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A Method of Removing and Recovering Clouds in Satellite Images based on Image Inpainting

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Abstract: Cloud cover is generally present in remotely sensed images, which limits the potential of the images for ground information extraction. Therefore, removing the clouds and recovering the ground information for the cloud-contaminated images is often necessary in many applications. In this project, propose a cloud removal approach based on image inpainting. The approach removes cloud-contaminated portions of a satellite image and then reconstructs the information of missing data utilizing temporal correlation of multi temporal images. In order to remove the noise in the classified image weighted trimmed median filter is used. It is possible to remove the isolated shadow pixels in the non-shadow area and isolated non-shadow pixels in the shadow area of the classified image. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. Comparisons with existing algorithms our approach achieves better results in terms of misclassification probability and, in particular, to be very effective in cloud removal.

Keywords: Cloud Detection, Remote Sensing, Satellite Imaging, Image inpainting.

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.

Most remotely sensed images encompass the presence of clouds that, especially in the visible and infrared range, strongly affect the received electromagnetic radiation. Depending on the application, clouds act as an unwanted corruption or, rather, as an information source. Therefore, the detection of pixels affected by the various types of cloud formations plays a fundamental role in the processing of remotely sensed scenes and has attracted a large number of scientific contributions. In particular, the cloud masking problem, namely, the binary classification task aimed at distinguishing between cloudy and non cloudy pixels, constitutes a key step in many applications and is the object of the current study.

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, histogram schemes, and multispectral approaches. 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 [3]. Most of the texture-based cloud classification methods in the past used statistical measures based on gray level cooccurrence matrix (GLCM) [4] and its variant, such as gray level difference vector (GLDV), gray level difference matrix (GLDM) and sum and difference histogram (SADH).

In this paper propose a cloud removal method using image inpainting after detecting cloud by using spatio-temporal (Markov Random Field) MRF method. A recurrent concern in cloud detection approaches is the high misclassification rate for pixels close to cloud edges. Solve 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 we 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 a region matching procedure based on a maximum cross-correlation (MCC) that is characterized by low computational load. Through extensive tests on simulated images and real data, acquired by the SEVIRI sensor, both methods show a clear performance gain in comparison with classical spatial MRF-based algorithms. But this spatio-temporal MRF method does not consider cloud removal and it is not suitable for high level noise. So for solving this problem here introduce two techniques. The first one is a weighted trimmed median filter for handling high level noise and an adaptive inpainting algorithm for cloud removal. After detecting the cloud removes the cloud region using image inpainting. This approach removes cloud-contaminated portions of a satellite image and then reconstructs the information of missing data utilizing temporal correlation of multi temporal images. In order to remove the noise in the classified image weighted trimmed median filter is used. It is possible to remove the isolated shadow pixels in the non-shadow area and isolated non-shadow pixels in the shadow area of the classified image. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. Comparisons with existing algorithms our approach achieves better results in terms of misclassification probability and, in particular, to be very effective in cloud removal.

II. TRADITIONAL CLOUDDETECTION METHODS

Basic pixel-wise algorithms, namely, considering each pixel individually without reference to the context, have been largely exploited in the past by means of both supervised [5] and unsupervised [6] approaches. More in detail, simple and popular techniques, which require a preliminary careful study of the spectral properties of clouds, rely on multiple threshold tests, which are also able to separate snow and cloud sand different classes of clouds. Other widely used supervised algorithms are based on support vector machines (SVMs), which have been successfully applied to hyperspectral image classification in general and to cloud detection in particular.

On the other hand, recent studies based on semi supervised neural network [7] approaches use such spatial consistency for augmenting the training set by means of unlabeled samples. However, the most successful framework exploiting the statistical dependence of adjacent pixels consists in modeling the label distribution as a Markov random field (MRF). This method, which was proposed, has soon pervaded the image processing literature. The reason of such success is that MRF-based approaches [8] combine the conflicting requirements of accuracy and computational ease, the latter by limiting the number of pixels relevant to the prediction of the targeted one. Thus, they have been widely used to model (for segmentation and classification purposes) not only optical images (both hyperspectral and high-resolution ones) but also SAR data (both polarimetric and intensity images). Other emerging applications of MRF are related to hyperspectral image unmixing and to image enhancement, such as the regularization techniques in microwave tomography, the despeckling of SAR images, and the restoration algorithms for an optical image. Classical MRF methods account only for spatial dependence relations, thus neglecting the temporal information often avail-able in image sequences.

In fact, some authors have proposed to consider also the temporal correlation among pixels belonging to subsequent images. However, the identification of the effective definition of spatiotemporal adjacency turns out to be nontrivial. Until now, this problem has been faced by general statistical approaches and physical methods. Despite the intrinsic difficulty in the modeling phase, the introduction of temporal correlation has permitted to achieve noticeable results in many applications, such as video coding and object detection and tracking.

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Spatio-temporal MRF method 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 [9], [10], by exploiting the cloud motion as an additional discriminant feature against the static background. We account for temporal dependence relations, such as those present in image sequences acquired by sensors with a high acquisition rate (w.r.t. the dynamics of the underlying physical phenomena), by contaminating the classical structure of the MRF framework through a penalty function that quantifies the belief that a pixel belongs to the cloud class, as it can be inferred from the history of cloud locations across the previous images. Thus, the classification performed on the current image also takes into account the cloud motion dynamics by means of multitarget tracking (MTT) techniques.

To improve the classification rate, such term, for which we 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 a region matching procedure based on a maximum cross-correlation (MCC) that is characterized by low computational load. Through extensive tests on simulated images and real data, acquired by the SEVIRI sensor, both methods show a clear performance gain in comparison with classical spatial MRF-based algorithms. This method performs efficient cloud detection than other methods and achieve low misclassification rate and low computational load.

III. PROBLEM STATEMENT

Cloud cover is generally present in remotely sensed images, which limits the potential of the images for ground information extraction. Therefore, detecting and removing cloud-contaminated images is often necessary in many applications. Here detecting cloud using spatiotemporal Markov Random Field (MRF) approach and cloud removal approach based on image inpainting.

To improve the classification rate, such term, for which we suggest two different functional forms, ac-counts 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. Through extensive tests on simulated images and real data, acquired by the SEVIRI sensor, both methods show a clear performance gain in comparison with classical spatial MRF-based algorithms. Then removes cloud-contaminated portions of a satellite image and then reconstructs the information of missing data utilizing temporal correlation of multi temporal images. In order to remove the noise in the classified image weighted trimmed median filter is used. It is possible to remove the isolated shadow pixels in the non-shadow area and isolated non-shadow pixels in the shadow area of the classified image. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. Comparisons with existing algorithms our approach achieves better results in terms of misclassification probability and, in particular, to be very effective in cloud removal.

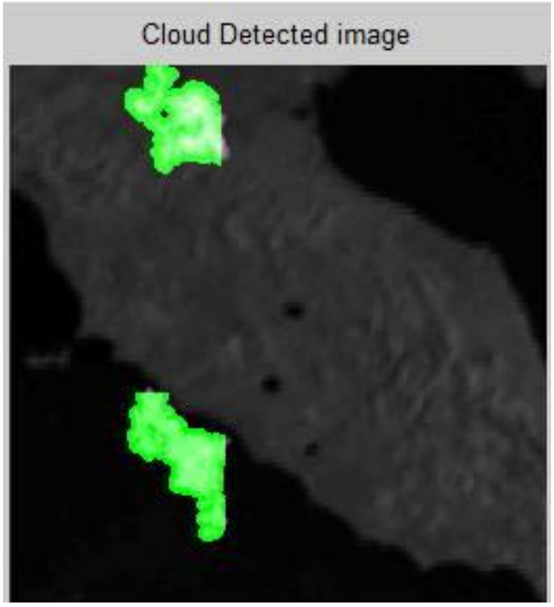

Fig 1: Cloud region in the satellite image is detected using spatio-temporal MRF method (green colour shows cloud region).

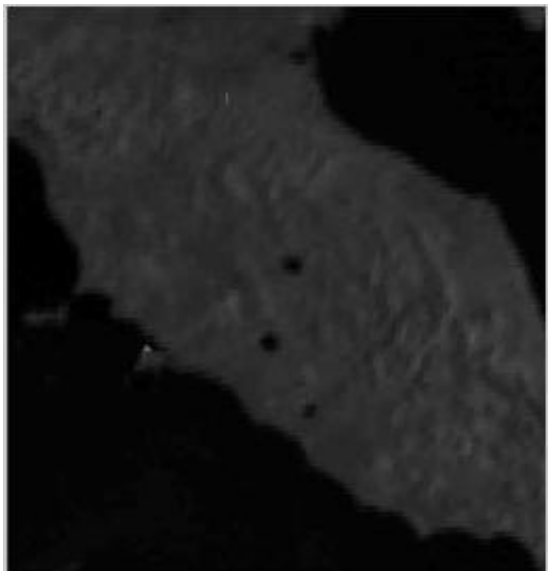

Fig 2: After detecting cloud region removing and recovering Cloud region by using image inpainting

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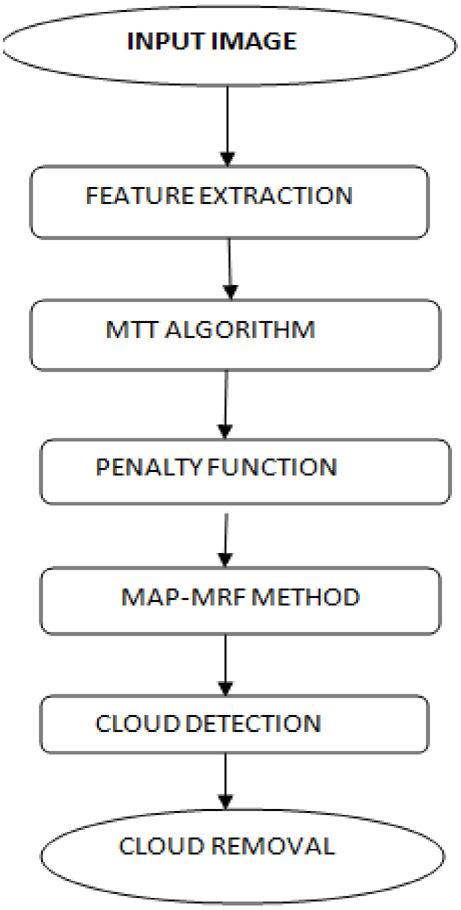

Fig 3: Block diagram of cloud detection and removal Method

A. Input image
The input cloud image is stored and read from the data base.

B. Feature Extraction
Cloud features, such as position, extension, and velocity are extracted. We adopt the bounding box (BB) approach, in which the cloud volumes are represented as the rectangles that circumscribe them. Accordingly, it is possible to define, for each time instant k, a set B(k)={B(k)1,B(k)2,...,B(k)Q (k)} of Q (k) BBs, described by their center coordinates {(c(k)l, 1,c(k)l, 2) }l =1,...,Q (k)and their sizes {(w(k)l,h(k) l)}l =1,...,Q (k).

C. MTT algorithm
We present here an MTT approach based on the finite set statistics (FISST), which allows to jointly track a changing number of targets. In fact, the multi target state X(k) = $\{\mathbf{x}_1^{(k)}, \ldots, \mathbf{x}_{M(k)}^{(k)}\} \in \mathcal{X}$ at time k is composed by a variable number of M (k) elements, consisting of centers, sizes, and velocities of each BB, i.e., each component of X(k) is a vector $\mathbf{x}_l^{(k)} = [c_{l,1}^{(k)}, \dot{c}_{l,1}^{(k)}, c_{l,2}^{(k)}, \dot{c}_{l,2}^{(k)}, w_l^{(k)}, h_l^{(k)}]^T$ with l =1,...,M (k) . This situation is handled by modeling the state as an RFS, which is the union of the relevant features of the survived targets S(k), those of the spawned targets T(k) ,and those of the newborn targets Γ(k), namely

$$X^k = s^{(K)}(X^{(k-1)}) \cup T^{(k)}(X^{t(k-1)}) \cup \Gamma^{(k)}$$

In addition, the multi target observation set $z^k = \{z_1{}^k, \ldots, z_{N(k)}{}^k\}$ is an RFS, whose components zl, l =1,...,N(k)are the centers and the sizes of the BBs detected at time k , comprising detected observations generated by the targets, for example, Ek((k), and those arising from the clutter, for example, C(k), namely

$$z^{(k)} = E_{(k)}(X^{(k)} \cup C^{(k)})$$

D. MAP-MRF
The maximum a posteriori probability (MAP) rule namely

$$I^k = \arg\max_{I_k} \lfloor p\,(I^k\,|d^{(0:k)})\rfloor$$
$$= \arg\max_{I_k} \lfloor p\,(d^k\,|I^k, d^{(0:k-1)})p(I^k\,|d^{(0:k-1)})\rfloor$$

$$= \arg\max_{I_k} \lfloor p\,(d^k\,|I^k)p(I^k\,|d^{(0:k-1)})\rfloor$$

In which the last equality follows from the widely accepted hypothesis that the current image d(K) is conditionally inde-pendent of the previous ones, given the current classification l(K). Two terms can be evidenced: $p(d^k|I^{(k)})$is the likelihood that takes into account the data acquired at time K; $p(I^k|d^{(0:k-1)})$is the a priori probability that models the information that can be derived from the past.

E. Cloud removal
The steps are,

1. Read the present and previous image.
2. Image is divided into multiple blocks.
3. Replace the block and get approximate image.
4. For fine tuning apply inpainting.

IV. ALGORITHM IMPLEMENTATION

a) Weighted trimmed median filter
The pixels $I_1, I_2, \ldots I_{m-1}, I_m, I_{m+1}, \ldots I_N$ in the moving window associated with the center pixel Ic, have been sorted in an ascending (or descending) order, with Im being the median value. The key generalization to the median filter which is introduced in the alpha-trimmed mean (α-TM) filter, is to employ a median basket in which one collects the same predetermined number of pixels above and below the median pixel. The values of these selected pixels are then averaged to give the filtering output, A c, as an adjusted replacement to Ic, according to

$$A_c = \frac{1}{2L+1}\sum_{j=m-L}^{m+L} I_j,$$

Where $L = \lfloor \alpha N \rfloor$, with $0 \le \alpha \le 0.5$. It is evident that a single-entry median basket (L =0) α-TM filter is equivalent to the median filter and a N-entry (L =0.5N) median basket is equivalent to the simple moving average filter. The general trimmed mean (GTM) filter uses a median basket in the same way as one does in the α-TM filter to collect the pixels. The pixel values in the median basket and the center pixel Ic in the moving window are then weighted and averaged to give the GTM filtering output:

$$G_c = \frac{w_c I_c + \sum_{j=m-L}^{m+L} w_j I_j}{w_c + \sum_{j=m-L}^{m+L} w_j}$$

where Gc is the GTM filtering output, and wc and wj's are the averaging weights for the center pixel and the pixels in the median basket, respectively. When wc =0 and all wj's are equal to each other (nonzero), the GTM filter becomes the α-TM filter. In the GTM filter, all the weights are predetermined and are fixed during filtering procedure. However, it is possible to further improve the GTM filter by varying the weights according to the absolute difference between the pixel values in the median basket and the median value. For the removal of impulse noise, we set wc=0, and the varying weight trimmed median (VWTM) filter is given by

$$V_c = \frac{\sum_{j=m-L}^{m+L} w(x_{jm}) I_j}{\sum_{j=m-L}^{m+L} w(x_{jm})},$$

where xjm has a value in the range of [0,1], defined by

$$x_{jm} = \frac{|I_j - I_m|}{B},$$

with B being the maximum pixel value of a given type of image (e.g., B =255 for a 8-bit, gray-scale image).The weight w(x) is a decreasing function in the range [0,1] and is chosen to be

$$w(x) = \exp\left(-A\left(\frac{x}{x-1}\right)^2\right).$$

Notice that w(0)=1 and w(1)=0, so the median value always has the largest weight (w(xmm)=1). The larger the absolute difference between the pixel values in the median basket and the median value, the smaller the weight will be. As is well known, the median value has the least probability to be impulse noise corrupted because the impulses typically occur near the ends of the sorted pixels. However, although not corrupted, the median value may not be the optimal value to replace the center pixel value because it may differ significantly from the noise-free value. The weight of the median value is the largest and the weights of other pixels in the median basket vary according to their difference from the median value. If an impulse noise corrupted pixel happens to be selected for inclusion in the median basket, its contribution to the average will be small because xjm is large. In general, the weight function can assist in eliminating impulse noise while providing a well-adjusted replacement value for the center pixel Ic.

b) Adaptive inpainting algorithm

The basic procedure of the presented inpainting algorithm consists of a one-time initialization step executed at the beginning as well as an iterative part.

c) Initialization

To each image pixel an individual value is assigned, henceforth referred to as confidence. The initialization step of the presented algorithm implies setting the confidence to an initial value. Pixels belonging to the known image areas receive a confidence C= 1while the masked pixels of the unknown region receive a confidence C= 0. Thus the initial confidence distribution is the inverse of the disocclusion mask.

d) Inpainting loop

After the initialization, the actual inpainting-process is repeated iteratively until the algorithm terminates. Each iteration starts with the determination of so-called front pixels, which are those unknown pixels located on the edge to the known image region. After their identification, these front pixels are sorted by a pixel-specific priority value to obtain a sensible inpainting order. Afterwards, a window of fixed size centered around the front pixel of highest priority is filled by means of a block-matching-approach. Finally, the confidence values of all affected pixels are updated.

e) Front pixel priority

The information required to fill in a gap can only be gathered from the surrounding image regions known to the algorithm. Hence, inpainting always propagates successively from the border between known and un-known regions inwards. As a result, merely the front pixels located at this border are of interest within an inpainting step. These front pixels can be captured by subtracting the occlusion mask from a dilated occlusion mask and multiplying the image by the resulting difference. After detection of the current pixel front, a prior-ity value for each front pixel is determined as a product of several characteristics that depend on the front pixel neighborhood. The purpose of the front pixel priority is to indicate, which front pixel should be favored in the succession of inpainting in order to conserve important image structures, such as edges leading into the unknown area. The priority value Pj, which could be supplemented with arbitrary factors further contributing to the inpainting order such as the edge angle of incidence, is computed as

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$$P_j = E_j . C_j$$

Where Ej is the edge energy and Cj is the confidence in Pixel j. The normalized edge energy Ej sums up the gradient energy of the surrounding area of the front pixel. The more edges are close to the front pixel, the bigger Ej will be. The factor Ej thus ensures that edges are continued into the unknown region prior to smooth regions with less contribution to the image structure.

The confidence Cj describes the ratio of known pix-els to unknown pixels within the fixed-sized pixel block around a considered front pixel. The factor Cj hereby makes front pixels surrounded by many known texture pixels more likely to be selected for inpainting.

f) Block matching
After the front pixel of highest priority is determined, a pixel block centered around it as well as a surrounding search area are defined. Both the block size and the size of the search area are fixed and forwarded to the algorithm in advance of the inpainting process. Within the search area all completely known blocks of the same size as the partly unknown block are compared to that sought one for the purpose of finding the best matching block. The criterion for finding that most fitted pixel block is the luminance value difference between the known pixels of the partly unknown block around the front pixel and those of same relative position within the reference block. The reference block yielding the minimum mean squared error is then chosen and referred to as the best match. Afterwards, each unknown pixel within the sought block, including the central front pixel, receives the color value of the corresponding pixel within the best match.

In the presented algorithm, the best match approach is improved by a weighted match method superimposing multiple weighted reference blocks Bi. This is similar to an approach used for denoising images, presented as the Non-local Means Algorithm, which is also built upon the idea of superimposing weighted references. The individual weighting factors Wi of the weighted matches method are com-posed as products of three factors which are weighting functions themselves.

$$B_{\text{overall}} = \sum_i W_{\text{block}_i} \cdot B_i \text{ with } i \in \{blocks\}$$

$$W_{\Delta\text{lum}_i} = \sum_j \Delta\text{lum}_j \text{ with } j \in \{pixels\}$$

$$W_{\text{dist}_i} = |\vec{x}_{\text{center}_i} - \vec{x}_{\text{front pixel}}|$$

$$W_{\text{conf}_i} = \frac{1}{J} \cdot \sum_j C_j \text{ with } J \mathrel{\hat{=}} \text{pixels per block}$$

$$W_{\text{block}_i} = W_{\Delta\text{lum}_i} \cdot W_{\text{dist}_i} \cdot W_{\text{conf}_i}$$

To these belong an average luminance difference (WΔlumi), the spacial distance between the reference block and the sought one (Wdisti) as well as the average confidence (Wconfi). The individual block weights are ad-ditionally weighted by a normal distribution function to form the overall reference block. The variance is chosen to be relatively small and the conventional best match method is used as a fall back mode when no block matches with weights above a certain threshold can be found.

g) Update of Confidence Values
In the end of each iteration, the confidence C of the currently considered front pixel is assigned to all recently filled in texture pixels within the sought pixel block.

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

No	Algorithm	Advantages	Disadvantages
1	Semi supervised	Simple	Need large training set.
2	MODIS imagery	effective	Time consuming.
3	Neural network	Less complexity	Not consistent.
4	MRF approach	Simple, popular.	Low accuracy, Need preprocessing.
5	Spatio-temporal MRF approach.	Improved classification rate.	Not suitable for high level nose, Does not consider cloud removal.

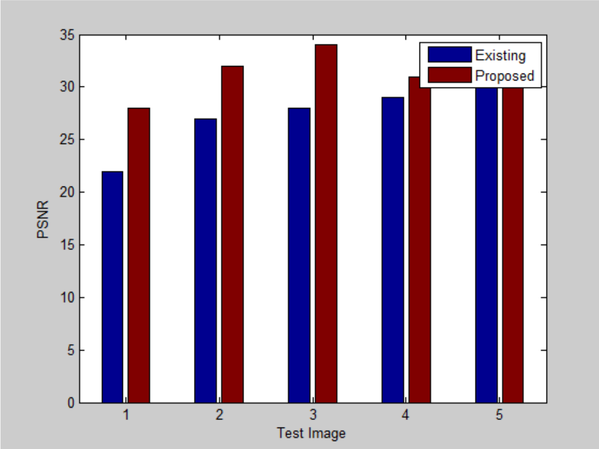

Fig 3: performance analysis of existing and proposed system.

V. CONCLUSION

Removing and recovering cloud region from satellite images after cloud detection using maximum a posteriori probability–Markov random field (MAP-MRF) method has been proposed. Cloud cover is generally present in remotely sensed images, which limits the potential of the images for ground information extraction. Therefore, removing the clouds and recovering the ground information for the cloud contaminated images is often necessary in many applications. In this project, we propose a cloud removal approach based on image inpainting. The approach removes cloud-contaminated portions of a satellite image and then reconstructs the information of missing data utilizing temporal correlation of multi temporal images. In order to remove the noise in the classified image weighted trimmed median filter is used. Adoption of this approach in different applications, such as meteorological forecasting, urban area control, and oil spills monitoring, in which significant improvements are expected by capitalizing on multiobject detection and tracking. Comparisons with existing algorithms our approach achieves better results in terms of misclassification probability and, in particular, to be very effective in cloud removal.

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