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Domain Adaptation Based Active Learning Approach for Classification of Satellite Images

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Abstract—Satellite cloud image is a kind of useful image which includes abundant information, for acquired this information, the image processing and character extraction method adapt to satellite cloud image has to be used. 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. The paper proves that the research and of satellite cloud image processing is valuable, which could improve the classification efficiency more. To determine the cloud type of a pixel or group of pixels in satellite imagery, an appropriate classification algorithm must be selected. In this paper, we propose an interactive domain Adaptation technique for the classification of cloud images that allows one to exploit the consistent information of the source image to classify the target image. The number of target samples to be labeled can be significantly reduced by this way. This approach can significantly reduce the number of new labeled samples to be collected from the target image.

Index Terms—*Satellite Image, Domain Adaptation, Active learning, Clustering, GLCM*

I. Introduction

The objective of this study is the development of a fully automated algorithm classifying all cloud images in real-time with high accuracy. To create an image set required for feature search and later training of the cloud type classifier, the complete data set are screened and selected cloud images. Clouds are one of the most important forces of Earth's heat balance and hydrological cycle, and at the same time one of the least understood. Large-scale cloud information is available from several satellites, but such data is provided in a low resolution and may contain errors. [2]. For example, small clouds are often overlooked due to the limited radiometer field of view. Low or thin clouds and surface are frequently confused because of their similar brightness and temperature.

A lot of research work has been undertaken and is being carried out for developing an accurate classifier for classifying cloud images. Features of an image are to identify different cloud image types with better accuracy [15]. The designed system reads the features of gray level images to create an image space. This image space is used for classification of images. Existing used techniques have some issues: requires more training time, exploit more processing time and have limited accuracy[6] [8] [13]. From a machine learning perspective, this class of problems can be modeled in the framework of transfer learning, and in particular of domain adaptation (DA), which goal is to transfer the information learned by the classification system from a source domain (associated with the first image) to a target domain (associated to the second image) [8], [9]. In such problems, it is usually assumed that source and target domains have similar characteristics [8], i.e., they share the same set of information classes, and the related class distributions are correlated (but not the same). Thus, the technique for addressing DA problems has to cope with the spatial/temporal variability of the spectral signatures of the different cloud types in order to adapt the model of the classifier from source to target domain. The quality of the map depends of the number of information of the labeled pixels, active learning methods are used to select the most informative samples to increase confidence in class membership.

II. Background

A Domain Adaptation

In the context of domain adaptation, the situation becomes more complicated. We assume that we are given two sets of training data, D(o) and D(i), the “out-of-domain" and “indomain" data sets, respectively. We no longer assume that there is a single fixed, but known distribution from which these are drawn, but rather assume that D(o) is drawn from a distribution p(o) and D(i) is drawn from a distribution p(i). The learning problem is to find a function f that obtains high predictive accuracy on data drawn from p(i). (Indeed, our model will turn out to be symmetric with respect to D(i) and D(o), but in the contexts we consider obtaining a good predictive model of D(i) makes more intuitive sense.) We will assume that |D(o)| = N(o) and |D(i)| = N(i), where typically we have N(i) <=N(o). As before, we will assume that the N(o) out-of-domain data points are drawn iid from p(o) and that the N(i) in-domain data points are drawn iid from p(i). Obtaining a good adaptation model requires the careful modeling of the relationship between p(i) and p(o). If these two distributions are independent (in the obvious intuitive sense), then the out-of-domain data D(o) is useless for building a model of p(i) and we may as well ignore it. On the other hand, if p(i) and p(o) are identical, then there is no adaptation necessary and we can simply use a standard learning algorithm. In practical problems, though, p(i) and p(o) are neither identical nor independent. the DA technique should be able to automatically detect and remove such inconsistent samples from the training set, preventing them to reduce prediction accuracy on the target image.

B Active Learning

Active learning is a recent field of research in remote sensing data analysis aiming at defining efficient training sets, usually by user–machine interaction[2][10]. Basically, active learning algorithms minimize the number of labeled pixels necessary to build an optimal classifier. Active learning (AL) has received an increasing interest in the remote sensing community in the context of supervised classification techniques [1]-[7]. AL aims to build up non-redundant and effective training sets according to an iterative process that requires an interaction between a human expert and the automatic classification system To do so, the algorithm proposes to the user the most uncertain pixels that, once labeled, will help the model to improve its performance. Several strategies exist based on committees of models [5], [6], support vector machines (SVMs), and posterior probabilities in the prediction of the unlabeled samples . In all these studies, it has been shown that active learning heuristics significantly improve the results obtained by methods that select pixels randomly and that ensure convergence to better result with significantly less pixels AL is an approach to iteratively select the most informative samples for defining a training set by exploiting the classification rule [1]–[7].

To precisely describe the workflow of a general AL process, let us model it as a quintuple (G, Q, S, T,U) [25]. G is a supervised classifier, which is trained with the training set T. Q is a query function used to select the most informative unlabeled samples from a pool U of unlabeled samples on the basis of the current classification results. S is a supervisor who can assign the true class label to any unlabeled sample of U (e.g., a human expert). The AL process is an iterative process, where the supervisor S interacts with the system by labeling the most informative samples selected by the query function Q at each iteration. At the first stage, an initial training set T(0) of few labeled samples is required for the training of the classifier G. After initialization, the query function Q is used to select a set of samples from the pool U, and the supervisor S assigns them the true class label. Then, these new labeled samples are included into T(i) (where i refers to the iteration number), and the classifier G is retrained using the updated training set. The closed loop of querying and retraining continues until a stopping criterion is satisfied. Algorithm 1 gives a description of a general AL process.

Algorithm 1: Active Learning procedure
1) Train the classifier G with the initial training set T
2) Classify the unlabeled samples of the pool U
Repeat
3) Query a set of samples (with query function Q) from the pool U
4) A label is assigned to the queried samples by the supervisor S
5) Add the new labeled samples to the training set T
6) Retrain the classifier
Until a stopping criterion is satisfied

III. DATA

A Satellite Data

METSAT (renamed as Kalpana- 1) is the first in the series of exclusive meteorological satellites built by ISRO. *It* is a multipurpose satellite for meteorological services including disaster-warning services. Very High Resolution Radiometer (VHRR) with 2km resolution in visible band and

8km resolution in infrared and water vapor band. Charge Coupled Device (CCD) camera operating in visible, near infrared and short wave infrared band with 1km resolution. The weather monitoring using satellite imageries play an important role in National Development. INDIAN NATIONAL SATELLITE SYSTEMS provide continuous monitoring of weather pattern through a series of satellites located over Indian Ocean region [14]. Kalpana-1 is a geostationary satellite positioned at 72˚E observing earth with an imaging radiometer in three channels, viz., VIS, IR and WV with central frequency of 0.7, 10.5 and 6.3 µm, respectively. The temporal resolution of each image is 30-minute and the spatial resolution is 8 km for IR and WV channels and, 2 km for the VIS channel. Due to registration and navigational issues in the full disk kalpana-1 images, a re-sampled image popularly known as sector generated image (SGP) has been made available for the retrieval community, for all types of clouds.

B. Classification of cloud images

In contrast to other publications handling automated cloud classification, the phenomenological classes are used to be separated according to the International Cloud Classification System (ICCS). Therein, four genera are defined which represent the basis of the cloud classification. Using this standardized information from the human observers on the ground and the expertise of a meteorologist, cloud types were identified on the satellite images are classified. Table 1 shows the different cloud types. Besides, it must be noted that the class of clear sky includes not only images without clouds, but also images with cloudiness below 10%.

Label	**Cloud genera according to WMO**	**Description**
Class1	*Clear sky*	No clouds and cloudiness below 10%
Class2	*Low Level Clouds*	Low, puffy clouds with clearly defined edges, white or light-grey
Class3	*Mid Level Clouds*	Low or mid-level, lumpy layer of clouds, broken to almost overcast, white or grey
Class4	*High Level Clouds*	High patched clouds of small cloudlets, Dark, thick clouds, grey

Table 1. Cloud Classes

IV. METHODOLOGY

The classification methods to process cloud images into a set of disjointed cloud patch regions. Informative features are extracted from cloud patches and classified into a number of patch groups based on the similarity of selected features, such as patch size and texture. The process is given below.

a) Separately cloud images into distinctive cloud patches
b) Extracting cloud features, including, coldness, geometry and texture
c) Clustering cloud patches into well organized subgroups.

A Feature Extraction

Extract information on the cloud image, there by obtaining cloud classes. Based on this cloud extraction cloud classes are developed. In general, physical features have certain association with spectral features, hence they can be identified by using multi-spectral information from the remotely sensed images [11]. Features of the image can be divided into two categories .i)Spectral Features or thematic Map ii) Textural Features.

i)Spectral Features. Spectral features describe the average color and tonal variation of an image.

ii)Textural features. To describe the texture of an image, statistical measures computed from Grey Level Co-occurrence Matrices (GLCM) may be used. GLCM method comes under the statistical measures based on the spatial distribution of grey levels within the band of the remotely sensed imagery (Ref. Fig. 2).GLCM matrix is computed from a relative displacement vector (d,ɵ) which is formed based on the relative frequencies of grey level pairs of pixels separated by a distance d in the direction.[7] The most texture measures are:

$$Energy = \sum_i \sum_j P_d^{\,2}(i, j)$$

$$Entropy = -\sum_i \sum_j P_d^{\,2}(i, j) \log P_d(i, j)$$

$$Correlation = \sum_i \sum_j \frac{(i-\mu)(j-\mu) P_d(i, j)}{\sigma_x \sigma_y}$$

$$Inertia = \sum_i \sum_j (i-j)^2 P_d(i, j)$$

$$Homogenity = \sum_i \sum_j \frac{P_d(i, j)}{1+(i-j)^2}$$

$$Autocorrelation = \sum_i \sum_j ij P_d(i, j)$$

Where P_d is the probability matrix obtained through GLCM, μ is the mean of P_d and σ_y are the standard deviations of $P_d(x)$ and $P_d(y)$ respectively.

Algorithm for GLCM measures calculated for whole image

1. The input color image is first converted into grey level image

2. The pixel value in the matrix is compared with the neighbouring pixel values.

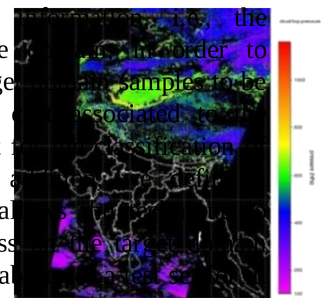
3. The occurrence of each pixel with respect to the neighbour is noted.

*4. The resulting matrix has a dimension of 256 * 256.*

5. From the matrix obtained, the various features such as energy, entropy, mean, and variance are calculated.

V. Implementation

Experimental results confirmed that the proposed technique provided a very good tradeoff among robustness to biased initial training samples, classification accuracy, computational complexity, and number of new labeled samples necessary to reach the convergence Adapting the classifier trained on a source domain to recognize instances from a new target domain to recognize instances from a new target domain is an important problem that is receiving recent attention A matrix representation of classification accuracy test (%) for cloud free and cloud types is constructed.[3] Obtaining training data for cloud cover classification using remotely sensed data is time consuming and expensive especially for relatively inaccessible locations. The focus of this paper is on hyperspectral image classification using very few labeled data points. The goal of the active learner is to select the most informative data points so as to accurately learn from the fewest such additionally labeled data points. In a typical active learning setting a classifier is first trained from a small amount of labeled data.[14]. This paper presents a novel technique for addressing domain adaptation (DA) problems with active learning (AL) in the classification of remote sensing images. DA models the important problem of adapting a supervised classifier trained on a given image (source domain) to the classification of another similar but not identical image (target domain) acquired on a different area. The main idea of the proposed approach is iteratively labeling and adding to the training set the minimum number of the most informative samples from the target domain, while removing the source-domain samples that do not fit with the distributions of the classes in the target domain.[15] In this way, the classification system exploits already available i.e., the labeled samples of\ source in order to minimize the number of targe samples to be labeled, thus reducing the associated to definition of the training set classification the target domain[20]. In a convergence criterion that al stop the iterative AL process without relying on the availal



This is an important contribution, as in operational applications, it is not realistic to assume that a test set for the target domain is available. Experimental results obtained in the classification of very high resolution and hyperspectral images confirm the effectiveness of the proposed technique.

Fig A

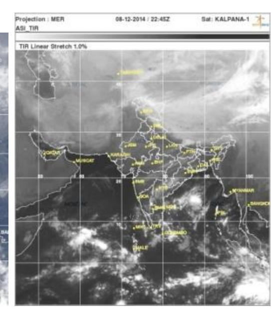


Fig B

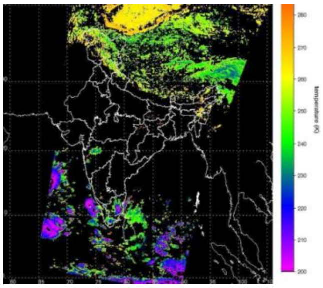


Fig C Cloud Top Temperature Fig D Cloud Top Pressure

Fig A shows the original satellite image, Fig B shows the grayscale satellite image, Figure C and D shows the classified image based on cloud Top Temperature and Cloud Top Pressure.

VI. Result and Discussion

For each pass of the satellite the program puts each AVHRR pixel into boxes labeled either cloud-free, partially cloudy, fully cloudy, or snow-covered. This is achieved by applying several threshold tests to each pixel. The result is stored in a so-called cloud-mask (a reference source), together with a mask identifying whether the pixels in the image are land or sea, and information about sun glint, solar zenith, and satellite observation angles. From these data, cloud cover can be computed for each pixel, the categories being total, thick (low, medium, high) or thin cover. Results were contained to investigate the performance of our proposed method. We compared the learning rates with those of other classifiers that select data points either at random or via another related active learning method.

Classes	Clear sky (%)	Low level Clouds (%)	Mid level Clouds (%)	High level Clouds (%)
Clear sky	91%	5%	3%	2%
Low level clouds	6%	85%	5%	4%
Mid level clouds	7%	3%	88%	2%
High level clouds	4%	7%	6%	83%

Table 1. Confusion Matrix for cloud classes.

The performance of the designed classifier was evaluated with the help of the confusion matrix. The confusion matrix is as shown in Table 2. This gives the summary of cloud type classification results for the four classes of testing. In this table, the diagonal values represent the samples that have been classified correctly. Large diagonal values mean better accuracy. The percentage values of each row represent samples that come from the class of that row but are classified incorrectly to other classes, and they are called omission error. The values in each column represent samples that are classified falsely as class of that column but come from other classes, and they are called commission error.

AL for domain adaptation in the supervised classification of remote sensing images.AL learning query functions have been studied to reduce the number of queries to a choice a classification performance with excellent results on hyperspectral and multispectral VHR classifier [18]. AL is nowadays reaching a level of algorithmic maturity that raises the urge of applying the developed heuristics. Image classification of image convert into semantically defined classes (pixel labeling) is a basic problem of remote sensing imaging.

VI. Conclusion

Cloud type recognition and developing more complex algorithms for automatic classification of images according with its different features. Two different kinds of features have been explored in this work: statistical features and textural features based on the active learning method. It will give high speed processing with relatively better accuracy. The developed system was able to correctly classify cloud images with a success rate of 84% for the classes. The importance of this work stems from the fact that the satellite cloud images utilized were labeled after a respective ground observation, in an effort to develop a system which will be able to classify clouds based on their satellite images and which classification will be in agreement with the ground observation. Such a system will facilitate the automated objective interpretation of satellite cloud images and can be used as an operational tool in weather analysis

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