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Crowdsourced GNSS Satellite SNR in Degraded Environments for Dependability Improvement

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Abstract—Global Navigation Satellite Systems (GNSS) localization uses time of arrival (TOA) to measure the distance between satellite and rover antenna. The key for TOA technique is the signal propagation should be straight geometrically. However, when the train runs in harsh environments, the GNSS signal quality can be degraded due to obstacles. GNSS signals are usually blocked by buildings and other obstacles, resulting in reflection and reflection, which leads to multipath positioning errors of LOS and NLOS. In the case of LOS multipath error, the GNSS receiver tracks the direct and reflected / diffracted composite signal, and the reflected / diffracted signal affects the correlation function tracking loop of the direct signal in GNSS. In the case of NLOS multipath error, GNSS receiver directly tracks reflected or diffracted signal because there is no direct satellite signal. In both cases, the multipath signal will have a large noise error range which is reflected in the change of SNR. In the GNSS solution, various GNSS receivers are used to obtain the SNR of each satellite to achieve the fully coverage of the satellite signal reception quality. Thus with limited GNSS receiver observation results, of the crowdsourcing of NLOS signal inspection will deliver the observation results in a more convenient way. In the open environment scenario, the relationship between elevation angle and SNR can be fitted by a linear function. However, in GNSS signal reception degraded environments (urban canyon etc.), the SNR at the elevation angle of the occlusion boundary will be drastically reduced. This will give us the boundary of the occlusion range. Based on this principle, we can map the environmental characteristics of different sections of the railway. The railway environment can generally be divided into open scenario, road cutting scenario, half sky scenario, urban canyon scenario and tunnel scenario. 5 typical scenario all have distinct environmental characteristics. By matching the segment with the typical environmental characteristics, the scenario situation of the segment is determined, and then the accuracy of satellite positioning is given.

Keywords—railway, scenario, environment characteristics, SNR, Crowdsourced

I. INTRODUCTION

China's railways cover a wide range, and the surrounding environment along the line is diverse and complex. It is necessary to accurately locate the train to ensure the safety of

its operation. In the open scenario, the use of GNSS positioning can easily obtain accurate information on their location. However, when the train passes through harsh areas, obstacles such as buildings, mountains, bridges, and trees will block satellite signals, non-line-of-sight (NLOS), and multipath effects. It has an impact on the pseudorange used by the receiver to calculate the position, causing deviations in GNSS positioning. Undoubtedly, in these occluded scenarios, a single GNSS positioning cannot meet the continuity, accuracy, and reliability of positioning that users expect. In order to solve this problem, many scholars have proposed the concept of combined or assisted navigation, by integrating sensors, filters and measurement units in the GNSS positioning module to correct the influence of pseudorange deviation on positioning. Natthanarong Nilchan[1] proposed the measurement bias compensation method based on the mean of residual vectors. He modifies the conventional Kalman filter by including this compensation in the estimation step. Xu[2] developed a machine learning model to improve the use of GNSS position in loosely coupled GNSS/IMU systems using GNSS position as a Kalman filter measurement update.

However, in different scenarios, the compensation models and methods of other auxiliary positioning methods should vary with the environment. As shown in Fig 1, take satellite and inertial integrated navigation as an example. Usually, when fusion is performed, an algorithm that is applicable to all scenarios is used. This will lead to failure of fusion positioning in certain specific scenarios.

Fig. 1. Train sensor fusion algorithm

To solve this problem, you can add scenario type discrimination before fusion as shown in Fig 2. The railway environment can generally be divided into open scenario, road cutting scenario, half sky scenario, urban canyon scenario and tunnel scenario. By identifying the scenario where the train is located, the train positioning fusion algorithm model can be changed with changes in the environment.

Fig. 2. Train sensor fusion algorithm based on environmental scenario identification

The environmental characteristics of different scenarios can be extracted from the satellite observation data in the railway section. When the satellite observation data reaches a certain amount, environmental features can be aggregated by the satellite spatial distribution of each observation epoch. Obstacles usually divide the elevation angle into a visible area and an invisible area. As shown in Fig 3, the SNR in the visible area is higher, and the SNR in the invisible area is lower. Based on the change in SNR, the occlusion boundary in a certain direction can be determined.

Fig. 3. Schematic diagram of occlusion boundary

This paper proposes a train scenario recognition algorithm based on crowdsourced GNSS data. Delineate the environmental characteristics of each railway section through the satellite observation data of the train. According to the five types of typical scenario on the railway, the railway section is classified and identified. And verify the positioning accuracy of trains in different scenarios to judge whether the method proposed above is effective.

II. SCENARIO ENVIRONMENT FEATURE CONSTRUCTION

A. Railway environmental scenario classification

As shown in Fig4, Common types of railway environment scenarios include open, half the sky, road cuts, urban canyons, tunnels, etc. The positioning performance, error, and geometric distribution of satellites are different in each type of scenario.

Fig. 4. Schematic diagram of occlusion boundary

The characteristics of each scenario are as follows:

Open scenario: This scenario occupies the largest proportion of the railway, and the two sides of the railway are empty, with excellent satellite visibility.

Road cut scenario: There are distant buildings or mountains obscured on both sides of the railway, which affects the reception of low-elevation satellite signals.

Half sky scenario: One side of the railway is obscured by tall buildings or mountains. Only the satellites on one side are visible.

Urban canyons scenario: There are a lot of tall buildings and mountains on both sides of the railway. The receiver can only receive overhead satellite signals and reflected satellite signals, and the satellite accuracy is very poor.

Tunnel scenario: The satellite signal is completely blocked by the tunnel. The receiver cannot perform satellite positioning.

B. Constructing the environmental characteristics of the typical railway scenario

In order to more accurately identify the railway environment scenario, this paper idealizes the occlusion boundary of the typical scenario. Among them, the sky occlusion boundary of road cut and half sky and urban canyons scenario contains straight line boundary, and the parameters of the straight line occlusion boundary are generated through the geometric model. l represents distance from point O to boundary, and θ represents azimuth angle. Occlusion boundary elevation angle can be calculated by (1).

$$ele_i = \frac{l}{|\sin \theta_i|} \quad (1)$$

Fig. 5. Simulation model of sky occlusion line boundary

Based on this geometric model, three types of idealized environment characteristics of typical scenarios are constructed. Light purple represents the actual visible area, and red represents the idealized straight line boundary.

Fig. 6. Idealized environmental characteristics of five types of typical scenarios

C. Construction of environmental characteristics of railway sections

The environmental characteristics of the section are derived from the azimuth, elevation and SNR of the satellite in the satellite observation data. The following will explain how the geometric distribution of satellites generates environmental features.

1) the relationship between SNR and positioning error

Generally, when the GNSS receiver is performing position calculation, in order to ensure a good satellite spatial configuration, a medium elevation angle satellite is added to the calculation. However, satellites with moderate elevation angles are easily affected by obstructions. In Fig. 7, It shows the relationship between satellite SNR and positioning error at different elevation angles.

Fig. 7. The relationship between SNR and positioning error at different elevation angles

By comparing elevation angles at different altitudes, it can be found that SNR changes at lower elevation angles will have a greater impact on the error.

2) determine the occlusion boundary by SNR

If the elevation angle and the maximum SNR of the observed satellite are plotted on the graph, it can be found that the relationship between the elevation angle and the maximum SNR can be described by a linear function.

Fig. 8. Linear fit of elevation angle and maximum SNR

By using the fitted straight line as a reference, the difference between the observed satellite SNR and the fitted value is made.

$$SNR_{dif} = SNR_{fit} - SNR_{ob} \quad (2)$$

In order to avoid the deviation of linear fitting, use $SNR_{dif} = 2$ as the baseline to determine the occlusion boundary.

Fig. 9. SNR to determine the occlusion boundary schematic diagram

3) draw section environmental characteristics

Crowdsourcing satellite navigation signal quality observation data has a limited amount of data, and it is impossible to ensure that every azimuth has a corresponding visible satellite distribution. By setting the azimuth division range, the sky map is equally divided into 12 areas for environmental feature construction. For a given azimuth domain, the SNR difference calculated elevation angle as of a shielding boundary. The algorithm flow of using SNR to construct environmental characteristic parameters proposed in this paper is as follows:

Algorithm 1: SNR-based environmental characteristic parameter construction algorithm

input: satellite spatial distribution information $S = \{s_1, s_2, \dots, s_K\}, S_i = (azi_i, ele_i, snr_i)$

output: environmental characteristic parameter sequence $F = \{f_1, f_2, \dots, f_m\}$

1. **while** S is not empty **do**
2. Obtain the reference straight line of SNR through the maximum SNR and elevation angle and SNR fit;
3. The SNR and elevation angle of the satellite are assigned to the corresponding angle domain according to the azimuth angle;
4. Calculate the difference between the SNR fitted value and the observed value SNR_{dif} ;
4. **for** All azimuth fields **do**
5. Comparison from the beginning of the elevation satellite and determine the elevation angle of $SNR_{dif} > 2$
6. Generate occlusion boundaries for each azimuth domain;
7. **end while**
8. Obtain the boundary and quantify the gradient to obtain the environmental characteristics F ;
9. **end while**

III. SCENARIO RECOGNITION OF RAILWAY SECTION

The foregoing features typical scenario creation environment and azimuth segment is divided into 12 regions. Therefore, the comparison between environmental features can be transformed into calculating the similarity between two discrete sequences of equal length. In order to calculate the similarity between the two ends of the sequence, this paper uses the time dynamic warping algorithm(DTW) to match.

A. Dynamic Time Warping

Assuming that the test data and reference data are represented by sequences A and B, respectively, in order to find the degree of similarity between A and B, you can first calculate the Euclidean distance matrix D of the two sequences point-to-point. Based on the Euclidean distance array D, the core of the DTW algorithm is to find a path from the upper left corner to the lower right corner of the matrix so that the sum of the elements on the path is the smallest. In terms of path finding rules, for an element on the path, its previous element can be one of the left, above and topleft as shown in Fig 10.

	A(1)=1	A(2)=1	A(3)=3	A(4)=3	A(5)=2	A(6)=4
B(1)=1	0	0	2	2	1	3
B(2)=3	2	2	0	0	1	1
B(3)=2	1	1	1	1	0	2
B(4)=2	1	1	1	1	0	2
B(5)=4	3	3	1	1	2	0
B(6)=4	3	3	1	1	2	0

Fig. 10. Schematic diagram of DTW algorithm finding path

The whole algorithm can be summarized as calculating the similarity and vector distance superposition between the test sequence and the reference sequence.

B. Environmental characteristic parameter sequence matching based on DTW algorithm

The reason for choosing the DTW algorithm is that in the matching process of two discrete sequences, the numerical value of each point must be considered, as well as the numerical change trend of the discrete sequence. The traditional calculation of the Euclidean distances of relative points and adding them cannot express the trend, and the calculation of the correlation coefficient can only reflect the trend of change and cannot make numerical judgments. The scenario recognition algorithm based on the discrete sequence matching of environmental characteristic parameters is shown in the following table:

Algorithm 2: Scenario Recognition Algorithm Based on Discrete Sequence Matching of Environmental Feature Parameters

input: environmental characteristic parameter sequence $F = \{f_1, f_2, \dots, f_m\}$ and typical environment characteristics $T = \{t_1, t_2, \dots, t_m\}$

output: segment recognition result $S = \{s_1, s_2, \dots, s_k\}$

1. **while** S is not empty **do**
2. **for** j=1:5 **do**
3. Use Euclidean distance to calculate the point-to-point distance matrix of sequence F_k and sequence T_j ;
4. Find the shortest distance through the DTW algorithm and get the corresponding scenario type;
5. **end for**
6. Output scenario type of this section s_k
7. **end while**
8. Obtain the scenario recognition results of the entire railway $S = \{s_1, s_2, \dots, s_k\}$;

IV. EXPERIMENT AND RESULT ANALYSIS

The lines in the Beijing Ring Railway Test Center include outer ring lines, inner ring lines, station yard lines, triangle lines, tie lines, and ring lines. The largest outer ring line is 9 kilometers in length, with a radius of 1852 meters, and the curve radius of the entire line is 1432 meters. . The inner ring line is about 8.5 kilometers in length and consists of a straight line and three curves with radii of 350, 600, and 1000 meters. All the ring lines are electrified.

Fig. 11. Beijing Round Track

Satellite observation data are recorded in NMEA format, including observation data from the US GPS and China's Beidou positioning system.

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A. DTW-based scenario classification and identification results

After checking on Google Maps, there is no tunnel section in the ring road, so according to the typical railway scenario, the environment identification is carried out for the open scenario, the road cutting scenario, the half sky scenario and the urban canyon scenario. Sampling the boundaries of typical scenarios is the same as the environmental features, and the division interval of the azimuth angle is all 30° , and the reference feature sequence obtained is shown in the table.

TABLE I. DISCRETE SEQUENCE OF ENVIRONMENT FEATURE BOUNDARY IN TYPICAL SCENARIO

Azimuth range ($^\circ$)	Elevation boundary ($^\circ$)			
	Open	Road cut	Half sky	Urban canyons
0-30	10	10	10	10
30-60	11.25	19.3	19.3	47.6
60-90	12.5	38.2	38.2	59.0
90-120	12.5	38.2	38.2	59.0
120-150	11.25	19.3	19.3	47.6
150-180	10	10	10	10
180-210	10	10	10	10
210-240	11.25	19.3	47.6	47.6
240-270	12.5	38.2	59.0	59.0
270-300	12.5	38.2	59.0	59.0
300-330	11.25	19.3	47.6	47.6
330-360	10	10	10	10

Each type of scenario segment identified from the observation data is indicated on the map. Yellow represents an open scenario; green represents a road cutting scenario; red represents a half-sky scenario; blue represents an urban canyon scenario.

Fig. 12. The overall scenario recognition result of round track

Randomly extract the occlusion situation of the segments in the four types of scenarios, which is similar to the ideal occlusion situation of the typical scenario as shown in Fig 13.

Fig. 13. Skyplot of occlusion conditions in different scenarios

B. Evaluation of positioning performance in different scenarios

In general, comparing open scenarios with low-occlusion scenarios such as road cutting scenarios, it can be found that the vertical distance error is very small, and the average vertical error is within 1 meter. In high-occlusion scenarios such as Half the Sky and urban canyons, the vertical distance error increases significantly, with an average value greater than 1 meter, and the more occlusion in the surrounding environment, the faster the positioning error increases.

TABLE II. POSITIONING VERTICAL ERROR STATISTICS CORRESPONDING TO DIFFERENT SCENARIOS

Scenario type	Statistics(m)				
	Mean	Standard deviation	50% confidence	75% confidence	95% confidence
Open	0.59	0.43	0.50	0.82	1.32
Road cut	0.76	0.46	0.65	1.09	1.59
Half sky	1.21	0.47	1.17	1.55	1.84

Scenario type	Statistics(m)				
	Mean	Standard deviation	50% confidence	75% confidence	95% confidence
Urban canyons	1.80	1.09	1.76	2.33	4.30

From a detailed analysis, for open scenarios and road cutting scenarios, the occlusion situation has little interference with positioning errors. It is believed that the errors of these scenarios are dominated by satellite errors and spatial segment errors, and the ground environment has little influence on the errors. In the half-sky and urban canyon scenarios, half the sky has a larger zenith visible area, so the average error is smaller than that of the urban canyon. However, from the perspective of probability distribution and cumulative distribution, within an error of 0.75 meters, the probability of the half-sky scenario is less than the probability of the urban canyon. This is because in the urban canyon scenario, there will be some short surrounding buildings. In this case, although both sides are highly obscured, if there are more than 3 direct satellites overhead, the satellite distribution is better than in the half-sky scenario. Therefore, in the urban canyon, the error will be distributed in large quantities on both sides, while in the half-sky scenario, the error will be distributed in the middle part.

Fig. 14. Probability distribution of positioning error in different scenarios

Fig. 15. Cumulative distribution of positioning error in different scenarios

V. CONCLUSION

This paper proposes a scenario recognition based on GNSS crowdsourcing information. The SNR of the satellite signal is received by the receiver, and the reference relationship between the elevation angle and the signal-to-noise ratio is obtained by linear fitting. The difference between the fitted value of the SNR and the observed value is performed to obtain the occlusion boundary of the surrounding occluders, and then the environmental characteristics of the segment are obtained. Using the ideal environment characteristics of typical scenarios, the DTW algorithm is used to compare the similarity of the discrete sequences obtained from the environment characteristics, and then the scenario categories of all segments are obtained. Combining with the satellite observation data on the spot, a

statistical analysis of the positioning error in different scenarios is carried out, and it is determined that in different scenarios, the positioning error will increase as the degree of occlusion increases. It shows that the depiction of the segment scenario through GNSS crowdsourced information is successful and effective.

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