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A Survey of Cloud Detection Techniques For Satellite Images

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Abstract - ***The detection of clouds in satellite imagery has a number of important applications in weather and climate studies. Satellite images plays a major role for monitoring earth changes in land covers such as forest, cities, agriculture, coastal area etc. but presence of clouds is a challenging issue in most of the satellite imaging based applications. Accurate detection and removal of cloud region is very important for satellite images. In this paper a review of several cloud detection technique is presented. The major challenge of cloud detection approaches is high misclassification rate of cloud pixels due to lower contrast of cloud edges against the land or sea background. A posteriori probability–Markov random field (MAP-MRF) approach shows improved classification rate of cloud pixels than other cloud detection techniques, which solve high misclassification rate of cloud pixels. To improve the classification rate, two different functional forms are used. The first one is an effective and efficient implementation of the probability hypothesis density (PHD) filter, which is based on Gaussian mixtures (GMs). The second one is a region matching procedure based on a maximum cross-correlation (MCC).***

Key Words: *Cloud detection, image classification, satellite imaging.*

I. INTRODUCTION

The past two to three decades has seen a turnaround in our capacity to survey and map our global environment through use of satellite remote sensing technology. Remote sensing is closely related with satellite imaging. Images can be acquired by using different satellites such as ikonos, landsat, Quickbird and each satellite is used for different purposes like defense (change detection in regions), agriculture (for analysis of agriculture) etc . Every object in a satellite image is essential for accurate processing, so image quality is one of the most important factors in satellite images. But presence of clouds in satellite images will affect the Quality of image. It is difficult to avoid clouds in satellite images during image acquisition and it also causes many problems in the study of satellite image based applications. Removing cloud as a noise from an image will be helpful for better analysis of satellite imaging applications. Remote sensing has been commonly used in a wide variety of urban and environmental applications, such as monitoring land-use change, measuring water quality, and mapping vegetation [1]. Detection of clouds in satellite images is a very interesting remote sensing application such as Meteorological forecasting, Urban area control, Oil spills monitoring ,Traffic analysis, Environmental analysis. Cloudy and cloud-free pixels must be distinguished before automatic estimation of surface variables .

Traditionally both spatial and spectral techniques have been employed to identify cloud contaminated pixels in polar orbiting and geostationary satellite data. The key to the success of most of these algorithms lies in the selection of the thresholds for various spectral tests. In more robust algorithms, spatially and temporally varying thresholds, which better capture local atmospheric and surface effects, are used to improve their performance and broaden their application over algorithms with fixed thresholds for cloud tests. Extracting cloud field information from these images using visual/manual interpretation is a tedious and unreliable task and moreover the results are, to some extent, operator dependent. Therefore, highly efficient and robust cloud classification schemes are needed for automatic processing of satellite cloud imagery for climatological applications.

In recent years, considerable research has been focused on the cloud classification area. A good review of the available schemes is provided by Pankiewicz [2]. Generally, two broad categories of cloud features are most commonly used in the cloud classification field: spectral and textural features. The first class of features, which plays a more important role for cloud classification, extracts the information on the cloud radiance in different spectral bands. Some of the most commonly used methods in this category include threshold based schemes [3], histogram [4] schemes, and multispectral approaches [5], [6]. The spectral features due to their physical importance (albedo, temperature) are proven to be effective and simple. However, they also encounter some problems because of the spectral similarities of certain features such as ice cloud and snow. Other factors, such as moisture in atmosphere, may also alter the multispectral characteristics and thus affecting the final judgement. The second category, i.e., textural features, distinguish certain types of clouds by the spatial distribution characteristics of gray levels corresponding to a region in one specific channel. While the spectral characteristics of clouds may change, their textural properties are often distinct and tend to be less sensitive to the effects of atmospheric attenuation or detector noise [7]. Most of the texture-based cloud classification methods in the past used statistical measures based on gray level cooccurrence matrix (GLCM) [8] and its variant, such as gray level difference vector (GLDV), gray level difference matrix (GLDM) and sum and difference histogram (SADH) [9], [10]. For example, Welch et al. [9] used GLCM for feature extraction to classify stratocumulus, cumulus, and cirrus clouds. Kuo et al. [10] used GLDV method to differentiate between clouds and ice/snow. Another important group of textural extraction schemes explores the frequency characteristics of images. Garand et al. [11] have examined the power spectrum of ocean cloud images while Gu and Duncan [12] evaluated autocorrelation, textural edgeness and the GLCM approach to obtain cloud textural information. Gabor filter was also employed for cloud classification task by Lamei et al. [7] and Du [13]. Several comparative studies of these features have been conducted by Parikh [14], Gu [12], and Ohanian [15] where they suggested that GLCM provides the best features for cloud classification, while in [16] Gabor filters and Fourier features are recommended. There is no consistent and optimal feature extraction scheme determined at this time. Therefore, there is a need to develop efficient feature extraction schemes for cloud data analysis.

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 neighbour classifiers, and the neural-network classifiers which include: multilayer backpropagation neural network (BPNN), self organizing map (SOM) and probability neural network (PNN), etc. Owing to the fact that the characteristics of clouds are highly variable and difficult to classify, neural network classifiers through their adaptive learning nature offer attractive and computationally very efficient alternatives. Lee et al. [17] used a three-layer BPNN for cloud classification of LANDSAT multispectral scanning system (MSS) data while PNN was examined by Bankert et al. [18] for classification of AVHRR imagery. In [19], traditional linear discrimination and two neural-network classifiers namely BPNN and PNN were comparatively studied for the classification of polar clouds and surface. The results showed that BPNN-based solution achieved the highest classification accuracy, while PNN falls behind within a very small accuracy range. It is worthy to mention that the BPNN-based scheme was extremely time consuming in the training phase compared to the one-pass noniterative PNN training approach [18]. The unsupervised Kohonen SOM has also been examined for cloud classification [20]–[21].

II. CLOUD DETECTION TECHNIQUES

a. *Semisupervised Cloud Classification*

Remote sensing image classification constitutes a challenging problem since 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 training and test samples follow even slightly different distributions, classification is very difficult. This problem is known as sample selection bias. In this method, use a method to combine labeled and unlabeled pixels to increase classification reliability and accuracy. A semisupervised support vector machine classifier based on the combination of clustering and the mean map kernel is used. The method reinforces samples in the same cluster belonging to the same class by combining sample 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 [22]–[23], which have been successfully used in Remote Sensing data classification [24] [25]. 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 [26]. This is the field of semisupervised 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 depend upon training sample and also need large training set.

b. *Cloud Detection and Removal 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 lead higher misclassification rate of cloud pixels and it also a high time consuming process.

c. *Cloud Classification with Neural Networks*

The problem of cloud data classification from satellite imagery using neural networks is used here. Several image transformations such as singular value decomposition (SVD) and wavelet packet (WP) were used to extract the salient spectral and textural features attributed to satellite cloud data in both visible and infrared (IR) channels. In addition, the well-known gray-level cooccurrence matrix (GLCM) method and spectral features were examined for the sake of comparison. In this method, a neural-network-based cloud classification system is proposed. Several image transformation schemes namely singular value decomposition (SVD) and wavelet packets (WP's) were exploited to extract salient features of the cloud data. In addition, the conventional GLCM-based statistical features were also used for the purpose of benchmarking. The features from both the visible and IR channels were then combined together and fed to a neural-network classifier. However, these features do not remain consistent and vary at different time of the day and season.

d. Markov Random Field Approach for Classification Of Hyperspectral Imagery

An adaptive Markov random field (MRF) approach is proposed for classification of hyperspectral imagery. Hyperspectral imagery can provide detailed spectral information of various ground cover types due to its wide coverage of wavelength and high sampling rate. Conventional pixelwise classification methods, such as maximum-likelihood classifier (MLC), k-nearest neighbor, and support vector machines (SVMs), mainly take advantage of spectral features while ignoring spatial relationship with neighboring pixels [27]. In recent years, spatial context information has been used together with spectral information for improved classification [28], ranging from probabilistic label relaxation to texture feature generation [29], [30]. This is a widely used method for integrating spatial information and spectral information is Markov random field (MRF). It modifies the usual form of a spectral discriminant function through the addition of a spatial contribution term that recognizes contextual relationship of pixels. MRF has often classified remote sensing imagery based on the maximum-likelihood estimation for the spectral contribution part and the Gibbs distribution/Ising model for the spatial contextual information. In this method presents an adaptive-MRF (a-MRF) approach for spectral–spatial classification of hyperspectral imagery. Here introduce a relative homogeneity index (RHI) and use this index to find the suitable weighting coefficient of the spatial contribution for each pixel βm, in order to improve classification performance. But this method Consider only spatial dependence relations, thus neglecting the temporal information and also Time consuming and Computation complexity. This algorithm needs preprocessing so cloud edge detection accuracy is low.

e. *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 [31]: 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 subpixel clouds produced on the same pixel by cloud structures over land or sea [32]. 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 to the user 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 [33], 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.

f. 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. Solving this problem 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, 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 a spatiotemporal MRF methods to the cloud masking problem that is complicated by the nonrigid 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 [34] 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 good method than other cloud classification algorithm.

Table -1: Advantages and Disadvantages of existing cloud detection techniques.

Algorithm	Advantages	Disadvantages
Semisupervised	Simple	Need large training set.
MODIS imagery	Effective	High misclassificatio n rate. High tme consuming.
Neural network	Complexity less.	Not consistent.
MRF approach	Simple and popular.	Accuracy low. Need preprocessing.
ENVISAT/MERIS	Improved classification.	Time consuming.

The cloud detection by using MAP-MRF 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 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 good method than other cloud classification algorithm.

III. Conclusion

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 methods to the cloud masking problem that is complicated by the nonrigid nature of the masses. To improve the classification rate, two different functional forms, 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 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.

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