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Prediction of Underwater Airworthiness Zone Based on GA-BP Neural Network

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Abstract. The classification and prediction technology of adaptation zones for underwater navigation and positioning is of strategic significance. Gravity anomaly occurs due to the uneven density distribution inside the Earth, leading to a difference between the observed and theoretical normal gravity values. Areas with significant gravity anomaly changes enable high-precision positioning for navigation systems, while relatively flat changes result in lower positioning accuracy. Thus, establishing an adaptive zone classification prediction model applicable to various regions is crucial for ensuring the navigation accuracy of underwater vehicles. This article uses genetic algorithm to improve the robustness and convergence speed of BP neural network, establishes a GA-BP neural network underwater navigation adaptation zone prediction model, and obtains good gravity anomaly prediction effect. Based on this result, the adaptation zone can be predicted.

Keywords: Genetic algorithm, BP neural network, linear interpolation, Gradient.

1. Introduction

The positioning and navigation technology of underwater vehicles plays an important role in the development of marine economy and deep-sea exploration. As one of the navigation systems for underwater vehicles, the gravity assisted navigation system can provide accurate navigation by calibrating the navigation adaptation zone. The adaptation zone refers to a navigation area with high matching ability selected based on the gravity anomaly changes in the underwater vehicle navigation area presented by the gravity reference map of the research sea area.[1-2] Its calibration and identification technology is extremely challenging and is the key factor affecting navigation reliability and accuracy.[3]

By quantitatively analyzing the relevant indicators that affect the distribution of the adaptation zone, a GA-BP neural network adaptation zone prediction model is established, which can reduce the cost of frequent manual measurement of gravity anomalies and calibration of airworthiness zones due to changes in crustal activity and geological material over time.[4] This provides a reference for exploring the changes in gravity anomalies and calibrating airworthiness zones.

2. Related Work

At present, the navigation adaptation zone mainly obtains gravity field reference maps through shipborne gravity measurement, aerial gravity measurement, and satellite altimetry inversion. However, these methods are limited by time and space, require a large amount of manpower and equipment costs, and have the problem of low resolution of measurement reference maps[5].

The traditional methods for predicting the adaptation zone using gravity reference maps include Analytic Hierarchy Process, Principal Component Analysis, Factor Analysis, Threshold Method, etc[6,7]. Due to the fact that these features are fused with traditional feature parameters, there is a problem of ignoring the adaptability of the navigation area direction.

3. Construction of GA-BP neural network model

3.1. Data acquisition and data preprocessing

The gravity anomaly data is sourced from the Scripps Institution Of Oceanography, University of Califonia San Diego.

Select the gravity anomaly values of rectangular regions with latitude ranges of (115.0083E, 117.0083E) and (11.0068N, 9.0045N), and perform linear interpolation on the data to obtain a matrix of 200 rows and 200 columns.[8]

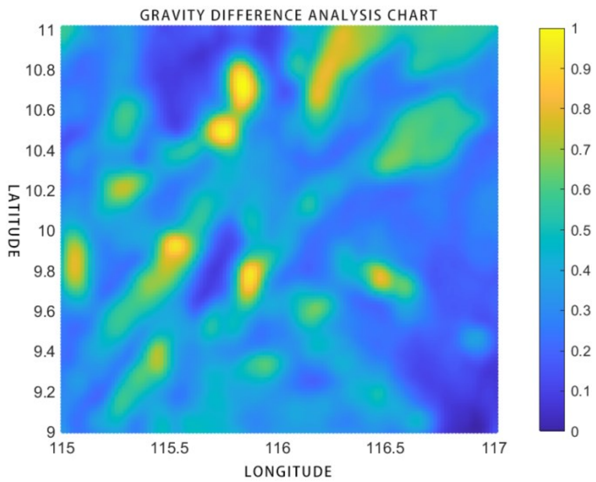

Figure 1. Gravity difference analysis chart

Data normalization processing: The values of gravity anomalies need to be controlled between 01 to improve the prediction accuracy of the model. The normalization method is shown in the formula.

$$X = \frac{X - X_{min}}{X_{max} - X_{min}}$$

3.2. Indicator selection

Determine 7 indicators within the specified latitude and longitude range: which are the three coordinates of the gravity anomaly gradient vector, the magnitude of the vector, seawater depth, crustal depth, and Moho interface depth.

To demonstrate the feasibility of the indicators, Pearson correlation tests were conducted on the above indicators.

3.3. Introduction of BP Neural Network

The BP neural network prediction model has the following characteristics:

1. Suitable for predicting large amounts of data;

2. It has the ability of nonlinear mapping, which can model and predict nonlinear relationships. This makes it highly adaptable when dealing with data with complex relationships;

3. By using backpropagation algorithm for adaptive learning of weights and biases, the network structure and parameters can be automatically adjusted to improve the accuracy of predictions.

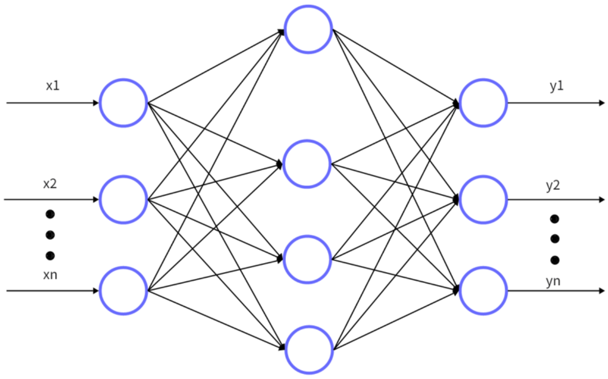

Figure 2. Structure of BP neural network

The content and steps of the BP neural network algorithm are as follows. First, define the variables and independent variables! Input layer vector: X=(x1, x2,... xi,..., xn);

Hidden layer input vector: H=(h1, h2,..., hj,..., hm);

Output layer output vector: Y=(y1, y2,..., yk,..., yi);

Expected output vector: D=(d1, d2,..., dk,..., di);

The weight connection matrix between the input layer and the hidden layer: V=(V1, V2,..., Vj,..., Vm);

The weight connection matrix between the hidden layer and the output layer: W=(W1, W2,…,Wk,…,Wi)。

The specific implementation steps of BP neural network are as follows:

Network initialization w The V matrix is determined by the range of activation function values during assignment. Determine the maximum training frequency M and learning accuracy value E, choose the activation function f (x), usually using a single limit sigmoid function:

$$f(x) = 1 / (1 + e^{-x})$$

$$h_j = f(T_j^T x^T), j = 1,2,3, \dots, m$$

$$y_k = f(w_k^T H^T), k = 1,2,3, \dots, 1$$

Calculate the error using the actual output value y and expected output value d of the network:

$$e = 1/2\ \Sigma_{k-1}^{1} (d_k - y_k)^2$$

Calculate the partial derivatives of the error function for each neuron in the hidden layer and output layer δ_j^h and δ_k^y separately:

$$\delta_j^h = \left(\sum_1^{k=1} \delta_k^y w_{jk}\right) * h_j * (1 - h_j), j = 1,2,3, \dots$$

$$\delta_k^y = (d_k - y_k) * y_k * (1 - y_k), k = 1,2,3, \dots$$

Adjust the connection weights of each layer using error signals, weight from hidden layer to output layer $w_{jk}^{N+1}$and weight from Input layer to hidden layer v_{ij}^{N+1}:

$$w_{jk}^{N+1} = w_{jk}^{N} + \varphi\delta_k^y h_j, k = 1,2,\dots,l \quad j = 0.1,\dots,m$$

$$v_{ij}^{N+1} = v_{ij}^{N} + \varphi\delta_j^h x_i, j = 1,2,\dots,m \quad i = 0.1,\dots,m$$

Calculate the global error E:

$$E = 1/2 \sum_{P=1}^{P} \sum_{k=1}^{l} \left(d_k - y_k\right)^2$$

3.4. GA optimized BP neural network

Genetic Algorithm (GA) is a stochastic global optimization algorithm based on the simulation of biological evolution and genetic processes.[9] Genetic algorithms have a greater likelihood of finding the global maximum, and therefore can be used to optimize BP neural networks, reducing their likelihood of getting stuck in local optima.

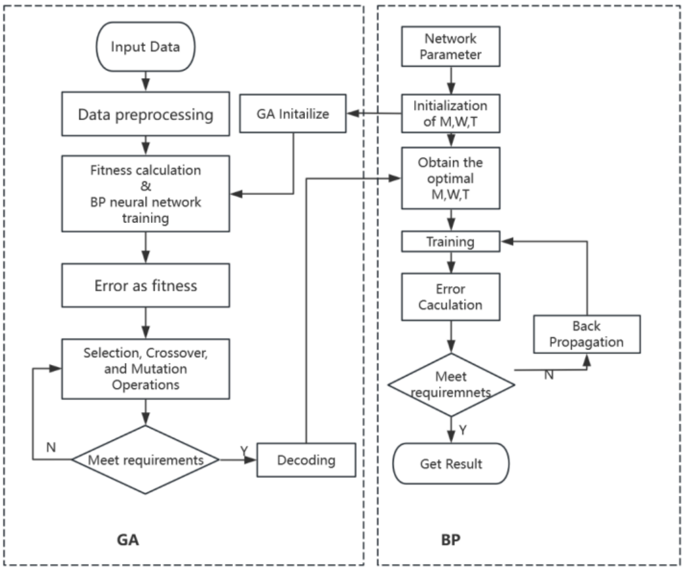

Figure 3. GA-BP overall structure

3.5. Calibration of adaptation zone

The gravity anomaly gradient value can well reflect the changes in gravity gradient, and then use gravity anomaly gradient to calibrate the adaptation zone.

Firstly, calculate the partial derivative for each element in the gravity anomaly matrix:

$$\vec{e_l} = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right)$$

Then, take the modulus of the partial derivatives of x and y:

$$\mathrm{grad}(x,y) = norm(\vec{e_l}) = \sqrt{\left(\frac{\partial f}{\sigma x}\right)^2 + \left(\frac{\partial f}{\sigma y}\right)^2}$$

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4. Result and Analysis

4.1. Gravity anomaly gradient matrix

By calculation, the gravity anomaly gradient matrix was obtained, and the following gravity anomaly gradient map was drawn using Matlab.

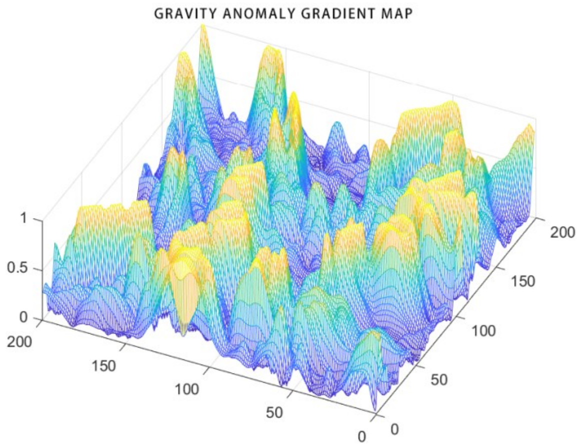

Figure 4. Gravity anomaly gradient map

4.2. GA-BP prediction model test results

Table 1. prediction results.

Pos	0	1	2	3	4	...	200
200	0.367888	0.373490	0.373490	0.397375	0.397375	...	0.397375
199	0.385902	0.316324	0.327875	0.334158	0.462722	...	0.117015
198	0.265213	0.252108	0.237683	0.256218	0.350215	...	0.080661
197	0.282388	0.222844	0.181711	0.167498	0.205831	...	0.122863
196	0.160771	0.127148	0.128481	0.154266	0.131024	...	0.108325
195	0.132919	0.108667	0.100919	0.122840	0.133519	...	0.146516
194	0.201402	0.174591	0.125798	0.096228	0.202123	...	0.096983
193	0.332105	0.411950	0.277660	0.328785	0.406832	...	0.148080
...	...	...	...	...	...	...	0.185986
0	0.181833	0.196783	0.239984	0.221140	0.221947	0.140358	0.210361

The adaptation values for different coordinates are [0,1], and the closer the value is to 1, the higher the degree of adaptation.

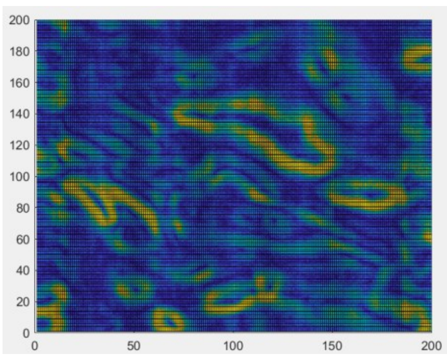

Figure 5. Original gravity gradient chart

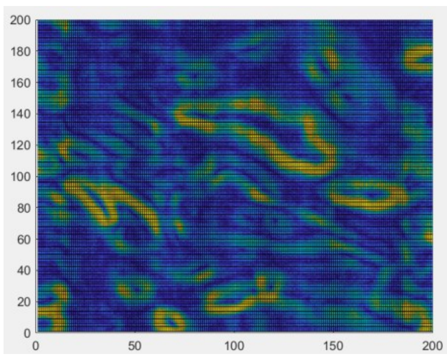

Figure 6. Predict result

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5. Conclusion

The GA-BP neural network uses genetic algorithm to optimize the number of hidden layer nodes and learning rate of the BP neural network, increasing the robustness and convergence speed of the model. Prediction of underwater airworthiness zone based on GA-BP neural network

The model can solve the problem of high cost in frequently measuring gravity anomalies due to changes in crustal activity and geological material over time. This model achieves the prediction of the adaptation zone by using seven indicators as input vectors, and the adaptation zone of the spacecraft (labeled as [0,1]) as output values.

After calculation, the predicted results are in good agreement with the actual calculated adaptation zone, with a similarity of 89.320% between the predicted gradient matrix and the calculated gradient matrix. The prediction accuracy is high, and the model prediction effect is good.

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