AUTO-IDENTIFICATION OF FOREST FIRE-POINTS
IN NOAA IMAGES BASED ON NEURAL NETWORK

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KEY WORDS  forest fire-point; auto-identification; neural network; NOAA images

ABSTRACT  Identification of forest fire-points in NOAA images is the basis of monitoring forest fire using NOAA satellite data. Traditional visual interpretation is difficult to settle for auto-identification with computer. The artificial neural network technique provides a new means for solving this problem. In this paper, the principles and method of using neural network technique to automatically identify fire-points in NOAA images are discussed and the test in the range of Hubei province is presented. The result of the test shows that the disciplined neural network has collected the character of fire-points and has ability to identify fire-points in NOAA images. Comparing neural network with visual interpretation, the conclusion is drawn that by using neural network the purpose of auto-identification of forest fire-points in NOAA images can be realized with the almost same precision.

1 Introduction

The identification of forest fire-points in NOAA images is the basis of monitoring forest fire using NOAA satellite data. The traditional approach of identification is visual interpretation. By the visual interpretation, better precision is obtained in practice, but experienced interpreters are needed and it is difficult to settle for auto-identification with computer, so there is always unfavorableness in the description of information distribution and the improvement of efficiency. In order to find out the forest fire in time and eradicate it quickly, it is very significant to make the fire-points auto-identified without making the precision digressive. Some researchers in remote sensing have done the work, for example, Yuan Fei and Li Yajun[1] used threshold method to identify fire-points, but the threshold is manually established. Qin Xianlin[2], et al built the model by using multivariate analysis for identifying small fire-points automatically, but the precision is not so high.

The artificial neural network theory (for short NN) developing rapidly in recent years provides a new means for solving this problem. Because the artificial intelligence technique imitating the neural network of life form, NN has the basal characters of human brains, such as learning, recollecting and generalizing. The peculiarity of NN is massive parallel computing, distributive memory of information, nonlinear dynamics of consecutive time, global behaviour, fault-tolerance and robust, self-organization, self-learning and real time processing. Due to these accounts, NN has been widely applied at pattern identification, signal processing, automation and classification of remote sensing images[3,4]. Thus far many kinds of NN model and their corresponding learning algorithms have been developed,
and back propagation (for short BP) NN is widely used. In this paper, the principles and method of using BP model to automatically identify fire-points in NOAA images are discussed and the test in the range of Hubei province is presented.

2 Basic principles and techniques

2.1 The basic principles of BP NN

In the 1980s, Rumehart, Webb, et al established back propagation learning algorithm, which aims at the feed-forward NN, which is the typical representation of multi-layers sensing machine. The BP model in common use contains three layers of neurons, which are the input layer at the bottom, the hidden layer in the middle and the output layer at the top respectively. Every neuron (also called node or unit) is connected with all the ones in the immediate layer by the coefficients of weights and thresholds, but it is not connected with others in the same layer (shown in Fig. 1).

![Fig. 1 The topology of BP NN model](image)

The mathematical model of BP NN is

\[ \hat{C} = f(\overline{WB} + \hat{b}_1) \]  
\[ \hat{B} = f(\overline{VA} + \hat{b}_2) \]

where \( \overline{A} \), \( \overline{B} \) and \( \hat{C} \) are respectively the vectors of the input layer, the hidden layer and the output layer, \( \overline{V} \) and \( \hat{b}_1 \) are respectively between the hidden layer and the output layer, \( \overline{W} \) and \( \hat{b}_2 \) are respectively interconnecting weights and thresholds between the input layer and the hidden layer, and is the active function of BP NN. S-shape function are adopted as:

\[ f(x) = \frac{1}{1 + e^{-x}} \]

By learning and training some samples and continually adjusting the interconnecting weights and thresholds of all the nodes, the non-linear relationship between the input and output of the samples is obtained. The cost function (also called energetic function) is introduced into BP NN,

\[ E = \frac{1}{2} \sum (\hat{C} - \hat{C}_0)^2 \]

where \( \hat{C}_0 \) is the expected output vector. The relation between the input and the output is established in the process of minimizing the cost function in BP NN. The basic principle is that if the expected output cannot be obtained when the forward propagation is executed using the existed weights and thresholds, the back propagation learning is adopted. The cost function is gradually reduced in revising repeatedly the weights and thresholds until it meets the predetermined requirements, that is, until it is the positive number which is small enough or it no longer reduces but repeatedly oscillates. In this way the training for BP NN is finished and the relation between the input and the output is established.

As some literature [5] states, if the nodes of the hidden layer can be unconditionally designed to meet the need, the three-layer BP NN can approach any precision of any continuous function.

2.2 The algorithm of BP NN

Suppose a BP NN has \( n \) nodes in the input layer, \( p \) nodes in the hidden layer and \( q \) nodes in the output layer respectively, and \( m \) is the number of sample model pairs \((A^k, C^k)\) where \( A^k \) and \( C^k (k = 1, 2, \cdots, m) \) are the input and the output respectively in the \( k \)th pair, then the steps of the algorithm of the BP NN are as follows:

1) The weight \( w_{hi} (h = 1, 2, \cdots, n; i = 1, 2, \cdots, p) \) from the nodes of the input layer to the ones of the hidden layer, the weight \( w_{ij} (i = 1, 2, \cdots, p; j = 1, 2, \cdots, q) \) from the nodes of the hidden layer to the ones of the output layer, the threshold \( b_i \) of the nodes of the hidden layer and the threshold \( r_j \) of the output layer are randomly given respectively. In general, the random numbers should be in the range from -1 to 1.

2) The pairs \((A^k, C^k) (k = 1, 2, \cdots, m)\) are dealt with according to the following moves.
Deliver $A^k$ into the nodes of the input layer and calculate the activated values of the nodes of hidden layer

$$b_i = f \left( \sum_{h=1}^{n} \alpha_{hk} A^k_h + \theta_i \right)$$

where $A^k_h$ is the input of the $h$th node of the input layer, $i = 1, 2, \cdots, p$, and $f$ is the same $S$-shape function as Eq. (3); 

② Calculate the activated values of the nodes of the output layer

$$c_j = f \left( \sum_{i=1}^{p} w_{ij} b_i + r_j \right)$$

where $j = 1, 2, \cdots, q$;

③ Calculate the common errors of the nodes of the output layer

$$d_j = c_j (1 - c_j) (\epsilon_j - c_j)$$

where $j = 1, 2, \cdots, q$, and $\epsilon_j$ is the expected output of the $j$th node of the output layer;

④ Calculate the errors of the nodes of hidden layer to every $d_j$

$$e_i = b_i (1 - b_i) \sum_{j=1}^{q} w_{ij} d_j$$

where $i = 1, 2, \cdots, p$. It can also express that the error of the output layer is back propagated to the hidden layer;

⑤ Adjust the interconnected weights from the hidden layer to the output layer

$$\Delta w_{ij} = \lambda h d_j$$

where $i = 1, 2, \cdots, p, j = 1, 2, \cdots, q$, and $\lambda$ is the learning rate ($0 < \lambda < 1$);

⑥ Adjust the interconnect weights from the input layer to the hidden layer

$$\Delta v_{hi} = \beta \delta_i$$

where $h = 1, 2, \cdots, n, i = 1, 2, \cdots, p$, and $\beta$ is the learning rate ($0 < \beta < 1$);

⑦ Adjust the thresholds from the hidden layer to the output layer

$$\Delta r_j = \lambda d_j$$

where $j = 1, 2, \cdots, q$;

⑧ Adjust the thresholds from the input layer to the hidden layer

$$\Delta \theta_i = \beta e_i$$

where $i = 1, 2, \cdots, p$.

3) Repeat Step 2) until the cost function

$$E = \frac{1}{2} \sum_{i=1}^{p} \sum_{j=1}^{q} (c_j - \epsilon_j)^2$$

becomes small enough or zero.

3 The selection of character of fire-points

In this paper, the NOAA/AVHRR data from 1994 to 1999 received by Wuhan Central Meteorological Observatory are used, in addition, the data of geographic contour and forest distribution in Hubei province at the scale of 1:1 000 000 from National Lab for Information Engineering in Surveying, Mapping and Remote Sensing. According to the daily record of monitoring forest fire by remote sensing, 43 NOAA images with fire-points are selected and 31 of them are regarded as training sets, the others as tested sets.

There is a variable called the contiguous temperature difference. It is defined as the difference in the third channel between the temperature of some image pixel and the average temperature of the background pixels around it. Its formula is

$$\Delta T = T - \overline{T}$$

where $T$ is the temperature of the pixel in the third channel, and $\overline{T}$ is the average temperature of the $5 \times 5$ pixels around it in the same channel.

According to the primal character of fire-points and the experience, a fire-point is correlative with 8 character factors, that is, the radiation-values of the 5 channels of NOAA/AVHRR, the altitude, the forest distribution and the contiguous temperature difference. The reasons are:

1) When the forest fire happens, the temperature in the third channel rises up obviously and the temperature in the 4th and the 5th channels also change in some degree. At the same time, in the third channel the temperature of the fire-point is higher than the temperature of the background.

2) The albedo in the first and the second channels can reflect the vegetation index of the forest.

3) The forest distribution and the altitude can respectively show the variety of vegetation and landforms and terrain in the forest.
4 The establishment of BP model

4.1 The design of BP model

The substance of fire-points identification is to classify the pixels of NOAA images into two types, fire-points and non-fire-points, which are used as the output of BP model by the form of (1, 0) and (0, 1). The eight factors of fire-points are used as the input of BP model. According to the methods for designing BP NN, the topology of the BP model in this paper is (8, 10, 2), viz., which means that the input layer has 8 nodes, the hidden layer 10 and the output layer 2. In the model the learning rate is selected as $\lambda = \beta = 0.1$ and the cost function is selected as $E = 0.025$.

4.2 The collecting of training samples

In order to expedite the convergence of BP NN, the factors of the all pixels in the NOAA images should be normalized, and the formula is

$$S = (X - X_{\min})/(X_{\max} - X_{\min})$$

where $X_{\max}$ and $X_{\min}$ are the maximum and the minimum of a factor, respectively, $X$ is the initial value of it, and $S$ is its value after normalization.

In the training sets, all the pixels with forest fire are selected as the training samples of fire-points, and some representative pixels without forest fire as the training samples of non-fire-points (the representative pixels refer to different kinds of pixels, such as cloud, water, land etc.), then the corresponding factors (normalized) of them are collected. In this paper, the fire-point samples are 189, and the non-fire-point samples are 205.

4.3 The training of BP model

Regarding the factors of the samples as the input of the BP model and the corresponding type of them as the output, repeatedly train the model. It shows that in course of the training, $E$ reduces stage by stage. When iteration is done 2 656 times, and $E$ is smaller than 0.025, the training is finished. Table 1 gives the expected output forms of 20 samples and the real output forms of them. It illustrates that the disciplined model has memorized the basic character of fire-point and non-fire-points and has ability to identify fire-points in NOAA images.

| No. | Real output | Expected output | Type      | Result |
|-----|-------------|-----------------|-----------|--------|
| 1   | 0.993 457   | 0.100 428       | 1 0       | Fire-point | True  |
| 2   | 0.999 992   | 0.000 009       | 1 0       | Fire-point | True  |
| 3   | 0.721 624   | 0.379 415       | 1 0       | Fire-point | True  |
| 4   | 0.834 271   | 0.180 066       | 1 0       | Fire-point | True  |
| 5   | 0.956 110   | 0.010 618       | 1 0       | Fire-point | True  |
| 6   | 0.827 878   | 0.120 034       | 1 0       | Fire-point | True  |
| 7   | 0.991 881   | 0.001 176       | 1 0       | Fire-point | True  |
| 8   | 0.580 933   | 0.468 565       | 1 0       | Fire-point | True  |
| 9   | 0.470 579   | 0.592 350       | 1 0       | Fire-point | True  |
| 10  | 0.779 032   | 0.278 803       | 1 0       | Fire-point | True  |
| 11  | 0.010 209   | 0.991 532       | 0 1       | Non-fire-point | True  |
| 12  | 0.216 833   | 0.803 346       | 0 1       | Non-fire-point | True  |
| 13  | 0.009 832   | 0.991 507       | 0 1       | Non-fire-point | True  |
| 14  | 0.400 789   | 0.700 533       | 0 1       | Non-fire-point | True  |
| 15  | 0.612 356   | 0.378 289       | 0 1       | Non-fire-point | False |
| 16  | 0.181 819   | 0.814 449       | 0 1       | Non-fire-point | True  |
| 17  | 0.167 404   | 0.833 074       | 0 1       | Non-fire-point | True  |
| 18  | 0.237 702   | 0.786 625       | 0 1       | Non-fire-point | True  |
| 19  | 0.000 809   | 0.999 863       | 0 1       | Non-fire-point | True  |
| 20  | 0.327 223   | 0.676 649       | 0 1       | Non-fire-point | True  |

4.4 Analysis on the precision

Input the factors of every pixel in tested sets into the disciplined model and according to the output judge whether it's a fire-point or not. This is the test process of the identification of forest fire-points in NOAA images.
In order to test the precision of the identification by NN, the visual interpretation is also used to do the identification in the test sets. The confounding matrix of the identification results by the contrasting two different methods is obtained, as Table 2 shows. In Table 2, the types in the first file show the real situation, the types in the first row show the judged situation, and the numbers outside and inside the brackets are the results of NN and of visual interpretation, respectively. According to Table 2, the identification precision can be calculated (The number of the pixels judged rightly and divided by the number of the total pixels is the precision). The precision of the NN is 92.4% which approaches 93.7%, the precision of the visual interpretation. Therefore it indicates that the rates judged falsely by the two methods are very small.

| Type         | Fire-point | Non-fire-Point | Number of total pixels |
|--------------|------------|----------------|------------------------|
| Fire-point   | 73(74)     | 6(5)           | 79                     |
| Non-fire-point| 4(6)       | 3 145 645(3 145 643) | 3 145 649               |

5 Conclusion

All of the above discussions show that NN can be used to identify forest fire-points in NOAA images with the almost same precision as the one of visual interpretation, and what is the most important is that NN realizes the purpose of auto-identification of forest fire-points. Therefore, after a new NOAA image has been received, as long as the corresponding the factors of the pixels of the image are input into a trained NN model, the forest fire-points can be quickly identified so that the efficiency of monitoring forest fire by remote sensing is greatly promoted.

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