Cloud Classification for Weather Information by Artificial Neural Network

Sanju Kuril, Indu Saini, and B. S. Saini

***Abstract*—Continuous cloud classification through satellite image is an approach which is very important in many atmospheric and Environment studies such as weather analysis and forecasting. The detection and classification of clouds of satellite image the most effective method for identifying the individual cloud type for weather analysis and forecasting. It involves two mainly Stages Feature Extraction and Classification, Feature extraction has been done by Haar DWT i.e. Haar Discrete Wavelet Transform and the classification has been done by ANN i.e. Artificial neural network. Classification and accuracy has been improved by using artificial neural network on satellite images. The performance of the designed classifier is evaluated and which gives the overall accuracy of 94.37 % with 91.66% for Low Level Clouds, 98.33% for Middle level Clouds and 93.33% for High Level Clouds.**

***Index Terms*—Feature extraction, discrete wavelet transforms, artificial neural network, radial basis function, cloud classification.**

I. INTRODUCTION

Cloud classification through satellite images is an approach of vital importance in many atmospheric and environmental studies such as weather analysis and forecasting [1]. It involves two main stages, feature extraction and classification. The goal of feature extraction is to determine features from the available channels that make the detection of changes in cloud characteristics easier. The classifier makes the decision on the basis of these features to categorize the image pixels to different cloud types. The purpose of feature extraction technique in image processing is to represent the image in its compact and unique form of single values or matrix vector. The wavelet transform is widely used in processing technique for object detection and classification. Wavelets have been applied in the past to analyze images [1] and are used in many applications in remote sensing, such as removing speckle noise from radar images [2], merging high spectral resolution images with high spatial resolution images, and texture analysis and classification [3]. Discrete Wavelets Transform (DWT) as an image processing technique produces the transformation values called wavelet coefficient. In [4], Classifier has been used as a feature extraction tool to analyze sub-band frequency of the wavelet transform. The most common technique used for feature extraction of DWT coefficient is by using neural network [5]–[7]. In this study, wavelets will be used in the analysis different type of satellite images of clouds since DWT allows decomposition of the image into different levels of resolution.

Manuscript received July 18, 2012; revised December 3, 2012.
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II. METHODOLOGY

The Proposed methodology in this work can be described in block diagram as shown in Fig. 1.

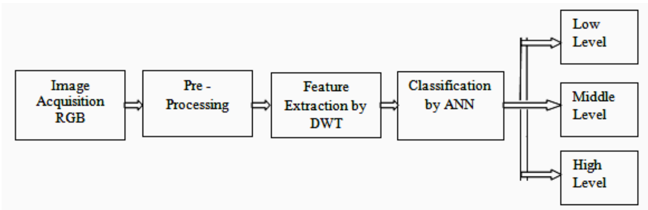

Fig. 1. Block diagram of proposed methodology.

A. Image Acquisition

In this work Indian meteorology department directory's cloud database is being used. Three kinds of clouds including Low level clouds, middle level clouds and High level clouds are selected from different images for analysis and recognition. The samples of data of each file, was taken for learning and testing purpose. The total number of data used is 990 where for training 630 and for testing 360. The first step involves the image acquisition task. Satellite images comprise of three types of clouds. These images of different types are available at different websites of world's major weather forecasting organizations [8]-[9].

B. Pre-Processing

The pre processing task involves converting RGB to gray scale and rescaling with the size of 200x180 gray images. Then Smoothing is done by median filter on the image for more defined features as shown in Fig 2.

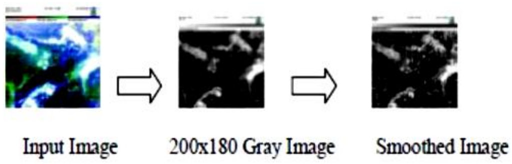

Fig. 2. Pre-processing of image

Median filter performs median filtering of the matrix A in two dimensions. Each output pixel contains the median value in the M-by-N neighborhood around the corresponding pixel in the input image. MEDFILT2 pads the image with zeros on the edges, so the median values of the points within [M N] /2 of the edges.

DOI: 10.7763/IJAPM.2013.V3.167

C. Feature Extraction Using Haar Wavelet Transform

Feature extraction is an important stage for classification, the feature like brightness, texture, size etc. These features are to categorize the image pixels to different cloud types. Low level feature extraction involves automatic extraction of features from an image without doing any processing method. In this work, the images are transformed into their respective coefficients that separate the vertical, horizontal and diagonal sub-bands.

Haar Wavelet is applied to each image to obtain statistical parameters at different levels of decomposition. Each level has both horizontal (H) and vertical (V) detail coefficients. As mentioned earlier there are statistical variables associated at each level and for both horizontal and vertical coefficients. So for each image, parameters are obtained for horizontal and vertical coefficients at each level. In those three detail components of a Haar.

Average components are detected by the LL sub band; Vertical components are detected by the HL sub-band; Horizontal components are detected by the LH sub-band; Diagonal components are detected by the HH sub-band.

D. Classification

1) Network topology

For designing classifier model, radial basis function network was chosen with three layers; one input, one output and one hidden layer. The number of neurons in input layer was taken to according to the features being used in classification. The output layer neuron number was fixed same as the number of classes to be discriminated i.e. Try to distinguish three types of clouds.

2) Implementation

1) Decide the number of cover images.
2) Each Image and here no. a band considered *K*=3
3) Calculate the Feature pixel vector x1, x2,…..xn
4) If M is the number of representatives, K*M centres are generated randomly.
5) Each Patter is assigned to its closest cluster centre by calculating the Euclidean Distance between the input vector image and each cluster in K dimensional space.
6) The new centre is generated by calculating the mean of each cluster again. The above process continues till the cluster centres are almost, within a required degree of accuracy.
7) Radial basis function output is calculated from the input training image to form the transform image matrix G. The weight matrix is then computed target classified image matrix is finally obtained multiplication of test image matrix to weight Matrix.

III. Wavelet Theory

In this study only consider Haar Wavelet is used because in Low level feature Extraction involves automatic extraction of features from an image without doing any processing method. By using the DWT it will give the spectral property of clouds. The basic idea of DWT is to provide the time-frequency representation. The 2D-DWT represents an image in terms of a set of shifting and dilated wavelet function $\Psi^{LH}, \Psi^{HL}, \Psi^{HH}$ and scaling function ϕ^{LL} Given a DWT, an image of $N \times N$ is decomposed as {LH,HL,HH} and In this paper LH, HL and HH are called wavelet or DWT sub-bands [10].

IV. Artificial Neural Network

Neural networks are powerful tools for pattern recognition and classification applications. In this paper, the RBF has been used with input, hidden and output layers. The RBF network was selected because it is faster to train than other neural networks and has a better performance in verification task. In cloud classification applications, the RBF neural networks are regarded as a mapping from the feature to the classes. Therefore, the number of inputs of RBF neural networks is determined by the dimension of input vectors [11].

V. Experimental Results

Experiments were performed on the cloud database. In the experiment, DWT algorithm is applied to the low frequency images, the meaningful features are extracted. At last, the extracted features as the input for the classifier which designed by the RBF neural network. The performance of the designed classifier was evaluated with the help of the confusion matrix. The confusion matrix is shown in Table I gives the summary of cloud type classification results for the three classes of testing. In this table, the diagonal elements give the number of correctly classified which comes out to be overall accuracy of 94.37%.

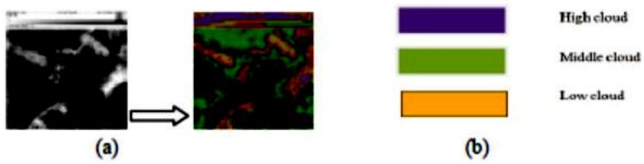

Fig. 3. (a) Classified image is generated by ANN from feature Extracted Image, (b) Classified Image shows the colour of different type of clouds.

TABLE I: Confusion Matrix by ANN

Cloud Classes	Low	Medium	High	Samples used For testing	Accuracy (%)
Low	110	7	3	120	91.66
Medium	2	118	0	120	98.33
High	2	6	112	120	93.33
Overall Testing Accuracy = 94.37%					

TABLE II: COMPARISON WITH DIFFERENT CLASSIFIERS

Methods	Accuracy (%)
Proposed Method	94.37%
SVD [12]	70-90%
BPNN (Back Propagation NN) [13]	71.80%
FLNN (Fuzzy Logic Neural Networks) [14]	81.00%

In order to test our method, SVD [12], BPNN (Back Propagation NN) [13], FLNN (Fuzzy Logic Neural Networks) [14], is used to compare with DWT and RBF neural network. Table II. gives the accuracy and duration of classification.

VI. CONCLUSION

A new cloud classification method using wavelet transform and RBF neural network has been reported and discussed in this paper. The classification rate is comparatively high. The research of future work will be Classification by PNN. We believe that the Classification rate will be improved as well as the Computational time will be low and enhanced greatly.

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