APPLICATION OF NEURAL NETWORK FOR THE CLOUD DETECTION FROM GEOSTATIONARY SATELLITE DATA

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ABSTRACT:

An efficient and robust neural network-based scheme is introduced in this paper to perform automatic cloud detection. Unlike many existing cloud detection schemes which use thresholding and statistical methods, we used the artificial neural network methods, the multi-layer perceptrons (MLP) with back-propagation algorithm and radial basis function (RBF) networks for cloud detection from Geostationary satellite images. We have used a simple scene (a mixed scene containing only cloud and clear sky). The main results show that the neural networks are able to handle complex atmospheric and meteorological phenomena. The experimental results show that two methods performed well, obtaining a classification accuracy reaching over 90 percent. Moreover, the RBF model is the most effective method for the cloud classification.

KEY WORDS: Neural network(NN), Cloud Detection, Multilayer-Perceptron(MLP), Radial Basis Function(RBF)

1. INTRODUCTION

In the derivation of geophysical information such as sea surface temperature from the radiance data measured by the instruments onboard satellite, the accuracy of cloud information is critically important in the accuracy of the derived geophysical information. Furthermore, information on the cloud presence in the interested pixel determines subsequent derivation chains. For example, if pixel is contaminated by cloud the pixel is used to derive information related with the cloud such as the cloud type, cloud optical depth and so on. While if the pixel is determined as cloud free, the information available with the cloud free such as surface temperature, humidity, and so on is derived. Thus, determination of cloud contamination for each pixel is the critical first step for the derivation of the other parameters in the satellite meteorology. There are many approaches for the cloud detection depending on the available radiance data and purposes (Saunders et al.,1988 and Simpson et al., 1995). However As the background characteristics changes with season, location, observation geometry, and others, these approaches can be affected to accuracy.

Here we introduces a neural network approaches for the detection of cloud and possibility for the extraction of cloud information such as the cloud type. As the underlying physical processes determining satellite measured radiances are generally nonlinear and vary both spatially and temporally, the neural network (NN) approach is a good candidate as an alternative cloud detection approach(Yhann and Simpson, 1995; Shaikh et al., 1996). The NN approach basically considers the known inputs and resulting outputs as a standard dataset and finds out a general pattern which relates the inputs and outputs to predict outputs from a new input. Thus, one of the most important process in the developing a NN model is finding out the general pattern which is usually non-linear and complex characteristics(Benediktsson et al., 1990; Heermann et al., 1992). Based on the choice of network architecture and structure, learning algorithm, and other parameters, there are many kinds of NN models. Here we present a multilayer perceptron and radial basis function model. The main goal of this study was to compare the performance of the RBF networks with that of the MLP and to examine probability for cloud detection in the future.

This paper is organized as follow. Section 2 provides a brief introduction to neural network model(including MLP and RBF) The result of model training with data set is shown in section 3. Application of the MLP and the RBF model to detect cloud using GOES-9 satellite data are compared in Section 4 and in Finally concluding remarks are drawn in Section 5.

2. THE NEURAL NETWORK (NN) MODELS

2.1 Multi-layer Percepron (MLP) Neural Networks

The Multilayer perceptrons(MLP) is one of the most common neural networks model and has been widely studied and applied to solve cloud detection problems(yhann et al., 1995; Lee et al., 1990). The input layer contains node for each input variable, and the output layer represents the target variable. In the context of cloud detection, nodes of input layer is determined by features in a pixel. MLP is feedforward neural networks which has one or more hidden layers. It uses sigmoid asctivation functions. The output of the hidden layer can be shown in (1) and H_j is the output that weighted sum of all inputs run through sigmoid activation function $f()$, here we use a logistic function and the linear function is used as the combination function.

$$H_j = f(X_j) = f(\sum_{i=1}^{n} w_{ij} x_i) \quad (1)$$

where w_{ij} = the weight between input and hidden layer

x_i = input variable

n = the number of input variable

The output in output layer is obtained by summation of the weight output of the hidden layer, which can be written as

$$Y = \sum_{j=i}^{m} c_j H_j \tag{2}$$

where c_j = the weights between hidden and output layer

m = the number of neurons in the hidden layer.

Determination of the weights, the proper number of input variables and hidden layers are the key for the model development. The back-propagation(BP) algorithm which minimizes difference between the estimated outputs and true outputs is used for MLP model training. A schematic diagram for the process is shown in Fig. 1. The initial weights are given randomly and the estimated outputs are obtained by running the model. The estimated output is compared with the truth output. If the difference is larger than preset threshold value, the weights are modified. Then the process is repeated until the difference between estimated and truth outputs is within the preset threshold value. For the determination of the number of hidden nodes, we use a trial-and-error approach varying from 1 to 20 with 100 repetitions.

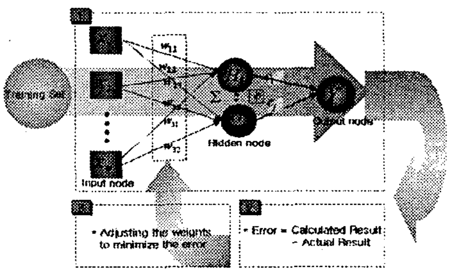


Figure 1. Structure of MLP by BP algorithm.

2.2 Radial Basis Function (RBF) Neural Networks

The RBF network consists of feedforward network with an input layer, single hidden layer with RBF nodes and an output layer. Compared to the MLP network, the RBF network has characteristics of fast learning time, a simple structure and a high classification capability (Moody. 1989). Also a RBF is used for the combination function. Fig 2 shows the structure of a typical RBF NN. RBF training is undertaken as two stage procedure, hybrid learning method. That is to divided as learning in the hidden layer and learning in the output layer. First, the learning transferring information from the input layer to the hidden layer is performed by using an unsupervised clustering method, the K-means algorithm. Each input data is attached to cluster minimizing euclidean distance between input and the cluster(hidden node) centers, width values. Then the radial basis function, the normal distribution gaussian function, are applied to each hidden node by (3).

$$\phi_j(x) = \exp\left\{ -\sum_{i=1}^{n} \frac{(x_i - \mu_{ij})^2}{2\sigma_j^2} \right\} \tag{3}$$

where μ_{ij} = mean of i th input in j th hidden node

σ_{ij} = width of the j th hidden node

x_i = input variable

n = the number of input variable

Learning in the output layer starts after learning in the hidden layer. The predicted output which has m number of hidden nodes for inputs performed by computing a linear combination of the activation of the radial basis functions(hidden nodes) and weights between hidden and output layers. And it can be expressed as (4).

$$Y = \sum_{j=1}^{m} w_{jk} \phi_j(x) \tag{4}$$

where w_{jk} = weights from j th hidden node to output

σ_{ij} = width of the j th hidden node

We can optimize the weights which minimizes difference between the estimated outputs and true outputs using the supervised learning method, the least squares approach. Within RBF network, determination of the number of hidden nodes, the center, width values, and the weights connecting the hidden layer to output layer nodes are the key that effect model accuracy.

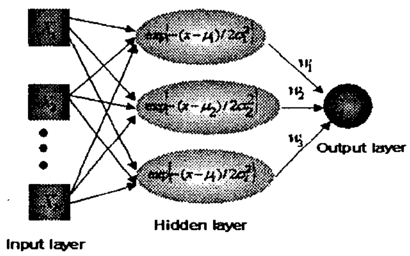


Figure 2. Structure of RBF Neural Network.

3. EXPERIMENTS

3.1 Data set and Feature

To collect training data on real cloud information is the most important task to be done before selecting an algorism and a architecture to construct the cloud detect model, and has the most impact on accuracy on cloud classification capability of the future model. Therefore, accurate cloud data in the past or the present are necessary, but because there is no practical data on cloud detect at present, training data which have the information on whether there are clouds or not are generated by applying experiential, dynamic threshold values to each pixel of Korea and Asia scenes that collected from GOES-9 by hour from September to November 2004. The GOES-9 satellite have five channels : Channel 1 to Channel 5. Input variables which have direct impacts on the model performance are used five channels from GOES-9 –visible(channel 1), short wave infrared(channel

2), watervapor(channe 3), Infrared,(channel 4 and 5) wavelength, reflectance values and brightness temperature. Since each channels' characteristic is different according to each surface condition, input variables for this are used, such as surface information on land and sea, solar zenith angle to tell day or night. And all the selected input data go through normalization that converts them to values between 0 and 1, and then are used for input data.

3.2 Model training

A total of training pixels were generated from GOES-9 images for cloud information. The data were divided into two set, training set, validation set. The 70 percent of the total number of data (clear and cloud pixel) were used as the training set. The validation set was formed by drawing pixel randomly from the remaining data. After constructing each model using above mentioned two methods with generated training data, is evaluated with validation data.
The number of hidden nodes is optimized by the trial-and-error method varied from 2 to 20. The repetition time is decide 100 from experience.

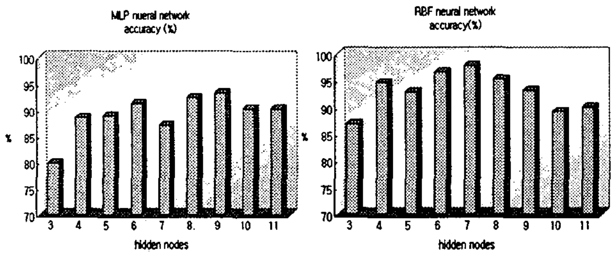


Figure 3. Accuracy(%) of neural networks model

First, the accuracy(%) is shown in Fig. 3. according to the number of hidden layer nodes. Four cases with the highest accuracy(%) among each models are shown in Table 1. MLP model shows more than 90% accuracy, and when there is nine hidden nodes, it shows the highest accuracy, 93.26% and low errors. And RBF model shows highest accuracy(%), 97.84%, when there is seven hidden nodes, This shows it has higher accuracy than MLP models.

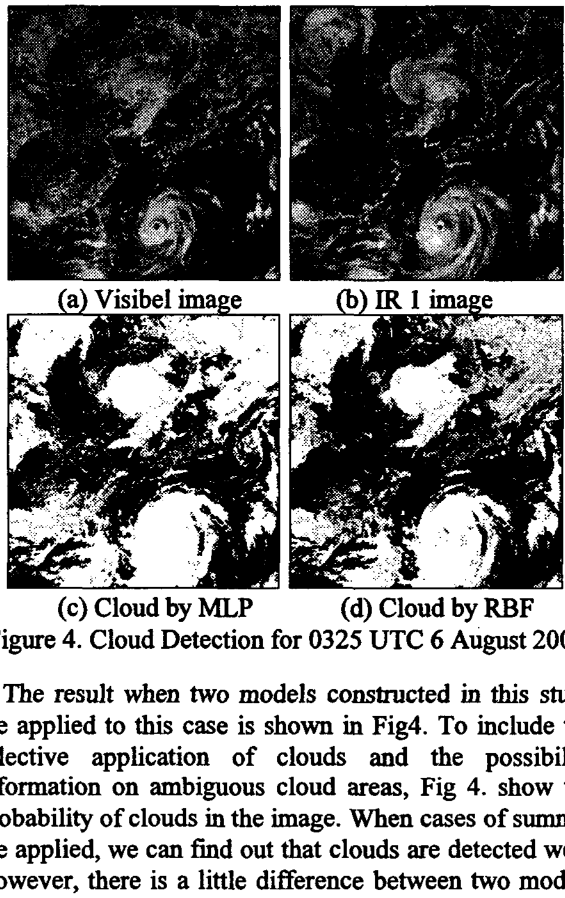
Table 1. Neural Network model training results

	MLP Neural Network Model			
hidden units	6	8	9	11
RMSE	0.323	0.245	0.223	0.467
misclassification pixel	54,76	48,318	42,412	61,845
Accuracy(%)	91.3	92.32	93.26	90.17

	RBF Neural Network Model			
hidden units	4	6	7	8
RMSE	0.156	0.072	0.068	0.123
misclassification pixel	33,974	21,391	13,602	29,947
Accuracy(%)	94.60	96.60	97.84	95.24

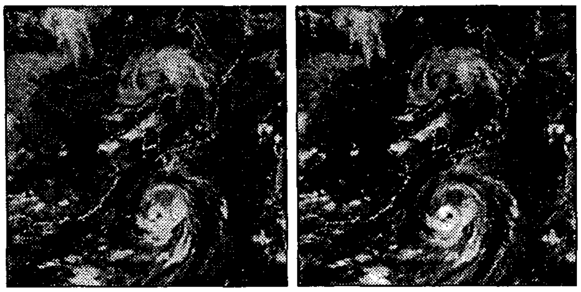
4. RESULTS AND DISSION

In order to find out how we can detect clouds in images of Asia according to season, for the heavy rain case in August 6, 2003, data from 0025 UTC to 2325 UTC are applied to models. Fig 4. shows the visible channel and the infrared channel images from GOES-9, during daytime, 0325 UTC. In this image, there are a typhoon coming up from the southern coast, clouds covering the Korean Peninsula and low-level clouds on the north east sea.

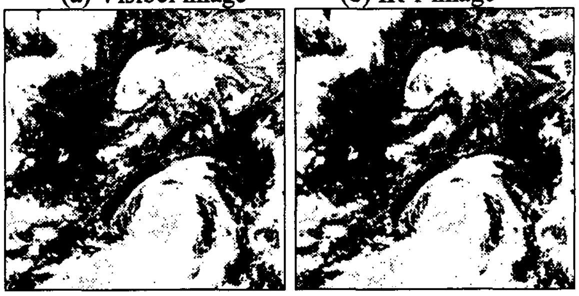


(a) Visibel image (b) IR 1 image
(c) Cloud by MLP (d) Cloud by RBF
Figure 4. Cloud Detection for 0325 UTC 6 August 2003

The result when two models constructed in this study are applied to this case is shown in Fig4. To include the selective application of clouds and the possibility information on ambiguous cloud areas, Fig 4. show the probability of clouds in the image. When cases of summer are applied, we can find out that clouds are detected well. However, there is a little difference between two models for the edge of clouds, low-level clouds and coast. Generally, the RBF model shows more sensitive probability information on these areas. Fig. 5. shows images during nighttime, 1325 UTC. There are a typhoon more coming up from the daytime, clouds still covering the middle part of Korea, and a little low-level clouds still on the north east sea. During the nighttime, though the visible channel is bad value, since daytime and nighttime information is already used for input by using the solar zenith angle, there is no negative impact on detecting clouds, and we can find good detecting results in Fig 5. Like summer day cases, two NN models show a good overall detecting performance, there is a little difference between two models in the edge of clouds. The MLP model intends to detect these parts are clouds for sure, and the RBF model shows a low possibility of clouds for these parts. Especially, the RBF shows more clearly clouds and the edges of clouds on north east sea.



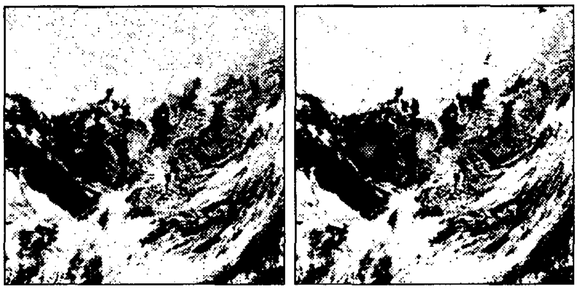
(a) Visibel image (b) IR 1 image



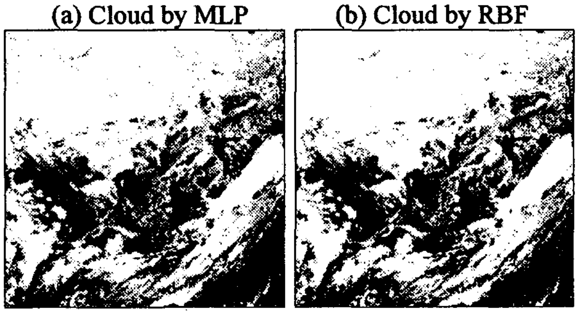
(c) Cloud by MLP (d) Cloud by RBF

Figure 5. Cloud Detection for 1325 UTC 6 August 2003

Next, to check winter cases, data on January 2, 2005 are applied to two models. In the Fig 6. which are the result from the NN model with winter image data, there are over detection of clouds in the most areas. Especially, the northern land is recognized as all the clouds, which is because the low surface temperature of winter brings in the low brightness temperature inputs. Since there plenty of surface features and conditions to be considered, we need to keep study how to apply these factors to models. Therefore, it is necessary to improve models by puting information according to season, hour and changes in space into training data, this study will be carried out.



(a) Cloud by MLP (b) Cloud by RBF



(c) Cloud by MLP (d) Cloud by RBF

Figure 6. Cloud Detection using NN model for 0325 UTC (a),(b) and 1525 UTC(c),(d) in 2 January 2005

5. CONSLUSION

This paper presents a scheme to detect to clouds with images data from satellites, and we study whether NN methods can be used to detect clouds, with regard to efficiency and accuracy in the future. MLP model shows high classification accuracy. However, considering the unpractical factors, slow learning time, many errors that are difficult to apply to real time data processing, the model learned based on Radial basis function(RBF) is studied, and it shows the fast learning speed and higher accuracy than the MLP model. We check the performance of these two models to detect clouds according to season and time, though there are some problems with winter data, they show reliable result for summer data and data of other times. However, since the number of training data used in the study is not enough, the characteristics of atmosphere which change constantly as time spatially are not reflected, and selected input variables are limited, it is hard to generalize in the global area. In the future, the study on the high level and integrated NN model that can detect clouds in the global area in real time, covering above weaknesses will be carried out.

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5.1 Acknowledgements (optional)

This study is implemented as a part of "Development of Meteorological Data Processing System of Communication, Ocean and Meteorological Satellite" project.