APPLICATION TO MULTISPECTRAL IMAGES OF A BLIND IDENTIFICATION SYSTEM FOR BLUR, ADDITIVE, MULTIPLICATIVE AND IMPULSE NOISES

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ABSTRACT

We address the problem of the identification of the preponderant degradation affecting an image, in the context of blind, processing where the identification has to be made from the observed image. Considering that the main difficulty for any pre-processing treatment is to find the good balance between the two contradictory aspects of preserving the fine details and removing the degradation effects, the estimation from the observed image of the degradation characteristics is crucial to choose the algorithms and the order in which to apply them. The degradations considered here involve a defocusing blur and a noise or a combinations of both. The noise can be additive, multiplicative or impulse. The system presented here is tested on images obtained from the CASI airborne hyperspectral imaging sensor.

1. INTRODUCTION

A major drawback of most powerful image acquisition systems, like satellites, airborne sensors or medical imagery, is the large amount of information to process. As a consequence the need for automatic procedures is important. Moreover there are inevitably various degradation effects during the generation, coding and transmission of an image. Opposed to that, the quality result of the interpretation depends on the quality of the image. To remove the defects of acquisition and improve the quality of images, filtering or restoration algorithms are applied prior to any higher level segmentation or interpretation. Most of these algorithms require some information about the degradation they fight against. It is in practice difficult to access to this information [1]. When no a priori information is available, as in the case of blind processing, the nature of the degradation and its statistical parameters have to be estimated from the observed image, so as to apply the most appropriate algorithm. Indeed, when one applies a contour detector insensitive to additive noise, when the image is degraded by a multiplicative noise, the detection performance are not optimal. In that perspective we present here an automatic system to identify the nature of the degradation affecting an image and select the appropriate algorithm (figure 1). We are interested in this paper in the optimization of the decision criteria to identify the nature of the degradation from the observed image.

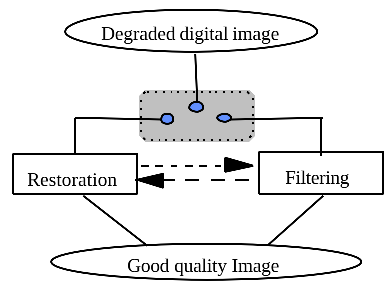

Figure 1 : Automatic pre-processing system

The first part of this study is devoted to the development of the identification procedure. In the second part the system is tested on images obtained from the CASI airborne hyperspectral imaging sensor. This imaging spectrometer allows a huge number of spectral bands to be collected for each element of the scene (up to several hundreds), while spatial resolution can reach a few dm at ground. Spectral bands acquired range from blue (≈ 400 nm) to the near infrared (≈ 900 nm) with a spectral resolution of 2 nm.

2. STATEMENT OF THE PROBLEM

An image can be altered by several sources of degradation, ending to different observation models. Each of these observation models corresponds to a hypothesis that has to be tested so as to select the type of processing to apply to the image. In previous studies we only considered two sources of degradation : a blur and a noise, acting alone or combined to each other. The noise was either additive [2, 3] or multiplicative [4]. Here we generalize the problem considering a total of four sources of degradation made of three different noises : additive, multiplicative and impulse noise and a defocusing blur. Thirteen observation models have been deduced from these four sources and are considered in the following. These models are :

$$g(x, y) = (f * h)(x, y), \quad (1)$$

$$g(x, y) = f(x, y) + b_p(x, y), \quad (2)$$
$$g(x, y) = (f + b_a) * h(x, y), \quad (3)$$
$$g(x, y) = (f * h)(x, y) + b_p(x, y), \quad (4)$$
$$g(x, y) = ((f + b_a) * h(x, y)) + b_p(x, y), \quad (5)$$

$$g(x, y) = f(x, y) \times b_p(x, y), \quad (6)$$
$$g(x, y) = (f \times b_a) * h(x, y), \quad (7)$$
$$g(x, y) = (f * h)(x, y) \times b_p(x, y), \quad (8)$$
$$g(x, y) = ((f \times b_a) * h(x, y)) \times b_p(x, y), \quad (9)$$

$$g(x, y) = f(x, y) \,!\, b_p(x, y), \quad (10)$$
$$g(x, y) = (f \,!\, b_a) * h(x, y), \quad (11)$$
$$g(x, y) = (f * h)(x, y) \,!\, b_p(x, y), \quad (12)$$
$$g(x, y) = ((f \,!\, b_a) * h(x, y)) \,!\, b_p(x, y). \quad (13)$$

where $g(x, y)$ is the observed image, $f(x, y)$ is the original image, $h(x, y)$ is the point spread function of the blur, $b_a(x, y)$ and $b_p(x, y)$ are independent noises applied before or after the blur.

Our objective is to identify the nature of the degradation from the observed image. The degradation can be a blur (1), or a noise (2), (6), (10), or a combination of both (3), (4), (5), (7), (8), (9), (11), (12), (13). In these last cases, the task of the identification procedure is to evaluate which source produces the predominant degradation effects. Considering that the main difficulty for any pre-processing treatment is to find the good balance between the two contradictory aspects of preserving the fine details and removing the degradation effects, the problem we address here is important. In the case of multiple sources of degradations, the choice of the algorithms and of the order in which they should be applied is essential. In that perspective the identification of the predominant degradation gives a crucial information.

3. DEVELOPED METHOD

The aim of the identification procedure is to divide large sets of acquired images into classes corresponding to the algorithm adapted to their type of degradation. For instance a filter for noisy images and a restoration algorithm for blurred images [5]. In that perspective, we seek to characterize the different possible degradations with attributes likely to discriminate them. We estimate global and local statistics from the original image or from the Laplacian of the original image. Let $g_{lap}(x, y)$ be the image obtained by convolution between the observed image $g(x, y)$ and the mask of the Laplacian operator H, $g_{lap}(x, y)$ contains information on the blur operator [6]. A blurred image is characterized by weak transitions of slopes of the Laplacian of the image, which is symptomatic of the presence of a blur.

Nine parameters have been selected for the classification of the degraded images.

- Global parameters
  - m_g : the mean of the grey levels,
  - s_g : the standard deviation of the grey levels,
  - R_g :the root mean square of the grey levels
  - γ : the contrast of the image.

- Local parameters
  - m_1 : the mean of the maximal slopes of the Laplacian,
  - σ : the standard deviation of the maximal slopes of the Laplacian,
  - c_1 : the skewness coefficient,
  - c_2 : the kurtosis coefficient,
  - σ_{noise} : the standard deviation of the noise computed on homogeneous regions.

The skewness and kurtosis coefficients are computed with the four first order statistics of the maximal slopes of the Laplacian. The search of the maximal slope of the Laplacian is made along the lines and columns of $g_{lap}(x, y)$, giving $Maxslope(x)$ and $Maxslope(y)$. For example, on each line:

$$Maxslope(x) = Max\big|\, |g_{lap}(x, y+1)| - |g_{lap}(x, y-1)| \,\big|. \quad (14)$$

The average of the maximal slope along the lines and the columns is then computed. The larger of both (noted m_1) is defined as the average of the maximal slopes of the Laplacian. If m_1 is larger when it is computed along the lines, then the other statistics of the maximal slopes of the Laplacian will only be computed along the lines.

The estimation of the standard deviation of the noise σ_{noise} is achieved from the analysis of an histogram of local standard deviations computed on homogeneous regions of the image. The homogeneous regions are obtained from a segmentation which allows to determine homogeneous regions of any shape [7]. This method is more accurate than techniques using fixed masks. Associated to the estimation of the standard deviation an identification procedure using the same homogeneous regions has been developed, which identifies the additive, multiplicative or impulse nature of the noise [8].

As any decision procedure, our system is made of two modules. A first one to compute statistics relevant to our identification problem. The nine parameters presented above, were selected to that purpose. A second module in charge of the decision itself. Here the decision is obtained from a classification of a set of degraded images. The classification is run by the CHAVL algorithm based on an ascendant hierarchical classification method by Analysis of the Likelihood of Bonds [9]. The originality of this method is based on the definition of similarity indices between elementary objects. The notion of bond likelihood between the different classes appears in the definition of the aggregation indices, ending to an aggregation criterion independent of a metric. Thus CHAVL is a non-parametric classification algorithm.

4. EXPERIMENTAL RESULTS

To validate the method presented here, we used images obtained from the CASI airborne hyperspectral imaging sensor. The CASI sensor can operate in two modes. The spatial mode allows 512 pixels to be obtained across the flight line with up to 40 spectral bands. The spectral mode allows more spectral bands with less pixels across the flight line. Different combinations are possible in the limit of 288 spectral bands. When this limit is reached, the number of pixel on the flight line falls down to 16.
The images were acquired in july 1998 above Plounérin in north of britany (France) with five bands detailed hereafter and a spatial resolution at ground of one meter.

Band 1: 560,8 nm ± 15,7 nm,
Band 2: 618,7 nm ± 20,2 nm,
Band 3: 690,2 nm ± 14,9 nm,
Band 4: 732,4 nm ± 19,5 nm,
Band 5: 799,9 nm ± 4,2 nm.

The flight lines are corrected for the plane attitude (pitch, roll and yaw) and mosaïked. A large region of 1370 m × 3830 m was produced out of which a square image of 256 × 256 pixels, corresponding to a 256 m^2 scene, was extracted. Each pixel is coded with 16 bits. The method has been tested on five images corresponding to the five bands of the image extracted from the acquisition. At first the noise identification algorithm was run on these images with the following results :

Band	Nature of noise	σ_{noise}
Band 1	Multiplicative	0,15
Band 2	Multiplicative	0,16
Band 3	Multiplicative	0,16
Band 4	Multiplicative	0,12
Band 5	Multiplicative	0,10

Table 1: noise identification on the original images

The five bands were filtered before being altered according to the degradation models (1 – 13). The defocusing blur operator was applied with a 5 × 5 support All the noises are gaussians, independant and their standard deviations take five different values : (3, 6, 8, 10, 12) for additive noises, (0.05, 0.1, 0.2, 0.3, 0.4) for multiplicative noises and finally (0.1, 0.15, 0.2, 0.25, 0.3) for impulse noises. Five samples of each degradation involving a noise were generated ending to 481 degraded versions of each band and a total of 2405 degraded images generated.
A table of attributes is computed for each of the five bands. Each table has 481 lines and 11 columns. The eight first columns correspond to the eight first attributes defined in section 3. The last three columns correspond to the noise identification and standard deviation estimation step. They are organized as follows : column 9 (respectively 10 and 11) contains the estimation of the standard deviation if the image is detected as altered by an additive (respectively Multiplicative and impulse) noise and a zero if it is detected as altered by another type of noise. Thus the tables of attributes not only contain quantitative information but also a qualitative information. Finally the CHAVL algorithm is applied to each of the five tables. All the different degraded versions of a same band are classified in four classes: preponderant additive noise, preponderant multiplicative noise, preponderant impulse noise or preponderant blur. As far as this last class is concerned, images with a weak noise (two smallest values of the standard deviation for each noise) applied after the blur operator are also considered as well classified if they are associated to that class. The global results are given in table 2. Table 3 presents the detailed results on band 4. The shaded boxes point out bad classifications.

Band (481 images)	Number of images correctly classified	Good classification rate
Band 1	426	**88,56%**
Band 2	388	**80,66%**
Band 3	387	**80,46%**
Band 4	449	**93,35%**
Band 5	377	**78,38%**
Global Result	2047	**84,28%**

Table 2: Global classification results

Model (population)	Class +	Class ×	Class !	Class blur
1				1
2(20)		20		
3 (20)	4			16
4, 5 (120)	109			11
6 (20)		19		1
7 (20)	2			18
8, 9 (120)	5	64		51
10 (20)			20	
11 (20)				20
12, 13 (120)			120	

Table 3: Band 4 classification results

Some points should be noted considering these results. First, when the class of an image corresponds to the result of the noise identification, the system not only identifies the preponderant degradation effect (noise or blur) but also identifies the nature of the noise and estimates its standard deviation. When the classification result (class +, class ×, class !) differs from the noise identification (+, ×, !) it comes out, that in general, the classification gives the good identification. This means that the classification as it is organized here, combining the result of the identification step with other parameters, allows to improve the performance of the identification alone. The only condition then, to choose the appropriate algorithm, is to make a new estimation of the standard deviation taking into account the final identification as shows the following example. Table 4 and figures 2 and 3 report of a case where the band 3 image degraded with model 4 (σ_{noise} = 8) was identified as altered with a multiplicative noise and classified in class +.

Original image		Identifidation result		Global result	
Model	σ_{noise}	noise	σ_{noise}	noise	σ_{noise}
4	8	×	0,34	+	10,64
8	0,25	×	0,277	×	0,277

Table 4 :Examples with the band 3 image

A second point is that 98,5% of the images involving an impulse noise are well classified. Finally, although the global percentage obtained here is smaller than those obtained in previous studies considering additive [2], [3] or multiplicative noises only [4], the problem addressed here is very complex and ambitious. Indeed most of the erroneous identifications occur for noise levels such that an additive noise is mixed up with a multiplicative noise. Finally the information worked out by this method is important to define the strategy in an automatic pre-processing system.

5. CONCLUSION.

The system presented here is a blind system to identify the preponderant degradation affecting an image. As we work in the blind context, the identification is made from the observed image. The degradations considered involve a defocusing blur and a noise or combinations of both. The noise can be additive, multiplicative or impulse. The method has been tested on 2405 degraded versions of images obtained from the CASI airborne hyperspectral imaging sensor. The result is that in 84 % of the cases the system detects the nature of the preponderant degradation effect giving the identification of the nature of the noise and the estimation of its standard deviation. Although the example of the restored images (figure 2) show the interest of the method, a systematic study on the same set of images has to be driven using the classical restoration quality criteria.

6. REFERENCES

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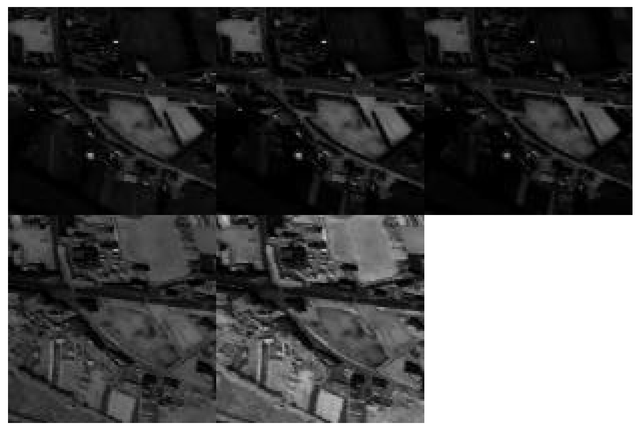

Figure 1 : Original images, bands 1 to 5

Figure 2 : (a) Band 3: degradation model 4, σ_{noise}= 8,
(b) After filtering (additive, σ_{noise}= 10,64.),
(c) After restoration.

Figure 3 : (a) Band 3: degradation model 8, σ_{noise}= 0,25,
(b) After filtering (multiplicative, σ_{noise} = 0,28.),
(c) After restoration.