A Comprehensive Study on Fast image Deblurring Techniques

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Abstract

Image deblurring refers to procedures that attempt to reduce the blur amount in a blurry image and grant the degraded image an overall sharpened appearance to obtain a clearer image. The point spread function (PSF) is one of the essential factors that needed to be calculated, since it will be employed with different types of deblurring algorithms. In this paper, the authors studied various fast deblurring techniques like Richardson – Lucy and its optimized version, Van Cittert and its enhanced version, Landweber, Poisson Map, and Laplacian sharpening filters. Furthermore, altered optimized versions of Landweber and Poisson Map algorithms have been presented. The usage of the PSF in the deblurring algorithm is explained and a comparison between the optimized, the enhanced algorithms and Laplacian sharpening filters in terms of the number of mathematical operations, number of iterations employed, computation time, deblurring in case of noise existence, and the accuracy measurement using peak signal to noise ratio (PSNR) for each technique is conducted.

Keywords: *Image deblurring techniques, blur, image degradations, point spread function (PSF), image restoration, iterative techniques, optimized algorithms, Van Cittert, Landweber, Richardson-Lucy, Poisson Map, Laplacian Sharpening Filters, PSNR, MSE, and Gaussian PSF*

1. Introduction

Captured images are considered as degraded versions of the original scene, artifacts such as blur and noise corrupt diverse sorts of images frequently. Image restoration is the process that attempts to recover the image from its corrupted version [9]. Degraded images can be described using the following equation [12]:

$$m = h \otimes f + n \tag{1}$$

Where, (m) is the degraded image, (f) is the original image, (h) is the blur operator, (n) is the additive noise and ($\otimes$) is the convolution process [3]. This paper deals with blur in particular. Blur affects an image due to many reasons such as Gaussian noise degrading the image [13], applying a denoising algorithm on the image [14], imperfect resolution of the imaging system [15], Image data lost throughout the image acquisition procedure [16], and low-pass filters blur the image, while reducing the noise [17]. The reason for doing this paper is to highlight the importance of image deblurring techniques in the image processing field. For example, it is necessary to use fast deblurring algorithms in surveillance systems, medical imaging systems, military applications, and digital cameras. The type of "blur" this paper will focus on is the Gaussian blur. The overall methodology of this paper consists of obtaining a clear non-degraded image, then, generates a point spread function (PSF) and convolves it with the image to form the blurry image. Moreover, additive white Gaussian noise is added to the image to simulate a blurry noisy version of the clear image. The purpose is to deblur the resulted degraded images by different fast deblurring techniques, such as the optimized Richardson-Lucy, the enhanced Van Cittert, the optimized Landweber, the optimized Poisson Map and Laplacian sharpening filters. The experiment is conducted in MATLAB environment on standard 256x256 grayscale flower image. The rest of the paper is organized in the following fashion: the fast deblurring techniques and their altered versions are discussed in Section 2. The type of point spread function (PSF) is presented in Section 3. The experimental results are described in Section 4. An explanation of the peak signal to noise ratio (PSNR) method to measure the accuracy will be presented in Section 5. An overall comparison of the fast deblurring techniques in terms of the number of arithmetic operations, number of iterations, computation time, deblurring in case of noise existence, and the accuracy measurement using peak signal to noise ratio (PSNR) are illustrated in Section 6. A comprehensive discussion about the results and the significance of this paper is conducted in Section 7, and the conclusion is exposed in Section 8.

2. Fast Deblurring Techniques

Five methods were chosen based on their good performance and popularity from various deblurring techniques that are available in the field namely:

2.1. Iterative Van Cittert Algorithm

The Van Cittert algorithm is a famous iterative algorithm in the area of image deblurring. It has many advantages, for instance, rapid deblurring, contain few numbers of variables, simple mathematical operations, no smoothness restrictions and prior information are required. On the other hand, it contains major limitations, for example, its sensitivity to the noise existence, and it tremendously increases the noise amounts in the deblurred image. Likewise, its unstable performance after an additional number of iterations is utilized, and the subsequent image would look shaky. The equation of the Van Cittert algorithm is [1]:

$$f^{n+1} = f^n + (g - Hf^n) \quad (2)$$

Where f^{n+1} is the new estimate from the previous one f^n, (g) is the blurred image, (n) is the number of the step in the iteration and (H) is the blur filter (PSF).

In this paper, an enhanced version of Van Cittert algorithm is used. It's similar to the original one, but the only difference is that (β) which is a constant that controls and regularizes the sharpening amount of the algorithm is added to obtain better results. Its equation can be described as the subsequent [20]:

$$f^{n+1} = f^n + \beta(g - Hf^n) \quad (3)$$

Where, in the first iteration, the value of (f^n) = g.

2.2. Iterative Landweber Algorithm

The Landweber algorithm is an enhanced version of Van Cittert algorithm, also Landweber is an iterative algorithm, and it works the same way as the Van Cittert algorithm, but it has an extra variable (H^T) which is the transpose of the point spread function (PSF). The use of this variable results a more stable algorithm against noise and more reliable when employing an additional number of iterations by resulting in an unshaken image. The equation of the Landweber algorithm is [2] [19]:

$$f^{n+1} = f^n + \beta H^T (g - Hf^n) \tag{4}$$

Where f^{n+1} is the new estimate from the previous one f^n, (g) is the blurred image, (n) is the number of the step in the iteration, (H) is the blur filter (PSF), (H^T) is the transpose of the point spread function (PSF) and (β) is a constant that controls and regularizes the sharpening amount of the algorithm.

In this paper, the same Landweber algorithm will be employed but the only difference is that instead of using (H^T) in the original equation, it will be replaced with (H) to reduce the number of operations needed and produce an optimized version of the Landweber Algorithm. The equation of the *optimized Landweber algorithm* can be described in the subsequent equation:

$$f^{n+1} = f^n + \beta H (g - Hf^n) \tag{5}$$

Where, in the first iteration, the value of (f^n) = g.

2.3. Iterative Richardson-Lucy Algorithm

The Richardson-Lucy algorithm is one of the most popular deblurring algorithms in the area of image processing due to many reasons such as it does not concern the type of noise affecting the image. In addition, it does not require any information from the original clean image and it is an iterative algorithm. In addition, this algorithm functions in the event of noise presence but the noise would be increased throughout the raised number of iterations. [5] [6]. The equation of the Richardson-Lucy algorithm is [8]:

$$f^{n+1} = f^n H^* \left(\frac{g}{Hf^n}\right) \tag{6}$$

Where f^{n+1} is the new estimate from the previous one f^n, (g) is the blurred image, (n) is the number of the step in the iteration, (H) is the blur filter (PSF) and (H^*) is the Adjoint of (H).

In this paper, the same Richardson-Lucy algorithm will be utilized but the only difference is that instead of using (H^*) in the original equation, it will be replaced with (H) to reduce the number of operations needed and produce an optimized version of the Richardson-Lucy Algorithm. The equation of the *optimized Richardson-Lucy algorithm* can be described in the subsequent equation [12]:

$$f^{n+1} = f^n H \left(\frac{g}{Hf^n}\right) \tag{7}$$

Where, in the first iteration, the value of (f^n) = g.

2.4. Iterative Poisson Map Algorithm

The Poisson Map algorithm is an iterative algorithm. Its variables are the same as Richardson-Lucy algorithm, the only difference between the two algorithms that the Poisson Map uses an exponential operation in the restoration process and, it uses an integer which is (1) for the subtraction operation. The equation of the Poisson Map algorithm is [7]:

$$f^{n+1} = f^n \, e^{\left[H^* \left(\frac{g}{Hf^n}\right) - 1\right]} \tag{8}$$

Where f^{n+1} is the new estimate from the previous one f^n, (g) is the blurred image, (n) is the number of the step in the iteration, (H) is the blur filter (PSF) and (H^*) is the Adjoint of (H).

In this paper, the same Poisson Map algorithm will be employed but the only difference is that instead of using (H^*) in the original equation, it will be replaced with (H) to reduce the number of operations needed and produce an optimized version of the Poisson Map Algorithm. The equation of the *optimized Poisson Map algorithm* can be described in the subsequent equation:

$$f^{n+1} = f^n \, e^{\left[H\left(\frac{g}{Hf^n}\right)-1\right]} \tag{9}$$

Where, in the first iteration, the value of (f^n) = g.

2.5. Laplacian Sharpening Filters

Laplacian filter is one of the well-known filters when it comes to image sharpening; image sharpening is also a term of image deblurring. Laplacian filter is a 3x3 matrix that comes in three types, -4, -8 and 9 core matrixes. Figure 1 illustrates the types of Laplacian kernels.

0	1	0
1	-4	0
0	1	0

1	1	1
1	-8	1
1	1	1

-1	-1	-1
-1	9	-1
-1	-1	-1

Figure 1. Illustrates the Laplacian Kernels

The Laplacian formula for the (-4) and (-8) core matrixes can be described as:

$$F = I - [I \otimes LK] \tag{10}$$

Where, (F) is the restored image, (I) is the degraded image by blur, (LK) is Laplacian kernel, and ($\otimes$) is the convolution process. Besides, The Laplacian formula for the (9) core matrix can be described as:

$$F = I \otimes LK \tag{11}$$

By applying the Laplacian kernel to the blurred image, the image would be sharpened. The amount of sharpening depend on the type of kernel used, for instance, the (-8) and (9) cores sharpen the image more than the (-4) core [4].

3. Type of Point Spread Function (PSF)

One of the most significant variables that required to be computed earlier to the deblurring procedure is the point spread function (PSF). The PSF is the degree that an imaging system or a technique spreads a point of light. The PSF basically is an approximation of the distortion operator (h) mentioned in eq. (1) that is convolved with the original image to produce a blurry image. During the deblurring process, the PSF will be used in the deblurring algorithm [12]. The category of PSF employed in this paper is the Gaussian PSF. In the Gaussian PSF, the blur parameter (sigma (σ)) need to be computed and the size of the PSF, the Gaussian PSF equation is [18]:

$$h_g(m,n) = e^{\frac{-(m^2+n^2)}{2\sigma^2}} \tag{12}$$

$$h(m,n) = \frac{h_g(m,n)}{\sum_m \sum_n h_g} \tag{13}$$

In this paper, the size of PSF is a 3X3 matrix and the blur parameter (sigma (σ)) is equal to 1. The PSF is highly required in the deblurring techniques since the quality of the image depends on it.

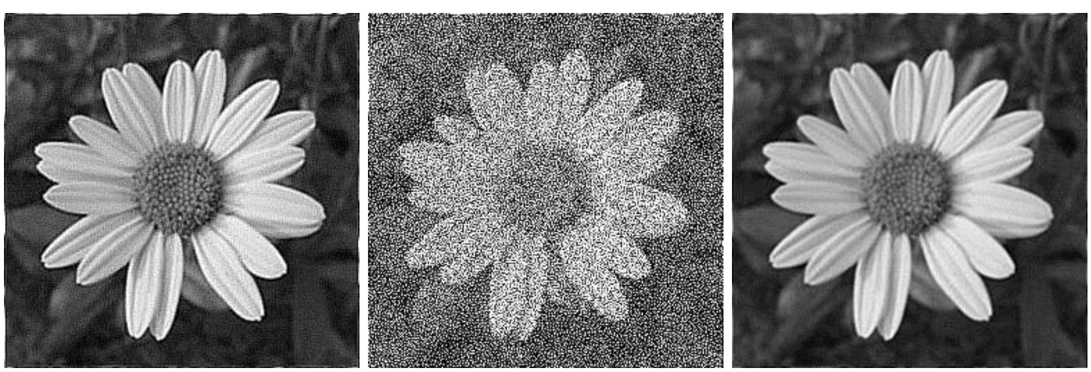
4. Experimental Results

The experiment of this paper is conducted by utilizing the metrics shown in Table 1, the experimental images are illustrated in Figure 2, and the experimental results can be seen in Figure 3.

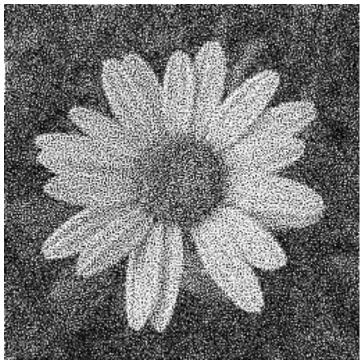
Table 1. The Experimental Metrics

OS	Microsoft Windows 7 64-bit
Environment	Matlab R2008a
CPU	Intel Core I5 2.3GHz
Memory	8 GB
Image size	256x256
Blur Type	Gaussian Blur
Blur Radius	1
Noise Type	Additive White Gaussian noise
Noise variance	0.002
Noise mean value	0
Type of image	Grayscale
Image resolution	8 Bits

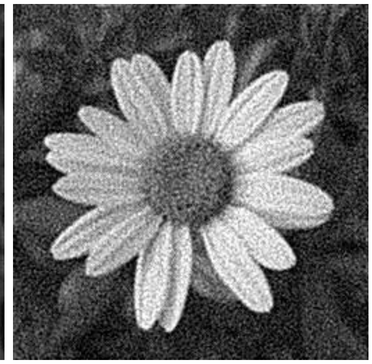
Figure 2. Images from left to right: Original Image, Blurry Image, and Blurry Noisy Image.



(a) **(b)** **(c)**


(d)


(e)


(f)

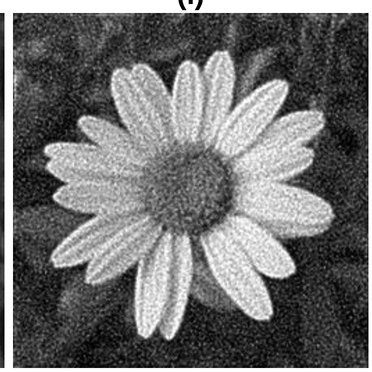

(g)


(h)

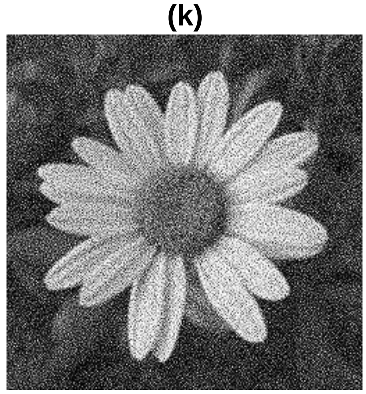

(i)

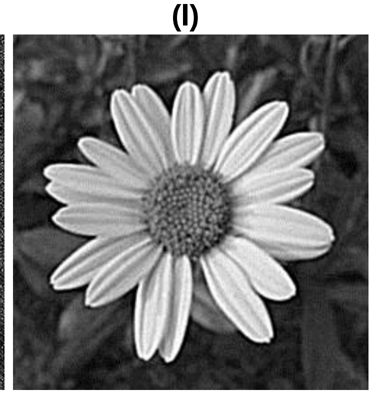

(j)


(k)


(l)


(m)


(n)


(o)

(p) (q) (r)

Figure 3. Demonstrates the experimental results of this paper. Restoration process from (a) to (d) with Enhanced Van Cittert Algorithm: blurry image restored with 5 iterations and (Beta (*β*)) = 1, blurry noisy image restored with 5 iterations and (Beta (*β*)) = 1, blurry image restored with 2 iterations and (Beta (*β*)) = 2, and blurry noisy image restored with 2 iterations and (Beta (*β*)) = 2. Restoration process from (e) to (h) with Optimized Landweber Algorithm: blurry image restored with 5 iterations and (Beta (*β*)) = 1, blurry noisy image restored with 5 iterations and (Beta (*β*)) = 1, blurry image restored with 2 iterations and (Beta (*β*)) = 2, and blurry noisy image restored with 2 iterations and (Beta (*β*)) = 2. Restoration process from (i) to (j) with optimized Richardson-Lucy Algorithm: blurry image restored with 5 iterations, and blurry noisy image restored with 5 iterations. Restoration process from (k) to (l) with optimized Poisson Map Algorithm: blurry image restored with 5 iterations, and blurry noisy image restored with 5 iterations. Restoration process from (m) to (r) with Laplacian Sharpening Filter: blurry image restored with (1) iteration and a -4 kernel, blurry noisy image restored with (1) iteration and a -4 kernel, blurry image restored with (1) iteration and a -8 kernel, blurry noisy image restored with (1) iteration and a -8 kernel, and blurry image restored with (1) iteration and a 9 kernel, blurry noisy image restored with (1) iteration and a 9 kernel.

5. Peak Signal to Noise Ratio (PSNR)

One of the common reliable methods to measure the accuracy in the image processing field is the (PSNR), the peak signal to noise ratio for a grayscale image can compute using the following equation [11]:

$$PSNR = 20 * Log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \tag{14}$$

Where MSE can be calculated using the following equation [3]:

$$MSE = \frac{1}{M*N}\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y) - \hat{f}(x,y) \tag{15}$$

Where, (M, N) are the dimensions of the image, $f(x, y)$ is the original image, $f'(x, y)$ is the restored image. The higher PSNR value means the image has a better quality in the deblurred image. This metric helps to deliver an unbiased standard to compare diverse techniques.

6. Comparison

In this section, an overall comparison of the fast deblurring techniques in terms of the number of arithmetic operations, number of iterations, computation time, deblurring in case of noise existence, and the accuracy measurement using peak signal to noise ratio (PSNR) will be stated. The Table 2 underneath describes the comparison about the conducted experiment in this paper were PSNR1 represents the peak signal to noise ratio of the blurry image and PSNR2 signifies the peak signal to noise ratio of the blurry noisy image.

Table2. comparison facts of the experiment

Technique Name	*No. of Arithmetic Operations*	*Iterations*	*Constant or Kernel*	*Computation Time (Seconds)*	*PSNR 1*	*PNSR 2*
Enhanced Van Cittert	4	5	1	0.144	23.29	8.48
Enhanced Van Cittert	4	2	2	0.100	30.61	11.88
Optimized Landweber	5	5	1	0.176	32.03	21.70
Optimized Landweber	5	2	2	0.117	33.57	23.24
Optimized Richardson-Lucy	4	5	N/A	0.176	31.98	21.75
Optimized Poisson Map	6	5	N/A	0.193	31.94	21.73
Laplacian	2	1	-4	0.054	35.37	13.70
Laplacian	2	1	-8	0.056	26.20	10.32
Laplacian	1	1	9	0.050	26.20	10.25

7. Discussion

From the stated facts in the Table 2 above, it is clear that the Laplacian sharpening filter gives the highest results in a lowest execution time with the image degraded with Gaussian blur only, but its' drawbacks are it performs poorly when the noise is presented, also the Laplacian filters cannot be tuned same as other iterative techniques. According to iterative techniques, the optimized Landweber algorithm with (Beta (β)) equal to two produces high results in terms of blurry and blurry noisy images with a low execution time. The enhanced Van Cittert algorithm performs poorly in terms of noisy blurry images; the reason is the algorithm is sensitive to noise. The optimized Richardson-Lucy and Poisson Map algorithms perform nearly the same, but the optimized Poisson Map is the slowest algorithm among the selected algorithms since it has six mathematical operations.

8. Conclusion

In conclusion, this paper presents an altered version of Landweber, and Poisson Map algorithms by replacing the (H^*) or (H^T) by (H) to reduce the execution time. Likewise, this paper proves that these algorithms work efficiently specially the optimized Landweber algorithm. Moreover, also confirms that the Laplacian sharpening filters work professionally with Gaussian blur but very poor with a blurry and noisy image. In terms of blurry and noisy image, the optimized Landweber algorithm is a better solution for a minor number of iterations but when major number of iterations is needed to restore a blurry and noisy image, the optimized Richardson-Lucy algorithm is a suitable choice.

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