RBF Neural Network Supported Classification of Remote Sensing Images Based on TM/ETM+ in Nanjing

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Abstract—The classification of remote sensing images is more and more important along with the development of society and economy. According to the defects general classification methods have, such as the accuracy, the efficiency etc, the design of ‘robust’ classification system based on a Gaussian RBF neural network is used in this article to classify the TM/ETM+ image in Nanjing. The choice of this neural network model is justified by some of its particular properties, i.e., local learning, fast training phase, ability to recognize when an input pattern has fallen into a region of the input space without training data, and capability to provide high classification accuracies on remote sensing images. For appraising the precision of the model in brief, over 1000 examples are chosen in this research, and the result shows that in the whole research area there is obvious improvement (86.6-89.7%) between MLC and this model. Besides, it is also better than the MLP NN model (87.9-89.7%). The result indicates that the model of RBF NN is a good approach for the classification of remote sensing in this area based on TM/ETM+. Of course, there are also many aspects need to be revised and improved in the future research such as the accuracy and for other data source.

Keywords- TM/ETM+; Nanjing; RBF Neural Network; MLC; BPMLP

I. INTRODUCTION

An important problem encountered in the classification of remote sensing data is that classical classifiers, once they have been trained on a data set related to a specific image, seldom attain acceptable classification accuracy on such remote sensing images, even if the land use types present in all images are similar. There are several factors contribute to the problems: differences in the atmospheric conditions at the image data, differences in soil moisture, difference in light conditions etc. However, the classification of images is more and more important along with the development of society and economy. According to this question, the design of “robust” classification system capable to perform efficiently on different images, irrespective of the acquisition dates or even the geographical areas considered, is a major challenge for the remote sensing community.

Different classification algorithms produces different result even with the same training set (Benediktsson et al., 1990a,b; Hepner et al., 1990; Key et al., 1990; Bischof et al., 1992; Kanellopoulos et al., 1992; Civco, 1993; Paola and Schowengerdt, 1994; Solaiman and Mouchot, 1994; Skidmore et al., 1997). Classical statistical algorithms, like the maximum likelihood (MLC) and the k-nearest neighbour classifiers, have been traditionally used to perform classification of remote sensing images (Swain and Davis, 1978). However, in recent years, the remote sensing community focused attention on the neural network approach to data classification, mainly because of this kind of approach for classification does not require any a priori knowledge of the statistical distribution of data and is characterized by intrinsic parallelism and fast classification time (Bischof et al., 1992).

The proposed classifier is based on a Gaussian RBF neural network (Bishop, 1995). The choice of this neural model is justified by some of its particular properties, i.e., local learning, fast training phase, ability to recognize when an input pattern has fallen into a region of the input space without training data, and capability to provide high classification accuracies on remote sensing images (Bishop, 1995; Bruzzone and Fernandez Prieto, 1999). It appears to be a more effective model for nonlinear function approximation and data classification in general, and remote sensing classification in particular. Theoretically, RBF networks can overcome some of the limitations of BPMLP with rapid training (up to 103 to 104 times), avoidance of chaotic behaviour and a simpler architecture (Bishop 1995; Bruzzone and Prieto 1999b; Sundararajan et al. 1999; Karayiannis et al. 1997; Karayiannis 1999). More importantly, RBF networks represent the posterior probabilities of the training data by a weighted sum of Gaussian basis functions with diagonal covariance matrices. When the components of the training data vectors (and the known test data vectors) are dependent, more basis functions are required so that data in the regions covered by each basis function can still be considered to have independent components. This results in high computational cost (Jianchen Luo and Yee Leung, 2004).

In this article, the detailed method and the classification of the image based on RBF Neural Network will be introduced,
II. THE RBF NEURAL NETWORK

2.1 Basic Structure of Radial Basic Neural Network

Radial basic functions have been embedded into a two-layer feed forward neural network. Such a network includes a set of inputs and a set of outputs. Between the inputs and outputs there is a layer of processing units called hidden units. Each of them implements with a radial basis function. The way in which the network is used for data modeling is different when approximating time-series and in pattern classification. In the first case, the network inputs represent data samples at certain past time-laps, while the network has only one output representing a signal value. In a pattern classification application the inputs represent feature entries, while each output corresponds to a class. The hidden units correspond to subclasses. Fig.1 shows the detailed process of RBF Neural Network for RSI classification.

![Fig.1 RBF neural network for RSI Classification](image)

Lots of functions have been tested as activation functions for RBF Neural Networks. In pattern classification applications the most used activation function is the Gaussian function. In time-serious modeling the thin-plate spline is preferred. Mixtures of Gaussians have been considered in various scientific fields. The Gaussian activation function for RBF networks is given by:

$$\phi_j(X) = \exp\left[-(X - \mu_j)^T \Sigma_j^{-1} (X - \mu_j)\right]$$

For $j = 1, \ldots, L$, where $X$ is the input feature vector, $L$ is the number of hidden units, $\mu_j$ and $\Sigma_j$ are the mean and the covariance matrix of the $j$th Gaussian components as in the Gaussian-mixtures estimation. Geometrically, a radial basis function represents a bump in the multidimensional space, whose dimension is given by the number of entries. The mean vector $\mu_j$ represents the location, while $\Sigma_j$ models the shape of activation function. Statically, an activation function models a probability density function where $\mu_j$ and $\Sigma_j$ represent the first and second order statistics.

The output layer has implemented a weighted sum of hidden-unit outputs:

$$\psi_k(X) = \sum_{j=1}^{L} \lambda_{jk} \phi_j(X)$$

For $k = 1, \ldots, M$ where $\lambda_{jk}$ are the output weights, each corresponding to the connection between a hidden unit and an output unit and $M$ represent the number of output units. The weights $\lambda_{jk}$ show the contribution of a hidden unit to the respective output unit. In a classification problem if $\lambda_{jk} > 0$ the activation field of the hidden unit $j$ is contained in the activation field of the output unit $k$.

In pattern classification applications, the output of the radial basis function is limited to the interval $(0,1)$ by a sigmoidal function:

$$Y_k(X) = \frac{1}{1 + \exp\left[-\psi_k(X)\right]}$$

For $k = 1, \ldots, M$.

The Model talking above about RBF Neural Network will be applied in the following test.

2.2 Problem in RBF Neural Network

In most of RBF networks, Gaussian functions is widely used as basis function and criterion for optimality. However, this type of RBF networks also suffers from one problem. The problem which has not been addressed yet by other researchers is to approximate a function with nearly constant values or constant values in some intervals under the considered domain. To eliminate this phenomenon, more terms must be added to the expansion. Of course, this will increase computational complexity, however, it will not influence the final result.

III. APPLICATION OF THE RBF NEURAL NETWORK IN NANJING AND COMPARISON

4.1 Introduction to research area and data

The research area –Nanjing is located in the southern part of Jiangsu Province. It is also situated in 31°14'-32°36'N, 118°47'-119°14'E. The climate there is belong to north subtropic monsoon climate area. It is very hot in summer and cold in winter. The spring and autumn are too short, the average temperature is 16 °C. The main direction of the wind is northeast in winter and southwest in summer.

The article looks the whole area of Nanjing as the main research area. It includes Gulou Section, Jianye Section, Yuhuatai Section, Qinhuai Section, Baixia Section, Xuanwu Section, Luhe Section, Gaochun Section and Jiangning Section. The main water information include part of Changjiang River, Qinhuai River, Xuanwu Lake, Mochou Lake and some small reservoirs. The main remote sensing datum is TM/ETM+ image in 2004. The resolution of multiply bands is 30 m, and the Pan band is 15 m.
4.2 Research framework

Initial attention focused on the situation in which all six classes were included throughout the classifications. The classifications derived from the MLC, MLP and RBF networks differed in the pattern of class allocation and provided the different overall accuracy.

The classification results are outlined in table1. To validate the RBF Neural Network algorithm, comparisons of classification accuracy between RBF and other classification algorithms were carried out. Two algorithms are taken into account: one is based on conventional maximum likelihood classifier (Duda and Hart 1973), The other is the MLP algorithm. From the comparison results list in the table1.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Classification Accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum likelihood</td>
<td>86.6</td>
</tr>
<tr>
<td>MLP</td>
<td>87.9</td>
</tr>
<tr>
<td>RBF Neural Network</td>
<td>89.7</td>
</tr>
</tbody>
</table>

From the accuracy and the comparison of the classification accuracy of different classification methods table above, we can see that the RBF Neural Network has reached the 89.7% and better than the other two classification methods which are only 86.6% and 87.9%(MLC and MLP), the RBF Neural Network algorithm yields the most accurate classification in the comparison.

The fig.4 is the classification result based on RBF neural network algorithm.
IV. CONCLUSION

We take the result from the RBF Neural Network algorithm to classify initial image in Nanjing, and compare the result with the image classified by MLC algorithm and MLP algorithm. By the necessary analysis, we can make a conclusion that the entire accuracy of the RBF is good.

For appraising the precision of the Model in brief, We choose about 1000 examples. The primary result tells us that in the whole research area there is obvious improvement (86.6-89.7%) between MLC and the model. Besides, it is also better than the BPMLP NN model (87.9-89.7%). Certainly, it is just the primary result, the final result will be sure in the final paper. The research indicates that the model of RBF NN is a good approach for the classification of remote sensing images in this area based on TM/ETM+. Of course, these is also lots of problems in the method for classifying the RSI, such as complexity and the time cost of the algorithm, it is also the next research direction in the future.

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