CHAPTER 5

Computational Analysis of Cloud Detection Techniques

5.1 Introduction

In the recent years the importance of climatic changes moved research towards the study of possible causes and their probable effects. Some of the regions of our planet seem to be more sensitive than other regions due to increase in surface temperature, or to a decrease in precipitation, or to a variation in the atmosphere's composition. Two of these sensitive areas are the Polar Regions [41]. The Arctic and Antarctic areas have very particular climatic regimes: a variation in global surface temperatures is expected to be amplified in these regions. The most important climatic processes are badly influenced by cloud cover and by the interactions between clouds and radiative fluxes. Particularly, Polar cloud cover variations affect sea-ice conditions and consequently attenuate the short wave radiation reaching the surface, increase down welling long wave radiation and modify the albedo feedback [42].

The lack of data availability due to the difficulty to obtain direct observations in these remote regions is compensated by the use of meteorological satellites. It allows a long term and quite continuous sensing of the areas of interest and provides an enormous quantity of data. But to interpret Polar satellite images is often very difficult due to the similarity of cloud and ice or snow surface spectral radiances [42]. Cloud detection algorithms from satellite sensor data have been developed using visible, near-infrared and thermal infrared measurements and they have been based on threshold methods, radiative transfer models and statistical classification schemes [43]. Most of the cloud detection methods were developed and successfully used for low and middle latitude data, but they are not applicable in the Polar regions. A historical review of cloud detection algorithms is given by [44]. The failure of the application of these methods to Polar data is caused by a number of reasons including: snow and ice-covered surfaces having the same radiative properties and the same temperatures as clouds; the darkness during the polar night makes data collected in the visible channels unusable; the thermal structure of the troposphere is characterized by frequent isothermal and inversion layers; satellite radiometers operate near the limits of their performance range due to extremely low surface temperatures and solar illuminations; rapid small-scale variations in cloud cover can cause a possible change in snow and ice concentration [43].

Specific cloud detection algorithms have been developed for the Polar Regions by modifying the middle latitude schemes or by developing ‘ad-hoc’ algorithms. A method was developed specifically for Arctic Advanced Very High Resolution Radiometer (AVHRR) data, based on ideas of the International Satellite Cloud Climatology Project (ISCCP)[43]. They also used the Scanning Multichannel Microwave Radiometer (SMMR) in order to detect the ice edge and produce sea-ice masks. For each pixel, nine spectral features are analyzed and four surface (snow-free land, snow-covered land, open water and sea ice) and three cloud classes are defined. The cloud classes are discriminated by the brightness temperature of channel 4, which is assumed as representative of the cloud top temperature [40].

5.2 Need of Cloud Detection

Cloud cover is the main obstacle for satellite imagery in visible and infrared spectral bands. Clouds are transient atmospheric features that consist of small ice and liquid water particles with dimensions from under a micrometer to a few millimeters, resulting from water condensation and freezing.

Cloud properties vary with height. In the visible and infrared part of spectrum, the liquid water and ice crystals contained in the clouds scatter and absorb radiation, so that thick clouds make it impossible to view the surface. At any time, clouds cover almost two-thirds of the globe.

Another important issue in the cloud data analysis is the choice of an appropriate classifier. There are basically two types of classifiers; traditional classifiers which include: linear discriminant, maximum likelihood and k-nearest neighbor classifiers, and the neural-network classifiers which include: multilayer back propagation neural network (BPNN), self organizing map (SOM) and probability neural network (PNN), etc. The characteristics and behavior of clouds are highly variable and difficult to classify, neural network classifiers through their adaptive learning nature offer attractive and computationally very efficient alternatives. Cloud detection and removals is an important preprocessing step in land remote sensing. We need cloud-free images to analyze accurate spectral signal of land surface such as extraction of biophysical variables, change detection, classification.

The Earth viewing sensor such as Geostationary Operational Environmental Satellites (GOES) provides visible and infrared images of Earth observation. While observing the earth by satellite the atmosphere plays a key factor affecting regional weather conditions, the presence or absence of clouds over a region may influence many aspects of weather (e.g. visibility, ceilings, insulation, temperatures and changes with time, etc.). The extraction of cloud information from these images is a key component in weather forecasting. The identification of clouds over a region in visible satellite images is relatively straightforward for a trained scientist during the day (although snow and other highly reflective surface features often add complexity to the problem), but this process is substantially more difficult at night when only thermal channels are available.

The detection of clouds automatically in GOES satellite imagery is not a simple task. Poor spatial resolution, changing solar incidence and instrument viewing angles, limited spectral' channels, instrument noise, and varying surface properties often limit the success of traditional cloud detection schemes when applied over a large area both during the day and at night. However, the use of data from new high resolution, multispectral instruments such as MODIS has alleviated some of these problems. The linchpin in even the most recent applications is often their dependence on fixed threshold values used in the various individual cloud tests. Often these threshold values do not represent the variety of atmospheric and surface conditions encountered in the retrieval process. The procedures presented in this paper address this .concerns by describing a composite method to develop dynamic thresholds applicable to the local environment. The procedure extends the concept of pixel-based dynamic thresholds based on radiative transfer modeling. The current approach utilizes recent satellite data itself to derive spatially and temporally varying thresholds: used in the various cloud tests. The approach is demonstrated for GOES Imager data but is applicable to other sensors on geostationary and polar orbiting platforms [63].

5.3 Bi-Spectral Composite Thresholds (BCT)

The BCT cloud detection method was developed to determine the sky condition for weather forecasting. The main principle of using BCT approach is that, the difference between the emissivity of clouds at thermal and at shortwave infrared wavelengths (such as 11.0µm and 3.9µm, respectively) varies from that of the surface such as land or ocean and can be detected from channel brightness temperature (TBT) differences. Spectral emissivity also varies with both wavelength and surface or cloud type with the emissivity. The infrared wavelengths are lower at the shortwave (SW) than that at the long wave (LW) infrared wavelengths resulting in lower emission temperatures at the shorter wavelengths. However, in the presence of solar radiation during day time the brightness temperature at the shorter wavelengths is greater than at the longer wavelengths and the emissivity is even less. Therefore, the cloudy pixels of satellite imagery can be calculated as the difference between (LW – SW) brightness temperatures, and will produce a negative value at the day time and a positive value at the night time due to the absence of solar radiation. The spatial transition from a clear region to a cloudy region in the satellite image is a discontinuity in the LW minus SW brightness temperature difference image. Because the emissivities vary with cloud type and their effect on the reflected object of the SW channel make the use of these channel differences for cloud detection a challenging problem. The key to the successful detection of clouds having these properties lies in the selection of an appropriate threshold value in an image which separates cloud-free pixels from cloudy pixels A fixed threshold is not going to produce good results.

5.4 Cloud Detection Techniques of Satellite Imagery

5.4.1 Semi-Supervised Cloud Detection

Remote sensing image classification is a very challenging task because very few labeled pixels are typically available from the analyzed scene. In such situations, labeled data extracted from other images modeling similar problems might be used to improve the classification accuracy. However, when the samples of training and test data show even slightly different distributions, classification becomes very difficult. This type of difficulty is known as sample selection bias [57]. In this method, the labeled and unlabeled pixels are combining together to increase reliability and accuracy of image classification. The combination of clustering and the mean map kernel is used in semi-supervised support vector machine classifier. The method reforms samples data in the same cluster belonging to the same class by combining sample data and cluster similarities implicitly in the kernel space. A soft version of the method is also proposed where only the most reliable training samples, in terms of likelihood of the image data distribution, are used. Capabilities of this method are illustrated in a cloud screening application using data from the Medium Resolution Imaging Spectrometer (MERIS) instrument onboard the European Space Agency ENVISAT satellite. Kernel methods and specifically support vector machines (SVMs) are a good choice for supervised classification. SVMs are accurate nonlinear robust classifiers [49, 50] which have been successfully used in Remote Sensing data classification [51, 52]. Using labeled data from other images could give rise to the sample selection bias problem if the data marginal distribution is not properly modeled, thus affecting the performance of supervised methods. In this situation, unlabeled samples extracted from the test image can be synergistically used with the available labeled training samples to increase the reliability and accuracy of the classifier, and to alleviate the problem [53]. This is the field of semi supervised learning (SSL), in which the algorithm is provided with some available supervised information in addition to the unlabeled data. But this method is not so efficient because it takes long computational time, accuracy depends upon training sample and also needs large training set.

5.4.2 Cloud Detection Algorithm for MODIS Remote Sensing Imagery

Cloud is one of the most common interferers in Moderate Resolution Imaging Spectrum-radiometer (MODIS) remote sensing imagery. Because of cloud interference, much important and useful information covered by cloud cannot be recovered well. How to detect and remove cloud from MODIS imagery is an important issue for wide application of remote sensing data. In this method, firstly, several preprocessing works need to be done for MODIS L1B data, including geometric precision correction, bowtie effect elimination and stripe noise removal. Furthermore, through analyzing the cloud spectral characters derived from the thirty-six bands of MODIS data, it can be found spectral reflections of ground and cloud are different in various MODIS bands. Therefore, cloud and ground area can be respectively identified based on the analysis of multispectral characters derived from MODIS imagery. Most cloud regions including both thin and thick types can be detected by this method. Clouds removal processing mainly aims at cloud regions rather than whole image, which can improve processing efficiency. As for thin clouds and thick clouds removal, different removal algorithms are used in this method. Experimental results demonstrate that these proposed methods can effectively detect and remove cloud from MODIS image, which can meet the demands of post processing for remote sensing imagery applications. But this method leads to higher misclassification rate of cloud pixels and it is also a high time consuming process [57].

5.4.3 Cloud-Screening Algorithm for ENVISAT/MERIS Multispectral Images

This method presents a methodology for cloud screening of multispectral images acquired with the Medium Resolution Imaging Spectrometer (MERIS) instrument on-board the Environmental Satellite (ENVISAT). The method yields both a discrete cloud mask and a cloud-abundance product from MERIS level-1b data on a per-pixel basis. The cloud-screening method relies on the extraction of meaningful physical features (e.g., brightness and whiteness), which are combined with atmospheric-absorption features at specific MERIS-band locations (oxygen and water vapor absorptions) to increase the cloud-detection accuracy. All these features are inputs to an unsupervised classification algorithm; the cloud-probability output is then combined with a spectral unmixing procedure to provide a cloud-abundance product instead of binary flags. Cloud-screening approaches, also referred to as cloud masking or detection, are generally based on the assumption that clouds present some useful features for its identification [54]: Clouds are usually brighter and colder than the underlying surface; clouds increase the spatial variability of detected radiance; and the spectral response is different from that of the surface covers. But, individually, each of these features in a given image is strongly conditioned by the sun elevation, variable path length, atmospheric water vapor, aerosol concentrations, variable reflectance, and sub pixel clouds produced on the same pixel by cloud structures over land or sea [55]. Some of these problems can be mitigated in the cloud-screening algorithm by including specific corrections (e.g., sun elevation or path length), avoiding bands with severe atmospheric effects, and providing the user with information about subpixel coverage. This method takes advantage of the high spectral and radiometric resolutions of MERIS and the specific location of some channels (e.g., oxygen and water- vapor absorption bands) to increase the cloud-detection accuracy. The method is capable of the following: 1) detecting clouds accurately and 2) providing probability or cloud abundance rather than merely cloud flags. The cloud-abundance product provided is not directly related to the retrieval of cloud optical properties [56, 57], such as the cloud optical thickness, which usually relies on radiative-transfer models. This added-value product allows the user to apply an adjustable cloud mask depending on the further processing stages and application of the MERIS image.

5.4.4 Cloud Detection Algorithms Based on a MAP-MRF Approach in Space and Time

A recurrent concern in cloud detection approaches is the high misclassification rate for pixels close to cloud edges. This problem can be solved by introducing a novel penalty term within the classical maximum a posteriori probability–Markov random field (MAP-MRF) approach. To improve the classification rate, such term, for which suggest two different functional forms are suggested, accounts for the predictable motion of cloud volumes across images. Two mass tracking techniques are proposed. The first one is an effective and efficient implementation of the probability hypothesis density (PHD) filter, which is based on Gaussian mixtures (GMs) and relies on finite set statistics (FISST). The second one is region matching procedure based on a maximum cross-correlation (MCC) that is characterized by low computational load. Classical MRF methods account only for spatial dependence relations, thus neglecting the temporal information often available in image sequences. In this method, apply spatiotemporal MRF methods are applied to the cloud masking problem that is complicated by the no rigid nature of the masses. This approach turns out to be especially valuable in mitigating the problem of misclassification rate at the cloud edges, which typically stems from low contrast against sea and land background [58] by exploiting the cloud motion as an additional discriminant feature against the static background. Cloud detection by using MAP-MRF approach is more efficient and better method than other cloud classification algorithm.

5.4.5 Cloud and Haze Boundary Detect

Because the thickness of cloud and haze in an image is not fixed, but gradually varies from the cloudiest region to the clearest region, different processing modes should be used in different regions [61]. Various types of clouds present different reflection and transmission characteristics. One might extract a thick cloud boundary easily because solar radiation has reflected completely, but the surface information within that thick cloud might be difficult to extract; past methods have extracted them [62]. Systematic methods can filter haze and enhance surface information for haze region because there is a correlation between the penetrating solar radiation and surface reflection, the surface features themselves indistinctly display in an indistinct condition.

In isolation, either one of the addendum of filtration methods is not very useful. However, separate processing for image region with different characteristics can produce better result. Therefore, we use the statistics from images to separate clean areas, haze areas, and cloudy areas.

More details are shown in Equation [1].

$$f(x,y) = \begin{cases} I(x,y) < I_{mean} \in 0 \\ I_{mean} < I(x,y) < I_{mean+std} \in 1 \\ I(x,y) > I_{mean+std} \in 2 \end{cases} \qquad \text{--------------------------(1)}$$

Where,

I(x,y) = cloud image value

I_{mean} = cloud image mean value

$I_{mean+std}$. = cloud image mean+standard deviation value

Thick cloud areas totally reflect all spectrum information, and cover land surface with masses of clouds. Information is totally lost; in the past, the mosaic method was the major mean to remove clouds from images. By contrast, this study applies filtration and reclassification to thin cloud areas [60].

5.5 Comparison Analysis of Cloud Detection Algorithms

Sl No	Algorithm Name	Benefit	Limitations
1	Semi supervised	Simple	Need large training set.
2	MODIS imagery	Effective	High misclassification rate. High time consuming.
3	ENVISAT/MERIS	Improved Classification.	Time consuming.
4	MRF approach	Simple and Popular.	Accuracy low. Need preprocessing.

Table 5.1 Comparative Analysis

5.6 Chapter Summary

Automatic and accurate classification of clouds to enhance weather forecasting is one of the important applications studied in meteorology. Many different approaches have been used to automatically detect clouds in satellite imagery. Most approaches are deterministic and provide a binary cloud – no cloud product used in a variety of applications. Some of these applications require the identification of cloudy pixels for cloud parameter retrieval, while others require only an ability to mask out clouds for the retrieval of surface or atmospheric parameters in the absence of clouds. A few approaches estimate a probability of the presence of a cloud at each point in an image. But these approaches lead to high misclassification of cloud edges. The use of MAP-MRF approach for cloud detection gives improved classification of cloud edges than other method. Here apply a spatiotemporal MRF method is applied to the cloud masking problem that is complicated by the non-rigid nature of the masses. To improve the classification rate, two different functional forms, account for the predictable motion of cloud volumes across images. Two mass tracking techniques are proposed. The first one is an effective and efficient implementation of the probability hypothesis density (PHD) filter, which is based on Gaussian mixtures (GMs) and relies on finite set statistics (FISST). The second one is a region matching procedure based on a maximum cross-correlation (MCC) that is characterized by low computational load. A penalty term is computed for previous image to improve classification of current image.