LETTER

# Blind Adaptive Method for Image Restoration Using Microscanning

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**SUMMARY** This paper presents a restoration method using several degraded observed images obtained through a technique known as microscanning. It is shown that microscanning provides sufficient spatial information for image restoration with minimal information about the original image and without knowing the interference function that causes degradation.
***key words:*** *image restoration, image processing, microscanning*

## 1. Introduction

Image restoration is a very popular area within image processing [1], [2]. It finds applications in medical images, microscopy, industry, etc. In most cases, the restoration methods are based on *a priori* knowledge of the degradation process and generally use a single observed scene to carry out restoration [3], [4].

In this paper, we present a method of restoration aimed at restoring images degraded by additive, multiplicative, and impulsive interferences. These degradations [5]–[8] are caused by nonuniform illumination, imperfections in the manufacturing process of sensors (i.e. Focal Plane Array), damaged sensors, etc. We use microscanning [9] to obtain a set of observed degraded images of the same scene with a controlled shift between the scene and camera. This technique may be used for image restoration if the original image and interferences are spatially displaced relatively each other during the microscanning process. Microscanning can be implemented either with a controlled movement (i.e. using a piezoelectric actuator for precision positioning) of a sensor array that captures images or with a controlled motion of a light source in the case of nonuniform illumination. The proposed method can be used for correction of nonuniform illumination, for restoring information at damaged sensor's elements, and for scene-based removal of nonuniform fixed-pattern noise in imaging array sensors. Using the set of the images, restoration is carried out by solving a system of equations that is derived from optimization of an objective function. In the proposed method, we suppose that the degradation function is unknown, that is a blind restoration. This paper is organized as follows. In Sect. 2 we present the used signal model and the proposed restoration method. Computer simulation and experimental results are provided and discussed in Sect. 3. Finally, Sect. 4 summarizes our conclusions.

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## 2. Restoration Method

Let us introduce some notation and definitions. Let $\{s^{(1)}_{i,j}, s^{(2)}_{i,j}, s^{(3)}_{i,j}\}$ be three observed degraded images captured during microscanning, and $i$, $j$ are the pixel coordinates. The size of images is $M \times N$ pixels. Let us define the sets $\{f_{i,j}\}$ as an original image $\{a_{i,j}\}$ as an additive degradation. The observed signal is also corrupted by additive and impulsive noises. The additive noise is modeled as a white Gaussian noise $\{n^{(k)}_{i,j}, k = 1, 2, 3\}$ with a zero mean and a standard deviation. The impulsive noise occurs with a given probability. Examples of additive interference, impulsive and additive noises are the photodetector's bias of imaging array sensors, damaged sensor's elements, and time-varying wideband thermal (electronic) noise of sensors [5], respectively.

When image degradation is caused by an additive nonuniform interference and additive noise, the observed scene can be described as

$$s^{(1)}_{i,j} = a_{i,j} + f_{i,j} + n^{(1)}_{i,j},\ 1 \le i \le M,\ 1 \le j \le N. \tag{1}$$

Using microscanning two frames with vertical and horizontal displacements can be obtained, that is,

$$s^{(2)}_{i,j} = a_{i+1,j} + f_{i,j} + n^{(2)}_{i,j},\ 1 \le i < M,\ 1 \le j \le N, \tag{2}$$

and

$$s^{(3)}_{i,j} = a_{i,j+1} + f_{i,j} + n^{(3)}_{i,j},\ 1 \le i \le M,\ 1 \le j < N. \tag{3}$$

We see that the additive interference and the original image are spatially displaced relatively each other by microscanning. The idea behind the proposed method is to use the information about the spatial relation between the degraded images along the rows and columns. Let

$$r_{i,j} = s^{(2)}_{i,j} - s^{(1)}_{i+1,j} = f_{i,j} - f_{i+1,j} + n^{(2)}_{i,j} - n^{(1)}_{i+1,j},\quad 1 \le i \le M-1,\ 1 \le j \le N, \tag{4}$$

be a gradient matrix for the vertical frame motion, and let

$$c_{i,j} = s^{(3)}_{i,j} - s^{(1)}_{i,j+1} = f_{i,j} - f_{i,j+1} + n^{(3)}_{i,j} - n^{(1)}_{i,j+1},\quad 1 \le i \le M,\ 1 \le j \le N-1, \tag{5}$$

be a gradient matrix for the horizontal frame motion. Utilizing the least-squares approach, the variance of additive noise contained in these matrices can be minimized. So, an objective function to be minimized can be written as

$$\begin{aligned}\tilde{F} &= \left\{ \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \left[ r_{i,j} - f_{i,j} + f_{i+1,j} \right]^2 + \left[ c_{i,j} - f_{i,j} + f_{i,j+1} \right]^2 \right\} \\ &+ \sum_{j=1}^{N-1} \left[ c_{M,j} - f_{M,j} + f_{M,j+1} \right]^2 + \sum_{i=1}^{M-1} \left[ r_{i,N} - f_{i,N} + f_{i+N,j} \right]^2, \end{aligned} \tag{6}$$

where the first term takes into account the noise information present into most of the image, and the two last terms are based on the noise information in the bottom row and the right column of the image, respectively. The minimization of the objective function with respect to elements of the image $f_{i,j}$, leads to a linear system of equations. In matrix-vector notation the linear system is given by

$$\mathbf{A}\mathbf{x} = \mathbf{b}, \tag{7}$$

where matrix $\mathbf{A}$ has the size $MN \times MN$, $\mathbf{x}$ is a vector version of $f_{i,j}$ of size $MN \times 1$, and vector $\mathbf{b} = \mathbf{b}^r + \mathbf{b}^c$ has the size $MN \times 1$. The vectors $\mathbf{b}^r$and $\mathbf{b}^c$ are given by

$$\mathbf{b}^r_j = r_{1,j}, \quad 1 \le j \le N, \tag{8}$$
$$\mathbf{b}^r_{iN+j} = r_{i+1,j} - r_{i,j}, \quad 1 \le i \le M-2,\ 1 \le j \le N, \tag{9}$$
$$\mathbf{b}^r_{NM-j} = -r_{M-1,N-j}, \quad 0 \le j \le N-1, \tag{10}$$
$$\mathbf{b}^c_{iN+1} = c_{i+1,1}, \quad 0 \le i \le M-1, \tag{11}$$
$$\mathbf{b}^c_{iN+j} = c_{i+1,j} - c_{i+1,j-1}, \quad 0 \le i \le M-1,\ 2 \le j \le N-1, \tag{12}$$
$$\mathbf{b}^c_{iN} = -c_{i,N-1}, \quad 1 \le i \le M. \tag{13}$$

The matrix $\mathbf{A}$ is sparse, and it is given by

$$\mathbf{A} = \begin{pmatrix} \mathbf{A}_1 & \mathbf{A}_3 & 0 & \dots & 0 \\ \mathbf{A}_3 & \mathbf{A}_2 & \mathbf{A}_3 & & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & \mathbf{A}_3 & \mathbf{A}_2 & \mathbf{A}_3 \\ 0 & \dots & 0 & \mathbf{A}_3 & \mathbf{A}_1 \end{pmatrix}, \tag{14}$$

where the matrices $\mathbf{A}_1$, $\mathbf{A}_2$ and $\mathbf{A}_3$, of the size $N \times N$, are written as

$$\mathbf{A}_1 = \begin{pmatrix} 2 & -1 & 0 & \dots & 0 \\ -1 & 3 & -1 & & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & -1 & 3 & -1 \\ 0 & \dots & 0 & -1 & 2 \end{pmatrix}, \tag{15}$$

$$\mathbf{A}_2 = \begin{pmatrix} 3 & -1 & 0 & \dots & 0 \\ -1 & 4 & -1 & & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & -1 & 4 & -1 \\ 0 & \dots & 0 & -1 & 3 \end{pmatrix}, \quad \text{and} \tag{16}$$

$$\mathbf{A}_3 = \operatorname{diag}\left[-1, -1, \dots, -1\right]. \tag{17}$$

The rank of the matrix $\mathbf{A}$ is $MN-1$, therefore the original image can be restored if one pixel of the image is *a priori* assigned to a constant, for instance the last pixel of the image is set to zero. After the restoration the obtained image is point-wise processed to have the same mean value (assumed to be known) with original image. In order to solve the linear system of equations we use an effective iterative conjugate gradient method [10]. The computational complexity of the proposed method is given by the execution order of the conjugate gradient and the size of an image to be restored. The conjugate gradient has $O(mk)$ operations, where $k$ is the number of iterations required for solving the system of equations, and $m$ is the number of nonzero entries in $\mathbf{A}$. Without loss of generality, we assume that $N = M$. Therefore, $m = O(5N^2)$ and $k = qN$, where $q$ depends on precision of the solution. The computational complexity of the method can be estimated as $O(5qN^3)$.

Impulsive noise is caused by sensor failures in the camera or transmission through a noisy channel. The proposed method is able to interpolate implicitly the pixel values corrupted with impulsive noise based on the information contained in neighboring pixels. This is because during microscanning the information of each pixel of the original image is captured in three different observed images. If one of the sensors is damaged, partial information about the pixel intensity of the original image could be available in the other observed images. For example, suppose there is a dead pixel at the point $(k, l)$. It can be shown that the value of $\tilde{f}_{k,l}$ is implicitly approximated with a linear combination of the central and neighboring pixels as follows:

$$\tilde{f}_{k,l} \approx \frac{1}{4}\left(f_{k+1,l} + f_{k,l+1}\right) + \frac{1}{2} f_{k,l}. \tag{18}$$

Sometimes, pixels corrupted by impulsive noise tend to form an impulsive noise cluster. It is interesting to note that the method of restoration is able to interpolate implicitly such pixel values. For example, if the cluster has the shape of a cross, one can show that the central pixel value is estimated as follows:

$$\begin{aligned}\tilde{f}_{k,l} \approx \frac{1}{12}\big(&f_{k+2,l} + f_{k+1,l} + f_{k,l+2} + f_{k,l+1} + f_{k-1,l+1} \\ &+ f_{k+1,l-1}\big) + \frac{1}{6}\left(f_{k+1,l+1} + f_{k-1,l} + f_{k,l-1}\right). \end{aligned} \tag{19}$$

We see, since there is no information on the central pixel in the three observed images, the interpolation of the central pixel uses only the neighboring pixels.

The original image can be degraded with multiplicative interference. A typical example of such degradation is nonuniform illumination. When the degradation is caused by multiplicative interference, and additive noise is low, the multiplicative degradation model can be converted to the additive model by applying to the observed degraded images the logarithmic transformation. Therefore, the described restoration method can be also used for multiplicative degradations. Finally, the restored image is obtained by applying to the solution of the linear system the exponential function.

## 3. Computer Simulations and Experimental Results

Here we analyze the performance of the proposed method in terms of the root mean square error (RMSE) criterion and a subjective visual criterion. The RMSE criterion is given by

$$\mathrm{RMSE}(f, \tilde{f}) = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(f_{i,j} - \tilde{f}_{i,j}\right)^2}{NM}}. \tag{20}$$

The signal range is $[0, 255]$. The size of test images is $256 \times 256$. The experiments were performed using a computer with the Intel Core 2 Duo 2.26 GHz processor and with 2 GB of RAM. The conjugate gradient method is used to solve the linear system. The convergence criterion is when the residual value drops below $10^{-10}$. The subjective visual criterion is defined as an enhanced difference between original and restored images. A pixel is displayed as gray if there is no error between the original image and the restored image. For maximum error, the pixel is displayed either black or white (with intensity values of 0 and 255, respectively).

The linear minimum mean square error method is a popular technique in image restoration. When the original signal and additive noise are stationary processes, and there is no blur, the method is the Wiener smoothing filter [5]. In our experiments, we assume that degradation parameters for the Wiener filter are exactly known. The proposed method does not need any information about the degradation function.

### 3.1 Additive Degradation Model

Figures 1 (a), 1 (b), and 1 (c) show a test original image, a nonuniform additive interference, and the observed image corrupted by additive noise, respectively. The additive noise is a white Gaussian noise with a zero-mean and a standard deviation of 2. The mean value and standard deviation of the interference image are 179 and 48, respectively. The restored image obtained with the proposed method is shown in Fig. 2 (a). The enhanced difference between the original and restored images is shown in Fig. 2 (b).

Figure 3 shows the performance in terms of the RMSE of the proposed method and the Wiener filtering using three observed images versus the standard deviation of additive noise. It can be seen that the performance of the proposed method is much better than that of the classical Wiener filtering with known parameters. It happens because the additive interference is spatially inhomogeneous, and therefore it cannot be considered as a realization of a stationary process and correctly used in the filtering. The time required to restore the image using the proposed method is approximately 43 sec. In this case, the iterative conjugate gradient algorithm requires about 1000 iterations.

### 3.2 Additive Degradation Model with Impulsive Noise

Figures 4 (a), 4 (b), and 4 (c) show the observed image, the restored image, and enhanced difference between the original and restored images, respectively. The observed image is corrupted with an additive nonuniform interference, a zero-mean white Gaussian noise with a standard deviation of 2, and impulsive noise with the occurrence probability of 0.07. The value of impulsive noise is zero.

Figure 5 shows the performance of the proposed method in terms of the RMSE versus the probability of impulsive noise. The observed images are corrupted by additive noise with a standard deviation of 2. One can observe that when the probability of impulsive noise increases, the restoration quality decreases.

Finally, we present computer simulation results when the observed images contain an impulsive noise cluster. Figures 6 (a), 6 (b), and 6 (c) show the observed image, the restored image, and enhanced difference between the original and restored images, respectively. The observed image is corrupted by the additive nonuniform interference, a zero-mean white Gaussian noise with a standard deviation of 2,

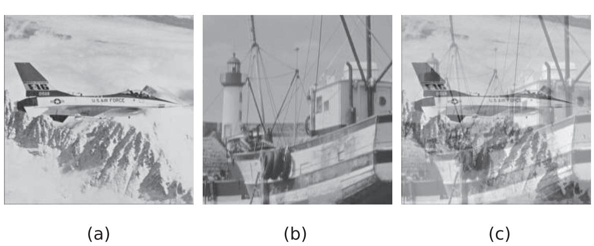


**Fig. 1** (a) Original image, (b) additive interference, (c) observed image degraded with additive interference and white noise with standard deviation of 2.

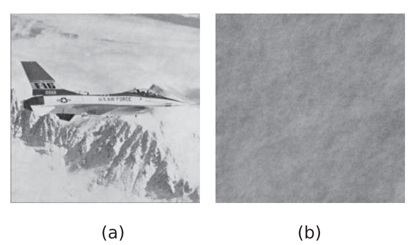


**Fig. 2** Performance of the proposed method for additive degradation: (a) restored image, (b) enhanced difference between the original image and restored images.

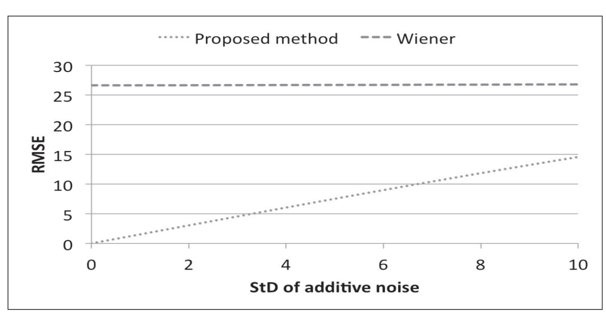


**Fig. 3** Performance of the proposed method for additive degradation: RMSE versus a standard deviation of additive noise.

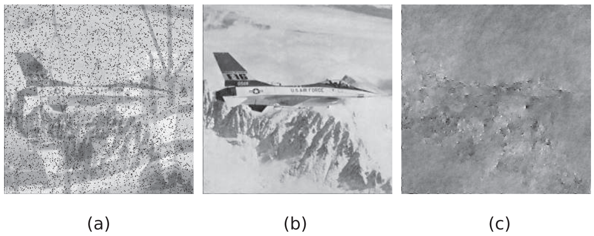


**Fig. 4** (a) Observed image degraded with additive interference, white noise with standard deviation of 2, and impulsive noise with probability of 0.07, (b) restored image, (c) enhanced difference between the original image and restored images.

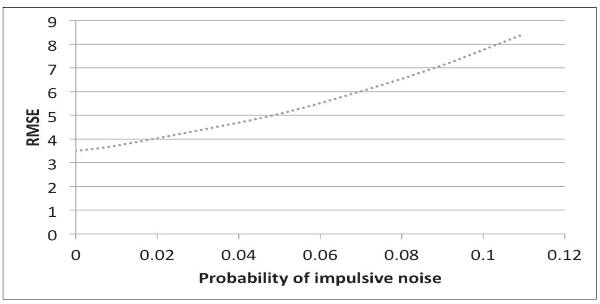


**Fig. 5** Performance of the proposed method for additive degradation with impulsive noise: RMSE versus probability of impulsive noise while the standard deviation of additive noise equals 2.

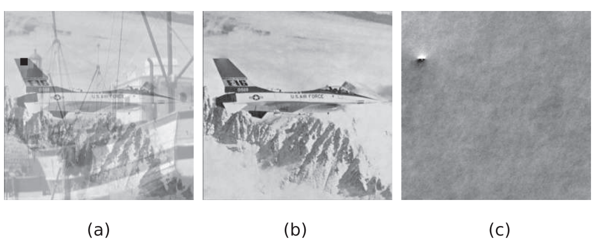


**Fig. 6** (a) Observed image degraded with additive interference, white noise with standard deviation of 2, and impulsive noise cluster (100 pixeles), (b) restored image, (c) enhanced difference between the original image and restored images.

and impulsive noise cluster of $10 \times 10$ damaged elements.

One can observe that the restoration performance of the method is good outside of the cluster area. At the location of the cluster the method attempts to carry out a smooth interpolation using information containing in the neighboring pixels.

### 3.3 Experimental Results

Here we present experimental results with a real-life image degraded by a multiplicative interference. The observed images were obtained as follows. A test image was displayed on a LCD screen. A printed transparency was placed between a camera and the screen in order to simulate a multiplicative degradation. Microscanning was performed by shifting the test image on the screen. Finally, the observed images were captured with the camera. The observed images have the size of $295 \times 284$ pixels. First, the observed images were passed through the logarithmic transformation. Next, the proposed method was utilized to obtain a resulting image. Finally, the exponential transformation was applied to the resulting image to restore the original image. The original image, multiplicative degradation, and one of the observed images taken by a camera are shown in Figs. 7 (a), 7 (b), and 7 (c), respectively. The restored image is presented in Fig. 7 (d).

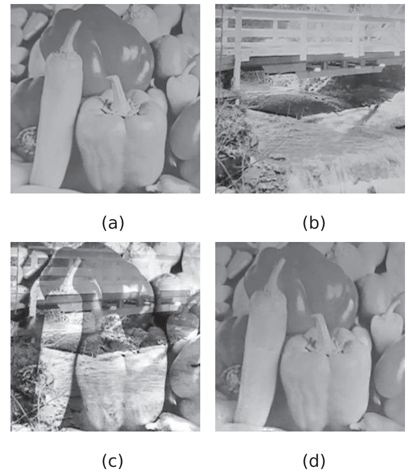


**Fig. 7** (a) Original image, (b) multiplicative interference, (c) observed image degraded with multiplicative interference, (d) restored image.

Since in the experiment the level of additive noise is low, the quality of the restoration with the proposed method is very good.

## 4. Conclusion

In this paper, we proposed a method for restoring images degraded with additive and multiplicative interferences, and corrupted by additive and impulsive noises. Using three observed images taken with a microscanning imaging system, an explicit system of equations for the additive signal model was derived. The restored image is a solution of the system. With the help of computer simulations and experimental results, we showed and discussed the performance of the proposed method.

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