Regional Gravity Structure Interpretation for Mineral Resource Prognosis Using Neural Network

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Abstract

In this paper, a correlative structure model based on regional gravity information is generated using back-propagation neural network. The gravity bouguer anomalies of samples are analyzed. The result has been used to process the 1:1,000,000 gravity horizontal derivation maps of the mining areas in the East Kunlun Mountain and the system can automatically extract structure axis from gravity interpretation maps. Comparing with the existent results, our method has the advantage to process non-linear data, and the system is self-adaptive. The resulting structure of gravity bouguer anomalies using neural network is more accurate than the existent results.

Keywords: Neural network, bouguer anomaly and geological structure, feature extraction

1. Introduction

In geoscience, gravity structure extraction is based on graphic element correlation and the superposition of relevant graphic elements. The correlations between graphic elements in the same continuation-bed plane are based on horizontal relation, and the connections between the graphic elements in different continuation-bed planes are based on vertical relations. Derivative axes in different directions can be deduced based on the horizontal derivations and the interpretation of a real-world geological tectonic line. The main task is to estimate which axis represents the tectonic line [5]. For above task, some researchers manually draw lines in planar isogram maps based on experiences and domain knowledge [1][2][3][4]. The computer processes gravity data and thereby forms the isogram maps of various fields. The connections between axes can be estimated by computers using a pre-designed numerical matching algorithm [5].

However, by experiment, the results using the above method are not accurate enough. Firstly, it is unreasonable to judge the connection between two axes in terms of pre-defined threshold values. Additional parameters such as length, distance and trend must be considered as well. Secondly, the algorithm is correspondingly sensitive to the changes of distance and height values about upward continuation. Thirdly, the algorithm will become inefficient under certain conditions.

Neural network has been widely and successfully applied for pattern recognition tasks, such as in geoscience, biology, chemistry and many other fields [10][11][12][13]. Back-propagation neural

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networks have following properties: automatic learning, automatic adaptation, automatic organization; and can fit non-linear functions [6]. This paper reports the application of neural networks to improve traditional regional gravity structure interpretations for mineral resource prognosis.

This paper focuses on automatically discovering the horizontal derivative axes in all possible directions, then on recognizing the derivative axes that represent the anomalies using neural network from the chosen horizontal derivative axes after the isograms of various fields have been generated by computers.

The process of interpreting the gravity bouguer anomalies in the mining areas in the East Kunlun Mountain are reported as follows: Firstly, four horizontal derivative axes in four different directions are discovered at a certain height of the upward continuation in gravitational field. Secondly, the abnormal line is estimated according to the horizontal relation of the four axes using the back-propagation neural network model. Thirdly, the gravity abnormal zone is estimated according to the vertical relation of the abnormal lines in the continuation-bed plane in several different heights. Finally, the distribution of regional gravity structure is worked out.

2. Regional Gravity Structure Interpretation Model Using Back Propagation Neural Network

Based on back-propagation neural network model [6], a three-layer regional gravity structure interpretation model is developed. It is used to estimate the connections between lines. The model consists of eight inputs, sixteen hidden neurons and one output.

2.1. Input Layer

Input neurons are selected according the characteristics of sample remote sensing data. The following eight inputs are used in this model. The unification of the inputs is required.

− Input 1 (EP_1): the ratio between the effective points of curve L_1 relative to curve L_2 to all points.

Definition: Given a point D on curve L_1 and a curve L_2, and L_2 is composed of n discrete points $d_{[0]}, d_{[1]}, \ldots d_{[n-1]}$.

If the normal distance from the point D to all line segments through $d_{[i]}$ and $d_{[i+1]}$, (n=0,1,⋯,n-1) is exist, the point D is a valid point to L_2.

Then

$$EP_1 = N_{1L_2} / N \quad (1)$$

Where N_{1L_2} is the number of valid points to curve L_2 on curve L_1. N is the total point number on L_1.

Node EP_1 reflects the similarity of curve L_1 and curve L_2.

− Input 2 (S_1): the average distance from the effective points of curve L_1 relative to curve L_2 to curve L_2.

Given a point D and a curve L, and L is composed of n discrete points, $d_{[0]}, d_{[1]}, \ldots d_{[n-1]}$, then the distance from D to $d_{[i]}$ is S_i, where i=0,1,…,n-1; the normal distance from D to line segment through $d_{[i-1]}$ and $d_{[i]}$ is as follows:

$$li = \begin{cases} ND_i & \text{Normal distance exists} \\ \infty & \text{otherwise} \end{cases} \quad (2)$$

Where ND_i is the normal distance from D to line through $d_{[i-1]}$ and $d_{[i]}$.

Then the distance from point D to curve L is $S(D,L) = \min(S_0, S_1 \cdots, S_{n-1}, L_1, L_2, \cdots, L_{n-1})$.

But the two curves offset distance is determined by the normal distance. Therefore we only take the valid points on L_1 to L_2. In addition, the value needs normalization.

Therefore,

$$S1 = arctg \left(\sum_{1}^{N_{1L2}} S_{(D_i, L_2)} \Big/ N_{1L2} \right) \quad (3)$$

Node S_1 has approximately reflected offset distance between two curves.

− Input 3 ($len1$): the length of curve L_1 after unification. If L_1 is composed of n discrete points $d_{[0]}, d_{[1]}, \ldots d_{[n-1]}$, $len_{[i+1]}$ is the length of line segment through d[i] and $d_{[i+1]}$ respectively, $(i = 0, 1, \cdots, n-1)$. Then

$$len1 = arctg \left(\sum_{1}^{n-1} len[i] \right) \Big/ \frac{\pi}{2} \quad (4)$$

− Input 4 ($Sl1$): the trend of curve L_1.
If L_1 is composed of n discrete points $d_{[0]}$, $d_{[1]} \ldots d_{[n-1]}$, $Sl[i]$ is the slope angle of line segment through $d_{[i]}$ and $d_{[i+1]}$. $(Sl[i] \in [0, 2\pi], i = 0, 1, \cdots, n-1)$. Then

$$Sl1 = \frac{\sum_{1}^{n-1} Sl[i] \Big/ n-1}{2\pi} \quad (5)$$

− Input 5 (EP_2): the ratio between the effective points of curve L_2 relative to curve L_1 to all points. It can be can calculated by formula (1).

− Input 6 (S_2): the average distance from the effective points of curve L_2 relative to curve L_1 to curve L_1. S_2 can be can be calculated by formula (3).

− Input 7 ($len2$): the length of curve L_2 after unification. It can be calculated by formula (4).

− Input 8 ($Sl2$): the trend of curve L_2. It can be calculated by formula (5).

2.2. Hidden Layer

In a back-propagation neural network, appropriate quantity of hidden neurons is important for system efficiency. It is difficult to solve the non-linear mapping problem if there are insufficient hidden neurons. Extra neurons result in slow convergence. In this model, single hidden layer is used. According to the experiments, sixteen hidden neurons are employed in the model.

2.3. Output Layer

Only one exclusive output is used with value 1 (related) or 0 (not related).

2.4. Learning Samples

Measurement data of gravity bouguer anomalies about the mining areas in the East Kunlun Mountain were adopted as sample data. The training was performed using the data of axial map and second order isogram map, which are obtained by means of the derivations in the following horizontal directions: 0° , 45° , 90° , 135° at the first, second, third and fourth upward continuation layers.

2.5. The Improvement in Training

The original back-propagation neural network has a disadvantage of slow convergence. Some algorithms, such as gradient self-adaptive algorithm and conjugate self-adaptive algorithm, have been developed to improve efficiency by altering the direction and step length [7][8][9]. Gradient self-adaptive algorithm adjusts learning rate through evaluation function. It efficiently speeds up the convergence in situation with gentle error surface. Conjugate self-adaptive algorithm adjusts learning rate using the conjugate direction method. It efficiently speeds up the convergence in shape of can-yon error surface. However, the usage of single algorithm leads to strong oscillation of error curves.
In this paper, the two algorithms are merged into “conjugate gradient self-

adaptive algorithm”. Different weighting revision methods and learning rate adjusting methods are used to merge gradient self-adaptive algorithm and conjugate self-adaptive algorithm. Due to space limitation, the details are omitted.
As shown in the table below, the method using conjugate gradient self-adaptive algorithm is the most efficient one. 120 sample data were used for the experiment. The accuracy level was set at 0.0001. The number of learning times using conjugate gradient self-adaptive algorithm was three times less than the other two methods.

Table 1. Comparison of different algorithms

Algorithm	Accuracy	Times of Learning (Number of Samples: 120)
Gradient self-adaptive	0.0001	1,389
Conjugate self-adaptive	0.0001	1,167
Conjugate gradient self-adaptive	0.0001	447

3. Case Study

Firstly, 1:1,000,000 gravity bouguer anomalies of mining areas in the East Kunlun Mountain were computed using multivariate statistics. Upward continuation and horizontal directional derivations were then computed to generate isogram maps. The manual interpretation of the isogram maps is shown in Fig. 1.

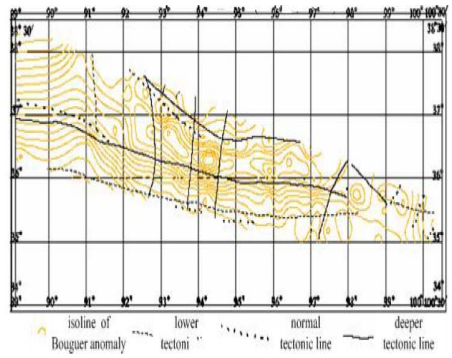

Fig.1. Gravity structure with bouguer anomalies of the mining areas in the East Kunlun Mountain using traditional method (1:1,000,000)

Secondly, the experiments were conducted using our back-propagation neural net-work model. The gravity and magnetic interpretation module of the model was used to interpret the isogram maps. The result is shown in Fig. 2.

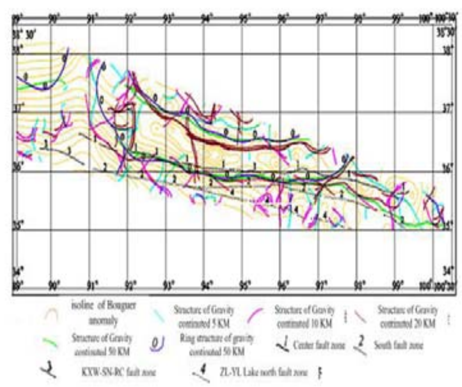

Fig.2. Gravity structure with bouguer anomalies of the mining areas in the East Kunlun Mountain using back-propagation neural network model (1:1,000,000)

Comparing Fig.2 with Fig.1, we have following conclusions:
− In Fig.1, the gravity tectonic lines are too simple to discover all possible gravity tectonic lines. Many gravity anomaly isograms in concentration area (gradi-ent zone) cannot be found. For instance, in

Fig.2, there is a gravity tectonic line from (east longitude 94°, north latitude 36° 35') to (east longitude 96°, north latitude 36° 30'). But the line is not shown in Fig.1.

− In Fig.2, the gravity tectonic lines, generated using back-propagation neural network model, match the gravity bouguer anomaly isograms very well. Fig.2 clearly illustrates the gravity distribution regulation.

Fig.2 shows that the gravity tectonic lines are accurately interpreted. It clearly shows the distribution of anomalies in several different depths.

4. Conclusion

In this paper, a connection structure model based on regional gravity information is generated using back-propagation neural network. We have compared with traditional methods through experiments. That regional gravity structure interpretation using back propagation neural network can produce accurate results. The neural network system can embody following characteristics: automatic learning, automatic adaptation, automatic organization, and non-linear function fitting. Using Neural Network, we need not worry the threshold value problem. In addition, the accuracy and the efficiency have been improved. The time to interpret regional gravity structure has been decreased from over ten days to several minutes. The regional gravity structure interpretation software based on MAPGIS using our method has been developed and used at several provinces in China. It becomes one of the best regional gravity structure interpretation tools.

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