COMPARISON OF SPECKLE REDUCTION METHODS FOR MULTISOURCE LAND-COVER CLASSIFICATION BY NEURAL NETWORK
: A CASE STUDY IN THE SOUTH COAST OF KOREA

RYU, Joo-Hyung, Joong-Sun WON and Sang-Wan KIM
Department of Earth System Sciences, Yonsei University
jhryu@yonsim.yonsei.ac.kr
Fax) +82-2-392-6527

Abstract - The objective of this study is to quantitatively evaluate the effects of various SAR speckle reduction methods for multisource land-cover classification by backpropagation neural network, especially over the coastal region.

The land-cover classification using neural network has an advantage over conventional statistical approaches in that it is distribution-free and no prior knowledge of the statistical distributions of the classes is needed.

The goal of multisource land-cover classification acquired by different sensors is to reduce the classification error, and consequently SAR can be utilized an complementary tool to optical sensors. SAR speckle is, however, an serious limiting factor when it is exploited for land-cover classification. In order to reduce this problem, we test various speckle methods including Frost, Median, Kuan and EPOS.

Interpreting the weights about training pixel samples, the "Importance Value" of each SAR images that reduced speckle can be estimated based on its contribution to the classification. In this study, the "Importance Value" is used as a criterion of the effectiveness.

I . Introduction

There is a growing interest in classification of multisource(optical and microwave) remote sensing images, due to the available civilian SAR systems and to the increasing demand for related applications.[1]

The availability of optical remote sensing data for land-cover applications is limited due to the weather conditions. SAR has been proven to be an effective remote sensing instrument because of 1) day/night and weather-independent imaging capabilities; 2) high resolution regardless of antenna altitude; 3) signal data characteristics unique the microwave revision of the EM spectrum.[2] But, the presence of speckle noise in radar image, produced by coherent illumination, will result in a high degree of misclassification.[3]

We will especially focus on coastal region where land-cover characteristics are quitely different from that of in-land. Because most remote sensing data in coastal region do not show a characteristic of single Gaussian distribution, we adopt the backpropagation neural network discussed in many publications as a classifier.

Neural network classifiers are importance free. That is data sources with different characteristics can be incorporated into the process of classification without knowing or specifying the weights on each data sources when neural networks are used.[4]

We have tested this approach using by interpreting the weight after training JERS-1 OPS and Radarsat SAR data in Nakdong-river area. The importance of each SAR data can be ranked based on its contribution to classification.

Table 1. Summary of Data sets

Satellite/ Sensor	Date	Time (h)	Sea-level (m)	pixel spacing (m)	Incidence angle (deg)	N o lo
Radarsat/ fine	1996 .8.5	18-19	0.63-0.61	3.125	43.8-45.6	
Radarsat/ standard	1996. 8.15	18-19	1.55-1.76	8.0	36.5-42.2	
JERS-1/ OPS	1997. 4.28	11-12	1.28-1.37	18.0		

Once the "Importance value" is estimated as a criterion of effectiveness, one can evaluate suitable speckle reduction methods for classification.

II. Data and Methodology

1. Data and speckle reduction method

Experiments are conducted using a 1024×1024 pixel of JERS-1 OPS with three bands and Radarsat SAR fine and standard mode. It covers the southern Nakdong-river region just the west to Pusan, and shows reclaimed areas in central part and waters in the eastern parts in Figure 1. Sigma nought, the measure of the strength of

Figure 1. Radarsat fine mode image of test area

radar signals reflected by a distributed scatterer, is calculated for Radarsat SAR data by CSA a method.[5] All data is resampled the same as Radarsat fine mode(pixel spacing 3.125×3.125 m) and geocoded.

Two categories of speckle reduction technique are distinguishable. The first one is of multilook processing in which independent looks of the same area are averaged.[3] A second way to reduce speckle is to average the values of neighboring pixels. Various speckle filters such as Frost, Kuan, Median and EPOS are in this class.

An overview of the algorithms for various filters may be found in some review papers and will not be recapitulated in this paper.

Since the speckle reduction capability of most filters depends on the window size, implementations of the filters used in this paper are fixed to a 5 ×5 matrix size except for EPOS(11×11).

2. Methodology

Backpropagation Neural Networks are found in many publications. So that, we will only discuss the result by testing the Importance-Free Characteristics of Neural Networks. Three-layered

Table 2. Statistics of the training pixel samples

mean (std)			water	forest	recl.*	ag1*	ag2.
JERS	1		141.5 (1.8)	115.3 (1.5)	255.0 (0)	178.9 (5.0)	136.1 (3.4)
	2		130.9 (2.9)	110.1 (3.7)	255.0 (0)	217.7 (4.6)	146.2 (3.3)
	3		79.7 (1.8)	181.2 (3.1)	254.4 (0.9)	186.8 (3.8)	132.3 (5.5)
Radarsat	standard		-22.1 (3.0)	-13.9 (2.3)	-6.5 (2.7)	-10.5 (1.5)	-11.2 (2.0)
	fine	raw	-24.7 (6.1)	-14.2 (5.9)	-10.9 (6.7)	-12.1 (6.9)	-9.2 (6.2)
		Frost	-24.8 (2.7)	-14.0 (2.6)	-10.4 (3.1)	-12.0 (3.8)	-8.7 (2.4)
		Median	-23.5 (2.8)	-13.4 (2.9)	-9.4 (2.7)	-10.8 (3.3)	-8.0 (2.2)
		Kuan	-24.8 (2.7)	-14.1 (2.5)	-10.4 (2.9)	-12.0 (3.6)	-8.8 (2.2)

recl*: reclaimed area ag*: agricultureal area

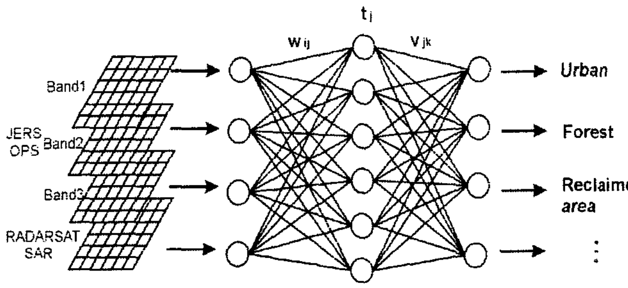

Fig. 2. Classification of Multisource Data by Neural Network

feed-forward networks were implemented in Matlab on the basis of the framework provided by Wesley.[6]

The structure of 4×10×5 are selected for the networks with input data normalized to the range 0.1 to 0.9. The learning rate is set to be 0.01 and the initial weights are randomly selected. From each of the 5 classes, 125 pixels are selected as training pixels.

The means and standard deviation of training pixels in each band are listed Table 2.

To test the speckle effect on classification, the experiments are carried out with three JERS-1 bands and additional SAR data as schematically described in Fig.2

This study is used unipolor sigmoid function as a activation function(f). As shown in Fig.2, w_{ij} and v_{jk} are the weights on the input-hidden and hidden-output connections, respectively.

NET_k is a function of the weights between the hidden and output layer, v_{jk}, and the outputs of the hidden layer nodes, y_i :

$$z_k = f(NET_k) = f(\sum_{j=0}^{J} \cdot v_{jk}\, y_j) \tag{1}$$

Methods for weight interpretation is described by [4]. From (1), the effect of an output y_j from a hidden layer node j on the output z_k from an output layer node k can be represented by the partial derivative of z_k with respect to y_j, such as

$$\frac{\partial z_k}{\partial y_j} = f\ (NET_k) \cdot v_{jk} \tag{2}$$

In the hidden layer, the importance of node j relative to another node j_0 can be calculated as the ratio of the absolute values from (2)

$$\frac{|\partial z_k|}{|\partial y_j|} / \frac{|\partial z_k|}{|\partial y_{j0}|} = \frac{|f\ (NET_k) \cdot v_{jk}|}{|f\ (NET_k) \cdot v_{j0k}|} = \frac{|v_{jk}|}{|v_{j0k}|} \tag{3}$$

From above equation, v_{j0k} is a mean of absolute hidden-output weighting value and t_{jk} is a normalized importance of node j with respect to node k

$$t_{jk} = \frac{|v_{jk}|}{\frac{1}{J} \cdot \sum_{j=1}^{J} |v_{jk}|} = \frac{J \cdot |v_{jk}|}{\sum_{j=1}^{J} |v_{jk}|} \tag{4}$$

Therefore, with respect to the same node, all the nodes in the output layer, the overall importance of node j can be calculated as

$$t_j = \frac{1}{K} \cdot \sum_{j=1}^{J} t_{jk} \tag{5}$$

In the input layer, the normalized importance of node i can be defined as (4). Consequently, the overall importance of node i with respect to node k is given by

$$ST_i = \frac{1}{J} \cdot \sum_{j=1}^{J} s_{ij} \cdot t_j \tag{6}$$

Ⅲ. Results and Discussion

Equation (6) was used to calculate the overall importance of input layer nodes for the classification results from three JERS bands and one additional SAR data.

As summarized in Table 3, on the basis of JERS data is contributed on classification in the order of band 3, 2 and 1 overall importance for each scheme. Among the additional SAR data, raw data of fine mode is turned out to be the lowest and EPOS filter data to be the highest. Therefor EPOS filter should be the best candidate for this purpose judging from importance value only.

Table 3. Comparison of Importance Value

Importance Value(ST_i)							
		Radarsat fine					Radarsat standard
		raw	Kuan	Frost	Median	EPOS	
JERS	1	26.3	23.4	16.9	21.4	21.4	21.3
	2	27.4	25.2	29.2	25.5	25.1	26.7
	3	30.3	28.8	30.8	29.7	29.3	28.2
additional SAR		16.0	22.6	23.0	23.2	24.2	23.7

However, speckle noise can not be evaluated by only importance value because it is affected by three criteria : 1) preservation of mean, 2) reduction of variance and 3) preservation of edges.[2] Although the test results presented in this paper has demonstrated its performance comparing the speckle reduction methods for multisource data classification, further tests should be followed to evaluate classification accuracy. Method for weight interpretation will be used for spatial analysis widely.

If some data sources are found to be unimportant, they can be spared in future classification processes to simplify the network structure and save computation time.[4]

Reference

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