Using RBF Algorithm for Landcover or Clutter Classification for Mobile Planning

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Abstract - In this paper, the authors consider the problem of classifying the service area for the planning of mobile network. A neural network (NN) algorithm based on Radial Basis Function (RBF) is proposed to classify land cover using information derived from a Geographic Information System (GIS). The comparison between the computed results and real data demonstrates the method is a practical approach with accuracy up to 93%.

I. Introduction

It is well known that for mobile network planning, the analysis of environment structures (building, trees, etc.) is an important subject as it has a significant effect on the received signal strength [1][2]. Therefore, it is important to determine the classes of a service area for systematic planning. Each of these service areas belonging to different classes has different traffic density, mobile users' average speed, different propagation losses and fading characteristics. For example, in downtown urban areas, the traffic density, propagation losses and fading depths are large, while the user's speed is slow. All of these factors affect one another, and their complex relationships are often difficult to be determined accurately. The presence of "clutter" data can significantly refine the prediction of signals, if one can exploit through data mining the digital maps in Geographic Information System (GIS) [3]. The task of classification of the service area is laborious and time-consuming. In this paper, we present a more efficient technique to perform this task automatically. After determining the various classes of the service area, a representative set of data is used to train a feed-forward neural network algorithm named Radial Basis Function (RBF).

After determining the various classes of the service area according to Table 1, a representative set of

data is used to train a feed-forward neural network algorithm named Radial Basis Function (RBF). Recently, RBF neural networks have proved to be a powerful technique in generalizing the data based on non-linear mapping [4].

Table 1 Table of Zone Classifications

Class ²	BAI%	$\overline{BSD}$ (m ²)	BVI%
1 - Seas and lakes	<0.1	<1	< 0.01
2 - Open space and parks	0.1-9	>1	> 0.01
3 - Industrial estate	9-80	>1000	< 0.5
4 - Low rise residential	12-30	<600	0.2 - 0.5
5 - High rise residential	13-30	600-1800	0.6 - 0.5
6 - Shopping area	>16	>1000	> 0.8
7 - Commercial area	30-45	>1800	2 - 3.5
8 - Skyscrapers	24-40	>1800	> 3.5

II. Procedure:

The service area (covered by the mobile network) is partitioned into grids of 500m × 500 m as shown in Figure 1 for the southern part of Singapore. Three variables used in the design are as follows:

1. BAI% i.e. Building Area Index is the percentage of area occupied with buildings.
2. $\overline{BSD}$ is the mean of the sizes of buildings.
3. BVI% Building Volume Index i.e. the percentage of the volume occupied by buildings (derived from building height).

These important variables were extracted from the information stored in the GIS, and input to the RBF neural networks (RBFNN).

Figure 1: Southern Map of Singapore with Gridlines

A brief description of the algorithm is given as follows. The RBFNN consists of 3 layers of neurons, which are fully interconnected as shown in Figure 2. The first layer is composed of input nodes. The number of nodes, p is equal to the dimension of the input vector $\mathbf{x}_i = (\text{BAI}\%, \overline{\text{BSD}}, \text{BVI})$ (i.e., the number of independent variables of the problem). The second layer is a hidden layer composed of multivariate Gaussian nonlinear units that are connected directly to all of the input layer nodes. The function in the neurons in the second layer is shown in equation (1).

$$h_i = \exp[-D_i^2/(2\sigma^2)] \quad (1)$$

where $\mathbf{x}$ is an input vector

$\mathbf{u}_i$ is weight vector of hidden layer neuron i .
(Note that this equals an input training vector.)

$$D_i^2 = (\mathbf{x} - \mathbf{u}_i)^T(\mathbf{x} - \mathbf{u}_i)$$

$\mathbf{x}$ and $\mathbf{u}$ are column vectors

T indicates the vector transpose

The output layer consists of a single linear unit, being fully connected to the hidden layer and produces the linear weighted summation of these inputs h_i .

$$y = \sum_{i=1}^n h_i w_i \quad (2)$$

where n is the dimension of the hidden layer.
 w_i is a weight in the output layer.

Fig. 2 Radial Basis Function Network

The RBFNN has to be trained with the input $\mathbf{P} = (x_1, x_2, \dots, x_N)$ data and the targets $\mathbf{T} = (t_1, t_2, \dots, t_N)$. The training is as follows. There is initially one neuron in the hidden layer. Firstly, (1) the network is trained by $\mathbf{P}$ and $\mathbf{T}$ and the input vector that will result in lowering the network error (mean squared error) the most, is used to determine the parameters of the neuron. Then, (2) the mean squared error (MSE) of the network is checked, and if the MSE is low enough, the training is finished. Otherwise (3) the next neuron is added. This procedure (1) to (3), called an *epoch*, is repeated until a selected MSE goal is met, or the maximum number of neurons N is reached. In this letter, we use the RBF spread [4] $\sigma = 1$ and limit the training data $N < 100$. After training, the other service areas can be classified using the network automatically

III. Training and Experimental Result

The numbers, 1, 2, ..., 7, 8 represent the classes as the target, such as seas and lakes, open space and parks, industrial estate, low rise residential, high rise residential, shopping area, commercial area and sky scrapers, respectively. We trained the network with different numbers of input vector and target, respectively. A typical curve of Sum of Mean

Fig.3 The Sum-Squared of Error

Squared of Error in training is shown as Figure 3. Fig. 3 shows that it requires approximately 79 epochs to train the RBFNN. After training, we use another set of data from another region as the input data to test the RBFNN. We compared the computed result with the real classes and determined the different error rate. The error rate E_r is given by equation (3).

$$E_r = \frac{E_n}{N} \times 100\% \quad (3)$$

where E_n is the number of errors as misclassification.
 N_t is the number of test data.

The result of training the RBFNN by using different training sizes is shown in Table 2. The accuracy improves with an increase number of training data. Using only 80 training data, it provides an accuracy of 94% for the classification. From this experiment, it is shown that the RBFNN algorithm is a good and practical approach for land use classification for mobile network planning. It is possible to improve the classification with more land usage information.

Table 2

Number of training vectors	60	65	70	75	80
Error rate (%)	26.7	25.0	11.7	9.7	6.7

IV. Conclusions

In this paper, the neural network algorithm using RBF was used to classify the service region for cellular mobile communication automatically. The service regions were classified according to the variables i.e. Building Area Index, Mean Building Density, and Building Volume Index for each grid generated through the GIS. We demonstrate that the RBFNN is capable of learning the relationships between the input variables and land classes with the accuracy of 74-93%.

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V. References

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