ABSTRACT

Filtering and restoration aim to improve the quality of an image to facilitate its interpretation. Most of these algorithms require a priori information about the degradation affecting the image. In the context of blind image processing, when no a priori information is available, the nature of the degradation has to be identified from the observed image. This operation is essential to select the algorithm adapted to the image. Noise, blur and combinations of both are the sources of degradation considered here. We present a blind identification procedure which involves the computation of local statistics and the execution of a non parametric ascendant hierarchical classification algorithm.

1. INTRODUCTION

We present here a method to identify the nature of the degradation affecting an image. This identification procedure aims to be integrated into an automatic image processing system [1], [2], [3]. Such systems are generally divided into several sequential steps, each with different purpose. The efficiency of the interpretation performed in the higher level steps obviously depends on the quality results of the first steps, concerned with image enhancement. Therefore it is important to improve the quality of an image with filtering or restoration algorithms. Most of these algorithms require prior information about the nature of the degradation altering the image. It is in practice difficult to access to this information [4]. In addition, an automatic system is expected to work in blind context. As a consequence, when no a priori knowledge is available, as in the case of blind processing, the nature of the degradation has to be identified from the observed image.

The sources of degradation considered here are additive noise and blur. These sources correspond to two of the major drawbacks of image acquisition. An image can be altered by only one of these sources or by a combination of them ending to four different observation models:

\[ g(x, y) = f(x, y) + b(x, y), \quad (1) \]
\[ g(x, y) = (f * h)(x, y) + b(x, y), \quad (2) \]
\[ g(x, y) = (f + b) * h(x, y), \quad (3) \]
\[ g(x, y) = f(x, y) * h(x, y). \quad (4) \]

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 and \( b(x, y) \) an additive noise. 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 [1].

The identification procedure comes to complete a filtering or restoration module, giving it the capacity to orient the images toward the appropriate algorithm. It comes that the purpose of the identification procedure is to distribute the images into classes corresponding to the algorithm adapted to the degradation present in the image. For example a filter for noisy images and a restoration algorithm for blurred images. When an image is degraded by a combination of noise and blur, the task of the identification procedure is then to evaluate which of both sources produces the predominant degradation effects.

2. DEVELOPED METHOD

As in any decision operation the developed procedure requires a sequence of two operations. At first the evaluation of statistics, followed by a selection operation based on these statistics. Considering the degradation identification, we have sought to characterize the different possible degradations with several attributes likely to discriminate them. Then the classification tool we have used, called CHAVL, is a non parametric ascendant hierarchical algorithm based on the analysis of the likelihood of bounds.
• CHAVL classification algorithm

Let us consider a table containing individuals × characters. The ascendant hierarchical classification method used here, classifies individuals in function of characters. It seeks first of all to put together the two closest individuals, and then to iteratively construct increasingly larger classes, either by regrouping individuals (as long as there is an isolated individual left), or by aggregating an individual to a class, or by aggregating two classes. Thus a succession of included partitions is obtained, described by the classification tree. This procedure requires the choice of a similarity measure between individuals, and an aggregation criterion as a similarity measure between classes of individuals [5].

Let \( O = \{ o_1, ..., o_n \} \) be the totality of the \( n \) individuals, and \( A = \{ a_1, ..., a_m \} \) the totality of the \( m \) numerical characters. The apprehension of object \( o_i \) is made from the succession of attributes \( (x_{i1}, ..., x_{im}) \), where \( x_{ij} = a_j(o_i) \) is the measure of the \( j \)-th character on \( o_i \), individual and \( \eta_i^j \) the corresponding reduced coefficient:

\[
\eta_i^j = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} (x_{ij})^2}}. \tag{5}
\]

The similarity coefficient, initially used to compare two individuals \( o_i \) and \( o_j \) taken in \( O \), is defined by:

\[
a_{ij}(o) = \eta_i^k \eta_j^k. \tag{6}
\]

These coefficients are then centered and reduced on the set \( P_2(O) \) of couples of individuals, ending to the normalized contribution of the character \( k \) to the comparison of the two individuals, defined as:

\[
A_k(i, j) = \frac{a_k(i, j) - moy(a_k)}{\sqrt{\text{var}(a_k)}}, \tag{7}
\]

where \( \text{moy}(a_k) \) and \( \text{var}(a_k) \) are respectively the mean average and the variance of the initial similarity coefficient on the set of individual pairs, denoted \( P_2(O) \).

The final similarity coefficient puts under the form of the sum of normalized contributions of the different characters:

\[
s(i, j) = \sum_{1 \leq k \leq m} A_k(i, j). \tag{8}
\]

This last coefficient between individuals is then relativised in probability by introducing a hypothesis of absence of link: the more the value of \( s(i, j) \) is improbable as compared to the null hypothesis of absence of link, the more two individuals are similar. The previous coefficient is then globally statistically normalized on the set \( P_2(O) \), to obtain:

\[
S(i, j) = \frac{s(i, j) - moy(s)}{\sqrt{\text{var}(s)}}, \tag{9}
\]

where \( \text{moy}(s) \) et \( \text{var}(s) \) are the empirical mean average and the variance of \( s(i, j) \) on \( P_2(O) \).

In these conditions, the probabilistic measure of the link likelihood writes under the form:

\[
P(i, j) = \phi[S(i, j)]. \tag{10}
\]

where \( \phi \) is the cumulative probability distribution function of the centered reduced normal law.

This last table is given as argument to the aggregation criterion of the maximal link likelihood. This criterion extends the similarity measure on individuals to a similarity measure among classes: the basis criterion is the maximum jump criterion. Let \( O_1 \) and \( O_2 \), be two subclasses of \( O \), the aggregation criterion, proposed by Lerman writes:

\[
\delta(O_1, O_2) = \left( \sup \{P(i, j); o_i \in O_1, o_j \in O_2\} \right)^{\text{card}(O_1) \cdot \text{card}(O_2)} \tag{11}
\]

Thus the CHAVL algorithm is a non parametric ascendant hierarchical classification algorithm.

To characterize the different degradations, we have estimated local statistics from the image and local statistics from the Laplacian of the image. Let \( g_{\text{ori}}(x, y) \) be the image obtained by convolution between the observed image \( g(x, y) \) and the mask of the Laplacian operator \( H \). \( g_{\text{ori}}(x, y) \) contains information on the blur operator [6]. As a matter of fact, a blurred image is characterized by weak transitions of slopes of the Laplacian of the image, which is symptomatic of the presence or not of a blur. Therefore statistics computed from the Laplacian of the image will be selected according to their discriminating power towards the presence of a blur. In addition a local statistic computed from the image will bring
information about the presence of an additive noise. Finally five local parameters have been selected. These parameters that will be used for the classification of the degraded images are defined here after.

- Local attributes

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:

$$Maxslope(x) = \max \|g_{lap}(x, y + 1) - g_{lap}(x, y - 1)\|,$$

(12)

The average of the maximal slope along the lines and the columns is then computed. The larger of both (noted $m_i$) is defined as the average of the maximal slopes of the Laplacian. If $m_i$ 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.

- $m_1$ : the mean of the maximal slopes of the Laplacian,
- $\sigma$ : the standard deviation of the maximal slopes of the Laplacian,
- $c_1$ : the skewness coefficient,

$$c_1 = \frac{3m_1m_3 + 2m_3^3}{\sigma^3},$$

(13)

- $c_2$ : the kurtosis coefficient,

$$c_2 = \frac{m_4 - 4m_1m_3 + 6m_2m_3^2 - 3m_1^4}{\sigma^4} - 3,$$

(14)

where $m_i$ is the ith order statistic of $Maxslope(x)$:

$$m_i = \frac{1}{N} \sum_i Maxslope(x)^i,$$

(15)

- $\sigma_{\text{noise}}$ : the standard deviation of the noise computed on homogeneous regions.

This parameter is obtained from histograms computed on several homogeneous regions of the observed image. The homogeneous regions are obtained from a segmentation of the image. The segmentation operation allows to determine homogeneous regions of any shape. Then the estimation of the standard deviation is achieved from the analysis of an histogram of local standard deviations computed on each of the homogeneous regions [7].

The process of automatically identifying the nature of the degradation affecting an image can be viewed as a two stage process. The first stage computes a set of attributes $P_1 = \{m_i, \sigma\}$. A first classification is run by CHAVL on $P_1$ to separate images in two classes. Class 1 includes images with preponderant noise. Class 2 includes all other images. The second stage computes the set of attributes $P_2 = \{m_i, \sigma, c_1, c_2, \sigma_{\text{noise}}\}$. A second classification is run by CHAVL on $P_2$ to subdivide class 2 in two subclasses. Class 2-a includes images altered by a combination of noise and blur, class 2-b includes images altered by a preponderant blur.

3. EXPERIMENTAL RESULTS

To validate the developed method, we have used six images from the CNRS-GDR-PRC-ISIS data bank (figure 1). These images present different characteristics (fine details, homogeneous regions textured or not). Each of these images has been altered with different noises, different blur operators or combinations of the two. We have considered three blur operators: defocusing, uniform motion and pillbox blurs. Each of them is applied to the image with a $5 \times 5$ support. All the noises are additives, Gaussians, their standard deviation takes four different values: 6, 8, 10 and 12. When the two types of degradations are combined (blur and noise), we only consider the defocusing blur operator to limit the number of combinations to take into account. Finally 15 degradations are applied to each of the six original images generating a sample set of 90 images.

With the set of parameters $P_1$, we have been able to separate images degraded by a preponderant noise from other images (class 2). We understand by preponderant noise images corresponding to either observation model (1) or to observation model (2) with a strong noise ($\sigma \geq 10$).

The second set of parameters $P_2$ is applied to class 2 in order to subdivide this class in two subclasses. This second step allows to separate images with a weak noise ($\sigma < 10$) applied after a blur operator (class 2-a) from images altered by a preponderant blur (class 2-b). We understand by preponderant blur, images corresponding to observation models (3) and (4). Results are summarized in the table 1:
The global good classification rate is: 96.66%. Knowing that the choice of the classification method conditions the result, we have also used the K-means fuzzy method. Results show that the CHAVL algorithm reaches better performance.

4. CONCLUSION

We have presented a blind automatic procedure to identify the nature of the degradation affecting an image. Identification is made from the observed image only and the degradations taken into consideration are blur and additive noise. The method, tested on a set of 90 degraded image, allowed to identify the nature of the degradation that produces the predominant effects. This result is essential in the definition of a strategy to decide how to process an image. When integrated in a filtering and restoration module, this step directs images to the most appropriate algorithm, for example a filter for noisy images and a restoration for blurred images. In the case of a combination of both sources of degradation, depending on the predominance of one source or not, a simple process or a combination of elementary processes can be applied. This last point [2] is an open question deserving further works.

5. REFERENCES


Figure 1: Images of the French CNRS-GDR-PRC-ISIS data bank