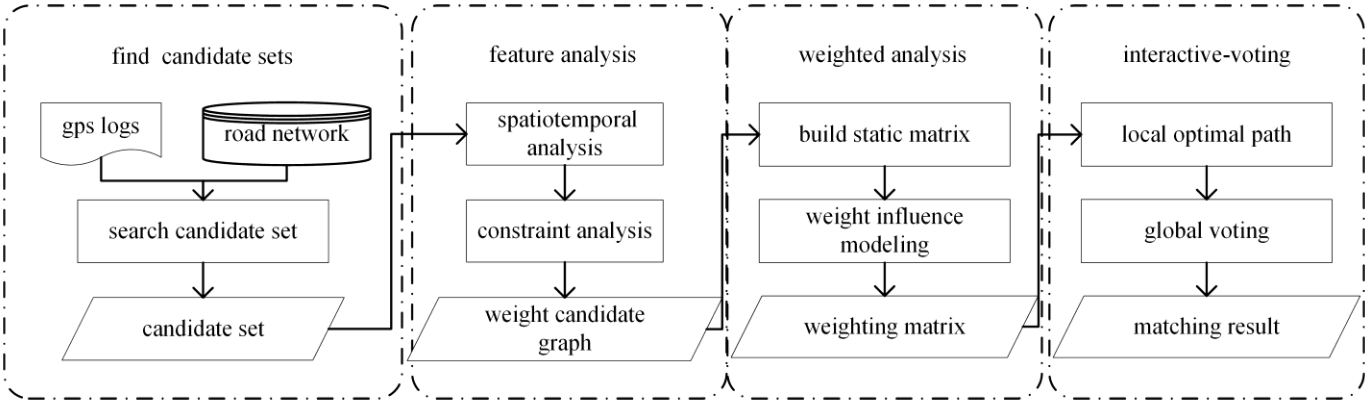

Fig. 2. Structure diagram of the PCIVMM

(1)Observation probability

Generally speaking, the closer a sampling point is to the matching candidate road segment, the more likely it is to drive on this road segment. The distance error from the sampling point to the real position of the object follows the Gaussian distribution $N(\mu,\sigma^2)$ [11], and the probability function formula for satisfying the distance factor is as:

$$f_d(c_i^j) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(d_i^j-\mu)^2}{2\sigma^2}} \tag{1}$$

where d_i^j is the Euclidean distance from the candidate point c_i^j to the sampling point p_i.

Secondly, there is a certain correlation between the real-time direction of the sampling point and the obtained direction of the candidate road segment, so the difference between the two is defined as the angle of the direction θ_i^j. The smaller the angle of the direction is, the higher the matching possibility that this candidate road segment is seen as the true driving road segment is, satisfying the probability function formula of the direction factor is defined as[17]:

$$f_\theta(c_i^j) = \frac{(1+\cos\theta_i^j)}{2} \tag{2}$$

In addition, some studies have pointed out [8] that when the sampling point drifts between two candidate road segments, the probability value obtained by relying on the distance and direction information of the sampling point cannot clarify which road segment the sampling point should match, so the real-time speed of the sampling point should be considered in the observation probability. The similarity between the real-time speed of the sampling point and the speed limit of the candidate road segment can weaken the possibility of matching with the wrong road segment, especially when the sampling point drifts on the highway and parallel roads (see Fig. 3). Through the speed analysis, the road segment on which the vehicle is traveling can be judged according to its speed. The probability function formula of the velocity factor is as:

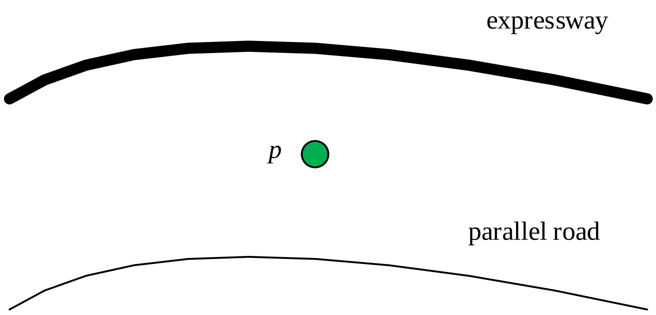

Fig. 3. Velocity analysis diagram

$$f_v(c_i^j) = \frac{v_{rj}}{|v_i - v_{rj}| + v_{rj}} \tag{3}$$

where v_i is the speed of the sampling point and v_{rj} is the speed limit of the candidate road segment.

Thus, taking account of the above factors, the observation probability is defined as:

$$N(c_i^j) = \gamma_1 f_d(c_i^j) + \frac{\gamma_2}{2}(f_\theta(c_i^j) + f_v(c_i^j)) \tag{4}$$

When the vehicle is nearing a stop or slows down at traffic lights, the reliability of the direction factor and the speed factor will be reduced if the real-time speed collected is too low. Therefore, different weights γ_1 and γ_2 are assigned under different conditions.

According to the actual recorded experience, when the speed of the sampling point is less than 10.8 km/h [14], the reliability of the collected direction angle is low, and in this case, γ_1 is set to 1 and γ_2 is set to 0. Otherwise, both γ_1 and γ_2 are set to 0.5.

(2)Transition probability

The closer the linear distance between two sampling points and the shortest path length between two candidate points, the higher the transition probability. This paper using an improved exponential function to describe this phenomenon is defined as:

$$V(c_{i-1}^s \to c_i^t) = 1 - \frac{10}{10 + e^{\frac{K/2 - |d_{(i-1,s)\to(i,t)} - w_{(i-1,s)\to(i,t)}|}{100}}} \tag{5}$$

where $d_{(i-1,s)\to(i,t)}$ is the Euclidean distance between two adjacent GPS sampling points, and $w_{(i-1,s)\to(i,t)}$ is the shortest path length of two candidate points. K is the limit threshold for the Euclidean distance between two adjacent GPS sampling points and the length difference of the shortest path between the two candidate points corresponding to the two sampling points.

As per literature [18], the value of 1000m is utilized.

By integrating the above observation probability and transition probability, the spatiotemporal analysis function is obtained, as shown in Equation (6).

$$F_s(c_{i-1}^s \to c_i^t) = N(c_i^j) \times V(c_{i-1}^s \to c_i^t) \tag{6}$$

1) Path correlation analysis

In the context of increasingly complex road networks, road congestion has become a common phenomenon when people travel during rush hours, and it has become a common phenomenon to take appropriate measures to save traveling time by taking long detours (see Fig. 4). The traditional ST-Matching algorithm and IVMM algorithm are based on the premise that people choose the shortest route, but today's complex road conditions will weaken their applicability.

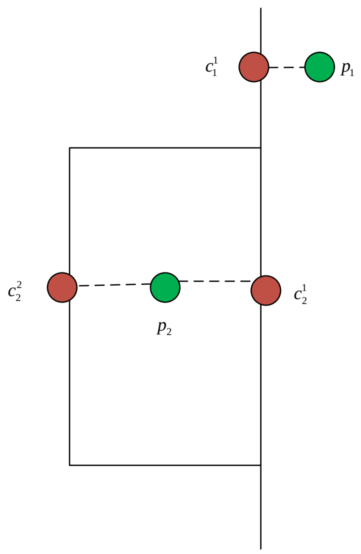

Fig. 4. Example diagram of path similarity analysis

In this paper, path similarity is introduced to correct the above described situation. In the process of vehicle driving, the actual speed of candidate points cannot be directly obtained, so the instantaneous speed of the two sampling points before and after is used as a reference. The estimated average speed of the vehicle between the two candidate points is calculated, and an estimated path length can be derived by incorporating the sampling times. Compared with the known candidate path lengths, the estimated path lengths are more similar to actual path lengths. The closer the ratio of the estimated path length to the candidate path length approaches 1, the greater the likelihood that this candidate path is the true path is. The function formula of path similarity analysis proposed in this paper is as:

$$F_l(c_{i-1}^s \to c_i^t) = \frac{\min\left(l, l(c_{i-1}^s \to c_i^t)\right)}{\max\left(l, l(c_{i-1}^s \to c_i^t)\right)} \tag{7}$$

where $l = \sum_{i=1}^{k} l_{r_i}$ is the length of the candidate path, and l_{r_i} represents the length of the ith road segment that constitutes the candidate path . The estimated path length $l(c_{i-1}^s \to c_i^t)$ is defined as:

$$l(c_{i-1}^s \to c_i^t) = \frac{\Delta t \cdot \left(v_{i-1} + v_i\right)}{2} \tag{8}$$

where Δt is the sampling interval, and v_{i-1} and v_i are the instantaneous velocities of the two sampling points p_{i-1} and p_i.

Based on the above spatiotemporal analysis and path similarity analysis, the comprehensive analysis function of sampling points is defined as:

$$F(c_{i-1}^s \to c_i^t) = F_s(c_{i-1}^s \to c_i^t) + \lambda \times F_l(c_{i-1}^s \to c_i^t), 2 \le i \le n \tag{9}$$

where λ is the proportional coefficient of path correlation analysis, generally set between 0.01 and 0.5.

2) Constraint analysis

The IVMM algorithm uses the cumulative maximum weight to determine the optimal path, and in this process, the error probability is also cumulative. When constructing the candidate graph, certain rules are adopted to eliminate some wrong candidate paths, which can reduce the accumulation of errors and reduce the computation of the subsequent voting process. Therefore, three constraints are set in this paper.

Constraint 1: The average velocity calculated based on the distance between the two candidate points and the sampling interval should fall within a reasonable range. Constraint 1 is defined as:

$$0 \le \bar{v}_{\left(c_{i-1}^s \to c_i^t\right)} \le f_v v_{\max} \tag{10}$$

$$\bar{v}_{\left(c_{i-1}^s \to c_i^t\right)} = \frac{l}{\Delta t} \tag{11}$$

where l is the candidate path length, Δt is the sampling interval, and f_v is the correction coefficient [9], typically ranging from 1.3 to 1.5.

Constraint 2: Generally speaking, the difference between the reliable direction of the sampling points and the candidate road segments is unlikely to be too significant. When the direction factor $f_\theta(c_i^j) < \delta$ is observed, the candidate road segment is filtered to reduce the cumulative error caused by mismatching.

Constraint 3: The probability value obtained by the observation probability function is applied to the limit constraint. When $\frac{\max N(C_i)}{N(c_i^j)} > \varepsilon$, the candidate road segment is filtered out to reduce the cumulative error caused by mismatching. C_i represents the set of candidate points at sampling point i.

C. Weighted analysis

The static matrix is established by utilizing the function values $F(c_{i-1}^s \to c_i^t)$ obtained from the comprehensive analysis between adjacent sampling points. Using this matrix, an optimal matching path can be obtained by backtracking based on the cumulative maximum weight. However, considering only the relationship between pre- and post-sampling points may lead to mismatching. Therefore, a distance weight matrix is defined based on the interrelationship between the spacing of all GPS sampling points in this trajectory. The closer the distance is, the stronger the influence relationship, the farther the distance, and the weaker the influence relationship become [12]. The static matrix and the distance weight matrix are combined to obtain the weighting matrix.

(1)Static matrix

Based on the function values obtained from the above comprehensive analysis, a static matrix $M = diag\left[M^{(2)}, M^{(3)}, \dots, M^{(n)}\right]$ can be established, where $M^{(i)} = \left(m_{ts}^{(i)}\right)_{b_{i-1}\times b_i} = \left(F(c_{i-1}^s \to c_i^t)\right)_{b_{i-1}\times b_i}$,b_{i-1} and b_i represent the number of candidate points for i-1 and i sampling points, respectively.

(2)Distance weight matrix

The distance weight matrix is an $n-1$ dimensional matrix modeling the distance between the current sampling point and other sampling points. It represents the degree of influence between p_i and p_j based on distance, denoted as $W_i = diag\left[w_i^{(1)}, w_i^{(2)}, \dots, w_i^{(i-1)}, w_i^{(i+1)}, \dots, w_i^{(n)}\right]$,where $w_i^j = e^{-\frac{\left(dist\left(p_i, p_j\right)\right)^2}{\beta^2}}$ $j = 1,2,...,n$, $dist\left(p_i, p_j\right)$ represents the Euclidean distance between p_i and p_j . β is a road network parameter[10].

(3)Weighting matrix

Weighting matrix represents the degree of similarity between all the candidate paths and the true path considering the distance effect, as below.

$$\begin{aligned} \boldsymbol{\phi}_i^{(j)} &= \left(\phi_{ts}^{(i,j)}\right)_{b_{j-1}\times b_j} \\ &= \begin{cases} \boldsymbol{w}_i^{j-1}\boldsymbol{M}^{(j)}, if \ 1 \le j \le i \\ \boldsymbol{w}_i^{j}\boldsymbol{M}^{(j)}, otherwise \end{cases} \end{aligned} \tag{12}$$

D. Interactive voting

Based on the above analysis, a weighting matrix is obtained for each sampling point, and a locally optimal path matching its candidate points is searched for. Subsequently, global voting and scoring are performed on all candidate points of the locally optimal path. The candidate points with the highest number of votes corresponding to the GPS sampling points are then connected to form the optimal path.

Specifically, the weighting matrix ϕ_i for each sampling point is used to find a locally optimal path of candidate points c_i^k passing through the ith sampling point. The local path of candidate points votes for all candidate points on the trajectory P. The candidate points of the sampling points with the largest number of votes are connected successively to obtain the optimal matching path.

As shown in Table 1, when the counting of candidates after voting is the same, the cumulative weight value is used to determine the more likely candidate points as matching points. Therefore, the matching result is $c_1^2 \to c_2^1 \to c_3^2 \to c_4^1$.

TABLE I
THE VOTING SCORE SHEET

candidate point	c_1^1	c_1^2	c_2^1	c_2^2	c_3^1	c_3^2	c_4^1	c_4^2
vote count	1	7	5	3	3	5	4	4
Cumulative weight value	1.2	1.2	1.1	1.1	0.9	1.1	0.8	0.7

IV. EXPERIMENT

A. Experimental simulation

To verify the effectiveness of the PCIVMM algorithm, simulation and testing are conducted. The road network test data for Jilin City was downloaded through OpenStreetMap, and vehicle driving data was collected through actual tests. The test area is the road area extracted above. The PCIVMM algorithm is compared with the ST-Matching algorithm, the IVMM algorithm and its improved version, the IIVMM algorithm. Parameter settings are detailed in Table 2.

TABLE II
PARAMETER SETTING

parameter	value
R	150m
μ	5m
σ	20m
λ	0.1
f_v	1.4
v_{max}	60km/h
δ	3/4
ε	5
β	5km

B. Experimental result

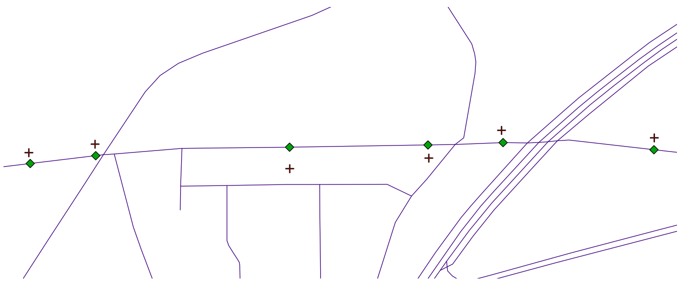

Fig. 5. IVMM algorithm visualization

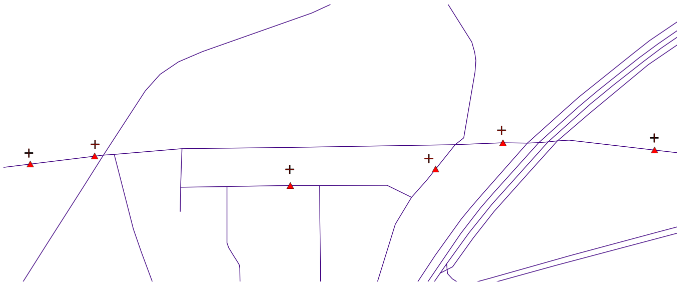

Fig. 6. PCIVMM algorithm visualization

Fig. 5 and Fig. 6 are visual trajectory diagrams after matching the IVMM algorithm and the PCIVMM algorithm in the same scene. The points marked by the cross represent the original GPS trajectory points, while the diamond markers in Fig. 5 and triangle markers in Fig. 6 represent the results of the IVMM algorithm and the PCIVMM algorithm, respectively. It is evident that the IVMM algorithm generates mismatches under the assumption that the shortest path is the matching path. On the other hand, the PCIVMM algorithm considers the instantaneous direction of the sampling point and analyzes the estimated path length with the average speed and sampling interval. This enables it to judge detour behavior of the vehicle at intersections more accurately and select the candidate road segment more precisely.

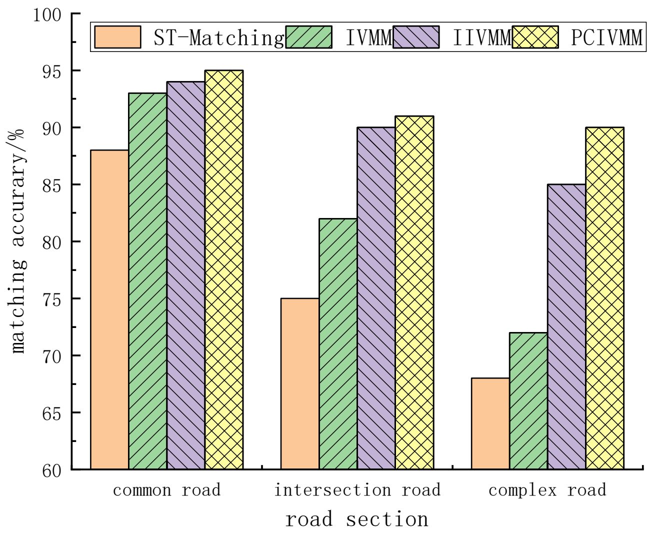

Fig. 7. Comparison of matching accuracy under different road conditions

Fig. 7 compares the matching accuracy rates of four matching algorithms under different road conditions. When driving on common roads, the full utilization of the distance factor and the relationship between adjacent sampling points enable all four algorithms to demonstrate good practicability, with a matching accuracy rate exceeding 88%. However, the ST-Matching algorithm and IVMM algorithm overlook the significance of the direction factor in intersection roads, resulting in a decline in matching accuracy due to insufficient utilization of sampling point information. On complex road networks, mismatching leads to error accumulation, significantly affecting matching accuracy. Both the IIVMM algorithm and the algorithm proposed in this paper employ constraint conditions to filter out incorrect road segments prior to matching. Additionally, in addition to setting thresholds for limiting velocity and direction constraints, the PCIVMM algorithm also establishes thresholds for the observation probability of sampling points. This approach eliminates impossible matching road segments and mitigates cumulative errors. By incorporating path correlation and considering the relationship between real-time speed and road speed limits, the PCIVMM algorithm more accurately determines the matching road segment of the sampling point, thereby enhancing matching accuracy.

Figs. 8-11 show the simulation diagrams of the single point matching time selected by the four algorithms in the candidate region when the number of candidate road segments closest to the original GPS tracking point are 2, 3, 4, and 5. When there are five candidate road segments, the single-point matching time obtained by the proposed algorithm remains approximately 5.45 ms. This algorithm introduces constraints to eliminate some mismatched road segments in advance, reducing the accumulation of weight errors and the time required for subsequent route selection compared to the ST-Matching algorithm and the IVMM algorithm. In addition, compared with the IIVMM algorithm, the PCIVMM algorithm sets new constraints on observation probability. Integrating the advantages of traditional geometric methods in computational speed, it reduces the computational complexity of the algorithm while maintaining matching accuracy, thereby shortening matching time.

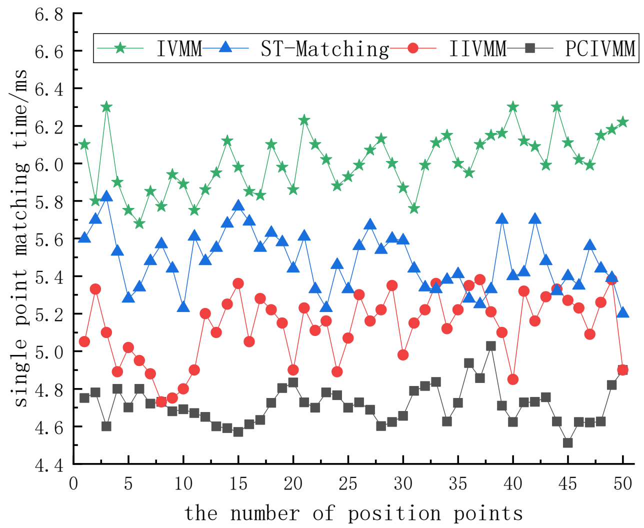

Fig. 8. Matching time of the two candidate road sections

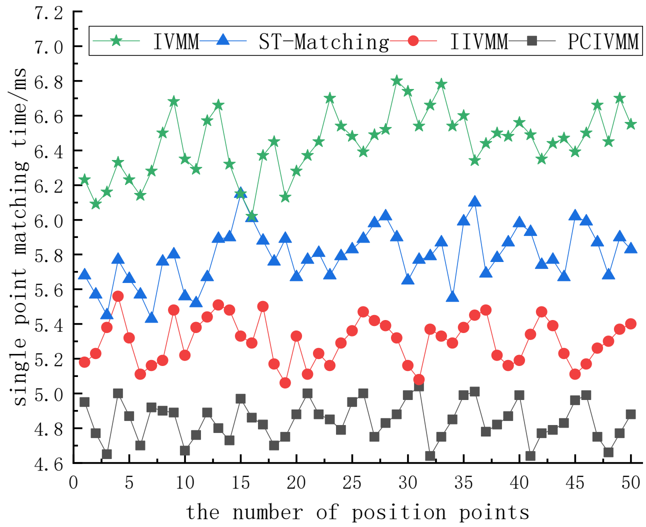

Fig. 9. Matching time of the three candidate road sections

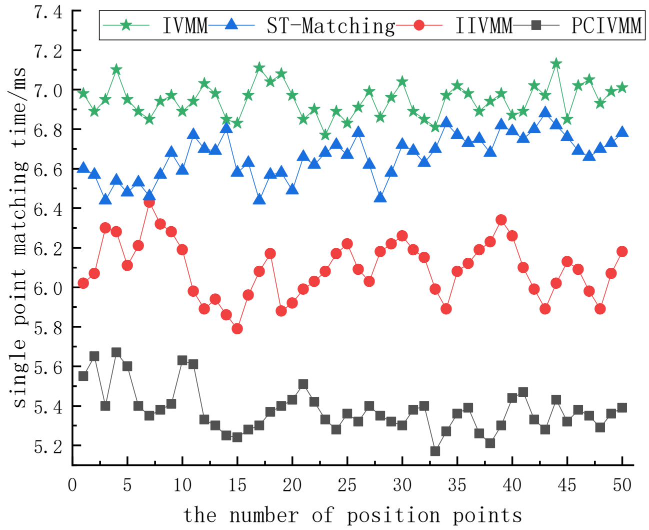

Fig. 10. Matching time of the four candidate road sections

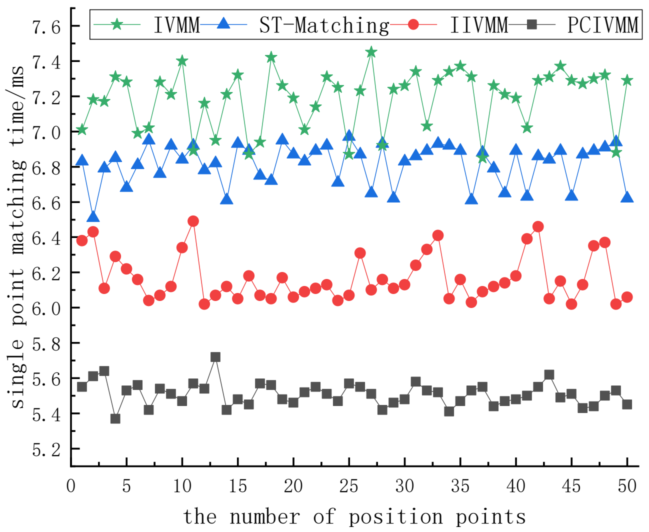

Fig. 11. Matching time of the five candidate road sections

V. Conclusion

Aiming at the problem of mismatching in a map matching algorithm with low sampling rates, we propose an improved interactive voting-based map matching algorithm considering path correlation. Based on the relationship between the real-time speed of the sampling point and the speed limit of the candidate road segment, the observation probability is improved, and the transition probability is optimized to reduce the matching error. The average speed and sampling interval between the front and rear sampling points are used to calculate the estimated path, and the long detour of the vehicle is taken into account to analyze the matching road correlation more accurately and improve the matching accuracy. We introduces new constraints to filter mismatched roads, reducing the time required for subsequent calculation and voting. The simulation results show that the proposed algorithm has good applicability and can maintain high accuracy when the vehicle is driving on different kinds of roads. To test the matching time with different numbers of candidate road segments, the proposed algorithm takes less time than the comparison algorithm. In the next stage, elevation information will be introduced to address the map matching problem of road segments with elevated roads and overpasses.

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