-*Deblurring average blur by using adaptive Lucy Richardson

Dr. Radhi Sh.Hamoudi Al-Taweel **Dr.Hazim G. Daway**

Mohammed.H kahmees

Al-Mustansiriyah University / College of education/ Department of physic

Abstract :

image deblurring is to try to restore the image based on a prior knowledge of the cause of degradation, there are several method to restore the image (Weiner filter, regularized filter, Lucy-Richardson algorithm, and non blind deconvolution). in this research it has been studied four methods and determine the best parameter of each method that have been better restored image , where the image corrupted by average blur. The result show the Lucy Richardson algorithm was the best and it was development the Lucy Richardson algorithm by using lightness enhancement and the result show the suggested algorithm give best result comparison with traditional algorithm.

ازالة الضبابية المعدلية باستخدام خوارزمية لوسي– ريشادرسون المطورة

د. راضي شدهان حمودي د. حازم كاطع دواي محمد حسن خميس

الجامعة المستنصرية / كلية التربية / قسم الفيزياء

الخلاصة:

ازالة الضبابية هي محاولة لاستعادة الصورة اعتمادا" على المعرفة المسبقة لعامل التردي(التشوه)، توجد عدة طرق لاستعادة الصورة منها (مرشح وينر، مرشح المنظم ، خوارزمية لوسي– ريشادرسون، تقنية فك غير الالتفاف المحجوب).

في هذا البحث تم دراسة الطرق الاربعة وتحديد افضل باراميتر تكون عنده افضل استعادة للصورة، اذ تم تشويه الصورة بالضبابية المعدلية . بينت النتائج ان خوارزمية لوسي– ريشادرسون هي

افضل الطرق وتم تطوير خوارزمية لوسي– ريشادرسون باستخدام تحسين الاضاءة واظهرت النتائج ان الخوارزمية المقترحة اعطت نتائج افضل في استعادة الصورة مقارنة مع الخوارزمية التقليدية.

1. Introduction

During image formation and acquisition, many types of distortions limit the quality of images [1]. Some distortions always arises in the recording of a digital image , because it is unavoidable that scene information spills over to neighboring pixels [2]. For example, the optical system in a camera lens may be out of focus, so that the incoming light is smeared out. The same problem arises, for example, in astronomical imaging where the incoming light in the telescope has been slightly bent by turbulence in the atmosphere. In these and similar situations, the inevitable result is that we record a blurred image[2].

Salem Saleh Al-amri and etal [3].produced method to recover the distorted image by average blur in two cases: first with point spread function (PSF) and they use (Weiner filter, regularized filter, Lucy-Richardson algorithm, and non blind deconvolution) Comparing the results show that (Weiner and regularized) are technical better to remove average blur with images of Remote Sensing and without the presence of noise, and with a the noise, the algorithm (Lucy- Richardson) is the best .in the second case without (psf) blind deconvolution was applied and the best result when size (psf) is (13*13) at iteration (50). Nourildean and Khalil [4].Introduced study to restore the original image using a mathematical model of the process of degradation where applied the four algorithms (Wiener filter, regularized filter, Lucy-Richardson algorithm and non blind deconvolution) the result show wiener filter and Lucy-Richardson algorithm give best result.in this study we have using the standard method to deblurring the average blur from the image with (psf) and determined the best parameter for every method that have been best image restoration, and development algorithm to better method by using lightness enhancement and comparison this method with the classic method at best parameter.

2.Blurring

Blur is unsharp image area caused by camera or subject movement, inaccurate focusing, or the use of an aperture that gives shallow depth of field. The Blur effects are filters that smooth transitions and decrease contrast by averaging the pixels next to hard edges of defined lines and areas where there are significant color transition.

In digital image there are 3 common types of Blur effects[3]:

1) Average Blur

The Average blur is one of several tools you can use to remove noise and specks in an image. Use it when noise is present over the entire image.

This type of blurring can be distribution in horizontal and vertical direction and can be circular averaging by radius R which is evaluated by the formula:

$R= \sqrt{g2} +f2$

Where: g is the horizontal size blurring direction and f is vertical blurring size direction and R is the radius size of the circular average blurring.

2) Gaussian Blur

The Gaussian Blur effect is a filter that blends a specific number of pixels incrementally, following a bell-shaped curve. The blurring is dense in the center and feathers at the edge. Apply Gaussian Blur to an image when you want more control over the Blur effect.

3) Motion Blur

The Motion Blur effect is a filter that makes the image appear to be moving by adding a blur in a specific direction. The motion can be controlled by angle or direction (0 to 360 degrees or –90 to +90) and/or by distance or intensity in pixels (0 to 999), based on the software used.

3. deblurring techniques

3.1 Wiener filters

The classic remedy is to employ Wiener filtering in the frequency domain, to remove those frequencies which would be dominated by noise. The Wiener filter is an optimal filter in the sense that it delivers the best estimate of the original, undegraded image in a least squares sense for additive Gaussian noise, i.e. it finds an estimate, $\hat{f}(x, y)$, of the uncorrupted image, f(x, y), such that the mean square error between them is minimized. This error measure is given by:[5]

$$e^2 = E\{(f(x,y) - \hat{f}(x,y))^2\} \tag{1}$$

where E{.} is the expected value of the argument. However, in order to realize the minimum mean square error estimate strictly the signal-to-noise ratio needs to be known precisely at every frequency:[5]

$$\hat{F}(u,v) = \left[\frac{1}{[H(u,v)]} \cdot \frac{[|H(u,v)|^2]}{[H(u,v)]+(|N(u,v)|^2/|F(u,v)|^2)]}\right]. G(u,v) \tag{2}$$

Where $|N(u,v)|^2$, $|F(u,v)|^2$ are the power spectra of the noise and the undegraded image, respectively , Fortunately, even crude approximations often work extremely well:[5]

$$\hat{F}(u,v) = \left[\frac{1}{[H(u,v)]} \cdot \frac{[|H(u,v)|^2]}{[|H(u,v)|^2+K]}\right].G(u,v) \tag{3}$$

$$\hat{F}(u,v)=\left[\frac{H^*(u,v)}{[|H(u,v)|^2+S_{nx}(u,v)]}\right].G(u,v) \tag{4}$$

Where $H(u,v)$: degradation function and $H^*(u,v)$: complex conjugate of $H(u,v)$, $\hat{F}(u,v)$: FFT for $\hat{f}(x, y)$, G(u,v) : FFT for $\hat{g}(x, y)$, $K=S_{nx}(u,v)$ is the inverse of the signal-to-noise ratio of the image averaged over all frequencies. More conveniently, K can be considered as an adjustable empirical parameter chosen to balance sharpness against noise.

3.1.a- algorithm of average blur

1 -input image i(r,c)

2 . input window size (k)

3. input s =k*k

4. calculate average blur psf = ones(k)./s

5.calculate the blur image from ib=i* psf

3.1.b-algorithm of wiener filter:

1. input image ib (r,c) which it is restore

2. input psf

3. . input specifying value nv where nv =noise variance

4 . calculate H= FFT(psf)

5. calculate the nv for image ib from the eq $var(Ib) = \sum \frac{Ib^2}{n} - \left(\sum \frac{Ib}{n}\right)^2$

Where n= r c size of image

6.calculate s_{nx}= nv/var(Ib)

3.2 Constrained Least Square Filtering(regularized):

The difficulties of the Wiener filter (computation of power spectrum of original image) and inverse filter (noise amplification) are overcome by constrained least square filter. Noise sensitivity problem is removed by using a smoothness measure for optimal restoration. The restoration is constrained by the parameters of the problem. The criterion function
C is minimized and is defined as,:[6]

$$C = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [\nabla^2 f(x,y)]^2 \quad (5)$$

subject to the constraint

$$\| g - \mathbf{H}\hat{f} \|^2 = \| \eta \|^2 \qquad (6)$$

where ‖x‖ is the Euclidean norm , $\hat{f}$ is the estimate of the true image, g is blur image, The solution of the above optimization problem is given as,[6]

$$\hat{F}(u,v) = \left[\frac{H^*(u,v)}{|H(u,v)|^2 + \alpha |Q(u,v)|}\right] .G(u,v) \qquad (7)$$

where parameter α is adjusted to satisfy the constraint defined in (6) and Q(u, v) is the Fourier transform of the Laplacian operator which is typically chosen as,

$$q(x,y) = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \qquad (8)$$

In this filtering, the value of α is selected manually to yield good results for high and medium noise conditions. Both filters produce almost equal results for low noise conditions. The constrained least square filter out performs Wiener filter when α is optimum. The parameter α is a scalar quantity whereas the value of K in Wiener filter is the ratio of two unknown quantities whose value is seldom constant.

3.2.a- algorithm of regularized filter:

1 -input image ib (r,c) which it is restore

2.input psf

3. input specifying value α

4. calculate H= FFT(psf)

5.compute regularized filter from eq(7)

6. compute IFFT for eq(7)

3.3 Iterative Lucy -Richardson Algorithm

The Lucy- Richardson 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 .The equation of the Lucy- Richardson algorithm is: [7,8].

$$f^{n+1} = f^{n} H^{*} (g/H f^{n}) \qquad (9)$$

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). the same Lucy- Richardson 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 Lucy-Richardson Algorithm. The equation of the optimized Lucy- Richardson algorithm can be described in the subsequent equation [9]:

$$f^{n+1} = f^{n} H \left(\frac{g}{Hfn}\right) \qquad (10)$$

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

3.3.a- algorithm of lucy-Richardson:

1 -input image ib (r,c) which it is restore

2.input psf

3. input specifying value (it) =[1,3,5,10,20,25]

4. . calculate H= FFT(psf)

5.compute Lucy- Richardson from eq(10)

6. compute IFFT for eq(10)

3.4 Non blind deconvolution Method

non blind deconvolution most popular method in this class., the method requires that the PSF be nonnegative with known finite support. The general method makes use of the fast-Fourier transform (FFT) algorithm. The capital letters represent fast-Fourier transformed versions of the corresponding signals. Subscripts denote the iteration number of the algorithm. After a random initial guess is made for the true image, the algorithm alternates between the image and Fourier domains, enforcing known constraints in each.[10]

$$\hat{F}(u,v) = \left[\frac{H^*(u,v)}{\frac{\alpha}{I^{(k-1)}(u,v))} + |H(u,v)|^2}\right] . G(u,v) \qquad (11)$$

where (.)* denotes the complex conjugate of (.). The real constant, α, represents the energy of the additive noise and is determined by prior knowledge of the noise contamination level, if available. The value of α must be chosen carefully for reliable restoration. The algorithm is run for a specified number of iterations, or until the estimates begin to converge.

3.4.a- algorithm of Non blind deconvolution :

1 -input image ib (r,c) which it is restore

2.input psf

3. input specifying value (α)

4. calculate H= FFT(psf)

5.compute Non blind deconvolution from eq(12)

6.compute IFFT for eq(12)

4.The proposed algorithm(Lucy based lightness enhancement)

It has been proposed a new algorithm to remove the blur of the image, where it was tested this method on a wide range of different types of standard images, results showed that the method works well compared with conventional Lucy algorithm, it is known that Lucy Richardson traditional (L-R method) are not reveal edge detection and a dim light image restored. Therefore, the proposed method is to reveal the edges by sobel operator and make clearer the image by using lightness enhancement histogram equalization (HE). This algorithm is implemented in several steps.

4.1 Sobel Operator

The Sobel edge detection masks look for edges in both the horizontal and vertical direction and then combine this information into single metric [11]. The Sobel operator performs a 2-D spatial gradient measurement on an image and so emphasizes regions of high spatial frequency that corresponds to edges. The operator consists of a pair of (3x3) convolution kernel.

W(I,j) =

1	2	1
0	0	0
-1	-2	-1

G_X

W(I,j) =

-1	0	1
-2	0	2
-1	0	1

G_Y

4.2 Histogram Equalization (HE)

the global technique that works well for a wide variety of images is histogram equalization(HE), If lightness levels are continuous quantities normalized to the range (0, 1), $p_r(r)$ which denote the probability density function (PDF) of the lightness levels in a given image, where the subscript is use for differentiating between the PDFs of the input and output images. Suppose that we perform the following transformation on the input levels to obtain output (processed) intensity levels [6],

$$s = T(r) = \int_0^r p_r(w)dw \tag{12}$$

Where w is a dummy variable of integration, that the probability density function of the output levels is uniform, that is[6]:

$$P_S(s)=\begin{cases}1 & for\ \ 0\le s\le 1\\ 0 & else\end{cases} \tag{13}$$

When dealing with discrete quantities we work with histograms and call the preceding technique histogram equalization, where [12]:

$$s_k=\sum_{j=0}^{k} p_r(r_j)=\sum_{j=o}^{k}\frac{n_j}{N} \qquad k=0,1,2,..L \tag{14}$$

L =255 for lightness band with 8 bit/pixel), s_k corresponding normalized intensity level of the output image and n_j being the number of pixel with intensity level j and n is the total number. The eq (14) is represent the cumulative probability density function (CPDF) . r_j is normalized intensity level of the input image corresponding to the (un –normalized) intensity level this algorithm summarized by using following steps:

4.a- algorithm of HE :

1.Input image C(n,m)
2. Normalize each component r_j= C(x,y)/ 255 and calculated frequency of occurrence each gradual level n_j , where j=0,1,..255 .
3. Compute histogram from $P(r_j)=n_j$ /N , where N being the size of image.
4. Calculate cumulative histogram by *:*

$$s_k=\sum_{j=0}^{k}\frac{n_j}{N} \qquad where\ k=0,1,..255\ .$$

5. Replace each normalized component r_j by value of s_k we get the output image

4.b- algorithm of this method:

1 -input image ib (r,c) which it is restore

2.input psf

3. input specifying value (it) =(1,3,5,10,20,25)

4. calculate H= FFT(psf)

5.compute Lucy- Richardson from eq(10)

6.compute IFFT for eq(10)

7.calculate the edge detection using sobel operator with constant value s=.9

8.calculate the HE for the image

5. Result and discussion

figure (1). shows the original image , where corrupted with the average blur with different value of the window size (k =7,9,11,13). Images were acquired described with fig.(2) Note that average blur lead to the distortion edge region , also when the window size large the distortion image large , and when we comparison the image distortion in fig.(2) with image restoration with wiener filter at the best parameter in fig.(3) observe the improvement in the appearance of images of all cases where in general, using Wiener filter lead to reduce the average blur of images that have been distorted . fig.(4) show restoration image with regularized filter at the best parameter where using regularized filter also lead to reduce the average blur of images that have been distorted but with less Structural Similarity Index Mean (SSIM) comparison with wiener filter ,while the fig.(5) show the result of using non blind deconvolution algorithm at the best parameter it was found that there is improvement of the image by the homogeneous regions and a lower rate in non homogeneous regions fig.(6) show the result of using Lucy- Richardson algorithm at the best parameter at Where we observe that there is improvement of the image distorted, but there is a distortion in the edge region, in fig.(7) we show result the adaptive L-R where observe enhancement in image blur, and fig.(8) Show the relationship between SSIM and window size(k) for standard method, When comparing the results in terms of standard quality SSIM it was found the Lucy- Richardson algorithm it's the best method, finally ,fig.(9) is show the suggested method and classic L-R algorithm

Figure (1). The original image

K = 7*7 K = 9*9 K = 11*11 K = 13*13

Fig(2). The group of images which corrupted with the average blur with different window size(k)

K = 7*7 K = 9*9 K = 11*11 K = 13*13

Fig(3). The group of images which restored with the wiener filter at the noise variance =10^3

K = 7*7 K = 9*9 K = 11*11 K = 13*13

Fig(4).the group of images which restored with the regularized filter at(it=10^4)

K = 7*7 K = 9*9 K = 11*11 K = 13*13

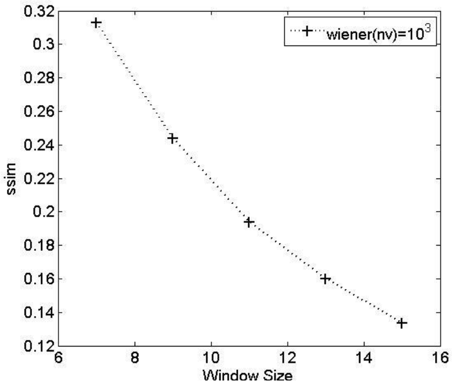
Fig(5). The group of images which restored with non blind deconvlution at (it=3)

K = 7*7 K = 9*9 K = 11*11 K = 13*13

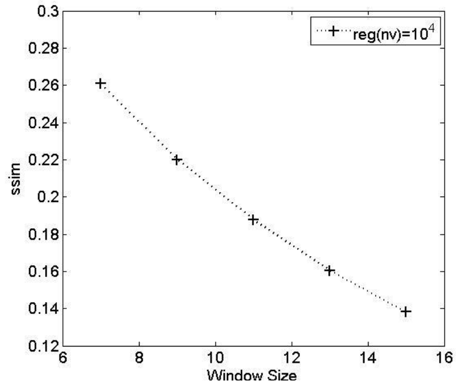
Fig(6).the group of images which restored with Lucy- Richardson at(it=1)

K = 7*7 K = 9*9 K = 11*11 K = 13*13

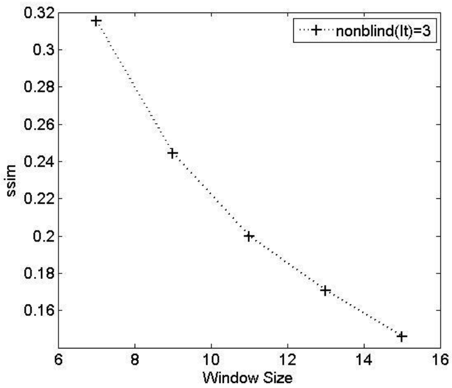
Fig(7).the group of images which restored with adaptive Lucy- Richardson at (it=20)



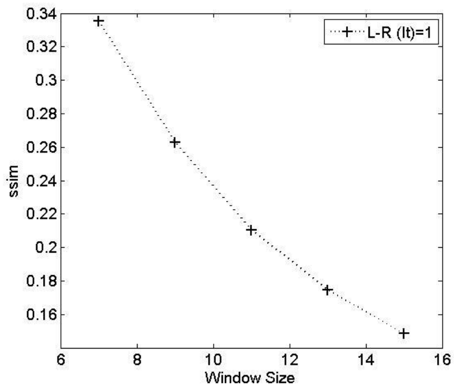
wiener filter (nv=10^3)



regularized filter (it=10^4)

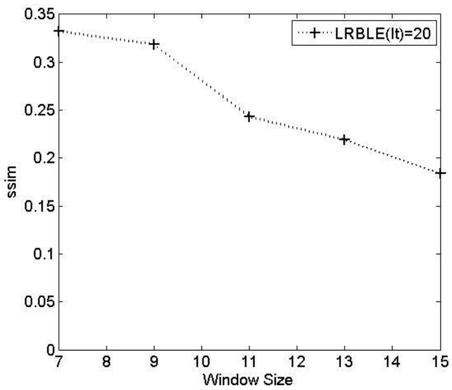


Non blind (it=3)

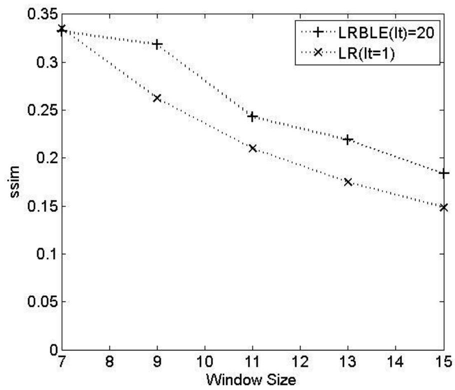


lucy algorithm (it=1)

Fig (8). Show the relationship between the standard quality SSIM and window size(k) for standard method



(a)



(b)

Fig (9). a.Show the relationship between the SSIM and window size(k) for proposed lucy algorithm , and b. comparison between the classic lucy and proposed lucy algorithm.

6.Conclusion

In this study We used the standard method (wiener filter, regularized filter, Lucy- Richardson algorithm, and non blind deconvolution) .it has been determined the best parameter to every method that have best image restoration ,well, the best parameter to wiener filter at noise variance ($nv=10^3$), the regularized filter at iteration ($it=10^4$), Lucy- Richardson algorithm at iteration(it=1), and non blind deconvolution at iteration(it=3).

It is concluded that the Lucy- Richardson algorithm the best method from the four method, also ,it is show the suggested method give best result compassion with the traditional Lucy- Richardson from were the standard quality SSIM was larger.

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