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An efficient PDE framework for satellite image classification

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Abstract - *In this paper, we present a method based on coupling between shock filter and diffusion process for image restoration. This method smoothes homogeneous part of the image, while it enhances edges efficiently. This selective smoothing propriety is used as a pretreatment step for an efficient classification of infrared satellite images, in order to cluster the solar field.*

Résumé - *Dans cet article, nous présentons une méthode basée sur le couplage entre le filtre de choc et le processus de diffusion pour la restauration de l'image. Cette méthode atténue la partie homogène de l'image, tout en améliorant les bords de manière efficace. Cette propriété sélective de lissage est utilisée comme une étape de prétraitement pour un classement efficace des images satellite infrarouge, afin de regrouper le domaine de l'énergie solaire.*

Mots clés: Couplage – Image – Satellite – Filtre de choc – Lissage.

1. INTRODUCTION

With the growing use of solar energy to supplement the conventional fuels, there has been an increase in the demand for solar data which can be used in feasibility and equipment design studies, in order to implement photovoltaic stations, which could convert a maximum of solar radiation into electrical energy. The solar radiation incident on the earth's surface in the visible and near-infrared wavelength range (0.3 µm - 2.0 µm) is measured on the ground by means of pyranometer.

Thus, several hundreds of such ground stations would be necessary to map the spatial variability of the solar irradiance for a larger region [1]. This is practically impossible for developing countries, because ground measurements suffer from high costs of purchasing of equipment, inadequate manpower for operation and maintenance along with time-consuming data screening requirement. An alternate solution to this problem is to detect the distribution of solar radiation incident on the earth through the analysis of images from meteorological satellites.

This analysis must rely on the quality of these images, which can present a blurry aspect and noisy appearance. Since images are not always in a good quality due to various types of degradations. Thus, image restoration is essential as a first step especially when the input image is blurred, noisy or blurred and noisy [2, 3].

An ideal restoration algorithm is expected to simultaneously remove noise and enhance edges in an image. In is paper, we present a method to restore satellite images, in order to be exploited efficiently in automatic classification of solar field.

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2. IMAGE DEGRADATION AND CLASSIFICATION

In the acquisition process of the image, two types of degradation can appear: the first one deals with the sensor itself. So, how can this sensor be faithful in the capturing of the image as an exact reproduction? Could it do not introduce any perturbation in the sharps that form the image? Roughly speaking, are all frequencies of the real image present in the captured one? Of course any real system has a transfer function that influences on the image spectrum. Indeed, in several cases, the captured image presents some blur. This blur is due to the cancelling of some high frequencies that determine edges. Thus, the output image can be considered as the convolution of the real image with the impulsive response of the sensor.

However, in the course of acquiring, transmitting or processing a digital image, some undesirable signal can involve the image. Thus, noise induced degradation may be dependent or independent of data. The noise is usually described by its probabilistic model.

So, two operations would be done: denoising and sharpening. Several deconvolution and denoising techniques have been proposed in the literature: Statistics based filters [4, 5], wavelets [6-8], PDE-based algorithms [9, 10] and variational methods [11-13]. In particular, a large number of PDE-based methods have been proposed to tackle the problem of image denoising with a good preservation of edges, and also to explicitly account for intrinsic geometry [14, 15].

Among the existing restoration algorithms, the approach that bases enhancement procedure on partial differential equations coupling has attracted a lot of attentions in recent years, where some methods based on diffusion-shock filter has been developed [16-19]. However, image classification is an important part of the remote sensing [20-22], where any algorithm must be able to classify the satellite image into different distinct clusters.

In our case, the infrared satellite image must be segmented in order to obtain different regions in function of gray level intensity, which can be made by a supervised or unsupervised classification method [23, 24].

3. PROPOSED ALGORITHM

By considering two kinds of PDEs: shock filter and diffusion process, we can exploit the image enhancement propriety of the first method [25] and the selective smoothing operation of the second [26], in order to yield to an original shock filter-diffusion coupling scheme, that synchronizes both effects: smoothing homogeneous regions and sharpening edges [27].

The proposed algorithm enhances edges efficiently with noise removing and preserves well the location of the shocks. It is given by the following set:

$$\begin{cases} u_t = |\nabla u| \operatorname{div}\left(g\left(|\nabla u_\sigma|\right) \dfrac{\nabla u}{|\nabla u|} \right) - \sigma \left|\nabla\left(f\left(|\nabla u_\sigma|\right)\right)\right|^2 (u - v) \\ v_t = \beta\left(1 - \left|\nabla\left(f\left(|\nabla u_\sigma|\right)\right)\right|^2\right) u_{\eta\eta} - \operatorname{sign}\left(G_\sigma \times u_{\eta\eta}\right) |\nabla u| \end{cases} \tag{1}$$

where $u(0) = u_0$ the initial degraded image, $v(t)$ is the just previous evolution of $u(t)$, u_σ is the smoothed image of $u(t)$ by the Gaussian function G_σ with the standard deviation σ and $\eta\eta$ is the direction of the gradient.

The functions $g(|\nabla u_\sigma|)$ and $f(|\nabla u_\sigma|)$ are decreasing functions on gradient magnitude with free parameters respectively k_d and k_c. The first function $g(|\nabla u_\sigma|)$ is used to assure an anisotropic behaviour, and to select 'small edges' to be smoothed according to the parameter k_d. However, $f(|\nabla u_\sigma|)$ is introduced to select which 'big edges' to be improved according to k_c. The parameters α and β are positive balance constants.

The first equation in (1) behaves like a nonlinear reaction-curvature diffusion process, where the second is a shock filter coupled to a kind of diffusion. This here diffuses the image only in the direction of the gradient, especially at isolated artificial edges, which can be created by noise.

This equation is used to remove noise as much as possible at noisy edges and to create a shock in these locations, where $|\nabla f(|\nabla u_\sigma|)|$ tends to zero. Thus, by choosing a value of the parameter β as a balance between diffusion and shock effects, isolated noise at edge locations will vanish very well under smoothing effect of $u_{\eta\eta}$.

However, the term in the right side of the first equation is introduced to ameliorate edges enhancement under modified curvature diffusion process. It is a reactive term of the sharpening operation using shock filter as a result of the second equation. Thus, the first equation excludes residual enhanced pixels by shock filter in smother zones and it sharpens edges.

Because, in homogeneous regions the value of $|\nabla f(|\nabla u_\sigma|)|$ is low, whereas at edges locations $|\nabla f(|\nabla u_\sigma|)|$ is high. Therefore, in the first case level set diffusion will operate smoothing noise. In other hand, the process will operate as a shock filter.

Hence, by the definition of the function $f(|\nabla u_\sigma|)$, we can deduce the following behaviour:

- at noisy and none noisy transitions $f(|\nabla u_\sigma|)$ is low;
- at none noisy transition $|\nabla f(|\nabla u_\sigma|)|$ is high, from where $1 - |\nabla f(|\nabla u_\sigma|)|$ is low.

Therefore, the first term of the second equation will be weakened and this equation will operate like a shock filter, which creates the reactive term $v(t)$. The first one becomes a nonlinear reaction diffusion-shock. The edge will be sharpened by the weighed difference between $u(t)$ and $v(t)$;

- at noisy transition $|\nabla f(|\nabla u_\sigma|)|$ is low and $1 - |\nabla f(|\nabla u_\sigma|)|$ is high (because this point) doesn't belong to any side of the edge).

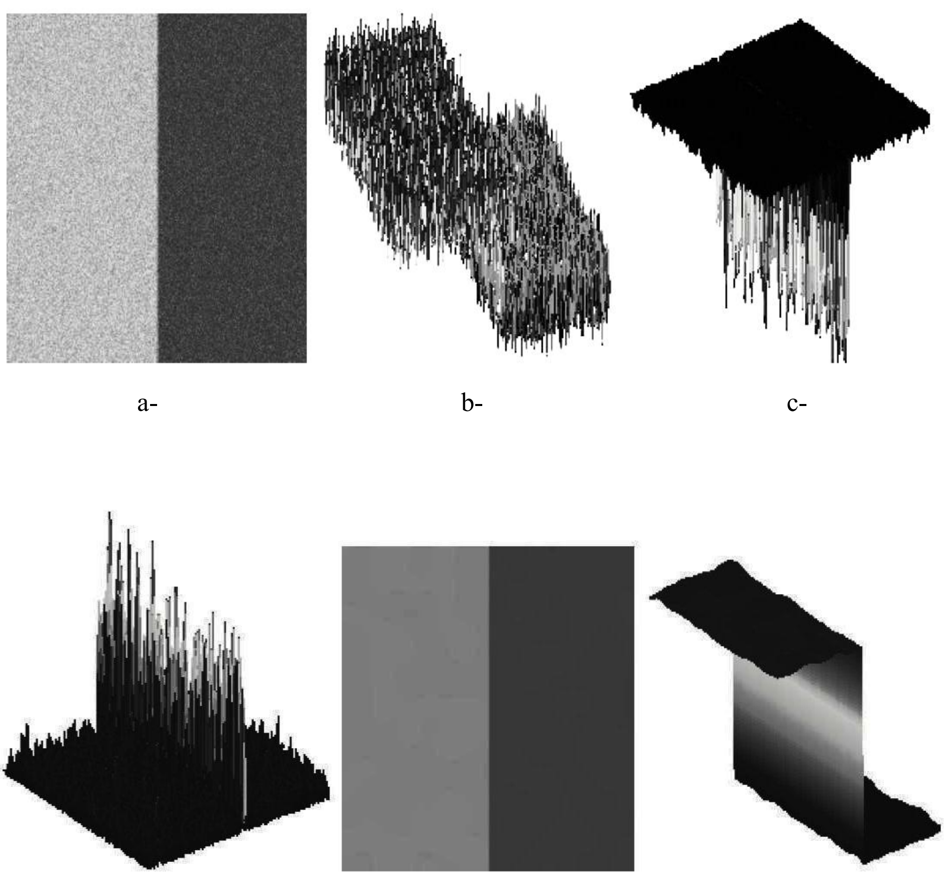
In this case, the first term of the second equation becomes a simple diffusion in gradient direction. We have here a linear reaction diffusion-shock eliminating noise. The edge will be denoised and sharpened.

In time, $f\left(\left|\nabla u_{\sigma}\right|\right)$ will be low and $\left|\nabla f\left(\left|\nabla u_{\sigma}\right|\right)\right|$ will be high. The process will tend to a nonlinear reaction diffusion-shock.

However, in flat areas:

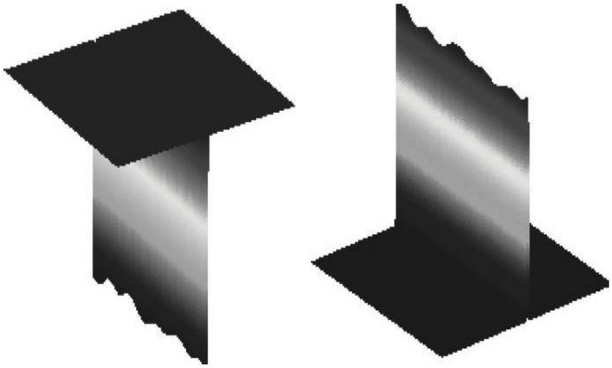
- at none noisy point $\left|f\left(\left|\nabla u_{\sigma}\right|\right)\right| \rightarrow 1$ and $\left|\nabla f\left(\left|\nabla u_{\sigma}\right|\right)\right| \rightarrow 0$. The first equation will tends to a linear diffusion, because the second term here is weakened. No shock effect;
- at noisy point $f\left(\left|\nabla u_{\sigma}\right|\right) \rightarrow f_0$ and $\left|\nabla f\left(\left|\nabla u_{\sigma}\right|\right)\right| \rightarrow \left|\nabla f_0\right|$. The first equation will tends to nonlinear diffusion-shock coupling process smoothing noise. In time, $f\left(\left|\nabla u_{\sigma}\right|\right) \rightarrow 1$ and $\left|\nabla f\left(\left|\nabla u_{\sigma}\right|\right)\right| \rightarrow 0$ and no shock effect.

Figure 1 shows an experiment on blurry and noised step function with SNR = 10 dB. Noise in flat areas has been removed, while edges have been enhanced. The curves of $f\left(\left|\nabla u_{\sigma}\right|\right)$ and $\left|\nabla f\left(\left|\nabla u_{\sigma}\right|\right)\right|$ confirm this behaviour.



a- b- c-

d- e- f-



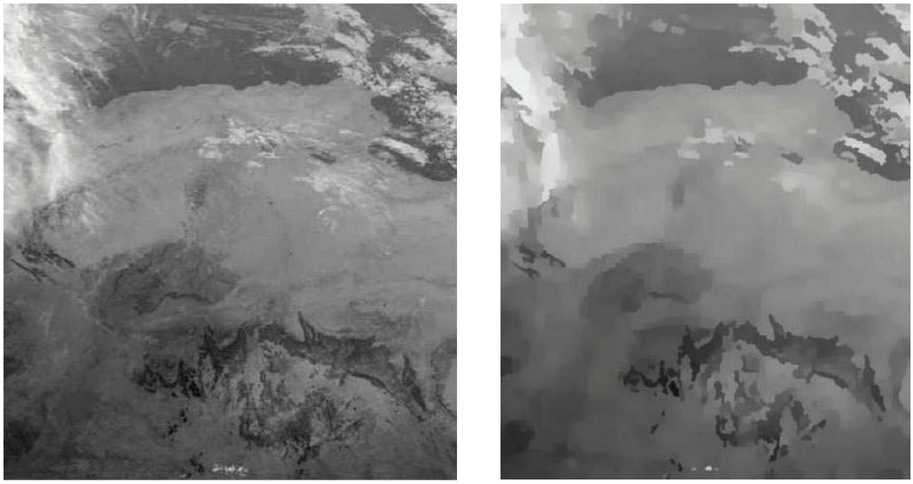
g- h-

Fig. 1: Application of the proposed filter on step function, a- Blurry and noised image; b- Curve of situation (a); c- $f\left(\left|\nabla u_\sigma\right|\right)$ curve of situation (a); d- $\left|\nabla f\left(\left|\nabla u_\sigma\right|\right)\right|$ curve of situation (a); e- Restored image; f- Curve of situation (e); g- $f\left(\left|\nabla u_\sigma\right|\right)$ curve of situation (e); h- $\left|\nabla f\left(\left|\nabla u_\sigma\right|\right)\right|$ curve of situation (e)

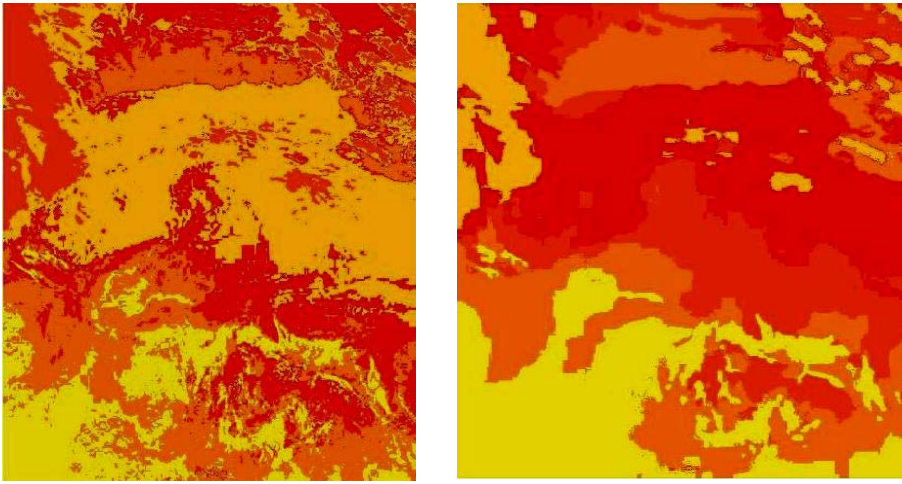
4. EXPERIMENTS ON SATELLITE IMAGE

We apply our method on an infrared satellite image of North Africa [28], and then we use a classification algorithm (k-mean Matlab function), in order to cluster both images: original and enhanced one.

We can see that the restored image by our method has a smooth appearance in homogeneous regions, with an efficient edge enhancement. This effect is well established in the segmented image, where the classification algorithm has successively clustered homogeneous part of the satellite image.



a- b-

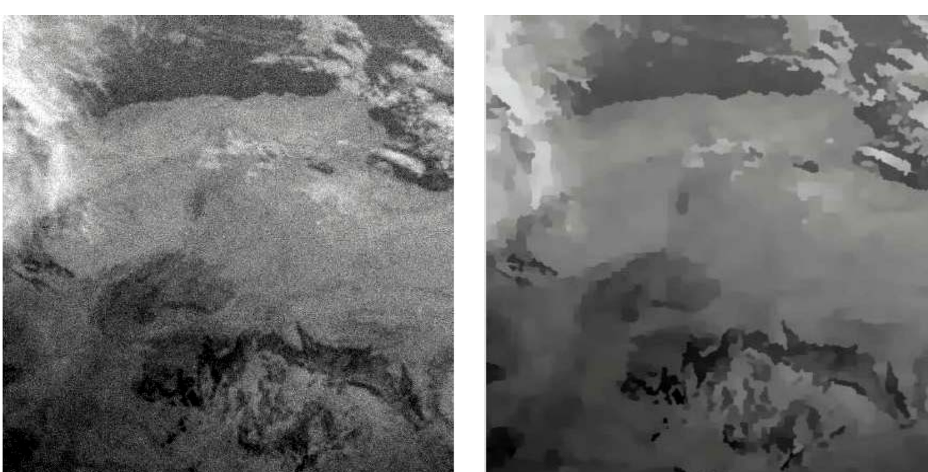


c- d-

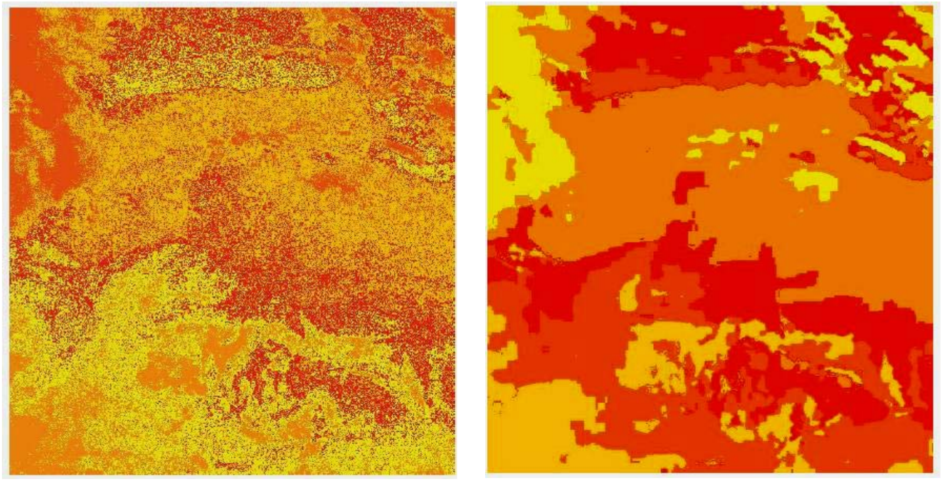
Fig. 2: Classification of satellite image
a- Original image, b- Enhanced image by the proposed method
c- Classification of situation (a); d- Classification of situation (b)

In order to proof the efficiency of our method as a good pretreatment algorithm, we now consider a blurry and noised satellite images (SNR = 8.38 dB) (Fig. 3).

We can obviously see how our method has eliminated noise with edge sharpening, this has facilitated the classification of the image, where clusters are well distinguished in our case referring of the degraded image.



a- b-



c- d-

Fig. 3: Classification of degraded satellite image
a- Blurry and noised image, b- Enhanced image by the proposed method
c- Classification of situation (a); d- Classification of situation (b)

5. CONCLUSION

Many domains are based on computer processing of captured images, where the need to these images is critical to take some decisions in satellite, medical imaging and other areas.

Thus, the resulting achievements must rely on the quality of acquired images. The proposed PDE method can be used as an efficient pretreatment algorithm for satellite infrared images classification, in order to determine the different solar fields.

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