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Iterative Richardson-Lucy Based Improved Fast Image Deblurring and Denoising Approach

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***Abstract**: Image deblurring submits the procedures that crack to lessen the amount of blur in the blurry image and provides the corrupted image an overall enhanced effect in order to achieve a better image. This paper mainly deals with the removal of blur in an image. The Point Spread Function (PSF) is the important factor which is needed to be considered, as it will be engaged with varied methods of deblurring algorithms. This paper deals with different deblurring techniques such as Richardson–Lucy algorithm, Van Cittert algorithm, Landweber algorithm, Poisson Map algorithm, and the Laplacian sharpening filter. The use of Point Sprean Function in above mentioned algorithm is enlightened and a correlation between those approaches and Laplacian sharpening filter by means of computational time, total number of iterations employed, deblurring with the presence of noise, and the accurateness measurement with the help of Peak Signal to Noise ratio (PSNR) for all the above mentioned techniques in the presence of blur and also in the presence of blur along with noise are accomplished.*

***Keywords:** Image degradation, Gaussian Point Spread Function (PSF), Image restoration, Iterative techniques, Peak Signal to Noise Ratio, Mean Square Error.*

1. INTRODUCTION

The obtained images suffer from artifacts such as blur and noise, and it is considered as the degraded version of the original image. Image restoration is the procedure that attempts to pull through the image from its degraded version [9].

Corrupted images can be explained using the following equation (1):

$$m = h\ f{+}n \text{ --------------- } (1)$$

where, the symbol "m" denotes the degraded image, "h" denotes the blur operator, "f" denotes the original image, "⊗" denotes the convolution process and "n" denotes the additive noise [3].

An image is degraded owing to a lot of causes such as noise [13], blur, applying various denoising algorithms [14], unsatisfactory resolution of the system [15], loss of image data while performing image acquisition [16], and blur while sending the image into low-pass filters, while removing the noise [17]. This work emphasizes the significance of image deblurring techniques in image processing. The use of fast image deblurring algorithm can be employed in medical imaging, surveillance systems, and various military applications. This paper focus on the removal of Gaussian blurs.

The general approach of this paper includes, achieving a better non-degraded image, subsequently, creates a point spread function (PSF) and merges it with the image with the help of convolution operator, to obtain the blurry image. Furthermore, additive white Gaussian noise is applied on to the image in order to create a blurry noisy translation of the original image. The reason is to deblur the obtained degraded images with the help of various fast deblurring techniques.

This paper deals with optimized Richardson-Lucy algorithm, and the result is compared with Van Cittert algorithm, Landweber algorithm, Poisson Map algorithm and Laplacian sharpening filter. The research is carried out in MATLAB environment on normal 256x256 grayscale image.

The whole paper is structured in the following manner: Section 2 discusses the fast deblurring methodologies. Section 3 presents the type of point spread function (PSF). Section 4 describes the experimental results, that includes comparison between various algorithms. Section 5 illustrates the entire comparison of the various fast deblurring techniques, with the help of the total number of iterations, computational complexity, image deblurring in the presence of noise and the reduction in degradation parameters using peak signal to noise ratio (PSNR). Section 6 exposes the conclusion.

2. VARIOUS FAST DEBLURRING TECHNIQUES

The below mentioned five methods are considered in this paper in order to remove the blur in the image. This section explains the iterative deblurring techniques in detail.

2.1 Iterative Van Cittert Algorithm

The most famous iterative algorithm in the field of image deblurring is the Van Cittert algorithm. This approach has much compensation, such as fast deblurring, containing fewer variables and uncomplicated numerical operations and without smoothness limitations. In addition with, it also contains major limitations, such as; its sensitivity to the existence of noise, results in the increase of noise in the deblurred image. Similarly, its unbalanced performance subsequent to an additional amount of iterations is employed, and the successive image would look shaking. The following equation explains the Van Cittert algorithm [1]:

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

where "fn+1" is the latest estimate of "fn", "g" is the blurry image, "n" is the number of iteration and finally "H" is the blur filter. This paper deals with an improved report of Van Cittert algorithm, which is similar to the existing one. Although the simply difference is the constant, (β), that manages and standardizes the amount of sharpening of the algorithm, in order to attain a better result. The equation can be explained as [20]:

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

2.2 Iterative Landweber Algorithm

The Landweber algorithm is an iterative algorithm and also the improved version of Van Cittert algorithm. This approach works in the same fashion as the Van Cittert algorithm. The only difference is an extra variable "HT" is used which is the transpose of PSF. The purpose of this variable is to obtain a more stable algorithm in the presence of noise. The following equation explains the Landweber algorithm [2] [19]:

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

where (HT) is the transpose of the point spread function (PSF) and the constant (β) controls and regularizes the sharpening amount.

This paper, employed the improved version of Landweber algorithm. The single difference is that "HT" is replaced by "H", in order to decrease the number of iterations. The equation of the optimized Landweber algorithm can be explained in the following equation:

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

2.3 Iterative Richardson-Lucy Algorithm

The Richardson-Lucy algorithm is the most popular deblurring algorithms in the field of image processing due to various reasons such as it do not concern the type of noise affecting the image. Adding to this, this algorithm does not need any information of the original image. Also, this algorithm functions in the presence of noise but the percentage of noise would be increased by the raise in the number of iterations [6]. The Richardson-Lucy algorithm can be depicted with the following equation [8]:

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

where "H*" is the Adjoint of "H".

In the new approach, the only variation is that, in order to decrease the number of operations, "H" will be used as an alternative to "H*". The subsequent equation explains the improved Richardson-Lucy algorithm [12]:

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

2.4 Iterative Poisson Map Algorithm

The alternative algorithm of Richardson-Lucy algorithm is the Poisson Map algorithm, in which, the chief difference is that, in Poisson Map approach, an exponential operation is used in the restoration process. Additionally, it makes use of an integer for the subtraction process. The following equation illustrates the Poisson Map algorithm [7]:

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

In the new approach, the chief difference is that, inorder to reduce the number of operations, "H*" is replaced by "H". The subsequent equation explains the improved version of the Poisson Map algorithm.

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

In all the above mentioned approaches, in the first iteration, the value of "fn" = g.

2.5 Laplacian Sharpening Filters

Laplacian filter is a well-known filter in the process of image sharpening; image sharpening is another term in image deblurring. The order of the Laplacian matrix is 3x3. This core matrix is of three types, viz, -4, -8 and 9. Figure 1 demonstrates the Laplacian kernels.

0	1	0	1	1	1	-1	-1	-1
1	-4	0	1	-8	1	-1	9	-1
0	1	0	1	1	1	-1	-1	-1

Figure 1: Illustration of Laplacian Kernels

Laplacian formula for the (9) core matrix can be described as:

$$F = I \otimes LK \quad \text{------------------- (10)}$$

On applying the Laplacian kernel on the corrupted image, the image will experience a sharpening effect. The percentage of sharpening relies on the choice of kernel. The result explains that (-8) and (9) kernels sharpens the image more accurately than the (-4) kernel [4].

3. POINT SPREAD FUNCTION

Point Spread Function (PSF) is one of the chief important variables that are needed to be determined for the deblurring process. The PSF is the level that an imaging scheme. In other words, it is a technique that spreads the point of light. The PSF on the whole, is an estimate of the distortion operator (h) as explained in eq. (1) which is convolved with the error free image in order to create a blurred image. The PSF is used in the deblurring algorithm [12]. The type of PSF used in the above mentioned algorithm is the Gaussian PSF. The blur constraint, sigma (σ) needs to be determined and the amount of the PSF is to be determined [18]: The size of PSF used in this paper is a 3X3 matrix and the sigma (σ) is equivalent to 1. The PSF is greatly essential in the deblurring techniques as the excellence of the image depends on it.

4. EXPERIMENTAL RESULTS

The experimentation of the above mentioned approaches is conducted by employing the metrics shown in the Table 1. The experimental images can be seen in Figure 2, and the results are shown 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: Image, and Blurry Noisy Image

The restoration process with improved Van Cittert Algorithm is shown in the figure (a) to figure (d): The figure (a) shows the blurry image restored with Beta (β) = 1 and 5 iterations, figure (b) shows the blurry noisy image restored with Beta (β) = 1 and 5 iterations, figure (c) shows the blurry image restored with Beta (β) = 2 and 2 iterations. The figure (d) shows the blurry noisy image restored with Beta (β) = 2 and 2 iterations. The restoration process with the help of Optimized Landweber Algorithm is shown from the figure (e) to figure (h): The figure (e) shows the blurry image restored with Beta (β) = 1 and 5 iterations. The figure (f) shows the blurry noisy image restored with Beta (β) = 1 and 5 iterations, the figure (g) shows the blurry image restored with Beta (β) = 2 and 2 iterations, the figure (h) shows the blurry noisy image restored with Beta (β) = 2 and 2 iterations. The restoration process with Optimized Richardson-Lucy Algorithm is shown in the figure (i) and figure (j): figure (i) shows the blurry image restored with 5 iterations, figure (j) shows the blurry noisy image restored with 5 iterations. The restoration process with the help of Optimized Poisson Map Algorithm is shown from figure (k) to figure (l): figure (k) shows the blurry image restored with 5 iterations, and the figure (l) shows the blurry noisy image restored with 5 iterations. The restoration process with the help of Laplacian Sharpening Filter is shown in the figure (m) and figure (r): figure (m) shows the blurry image restored with a -4 kernel and 1 iteration, (n) shows the blurry noisy image restored with a -4 kernel and 1 iteration, (o) shows the blurry image restored with a -8 kernel and 1 iteration, (p) shows the blurry noisy image restored with a -8 kernel and 1 iteration, (q) shows the blurry image restored with a 9 kernel and 1 iteration, and finally figure (r) shows the blurry noisy image restored with a 9 kernel and 1 iteration.

5. COMPARISON

In this segment, a general relationship of the various fast deblurring techniques in terms of the number of iterations, deblurring in the presence of noise, computation time, and the measurement of resolution with the help of peak signal to noise ratio (PSNR) is stated. The Table 2 shown below describes about the comparison between the restoration process of blurry image and the blurry noisy image. PSNR1 corresponds to the blurry image's the peak signal to noise ratio and PSNR2 corresponds to blurry noisy image's the peak signal to noise ratio.

TABLE 2: COMPARISON BETWEEN VARIOUS DEBLURRING APPROACHES

Algorithm	No of iterations	PSNR1	PSNR2	Time slot (Seconds)
Iterative Van Cittert	5	27.1703	19.4829	1.344365
Iterative Landweber	5	28.1362	18.3984	0.053894
Iterative Richardson-Lucy	5	31.2809	26.2398	0.904980
Laplacian Sharpening Filters	5	28.3744	16.2378	0.414925

6. CONCLUSION

This paper explains an improved version of Poisson Map algorithm and Landweber algorithm. Similarly, this paper confirms that the above mentioned algorithms work proficiently. Furthermore, the result also proves that the Laplacian sharpening filters works efficiently with Gaussian blur but poor in case of a blurry noisy image. The improved Landweber algorithm gives a better solution for a minimum number of iterations, in terms of blurry noisy image. If the major number of iterations is desired to restore a blurry noisy image, the improved Richardson-Lucy algorithm produces a promising result. From the Table 2, it is evident that the Laplacian sharpening filter produces more promising results for a minimum execution time for the image affected by Gaussian blur. But the main drawback is that, its performance is poor in the presence of noise. The performance of Van Cittert algorithm is poor in case of noisy and blurry images; as this algorithm is high responsive to noise. According to the above mentioned iterative techniques, the iterative Richardson Lucy algorithm gives more promising results in the case of blurry as well as blurry noisy images at low execution time.

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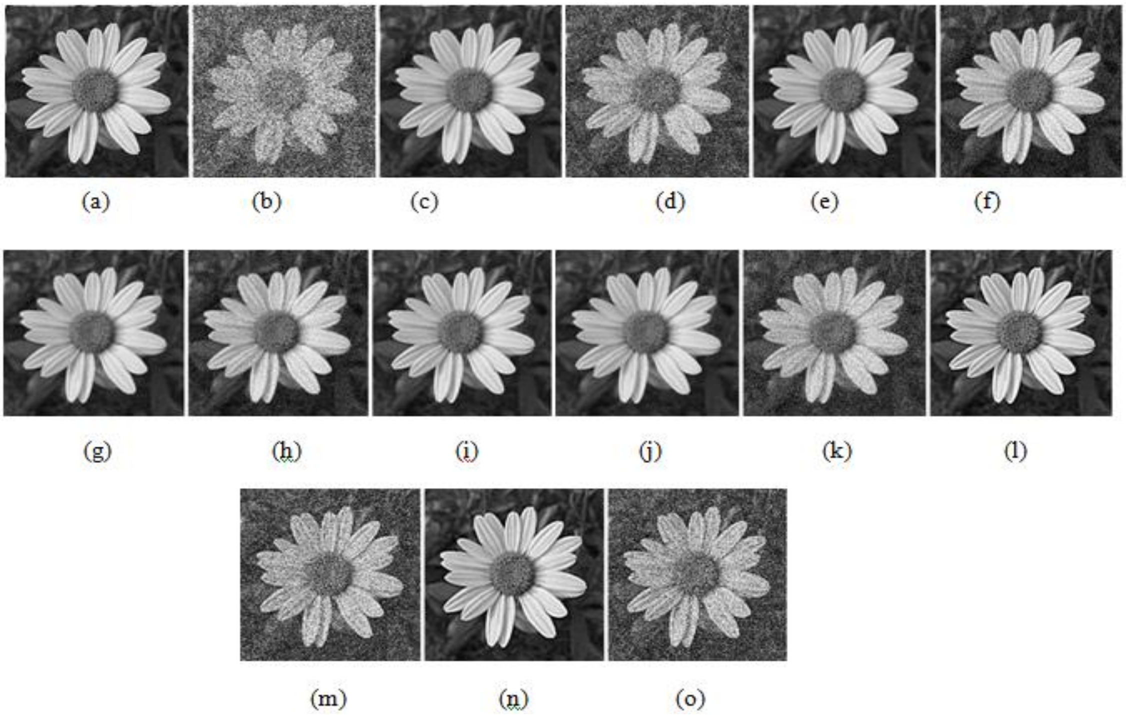

Figure 3: Demonstrates the experimental results of this paper.

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