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7.1 Global Single and Multiple Cloud Classification With A Fuzzy Logic Expert System

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1. INTRODUCTION

An unresolved problem in remote sensing concerns the analysis of satellite imagery containing both single and multiple cloud layers. While cloud parameterizations are very important both in global climate models and in studies of the Earth's radiation budget, most cloud retrieval schemes, such as the bispectral method used by the International Satellite Cloud Climatology Project (ISCCP), have no way of determining whether overlapping cloud layers exist in any group of satellite pixels. Coakley (1983) used a spatial coherence method to determine whether a region contained more than one cloud layer. Baum *et al.* (1995) developed a scheme for detection and analysis of daytime multiple cloud layers using merged AVHRR (Advanced Very High Resolution Radiometer) and HIRS (High-resolution Infrared Radiometer Sounder) data collected during the First ISCCP Regional Experiment (FIRE) Cirrus II field campaign. Baum *et al.* (1995) explored the use of a cloud classification technique based on AVHRR data. This study examines the feasibility of applying the cloud classifier to global satellite imagery.

Cloud classification based upon textural and spectral features provides a promising approach for determining whether mixed cloud or surface types exist within a group of pixels. A number of artificial intelligence approaches to cloud classification have been reported in the literature that involve maximum likelihood estimators (Ebert, 1987; Garand, 1988), neural networks (Welch *et al.*, 1992), or fuzzy logic (Tovinkere *et al.*, 1993). For this investigation, a fuzzy logic algorithm is developed for daytime midlatitude and tropical cloud retrieval. This algorithm is extremely adaptable to situations in which more than one cloud type is present. The strength of fuzzy logic lies in its ability to work with patterns that may include more than one class, facilitating greater information extraction from satellite radiometric data. The development of the fuzzy logic rule-based expert system involves training the fuzzy classifier with spectral and textural features calculated from accurately labeled 32x32 pixel arrays, or samples, of Advanced Very High Resolution Radiometer (AVHRR) 1.1-km data. A sophisticated new interactive satellite imagery visualization system (SIVIS) is used to label samples chosen from scenes. The training samples are chosen from predefined classes, chosen to be clear-sky (ocean, land, desert, or snow), unbroken stratiform, broken stratiform, and cirrus. The fuzzy logic method has the ability to assign mul-

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tiple cloud classes to a given sample that contains, for example, both thin cirrus and low-level stratus clouds. Further details of the fuzzy logic classifier may be found in Tovinkere *et al.* (1993). This paper focuses primarily on the development of the classifier for use with global data.

2. DATA

The fuzzy classifier is trained and tested using global NOAA-11 1.1-km AVHRR satellite imagery collected between 1992 and 1994 during winter, summer, and transitional season months. The spectral data consist of AVHRR channels 1 (0.55-0.68 micron), 2 (0.725-1.1 micron), 3 (3.55-3.93 micron), 4 (10.5-11.5 micron), and 5 (11.5-12.5 micron), which include visible (channel 1), near-infrared (channels 2 and 3), and infrared (channels 4 and 5) wavelengths. Channel 1 and 2 radiances are converted to bidirectional reflectances. The near-infrared (NIR) and infrared (IR) radiances are calculated from the raw counts provided in the NOAA Level 1-B data stream using the nominal calibration (Kidwell, 1991). The IR channels also include nonlinearity corrections reported by Brown *et al.* (1993).

Meteorological data are provided by global National Meteorological Center gridded temperature, humidity, and wind profiles at 0000 and 1200 UTC. An estimation of air mass type is derived from these profiles.

3. TEXTURAL AND SPECTRAL FEATURES

The textural features are computed using the gray level difference vector (GLDV) approach (Haralick *et al.*, 1973; Weszka *et al.*, 1976; Chen *et al.*, 1989). The GLDV approach is based on the absolute differences between pairs of gray levels I and J found at a distance d apart at angle Φ with a fixed direction. The GLDV probability density function $P(m)_{d,\Phi}$ is defined for $m = I - J$, where I and J are the corresponding gray levels having a value between 0 and 255. The function $P(m)_{d,\Phi}$ (henceforth P(m), where the dependence of P(m) on d and Φ is implicitly assumed) is obtained by normalizing the gray-level frequencies of occurrence by the total number of frequencies. Once P(m) has been formed, the following textural measures are computed for each of the five AVHRR spectral channels assuming a pixel separation distance of $d = 1$ and at an angle $\Phi = 0°$. The textural features used in this study are the mean, standard deviation, contrast, angular second moment, entropy, and local homogeneity. Explanations of these features may be found in Chen *et al.* (1989).

The spectral features are formed from the gray level representation of the bidirectional reflectances for AVHRR channels 1 and 2 and from the gray level representation of brightness temperatures for the NIR and IR channels. The gray level representation means that the range of possible values is scaled between 0-255.

4. METHODOLOGY

4.1 Description of Cloud Classes

The samples are separated initially into four major groups: clear-sky, low-level cloud, mid-level cloud, and high-cloud. Individual cloud samples are placed into a group based on cloud-top height. This has particular importance for convective clouds since they can fall into any cloud group depending on their state of development. Within a major group, each sample is labeled further with its appropriate synoptic cloud type, such as cirrus, cirrostratus, cirrocumulus, etc. These subclasses play an important role when separating uniform from broken cloud samples. For example, in the low-level cloud class, stratus would be considered uniform while cumulus would be considered broken.

4.2 Derivation of Training Sets

For the classifier to be useful for analysis of global satellite imagery, it must be robust enough to operate over a wide range of conditions. The ability of the classifier depends on the quality of the training set. To arrive at the most robust possible training set, arrays were chosen and labeled from a variety of locations across the world from summer, winter, and transitional seasons. Thus, the samples collected are from a variety of air masses ranging from sub-arctic to sub-tropical. The labeling process was facilitated with the help of an interactive software package called the satellite image visualization system (SIVIS). SIVIS provides a range of image processing functions along with morphological operations such as dilation and erosion. In addition to the graphics and image-processing capabilities, SIVIS software facilitates the ingest and display of ancillary data from a variety of sources. Among the ancillary data sets are a 1-minute resolution global map that provides the location of rivers, coastlines, state and country boundaries, and islands; a 10-minute map that provides surface elevation to the nearest 30 m; a 10-minute map for ecosystem type; and a 10-minute map that provides percentage of surface water cover. SIVIS can display temperature and humidity profiles, NWS surface synoptic observations, and aircraft flight tracks. The labeling process involves more than visual inspection of satellite imagery, taking into account evidence of temperature inversions, maxima in the humidity profile, meteorological analyses, surface elevation and ecosystem type, and other ancillary data.

4.3 Cohesion of Cloud Classes

From the full set of data samples, a training set is developed for each class. For each of the data samples within a given class, a set of statistical tests is performed with the radiance data. As examples, two of the statistical features calculated are the mean value and standard deviation of the radiances for each channel in a data sample. A hierarchical clustering analysis is performed subsequently using the the set of statistical values for each sample. The purpose of clustering is two-fold. First, sample clustering provides insight as to whether outliers exist within a group of samples. If only a few outliers exist, the suspect samples are re-inspected to determine whether they were inappropriately labeled. If many outliers exist, another category may need to be developed. This ensures that the classifier is being developed for a set of samples that exhibit uniformity. Second, clustering provides a mechanism to determine whether a set of data samples forms natural groupings as we expect. For example, it may become necessary to form groups of cloud samples based on air-mass type. Low clouds in an arctic air mass may exhibit much different characteristics than low clouds in an equatorial air mass.

5. RESULTS

Details regarding the mechanics of building a fuzzy logic classifier may be found in Tovinkere *et al.* (1993) or Baum *et al.* (1995) and will not be repeated here. Classification results will be shown for cloud classification over different surface types such as desert, ocean, and vegetated land. Improvements over conventional cloud classification methods based solely upon threshold techniques will be demonstrated.

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