

Research Article

Using MATLAB to achieve improved BP neural network model of remote sensing image classification

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Abstract: Application of improved BP neural network (NN) model to research the ETM + remote sensing (RS) data classification. Select six of LANDSAT 7 ETM + multi-spectral bands as the data source, through read the six ETM image respectively in each pixel's gray value, construct a six - dimensional input sample of the sample space: $V_i = \{V_{i1}, V_{i2}, V_{i3}, V_{i4}, V_{i5}, V_{i6}\}$. Through the experiment, ETM1, ETM3, ETM5, ETM7 was determined four wave bands as the input layer (the number of input layer neurons $M = 4$), and the geological object was divided into five categories (the number of output neurons $N = 5$), the optimal improved BP NN structure for the three-layers BP network, the number of the hidden layer nodes is 24, the input layer node number is 4, the output layer nodes is 5, excitation function for the S-type logarithmic function. The optimal network training parameters : the initial weights is 0.1, the learning rate is 0.9 , increasing rate of learning speed is 1.0 , decreasing rate of learning speed is 0.05 , the momentum factor is 0.001 , the network 's global error is 0.01 .Network model after 2000 times or less training, to achieve convergence. The model was applied to RS images of Mulei County of Xinjiang carry out geology type classification, the total classification precision reaches 89.06%, rapid classification quality is good, meet the production quality requirements.

Keywords: RS image; Improved BP model; Classification

1. Introduction

With the rapid development of computer technology and RS professional image processing software continuously upgrade perfect, the RS image processing and the thematic information getting become very easy. RS technology could provide more and more exact RS prospecting anomaly information for geological prospecting to rapid implement information classification, enhance the work efficiency and reduce the geological exploration risk¹. Geological workers can according to the understanding of the geological background, knowledge of metallogenic regularities and in a targeted manner to obtain a thematic RS information.

This paper selects U.S. terrestrial satellite LANDSAT-7 (number) RS image, combined with ERDAS software , pre-processing of RS image , the use of resources satellite LANDSAT- ETM data and Matlab programming language ability to deal with large amounts of data, using MATLAB to achieve improved BP NN for RS image classification, the application of artificial NN in RS image classification , establish suitable for fast classification process in a given area, to serve the land and resources , to improve the level of information .

2. Design improved BP NN

2.1 RS image preprocessing

In this study, Various pretreatment of RS images in the study area, including image cropping, image correction, color composite, principal component transformation, normalized data processing , data preparation for classification work well . Select six of LANDSAT- 7 ETM + bands: ETM1, ETM2, ETM3, ETM4, ETM5, ETM7. Through read the six ETM image respectively in each pixel's gray value, construct a six - dimensional input sample of the sample space: $V_i = \{V_{i1}, V_{i2}, V_{i3}, V_{i4}, V_{i5}, V_{i6}\}$. Start ERDAS IMAGINE, open the classification image, according to the different features in different bands of reflectance is different; choose the corresponding samples, each geological object selection of 100 samples. There are five kinds of geological objects, a total sample of 500, 300 of which as the training sample, 200 as test samples.

2.2 Construction of Improved BP NN

From ETM bands selected four bands as input layer neurons ($M = 4$), and then, according to the spectral correlation, choose the corresponding band data as input, the network input vector is

$P_M = (a_1, a_2 \dots, a_n)$. Due to the geological object is divided into five categories, so the output of the network neurons number $N = 5$, that is the geological object 1 is 10000, the geological object 2 is 01000, the geological object 3 is 00100, the geological object 4 is 00010, the geological object 5 is 00001.

After several tests, summed up the optimal improved BP NN structure for the three-layers BP network, the number of the hidden layer nodes is 24, the input layer node number is 4, the output layer nodes is 5, excitation function for the S-type logarithmic function. The optimal network training parameters: the initial weights is 0.1, the learning rate is 0.9, increasing rate of learning speed is 1.0, decreasing rate of learning speed is 0.05, the momentum factor is 0.001, the network's global error is 0.01.

In this under the control of the network structure and training parameters, the improved BP NN after

2000 or less training, network model to achieve convergence, can achieve good classification results.

3. Improved BP NN training process and procedures to achieve

The BP NN implementation procedure is as follows:

%A total of 300 of input training data, each type of sample 60, and normalization of the training data, the data is normalized to 0 to 1.

for i=1:4

$$P(i,:)=\frac{P(i,:)-\min(P(i,:))}{(\max(P(i,:))-\min(P(i,:)))}$$

end

In addition, considering the output layer excitation function value in the range of (0, 1), in order to speed up the convergence rate of the network, define the expectations output of training samples is shown in Table 1.

Table-1: Expectation output of training samples

Output Node Type	1	2	3	4	5
geological object 1	1	0	0	0	0
geological object 2	0	1	0	0	0
geological object 3	0	0	1	0	0
geological object 4	0	0	0	1	0
geological object 5	0	0	0	0	1

```
%The BP NN model and set the relevant parameters
net=newff(minmax(P),[24,5],{'tansig','logsig'},'traingdx','learnqdm','mse');
net.trainParam.show=100; % refurbishing the training figure after 100 times training
net.TrainParam.epochs=2000; % training times
net.TrainParam.goal=0.01 % target presenting the end of training
net.TrainParam.mc=0.001; % momentum factor
net.TrainParam.lr=0.9; % basic value of learning speed
net.TrainParam.lr_inc=1.0; % increasing rate of learning speed
net.TrainParam.lr_dec=0.05; % decreasing rate of learning speed
% Training the BP NN, error sum of squares curve is seen in Figure 1.
```

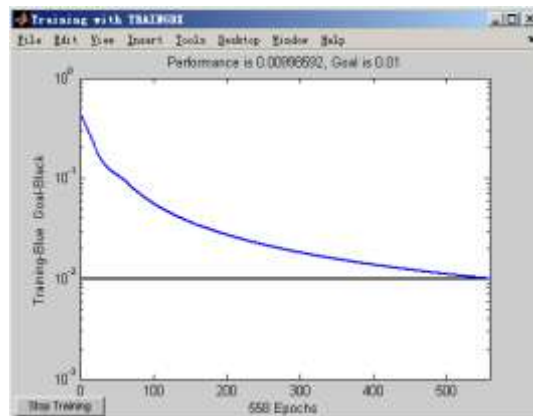


Fig-1: Error sum of squares curve

```
net=train(net,P,T)
```

After the codes run, the training state of the network will be displayed real time as follows:

```

TRAINIDX, Epoch 0/2000, MSE 0.441636/0.01, Gradient 0.106047/1e-006
TRAINIDX, Epoch 100/2000, MSE 0.0564091/0.01, Gradient 0.0258736/1e-006
TRAINIDX, Epoch 200/2000, MSE 0.0273646/0.01, Gradient 0.0124348/1e-006
TRAINIDX, Epoch 300/2000, MSE 0.0182401/0.01, Gradient 0.00813699/1e-006
TRAINIDX, Epoch 400/2000, MSE 0.0137801/0.01, Gradient 0.00609211/1e-006
TRAINIDX, Epoch 500/2000, MSE 0.0110986/0.01, Gradient 0.00488183/1e-006
TRAINIDX, Epoch 558/2000, MSE 0.00998592/0.01, Gradient 0.00435737/1e-006
TRAINIDX, Performance goal met.
% Output trained weights and thresholds
inputWeights=net.IW{1,1}
inputbias=net.b{1}
layerWeights=net.LW{2,1}
layerbias=net.b{2}
Y=sim(net,P) % simulated training data
error=Y-T % testing the errors of the simulation data
res=norm(error)
    
```

After initialization, use the function `traingdx` to 558 times after the training of network, network error sum of squares has reached the target requirement, `res=1.043`. Training process, the error sum of squares curve is seen in Figure 1. As can be seen from the

curve, error sum of squares gradually decreases as the number of training, until it reaches the required expectations error, stopped training. After training the threshold of each neuron of the output layer is seen in.

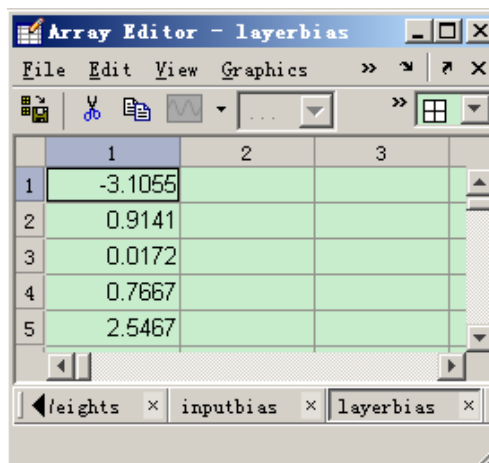


Fig-2: After training the threshold of each neuron of the output layer

4. The BP NN evaluation model

To test the correctness of the model, select the test in the test data, the test data of 25, and each sample of 5, as shown in table 2.

Input test data (see table 2), and normalized test data, the data normalization to 0 ~ 1, the simulation test data, the results are shown in table 3.

From table 3 shows that the actual output and desired output error of the model is very small,

predicted results almost entirely consistent with actual situation, and intuitive conclusion.

It is important to note that judge the stand or fall of network model generalization ability, primarily not to see the size of test sample error itself, but depends on whether the error of the test sample is close to the error of the training samples. `Res=1.005`, based on improved BP NN in RS image classification is feasible.

Table-2: Test data and category table

Type	TM1	TM2	TM3	TM4	TM5	TM7	Category
geological object 1-A1	89	73	74	35	74	75	10000
A2	88	67	68	33	72	74	10000
A3	86	71	73	35	80	77	10000
A4	84	68	70	33	71	72	10000
A5	83	67	69	31	68	70	10000
geological object 2-B1	75	59	61	30	55	51	01000
B2	80	61	59	27	49	45	01000
B3	85	63	67	33	51	45	01000
B4	86	66	62	30	45	36	01000
B5	82	63	64	28	45	42	01000
geological object 3-C1	85	65	73	37	94	99	00100
C2	87	73	81	40	96	91	00100
C3	88	75	85	41	103	101	00100
C4	84	68	73	39	92	96	00100
C5	90	77	83	37	98	89	00100
geological object 4-D1	100	85	93	43	90	88	00010
D2	105	92	102	44	95	87	00010
D3	102	85	88	42	90	81	00010
D4	105	89	96	43	82	81	00010
D5	106	88	93	41	81	76	00010
geological object 5-E1	122	110	120	53	90	81	00001
E2	115	100	113	52	82	74	00001
E3	118	104	113	52	79	70	00001
E4	112	97	104	48	79	71	00001
E5	121	113	129	59	95	86	00001

Table-3: The simulation results of the test data

Type	Predicted results	Actual results
geological object 1-A1	(0.9722 0.0362 0.0047 0.0081 0.0026) → (10000)	10000
A2	(0.9835 0.0008 0.0467 0.1073 0.0019) → (10000)	10000
A3	(0.9212 0.2871 0.0051 0.0032 0.0013) → (10000)	10000
A4	(0.9449 0.2713 0.0041 0.0021 0.0009) → (10000)	10000
A5	(0.9847 0.3367 0.1155 0.0013 0.0004) → (10000)	10000
geological object 2-B1	(0.0674 0.97755 0.0017 0.0016 0.0013) → (10000)	10000
B2	(0.0499 0.9720 0.0008 0.0039 0.0035) → (01000)	01000
B3	(0.0057 0.9985 0.0002 0.0179 0.0058) → (01000)	01000
B4	(0.0249 0.9924 0.0008 0.0035 0.0023) → (01000)	01000
B5	(0.0354 0.9654 0.0001 0.0584 0.0193) → (01000)	01000
geological object 3-C1	(0.0289 0.0004 0.9874 0.0231 0.0019) → (00100)	00100
C2	(0.0675 0.0003 0.9845 0.0144 0.0015) → (00100)	00100
C3	(0.0212 0.0004 0.9576 0.0013 0.0011) → (00100)	00100
C4	(0.0311 0.0004 0.9566 0.0019 0.0021) → (00100)	00100
C5	(0.0310 0.0003 0.9764 0.0061 0.0018) → (00100)	00100
geological object 4-D1	(0.0075 0.0004 0.0051 0.9836 0.0032) → (00010)	00010
D2	(0.0016 0.0006 0.0092 0.9428 0.0021) → (00010)	00010
D3	(0.0094 0.0006 0.0079 0.9257 0.0095) → (00010)	00010
D4	(0.0062 0.0004 0.0034 0.9688 0.0033) → (00010)	00010
D5	(0.0113 0.0002 0.0010 0.9458 0.0015) → (00010)	00010
geological object 5-E1	(0.0014 0.0032 0.0086 0.0056 0.9976) → (00001)	00001
E2	(0.0008 0.0032 0.0030 0.0045 0.9745) → (00001)	00001
E3	(0.0013 0.0043 0.0018 0.0022 0.9871) → (00001)	00001
E4	(0.0030 0.0044 0.0014 0.0034 0.9547) → (00001)	00001
E5	(0.0019 0.0036 0.0028 0.0018 0.9990) → (00001)	00001

CONCLUSION

The improved BP NN and the RS images of Mulei County of Xinjiang carry out geology type classification, the total classification precision reaches 89.06%, and the Kappa coefficient is 85.53%, and indicating that the classification quality is good. NN classification of RS data advantages: without data statistical distribution of prior knowledge, high degree of parallelism, highly nonlinear global role, good fault tolerance and associative memory function, and very strong adaptive self-learning capability. These features are worth our further in the field of RS classification to reasonable use, in order to further improve the precision of RS image classification, in order to meet our production and living needs.

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