RECONSTRUCTION OF SATELLITE IMAGE CONTAMINATED BY CLOUDS

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ABSTRACT

The presence of clouds within a satellite image limits their analysis of data for application in different fields. Therefore, the elimination of clouds in satellite images is a subject widely studied to solve this problem. One of the techniques used for the reconstruction of images is the inpainting, which consists in restoring a damaged area in visually plausible form using information outside the damaged domain. The proposed method is to use the Expectation-Maximization algorithm for the classical case of Gaussian mixtures, to find the classes (labels) within an image. For the process of searching for the most similar patch, it is proposed to use the sum square error (SSE) both for the brightness of pixels as well as for the classes (modes) found in the image. Combining the classes found in each neighborhood (patch) with the color information allows us to obtain a better description of the patches. Some experiments were conducted to compare the results with other methods presented in the literature.

***Key words** – Inpainting, Expectation-Maximization algorithm, Reconstruction of Images, Cloud removal, mixture model.*

1. INTRODUCTION

Nowadays, the use of satellite images to analyze their data in different fields is very important, but one of the biggest problems is the little obtaining of free satellite images completely free of clouds or of high resolution. The problem to be dealt with in this work is to recover the data that has been lost due to the presence of clouds or shadows of them in a satellite image. Thus, the problem will be developed as a theme of image reconstruction.

One of the techniques used for the reconstruction of images is the inpainting, which consists in restoring a damaged area in visually plausible form using information outside the damaged domain [1], [2].

In [3], a cloud screening method is introduced based on detecting abrupt changes along the time dimension, and it uses linear and nonlinear least squares regression algorithms for the prediction of the values.

In [4], a reconstruction of cloud-contaminated multitemporal multiespectral images is proposed using two methods to predict the missing value. The first contextual prediction is implemented by an ensemble of linear predictors, trained in an unsupervised way over a homogeneous local region (classes or modes). Such regions (classes) are obtained by the Expectation-Maximization (EM) algorithm. The second one, is based on the support vector machine approach.

We propose a modification of the inpainting technique to recover missing data due to the presence of clouds. For the process of searching for the most similar patch, it is proposed to use the sum square error (SSE) both for the brightness of pixels as well as for the classes (modes) found in the image. Combining the classes found in each neighborhood (patch) with the color information allows us to obtain a better description of the patches.

2. MATERIAL AND METHODS

Let us consider a image $I(x,y)$ with dimension of $M \times N$ pixels and partly damaged. In this work, we assume the missing part has been beforehand localized by an appropriate method. Therefore, the image I can be divided in two parts: a *target region* Ω, that represents the missing pixels and a *source region* Φ, from which the most similar patch is extracted for the reconstruction of Ω.

$$I = \Omega \cup \Phi \tag{1}$$

The boundary between target and source regions is called *fill front* and denoted by $\partial\Omega$. A patch is a small square region $\Psi_p(x,y)$ centered in $p(x,y)$, containing $W \times W$ pixels. The inpainting technique consists in finding the more similar patch $\Psi_q(x,y)$, after finding it, it is copied to replace the patch $\Psi_p(x,y) \in \Omega$ (see Fig 1).

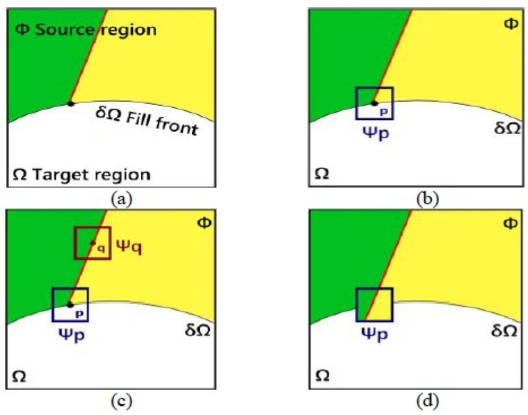

Figure 1: Inpainting Tecnique [2]

From the work of [1], to each pixel $p(x,y) \in \partial\Omega$ we assign an inpainting priority value $P(p)$ defined by:

$$P(p) = C(p).D(p)$$

where $C(p)$ and $D(p)$ represent the *confidence* and *data* terms respectively.

$$C(P) = \frac{\sum_{q\in\Psi_p\cap(I-\Omega)} C(q)}{|\Psi_p|} \text{ and } D(P) = \frac{|\nabla I_p^{\perp}.n_p|}{2^n}$$

2.1. Finite mixture model

In [4] the distribution of images can be approximated as a mixture of normally distributed sample. Thus, the probability distribution function (pdf) of a image X can be written as:

$$p(x) = \sum_{r=1}^{M} P(\omega_r).p(x|\omega_r)$$

where $P(\omega_r) = P_r$ is the prior probability and $p(x|\omega_r) = \mathcal{N}(\mu_r, \sigma_r)$ is the conditional pdf with the r-th Gaussian mode of the image. M is the number of modes, μ_r and σ_r are the mean and standard deviation parameters, respectively.

2.1.1. Expectation-Maximization algorithm

Expectation-Maximization (EM) algorithm is proposed to detect the different modes ω_r, ($r \in \{1, 2, \ldots, M\}$) present in the image I

Let X as incomplete data where the missing part is Z, i.e., its classification map. Suppose that L is the number of pixels in X, the missing part can be evaluated as a set of L labels $Z = \{z^{(1)}, z^{(2)}, \ldots, z^{(L)}\}$ associated with L labels, indicating which class is at the origin of each pixel realization. Each label is a binary vector,

$$z^{(i)} = [z_1^{(i)}, z_2^{(i)}, \ldots, z_M^{(i)}]$$

such that $z_r^{(i)} = 1$ ($r \in \{1, 2, \ldots, M\}$) if the $i-$th pixel x^i of X belongs to the $r-$th data ω_r, and $z_r^{(i)} = 0$ otherwise. The complete log-likelihood function, from which it would be possible to estimate the vector of parameters $\Theta = [P_1, P_2, \ldots, P_M, \mu_1, \mu_2, \ldots, \mu_M, \sigma_1, \sigma_2, \ldots, \sigma_M]$ if the complete data $\Psi = \{X, Z\}$ were observed, is given by:

$$\ell(\Psi|\Theta) = \log p(\Psi|\Theta) = \sum_{i=1}^{L}\sum_{r=1}^{M} z_r^{(i)} \ln[P_r p(x^i|\theta_r)] \quad (2)$$

where $\theta_r = [\mu_r, \sigma_r]$.

The EM algorithm is a powerful iterative technique that consists of expectation and maximization steps, which are iterated up to convergence [5].

E-step: Compute $z_r^{(i)}$ given the parameter estimates from the previous M-step

$$z_r^{(i)} = \frac{P_r.N(x^i|\mu_r, \sigma_r)}{\sum_{j=1}^{M} P_j.N(x^i|\mu_j, \sigma_j)} \quad (3)$$

M-step: Obtain new parameter estimates (denoted by the prime)

$$P_r^{'} = \frac{1}{L}\sum_{i=1}^{L} z_r^{(i)} \quad (4)$$

$$\mu_r^{'} = \frac{\sum_{i=1}^{L} z_r^{(i)} x^i}{\sum_{i=1}^{L} z_r^{(i)}} \quad (5)$$

$$\sigma_r^{'} = \sqrt{\frac{\sum_{i=1}^{L} z_r^{(i)}(x^i - \mu_r^{'})}{\sum_{i=1}^{L} z_r^{(i)}}} \quad (6)$$

The initial values of the parameters vector Θ can be chosen in different heuristic ways.

After the convergence of the EM algorithm, the last estimated parameters will define the Gaussian data classes (modes) available in the image X. Since the final estimates of $z_r^{(i)}$ stand the estimates of the posterior probabilities $P(\omega_r|x_i)$ ($i = 1, 2, \ldots, L$ and $r = 1, 2, \ldots, M$), we can assign to each pixel x^i of X the optimal class label $\hat{\omega} \in \Omega = \{\omega_r : r = 1, 2, \ldots, M\}$, such that:

$$\hat{\omega} = \arg\max_{\omega_r\in\Omega}\{P(\omega_r|x_i)\} \quad (7)$$

2.2. Proposed Method

The first step determine the data classes (modes) of the image X. Assigning the priority to the pixels in the boundary of the *target region* Ω, we started the inpainting technique in the pixel with the highest priority $\hat{p}$.

The proposed criterion for the search of the most similar patch includes the sum square error (SSE) both for the brightness of pixels as well as for the classes (modes) found in the image. Combining the classes found in each neighborhood (patch) with the color information allows us to obtain a better description of the patches.

$$\Psi_{\hat{q}} = \min_{\Psi_q\in\Phi} d(\Psi_{\hat{p}}, \Psi_q)$$

$$d(\Psi_{\hat{p}}, \Psi_q) = SSE(\Psi_{\hat{p}}, \Psi_q) + SSE(class(\Psi_{\hat{p}}), class(\Psi_q))$$

The last equation is evaluated in the pixels within the region Φ.

The sum square error is given by

$$SSE(\Psi_{\hat{p}}, \Psi_q) = \sum(\Psi_{\hat{p}} - \Psi_q)^2$$

Once the best patch was found, we replaced the missing pixels of the patch $\Psi_{\hat{p}}$ with the pixels of the patch found $\Psi_{\hat{q}}$.

3. RESULTS

The image used in this experiment represents a section of a scene taken by the Landsat-7 ETM+ sensor over the Trentino area in Northern Italy. The image has 220 × 290 pixel size, acquired in September 2000. (Fig. 2). The main land covers of this image are urban area, water, forest, ground, grass, and vineyards.

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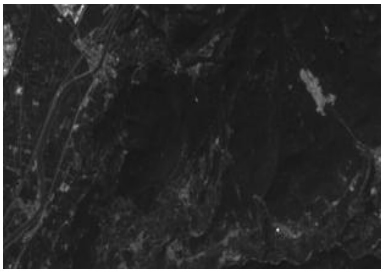


Figure 2: Trentino area in Northern Italy (September Band3, 2000)

The first step is use the EM algorithm for the classification of the nodes of the image (Fig. 3).

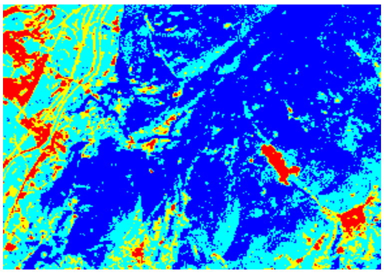
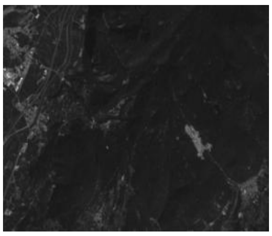


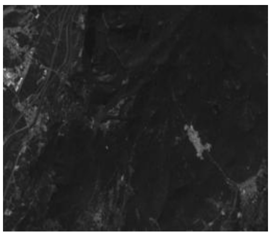
Figure 3: Class Image of the band 3

In order to make possible the quantify of the reconstruction accuracy of the proposed methods, we simulate the presence of clouds by partly obscuring the image. Also, for the purpose of comparison, we compared the proposed method with the original Criminisi inpainting method.

(a) Image with mask



(b) Criminisi' Method



(c) Proposed Method

Figure 4: Trentino area in Northern Italy (1) (September Band3, 2000)

For quantify the reconstruction accuracy, we use the Root-Mean-Square Error (RMSE) and Peak signal-to-noise radio (PSNR):

The improvement of the data recovery with the proposed method is shown numerically in the previous table.

Image	RMSE		PSNR	
	Criminisi	Proposed Method	Criminisi	Proposed Method 1
Trentino Band3	0.5970	0.5560	45.0774	47.4730

4. CONCLUSIONS

This work dealt with the complex problem of the reconstruction of images. In particular, eliminate clouds from satellite image. To achieve our goal we use information from the image itself where there is no obstruction of clouds and searching for the most appropriate patch (more similar classes). To find the classes (modes) of a image, we use the EM algorithm.

Combining the classes found in each neighborhood (patch) with the color information (pixel value) allows us to obtain a better description of the patches. This allows us to find the most appropriate patch, which will be used to replace the missing pixels by the presence of the clouds.

The simulated experiment performed show that the proposed methods are independent of the ground cover. Our experiment show a better reconstruction of the images, and they are visually almost equal to their original image.

In addition, the algorithm proposed is conceptually simple and easy to implement, the computational time depends on the size of the treated image. For our experiments, the computational time used was short.

5. REFERENCES

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