A multilayer fuzzy neural network approach for cloud classification

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Physical processes affecting cloud detection have been analyzed considering both cloud segmentation and cloud labeling in satellite data. Application of neural networks to cloud screening is examined with a special emphasis to cloud segmentation in AVHRR data. Some improved methods for analyzing and comparing satellite and surface observations of cloud patterns have been critically discussed. Finally, multilayer perceptron of neural network has been proposed as a possible better model for cloud label classification.

1 Introduction
The motivation for this work is mainly to develop new techniques for the purpose of detecting multilayered clouds from satellite imagery. Part of the problem is to know where multilayer clouds exist in the imagery before the development of algorithm to observe the macrophysical and microphysical properties of different cloud layers present. Welch et al. and Pankiewicz reviewed pattern recognition techniques for identification of cloud systems. Textural and spectral signatures have been used for classifying cloud and surface types from high resolution Landsat multispectral scanner imagery or from lower resolution imagers. But these classifications have limitations as they are designed for a particular area such as tropical regions, polar regions or maritime regions. Peak and Tag reported the development of automated cloud classification to distinguish primarily between various cloud types or surface types in clear sky condition but unable to distinguish properly whether there are more than one cloud layer or not.

2 Cloud labeling in satellite data
An approach for labeling clouds in satellite data is to apply a static radiance threshold test to each pixel value in an image. In this method, variants combine several thresholds on radiance channels or threshold the differences between channel radiances.

The accuracy of a static threshold is affected due to changes in aerosol type and concentration, atmospheric water vapor and seasonal variations in surface reflectivity and emissivity, and the albedo and brightness temperatures as observed by AVHRR sensor. Thus, different thresholds are required to accommodate cases occurred in large image data sets. Static thresholds can be avoided by determining the thresholds used in each image. The clustering procedure to segment the scene prior to labeling is a minor modification of the procedure for AVHRR data, but it incorporates reflectance and thermal information into segmentation and labeling processes.

3 Application of neural networks to cloud screening
It is observed that a multilayer feed-forward network can be configured for classifying complex data distribution. In practice, the physical processes governing the global environment are non-linear in general and also vary both temporally and spatially. This, coupled with changing atmospheric conditions and sensor noise, makes classification, analysis and modeling more complex. Though there are practical limitations in training time, in number of training samples and in number of nodes, networks can be developed to provide a more or less good sub-optimal solution to a complex problem. The other important attribute of neural networks is that they provide continuous classification output which is closely connected to the underlying data distribution. This is, in fact, in contrast to the traditional classification techniques which provide a binary classification.
Another significant aspect of neural network is that they can extract relationships between data built-up models. This neural networks have been widely used to develop regression models. This is extremely useful for remote sensing application, e.g., regressing the AVHRR channels 4 and 5 temperature differences to produce a split-window-atmospheric-water vapour correction for land temperature or sea-surface temperature.

3.1 Neural networks to cloud segmentation

In this section, the application of feed-forward neural networks to cloud segmentation in AVHRR data is critically focussed. The theory of these networks have already been well-developed. The basic structure of a feed-forward neural network is shown in Fig. 1. The circles in Fig. 1 represent nodes in the network which are the fundamental building blocks and consist of an adder and an activation function. The lines connecting the nodes indicate the data flow between the different inputs and outputs of the network nodes. The inputs to a node are weighted by a value as obtained during training. These are summed in the adder and passed through the activation function to the output. The activation function includes a threshold term which is treated as a weight connected to an input.

In a feed-forward network, data flow only in the forward direction from lower layers nodes to higher layers. These connection weights are the means by which the network model classifies data in different categories. When combined with the activation function each node behaves as a linear classifier of the input space, mapping its input to one of the two classes separated by a single hyperplane. Usually, the activation function belongs to the class of sigmoid function $g(x)$. By a combination of node outputs, the network can construct complex decision surfaces. In order to minimize an error function like the r.m.s., error between the network output node values, the feed-forward network is typically trained using gradient descent techniques. In reality, various gradient descent-based training methods exist which mainly differ in the number of training iterations necessary for learning the network. Neural network approaches have been utilized in remote sensing data classification. Neural networks with combined AVHRR and Scanning Multichannel Microwave Radiometer (SMMR) data have been applied for classifying data from a spatially and temporally limited data set. The fuzzy c-means algorithm is employed for cloud classification in AVHRR data. However, it is unable to make cloud classification with a high certainty. In general, neural networks in these cases are trained and tested on small sample sets and on purely localized data. To improve the neural network cloud screening performance for continuous network output, the method should be developed yet, such that

$$(i,j) \notin N_i^d$$

If $(k,l) \in N_i^d$, then $(i,j) \in N_i^d$.

Different ordered neighbours are defined considering different sets of neighbouring pixels of $(i,j)$. Thus,

$$N_i^{d} = \{ N_i^d \}$$

is obtained by taking four nearest-neighbour pixels. Similarly,

$$N_i^{2} = \{ N_i^2 \}$$

has eight pixels neighbouring $(i,j)$ and so on. This is illustrated in Fig. 2(a).

In Fig. 2(b) we depict the three-layer version of the network architecture. In every layer of this improved model, there are $M \times N$ neurons where each neuron corresponds to a single pixel. In addition to input and output layers, there are a number of hidden layers. In any layer each neuron is connected to the corresponding neuron in the earlier layer and to its neighbours (over $N^2$). Here, each neuron in layer $i (i > l)$ will have $|N^2| + l$ links to the $(i-l)$th layer, where $|N^2|$ is the number of pixels in $N^2$. Thus for $N^2$, a neuron has five links while for $N^3$ every neuron will be associated with nine links.

![Fig. 1 - A generic feed-forward neural network (It has 3 inputs, $N$ hidden layers with 4 nodes each and one output node)](image-url)
4 Multilayer perceptron (MLP) model for cloud level classification

In this section, we propose the MLP type of neural network\textsuperscript{20,21} as a model for cloud classification. The MLP needs several input patterns from different classes for learning as it behaves as multi-dimensional pattern discriminator\textsuperscript{14}. If the images have some common characteristics then the network can be trained with a set of images and the trained net can be used for future images. The learning techniques employed is self-supervised and the error of the system can be calculated using concepts of fuzzy sets. The network can be employed to extract objects from noisy environments. The word “perceptron” is defined as a network of elementary processors, which will be able to learn how to recognize and classify patterns in an autonomous manner\textsuperscript{23}. The invention of multilayer network with non-linear algorithms is called as the multilayer perceptron\textsuperscript{23}.

A schematic representation of a multilayer perceptron is presented in Fig. 2(c). The net is made up of sets of nodes arranged in layers. Nodes of two different consecutive layers are connected by links, but there is no connection among the elements of same layer. Between the input and output layers there are hidden layers and the output of nodes in one layer is transmitted to the nodes in another layer via links. The total unit ($I_i$) to the $i$th unit of any layer is obtained from

$$I_i = \sum w_{ij} \sigma_j$$

where, $w_{ij}$ is the connection weight between the $i$th node of one layer and $j$th node of the earlier layer while $\sigma_j$ is the output of the $j$th neuron in the earlier layer. The output of the node $i$ is,

$$\sigma_i = f(I_i)$$

where, $f$ is the activation function.

For an $M \times N$ image if we connect each neuron with every other one, then the connectivity becomes sufficiently high. With a view to describing the architecture of the network, it is required to define a neighbour. For an $M \times N$ lattice ($L$), the $d$th order neighbour $N_{ij}^d$ of any element $(i,j)$ is defined as, $N_{ij}^d = \{(i_j) \in L\}$.

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