Research on Geomagnetic Indoor Positioning Based on Different Spatial Interpolation Methods

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Abstract: The resolution of geomagnetic field is low. In geomagnetic indoor positioning in large-scale scenes, with the increase of the number of fingerprints, the geomagnetic characteristic values corresponding to different position coordinates will have more similarities, resulting in a higher probability of fingerprint positioning mismatch. To solve this problem, Spline interpolation, RBF interpolation and Kriging interpolation are applied to the construction of geomagnetic fingerprint database in the offline stage, and BP neural network model is used for matching and positioning in the online stage. The experimental results show that the geomagnetic fingerprint database constructed by RBF interpolation can effectively improve the positioning accuracy and stability.

Keywords: Indoor positioning, Geomagnetic fingerprint database, Spline interpolation, RBF interpolation, Kriging interpolation

1. Introduction

Studies have shown that nearly 80% of people's daily activities are indoors [1]. Therefore, high-precision indoor positioning can not only enrich people's daily activities, but also indirectly enhance the economic benefits of enterprises. However, the indoor environment is complex and changeable, and because of the shelter of house walls, the signal intensity of GNSS signals can hardly be used for direct positioning when they are transmitted indoors [2]. Therefore, how to acquire indoor positioning technology with wide range, precision and stability has become a difficult task. Geomagnetic field has spatial difference: in the building area, the influence of reinforced concrete components and indoor fixed iron equipment on geomagnetism has strengthened the difference of geomagnetic vector values in different positions, which provides the foundation for geomagnetic indoor positioning. Compared with wireless signal indoor positioning, geomagnetic positioning has strong continuity, and does not need additional indoor physical facilities to support it, so it has a considerable development prospect.

However, the resolution of the geomagnetic field is low. If the low-resolution geomagnetic fingerprint database is established directly without processing, there will be a large error matching probability in the online matching stage, which will reduce the positioning accuracy and stability. If the resolution is improved by collecting more dense fingerprint data, it will consume a lot of manpower and material resources, which is difficult to achieve in large-scale location. To solve this problem, Wang Cunhua and others used the optimized BP neural network to make regression prediction and build geomagnetic datum map, and achieved good results [3]. Literature [4] vectorizes the continuous geomagnetic signal based on the trajectory sequence, and uses the time convolution network to extract its features, which improves the resolution of geomagnetic fingerprint and the positioning accuracy. Wu Zhidong et al. put forward the concept of geomagnetic potential energy gradient, and used Gaussian regression and Rprop algorithm to optimize related parameters to build a space magnetic field. This method can simulate the real geomagnetic environment in different types of areas [5]. Scholars in literature [6] combine RSSI signal with geomagnetic component, and vectorize it for deeper extraction, which makes up for the low resolution defect of geomagnetic signal.

In this paper, the spatial interpolation method is used to improve the resolution of fingerprint database. After the geomagnetic data is preprocessed, the off-line phase uses Spline interpolation, RBF interpolation and Kriging interpolation to construct the fingerprint database with the same resolution as input, and the online phase uses BP neural network to output the predicted coordinates, and the positioning accuracy and stability are compared and analyzed.

2. Spatial interpolation method

2.1. Spline interpolation

The Spline interpolation method can be regarded as the use of function approximation to fit the space surface [7]. The principle is: set the cubic spline function S(x) on the interval [a, b] and satisfy the constraint $G(x_i)=f(x_i)$, $(i=1,2,3,\cdots,n)$. Divide the interval n into equal parts. If S(x) is required, n undetermined coefficients are required for each small interval. Since S(x) is continuous and second-order derivable in the interval [a, b], the node x_i in the interval should satisfy the following conditions:

$$\begin{cases} S(x_i - 0) = S(x_i + 0) \\ S'(x_i - 0) = S'(x_i + 0) , i = (1 \sim n - 1) \\ S''(x_i - 0) = S''(x_i + 0) \end{cases}$$
 (1)

At the same time, according to the boundary conditions of the interval [a,b], there are the following two constraints:

(1) If the first derivative and the second derivative at both ends of the interval are known, there are:

$$\begin{cases} S'(x_0) = f'(x_0), S'(x_n) = f'(x_n) \\ S''(x_0) = f''(x_0), S''(x_n) = f''(x_n) \end{cases}$$
 (2)

(2) If f(x) is a periodic function with b-a as the period, then S(x) is also required to be a periodic function. Therefore, the boundary conditions should satisfy:

$$S^{(j)}(x_0) = S^{(j)}(x_n), (j = 0, 1, 2)$$
(3)

Let the value of f'(x) at node x be m_i , and use the cubic Hermite interpolation formula in each interval divided by n as shown in formula (4):

$$S(x) = \alpha_{i(x)y_i +} \alpha_{i+1}(x)y_{i+1} + \beta_i(x_i)m_i + \beta_{i+1}(x_i)m_{i+1}, x \in [x_i, x_{i+1}] \tag{4}$$

After expanding the above formula, we get:

$$S(x) = \frac{(x - x_{i+1})^2 [h_i + 2(x - x_i)]}{h_i^3} y_i + \frac{(x - x_i)^2 [h_i + 2(x_{i+1} - x)]}{h_i^3} y_{i+1} + \frac{(x - x_{i+1})^2 (x - x_i)}{h_i^2} m_i + \frac{(x - x_i)^2 (x - x_{i+1})}{h_i^2} m_{i+1}$$
(5)

Since $h_i = x_{i+1} - x$, all node values x_i and $i = (1 \sim n - 1)$ are known. Therefore, the value of S(x) can be found only by finding m_i . Generally, the method of second-order derivation at both ends can be used to evaluate.

2.2. RBF (Radial Basis Function) interpolation

Similar to Spline interpolation, RBF interpolation also uses function approximation to fit spatial surface, but the difference is that kernel function is needed to highlight some local features of data [8]. Common kernel functions of are shown in Table 1:

Table 1: Kernel function types

Function	Express		
Gaussian	$\varphi(r) = \exp\left(-\frac{r^2}{2\sigma^2}\right)$		
Multiquadrics	$\varphi(r) = \sqrt{1 + \frac{r^2}{\sigma^2}}$		
cubic	$\varphi(r)=r^3$		
Thinplate	$\varphi(r)=r^2\ln(r+1)$		

Among them, RBF can be regarded as a combination of nonlinear functions $\varphi(r)$. The value of its parameters depends on the Euclidean distance norm between multi-dimensional space samples, and its expression is shown in formula (6):

$$\begin{cases}
\varphi(r) = \varphi(\|x - x_i\|) \\
\|x - x_i\| = \sqrt{\sum_{m=1}^{n} (x_m - x_{i,m})^2}
\end{cases}$$
(6)

Then the basic expression of RBF is shown in formula (7):

$$f(x) = a_0 + a_1 x + \sum_{i=1}^{n} \lambda_i \varphi(||x - x_i||)$$
 (7)

Here, a0, a1, and λ_i are all coefficients of f(x).

If there is a data point set Xj, Yj containing n samples, the above formula can be expressed in the form of a matrix, as shown in formula (8):

$$\begin{bmatrix}
\varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n} \\
\varphi_{21} & \varphi_{22} & \cdots & \varphi_{2n} \\
\vdots & \vdots & & \vdots \\
\varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n}
\end{bmatrix}
\begin{bmatrix}
\omega_{1} \\
\omega_{2} \\
\vdots \\
\omega_{n}
\end{bmatrix} =
\begin{bmatrix}
y_{1} \\
y_{2} \\
\vdots \\
y_{n}
\end{bmatrix}$$
(8)

Among them, Φ is an interpolation matrix, generally a symmetric matrix, W is a coefficient matrix, and Y is an output matrix. Therefore, the least squares method can be used to obtain the coefficient value of a data point:

$$\omega_{i} = \sum_{i=1}^{n} \Phi_{i,j}^{-1} y_{j}$$
 (9)

When there is a certain amount of data, RBF interpolation can fit the best smooth surface. At the same time, similar to Spline interpolation, this interpolation method is difficult to estimate the interpolation error directly.

2.3. Kriging interpolation

Kriging interpolation is one of the spatial local interpolation methods commonly used in geological statistics. There are many kinds of Kriging interpolation methods, including ordinary Kriging, simple Kriging, Co-Kriging, universal Kriging and so on [9]. Considering the data structure and complexity of calculation, this paper chooses ordinary kriging interpolation, and its calculation principle is as follows: Assuming that there is a known point (x_i, y_i) in the uniform space Z, and the point to be interpolated is (x_0, y_0) , the basic formula of Kriging interpolation is shown in formula (10):

$$o(x_0, y_0) = \sum_{i=1}^{n} \lambda_i o(x_i, y_i)$$
(10)

Among them, $o(x_i, y_i)$ is the measured value of the known point, $o(x_0, y_0)$ is the estimated value of the point to be measured, and λ_i is the weight coefficient. This coefficient can satisfy the minimum difference between the measured value and the estimated value, and at the same time satisfy the unbiased estimation condition, namely:

$$E\left| \stackrel{\wedge}{o}(x_0, y_0) - o(x_i, y_i) \right| = 0 \tag{11}$$

Then the weight coefficient needs to satisfy the following equations, as shown in Equation (12):

$$\begin{cases} \sum_{i=1}^{n} \lambda_{i} \gamma(l_{ij}) + \mu = \gamma(l_{0j}) \\ \sum_{i=1}^{n} \lambda_{i} = 1 \end{cases}, j = 1, 2, 3, ..., n$$
(12)

Among them, l_{ij} is the spatial distance between the known point (x_i, y_i) and the known point (x_j, y_j) , μ is the Lagrangian coefficient, and γ is the cost function. l_{0j} is the spatial distance between the point (x_0, y_0) to be interpolated and the known point (x_j, y_j) . Finally, the Lagrange multiplier method is used to solve the equations, so as to obtain the value of the weight coefficient λ_i , and finally obtain the optimal estimated value of the point to be interpolated. Kriging interpolation can perform spatial interpolation without collecting all regional data, but it is complicated in calculation and takes a long time to run.

3. BP neural network location model

Artificial Neural Network (ANN) is one of the research hotspots of machine learning models in recent years. It has the advantages of good generalization and nonlinear mapping ability, and is widely used in function prediction, pattern recognition and other fields [10]. Back propagation algorithm is a supervised learning algorithm applied to artificial neural networks. When receiving the training of the sample signal, the signal passes through the input layer, the hidden layer and reaches the output layer for output through one-way transmission. Usually, the output results will be less than expected, so the BP neural network will feed back this error, and the hidden layer will constantly adjust the "state" according to the error information, and then re-transmit the improved signal to output the results. If the result still does not meet the requirements, continue to repeat the above steps until a satisfactory output result is obtained. Figure 1 is the structure diagram of the multilayer BP neural network constructed in this paper.

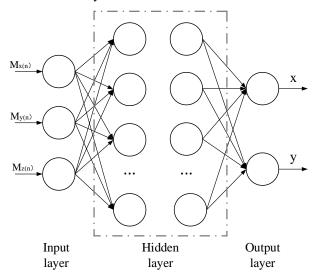


Figure 1: Structure diagram of multilayer BP neural network

The geomagnetic data of fingerprint database with different interpolation methods are used to construct a three-dimensional matrix as input, and the corresponding coordinate values are used to construct a two-dimensional matrix as output. The training sample is shown in Formula (13):

$$\begin{cases} input = \begin{bmatrix} M_{X(n)} \\ M_{Y(n)} \\ M_{Z(n)} \end{bmatrix} & n = (1, 2, 3, \dots, N) \\ output = \begin{bmatrix} x_n \\ y_n \end{bmatrix} \end{cases}$$
(13)

The number of neurons in the hidden layer of the BP neural network is shown in formula (14):

$$g = \sqrt{h+l} + a \tag{14}$$

Among them, h and l are the number of nodes in the input layer and output layer, respectively, and a is a constant between [1, 10]. Its mean square error function is shown in formula (15):

$$E = \frac{1}{2} \sum_{n=1}^{i} (y_k - \hat{y_k})^2$$
 (15)

Among them, i is the number of neurons in the output layer, y_k is the expected output, and y_k is the output layer output after the kth iteration. The positioning error formula in this paper is shown in formula (16):

$$G(x) = \sum_{i=1}^{N} \sqrt{(x'_i - x_i)^2 + (y'_i - y_i)^2}$$
 (16)

In the formula, N is the number of database sample points. x'_i and y'_i are the coordinates of the predicted anchor point of the $i(i \in [1, N])$ -th sample, respectively. x_i and y_i are their actual coordinates, respectively.

4. Experimental result analysis

In this paper, the first floor of the School of Spatial Information and Surveying and Mapping Engineering of Anhui University of Science and Technology is selected as the experimental site, with a size of $10 \text{ m} \times 17 \text{ m}$, as shown in Figure 2. The whole test site is evenly divided into $1 \text{ m} \times 1 \text{ m}$ grids, and geomagnetic triaxial data acquisition is carried out at each grid node. The acquisition equipment is VIVO S9, the acquisition frequency is set at 20Hz, and each point is acquired for 60s. In order to avoid the interference caused by the change of the attitude of the acquisition equipment, the attitude of the equipment remains unchanged during the acquisition process.

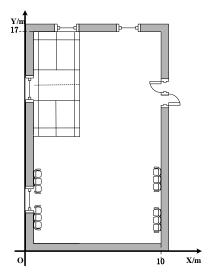


Figure 2: Plan of experimental area

4.1. Fingerprint database construction

After de-noising the data in the off-line stage, we choose Spline interpolation, RBF interpolation and Kriging interpolation with the same resolution to establish fingerprint database for experiment. The interpolation resolution selected in this paper is 0.3m*0.3m, and the geomagnetic distribution of the original data scene and that of the interpolated scene are shown in Figure 3, Figure 4, Figure 5 and Figure 6 respectively:

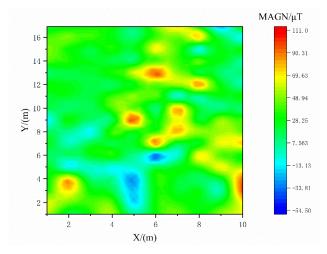


Figure 3: No Interpolation

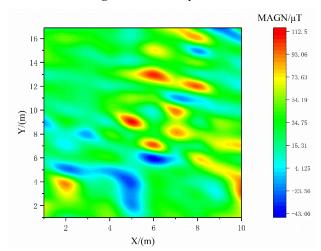


Figure 4: Spline Interpolation

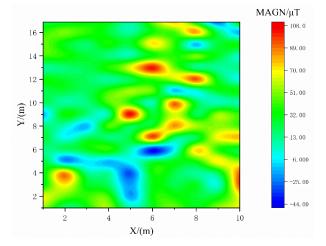


Figure 5: RBF Interpolation

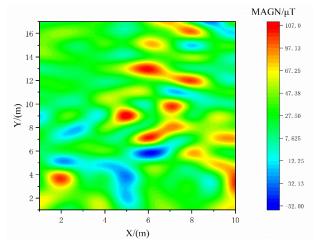


Figure 6: Kriging Interpolation

It can be seen from the above that the geomagnetic fingerprint resolution of the scene without interpolation is low. With the increase of the number of fingerprints, the geomagnetic characteristic values corresponding to different position coordinates will have more similarities, which leads to a higher probability of single-point positioning mismatch. After interpolation, the data distribution of fingerprint database is smoother, which can better improve the above situation. At the same time, the influence of three different interpolation methods on the positioning effect can't be seen directly in the figure, and the interpolation process itself will also cause errors in the fingerprint database data, so it is necessary to further compare the positioning experiments.

4.2. Positioning experiment

70 identical initial point are randomly selected from that fingerprint database without interpolation, the fingerprint database with Spine interpolation, the fingerprint database with RBF interpolation and the fingerprint database with Kriging interpolation. As test points, they are input into the established BP neural network positioning model, and the positioning results are compared and analyzed. The location results of the above four fingerprint databases are shown in Figure 7 and Table 2:

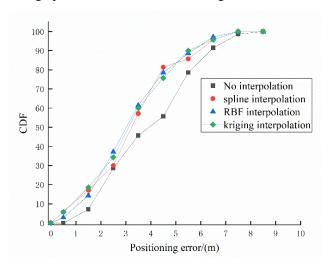


Figure 7: Cumulative error distribution diagram

As shown in fig. 7, the maximum positioning error of the non-interpolated fingerprint database is over 8m, and the minimum positioning error is over 1m, but this situation does not exist in the interpolated fingerprint database. Among them, Spline interpolation has 17.1% probability positioning error within 1.5m, 30.0% probability positioning error within 2.5m and 57.1% probability positioning error within 3.5m. RBF interpolation has 14.3% probability positioning error within 1.5m, 37.1% probability positioning error within 2.5m and 61.4% probability positioning error within 3.5m. Kriging interpolation has 18.6 probability of positioning within 1.5, 34.3% probability of positioning error within 2.5m, and 60.0% probability of positioning error within 3.5m.

Table 2: Comparison of positioning errors

Interpolation method	Average error/(m)	Max error/(m)	Min error/(m)	standard deviation
No Interpolation	4.44	8.22	1.25	1.81
Spline	3.82	7.60	0.57	1.67
RBF	3.67	7.31	0.57	1.52
Kriging	3.71	7.32	0.54	1.70

As can be seen from Table 2, the average positioning error, the maximum positioning error, the minimum positioning error and the standard deviation of the fingerprint database after interpolation are all better than those of the fingerprint database without interpolation. Therefore, using spatial interpolation method to process geomagnetic fingerprint database can effectively improve the positioning accuracy and stability. Among all interpolation methods, the average positioning error of RBF interpolation is the lowest, and the positioning accuracy is improved by 0.77m compared with that of fingerprint database without interpolation, and the standard deviation is the lowest, which has the best positioning accuracy and stability.

5. Conclusions

The resolution of the earth's magnetic field is not high, and there will be cases where several positioning areas have similar magnetic field strength values. However, the low-resolution geomagnetic fingerprint database will increase the probability of mismatch. If you want to increase the resolution by increasing the number of fingerprints, you need to collect a large number of geomagnetic fingerprints at a single point in the early stage, which is time-consuming and laborious. In view of the above situation, this paper uses three spatial interpolation methods, Spline, RBF and Kriging, to process geomagnetic fingerprint database. The experimental results show that the three interpolation methods can effectively improve the accuracy and stability of geomagnetic indoor positioning. Among them, the fingerprint database processed by RBF interpolation has the best positioning effect when online matching. On this basis, the next step can be to study the optimization of geomagnetic matching algorithm, and further improve the positioning accuracy and stability of geomagnetic indoor positioning.

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