# COMPARATIVE RESEARCHES ON PROBABILISTIC NEURAL NETWORKS AND MULTI-LAYER PERCEPTRON NETWORKS FOR REMOTE SENSING IMAGE SEGMENTATION

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**ABSTRACT:**

Image segmentation is one of the most important methods for extracting information of interest from remote sensing image data, but it still remains some problems, leading to low quality segmentation. The research focuses on image segmentation based on PNNs and MLPNs. It presents to construct a PNN model and tunes a satisfied PNN for hyper-spectral image segmentation. Furthermore, the paper gives a comparative study on segmentation methods based on PNNs and MLPNs. It is concluded that PNNs have quick speed of learning and training. The main advantage of a PNN is its ability to output probabilities in pattern recognition. Image segmentation based on PNNs is an effective and efficient method in image analysis, it obtains a bit higher segmentation overall accuracy than MLPNs.

## 1. INTRODUCTION

The amount of remote sensing data is very large, ranging from several megabytes to thousands megabytes, it leads to difficult and complex image processing. A neural network is an information processing system that intends to simulate the architectures of the human being's brains and how they work. It is a kind of self-adapted and non-linear system, which consists of a large number of connected neurons. Even though a single neuron has simple structure and function, the systematic behaviour of a great quantity of combinatorial neurons could be very sophisticated. Neural network has advantage of dealing with non-linear problems and consequently is applied to more and more research fields, and its principle is usually used for pattern recognition. Extraction of remote sensing image information based on neural networks developed rapidly recently, and it has gained satisfied results in practical works. Image segmentation is essential for information extraction from remote sensing image; it is one of the most important and fundamental technologies for image processing; and it is indispensable to all understanding system and auto recognition system.

Both PNNs and MLPNs are typical neural networks. As a classifier, MLPN has been successfully applied to classification of remote sensing image and PNN is seldom applied to such work. In previous work, such low quality segmentation problems as object merging, object boundary localization, object boundary ambiguity, object fragmentation are still existed in segmentation based on neural networks. This research focuses on remote sensing image segmentation based on PNNs and MLPNs; it presents to build a PNN model for segmentation and gives a comparative study on segmentation based on PNNs and MLPNs.

In the past, some researchers were interested in studying on correlated works. Han did works on classification model of RS images based on artificial neural network — MLP (Han, 2004). Tang, etc. studied on images classification based on spectral decomposition of graphs using probabilistic neural networks (Tang, etc. 2006). Several studies exist on Matlab realization of sensing image classification based on probabilistic neural network (Li, etc. 2008). Researchers have studied about probabilistic neural networks for extracting remote sensing information of rice planting Area (Yang, etc. 2007). Wu worked on classification for remote sensing fused image and TM image using MLP (Wu, etc. 2001).

## 2. PNNS AND MLPNS

### 2.1 Structure of PNNs and MLPNs

The aim of neural network computation is to perform easily and simply on the networks themselves. PNNs were proposed by Specht in 1989, it is a type of Radial Basis Function (RBF) network, which is suitable for pattern classification. The PNN classifier is basically a classifier, of which the network formulation is based on the probability density estimation of the input signals. One of its uses is to examine unknowns and to decide to which class they belong (Specht, 1989).

Specht adopted Bayes classification rule and density estimation based on Gaussian function, which was proposed by Parzen. He constructed a type of four layer parallel processing network, including input layer, pattern layer, summation layer and output layer (See Figure 1 below).

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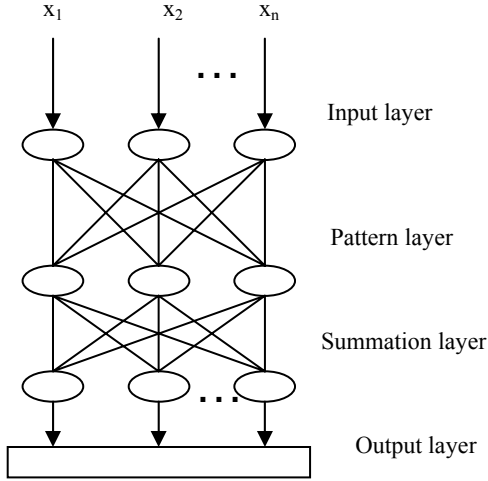\* Corresponding author.  liugangwh@hotmail.com

Figure 1. Typical structure of a PNN

A typical structure of PNNs is shown in above figure. The input layer accepts input vectors. The non-linear dot product processing of input vectors and weight vectors is implemented in the pattern layer. The pattern layer is the core of a PNN. During training, the pattern vectors in the training set are simply copied to the pattern layer of the PNN. The classified samples' probabilities are calculated in the summation layer. The output layer is a threshold discriminator that decides which of its input from the summation units is the maximum, and finally output classified results.

Perception network was proposed by Rosenblatt in 1957. Rumelhart presented a model of MLPNs, which is a network with supervised learning algorithm. A MLPN is a popular neural network in a lot of applications. It is a feed-forward, or non-recurrent neural network.

A MLPN usually has one or several hidden layers between input layer and output layer. Each layer contains a series of neurons, and neurons in a layer do not connect to each other. There is only one-way connection with neighbour layers. Information could only transmit along the direction that is from input layer to output layer. After weight summation of the inputs and implementation of non-linear excitation function, the outputs could be obtained.

## 2.2 Algorithms of PNNs and MLPNs

In hierarchical model of a PNN, the summation layer only connects to pattern layer of corresponding categories. A PNN does not use an iterative training algorithm and it usually uses exponential functions instead of sigmoid functions. The summation estimated probabilities are on the basis of Parzen's method. The algorithm of conditional probability is as follows (Equation 1).

$$p(X / f_k) = \frac{1}{(2\pi)^{m/2} \sigma^m n} \sum_{p_i \in f_k} \exp\left[\frac{X^T W - 1}{\sigma^2}\right] \tag{1}$$

Where   X = sample vectors to be identified
         W = training sample vectors
         m = vector dimensions
         $\sigma$ = smoothing factor
         $f_k$ = classification mode

n = quantity of classification mode
$X^T$ = transposition matrix

The core of such conditional probability estimating method is calculating the sum of Gaussian node function. The centre of nodes is sampling points of training pattern. The smoothing factor is standard deviation $\sigma$ of Gaussian function.

In output layer, according to probabilities evaluation of input vectors, Bayes classification rule would assign the input vectors to the class with maximum posterior probability. A biggest advantage of PNNs is the fact that the output is probabilistic, which makes interpretation of output easy.

Back Propagation (BP) learning algorithm is often widely used in MLPNs model, it turns the input and output problem of samples to non-linear optimization problems. It is trained by error back propagation.

BP algorithm is a sort of supervised learning algorithm, it has hidden nodes. It minimises a continuous error function or objective function. BP is a gradient descent method of training. If there is existed deviation when compared the output gained by network forward reasoning to expected output sample, the weight coefficient should be adjusted. For forward propagation, the BP algorithm is as follows (Equation 2). The algorithm of learning process is shown in Equation 3. The algorithm for output nodes is shown in Equation 4 and that for non-output nodes is shown in Equation 5.

$$Y_j = f\left(\sum_{i=1}^{n} W_{ji} \cdot X_i\right) \tag{2}$$

$$W_{ji}(n+1) = W_{ji}(n) + \eta \cdot \delta_j \cdot x_i \tag{3}$$

$$\delta_j = (T_i - Y_i) f'\left(\sum_{i=1}^{n} W_{ji} \cdot x_i\right) \tag{4}$$

$$\delta'_j = f'\left(\sum_{i=1}^{n} W_{ji} \cdot x_i\right) \cdot \sum_{i=1}^{n} \delta_k W_{ji} \tag{5}$$

Where   $f(x) = \dfrac{1}{1 - \exp(-x)}$ , action function of networks
      X = input samples
      Y = output samples
      T = expected output samples
      $\eta$ = learning rate
      $\delta$ = error signal
      $W_{ji}$ = weight coefficient
      $f'(x)$ = derivation of f(x)

At the beginning of network training, the minimum random interconnected weight values and threshold values should be selected. Under the condition of samples cyclic loading and weight values adjusting, the cost function could descend to accepted tolerance and the actual output is equal to desired output in some error ranges. The learning process of BP algorithm includes forward propagation and back propagation. In a word, the algorithm of BP consists of three stages: feed-forward of the input training pattern, calculation and back propagation of the associated errors and weight adjustment.

## 3. METHODOLOGY

### 3.1 Data source

Hyper-spectral remote sensing data are selected to test and evaluate the processing and obtained results. Therefore, it could lead to an easy and clear procedure to segment different land covers by selected bands image.
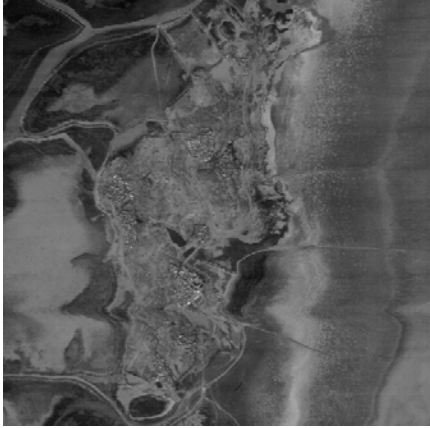
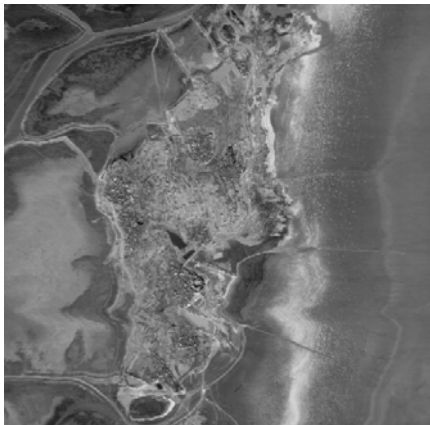

Figure 2. Band 1 original image
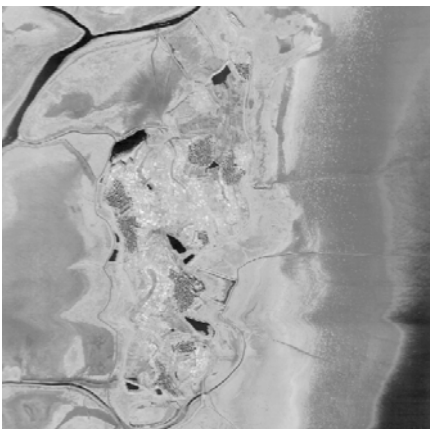


Figure 3. Band 9 original image



Figure 4. Band 21 original image

The original data are gained in Poyang Lake, Jiangxi province, P. R. China, which have 30 bands images and the size of each image is 512 cols × 512 rows. To achieve the study goal, the data should include distinguishable land covers. This makes the study typical and available.

The original images are shown as Figure 2, Figure 3 and Figure 4 above. Among the 30 bands of the provided image data, only the band 2, band 9 and band 21(respectively shown in Figure 2, Figure 3, and Figure4) are kept for processing through this study. The reason is that different spectral characteristics of different bands lead to the representative uses of them and different segmented results.

### 3.2 Data processing

Before segmentation, image data pre-processing including noise elimination, geometric correction, atmospheric correction and dimensional reducing, should be done.

In image processing, the performance of a MLPN and a PNN are affected by some factors, such as input data types, input data sequence, number of nodes in different layers, and different training parameters including momentum, learning rates and number of epochs.

On the basis of principles described before, firstly the training area of different land covers is selected from the same area in original image data. The 20×20 pixels in an image are selected as a sample corresponding to each category. The different bands of image are selected as inputs (Here band 1, band 9 and band 21 are used), and the areas with corresponding land covers are as outputs. The network training and image segmentation are implemented with those learning samples.

Because of its importance in testing, the spread rate of a PNN model should be adjusted constantly, in order to get an ideal value. In the experiments, the better segmented image is obtained when the spread rate is assigned to 0.01. In the mean time, a MLPN with an optimal BP algorithm is tested using the same samples dataset.

As to the method of PNNs, sometimes the probabilities belong to different categories might be equal because of uncertainty. For example, the difference of probabilities is little, and then it is difficult to determine the results even though we can find the absolutely biggest probability. To solve this problem, adjustment of training parameters and training data could be performed.

### 3.3 Experimental results

Only two selected images of the obtained experimental results are shown in Figure 5 (Segmented image by MLPN, system error = 0.07, training momentum = 0.5, coefficient = 0.7, learning rate = 0.7) and Figure 6 (Segmented image by PNN, σ = 0.1, allowable error = 0, training RSM = 0.1). Each image has been segmented into four obvious categories, which separately represent different areas of water, beach, grassland and soil.
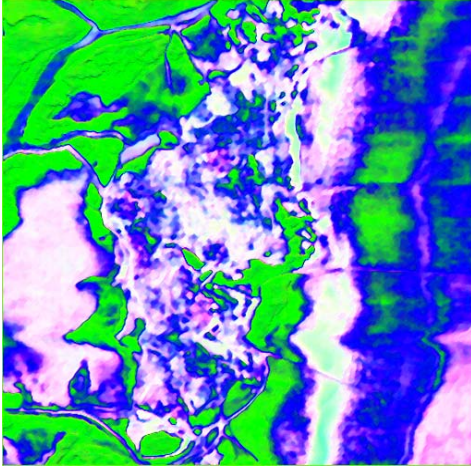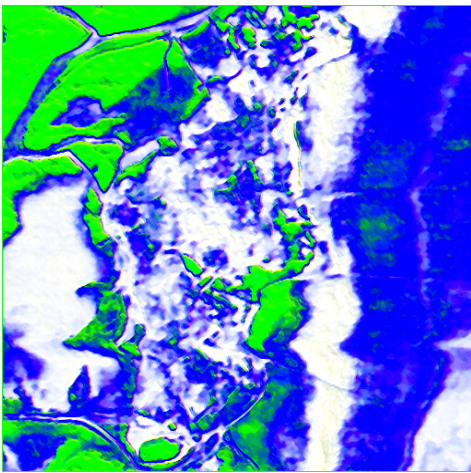
Figure 5. Segmented image by MLPNs



Figure 6. Segmented image by PNNs

There are some difference between Figure 5 and Figure 6. Firstly, the segmented regions have different ranges. Secondly, the segmented image by PNNs (Figure 6) looks smoother. Third, there is more unsegmented region in Figure 5 (Segmented images by MLPNs).

The overall accuracy is calculated by the ratio of the sum of correctly segmented pixels in all classes to the sum of the total number of pixels tested. In this case, the ground truth points are used as references. The overall accuracy by MLPNs and PNNs are shown in Table 1 and Table 2.

|  |  | Ground truth class | | | | |
|---|---|---|---|---|---|---|
|  | Class Total | I | II | III | IV | |
| Segmented class | I | 22 |  | 2 | 2 | 26 |
|  | II | 1 | 16 |  | 3 | 20 |
|  | III | 1 |  | 12 |  | 13 |
|  | IV |  | 2 | 2 | 17 | 21 |
| **Total** |  | 24 | 18 | 16 | 22 | |

Table 1. MLPNs overall accuracy = 83.75%

|  |  | Ground truth class | | | | |
|---|---|---|---|---|---|---|
|  | Class Total | I | II | III | IV | |
| Segmented class | I | 21 | 2 | 2 |  | 25 |
|  | II |  | 15 |  | 1 | 16 |
|  | III | 1 |  | 13 | 1 | 15 |
|  | IV | 2 | 1 | 1 | 20 | 24 |
| **Total** |  | 24 | 18 | 16 | 22 | |

Table 2. PNNs overall accuracy = 86.25%

As shown in above tables, segmentation based on MLPNs and PNNs separately obtain 83.75% and 86.25% overall accuracy in the experiments. The evaluation indicates PNNs gain a bit higher accuracy. In fact, numbers of samples strongly influence the accuracy statements. If we could get more ground truth points, or we segment a image into more categories, the evaluating error would be decreased.

### 3.4 Discussions

The experiments demonstrate that applying the methods of neural networks to image segmentation. MLPNs have steady working state and simple configuration. But it still has some disadvantages, for example, it needs enough samples for network training and the network easily get into the problem of local minimum. PNNs could avoid these disadvantages because it is based on the thoughts of probability statistics and Bayes classification rule.

In experiments, if more classes would be obtained, the structure of MLPNs should be more complicated. With the result that MLPNs would not get the same high quality segmentation as PNNs. It is not easy to know how strongly the different parameters of a network influence the performance. The optimal learning parameters and training parameters should be defined under the conditions of various tests.

In specific procedure of segmentation, the problems are its under-constrained nature and the lack of definition of the correct segmentation. As a result, it is difficult to know the quality of segmented image before the results come out. There exist many methods of performance improvement, including optimising smoothing factor $\sigma$, adjusting some parameters of PNNs' construction and employing separate sigma weights.

### 4. CONCLUSIONS

The experiment obtains ideal effects in the study. The overall accuracy of segmentation achieves 83.75% and 86. 25%. The time cost of segmentation with MLPN and PNN is also satisfied.

In conclusions, MLPNs and PNNs have better ability in pattern recognition. One main advantage of using PNNs is the ability to output a probability for each of its classification; the other is PNNs need not repetition of network training. MLPNs need adequate amount of samples in network training. With compared to MLPNs, the architecture and network designing of PNNs are simple. PNNs have quick convergence speed; they could not easily fall into local minimum problems. Consequently, PNNs have high processing efficiency and they are quite suitable for data real time processing. Because of stable neurons of network layers, MLPNs and PNNs could be

simply implemented in computer hardware. PNNs have better characteristic of fault tolerance. It is discovered that the characteristic vectors dimensions strongly influenced accuracy statements. With the increasing of characteristic vector dimensions, the segmentation accuracy could be improved.

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