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Cloud Removal From Multi-temporal Satellite Images Using Information Cloning and Information Reconstruction

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Abstract

In this paper, we propose a cloud detection and removal approach based on information cloning. 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[1]. The basic idea is to clone information from cloud-free patches to their corresponding cloud-contaminated patches under the assumption that land cover change insignificantly over a short period of time. Firstly, cloud is detected by using simple thresholding approach. Then a semi automatic approach is used to detect the cloud regions and the SSIM index for both the target and reference images is calculated to sort out according to image similarity. Finally the patch-based information reconstruction is mathematically formulated as a Poisson equation and solved using a global optimization process. Thus, the proposed approach can potentially yield better results in terms of radiometric accuracy and consistency.

Keywords*:* Cloud removal, information cloning, Poisson equation.

I. Introduction

Globally, the Enhanced Thematic Mapper Plus(ETM+) land scenes[2] are, on average, about 35% cloud covered, indicating that cloud covers are generally present in optical satellite images. This observable fact limits the usage of optical images and increases the difficulty of image analysis. Thus, considerable research efforts have been devoted to the topic of cloud removal to ease the difficulties caused by cloud covers. If multi temporal images are acquired, the cloud-cover problem has a chance to be eased by reconstructing the information of cloud contaminated pixels under the assumption that the land covers change insignificantly over a short period of time. The aim of this study is to remove clouds and reconstruct information of missing data by taking advantage of the temporal correlation of multi temporal images. An information cloning algorithm is introduced to consistently reconstruct the information of cloud-contaminated region using several high similarity and cloud-free patches acquired at different times. Instead of reconstructing information pixel by pixel, which may have the problem of radiometric inconsistency, we propose a patch-based approach that mathematically formulates the reconstruction problem as a Poisson equation and then solve this equation using a global optimization process. In the optimization, the selected cloud-free patches are globally and consistently cloned in the corresponding cloud-contaminated region. This process potentially results in good cloud removal results in terms of radiometric accuracy and consistency.

II. CLOUD REMOVAL ALGORITHM

Cloud and Cloud-Shadow Detection

Fig.1 shows a cloud-contaminated image, called target image and denoted as *IT* , and a set of its corresponding images captured.

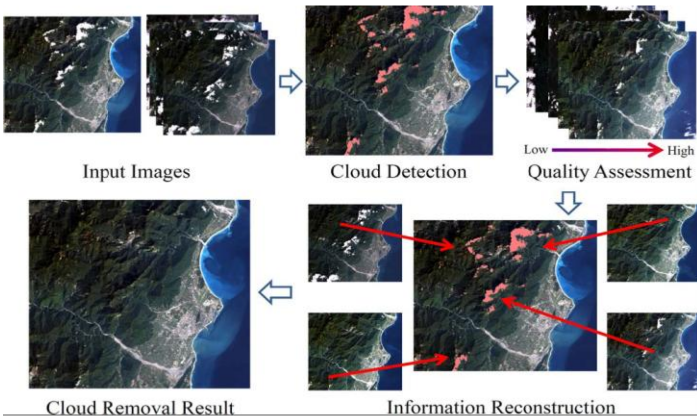


Fig 1. Workflow of cloud removal algorithm

at the same position but at different times, called reference images and denoted as *{IR*1, . . . , *IRn}*, the aim is to remove clouds and cloud shadows and to reconstruct the information of missing data in the target image *IT* using the reference images *{IR*1, . . . , *IRn}*. Firstly we designed a simple thresholding approach to detect the clouds. As a result of this we got the edge detected output, their shadow detection and the cloud detection. Then in the next step, a semiautomatic approach is adopted to detect clouds and cloud shadows in both the target and reference images. Once the cloud pixels are identified, their shadows are roughly predicted according to the cloud location and the solar illumination direction. The dark and connected components within the neighborhood of the predicted shadows are identified as the shadow components.

Image Quality Assessment

Once the cloud-contaminated pixels in the target and reference images are identified, several cloud-free patches are selected from the reference images *{IR*1, . . . , *IRn}* to reconstruct the information of cloud-contaminated regions in the target image *IT* . Taking radiometric accuracy into account, the cloud-free patches are selected based on image similarity. The simplest and most widely used similarity metric is the mean square error (MSE)[6,7], which is computed by averaging the squared intensity differences of pixels in the target and reference images. The MSE can be simply calculated and has a clear physical meaning. The SSIM index is briefly described in the following formulas, wherein this similarity measurement has three components, namely, illumination *L*(*IT* , *IR*), contrast *C*(*IT* , *IR*), and structure *S*(*IT* , *IR*):

$$\mathcal{L}(I_T, I_R) = \frac{2\mu_{I_T}\mu_{I_R} + C_1}{\mu_{I_T}^2 + \mu_{I_R}^2 + C_1}$$
$$\mathcal{C}(I_T, I_R) = \frac{2\sigma_{I_T}\sigma_{I_R} + C_2}{\sigma_{I_T}^2 + \sigma_{I_R}^2 + C_2}$$
$$\mathcal{S}(I_T, I_R) = \frac{\sigma_{I_T I_R} + C_3}{\sigma_{I_T}\sigma_{I_R} + C_3} \qquad (1)$$

where μI and σI represent the mean intensity and the standard deviation of image *I*, respectively, and $\sigma IT\ IR$ represents the covariance coefficient between images *IT* and *IR*. The constants *C*1, *C*2, and *C*3 are used to avoid instability when the denominators are nearly zero. By combining these three similarity components, the SSIM index is formulated as follows:

$$SSIM(I_T,I_R)=[L(I_T,I_R)]^{\alpha}[C(I_T,I_R)]^{\beta}[S(I_T,I_R)]^{\gamma} \quad (2)$$

where α, β, and γ are the weighting factors for the similarity components. And the weighting factors are all set to 1.0, and $C3 = C2/2$. This results in the following simplified form of SSIM index:

$$SSIM(I_T,I_R)=\frac{(2\mu_{I_T}\mu_{I_R}+C_1)(2\sigma_{I_TI_R}+C_2)}{(\mu_{I_T}^2+\mu_{I_R}^2+C_1)(\sigma_{I_T}^2+\sigma_{I_R}^2+C_2)}. \quad (3)$$

Information Reconstruction

We have done the information reconstruction [8]An in painting technique is also adopted . This is a technique of reconstructing the deteriorated parts of images and videos. Instead of correcting radiance and locally smoothing boundaries of cloud-contaminated regions or reconstructing information pixel by pixel, the problem is mathematically formulated as a Poisson equation and solved using a global optimization process. The cloud contaminated region in the target image *IT* is denoted as Γ, and its boundary is denoted as ∂Γ. Let *f* be an unknown image intensity function defined over the cloud-contaminated region Γ. Let *f*∗ be the image intensity function defined over the target image *IT* minus the cloud-contaminated[3] region Γ, and let **V** be a guidance vector field defined over the cloud-contaminated region Γ. The vector field **V** is defined as the gradient of the selected patches and is used to guide the reconstruction process to optimize the pixel intensities in the cloud-contaminated regions. To find an accurate and optimized reconstruction result the problem is formulated as an optimization equation with the boundary condition $f|\partial\Gamma = f*|\partial\Gamma$:

$$\min_f \iint_\Gamma |\nabla f - \mathrm{V}|^2, \quad \text{with } f|_{\partial\Gamma} = f^*|_{\partial\Gamma} \quad (4)$$

where $\nabla = ((\partial/\partial x), (\partial/\partial y))$ is the gradient operator and can be calculated by the following finite difference method:

$$\frac{\partial f(x,y)}{\partial x} = f(x+1,y) - f(x,y)$$
$$\frac{\partial f(x,y)}{\partial y} = f(x,y+1) - f(x,y). \quad (5)$$

Equation (4) aims to derive result *f* with a gradient that is as close to the guidance vector field **V** (i.e., the details of selected patches) as possible. The solution to (4) is the unique solution of the following Poisson equation[9] with Dirichlet boundary conditions:

$$\Delta f = div\ \mathrm{V} \text{ over } \Gamma, \quad \text{with } f|_{\partial\Gamma} = f^*|_{\partial\Gamma} \quad (6)$$

where $\Delta = (\partial 2/\partial x2) + (\partial 2/\partial y2)$ is the Laplacian operator and $div\mathbf{V} = (\partial v1/\partial x) + (\partial v2/\partial y)$ is the divergence of the vector field $\mathbf{V} = (v1, v2)$. Similarly, the second derivatives $\partial 2/\partial x2$ and $\partial 2/\partial y2$ can be calculated using the finite difference method as follows:

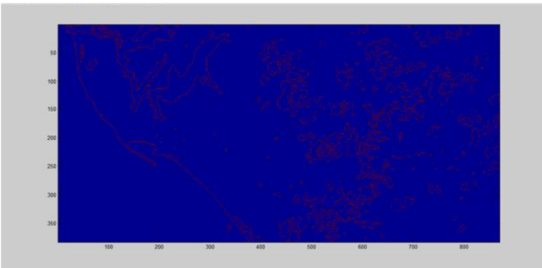
$$\frac{\partial^2 f(x,y)}{\partial x^2} = f(x+1,y) + f(x-1,y) - 2f(x,y)$$
$$\frac{\partial^2 f(x,y)}{\partial y^2} = f(x,y+1) + f(x,y-1) - 2f(x,y). \quad (7)$$

III. RESULTS AND DISCUSSION

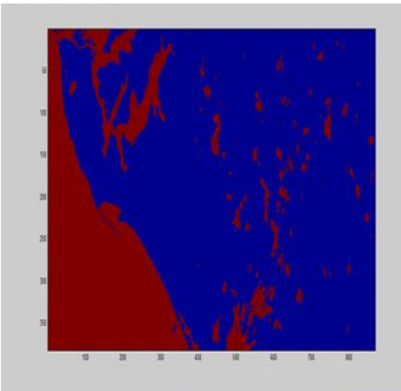
The first step of cloud removal algorithm that is cloud detection, which is done by a simple thresholding approach. Here a threshold is set and values greater than this threshold is considered as bright area and less than threshold becomes the dark regions.

Input Image

To this input image we applied the thresholding approach[5] and as a result of this edge detection and cloud detection has been done.



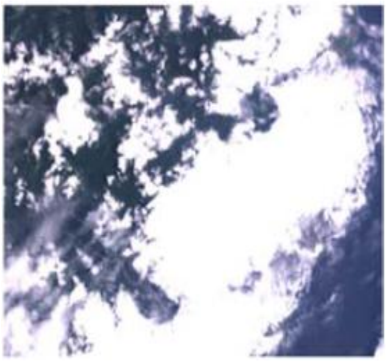
Edge detected output



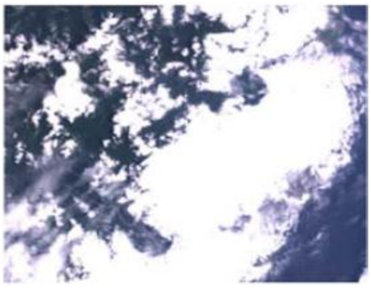
Cloud detection

The next result is the calculation of SSIM index. For this we have taken another input image as the target image and 5 reference images. According to SSIM calculation, we have sort the reference images according to the similarity by comparing the SSIM values. And from these reference images we can adopt the information to be cloned to the cloud contaminated portions of the target image.

Input image



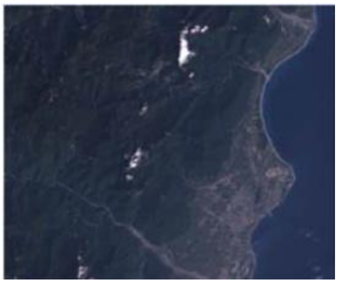
Reference image 1



Reference image 2

Reference image 3

Reference image 4



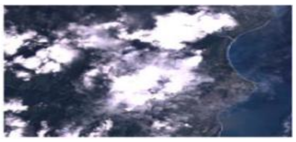
Reference image 5

The next step is sorting the images according to the SSIM values and the cloud amount.

SSIM:0.8

SSIM:0.7

SSIM:0.7



SSIM:0.2

SSIM:0.0

The last step is the information reconstruction process and this can be done by utilizing the information from the sort out reference images. The SSIM approximate to 1 are more similar and that to -1 are dissimilar. Then by applying the Poisson's solver equations we can consistently reconstruct[4] the information of missing data in the target image.

RECONSTRUCTED OUTPUT

IV. CONCLUSION

In this paper, a novel cloud removal algorithm has been introduced. The cloud-contaminated portions of a satellite image are removed, and then the information of missing data is reconstructed using the correlation of multi temporal images. Our approach is based on the patch-based information reconstruction strategy with the global optimization process. The major improvement is that this approach makes better use of appropriate temporal information to reconstruct the information. Thus, our approach can potentially yield better results in terms of radiometric accuracy and consistency, compared to the related approaches. This approach yields an advantage that the cloud regions boundary is not specific so it cannot be appropriately detected by using a region growing based approach. In this approach we can detect the cloud by specifying its appropriate boundary.

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