

Classification Prediction of Underwater Navigation Fitness Zones Based on BP Neural Network Modeling

Zichen Zhao^{*}, Zhaojun Gu, Shang Gao

College of Marine Electrical Engineering, Dalian Maritime University, Dalian, China, 116026

^{*} Corresponding Author Email: 13370621647@163.com

Abstract. In order to realize high-precision underwater navigation, it is necessary to establish a classification prediction model of the fitness area to realize the fitness assessment of different sea areas. The data are finely gridded, and the variance of the gravity anomalies at the four vertices of the gridded area is calculated as the classification feature to measure the significant degree of change of the gravity anomalies in the area, and the C-mean cluster analysis is applied to cluster the classification feature values, and all the areas are calibrated into seven fitness classes. And the visualization was carried out. Applying the BP neural network model, the latitude, longitude and corresponding gravity anomalies of the data were used as inputs, and the calibrated grades were used as the results, and the final fitting effect of the trained model was basically in line with the expected values. And the model is applied to the prediction of fitness zone classification in other sea areas, comparing the predicted value with the real value, through the visualization analysis and the error analysis of the model, the predicted fitness calibration result has a smaller error with the actual value, and the fitness grade distribution map of the predicted value and the actual value has an obvious consistency, so that the established BP neural network model has applicability for the classification of fitness zones for underwater navigation in different regions.

Keywords: Underwater Navigation, Gravity Anomaly, C-mean Cluster Analysis, BP neural Network Classification Prediction.

1. Introduction

In the context of realizing the strategy of "ocean power", the innovation and development of marine high-tech fields are becoming more and more important, and the classification and prediction technology of the adaptive zone for underwater navigation and positioning is one of the key core technologies[1-2]. Underwater navigation and positioning is one of the key core technologies. In addition to satellite navigation and magnetic field navigation, gravity-assisted navigation plays a key role in the improvement of navigation accuracy, so the classification of gravity-assisted navigation's fitness zone becomes particularly important. The calibration and identification technology of the fitness zone is the prerequisite for selecting the fitness zone. In areas with significant changes in gravity anomalies, the navigation system can obtain higher positioning accuracy; conversely, the navigation system may be insensitive to positioning accuracy.

In the paper, scholars such as Bo Wang mentioned that gravity gradient-matched positioning is an important means of underwater vehicle navigation, and summarized the current research status of four key technologies of underwater INS/gravity gradient-matched navigation to realize the application of gravity gradient-matched navigation key technologies on AUVs[3]. In his paper, Fangming Li proposed a method of fusing multi-source gravity anomaly data to generate a reference map, optimized the real-time ICCP algorithm by using effective techniques such as discrete wavelet transform to improve the positioning accuracy, established a comprehensive assessment model, and proposed a method of analyzing the directional navigation suitability based on the Log-Gabor filter bank and selective integrated learning to improve the accuracy of the analysis[4].

On this basis, this paper assumes that there are one or more metrics that can reflect the degree of change in the gravity anomaly values as a way to analyze the change in gravity anomalies in the area where navigation is provided based on the gravity datum map to determine whether this area is a fitness zone or not[5]. The following is an example of a gravity anomaly analysis. Based on some of the gravity anomaly data and the fitness situation, a machine learning algorithm is applied to use the

gravity anomaly value of the area to be calibrated to predict whether the area is a fitness zone for underwater navigation.

2. Categorical calibration of underwater navigation adaptation zones

2.1. Data sources

The gravity anomaly data analyzed in this paper were obtained from <https://cxcy.upln.cn/>, parts of which are shown in Table.1.

Table.1. Gravity anomaly data excerpt table

longitude	latitude	gravitational outlier
115.0083	11.0068	59.3
115.025	11.0068	58.1
115.0417	11.0068	52.5

2.2. Calibration of fitness zones for underwater navigation

2.2.1 Ideas for solving the problem

The gravity anomaly data are gridded by latitude and longitude, and the variance values of gravity anomalies at four points of this grid are derived. The variance value is used as the feature of the aptitude zone division, and the C-mean clustering analysis is performed on the derived features to divide them into seven categories, and this result is visualized. The BP neural network model is trained with this classification result and error analysis is performed.

2.2.2 Variance eigenvalue calculation

The data are gridded with a resolution of 1' x 1' for each grid point, dividing the whole region into a number of neighboring grids. a , b , c , and d denote the coordinate points of the four vertices of the rectangular region, respectively. Where: X_i and Y_j are the longitude and latitude values corresponding to the lower-left and upper-right vertices of the rectangular region defined with cyclic indexes. The longitude and latitude coordinates of any position of the rectangle can be defined by the cyclic indexes i and j .

$$\begin{cases} a = [X_i, Y_j] \\ b = [X_i, Y_{j+1}] \\ c = [X_{i+1}, Y_j] \\ d = [X_{i+1}, Y_{j+1}] \end{cases} \quad (1)$$

Find the variance of the gravity anomalies represented by the corners of the rectangular grid, representing the degree of dispersion within the grid area, assign each point the gravity anomaly value of.

$$\begin{cases} G_1 = A(m_{1,3}) \\ G_2 = A(m_{2,3}) \\ G_3 = A(m_{3,3}) \\ G_4 = A(m_{4,3}) \end{cases} \quad (2)$$

Of which.

G_1 Gravity anomaly corresponding to the lower left vertex of the mesh G_2 Gravity anomaly corresponding to the upper left vertex of the mesh G_3 Gravity anomaly corresponding to the lower right vertex of the mesh G_4 Gravity anomaly corresponding to the upper right vertex of the mesh

The variance of the gravity anomalies at the four points of the grid is selected, and a large variance in a region indicates that the gravity anomalies in the region change drastically and fluctuate strongly, and vice versa. Therefore, the variance can reflect the unevenness of the distribution of gravity anomalies in the region, which is an important reference index for evaluating and delineating the navigational suitability zone.

$$\bar{G}_i = \frac{1}{4} \sum_{i=1}^n G_i \quad (3)$$

$$S^2 = \frac{1}{4} \sum_{i=1}^n (G_i - \bar{G}_i)^2 \quad (4)$$

The corresponding variance values can be solved according to the above variance formula, and some of the characterized data are shown in Table.2.

Table.2. Table of variance of gravity anomalies in the gridded region

longitude	latitude	Outlier Vertex I	Outlier Vertex II	Outlier Vertex III	Outlier Vertex IV	variance (statistics)
115.0167	10.9986	60	59.3	56.1	58.1	2.9158
115.0334	10.9986	56.1	58.1	49.2	52.5	15.5025
115.05	10.9986	49.2	52.5	42.2	45.5	19.9633

2.3. Adaptation zone delineation calibration

In order to classify the variance values of the gravity anomalies into classes, C-mean cluster analysis was used, and for visualization purposes, they were divided into seven classes.

Principles of C-mean clustering

The C-mean clustering algorithm can be used for simple iterative clustering algorithms that use distance as a similarity metric so as to discover C classes in a given dataset and each class has a cluster center, i.e., a center of mass, which is obtained for each class based on the mean of all values in the class.[6] .

Based on the computational results given a dataset X of 14641 one-dimensional data points and a category K to be classified, the Euclidean distance is chosen as the similarity metric. Clustering is performed such that the sum of squares of clusters for each category is minimized, i.e., minimized:

$$J = \sum_{k=1}^K \sum_{i=1}^i \|u_i - u_k\|^2 \quad (5)$$

Euclidean distance formula:

$$d(x, z) = \|x - z\| = \sqrt{\sum_{d=1}^D (x_d - z_d)^2} \quad (6)$$

Constantly calculating the class centers and adjusting the classes of each pattern minimizes the sum of the squared distances of each pattern feature vector to the class to which it belongs.[7] .

The results of the C-mean cluster analysis section are shown in Table.3.

Table.3. C-mean clustering table

longitude	latitude	Outlier Vertex I	Outlier Vertex II	Outlier Vertex III	Outlier Vertex IV	variance (statistics)	Adaptability Calibration
115.0167	10.9986	60	59.3	56.1	58.1	2.9158	1
115.0334	10.9986	56.1	58.1	49.2	52.5	15.5025	2
115.05	10.9986	49.2	52.5	42.2	45.5	19.9633	2

According to the principle that the more accurate the navigation accuracy is when the gravity anomaly changes drastically, the results of the C-mean clustering analysis are matched for the degree of fitness, and the results are shown in Table.4.

Table.4. ANOVA cluster analysis fitness control table

variance range (statistics)	Fitness calibration results	fitness level
0-7.7866	1	low adaptation  high adaptability
7.7958-22.1500	2	
22.1533-43.9833	3	
44.0167-75.6700	4	
75.7667-121.6867	5	
122.3400-189.2333	6	
190.9092-317.1892	7	

The resulting C-mean clustering results were visualized using a heat map with latitude and longitude geographic locations as coordinates, and the visualization results are shown in Figure 1.

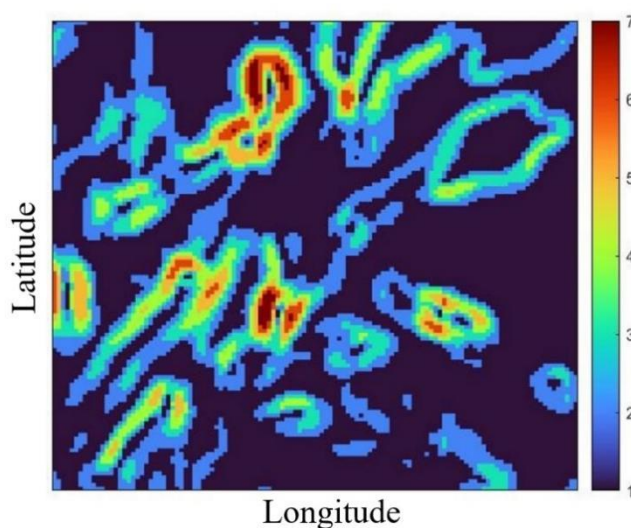


Figure 1. Calibration of the distribution of regional adaptation levels

2.4. BP neural network modeling and training

Choose BP neural network classification model, the principle is as Figure 2. The learning rule of bp neural network is to use the most rapid descent method to continuously adjust the weights and thresholds of the network through back propagation to minimize the classification error rate of the network. The BP neural network classification model has a flexible classification ability, strong nonlinear mapping ability and adaptive learning ability, which can effectively deal with a variety of classification problems, and has certain generalization ability[8] .

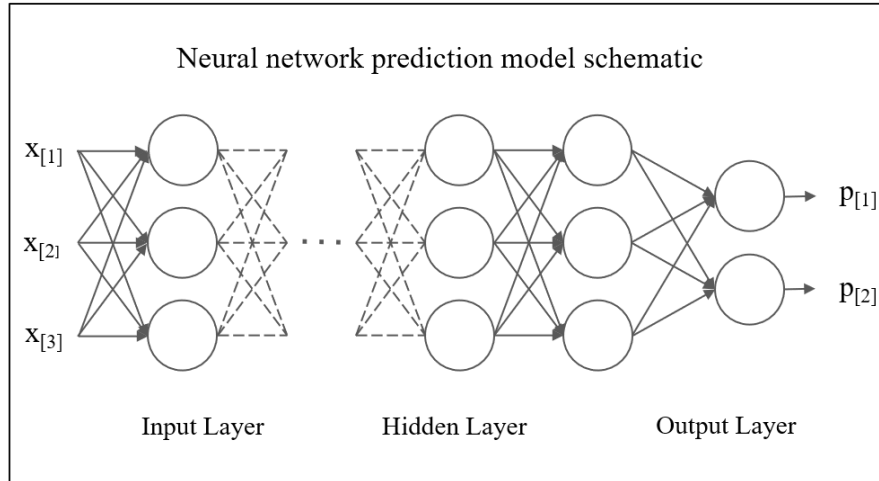


Figure 2. Neural network model schematic

The output of the implicit layer is set as F_j , the output layer's output m quantity is set to O_k , the excitation function of the system is set as G , the learning rate is set as β , then there is the following mathematical relationship between the three layers.

$$\begin{cases} F_j = G(\sum_{i=1}^m w_{ij}x_i + a_j) \\ O_k = \sum_{j=1}^l F_j w_{jk} + b_k \end{cases} \quad (7)$$

The desired output of the system is set as T_k , then the error of the system E can be expressed by the actual output value and the desired variance, the collective relationship equation is as follows.

$$E = \frac{1}{2} \sum_{k=1}^n (T_k - O_k)^2 \quad (8)$$

And let $e_k = T_k - O_k$, using the principle of gradient descent, then the update formula of the system weights and bias is as follows.

$$\begin{cases} w_{ij} = w_{ij} + \beta F_j (1 - F_j) x_i \sum_{k=1}^n w_{jk} e_k \\ w_{jk} = w_{jk} + \beta F_j e_k \end{cases} \quad (9)$$

$$\begin{cases} a_j = a_j + \beta F_j (1 - F_j) x_i \sum_{k=1}^n w_{jk} e_k \\ b_k = b_k + \beta e_k \end{cases} \quad (10)$$

The first 10,000 rows of the C-mean clustering results were used as training data and the last 4,641 rows were used as prediction data[9]. Set the structural parameters of the network as follows:

Inputnum=6, Hiddennum=7, Outputnum=1.

The input layer nodes include latitude, latitude, grid gravity anomalies, and fitness calibration results that set the parameters for network training:

Number of training sessions: 50000, Learning rate: 0.05, Minimum error of training target: 0.00065

After training, the model fitting effect is shown in Figure 3, and the relationship between the number of training times and the mean square error is shown in Figure 4, after data analysis, the fitting effect is better, and the error basically meets the demand.

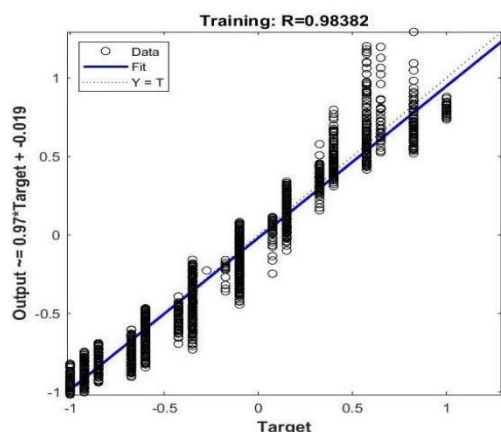


Figure 3. Training model fit

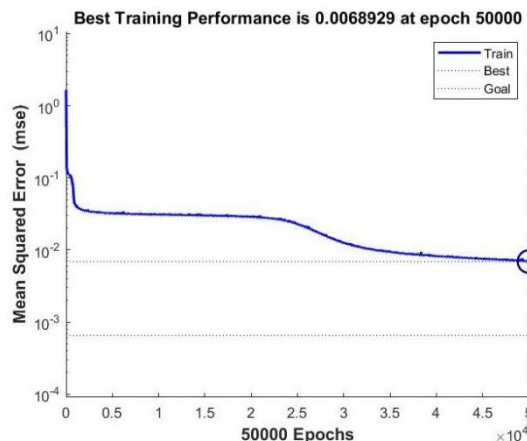


Figure 4. Plot of number of training sessions vs. mean square error

3. Underwater navigation fitness zone prediction based on BP neural network modeling

A new set of gravity anomaly data from other regions is calibrated with the above fitness zone results and the new data is fed into the BP neural network model built and trained as described above to make migration predictions for the new data from other regions[10] .

Plot of number of trainings versus mean square error for predictive model Figure 5 and number of trainings versus mean square error for model Figure 6.

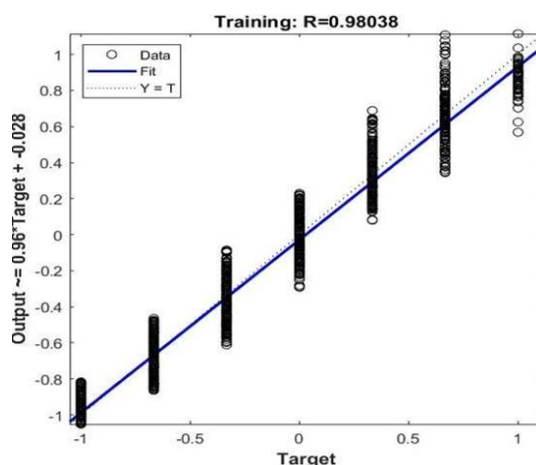


Figure 5. Plot of the number of training sessions of the prediction model versus mean square error

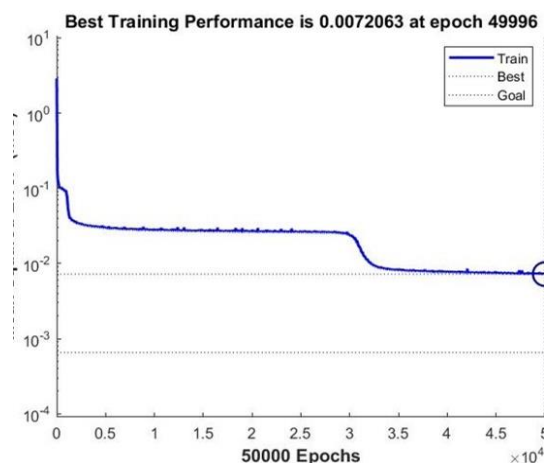


Figure 6. Plot of the number of training sessions of the prediction model versus mean square error

fitted function is:

$$\text{Output} = 0.96 * T \text{arget} - 0.028 \quad (11)$$

The fit between the training and prediction outputs is very close to a proportional function, which is a good fit. The mean square error of the prediction model is less than 10^2 after about 35,000 training sessions, and the magnitude converges after 50,000 training sessions.

Some of the calibration results predicted by the BP neural network model are shown in Table.5.

Table.5. Excerpts from predictive value calibration results

longitude	latitude	Outlier Vertex I	Outlier Vertex II	Outlier Vertex III	Outlier Vertex IV	variance (statistics)	Adaptability Calibration
113.3667	8.99625	24.7	25.7	25.5	25.1	0.196667	1
113.3834	8.99625	25.5	25.1	24.8	23.5	0.749167	1
113.4	8.99625	24.8	23.5	22.3	21.1	2.5225	2

The results of the fitness calibration of the predicted values of the BP neural network model with the derived actual values are visualized as in Figure 7 and Figure 8.

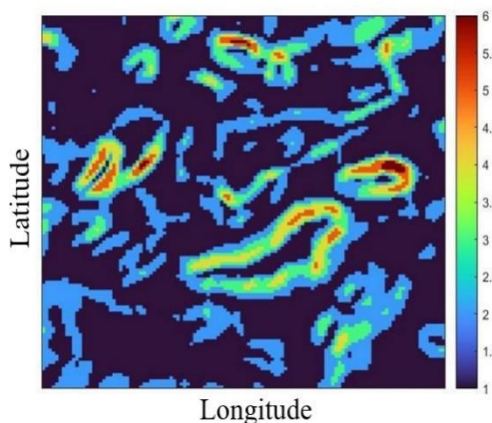


Figure 7. Distribution of predicted fit levels

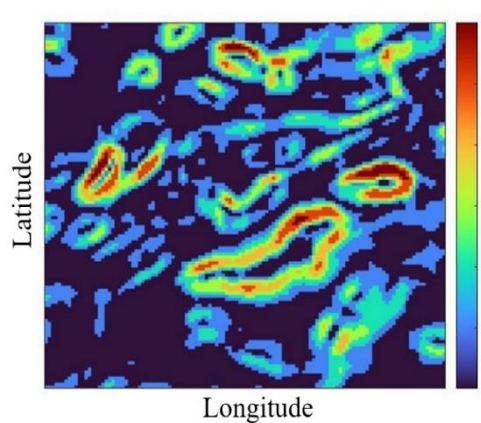


Figure 8. Actual Adaptation Level Distribution Map

By comparing the predicted and actual fitness level criterion distributions, there is a clear consistency between the contents of the two distributions, and it can be concluded that this modeling algorithm has some applicability.

The relative error between the predicted and actual values is calculated using MATLAB through the following equation, which yields the partial value of the error value between the predicted and actual values as Table.6.

$$\delta_i = \frac{|y_i - \hat{y}_i|}{y_i} \quad (12)$$

Table.6. Excerpt from the table of error values between predicted and actual values

longitude	latitude	Outlier Vertex I	Outlier Vertex II	Outlier Vertex III	Outlier Vertex IV	relative error
113.0167	8.99625	-16.4	-12.4	-18.1	-14	0.5
113.0334	8.99625	-18.1	-14	-18	-13.7	0.5
113.05	8.99625	-18	-13.7	-16.2	-11.7	0.5

Through the partial table analysis of the predicted and error values, the direct error between the predicted and actual values is small, and the prediction results are more consistent with the actual

values, which concludes that the BP neural network model has a better migration prediction performance and can be applied to the new gravity anomaly data.

4. Conclusions

In this paper, the navigation accuracy of gravity-assisted navigation is improved by delineating and calibrating the adaptation zone for underwater navigation. In the delineation of the aptitude zone, the variance value of the vertices of the grid area is selected as the delineation feature, and the fuzzy C-mean clustering is used to divide the feature value into seven classes, and the heat map of the aptitude zone is obtained by visualization. On this basis, the BP neural network model is trained to predict the division of other regions. Of course, because machine learning requires a large number of model training, the amount of data used in this study is still insufficient, and there is still a certain error between the predicted value and the actual value, and if the data sample is sufficient, the prediction accuracy of the model will be higher. In the selection of delineation features, there have been people using gradient as features and realized the application of gravity gradient navigation. In this paper, the variance of the gravity anomalies at the grid vertices is used as the dividing feature, and the machine learning method combined with the BP neural network model is used for the prediction and division of the adapted area, which is less difficult to apply and has a higher accuracy, and it can provide a new method for the improvement of the accuracy of the gravity-assisted navigation for underwater navigation.

References

- [1] Yi Aijun, Ji Ziang, Shen Tingting et al. Research on Leading the Construction of a Strong Marine Country by Scientific and Technological Innovation[J]. *Continental Bridge Perspectives*,2023(10):49-51+55.
- [2] Wang Hong. Promoting Chinese-style modernization with new action of building a strong marine country[N]. *Study Times*,2023-09-22(001).
- [3] WANG Bo, LI Tianjiao, LI Xiaoping. A review of underwater inertial/gravity gradient matching navigation[J]. *Tactical Missile Technology*,2023(04):1-12+183.
- [4] Li Fangming. Research on underwater gravity-assisted localization and gravity map navigation adaptability[D]. Harbin Engineering University,2021.
- [5] WANG Bo, ZHOU Minglong. Research progress on the selection of underwater gravity-assisted navigation adaptation zone[J]. *Journal of Navigation and Positioning*, 2020, 8(3):8.
- [6] Yu Yang. Research on the calculation method of fuzzy c-mean clustering in fuzzy cluster analysis [D]. Shenyang University of Technology [2024-03-20].
- [7] Sun Hao Cheng, Liu Li, Li Fan Chang. Li group fuzzy C-mean clustering image segmentation algorithm[J/OL]. *Journal of Software*:1-20.
- [8] Wang FF. Exploration of mechanism and application of BP neural network based algorithm[J]. *Science and Technology Innovation Herald*,2020,17(13):150-151.
- [9] LI Chao,JIANG Yule,HU Mingke et al. Research and application of cellular neural network in gravity anomaly differentiation[J]. *Computational Technology for Physical and Chemical Exploration*,2015,37(01):16-21.
- [10] ZHANG Tao,ZHANG Wenbo,GAO Dong et al. A neural network prediction model error method for geomagnetic navigation[J]. *Aerospace Control*,2024,42(01):37-42.