Front. For. China 2009, 4(3): 363–367
DOI 10.1007/s11461-009-0054-y

RESEARCH ARTICLE

Yongjun SHI, Xiaojun XU, Huaqiang DU, Guomo ZHOU, Wei JIN, Yufeng ZHOU

Remote sensing monitoring of a bamboo forest based on BP neural network

Abstract The collection of information on bamboo forests plays a crucial role in the calculation of carbon content reserves, and the acquisition of high-precision information will be good for reducing estimation errors. High precision is obtained with the adoption of a back propagation (BP) neural network to extract information on bamboo forests from Enhanced Thematic Mapper + (ETM +) remote sensing images with the assistance of neural network modules provided by Matlab. We obtained a production precision of 84.04% and a user precision of 98.75%. We also conducted a comparison of classification differences of three training functions, i.e., the, Levenberg-Marquardt BP algorithm function (Trainlm), a gradient decreasing function of adaptive learning rate BP (Traingda), and a gradient lowering momentum BP algorithm function (Traingdm). Our analysis suggests that Traingda had the highest precision while Trainlm function required the shortest training time.

Keywords forest management, Back Propagation (BP) neural network, bamboo forest, classification, remote sensing, Enhanced Thematic Mapper + (ETM +)

1 Introduction

Characteristics such as distributed parallel processing, nonlinear mapping, adaptive learning, and fault tolerance have equipped artificial neural networks with a unique capacity for information processing and calculation, embodying powerful advantages in high-dimensional nonlinear systems with unclear mechanisms (Rogers and Kabrisky, 1991). Presently, artificial neural networks have been widely applied in remote sensing image classification, such as BP neural networks (Jia et al., 2001; Kavzoglu and Mather, 2004; Verbeke et al., 2004; Liu and Zhang, 2005; Wang and Zhao, 2005), self-organizing competitive neural networks (Du and Fan, 2003; Li and Sha, 2006), RBF neural networks (Foody, 2004), and fuzzy neural networks (Mao and Wang, 2001), and others. Among these the BP neural network is the most outstanding and frequently used technique. It can classify input vectors in properly defined ways. By adopting differentiable conversion functions, the neurons can realize arbitrary nonlinear mapping between input and output. It has, therefore, a sound automatic classification effect in the recognition of remote forest sensing images with severe phenomena of "same object with different spectra" and "different objects with the same spectrum" (Li, 1998; Yu et al., 1999; Hu, 2001; Li et al, 2003; Wang and Zhao, 2005). Based on a BP neural network, our research classifies remote sensing imaging by combining the need of our subject research, i.e., estimating bamboo forest carbon reserves by remote sensing, in order to extract an accurate estimate of the bamboo forest area and information of its distribution.

2 General situation of study area

Our study area was located in Lin'an City, Zhejiang Province, with the geographic coordinates of 29°56′–30°23′N, 118°51′–119°52′E. The climate is of subtropical monsoon type, wet, and with abundant rainfall. The forest vegetation within the region is of an eastern subtropical evergreen broad-leaved forest. The forest coverage of the city is 76.55%. A bamboo forest with an area of 53000 hm^2, accounting for more than 20% of the forest

Translated from *Journal of Zhejiang Forestry College*, 2008, 25(4): 417–421 [译自: 浙江林学院学报]

Yongjun SHI (✉), Xiaojun XU, Huaqiang DU, Guomo ZHOU, Wei JIN, Yufeng ZHOU (✉)
School of Environmental Sciences and Technology, Zhejiang Forestry College, Lin'an 311300, China
E-mail: syjwwh@163.com, zhougm@zjfc.edu.cn

land belonging to the city, is regarded as one of the ten "bamboo hometowns" in China.

3 Data collection

The data used in this study are the ETM + remote sensing data received on March 26, 2003. The quality of the original data is good and has been adjusted by geometric and radiometric corrections with a linear regression method. We took the area with a large bamboo forest distribution on remote sensing image maps as our test area, with the dimension of 789×1093 pixels. From field investigations, visual interpretation, and band selection, we used three bands, i.e., ETM + 5, 4, and 3, which were found to have good bamboo forest recognition effect from artificial color image compounding. A normalized vegetation index (NDVI) image can be obtained by using the ERDAS IMAGINE9.1 remote-sensing software, and four-dimensional remote sensing data can be formed by combining the NDVI image as a layer with ETM + 5, 4, and 3 bands through the function of Layerstack. In order to obtain the information on bamboo forests, the land was divided into five categories according to the need of remote sensing classification, i.e., bamboo forests (bamboo), evergreen broad-leaved forest and coniferous forests (clt), a residential zone (city), deciduous broad-leaved forests and reforested and barren hills (lzh), and water.

4 Methods

4.1 Selection and analysis of training sample

We selected typical samples of each category in order to utilize the Area of Interest (AOI) in the toolbar of the remote sensing software and then obtained training sample data of each category through the function of "Convert pixels to ASCII." The pixels of the categories were 543, 964, 828, 942, and 854. We then picked up the even-numbered sequence of the pixel value data of the sample by a MATLAB sub-program as the network training input value, referred to as bamboo, clt, city, lzh, and water with pixels 270, 480, 412, 469, and 425, respectively. Finally, we randomly selected some data from the odd-numbered sequence pixel value as the network testing sample, 1,031 pixels in all.

The Jeffries-Matusita distance method can measure the separability of samples in different categories (Li et al, 2007), with parameter values between 0 and 2.0, representing the separability among the regions of interest. A value > 1.9 suggests there is good separability among the interested zones. Given the sample calculations of the Jeffries-Matusita distances, we can see from Table 1 that there is excellent, almost perfect separability among the categories.

Table 1 Jeffries-Matusita values between categories

categories	Jeffries-Matusita	categories	Jeffries-Matusita
bamboo_clt	1.99547648	clt_city	2.00000000
bamboo_water	1.99999937	clt_lzh	2.00000000
bamboo_lzh	1.99999957	city_lzh	1.98480114
bamboo_city	2.00000000	city_water	1.99776762
clt_water	1.99997702	lzh_water	2.00000000

4.2 Classification of BP neural network remote sensing images

4.2.1 BP neural network algorithm

Whole thinking of BP neural network: the input information is propagated forward to the node of hidden layers; after the calculation of the sigmoid transfer function, the output information is propagated to the output node which provides the final output results. The network study process is made up of forward propagation and back propagation. In the process of forward propagation, the status of each neuron layer only has an effect on the next layer. If the output layer cannot obtain the expected output, then the error between the actual output and the expected output is larger than the expected output. Therefore, in a back propagation process, the error signal is returned along the former connection. By amending the weight and threshold of each neutron layer, we conduct the calculations successively in the input layer. We return to the forward propagation to force the error signal to achieve the expected error through repeated calculations of the two processes, after which the study process ends (Science and Technology Product Research Center of Fei Si, 2003).

1) Output algorithm of the output node

Output of hidden node: $y_i = f\left(\sum_j IW_{ij}x_j - \theta_i\right)$

Output of output node: $O_l = f\left(\sum_i LW_{li}y_i - \theta_l\right)$

where x_j represents the j th input of the input node; y_i represents the hidden node output; O_l is the output of the output node; IW_{ij} is the connection weight of the l th neuron of the output layer and the i th neuron of the hidden layer; θ_i represents the i *th* neuron threshold of the hidden layer; θ_l is the l th neuron threshold; and f is the transfer function, which usually is a sigmoid type, i.e., $f(x) = {}^{1}\!/_{(1+e^{-x})}$.

2) Output layer (between the hidden node and the output node) correction algorithm

Error control: error of one sample $e_k = \sum_{l=1}^{n} \left| t_l^{(k)} - O_l^{(k)} \right|$;

error of all samples $E = \sum_{k=1}^{p} e_k < \varepsilon$

Error formula:

$$\delta_l = (t_l - O_l) \times f'\left(\sum_i LW_{li} y_i - \theta_l\right)$$
$$= (t_l - O_l) \times O_l \times (1 - O_l)$$

Weight correction: $LW_{li}(k+1) = LW_{li}(k) + \eta \delta_l y_i$

Threshold correction: $\theta_l(k+1) = \theta_l(k) + \eta \delta_l$

where t_l represents the expected output of the lth neuron in the output node; p is the number of input samples; n is the number of output nodes; k is the number of iterations; η is the learning rate; and δ_l is the error of the output layer.

3) Hidden node layer (between the input node and the hidden node) correction algorithm

Error formula : $\delta°_i = y_i(1 - y_i) \sum_l \delta_l LW_{li}$

Weight correction: $IW_{ij}(k+1) = IW_{ij}(k) + \eta \delta°_i x_j$

Threshold correction: $\theta_i(k+1) = \theta_i(k) + \eta \delta°_i$

where $\delta°_i$ is the error of the hidden node layer. All these formulas have been obtained from Wen et al. (2003) with a few appropriate amendments.

4.2.2 BP neural network construction

Remote sensing classification was carried out by constructing a three-layer BP network with a number of Matlab7.1 neural network modules. We made the following assumptions: 1) the input layer is composed of four neurons; 2) there are 13 neurons in the hidden layer according to the number of training samples and the dimensions of the input and output layers; and 3) the number of output neurons is the same as that of the number of classifications, i.e. five. The construction principle of the output layer is as follows: the output value of different classifications is stipulated to be 1 in the corresponding position and 0 in other positions. For example, the corresponding output value of bamboo is [1; 0; 0; 0; 0]. Likewise, the output result is processed by a competitive function in order to make the maximum output value of each pixel become 1 and other values become 0. This is to avoid the impurity of the output results and to meet the requirements of a hard classification of remote sensing images. The transfer function combination of the network hidden layer and its output layer uses Tansig-Logsig function. Our method uses three kinds of training functions, i.e., the Levenberg-Marquardt BP algorithm function (Trainlm), the adapting learning rate BP gradient decreasing function (Traingda), and a gradient lowering momentum, according to the principle of the highest correct simulation rate and the shortest time of the network testing sample. We selected the most optimal training function (refer to Table 2 for network training parameters). According to the constructed BP network, we trained the network with training samples and when the network performance attained its goal, we conducted a normalization process towards the four bands, i.e., ETM + 3, ETM + 4, ETM + 5, and NDVI, and then entered these into the network for classification. It can be seen from Table 2 that, in network training, the Trainlm functions in the shortest possible time, followed by the Traingda function. It can be concluded from Fig. 1 that the correct rate of the Traingda function network testing sample simulation is the highest at 93.5% and the Trainlm ranks No. 2. Given our overall consideration of the correct rate and time requirements, we adopted the Trainlm function to make the classification of all of our remote sensing images.

Table 2 Network training parameters

training function	training times	training goal	momentum factor	learning rate	intervals	time consuming/s	other parameters
Trainlm	9	0.01	—	—	20	15.8	default
Traingda	395	0.01	—	0.08	20	52.0	default
Traingdm	7933	0.01	0.8	0.40	50	240.8	default

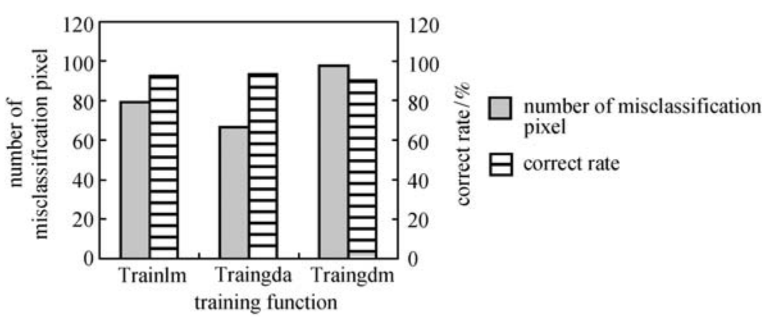

Fig. 1 Simulated results of test samples

5 Result and analysis

By carrying out a category cluster treatment of the classified images, a 3×3 morphological operator was used to combine adjoining similar regions into one cluster and eliminate the spots or holes in the classified regions, in order to achieve the effect of a smooth image (Li et al., 2007). By continuing the survey of the fixed sample plots as well as the information of latitude and longitude collected in our field investigation, we obtained a confusion matrix and made precision evaluation (Table 3 for the precision evaluation). By converting the BP network output classification diagram from TIFF format into GRID format and then using the Arcview 3.2 software to make thematic maps, we obtained a thematic map of bamboo classification and a total classification map (Figs. 2 and 3).

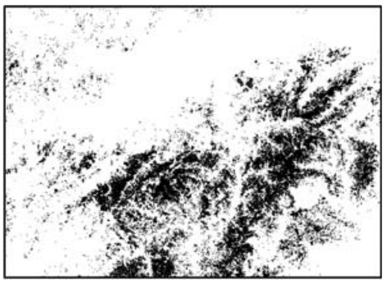

Fig. 2 Thematic map of bamboo classification

We can see from Table 3 that the classification precision is high when the total classification precision is 93.48% and the Kappa coefficient 0.9178. The misclassification error of the bamboo forest is 1.25% and the leaking classification error 15.96%. The manufacturer precision and user precision are 84.04% and 98.75%, which meet the requirement of production and the user. Comparatively speaking, it is easy to confuse bamboo forests, evergreen broad-leaved forests, and coniferous forests. There is also some confusion in the delineation of the residential zone, the deciduous broad-leaved forest, and the reforested and barren hills.

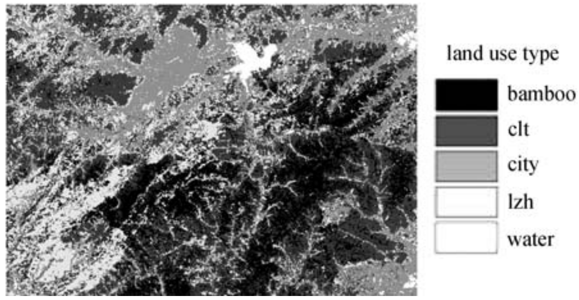

Fig. 3 Thematic map of BP network classification

6 Conclusion and discussion

The result of remote image classification by applying a BP neural network suggests: 1) Under the premise of training sample selection with high precision and a suitable setting of network weights and thresholds, a BP neural network remote sensing classification can effectively separate the bamboo forest and the evergreen broad-leaved forest from the coniferous forest and deciduous broad-leaved forest, and obtain the bamboo forest area and space distribution information with high precision. The classification errors mainly result from the similar spectral characteristics of the bamboo forest, the evergreen broad-leaved forest, and the coniferous forests. It may also be related to the sample selection error and the complex calculation mechanism inside the network weights and thresholds, which need further validation. 2) From the comparison of the three training functions, i.e., Trainlm, Traingda, and Traingdm, we conclude that the classification precision of the gradient

Table 3 Confusion matrix analysis of BP classification

type of measured data	classification data type piece					total/ piece	misclassification error/%	user precision/%
	bamboo	Clt	city	Lzh	water			
unclassified	0	0	0	6	0	6		
bamboo	237	3	0	0	0	240	1.25	98.75
clt	29	332	0	0	0	361	8.03	91.97
city	0	0	235	9	6	250	6.00	94.00
Lzh	16	6	11	240	0	273	12.09	87.91
water	0	0	0	0	188	188	0	100
total	282	341	246	255	194	1318		
leaking classification/%	15.96	2.64	4.47	5.88	3.09			
manufacturer precision/%	84.04	97.36	95.53	94.12	96.91			
total precision/%	93.48							
Kappa coefficient	0.9178							

decreasing function had the highest precision while the Levenberg-Marquardt training function required the shortest training time. Therefore, a suitable function should be selected to conduct the network training according to the actual situation when utilizing a neural network to make the classification.

Acknowledgements This study was financially supported by the National Natural Science Foundation of China (Grant Nos. 30700638, 30771725).

References

Du H Q, Fan W Y (2003). The application of self-organizing neural network to remote sensing image classification based on Matlab. J Northeast For Univ, 31(4): 51–53 (in Chinese)

Foody G M (2004). Supervised image classification by MLP and RBF neural networks with and without an exhaustively defined set of classes. Intl Remote Sens, 25: 3091–3104

Hu S Y (2001). The application of mixed GA-BP algorithm on image recognition. J Zibo Univ, 3(4): 21–24 (in Chinese)

Jia Y H, Zhang C S, WANG A P (2001). Classifying of multi-sources remote sensing imagery based on BP neural network. Xi'an Univ Sci Technol, 21(1): 58–60 (in Chinese)

Kavzoglu T, Mather P M (2004). The use of back-propagating artificial neural networks in land cover classification. Intl Remote Sens, 24: 4907–4938

Li C H, Sha J M (2006). Knowledge based self-organizing neural network remote sensing image classification approach. Remote Sens Technol Appl, 21(6): 507–511

Li F X, Li M C, Zhao S H (2003). Study on model of ANN combined with decision tree algorithm for image classification. Remote Sens Inform, 3: 23–26 (in Chinese)

Li X J, Gong Z H, Liu X M, Liu X M (2007). Remote Sensing Image Process Tutorial Based on ENVI (Translation). Beijing: China Environment Science Press (in Chinese)

Li Z Y (1998). Supervised classification of multi-spectral remote sensing image using BP neural network. J Infr Mill Wave, 17(2): 153–156 (in Chinese)

Liu X S, Zhang X L (2005). Remote sensing classification of forest vegetation based on artificial neural network. For Res Manage, 1: 51–54 (in Chinese)

Mao J X, Wang Y N (2001). Remote sensing image classification based on fuzzy gauss function neural network. Remote Sens Technol Appl, 16(1): 62–65 (in Chinese)

Rogers S K, Kabrisky M (1991). An Introduction to Biological and Artificial Neural Networks for Pattern Recognition. Washington: SPIE Opt Eng Press

Science and Technology Product Research Center of Fei Si (2003). Neutral Network Analysis and Design Based on MATLAB 6.5. Beijing: Electron Industry Press (in Chinese)

Verbeke L P C, Vabcoillie F M B, Dewulf R R (2004). Reusing back-propagating artificial neural network for land cover classification in tropical savannahs. Intl Remote Sens, 25: 2747–2771

Wang L H, Zhao Z Y (2005). Automatically classifying and identifying the TM remote sensing images of forest mixed with conifer and broadleaves using improved BP ANN. Sci Silv Sin, 41(6): 94–100 (in Chinese)

Wen X, Zhou L, Li X, Zhang B W (2003). Neural Network Simulation and Application. Beijing: Science Press (in Chinese)

Yu X L, Qian G H, Zhou J L, Jia X G (1999). Learning sample selection in multi-spectral remote sensing image classification using BP neural network. J Infr Mill Wave, 18(6): 449–454 (in Chinese)