

THE BP-ANN-GA ALGORITHM FOR DATA FUSION OF LANDSAT ETM AND ERS SAR IN URBAN AREA

Ya-Qiu Jin and Guangzhen Cao

Key Laboratory for Wave Scattering and Remote Sensing Information (Ministry of Education)
Fudan University, Shanghai 200433, China
Email: yqjin@fudan.ac.cn

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ABSTRACT: A hybrid algorithm of the BP-ANN/GA (Back Propagation Artificial Neural Network and Genetic Algorithm) is developed to optimize the initial weights and make fast convergence of the BP-ANN. This algorithm is applied to data fusion of Landsat ETM+ and ERS-2 SAR for classification of the urban terrain surfaces. An example of the Shanghai Pudong area using both the Landsat ETM+ and ERS-2 SAR image data well demonstrates the classification speed and accuracy of our fusion algorithm.

1. INTRODUCTION

Remote sensing of multi-sensors, e.g. at visible, infrared and microwave frequencies, present different view angles on the geometries and spectrum reflectance of the terrain surfaces because of their different measuring physics. Retrieving information from a single sensor's data is always restrictive. Data fusion of multi-sensors is a new tool to retrieve more accurate and richer information in remote sensing applications. To make the terrain surface classification, the minimum distance method and Maximum Likelihood (ML) method based on the data statistics with the prior probability knowledge are usually applied (Devijver *et al.* 1982). During recent years, the ANN method, especially the most popular BP-ANN, has been employed to study information retrieval of remote sensing (Yoshida *et al.* 1994, Jin *et al.* 1997, Hansen *et al.* 2001, Paola *et al.* 1995). But it is known that slow convergence of the BP-ANN might easily stuck in the local minima because of its gradient descending algorithm for the weights calculation. The GA, as a new optimization algorithm, can be of helpful to improve the BP-ANN convergence.

In this paper, a hybrid algorithm of BP-ANN/GA is developed to optimize the initial weights and make fast convergence of the BP-ANN. After reducing the speckle noise of the SAR image and making the registration with the infrared image, the samples of surface classification are selected from each band of the infrared image and input to training the BP-ANN. According to the error of the BP-ANN output and its convergence speed, the GA is selected to initialize its weights and the BP-ANN/GA algorithm is created to make faster and more accurate classification. To take the good capability of the SAR image for detecting the man-made objects in complex urban areas, the infrared Landsat ETM+ and microwave ERS SAR images over the same study area are fused with the principal components analysis (PCA) method. Then, the samples of each surface class from the first three components are input into the training BP-ANN/GA to yield better surface classification than single sensor data. An example of the Shanghai Pudong area using the data fusion of the Landsat ETM+ and ERS-2 SAR images well demonstrates the classification speed and accuracy of our BP-ANN/GA algorithm.

2 DATA PREPROCESSING

The study area is located near the Century Park of Shanghai Pudong Destrict, China where there are river and lake, new buildings, flat grass fields etc. The infrared data was acquired by the Landsat ETM+ on the November 27th 2002. Its spatial resolution is 30m. The ERS-2 SAR data was acquired on April 9th 2002 at 5.3 GHz, VV polarization and spatial resolution 12.5m.

In complex urban areas, the existence of various man-made objects such as the buildings and roads with different materials, heights and orientations etc. attributes more randomness to the image noise character. As the first step, the Gamma adaptive filter with a 3×3 window is employed to deduce the image noise and keep the main details of the image (Lopbs *et al.* 1993).

In order to make data fusion, two different images are projected to the same geometry and grey space. The quadratic method and the cubic convolution method are employed (Jensen 1996). Then, the images of 400×400 pixels of Landsat ETM+ and ERS-2 SAR are ready as shown in Fig.1 and Fig.2, respectively.

Employing the activation function (Sigmoid function) in the BP-ANN, all input data are normalized.



Figure 1. the Landsat ETM+ image at the band 4

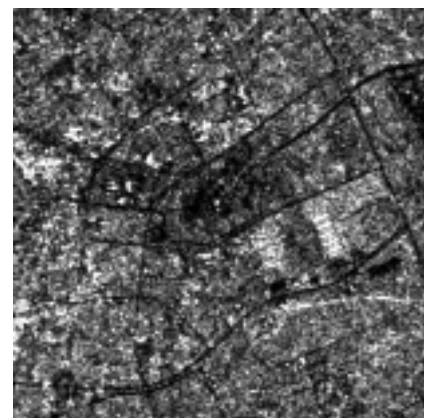


Figure 2. ERS-1 SAR image

3. THE ANN TRAINING

(1) ANN

The BP-ANN is popular in solving many non-linear problems (Klein 1999). The feature vectors extracted from the image are fed into the input layer and the classifications are then the output through the trained ANN.

Three layers (one input, one hidden and one output) of BP-ANN are constructed in this paper. The number of neurons of the input and output layers are equal to the features of the image (3) and the number of the classes (5), respectively. Twelve neurons are taken in the hidden layer to make good accuracy and fast convergence. The activation functions used in the hidden layer and the output layer are both Sigmoid function.

The desired outputs for the 5 surface classes: water, grass, building, road and flat land-field are defined as (1 0 0 0 0), (0 1 0 0 0), (0 0 1 0 0), (0 0 0 1 0) and (0 0 0 0 1), respectively. If the ANN output is beyond the allowed error, the error between the real output and the desired output are evaluated. Then, the error feedback is propagating in the opposite direction to adjust the weights until the satisfied results are acquired. We first choose the training data for BP-ANN from the Landsat ETM+ image at the bands 4, 5, 7 and four samples are chosen for each class.

The minimum and maximum errors between the real and desired output are 0.1964 and 36.6402, which indicate some misclassification. It can be seen that the BP-ANN seems good for classification of water body and flat land-fields, but becomes poor for the types such as building, road and grass fields. It can be seen that the real output of the third sample of building is (0.0149 0.0098 0.5947 0.0329 0.0107), which is especially poor and much deviated from real (0 0 1 0 0).

The GA algorithm is used to initialize the weights of BP-ANN. With the help of the GA to optimize the weights, the training speed and classification accuracy are improved.

(2) BP-ANN/GA

The GA is an adaptive optimization algorithm to simulate the inheritance and evolution of the biology in the nature (Bäck 1996, Jin *et al.* 2001). Training BP-ANN with GA is divided into two parts: the first one is to optimize the weights with GA, and the second one is to train the BP-ANN with the result of GA.

Because the weights of BP-ANN are real, the chromosomes are real coded, different from conventional binary codes. Responding to the 96 weights in the BP-ANN, each chromosome of the population has 96 genes. The population scale designed is 60 and the initial population is selected randomly between 0 and 1. The whole evolution generation is 200. The selection operation follows that the higher fitness and the more probabilities. Arithmetic crossover and Gaussian mutation operations are chosen according to the real genes. The crossover and mutation probabilities are 0.6 and 0.05, respectively.

At last, we choose the chromosome with the minimum error from the last generation of the GA algorithm as the initial weights of BP-ANN to make BP-ANN training with the infrared data. The real output and desired output of BP-ANN/GA are compared.

It shows that the minimum and maximum errors between the real output and the desired output of the BP-ANN/GA are 0.0155 and 14.0632, which are both better than the BP-ANN without GA. The training speed of ANN in this case is also speeded up. The classification accuracy for all surfaces are improved. For example, the building class takes a better output as (0.0148 0.0001 0.8610 0.0089 0.0081) with a little difference from (0 0 1 0 0).

(3) BP-ANN/GA with fusion of infrared and SAR images

It is well known that the infrared image may show rich spectral information, but is lack of sensitivity to mistakes of different spectrum for the same object and the same spectral for different objects. On the other hand, the SAR image has spatially

high resolution to make view on different geometric objects, but some measurements of back-scattering, such as for water body, flat fields and roads, are often not distinguishable. To take both advantages of infrared and microwave observations, the principal component analysis (PCA, Gonzalez 2003) is applied to fusing the infrared and microwave image data.

PCA is an orthonormal linear transformation to derive the uncorrelated eigenvectors. It can decrease the data dimensions without much information lost. The eigenvalues of the images' covariance matrices are calculated and arranged in descending order at first. Then, a transformation matrix is constructed by the eigenvectors, correspondingly, with which we can transform the images into their components.

The first three components of the Landsat ETM+ infrared data and ERS-2 SAR data are presented in Figs. 3(a-c). The fourth component is also obtained and ignored here due to little information. It can be seen that the figures of PCA1 and PCA2 contain most of images information (Fig.3(a,b)) and the figure of PCA3 supplements some information for the surfaces such as water body, grass field and wide road (Fig.3(c)). Taking 4 samples of each surface type from these three components as input into training BP-ANN/GA, the real output and desired output are compared.



(a)PCA1



(b) PCA2



(c) PCA3

Figure 3. The different components of PCA

It can be seen that the minimum and maximum errors between the real output and the desired output become smaller, as 0.0154 and 11.0149. It means that fusing the infrared and SAR images improves the classification accuracy.

4. THE ANN STUDYING

After ANN training, three cases of the ANN studying and surface classifications are made: the infrared image of Landsat ETM+ 457 as input into the BP-ANN and the BP-ANN/GA, respectively, and the fused infrared and SAR images as input into the BP-ANN/GA. The classification results are, respectively, shown in Fig. 4, Fig. 5 and Fig. 6. In these classification images, five colors refer to five classes: blue color standing for water body (river and lake), green color for grass field, orange color for building area, yellow color for flat land-field and brown color for road. The classifications of grass and flat land-fields in Figs. 4 and 6 are similar, but the classification of water body seems poor. The BP-ANN/GA is better than the BP-ANN, including the continuous roads. At the up-right corner of Fig. 5, many small paths are also detected.

However, many rectangular areas of building are largely mixed with roads. It might be due to the fact that the materials of the buildings and roads are similar in view of the infrared spectral reflectance.

Fig. 6 employs data fusion and BP-ANN/GA, and shows the best classifications of all 5 surfaces. It is interesting to compare Fig.67 with the Shanghai tourist map of Fig. 7.

High spatial resolution and good sensitivity of backscattering from geometrically different buildings and roads offer good capability to the SAR image. Because two images of Landsat ETM+ and ERS-2 SAR in our case are acquired at different time, it might be another reason that seasonal cycle might affect final accuracy of fusion classification.

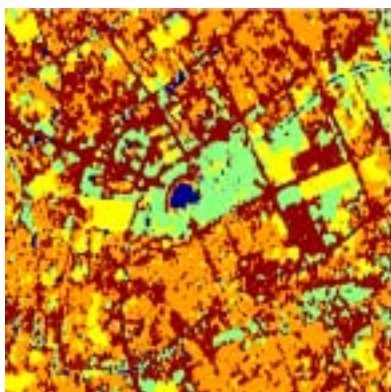


Figure 4. BP-ANN classification of ETM+457

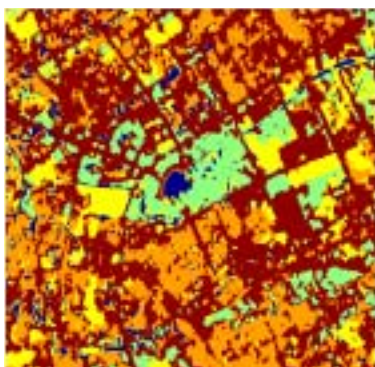


Figure 5. BP-ANN/GA classification of ETM+457

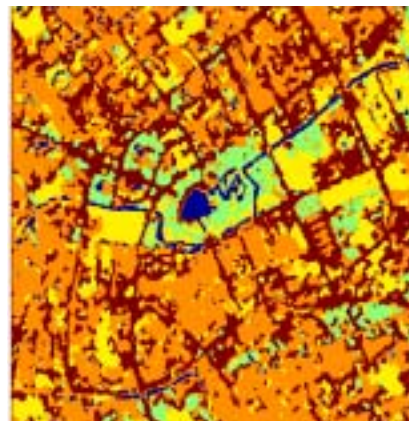


Figure 6. BP-ANN/GA classification of the fusion of ETM+457 and SAR



Figure 7. The tourist map of the studying area

5 CONCLUSION

This paper develops a hybrid algorithm of BP-ANN/GA to optimize the initial weight and make fast convergence of BP-ANN. This algorithm is applied to data fusion of Landsat ETM+ and ERS-2 SAR for automatic classification of the complex urban terrain surfaces.

(1) Applying the GA algorithm to initialize the weights of the BP-ANN can take its advantage of optimization and overcome the shortcomings of the BP-ANN's slow convergence and stuck in the local minima.

(2) Fused images from multi-sensors, such as infrared ETM and microwave SAR images can yield better classification of complex terrain surfaces. Using the BP-ANN/GA and multi-sensor's fused data, all of their advantages can be synthesized together to make better surface classification.

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REFERENCES

- Bäck T. (1996), *Evolutionary Algorithms in Theory and Practice*. New York: Oxford University Press.
- Devijver P.A., Kittler J. (1982), *Pattern Recognition: A Statistical Approach*, New York: Prentice-Hall.
- Gonzalez R. C., Woods R. E. (2003), *Digital image processing (second edition)*. New York: Prentice-Hall.

- Hansen J.V., McDonald J.B. (2001), Some experimental evidence on the performance of GA-designed neural networks. *Journal of Experimental & Theoretical Artificial Intelligence*, 13(3): 307-321.
- Jensen J. R. (1996), *Introductory Digital Image Processing: A Remote Sensing Perspective* (second edition), Englewood Cliffs, N. J.: Prentice-Hall.
- Jin Y.Q. and Liu C. (1997), Biomass Retrieval from High-Dimensional Active/Passive Remote Sensing Data by Using Artificial Neural Networks, *International Journal of Remote Sensing*, 1997, 18(4): 971-979.
- Jin Y. Q. and Wang Y. (2001), A Genetic Algorithm to retrieve multi-parameters of Land Surface Roughness and Soil Moisture. *International Journal of Remote Sensing*, 22(16): 3093-3099.
- Klein L.A. (1999), *Sensor and Data Fusion Concepts and Applications* (Second Edition), Bellingham, Washington: SPIE Optical Engineering Press.
- Lopbs A., Nezry E., Touzi R., Laur H. (1993), Structure detection and statistical adaptive speckle filtering in SAR images. *International Journal of Remote Sensing*, 14(9): 1735-1758.
- Paola J. D., Schowenger R. A. (1995), A detail comparison of backpropagation neural network and maximum-likelihood classifiers for urban land use classification. *IEEE Trans. on Geosci. and Remote Sens.*, 33(4): 981-996.
- Yoshida T., Omatu S. (1994), Neural network approach to land cover mapping. *IEEE Trans. Geosci. Remote Sens.*, 32(5): 1103-1109.