Image Restoration Using a Combination of Blind and Non-Blind Deconvolution Techniques

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***Abstract*—** *One of the important implementations in image-processing field is the image restoration. Image restoration deals with the recovery of an original image from a degraded image using a mathematical model of degradation and restoration for image. Image restoration is becoming more and more important in the image-processing field, and it is very important in many applications like medical, satellite and photography. In spite of the various existing solutions available to image restoration, there is always a need for more efficient methods. In this paper, several restoration and deconvolution techniques, experimented and tested, we used both blind and non-blind techniques. Then we propose a combination between blind and non-blind techniques in order to improve the quality of the restored image. Several types of noise are added to the image after it has been blurred. We have tested the behavior of the different filters and techniques in removing each type of noise. The evaluation of the filters behaviors and the conclusion are done based on various metrics like PSNR, MSE, RMSE and IEF.*

Keywords*— *Image processing, Image restoration, blind and non-blind techniques, Noise, Metrics.

I. INTRODUCTION

The restoration of the image is an area that also deals with improving the appearance of an image [1][3]. However, unlike image enhancement, which is subjective, the image restoration is objective in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation. In order to obtain a better restoration technique, it is necessary to study and compare the details of the existing restoration filters and then to develop a more powerful filter, which can fulfill the desire to have a cleaner image after removing the noise from it, and achieve a powerful solution for the issues facing image restoration filters. In this paper one image, will be restored, using several restoration techniques, after being degraded by being blurred and noise added. Several types of noise will be used in the degradation process. Noise in the image, is that degradation of an image signal, caused by an external disturbance when the image sent from one place to another place by satellite, wireless, or cable network. There are many types of images noise, in this paper we will use the most common four types: 1- Salt & Pepper noise, which known as shot noise, impulse noise or Spike noise. Its appearance is randomly scattered white or black or both pixel over the image. 2- Gaussian noise which can caused by random fluctuations in the signal; it is modelled by random values added to an image. This noise has a probability density function (pdf) of the normal distribution. It is also known as Gaussian distribution. 3- Speckle noise, it can be modelled by random values multiplied by pixel values of an image. 4- Poisson noise. Individual photon detections can be treated as independent events that follow a random temporal distribution. As a result, photon counting is a classic Poisson process [24][26].In section 2, we will declare image restoration steps; provide a brief description of the blur function, degradation model, and restoration model. In section 3, the restoration techniques are described. In section 4, a proposed method will be illustrate and explained. Section 5, experimental results are shown. Finally section 6, we will give our conclusions.

II. IMAGE RESTORATION STEPS

The term Image Restoration means, to restore an image from the degraded condition into a clear and restored condition. In other words it process is the degraded images, which suffers from a blur and a noise, in order to produce the output clear image.

2.1 PSF function

Blur occurs commonly by a point spread function PSF. Image restoration techniques are divided into two classes according to prior knowledge about the PSF:

Blind Image Restoration: The blind image restoration method allows the original images to be rebuilt from degraded images even with no knowledge or few knowledge about PSF. An example of the blind image restoration methods is the Blind Image Deconvolution (BID) [1].

Non-Blind Image Restoration: In this type of restoration, a prior knowledge of the PSF that blurred the original image is occurred. This will help the restoration technique in rebuilding the degraded image. Deconvolution using Lucy Richardson Algorithm (DLR), Deconvolution using Weiner Filter (DWF), Deconvolution using Regularized Filter (DRF) are Non Blind Algorithms[1].

2.2 Image Degradation Model

In degradation model the image is blurred using degradation function *H*, and then the noise is been added. The image degradation process can be modeled by (1) [1]:

$$g(x,y) = H(x,y).\, f(x,y) + n(x,y) \tag{1}$$

where, $H(x,y)$, $g(x,y)$, $f(x,y)$, and $n(x,y)$ represent respectively the degradation function, the observed or degraded image,the original image or input image and the additive noise respectively.

The function *H* represents a convolution matrix that models the blurring that many imaging systems introduce. For example, the function *H* can model camera defocus, motion blurs, imperfections of the lenses all.

2.3 Image Restoration Model

In the restoration model, the image $g(x,y)$ was degraded is built back by the restoration filters.The restoration process is implemented by inversing the degradation process by removing the blur factor and the additive noise. We obtain an estimate of the original image after the restoration. The closer of the restored image $f(x,y)$ to the original image the more efficient is the filter.

III. RESTORATION TECHNIQUES

Different restoration techniques has been proposed in the restoration domain [2][4]. In our paper, we choose mostly common techniques to examine, and test it by using different noise types applied on two different images format.

3.1 Non-Blind Deconvolution Techniques

The non-blind techniques is that techniques which requires a prior knowledge about the blur function in order to process the restore operation. In our paper, we offer the following techniques:

3.1.1 Lucy Richardson Algorithm

The Richardson–Lucy deconvolution algorithm, which is also named as Lucy Richardson Deconvolution (LRD), is a famous technique in the field of image restoration [22]. Initially Leon Lucy and William Richardson derived it on the basis of the Bayes's theorem in the early 1970's [8]. This method is categorized as non-blind deconvolution as it needs to know the PSF used to blur the image. It is also an iterative procedure. The pixels in the observed image are represented as in (2):

$$d_i = \sum p_{ij}\, u_j \tag{2}$$

where, d_i is the observed value at the i^{th} position of the pixel, p_{ij} is the PSF, it represent the fraction of the light that comes from the true location *j* which has been spotted at position *i*, u_j represent the concealed image pixel value at the j^{th} position.

Our main goal is to calculate the most likely u_j with the existence of the observed d_j and the already known PSF p_{ij} as following:

$$u_j^{(t+1)} = u_j^{(t)} \sum_i \frac{d_i}{c_i} p_{ij} \tag{3}$$

where,

$$c_i = \sum_j p_{ij}\, u_j^{(t)} \tag{4}$$

Lucy Richardson Deconvolution is easy to implement, and it preserves edges, as it is a nonlinear method. Specifically, a big problem we face here is the noise amplification. The main issue for all maximum likelihood techniques, which attempt to fit the data as closely as possible. When performing too much L-R iterations on an image that may contained an extended object such as a galaxy, the extended emission usually develops a "Speckled" appearance [10].

3.1.2 Regularized Filter

Regularized filter is one of the non-blind convolution family, i.e. it de-blur an image with a prior knowledge of the blur function that blurred the image. This filter is considered an approximation for the Weiner filter, and it result with a close result to that of the Weiner filter. Anyway, the regularized filter need less information about the blurred function in order to restore the image. Regularized filtering is used in effective way when a few information is known about the additive noise. The regularized filter uses constrained least square algorithm to restore the noisy and blurred image. Regularized filter is usually classified as a discrete laplacian filter [1].Regularized filter is easy to implement and needs less information about the blurred function. However, it has to have prior information about the blur function.

3.1.3 Weiner Filter

Considered a linear filter, Weiner filter is also considered as non-blind deconvolution, it removes the noise from the degraded image with a prior knowledge about the PSF [1]. At the same time, it eliminates the additive noise and inverts the blur effect. Weiner filter implements the deconvolution technique with the means of high pass filter - inverse filter -, accompanied with a compression operation - low pass filtering- to remove the noise. It compares with an estimation of the desired noiseless image. The process of the Weiner filter is to input the degraded image to the filter, the output restored image by means of the filter is obtained by (5):

$$\hat{f} = g * (f + n) \tag{5}$$

where, f, $\hat{f}$, n and g represent respectively the original image, the output or the estimated image, the noise, and the Weiner filter's response.

We can use wide window in order to eliminate the Speckle noise, to preclude the blurring of the edges we can use small window. One of the main disadvantages of the Weiner filter is the mandatory of the knowledge the power spectra of the ungraded image and the noise. In the case of randomly noise, it is hard to estimate a typical restoration for the image.

3.2 Blind Deconvolution Techniques

Unlike the non-blind deconvolution techniques, the blind deconvolution technique does not require any prior knowledge of the blur function in order to process the restore operation. The several techniques we choose to test and examine are listed below.

3.2.1 Mean Filter

The Mean filter, or in other words the A**verage filter** is linear class windowed filter that is used to restore images from noise. The filter is kind of a low pass filter. The main idea of the filter is, to deal with each pixel of the noisy image as follows:

It takes the pixel and the surrounded neighborhood pixels according to the window size has been specified, then sums all the values and divide by the number of the elements. This is the average value; at last, the filter replaces the old pixel with the new average value and so on until all the pixels in the noisy image are replaced by the average value. The process now is completed; we have the filtered or resultant image. This operation is considered by(6) and fig.3:

$$g(i,j) = \frac{1}{M \times N} \sum f(m,n) \qquad m = 1,2, \dots \dots M, \; n = 1,2, \dots . . N \tag{6}$$

Mean filtering is a simple to build, and easy to implement. On the opposite, any undesired value of one pixel can strongly affect the mean value of all neighborhood pixels. The filter will replace incorrect values for the edge pixel, which will yield to a blurry image [3].

3.2.2 Median Filter

The technique of the median filter is similar to that for the mean filter but in median filter [3], we don't calculate the mean value, the filter arrange the values of the pixels in ascending order within the window, and then choose the median value to replace the tested image. The (7) below describes the work of the Median filter:

$$\hat{f}(m,n) = median\{g(\mathrm{i},\mathrm{j}), (i,j) \in w\} \tag{7}$$

where $\hat{f}(m,n)$, $g(i,j)$ and w are respectively the restored image, the noisy image, and the window.

Since the Median chooses one of the pixels value that already exist, that means it produces no new values. Implementation of the Median filter is very easy. The Median filter is less sensitive than the Mean to extreme values (outliers); median removes these extreme values in more efficiency way. The Median filter works well almost only with the salt and pepper noise. It is not effective with other kinds of noise [3].

3.2.3 Wavelet Deconvolution

The wavelet method is used widely in image processing fields' such as image compression, and in image restoration [3][12]. Unlike conventional Fourier transform, wavelet transforms based on small waves, called wavelets. Wavelets, which means the little waves, such as Haar, Daubechies, Morlet, etc. Wavelets are functions that are concentrated in frequency domain and in time domain surrounding a fixed point. The wavelet transform is designed in such a manner to give a reasonable frequency resolution with low frequency component, which are the average intensity values of the image, and good temporal resolution with high frequency components, which are the edges of the image. We can summary the process of restoration an image with wavelet deconvolution technique into three main stations; wavelet transform or decomposition [3],threshold [13], and finally the noise removing [14], Wavelet transform, it is computationally very fast, also it is easy to perform. On other hand, It is shift sensitive because input-signal shifts generate unpredictable changes in DWT coefficients, and it lacks the phase information that accurately describes non-stationary signal behavior [3][14].

3.2.4 Bilateral Filter

The Bilateral filter [15] is proposed by Tomasi and Manduchi; it is a nonlinear filter and is used to reduce impulse noise from images. Bilateral filtering smooths images and preserves the sharp features of edges, with the help of a nonlinear combination of nearby image values. This method is non-iterative and simple. The Bilateral filter kernel, w_b, is the product of two sub-kernels (Gray-level sub-kernel, w_g, Distance sub-kernel, w_d) [5].

The Gray level sub-kernel w_g is given by:

$$w_g = exp\left(-\frac{1}{2}\left(\frac{d_g}{\sigma_g}\right)^2\right) \tag{8}$$

where, $d_g = [|g^2(x_1,y_1) - g^2(x,y)|]^{\frac{1}{2}}$ and σ_g is the standard deviation of w_g.

The distance sub-kernel is defined by:

$$w_d = exp\left(-\frac{1}{2}\left(\frac{d_s}{\sigma_d}\right)^2\right) \tag{9}$$

where, $d_s = \sqrt{(x_1,x)^2 + (y_1,y)^2}$ and σ_d is the standard deviation of w_d

In order to reduce the noise, this kernel must slide throughout the noisy image, and after filtering the estimated output is given by (10):

$$\hat{f}(x,y) = \frac{\sum_{s=-a}^{a}\sum_{t=-b}^{b} g(x+s,y+t)}{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w_b(s,t)} \tag{10}$$

The filter has been used for many applications such as texture removal, dynamic range compression, and photograph enhancement. The main advantage of bilateral filter is that it can remove high density of noise from the images which other filters cannot remove. Bilateral filter is not effective with impulse noise like Salt & Pepper noise. Also, it replaces the noisy and not noisy image pixels with filtered value, and the resultant images are smoothed but not sharpen.

3.2.5 Adaptive local Filter

Adaptive local filter [2] is also one of the famous filters that applied on the degraded image. The restoration technique in this filter depends on two statistical measurements mean and variance, with a specific $m \times n$ window:

$$\hat{f}(x,y) = g(x,y) - \left(\frac{\sigma_n^2}{\sigma_l^2}\right) [g(x,y) - m_l] \tag{11}$$

where, $\sigma_l^2, m_l, \sigma_n^2, g(x,y)$ and $\hat{f}(x,y)$ are respectively the local variance of the local region, the local mean, the variance of overall noise, the pixel value at the position (*x*,*y*) and the restored value.

The Adaptive local filter is simple to design and fast. In general, it has weak response due to its slow convergence.

3.2.6 Blind Image Deconvolution

In Blind Image Deconvolution (BID), unlike the Lucy Richardson, Weiner, and Regularized techniques, the restoration techniques process the degraded image without a previous known of the blurring function. This restoration technique works primarily to estimate the blurring function, PSF, secondly, it acquires the degraded image using the estimated PSF that was done at the first step. Technically, this operation can be executed in either ways, iterated or non-iterated. In the iterated process, the estimated PSF would get better more and more with each iteration, and then the restored image would be acquired from the degraded image using the estimated PSF. In the non-iteration process, the PSF will be obtained by one application of the algorithm, which based on extract information. Then they obtained PSF will be used to restore the image from the degraded image. The main target of the blind image restoration technique is to estimate the blur function and the original image [1].

An advantage of BID is that there is no need to know previously about the blur function (PSF), any way the BID is effective at low noise intensities.

IV. PROPOSED METHOD

Our method is to combine an image restored from a non-blind deconvolution, with the same image restored by blind deconvolution in order to improve the quality of the restored image. We will use a combination method, to combine a two of resultant images and obtain an image that is better, this method called image fusion [19]. Image fusion has several types such as the high pass filtering, which is the classic method. Other modern methods exist such as: fusion based on laplacian pyramid, uniform rational filter bank, and discreet wavelet transform. We will implement the combination using fusion based on discreet wavelet transform [20]. The process of the fusion method is illustrated in fig. 1

The effective work in the wavelet based image fusion is to combine the coefficients, in other words, is to find the most convenient way to integrate the coefficients in such a way to have the best quality of the fused image. There are many ways to achieve this goal; the simplest way is to calculate the average of the coefficients to be integrated [27].

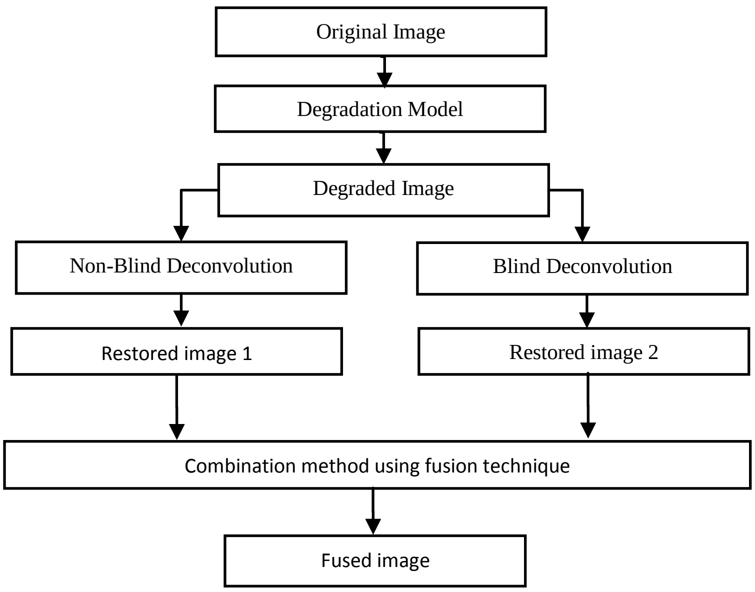


FIGURE 1 PROPOSED METHOD FOR IMAGE RESTORATION DIAGRAM

V. RESULTS

5.1 Evaluation of the different techniques

To evaluate the performance of our deconvolution methods, we will apply it the bateau.jpg image. Four types of noise and blurring will be applied to the image before restoration. The evaluation of the performance of the restoration methods will be made based on the following metrics: *RMSE* (the root of the *MSE*), *PSNR*, *IEF*, and the execution time. *MSE*, *PSNR* and *IEF* are given by [5]:

The Mean Square Error (*MSE*) is defined by (12):

$$MSE = \frac{\sum \left| f(i,j) - \hat{f}(i,j) \right|^2}{rows \times col} \tag{12}$$

where, $f(i,j)$ and $\hat{f}(i,j)$ denote the intensity of (i,j) th pixel of the original and filtered images.

The Peak Signal to Noise Ratio (*PSNR*) is giving by(13):

$$PSNR = 10\log_{10}\left[\frac{255 \times 255}{MSE}\right] \tag{13}$$

The Image Enhancement Factor (*IEF*) is giving by (14):

$$IEF = \frac{\sum_i \sum_j (g(i,j) - f(i,j))^2}{\sum_i \sum_j (\hat{f}(i,j) - f(i,j))^2} \tag{14}$$

where, $g(i,j)$ is the intensity of (i,j) th pixel of the degraded image.

Our work has several dimensions, in order to examine the several restoration techniques and declare the difference of the behavior between it, we choose to apply several types of noise on our image, deeper we will apply the different deconvolution methods on jpg image format. Salt & Pepper noise will be applied at density of 0.06, Gaussian noise will have 0 mean and variance of 0.06, Speckle noise with 0 mean and variance of 0.04 and poisson noice with mean of 10. On other dimension, we will examine the behavior of the restoration techniques with presence of blur only, noise only, and blur with noise. We will apply the blur only, noise only and blur plus noise cases on the image bateau.jpg, for fusion technique, we will apply it on the image bateau.jpg only. The blur (*H*) or PSFfunction we will apply in our work is a Gaussian lowpass filter of size 5, with standard deviation of 5.

We used MATLAB® 2015 to obtain our metric results and the resulted images.

5.2 Results of the image restoration

The bateau.jpg image is a gray image with size of 256×256, 65536 bytes and uint8 class shown in fig.2. We will use this image in our three cases, first, the blur only, second, the noise only and third the blur plus noise. The four types of noise we mentioned in the previous section will affect the image, and then it will be denoised. After that, a fusion technique will applied in the sake of improvement the restoration result.

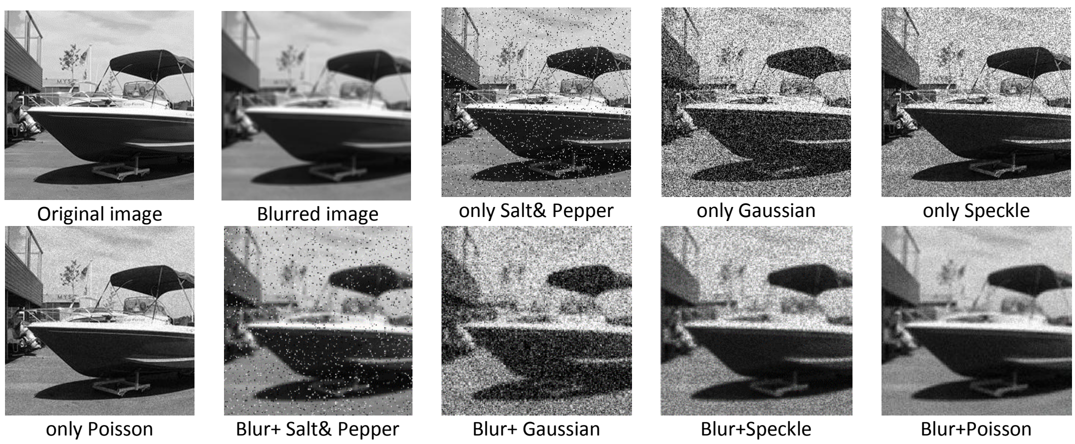


FIGURE 2: ORIGINAL AND DEGRADED IMAGES

5.2.1 Case of Blur only

In this section we will test the behavior of the deconvolution techniques in restoring the image with the blur only and no noise existing. The blur process is done with the PSF function, which is a Gaussianlowpass filter of size 5, with standard deviation of 5.Then after the deconvolution of the blurred image with the deconvolution techniques, we will choose the best result from the blind deconvolution techniques and the best result from the non-blind deconvolution techniques and propose the combination method of the two images in order to get a restored image with a better quality. In fig.2, we show the blurred image.

TABLE 1
RESULTS OF DECONVOLUTION TECHNIQUES WITH BLUR ONLY EXISTING

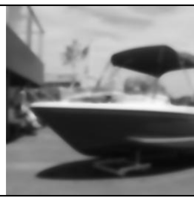
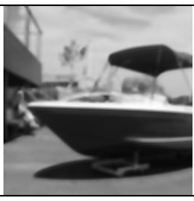
Filter	Mean 3*3	Median 3*3	Weiner	Lucy Richardson	Bilateral
RMSE	20.0799	19.9276	16.1429	13.8786	20.9403
PSNR	22.0756	22.1889	24.0266	25.1146	21.7111
IEF	0.8758	0.9857	1.8597	1.4006	0.8053
Restored image					

TABLE 2
RESULTS OF DECONVOLUTION TECHNIQUES WITH BLUR ONLY EXISTING

Filter	Adaptive	Wavelet	Regularized	BID	Fusion Technique
RMSE	20.1879	19.41	17.037	21.2309	14.2
PSNR	22.029	22.3703	23.503	21.5914	25.92
IEF	58.5364	0.0722	1.2167	0.9259	1.72
Restored image					

In the Tables, 1 and 2, we illustrate the results of de-blurring the blurred bateau.jpg image and the resulted fusion technique. We can notice that Lucy-Richardson deconvolution is the best over the others non-blind with PSNR of 25, in the other hand, Wavelet deconvolution has the best result over the other blind deconvolution techniques with PSNR of 22.We combine two images using the wavelet based fusion method, first of lucy-richardson deconvolution and second of wavelet deconvolution, the resulted fused image has better results.

5.2.2 Case of noise only

In this section, we will examine the behavior of several deconvolution techniques in the case of noise presence only, we will use the most common four types of noise. Salt & Pepper noise with density 0.06, Gaussian noise with mean of zero and variance of 0.06, Speckle noise with mean of zero and variance of 0.08 and Poisson noise distribution with mean 10. We will adapt these values for the noises in our paper. After the noise is added to the image, the noisy image will be denoised using the deconvolution techniques. After that, we will combine the image which has the best result of the blind methods with the image obtained from the Weiner filter. The noisy images for our four noise types are illustrated in fig. (2).

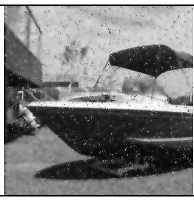
5.2.2.1 Salt & Pepper noise

In this section, we will examine the restoration techniques for restoring the bateau.jpg in presence of Salt & Pepper noise only with density of 0.06. The resulted images and the resulted metrics are stated in Tables 3 and 4 below.

TABLE 3
RESULTS FOR DECONVOLUTION TECHNIQUES FOR SALT & PEPPER NOISE WITH DENSITY 0.06.

Filter	Mean 3*3	Median 3*3	Weiner	Bilateral
RMSE	19.49	11.46	20.86	18.54
PSNR	22.33	26.21	21.74	22.76
IEF	3.56	10	3.04	3.86
time/m-sec	17	26	12	2085
Restored image				

TABLE 4
RESULTS FOR DECONVOLUTION TECHNIQUES FOR SALT & PEPPER NOISE WITH DENSITY 0.06.

Filter	Adaptive	wavelet	Fusion
RMSE	21.72	20	9.01
PSNR	21.38	22.1	27.45
IEF	50.24	0.01	11.12
time/m-sec	2876	180	1080
Restored image			

In Tables 3 and 4, we showed the resulted images and the obtained metrics after denoising the bateau.jpg image by the chosen deconvolution techniques, and the results of the fuse technique. We note that the most effective blind technique to remove the Salt & Pepper noise is the Median3*3 with highest PSNR and lowest RMSE, so the image resulted from it will be fused with the image resulted from the Weiner deconvolution. We can notice the improvement in the quality of the resulted image, and also the improvement in the metrics measured, PSNR=27.45 and RMSE=9.01.

5.2.2.2 Gaussian noise

In this section, we will examine the restoration techniques for restoring the bateau.jpg in presence of Gaussian noise only with mean of zero and variance of 0.06. The resulted images and the resulted metrics of the deconvolution methods and fusion techniques are stated in the Tables 5, and 6 below

TABLE 5
RESULTS FOR DECONVOLUTION TECHNIQUES FOR GAUSSIAN NOISE WITH MEAN OF ZERO AND VARIANCE OF 0.06.

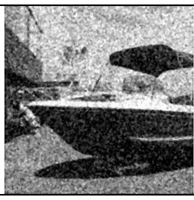
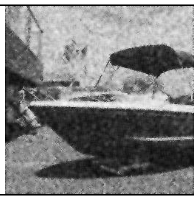
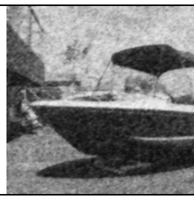
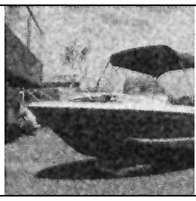
Filter	Mean 3*3	Median 3*3	Weiner	Bilateral
RMSE	25.11	27.88	23.65	22.95
PSNR	20.13	19.22	20.65	20.91
IEF	4.49	3.58	5.03	5.32
time/m-sec	37	26	130	2049
Restored image				

TABLE 6
RESULTS FOR DECONVOLUTION TECHNIQUES FOR GAUSSIAN NOISE WITH MEAN OF ZERO AND VARIANCE OF 0.06.

Filter	Adaptive	Wavelet	Fusion
RMSE	24.64	24.34	16.53
PSNR	20.29	20.4	23.71
IEF	29.6	0.02	6.53
time/m-sec	2978	194	850
Restored image			

In Tables 5 and 6, we showed the resulted images and the obtained metrics after denoising the bateau.jpg image by the chosen deconvolution and fusion techniques. We note that the most effective technique to remove the Gaussian noise is the Bilateral filter, the image obtained from it is fused with the image resulted from the Weiner deconvolution. We can notice the improvement in the quality of the resulted image, and the improvement in the metrics measured.

5.2.2.3 Speckle noise

In this section, we will examine the restoration techniques for denoising the bateau.jpg in presence of Speckle noise only with zero mean and variance of 0.04. The resulted images and the resulted metrics are stated in Tables7 and 8 below.

TABLE 7
RESULTS FOR DECONVOLUTION AND FUSION TECHNIQUES FOR SPECKLENOISE WITH VARIANCE 0.04.

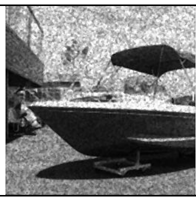
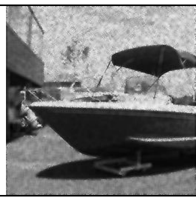
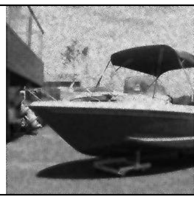
Filter	Mean 3*3	Median 3*3	Weiner	Bilateral
RMSE	19.90	23.59	19.17	19.95
PSNR	21.65	20.67	22.47	22.05
IEF	3.33	2.35	3.54	3.32
time/m-sec	17	23	12	1961
Restored image				

TABLE 8
RESULTS FOR DECONVOLUTION TECHNIQUES FOR SPECKLE NOISE WITH VARIANCE 0.04.

Filter	Adaptive	Wavelet	Fusion
RMSE	19.86	20.26	16.89
PSNR	22.17	21.58	24.21
IEF	60.43	0.01	68.17
time/m-sec	2932	189	1125
Restored image			

In Tables 7 and 8, we illustrated the resulted images and the obtained metrics after denoising the bateau.jpg image by the chosen deconvolution techniques and the fusion technique. We note that the most effective blind technique to remove the Speckle noise is the Adaptive, so the image resulted from it been fused with the image resulted from the Weiner deconvolution. We can notice the improvement in the quality of the resulted image, also the improvement in the metrics measured.

5.2.2.4 Poisson noise

In this section, we will examine the restoration techniques for restoring the bateau.jpg in presence of Poisson noise only with mean of 10. The resulted images and the resulted metrics are stated in the Tables 9 and 10 below.

TABLE 9
RESULTS FOR DECONVOLUTION TECHNIQUES FOR POISSON NOISE.

Filter	Mean 3*3	Median 3*3	Weiner	Bilateral
RMSE	14.6269	11.7831	10.7767	16.8529
PSNR	24.8278	26.7056	27.4811	23.5973
IEF	0.5508	0.8371	1.0105	0.4117
time/m-sec	17	24	17	2069
Restored image				

TABLE 10
RESULTS FOR DECONVOLUTION TECHNIQUES FOR POISSON NOISE.

Filter	Adaptive	wavelet	Fusion
RMSE	11.3735	15.8774	8.9562
PSNR	27.0129	24.1152	28.9281
IEF	184.053	0.091	54.2584
time/m-sec	2903	183	985
Restored image			

In Tables 9 and 10, we illustrated the resulted images and the obtained metrics after denoising the bateau.jpg image by the chosen deconvolution techniques and the fusion technique. We note that the most effective blind technique to remove the Poisson noise is the Adaptive filter, so the image resulted from is fused with the image resulted from the Weiner deconvolution, and we can see that fusion technique has improved the quality of image and the PSNR results.

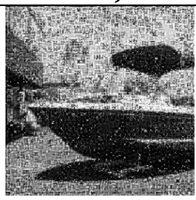
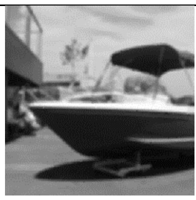
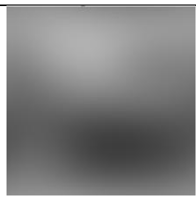
5.2.3 Case of blur and noise

In this section, we will take into consideration the presence of blur plus noise. We test the restoration techniques on the bateau.jpg image with the four types of noise, and then we will apply the fusion techniques on a two resultant images in order to improve the quality of the resulted image.

5.2.3.1 Blur with Salt & Pepper noise

Now we will examine the restoration techniques by adding Salt & Pepper noise to the blurred image bateau.jpg, and then will see the restored images and the resulted metrics. The Salt & Pepper will be added with the density of 0.06. Then we will combine the best resulted image from the blind deconvolution methods with the best of the non-blind convolution methods. In Tables 11 and 12 we will show the resulted images and metrics.

TABLE 11
RESULTANT IMAGES FOR THE SEVERAL RESTORATION TECHNIQUES WE USED TO REMOVE THE NOISE OF THE SALT & PEPPER NOISE WITH DENSITY OF 0.06, AND RESULTANT FUSED IMAGE

 Degraded image	 Adaptive	 BID	 Bilateral
 Lucy-Richardson	 Mean 3*3	 Median 3*3	 Regularized
 Wavelet	 Weiner	 Fused image	

In the Table 11, we showed the resulted images obtained from the deconvolution methods and the resultant fused image when applied on the degraded image bateau.jpg with the different densities of Salt & Pepper type of noise. We can notice the superiority of the Median 3*3 filter over the other methods; also we can notice the better vision of the fused image.

TABLE 12
RMSE, PSNR, IEF AND TIME EXECUTION VALUES FOR THE RESTORED IMAGE OF BLUR PLUS SALT & PEPPER NOISE, AND THE FUSION TECHNIQUE.

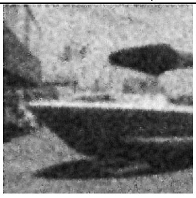
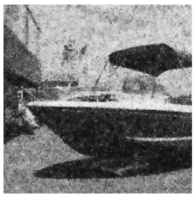
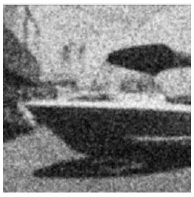
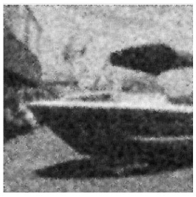
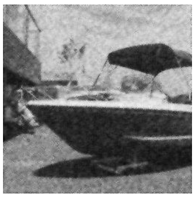
	Mean 3*3	Median 3*3	Weiner	Lucy Richardson	Bilateral	Adaptive	Wavelet	Regularized	BID	Fusion
RMSE	24.1545	19.04612	21.26462	40.6325	33.6957	27.906	22.8429	60.60693	66.90217	13.46
PSNR	20.471	22.535	21.578	15.953	17.579	19.217	20.955	12.48	11.622	25.34
IEF	2.8588	4.5617	2.9382	1.025	1.1488	30.4938	159.936	0.4494	0.3909	5.35
Time m-sec	6.916	15.083	12.291	63.775	2319.2	2756.2	189.93	237.92	186.68	1142

Table 12, shows the metrics obtained for the Blur with Salt & Pepper noise bateau.jpg image restored by the different restoring methods. With the highest PSNR and RMSE, the Median 3*3 is the best filter in restoring image with Blur and Salt & Pepper noise. As seen the value of the PSNR, and IEF has increased in the fusion image, also the value of RMSE has decreased in the fusion image.

5.2.3.2 Blur with Gaussian noise

In this section, we will examine our deconvolution methods with blur and Gaussian noise presence. In our paper, we will consider that Gaussian noise with mean of zero, and the value of variance 0.06. After that we will apply the fusion combination on the best resulted image of the blind convolution methods with the best image resulted from the non-blind convolution methods. Resulted images and obtained metrics shown in Tables13 and 14.

TABLE 13
RESULTANT IMAGES FOR THE SEVERAL RESTORATION TECHNIQUES WE USED TO REMOVE THE GAUSSIAN NOISE WITH VARIANCE OF 0.06, AND THE RESULTANT FUSED IMAGE.

 Degraded image	 Adaptive	 BID	 Bilateral
 Lucy-Richardson	 Mean 3*3	 Median 3*3	 Rgularized
 Wavelet	 Weiner	 Fused image	

In Table13, we showed the resulted images obtained from the deconvolution methods when applied on the degraded image bateau.jpg with Gaussian type of noise. We can notice the bilateral filter has the better result. Now we will show the resulted metrics obtained in this section. Fused image is the resulted combination of the Bilateral and Weiner methods.

TABLE 14
RMSE, PSNR, IEF AND TIME EXECUTION VALUES FOR THE RESTORED IMAGE OF BLUR PLUSGAUSSIAN NOISE, AND THE FUSION TECHNIQUE.

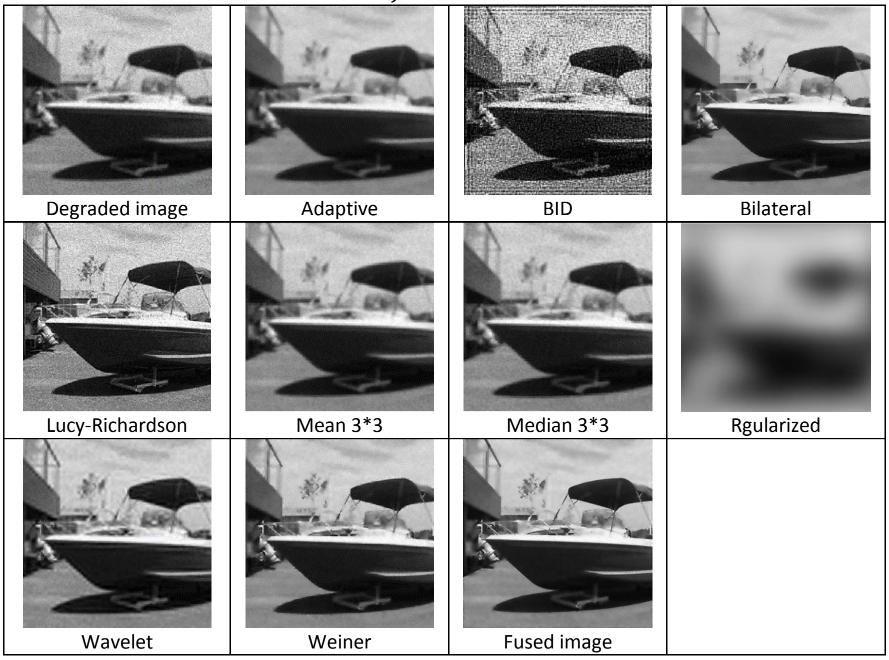
	Mean 3*3	Median 3*3	Weiner	Lucy Richardson	Bilateral	Adaptive	Wavelet	Regularized	BID	Fusion
RMSE	28.9903	31.61048	28.00074	68.51861	25.38685	29.30364	26.4214	46.50054	85.48392	21.11
PSNR	18.886	18.134	19.187	11.415	19.996	18.792	19.691	14.782	9.4931	21.63
IEF	3.8843	3.2601	4.1517	0.608	2.8451	21.588	67.212	1.5123	0.4473	5.07
Time/m-sec	7.515	16.386	13.953	119.45	2386.9	21.588	67.212	1.5123	0.4473	695

In Table 14, the results obtained from the bilateral filter has the highest value in PSNR and IEF, on the other hand it has the lowest value of RMSE, and we notice the improvements of the fusion technique.

5.2.3.3 Blur with Poisson Noise

In this section, we will examine our deconvolution methods with blur and Poisson noise presence with mean of 10. After that we will apply the fusion combination on resulted image of the blind convolution methods with the best image resulted from the non-blind convolution methods.

TABLE 15
RESULTANT IMAGES FOR THE SEVERAL RESTORATION TECHNIQUES WE USED TO REMOVE THE NOISE OF THE POISSON NOISE, AND THE FUSED IMAGE



In the Table 15, we showed the resulted images obtained from the deconvolution methods when applied on the degraded image bateau.jpg poisson type of noise. We can notice the Weiner best result compared to other non-blind deconvolution techniques, also the bilateral has best result compared to that of blind deconvolution techniques. Now we will show the resulted metrics obtained in this section. Fused image is the resulted combination of the Bilateral and Weiner methods.

TABLE 16
RMSE, PSNR, IEF AND TIME EXECUTION VALUES FOR THE RESTORED IMAGE OF BLUR PLUS POISSON NOISE, AND THE FUSION TECHNIQUE.

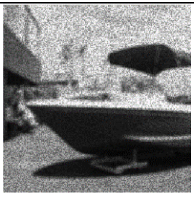
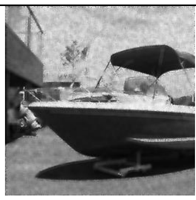
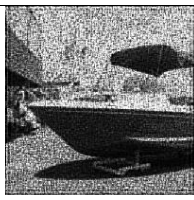
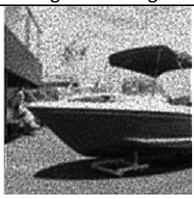
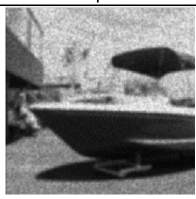
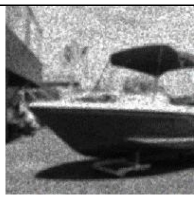
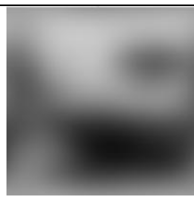
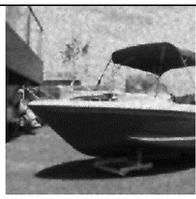
Filter	Mean 3*3	Median 3*3	Weiner	Lucy Richardson	Bilateral	Adaptive	wavelet	Regularized	BID	Fusion
RMSE	20.37	19.59	10.70	17.21	11.66	20.67	19.83	45.81	49.72	9.58
PSNR	21.94	22.28	27.53	23.41	26.793	21.82	22.18	14.91	14.19	28.21
IEF	1.1289	1.2314	1.009	0.466	0.853	55.80	318.9	0.29	0.21	1.53
Time/m-sec	8.763	16.57	19.067	67.20	2399.497	2774.292	193.981	91.569	338.679	1125

In Table 16, the results obtained from the bilateral filter has the highest value in PSNR and IEF compared to that of blind deconvolution techniques, on the other hand it has the lowest value of RMSE. On the other hand, the Weiner deconvolution has the best metrics compared with other non-blind deconvolution methods. We can notice the improvement of the fusion technique on the resultant metrics.

5.2.3.4 Blur with Speckle noise

In this section, we will examine our deconvolution methods with blur and Speckle noise presence. In our paper, we will consider that Speckle noise with mean of zero, and variance of 0.04. After that we will apply the fusion combination on resulted image of the blind convolution methods with the best image resulted from the non-blind convolution methods.

TABLE 17
RESULTANT IMAGES FOR THE SEVERAL RESTORATION TECHNIQUES WE USED TO REMOVE THE NOISE OF THE SPECKLE NOISE WITH DENSITY OF 0.04, AND THE RESULTED FUSED IMAGE.

 Degraded image	 Adaptive	 BID	 Bilateral
 Lucy-Richardson	 Mean 3*3	 Median 3*3	 Regularized
 Wavelet	 Weiner	 Fused image	

In the Table 17, we showed the resulted images obtained from the deconvolution methods when applied on the degraded image bateau.jpg with Blur and Gaussian type of noise. We can notice the Bilateral filter has the better result among the blind deconvolution techniques, while the Weiner has the better result among the non-blind deconvolution techniques. The fused image is the resulted combination of the Bilateral and Weiner methods.

TABLE 18
RMSE, PSNR, IEF AND TIME EXECUTION VALUES FOR RESTORED IMAGE OF THE SPECKLE NOISE, AND THE FUSED RESULTED METRICS.

	Mean 3*3	Median 3*3	Weiner	Lucy Richardson	Bilateral	Adaptive	Wavelet	Regularized	BID	Fusion
RMSE	22.8283	24.2051	20.225	32.406	19.958	92.669	22.842	54.255	51.115	17.26
PSNR	20.961	20.453	22.48	17.918	22.633	8.792	21.269	13.96	13.442	23.91
IEF	2.3798	1.852	3.0922	1.031	3.1969	3.2761	253.988	0.414	0.3821	4.31
Time/m-sec	7.13	13.894	20.942	880.54	2413.1	2819.3	179.76	197.71	220.63	1002

In Table 18, the results obtained from the bilateral filter has the highest value in PSNR and IEF compared to that of blind deconvolution techniques, on the other hand it has the lowest value of RMSE. On the other hand, the Weiner deconvolution has the best metrics compared with other non-blind deconvolution methods. We can notice the best results of the fusion technique.

VI. CONCLUSION

In our paper we made two kinds of comparison, the first is a comparison of several restoration techniques in restoring an image that has been degraded with a blur function and several kind of noise. We used several criteria to evaluate the performance of each restoration technique: PSNR, RMSE, IEF, and the time of execution of each of the restoration techniques, which has been illustrated in the previous chapter. The Restoration Techniques, overall, the Bilateral filter has the best results among the several types of noise, but in the presence of the Salt & Pepper noise the best result it is that been obtained by the median filter, from this point of view we can state that the nature of the noise effect the efficiency of the deconvolution method. On the other hand, the blind image deconvolution (BID) and the regularized filter has offered the lowest results comparing to the rest restoration techniques. On the other hand, the efficiency of the blind image deconvolution and the non-blind deconvolutions is very high at blur only images. The proposed combination of two restored images has generated an image with a better vision and higher values in PSNR, and lower values in MSE results.

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